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Développement d'un Jumeau numérique d'une salle d'opération chirurgicale

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Abstract

Development of a Digital Twin for a Surgical Operating Room

This study aims to develop an IoT-based healthcare system for real-time ECG analysis and comprehensive patient monitoring, leveraging deep learning algorithms. The objectives are to create a system capable of accurately detecting ECG R-R peaks, classifying ECG signals into multiple disease categories, and integrating real-time data acquisition with a Digital Twin (DT) model for the surgical operating room.

The system utilizes IoT devices, including ECG sensors and Raspberry Pi microcontrollers, to capture patient vitals such as ECG, SpO2, and temperature. Two deep learning models, trained on the MIT-BIH dataset, are employed: one for R-R peak detection and the other for ECG signal classification. The system integrates with Node-RED for data transmission and visualization, using MQTT for secure communication between devices.

The models achieved an accuracy of approximately 99% in both peak detection and ECG classification. The real-time data processing system, operating with a response time of 55 to 164 ms, provides healthcare professionals with immediate insights into patient health, facilitating rapid decision-making and timely interventions.

The proposed system demonstrates the potential of combining IoT and deep learning technologies for accurate, real-time healthcare monitoring. The integration with Digital Twin technology opens new opportunities for enhancing surgical decision-making, patient safety, and operational efficiency in the operating room. The study sets the stage for future work focused on expanding system capabilities and addressing data security concerns in healthcare applications.

Keywords: AI, CNN, DL, DT, ECG, Healthcare, IoT, Node-RED, OR, Predictive Analytics, RNN, Surgery.

Résumé

Développement d’un Jumeau numérique d’une salle d’opération chirurgicale

Cette étude vise à développer un système de santé basé sur l'Internet des objets (IoT) pour l’analyse en temps réel de l’ECG et une surveillance complète des patients, en exploitant les algorithmes d’apprentissage profond. Les objectifs sont de concevoir un système capable de

détecter avec précision les pics R-R de l'ECG, de classer les signaux ECG en plusieurs catégories de maladies, et d'intégrer l'acquisition de données en temps réel avec un modèle de jumeau numérique (Digital Twin) pour la salle opératoire.

Le système utilise des dispositifs IoT, notamment des capteurs ECG et des microcontrôleurs Raspberry Pi, pour capter les constantes vitales du patient telles que l'ECG, la SpO2 et la température. Deux modèles d'apprentissage profond, entraînés sur la base de données MIT-BIH, sont utilisés : l'un pour la détection des pics R-R, l'autre pour la classification des signaux ECG. L'ensemble est intégré à Node-RED pour la transmission et la visualisation des données, en utilisant le protocole MQTT pour une communication sécurisée entre les dispositifs.

Les modèles ont atteint une précision d'environ 99 % pour la détection des pics et la classification ECG. Le système de traitement en temps réel, avec un temps de réponse variant entre 55 et 164 ms, fournit aux professionnels de santé des informations immédiates sur l'état du patient, facilitant ainsi des décisions rapides et des interventions opportunes.

Le système proposé démontre le potentiel de la combinaison entre l'IoT et l'apprentissage profond pour une surveillance médicale précise et en temps réel. L'intégration avec la technologie de jumeau numérique ouvre de nouvelles perspectives pour améliorer la prise de décision chirurgicale, la sécurité des patients et l'efficacité opérationnelle en salle d'opération. L'étude constitue une base pour des travaux futurs visant à étendre les fonctionnalités du système et à traiter les enjeux liés à la sécurité des données dans les applications médicales.

Mots clés: Analyse Prédictive, Chirurgie, CNN (Réseaux de Neurones Convolutifs), DL (Apprentissage Profond), DT (Jumeau Numérique), ECG (Électrocardiogramme), IA (Intelligence Artificielle), IoT (Internet des Objets), Node-RED, OR (Bloc Opératoire), RNN (Réseaux de Neurones Récurrents), Santé.

ملخص

تطوير توأم رقمي لغرفة عمليات جراحية

تهدف هذه الدراسة إلى تطوير نظام رعاية صحية يعتمد على تقنيات إنترنت الأشياء (IoT) لتحليل تخطيط القلب (ECG) في الوقت الحقيقي ومراقبة شاملة للمريض، مع الاستفادة من خوارزميات التعلم العميق. تشمل الأهداف تصميم نظام قادر على الكشف الدقيق عن قمم R-R في إشاراتECG ، وتصنيف هذه الإشارات ضمن فئات متعددة من الأمراض، ودمج جمع البيانات الفوري مع نموذج التوأم الرقمي (Digital Twin)لغرفة العمليات الجراحية.

يعتمد النظام على أجهزة IoT مثل مجسات ECG ووحدات Raspberry Pi لالتقاط المؤشرات الحيوية للمريض، بما في ذلكECG ، ومستوى الأوكسجين في الدم(SpO2) ، ودرجة الحرارة. تم تدريب نموذجين من التعلم العميق على مجموعة بيانات :MIT-BIH أحدهما لاكتشاف قممR-R ، والآخر لتصنيف إشارات ECG.كما تم دمج النظام مع منصة Node-RED لنقل البيانات وتصويرها، باستخدام بروتوكول MQTTلضمان التواصل الآمن بين الأجهزة.

حقق النموذجان دقة تقارب 99٪ في كل من اكتشاف القمم والتصنيف. يعمل النظام في الوقت الحقيقي بزمن استجابة يتراوح بين 55 و164 ميلي ثانية، ما يتيح للكوادر الطبية الاطلاع الفوري على حالة المريض، ويُسهم في اتخاذ قرارات سريعة وتدخلات دقيقة في الوقت المناسب.

يُظهر هذا النظام المقترح إمكانيات الدمج بين تقنيات إنترنت الأشياء والتعلم العميق في تقديم مراقبة صحية دقيقة وفورية. كما أن تكامل النظام مع تقنية التوأم الرقمي يفتح آفاقاً جديدة لتحسين القرارات الجراحية، وسلامة المرضى، وكفاءة العمل داخل غرفة العمليات. وتمهّد الدراسة الطريق لأعمال مستقبلية تهدف إلى توسيع قدرات النظام ومعالجة مخاوف الأمان المرتبطة بالبيانات في تطبيقات الرعاية الصحية.

كلمات مفتاحية: التحليلات التنبؤية، الجراحة، الشبكات العصبية التلافيفية، التعلم العميق، التوأم الرقمي، تخطيط القلب الكهربائي، الذكاء الاصطناعي، إنترنت الأشياء، غرف العمليات، الشبكات العصبية المتكررة، الرعاية الصحية، نود راد.

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Table of Contents

Acknowledgment .....

Abstract 4

Résumé 4

List of publication and communication 7

Table of Contents 8

List of Figures 12

List of Tables 14

List of Acronyms 15

General introduction

I.1 Problematic Statement 2

I.2 Motivation 2

I.3 Contribution 3

I.3.1 Development of an IoT-Driven Healthcare System 4

I.3.2 Integration of DL Algorithms for Predictive Analytics 4

I.3.3 Addressing Data Privacy and Security Challenges 4

I.4 Organization of the Manuscript 4

Medical Concepts and Key Parameters for Healthcare Monitoring

II.1 Introduction 6

II.2 Introduction to the Operating Room 7

II.2.1 Operating Room Infrastructure 7

II.2.2 Medical Devices in the Operating Room 9

II.2.3 Utility Systems 10

II.3 Electrocardiogram (ECG) 11

II.3.1 Definition 11

II.3.2 Function 11

II.3.3 Waves and Intervals of the ECG 12

II.3.4 Importance in Health Monitoring 13

II.4 Cardiovascular System 14

II.4.1 Definition 14

II.5 Relevance to Healthcare Monitoring 15

II.6 Blood Oxygen Saturation (SpO_2) 16

II.6.1 Definition 16

II.6.2 Measurement and Significance 17
II.7 Heart Rate 18
II.7.1 Definition 18
II.7.2 Normal Ranges and Variability 18
II.7.3 Significance in Health Monitoring 19
II.8 Blood Pressure 20
II.8.1 Definition: 20
II.8.2 Monitoring and Clinical Importance 20
II.9 Respiratory Rate 22
II.9.1 Definition 22
II.9.2 Measurement in Healthcare Systems 22
II.10 Conclusion 23

Digital Twin, IoT, and Deep Learning: Foundational Concepts and Integrative Perspectives

III.1 Introduction 24
III.2 Digital Twin 24
III.2.1 Definition 24
III.2.2 Development and History of DT 25
III.2.3 State of the Art of DT 26
III.2.4 DT in Manufacturing 27
III.2.5 DT in City Management 28
III.2.6 DT in Aerospace 28
III.2.7 DT in Healthcare 28
III.3 Internet of Things 38
III.3.1 Definitions 38
III.3.2 Development and History of IoT 38
III.3.3 Applications of IoT 40
III.4 Deep Learning 42
III.4.1 DL Definitions 42
III.4.2 Development and History of DL 43
III.4.3 DL Architectures 44
III.4.4 DL Challenges and Limitations 47
III.4.5 Recent Advances in DL 49
III.5 Hardware and Software Tools 50
III.5.1 Hardware Used 51
III.5.2 Software Used 59
III.5.3 Node-RED Server 63

III.6 conclusion 70

A Concept of Operation Room Digital Twin

IV.1 Introduction 71
IV.2 Types of Surgical Instruments and Their Role in the Operating Room 72
IV.2.1 Surgical Lighting 72
IV.2.2 Medical Gases and Their Role in Surgery 73
IV.2.3 System Integration in the DT 77
IV.3 Medical instruments 78
IV.3.1 Anesthesia Machines 78
IV.3.2 Patient Monitoring Systems 79
IV.3.3 Infusion Pumps 79
IV.3.4 Electrosurgical Units (ESUs) 80
IV.3.5 Imaging Systems (X-rays, MRI, CT Scanners) 81
IV.3.6 Surgical Robots in a DT System 81
IV.3.7 Surgical Microscopes 83
IV.3.8 Patient Monitoring via Cameras 83
IV.4 Communication 86
IV.4.1 Direct Communication Systems 86
IV.4.2 Indirect Communication Systems (with Controllers) 87
IV.4.3 Hybrid Communication Systems 88
IV.5 The proposed Digital Twin 88
IV.6 Conclusion 89

The Proposed Framework: Integrating IoT and Deep Learning for Healthcare Systems

V.1 Introduction 90
V.1.1 Objectives 91
V.1.2 Challenges and Solutions 91
V.2 System Architecture 92
V.2.1 Data Transmission 93
V.2.2 Data analysis and visualization 93
V.2.3 Integrated User Interface with Local and Remote Access 94
V.2.4 System Architecture and Workflow Integration 94
V.3 DL Models 95
V.3.1 DL model for ECG peak detection 95
V.3.2 DL model for ECG classification 100
V.4 Embedded health monitoring system setup 109
V.4.1 IoT Architecture 111

V.4.2 Models integrated into Node-Red 112
V.4.3 Visualization 116
V.4.4 Final Node-RED dashboard 119
V.5 Performance Evaluation 120
V.5.1 Response Time Estimation for Real-Time ECG Monitoring 120
V.5.2 Comparison with our result and related work 120
V.6 Conclusion 121
General Conclusion and Perspectives
VI.1 General Conclusion 123
VI.2 Perspectives 124
Bibliography 126

List of Figures

Figure II.1 The operating room 7
Figure II.2 Electrode Leads Placement for ECG 11
Figure II.3 ECG Waves and Intervals 12
Figure II.4 Cardiovascular system 14
Figure II.5 Blood oxygen saturation percentage signification 17

Figure III.1 Technologies & tools of DT for healthcare sector 29
Figure III.2 DT Health modeling process 32
Figure III.3 Digital twin elements 34
Figure III.4 Digital twin features Capabilities 35
Figure III.5 Health modeling process 37
Figure III.6 Application scenarios of the IoT 41
Figure III.7 The relation Between AI,ML &DL 42
Figure III.8 Feedforward Neural Networks 44
Figure III.9 Convolutional Neural Networks example 45
Figure III.10 Recurrent Neural Networks architecture 46
Figure III.11 Self-Supervised Learning 49
Figure III.12 Transfer learning diagram 50
Figure III.13 Edge of AI 50
Figure III.14 The health monitoring system tools 51
Figure III.15 Raspberry Pi 4B presentation 52
Figure III.16 Raspberry Pi 4 B Pinout 53
Figure III.17 ESP32 54
Figure III.18 ECG sensor AD8232 55
Figure III.19 MAX3010A SpO2 Sensor 56
Figure III. 20 Human Body Temperature Sensor 56
Figure III.21 Temperature and Humidity sensor DHT11 57
Figure III.22 Analog to Digital Converter ADS1115 57
Figure III.23 Oled Display 58
Figure III. 24 Lithium Battery EB615268VU 59
Figure III.25 google colab platform 61
Figure III.26 Arduino IDE platform 63
Figure III.27 Node-red editor 64
Figure III.28 Node-red palette 66
Figure III.29 Some Available Nodes in Node-RED Editor 68
Figure III.30 Node-RED Dashboard 69

Figure IV.1 real operation room from Medea Hospital 72
Figure IV.2 Surgical Lighting System 73
Figure IV.3 Lighting Sensors and Control in DT 73
Figure IV.4 gases distribution in hospital 74
Figure IV.5 Anesthesia machine 78
Figure IV.6 Infusion pumps 80
Figure IV. 7 Electrosurgical Units (ESUs) 80
Figure IV.8 operation room DT 89

Figure V.1 System setup Architecture presentation 92
Figure V.2 Dataset distribution of the peak counts 96
Figure V.3 Dataset presentation with Peak Marker 96
Figure V.4 peak detection model architecture 98
Figure V.5 Test and Validation Loss Over Training Epochs for the Peak Detection Model .. 99
Figure V.6 Graphical presentation of Dataset class distribution 103
Figure V.7 t-SNE and PCA visualization 104
Figure V.8 ROC curve for the multi-class classification 104
Figure V.9 Presentation of Dataset Classes in the ECG signal 105
Figure V.10 classification model architecture 106
Figure V.11 classification model result 108
Figure V.12 Confusion matrix validation 109
Figure V.13 Hardware implementation of the Health Monitoring System 110
Figure V.14 Node-RED DL models integration 113
Figure V.15 Node-RED sensors integration 114
Figure V.16 Node-RED patient alert 115
Figure V.17 Node-RED login interface 116
Figure V.18 Node-RED display block 116
Figure V.19 Final Dashboard Presentation 120

List of Tables

Table III.1 IoT Key Milestones and Developments 39
Table III.2 measures evaluation 48

Table IV.1 The main medical fluids, their chemical code, their color and their pressure 75
Table IV.2 key elements of patient and medical staff monitoring within the DT system..... 85

Table V.1 Comparison of our result and related work 121

List of Acronyms

AI	Artificial Intelligence
CNN	Convolution Neural Network
COPD	Chronic obstructive pulmonary disease
CVDs	Cardiovascular diseases
CT	Computed Tomography
DL	Deep Learning
DT	Digital Twin
DTS	Digital Twins
ECG	Electrocardiogram
EHRs	Electronic health records
ESUs	Electrosurgical Units
FNNs	Feedforward Neural Networks
HR	Heart rate
HRV	Heart rate variability
IoT	Internet of Things
ML	Machine Learning
MRI	Magnetic Resonance Imaging
RNN	Recurrent Neural Network

Chapter I

General introduction

Cardiovascular diseases and critical health conditions remain among the leading causes of mortality worldwide, underscoring the urgent need for intelligent and responsive healthcare systems. In high-stakes environments such as surgical rooms, intensive care units, and emergency departments, the ability to monitor patient vitals in real time, anticipate complications, and support rapid clinical decisions can significantly influence patient outcomes[1][2].

Recent technological advancements have opened new pathways for transforming conventional healthcare practices. Among these innovations, the Internet of Things (IoT) plays a pivotal role by enabling real-time data acquisition through a network of interconnected medical sensors and devices. These systems gather continuous streams of physiological and environmental data, such as ECG signals, temperature, oxygen saturation, and equipment status, and transmit them for real-time analysis[3][4][5].

Simultaneously, Digital Twin (DT) technology has gained attention for its capacity to create real-time, virtual replicas of physical systems. Initially adopted in aerospace and manufacturing, DT technology is increasingly being explored in healthcare for simulating patient conditions, medical equipment behavior, and surgical environments[6][7].

By integrating real-time sensor data, DTs enable healthcare providers to simulate, monitor, and predict clinical events with high precision[8][9]. This capability is particularly relevant in environments such as the operating room, where rapid and informed decision-making is critical. The emergence of Artificial Intelligence (AI), especially Deep Learning (DL), further enhances these systems by enabling automatic detection, classification, and prediction from complex medical data streams. DL models have shown significant promise in various diagnostic tasks, including ECG signal interpretation, anomaly detection, and disease prediction[10][11][12]. These models contribute to improving the accuracy and efficiency of medical systems by providing timely insights that can support critical clinical decisions.

The convergence of IoT, DT, and DL offers a powerful framework for building intelligent, real-time, and patient-centered healthcare solutions. However, challenges remain, including the need for robust data integration, real-time processing, system interoperability, and stringent

data privacy and security measures[13][14]. This research aims to address these challenges by developing an integrated system that combines these technologies to improve real-time ECG analysis and patient monitoring in the operating room.

I.1 Problematic Statement

The surgical room is a highly critical and dynamic environment where real-time data collection, processing, and intelligent decision-making are essential for ensuring patient safety and improving outcomes. Despite advances in medical equipment, many surgical environments still lack the infrastructure to seamlessly integrate and process heterogeneous data sources, including vital signs, medical imaging, environmental parameters, and device statuses.

The IoT provides a promising foundation to address these challenges by enabling continuous, real-time data acquisition through interconnected sensors and devices. However, the potential of IoT in surgical settings remains underutilized, particularly in terms of integrating AI models for predictive analytics and creating synchronized virtual representations of the operating room and patient.

This research addresses this gap by proposing an IoT-driven architecture that not only facilitates robust data collection and communication but also integrates DL models for anomaly detection and DT technology for real-time visualization and simulation. The goal is to create an intelligent, modular, and scalable system capable of enhancing clinical decision-making, reducing response time during emergencies, and improving overall operational efficiency in surgical rooms.

I.2 Motivation

In modern healthcare, particularly in the operating room, the need for more effective and efficient methods of monitoring and decision-making has never been more critical. As surgical procedures become more complex and patient conditions increasingly intricate, the ability to monitor vital parameters and anticipate complications in real time is essential. Traditional methods of monitoring and diagnosis can often be slow, manual, and prone to human error, which can lead to delayed interventions or suboptimal care during critical moments. This research seeks to address these issues by proposing a system that enhances real-time clinical decision-making through innovative technological integration.

The primary motivation behind this study is to harness real-time data analysis for improved patient outcomes during surgery. The collection and interpretation of continuous patient data can significantly reduce response times and improve the accuracy of clinical decisions. By utilizing advanced data processing capabilities, the research aims to provide healthcare providers with immediate access to accurate and actionable insights, enabling faster, better-informed decisions during surgeries.

Furthermore, the growing complexity of surgical procedures calls for a dynamic and adaptive system capable of integrating and analyzing a variety of patient and environmental data simultaneously. This research is motivated by the idea of creating a system that not only provides real-time data but also utilizes predictive analytics to anticipate patient needs and potential complications before they arise. In environments like operating rooms, where split-second decisions can mean the difference between life and death, the ability to forecast risks based on current data is invaluable.

Another key motivation is to explore the potential for seamless integration of various data streams into a cohesive and efficient system. While many modern systems focus on individual components of patient monitoring, this research seeks to connect multiple data sources—such as ECG readings, patient vitals, and surgical tool data—into a unified framework that allows for intelligent real-time analysis. By making these data streams more interconnected, this research proposes a more holistic approach to patient care, where each piece of information contributes to a larger, real-time decision-making process.

Finally, this study is motivated by the vision of a new era of precision surgery, where medical interventions are guided not just by static data but by continuously updated, real-time models of both the patient and the surgical environment. By implementing technologies that simulate patient conditions and surgical outcomes, the system proposed in this research aims to empower surgeons to not only observe patient data but also to simulate various surgical scenarios and predict outcomes. This can drastically reduce uncertainty and improve surgical precision, ultimately leading to safer and more effective surgeries.

I.3 Contribution

This work makes significant contributions to the field of IoT-driven healthcare technology with a focus on the integration of real-time data systems and predictive models in surgical settings. The contributions include:

- Development of an IoT-driven healthcare system for continuous monitoring of surgical environments using diverse sensors.

- Integration of deep learning algorithms to process and analyze the collected data, enabling real-time decision-making.

- Establishing the connection between the IoT-based healthcare system and the Digital Twin (DT) framework, enabling real-time data integration and visualization for the surgical operating room. This connection provides the foundation for the creation of a dynamic, fully functional Digital Twin that enhances decision-making and operational efficiency during surgeries.

I.3.1 Development of an IoT-Driven Healthcare System

A robust framework that utilizes IoT-enabled devices to create a dynamic, real-time model of the surgical environment. The framework ensures seamless integration of various data sources, facilitating real-time operation of DTs without latency or data loss, offering an accurate and up-to-date representation of health parameters.

I.3.2 Integration of DL Algorithms for Predictive Analytics

DL models are used to enhance the predictive power of the DT, offering real-time recommendations and alerts during surgical procedures. These models process large datasets, including patient history and real-time intraoperative data, to optimize surgical decision-making.

I.3.3 Addressing Data Privacy and Security Challenges

Exploring the connection between IoT-driven systems and Digital Twin (DT) technology within surgical operating rooms, emphasizing the critical role of secure real-time data integration. It addresses the necessary technical and operational frameworks to ensure the smooth interaction of IoT devices with the DT, facilitating continuous monitoring and predictive analytics.

I.4 Organization of the Manuscript

The manuscript is organized into several chapters that systematically explore the development and implementation of a healthcare IoT-driven system. After this comprehensive general

introduction, Chapter II provides an overview of medical concepts and vital healthcare monitoring parameters. It discusses essential physiological metrics, such as heart rate, blood oxygen saturation, and ECG readings, emphasizing their significance in real-time health monitoring.

In Chapter III, the focus shifts to a detailed review of the fundamental technologies, including Digital Twin (DT), the Internet of Things (IoT), and Deep Learning (DL). This chapter presents their definitions, historical development, and state-of-the-art applications, particularly in healthcare.

Chapter IV highlights the conceptual design and implementation of the Digital Twin for the surgical operating room. It explores the integration of medical instruments, communication systems, and the role of environmental monitoring within the DT framework.

In Chapter V, the manuscript delves into the IoT-driven system and its integration with DL techniques. This chapter describes the hardware and software tools used, such as Raspberry Pi, ECG sensors, Node-RED, and DL algorithms. It also includes system architecture, performance evaluation, and a discussion of the results.

Finally, in Chapter VI, the manuscript concludes by summarizing the contributions and findings of the research. It also outlines future perspectives, including potential advancements in AI-driven predictive models and the expansion of Digital Twin applications in healthcare.

Chapter II

Medical Concepts and Key Parameters for Healthcare Monitoring

II.1 Introduction

In modern healthcare, surgical operating rooms (ORs) are critical environments where precision, efficiency, and safety are paramount. These highly specialized spaces integrate advanced technologies and systems to support complex medical procedures. A deep understanding of their infrastructure, operational workflows, and the vital physiological parameters monitored during surgeries is essential for accurate diagnosis, effective monitoring, and timely treatment.

Operating rooms are equipped with interconnected systems, including surgical instruments, anesthesia machines, lighting systems, and patient monitoring devices. These components work together to ensure optimal conditions for both the medical team and the patient. Monitoring systems, in particular, play a crucial role in tracking vital signs like heart rate, blood pressure, and oxygen saturation, providing real-time feedback that guides critical decisions during surgery.

As technology continues to evolve, the integration of the Internet of Things (IoT) and Artificial Intelligence (AI) has transformed healthcare monitoring. IoT-enabled devices now capture and transmit real-time medical data, while AI-driven analytics provide actionable insights to enhance patient care. These advancements are especially impactful in surgical environments, where they enable continuous monitoring, early anomaly detection, and improved surgical outcomes.

This chapter begins with a comprehensive overview of surgical operating rooms, detailing their infrastructure and monitoring systems. It then explores essential medical parameters such as the Electrocardiogram (ECG), blood oxygen saturation (SpO2), heart rate (HR), respiratory rate, blood pressure, and body temperature. These parameters are central to understanding patient health and are closely monitored in IoT-based systems for real-time feedback and preventive care. [18][19]

By establishing the context of the operating room and its monitoring systems, this chapter lays the groundwork for understanding the integration of IoT, AI, and Digital Twin (DT) technologies in healthcare. These technologies collectively enable smarter, more efficient monitoring solutions that enhance patient safety and improve clinical outcomes.

II.2 Introduction to the Operating Room

The operating room (OR) is a highly specialized and controlled environment designed for performing surgical procedures with utmost precision, safety, and efficiency. It is equipped with advanced medical devices and technologies, meticulously designed infrastructure, and a multidisciplinary team of professionals, including surgeons, anesthesiologists, nurses, and clinical engineers. This space serves as the epicenter of invasive medical care within a healthcare facility[20].

The operating room (Figure II.1) is integral to ensuring positive surgical outcomes. It balances the complex interplay of technology, infrastructure, and human expertise, all orchestrated to provide high-quality patient care. A successful OR environment not only relies on cutting-edge devices but also on adherence to strict safety, asepsis, and workflow protocols[21].



Figure II.1 The operating room

II.2.1 Operating Room Infrastructure

1. Facility Layout and Design

Operating rooms are part of a larger surgical suite comprising preparation areas, recovery spaces, and sterilization units. These suites are designed to optimize workflow and maintain

sterility. A standard OR is typically at least 400 square feet in size, with larger rooms accommodating specialized equipment or complex surgeries. Common layouts include square, rectangular, and circular designs, all aimed at minimizing movement and enhancing accessibility.

The central placement of the surgical table allows the surgical team to perform efficiently, with the anesthesiologist and equipment located at the head of the table. Nearby, scrub nurses have access to sterile instrument tables, and other devices like defibrillators, electrosurgical units, and bypass machines are placed outside the immediate sterile field [22].

2. Environmental Control

The operating room environment is tightly regulated through advanced Heating, Ventilation, and Air Conditioning (HVAC) systems to maintain optimal airflow, temperature, and humidity. Critical requirements include:

- Temperature control: Adjustable between 72°F to 78°F to suit specific procedures, such as pediatric surgeries or burn treatments.
- Humidity levels: Maintained at 55-60% to reduce risks of static discharge and ensure patient safety.
- Air changes: At least 15 air changes per hour, with three involving fresh air, ensure a sterile environment.
- Positive pressure: Prevents inflow of contaminated air, critical in reducing surgical site infections.
- HEPA filtration: Filters out contaminants like pollen, viruses, and dust, ensuring microbiological air quality.

3. Electrical Systems

ORs house numerous electrically powered devices, necessitating robust and safe electrical power distribution systems. Key features include:

- Dual power sources: A primary public utility line and a backup generator for uninterrupted operations.
- Isolated ungrounded power systems: Minimize leakage currents in wet environments.
- Ground-Fault Circuit Interrupters (GFCIs): Protect against electrical shocks.
- Explosion-proof outlets: Historically used due to volatile anesthetic gases but remain relevant for safety.
- Conductive flooring: Prevents static buildup and discharge.

II.2.2 Medical Devices in the Operating Room

1.Anesthesia Equipment

Anesthesia machines are pivotal for managing patient consciousness and pain during surgery. They deliver medications, oxygen, and other gases like nitrous oxide and sevoflurane. Key components include :

- Ventilators: Ensure effective breathing for immobilized patients.
- Capnography systems: Monitor expired CO2 levels for gas exchange efficiency.
- EEG-based anesthesia monitors: Quantify sedation depth on a scale of 0 to 100.

2. Surgical Instruments and Technology

Electrosurgical Units (ESUs): Use electrical waveforms to cut tissue and coagulate blood vessels. These devices operate in monopolar or bipolar modes and require smoke evacuation systems for safety[23][24].

- Laser Systems: Such as carbon dioxide (CO2), Nd:YAG, and argon lasers, enable precise tissue modification.
- Minimally Invasive Tools: Including laparoscopes and endoscopes, enable procedures through small incisions, reducing recovery times.
- Surgical Microscopes: Binocular systems for enhanced visualization of fine structures.

3. Imaging and Robotics

Modern ORs often integrate imaging technologies and robotic systems:

- Imaging tools: Real-time visualization, including X-rays and ultrasound, enhance surgical precision.
- Robotic systems: Controlled by surgeons, these devices offer refined and minimally invasive interventions, crucial for complex surgeries.

4. Thermal Regulation Devices

Maintaining patient body temperature is critical. Technologies include:

- Blanket warmers: Circulate warm air for patient comfort.

- IV fluid warmers: Ensure body-temperature fluid administration.
- Radiant warmers: Mounted overhead for targeted heating.

II.2.3 Utility Systems

1. Gas Pipelines

Medical gases, including oxygen, nitrous oxide, and compressed air, are supplied through centralized systems to wall outlets in the OR. These gases are essential for anesthesia and powering pneumatic surgical tools. Backup systems ensure continuous supply[23].

2. Central Vacuum Systems

Vacuum systems support suctioning during surgery and the evacuation of waste gases. Dual pumps provide redundancy to meet demand.

3. Lighting

Specialized surgical lighting ensures shadow-free illumination for precision. Key features include adjustable intensity, minimal heat production, and maneuverable mounting.

4. Communication Systems

Advanced communication tools, such as intercoms, pagers, and integrated computer systems,

5. Safety Measures

Ensuring safety in the OR is paramount. This involves:

- Fire protection systems: Smoke detectors, sprinklers, and fire-resistant materials minimize risks associated with oxygen-enriched environments and flammable substances.
- Aseptic protocols: Strict adherence to hygiene practices prevents infection.
- Clinical engineering support: Routine maintenance of devices and adherence to safety standards ensure reliable operations.

II.3 Electrocardiogram (ECG)

II.3.1 Definition

An ECG is a medical test that records the heart's electrical activity to assess the heart's health and detect any abnormalities. This diagnostic tool is invaluable in identifying irregularities such as arrhythmias, ischemic heart disease, and myocardial infarction (heart attack). The ECG has been an essential component of cardiovascular diagnostics for decades and remains one of the most widely used tools in clinical cardiology. In addition to its diagnostic role, ECGs are increasingly being used in preventive care, particularly in remote monitoring and IoT-enabled healthcare systems[25].

The ECG test is non-invasive, painless, and quick, making it suitable for both emergency settings and routine examinations. Electrodes are placed on the skin at specific locations to measure the heart's electrical activity, which is then displayed as a series of waveforms on an ECG monitor. These waveforms provide insight into the heart's rhythm, rate, and electrical conduction pathways, offering clues to potential health issues even before symptoms arise. The widespread use of ECGs has made it a standard in clinical settings for detecting heart-related disorders [26].

II.3.2 Function

The function of an ECG is to capture the heart's electrical activity, which results from the depolarization and repolarization of heart muscles during each heartbeat. As the heart pumps, it generates electrical impulses that spread through the heart's chambers. These impulses are detected by the electrodes placed on the patient's chest arms, and legs as in Figure II.2. The electrical activity is then graphically represented on an ECG strip as a waveform that consists of several components, each representing a specific phase of the heart's activity[18]

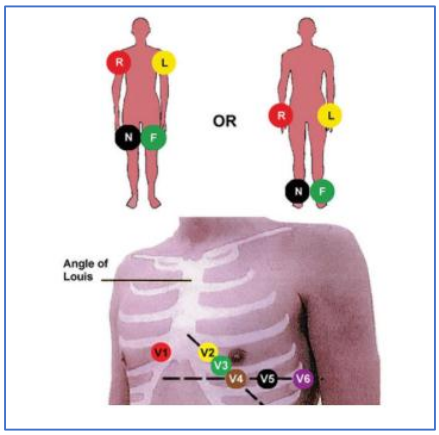


Figure II.2 Electrode Leads Placement for ECG

The P wave represents atrial depolarization, which precedes the contraction of the heart's upper chambers. The QRS complex reflects ventricular depolarization, marking the contraction of the heart's lower chambers, and is the most prominent part of the waveform. The T wave indicates ventricular repolarization as the heart's muscles prepare for the next beat. Abnormalities in any of these components can indicate a variety of cardiovascular conditions, from arrhythmias to ischemia [19][27].

ECG machines utilize sophisticated algorithms to analyze and interpret the waveform, delivering immediate feedback to healthcare providers. Recent developments in wearable technology have facilitated continuous, real-time ECG monitoring via portable devices that can wirelessly transmit data to medical professionals. These wearable devices enable long-term heart monitoring beyond traditional clinical environments, which is instrumental in the early detection of cardiovascular conditions and enhances patient outcomes[28]

II.3.3 Waves and Intervals of the ECG

The recorded trace, called an ECG , presents a characteristic appearance; its distortions indicate abnormalities in cardiac function[29]. Any interpretation of the ECG refers to the shape and width characteristics of the normal ECG signal waveform presented in *Figure II.3*.

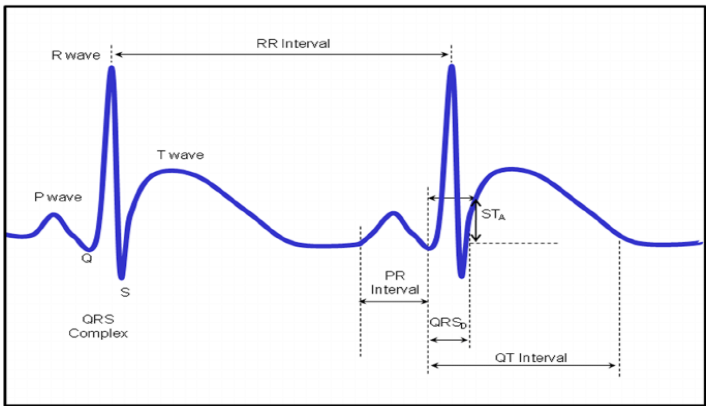


Figure II.3 ECG Waves and Intervals

- **P Wave:** It corresponds to the depolarization of the atria from the sinus node to the atrioventricular node. It can be positive or negative, with a duration of approximately 90 ms. This is the wave that precedes the QRS complex, and it is generally difficult to observe on the ECG, especially in noisy conditions.
- **QRS Complex:** It corresponds to the ventricular depolarization preceding the mechanical contraction effect. It has the highest amplitude of the ECG signal and is composed of three attached waves that follow the P wave: the first is the Q wave, which is negative in amplitude, followed by the R wave, which is positive in a normal ECG, and finally the S

wave, which is negative. The normal duration of the QRS complex is between 85 and 95 ms.

- **T Wave:** This wave corresponds to the repolarization of the ventricles. It can be positive, negative, or biphasic. The T wave follows the QRS complex after returning to the isoelectric line (except in specific pathologies). Its amplitude is smaller than that of the QRS complex.
- **PR Interval:** The PR interval has a duration between 0.14 and 0.2 seconds, measured between the beginning of the P wave and the beginning of the QRS complex, representing the duration between the depolarization of the atria and the AV node. This time corresponds to the time needed for an electrical impulse to pass from the sinus node to the ventricles. It is used to detect arrhythmia and heart rate variability (HRV).
- **ST Segment:** Also known as the duration of complete ventricular stimulation. It corresponds to the interval during which the ventricles remain in an active depolarized state. This is the time between the end of the S wave and the beginning of the T wave.
- **PQ Interval:** This is the time interval between the onset of atrial depolarization and ventricular depolarization. It represents the propagation time of the electrical impulse from the sinus node to the ventricles. It is measured between the beginning of the P wave and the start of the QRS complex.
- **QT Interval:** This interval corresponds to the time of ventricular systole, from the beginning of ventricular excitation to the end of their relaxation. It is measured as the time between the start of the QRS complex and the end of the T wave.

II.3.4 Importance in Health Monitoring

The significance of ECG in health monitoring cannot be overstated, particularly in the realm of IoT-based healthcare systems. Traditionally, ECGs were performed in hospitals or clinics, but the rise of wearable ECG devices and IoT technology has revolutionized the way we monitor cardiovascular health. These devices can continuously track heart rhythms in real-time, transmitting the data to cloud platforms for further analysis. In the event of an abnormal reading, such as arrhythmias, alerts can be sent to healthcare providers, allowing for timely interventions[26] .

One of the primary benefits of continuous ECG monitoring is the early detection of arrhythmias such as atrial fibrillation or ventricular tachycardia, which are often asymptomatic but can lead to serious complications if left untreated. Real-time monitoring also provides valuable insights into HRV, a parameter linked to the autonomic nervous system and an important indicator of overall heart health. Additionally, ECG monitoring is critical for patients with chronic

conditions like congestive heart failure and those recovering from a heart attack, enabling clinicians to monitor their recovery and detect any signs of deterioration. [28]

Moreover, the integration of AI and DL in ECG analysis is accelerating the ability to detect subtle heart anomalies that might be missed by traditional methods. AI-powered systems can analyze large datasets, such as those available from platforms like PhysioNet, identifying patterns that indicate early stages of disease or helping to differentiate between benign and serious conditions[26] .This capability, combined with the real-time data provided by IoT devices, represents a significant advancement in cardiovascular care, moving us toward a future of proactive and personalized healthcare.

II.4 Cardiovascular System

II.4.1 Definition

The cardiovascular system is a complex network responsible for the circulation of blood, nutrients, gases, hormones, and metabolic waste products throughout the body as in Figure II.4. Comprising the heart, blood vessels (arteries, veins, and capillaries), and blood, the cardiovascular system plays a central role in maintaining homeostasis and ensuring the proper function of bodily tissues. The heart functions as a pump, propelling oxygen-rich blood through arteries to tissues and organs, while veins return deoxygenated blood to the heart, where it is sent to the lungs for oxygenation [25].

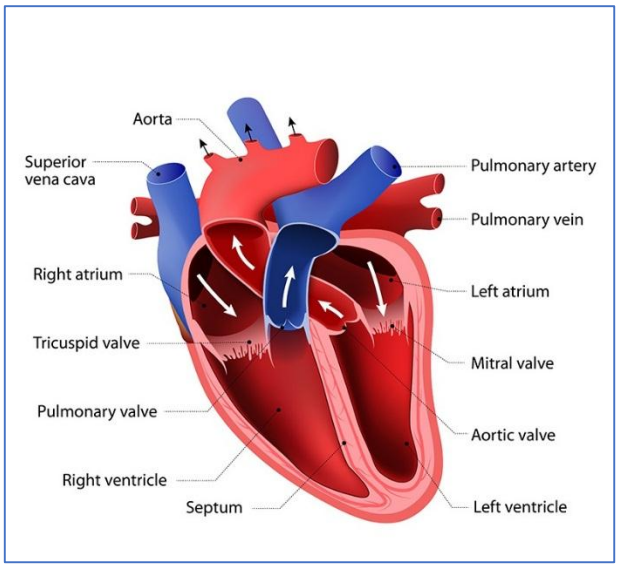


Figure II.4 Cardiovascular system

The system is essential not only for sustaining life but also for adapting to changing physiological demands, such as during exercise or periods of stress [30].

At the core of this system is the heart, a muscular organ divided into four chambers (two atria and two ventricles), which work in concert to pump blood. Electrical signals trigger the contraction and relaxation of heart muscles, resulting in rhythmic heartbeats that propel blood through the circulatory system. Blood vessels serve as conduits for this blood flow, with arteries carrying oxygenated blood away from the heart, and veins returning deoxygenated blood to the heart. The smallest vessels, capillaries, facilitate the exchange of gases, nutrients, and waste products between blood and tissues[31][29]. Together, these components form a dynamic system that is crucial for transporting essential substances and maintaining the body's internal environment.

II.5 Relevance to Healthcare Monitoring

Cardiovascular health is one of the most critical metrics in healthcare, particularly in the context of IoT-based health monitoring systems. Monitoring cardiovascular function provides essential insights into a person’s overall health status, with cardiovascular diseases (CVDs) such as coronary artery disease, hypertension, and heart failure representing some of the leading causes of morbidity and mortality globally[32]. Given the rising prevalence of CVDs, early detection and continuous monitoring have become essential components of healthcare, particularly with the emergence of connected technologies such as the IoT and wearable devices. These advancements enable real-time health monitoring, facilitating timely interventions and improving patient outcomes [33].

IoT-enabled healthcare systems, which integrate real-time monitoring devices and data analytics, are transforming cardiovascular care. These systems rely on sensors that capture critical health parameters, such as HR, blood pressure, and ECG readings, providing a continuous stream of data to healthcare providers. For example, wearable devices that measure HR and detect abnormalities in heart rhythms are now widely available and used to monitor patients with conditions such as arrhythmias, hypertension, and heart failure[26] . This real-time data can be transmitted to cloud platforms, where it is analyzed by AI algorithms to detect early signs of cardiovascular disease and generate actionable insights for healthcare providers [34].

In addition to real-time monitoring, cardiovascular data is crucial for developing DT models in healthcare. A DT of a patient's cardiovascular system can be created using data collected from wearable devices and medical records. These models allow healthcare providers to simulate various scenarios and predict how a patient's heart might respond to different treatments or

interventions. This approach enhances personalized medicine by providing tailored treatment plans that account for an individual's unique physiological characteristics [35] Furthermore, these systems enable remote patient monitoring, reducing the need for frequent hospital visits and allowing for continuous care outside clinical settings.

The role of cardiovascular monitoring extends beyond individual patient care, as IoT systems also contribute to broader public health initiatives. Data collected from millions of users can be aggregated and analyzed to identify trends in cardiovascular health across populations. This information can inform public health policies, guide preventive measures, and support early intervention efforts on a larger scale. For example, real-time cardiovascular data can be used to predict and prevent heart attacks, stroke, and other life-threatening events, reducing hospitalizations and improving long-term outcomes for patients with chronic cardiovascular conditions [36].

In conclusion, the cardiovascular system is fundamental to human health, and its continuous monitoring is integral to both individual and population health management. With the increasing prevalence of IoT-based healthcare systems, the ability to monitor cardiovascular function in real time has become more advanced and accessible. By leveraging wearable technology, cloud computing, and AI, healthcare providers can now offer more personalized, proactive care, ensuring better management of CVDs and improving patient outcomes.

II.6 Blood Oxygen Saturation (SpO_2)

II.6.1 Definition

Blood oxygen saturation (SpO_2) refers to the percentage of hemoglobin molecules in the blood that are saturated with oxygen. This measurement is crucial for assessing how effectively oxygen is being transported from the lungs to the tissues throughout the body. Normal SpO_2 levels typically range from 95% to 100%. Values below this threshold can indicate hypoxemia, a condition where the body does not receive enough oxygen to meet its physiological needs as presented in *F*igure II.*5*. Maintaining adequate oxygen levels is vital for sustaining cellular functions and overall health, as every organ relies on oxygen for energy production and metabolic processes [37].

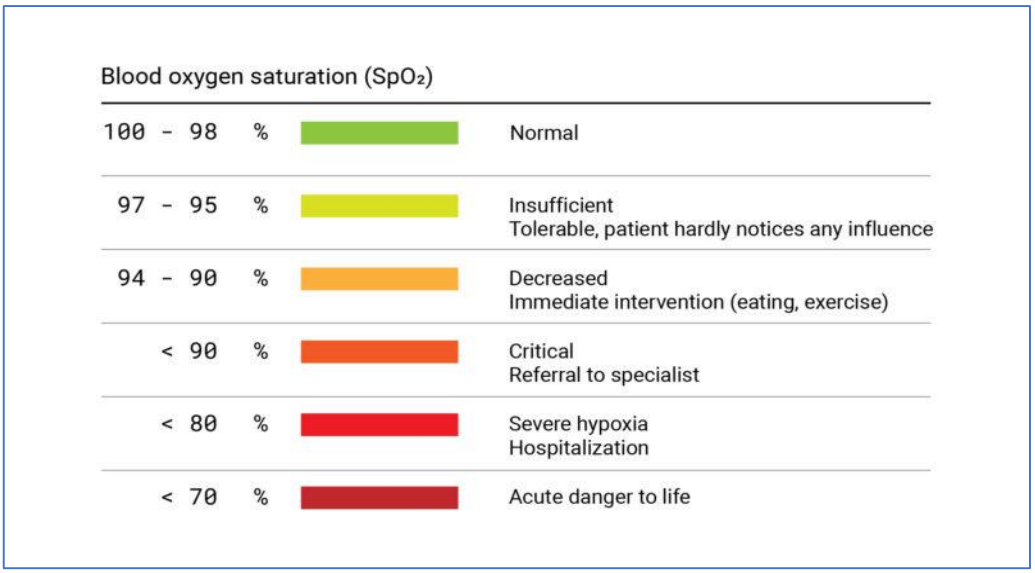


Figure II.5 Blood oxygen saturation percentage signification

Oxygen saturation levels can fluctuate due to various factors, including altitude, physical activity, and the presence of underlying medical conditions. For instance, individuals with chronic respiratory diseases such as chronic obstructive pulmonary disease (COPD) or asthma may experience lower SpO_2 levels due to compromised lung function, leading to decreased oxygen uptake[38] .Therefore, monitoring SpO_2 is essential for managing these conditions and ensuring adequate oxygenation.

II.6.2 Measurement and Significance

SpO_2 is commonly measured using a device called a pulse oximeter, a non-invasive instrument that estimates the oxygen saturation of hemoglobin in arterial blood. Pulse oximeters work by shining light through the skin, typically on a fingertip or earlobe, and measuring the light absorption characteristics of oxygenated and deoxygenated hemoglobin. The device provides real-time readings of SpO_2, allowing healthcare providers to monitor a patient's oxygen status continuously[39].

The importance of SpO_2 measurement extends beyond individual assessments, as it is vital in monitoring patients with respiratory and cardiovascular conditions. This measurement is especially crucial during sedation or anesthesia procedures and in emergency situations where rapid fluctuations in oxygen levels may occur. Regular monitoring of SpO_2 in patients with chronic conditions aids in the early detection of exacerbations or complications, facilitating timely interventions. For instance, a sudden decrease in SpO_2 can indicate an acute exacerbation in a patient with COPD, necessitating immediate medical attention[40] [41].

In the context of IoT-based healthcare systems, pulse oximeters can be seamlessly integrated into wearable devices, facilitating continuous SpO_2 monitoring outside traditional clinical settings. This capability allows for the remote management of patients, enabling healthcare providers to track oxygen levels in real-time and proactively respond to potential health crises [42][43].Furthermore, data collected from these devices can be aggregated and analyzed to identify trends in oxygen saturation levels across populations, facilitating public health initiatives aimed at addressing respiratory diseases and promoting wellness [44]

Blood oxygen saturation (SpO_2) is a vital physiological parameter that reflects the efficiency of oxygen transport in the body. Its measurement using pulse oximeters is a cornerstone of modern healthcare, particularly for patients with respiratory and cardiovascular conditions[45]. With the integration of IoT technologies, SpO_2 monitoring is becoming increasingly accessible and essential for promoting proactive health management and improving patient outcomes.

II.7 Heart Rate

II.7.1 Definition

HR refers to the number of times the heart beats per minute (BPM). It serves as a fundamental physiological parameter that reflects the heart's ability to pump blood throughout the body. The HR is influenced by numerous factors, including physical activity, emotional states, overall cardiovascular health, and the body's demand for oxygen and nutrients. A normal resting HR for adults typically ranges between 60 to 100 BPM. However, factors like fitness levels, age, medications, and underlying health conditions can cause variations in this range [46].
HR measurement is essential for understanding how the heart responds to various physiological demands. During exercise or stressful situations, the HR naturally increases to meet the body's heightened need for oxygen. Conversely, during rest or sleep, the HR decreases as the demand for oxygen diminishes. By analyzing HR patterns, clinicians can assess the cardiovascular system's ability to adapt to these varying conditions [47].

II.7.2 Normal Ranges and Variability

The normal resting HR varies among individuals and can be influenced by factors such as age, fitness level, and emotional state. For most adults, a resting HR between 60 and 100 beats per minute (BPM) is considered normal. Athletes or highly active individuals may exhibit lower resting heart rates, often ranging from 40 to 60 BPM, due to the enhanced efficiency of their cardiovascular systems [48].

On the other hand, higher resting heart rates can be a sign of poor cardiovascular health or an underlying medical condition, such as hyperthyroidism, dehydration, or heart disease.

HRV is a key indicator of the heart's ability to adapt to stressors. HRV refers to the variation in the time intervals between consecutive heartbeats, which reflects the autonomic nervous system's regulation of the heart. High HRV is typically associated with good cardiovascular health and resilience to stress, while low HRV can indicate autonomic dysfunction, which may be related to conditions such as heart failure, hypertension, or diabetes[49]. Monitoring HRV enables clinicians to evaluate how effectively the heart adjusts to physiological demands, providing valuable insights into a patient's overall cardiovascular health. By analyzing HRV, healthcare providers can better understand an individual's autonomic regulation and identify potential health risks associated with cardiovascular conditions [50][51].

II.7.3 Significance in Health Monitoring

HR is one of the most widely monitored vital signs in both clinical and home settings. It is a critical marker for detecting various medical conditions, such as tachycardia (elevated HR), bradycardia (low HR), and arrhythmias (irregular heart rhythms). Monitoring HR can help identify early signs of cardiovascular disease, especially when paired with other diagnostic tools like electrocardiograms (ECGs) [52]. For example, a consistently high resting HR, particularly above 100 BPM (a condition known as tachycardia), can indicate underlying issues such as heart failure, hyperthyroidism, or dehydration. Conversely, a very low HR (below 60 BPM), especially in non-athletes, may suggest conditions like bradycardia, which could lead to inadequate blood flow and necessitate medical intervention [53].

In modern healthcare, particularly with the rise of IoT-based health monitoring systems, continuous HR monitoring has become increasingly accessible. Wearable devices such as smartwatches and fitness trackers equipped with HR sensors provide real-time data, enabling individuals and healthcare providers to monitor heart health remotely [43]. This capability for continuous monitoring facilitates the early detection of irregularities, allowing for timely interventions, which is particularly beneficial for patients with chronic conditions such as hypertension, arrhythmia, and heart failure.

The integration of HR data with advanced analytics, DL, and AI systems further enhances its diagnostic potential. These systems can process large datasets from wearable devices to identify patterns and predict potential cardiovascular events, offering a new level of personalized healthcare and proactive disease management[54].

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II.8 Blood Pressure

II.8.1 Definition:

Blood pressure (BP) refers to the force exerted by circulating blood on the walls of blood vessels and is one of the most critical vital signs used to assess cardiovascular health. Blood pressure is recorded as two values: systolic blood pressure (SBP) and diastolic blood pressure (DBP). Systolic pressure, the higher of the two numbers, represents the pressure in the arteries when the heart contracts (beats) and pumps blood. Diastolic pressure, the lower value, measures the pressure in the arteries when the heart is at rest between beats [57].

A normal adult blood pressure reading is typically around 120/80 mmHg. However, consistent readings above this range may indicate hypertension (high blood pressure), while values below the normal range may suggest hypotension (low blood pressure). Hypertension is a significant risk factor for CVDs, including heart attacks, strokes, and kidney failure. Conversely, hypotension can lead to dizziness, fainting, and, in severe cases, shock [58].

II.8.2 Monitoring and Clinical Importance

Blood pressure monitoring is a critical practice in healthcare for diagnosing and managing various cardiovascular conditions. Given the strong association between hypertension and severe health complications, regular blood pressure monitoring is essential for early detection and management. Research has demonstrated that effectively controlling high blood pressure significantly reduces the risk of cardiovascular events such as heart attacks, strokes, and heart failure[57].

Traditionally, blood pressure is measured using a sphygmomanometer in clinical settings. However, the development of digital blood pressure monitors has enabled patients to monitor their blood pressure at home. These devices measure both systolic and diastolic pressures and often have the capability to store data for trend analysis. Home monitoring is especially useful for individuals diagnosed with white coat hypertension, a condition where a patient's blood pressure rises in clinical settings due to stress or anxiety[59].

In IoT-based healthcare systems, continuous blood pressure monitoring is increasingly feasible through wearable sensors. These devices provide real-time data, allowing patients and healthcare professionals to track blood pressure trends over time. This capability is particularly advantageous for patients with hypertension, as it facilitates timely interventions and adjustments in treatment[58] .

Interventions, medication adjustments, and lifestyle changes can be facilitated by continuous blood pressure monitoring[60] . In high-risk patients, this monitoring can detect sudden spikes or drops in blood pressure, preventing emergencies such as hypertensive crises or fainting due to hypotension.

The use of IoT and digital technologies in blood pressure monitoring is also invaluable in remote patient monitoring (RPM). For instance, patients in rural or underserved areas can benefit from wearable blood pressure monitors that transmit data to healthcare providers via mobile applications or cloud-based platforms. This approach allows for continuous monitoring without the need for frequent hospital visits, thereby improving patient outcomes and reducing healthcare costs[58].

Moreover, integrating AI into blood pressure monitoring systems can enhance accuracy by analyzing patterns in blood pressure fluctuations. AI algorithms can help identify at-risk patients, predict future hypertensive episodes, and offer personalized treatment recommendations based on continuous blood pressure data[61]. This proactive approach to blood pressure management is expected to significantly improve patient care, particularly for those with chronic hypertension or those at risk for cardiovascular events.

II.9 Respiratory Rate

II.9.1 Definition

The respiratory rate (RR) refers to the number of breaths taken per minute and is a vital sign that provides crucial insights into an individual's respiratory health and overall well-being. While the respiratory rate can vary based on a person's activity level, the normal range for adults at rest is generally between 12 and 20 breaths per minute. Deviations from this range can signal underlying health issues. Tachypnea, defined as a higher-than-normal respiratory rate, may indicate problems such as respiratory infections, metabolic acidosis, or cardiovascular stress. Conversely, bradypnea, or a lower-than-normal respiratory rate, can be associated with conditions such as drug overdose, neurological disorders, or severe respiratory failure [62].

Monitoring respiratory rate is critical for detecting and managing various conditions, including COPD asthma, pneumonia, and congestive heart failure. Sudden or sustained changes in respiratory rate can serve as early warning signs of clinical deterioration, particularly in critical care settings[63]

II.9.2 Measurement in Healthcare Systems

In healthcare systems, respiratory rate is measured both manually and through technology-assisted methods. Traditionally, healthcare professionals count breaths over a period of one minute by observing chest movements. However, manual methods can be prone to human error, particularly in critical care settings where rapid changes in breathing patterns must be detected promptly [64].

In recent years, the integration of the IoT in healthcare has revolutionized the way respiratory rate is monitored. IoT-based monitoring systems utilize wearable sensors that continuously track respiratory patterns in real time. These systems employ technologies such as accelerometers, piezoelectric sensors, and optical sensors embedded in smart wearables or medical devices. For instance, advanced IoT-based pulse oximeters or respiratory belts can capture respiratory data continuously, providing a reliable and non-invasive method for tracking respiratory health, especially for patients with chronic conditions[65].

In the context of respiratory issues such as asthma or COPD, real-time monitoring can help prevent exacerbations by alerting healthcare providers to abnormal patterns. The continuous nature of IoT-based systems allows for a proactive approach to healthcare, enabling earlier interventions and reducing hospital admissions for respiratory complications. Additionally, these systems are particularly beneficial for monitoring respiratory rate in home care settings,

especially for patients in rural areas or those requiring long-term monitoring without frequent hospital visits[66].

With advancements in machine learning (ML) and AI, IoT-based systems can now utilize algorithms to predict respiratory events such as apnea or hypoventilation. By analyzing trends in respiratory data, these systems offer real-time feedback that can trigger automated alarms in cases of respiratory distress, thereby improving patient outcomes in emergency situations.

II.10 Conclusion

In this chapter, we have explored the fundamental concepts and components of the ECG as a crucial tool in cardiac monitoring and diagnostics. By understanding the significance of the various ECG waves and intervals such as the P wave, QRS complex, and T wave, along with the PR, ST, PQ, and QT intervals healthcare professionals can identify and interpret key indicators of heart health. These signals reflect the electrical activity within the heart, allowing for the detection of abnormalities such as arrhythmias, conduction disorders, and other cardiovascular issues. The precise measurement of these waves and intervals is vital for diagnosing heart conditions, guiding treatment, and improving patient outcomes.

In an IoT-driven healthcare system, where continuous monitoring and real-time data analysis are becoming more prevalent, the role of ECG becomes even more significant. The ability to track heart activity remotely and in real time provides valuable insights into patient health, enhancing the efficiency of modern healthcare systems. Moving forward, the integration of ECG data with advanced technologies like AI and DL algorithms promises to further revolutionize cardiovascular care, enabling earlier detection, personalized treatment, and better management of heart-related conditions.

Chapter III

Digital Twin, IoT, and Deep Learning: Foundational Concepts and Integrative Perspectives

III.1 Introduction

The integration of DT, IoT and DL technologies has enabled transformative capabilities across various industries. These technologies empower organizations to monitor systems in real-time, simulate operations, and make data-driven decisions. By leveraging IoT data, advanced analytics, and DL models, industries can create digital replicas of physical entities that enable enhanced control and optimization.

The application of these technologies is particularly evident in sectors like healthcare, manufacturing, aerospace, and smart cities. This chapter delves into the development, definitions, and use cases of DT, IoT, and DL technologies, as well as their synergy in enabling more efficient and intelligent systems.

III.2 Digital Twin

Digital Twin technology serves as a cornerstone of digital transformation, enabling organizations to connect physical systems with their digital counterparts for enhanced performance and decision-making.

III.2.1 Definition

A DT is a sophisticated virtual model designed to accurately replicate the characteristics and behavior of a physical object, system, or process in real-time. By utilizing continuous synchronization with real-world data collected through various sensors and IoT devices, DTs enable comprehensive real-time monitoring, predictive modeling, and system optimization. This real-time data flow allows organizations to gain insights that can significantly enhance operational efficiency, reduce downtime, and mitigate potential risks.[67]. DTs encompass multiple layers of data integration, including physical attributes, operational data, and environmental conditions. They are often constructed using advanced simulation techniques

and AI-driven algorithms, which facilitate predictive analytics and automated decision-making processes [68]. For instance, in manufacturing, a DT can simulate production processes, enabling operators to test changes in a virtual environment before applying them in the real world, thus minimizing costly errors [69].

Furthermore, DTs are not static; they evolve over time as more data is collected and analyzed. This continuous learning aspect enables them to adapt to changes in the physical counterpart, such as wear and tear, new operational conditions, or design alterations [70] . As a result, organizations can leverage DTs for a variety of applications, including predictive maintenance, product lifecycle management, and smart city planning.

The integration of DT technology into various sectors, such as healthcare, aerospace, and smart manufacturing, highlights its versatility and potential to drive innovation. By providing a virtual representation that mirrors the complexities of the physical world, DTs empower organizations to make data-driven decisions, enhance performance, and ultimately create a more resilient and efficient operational framework [7].

III.2.2 Development and History of DT

The concept of DT technology has its roots in the 1960s when NASA pioneered its use to monitor spacecraft. This early implementation aimed to create a virtual representation of space vehicles, allowing engineers to simulate and analyze various conditions that could affect the spacecraft's performance and safety during missions. By mirroring the physical systems in a virtual environment, NASA was able to enhance monitoring and predictive capabilities for critical missions.

The term "Digital Twin" was formally coined by Dr. Michael Grieves in 2003 as part of Product Lifecycle Management strategies. Dr. Grieves introduced this concept to facilitate the integration of data across the entire lifecycle of a product, from design and manufacturing to maintenance and decommissioning. This framework emphasized the importance of maintaining a dynamic digital representation that could provide insights throughout a product's life.

Since its inception, the application of DTs has expanded significantly beyond the aerospace industry. Today, they are utilized in a diverse array of fields, including healthcare, where they enable personalized medicine by simulating patient responses to treatments; smart manufacturing, where they optimize production processes and predictive maintenance; and urban infrastructure management, where they facilitate the modeling of complex systems for better city planning and resource management[67][17].

The evolution of DT technology has been significantly shaped by advancements in IoT, data analytics, and AI. These innovations have enabled the seamless integration of real-time data, which has greatly enhanced the capabilities of DTs in providing actionable insights and fostering innovation across various sectors. With the continuous recognition of the value DTs bring, their adoption is projected to expand, paving the way for smarter, more efficient systems and processes across numerous industries[71][72].

III.2.3 State of the Art of DT

The Digital Twin (DT) concept, introduced by Michael Grieves in the early 2000s during his work on Product Lifecycle Management (PLM), marked a significant milestone in bridging physical and virtual systems. Grieves conceptualized DTs as systems comprising two primary components: the physical entity and its corresponding virtual representation. This virtual component acts as a dynamic and real-time mirror of the physical system, enabling enhanced analysis, decision-making, and predictive simulations [73][74][67].

However, in its early years, DT adoption faced significant challenges due to technological constraints, necessitating advances in areas such as IoT, big data analytics, and simulation technologies to enable practical implementation[75] .

The initial phase of DT development, often termed the "formation stage" (2003–2011), was primarily theoretical, with limited real-world applications. During this period, the aerospace industry emerged as a pioneer in exploring DT technology. For instance, NASA employed DTs for simulation-based flight preparation and operational testing, as seen in the Airbus Iron Bird, which utilized hardware twins to replicate real-world conditions [76][75].

However, the technological foundations such as advanced sensor networks, cloud computing, and data integration required for DT functionality were still immature, limiting broader adoption during this period.

From 2011 to 2014, DTs entered the "incubation stage," where significant advancements in enabling technologies facilitated the first practical applications. This period saw NASA formalize its definition of DTs in its Technology Roadmaps in 2012, envisioning broader uses beyond aerospace [76][75]. Around the same time, the rise of Industry 4.0 focusing on digitization, interconnected systems, and smart manufacturing created a fertile ground for DT adoption. In manufacturing, companies such as General Electric (GE) implemented DTs to optimize gas turbine performance. By leveraging real-time data and predictive maintenance, GE demonstrated the operational benefits of DTs, including reduced downtime and cost savings [15] . The healthcare industry also began to explore DT applications, using them to simulate

patient outcomes, refine surgical planning, and integrate real-time data from IoT-enabled medical devices[77] .

By 2014, DTs entered the "growth stage," marked by their adoption across a wide range of industries and the establishment of a more comprehensive theoretical framework. This framework outlined five critical dimensions essential to DT functionality: Physical Entity, Virtual Entity, Data, Connection, and Service. Among these, data plays a central role, enabling DTs to integrate real-time information, simulate scenarios, and generate actionable insights. This structured approach positioned DTs as a pivotal tool for enhancing reliability, productivity, and innovation in diverse fields [75].

The versatility of DTs has expanded their applications beyond manufacturing and aerospace into urban planning, energy management, and transportation. In smart cities, for instance, DTs are used to model urban infrastructure, optimize traffic systems, and manage energy resources. In energy, DTs enhance the efficiency of power grids and renewable energy systems, enabling predictive maintenance and load balancing. These advancements underscore the adaptability of DTs to address complex system challenges across various sectors.

In recent years, DTs have continued to evolve, driven by technological advancements in AI, 5G, and autonomous systems. Major corporations, including IBM, Siemens, and GE, have spearheaded DT innovations, offering solutions that improve cost-efficiency, operational effectiveness, and decision-making [73]. The transformative potential of DTs was highlighted in 2017 and 2018 when Gartner identified them as one of the top ten most promising technological trends of the next decade[75].

As industries increasingly embrace digitization, the role of DTs is set to grow further. Emerging applications include personalized medicine in healthcare, where AI-powered DTs could revolutionize patient-specific treatment plans. Similarly, advances in simulation capabilities and real-time data processing are expected to expand DT utility in fields like autonomous systems and disaster response. The continued convergence of technologies such as IoT, big data, and AI ensures that DTs will remain at the forefront of innovation in the coming years.

III.2.4 DT in Manufacturing

In the manufacturing sector, DT technology allows organizations to simulate production processes, monitor equipment, and predict potential failures. Siemens, for example, uses DTs to monitor its production lines, reducing equipment downtime and increasing operational efficiency. By integrating real-time data from IoT sensors, manufacturers can make data-driven decisions to optimize production[15].

DTs also enable companies to simulate different design options and production scenarios, improving product quality and reducing time-to-market [17].

III.2.5 DT in City Management

DTs are being adopted in smart city initiatives to optimize urban infrastructure management, traffic control, and energy consumption. A DT of a city can simulate different infrastructure scenarios, helping planners make informed decisions. Singapore has employed DT technology to manage urban resources, ensuring the city's energy efficiency and improving public safety[77].

III.2.6 DT in Aerospace

The aerospace industry has long been a pioneer in the use of DTs. Companies like Boeing use DT technology to monitor aircraft in real-time, predicting maintenance needs and enhancing safety. DTs allow engineers to simulate flight conditions, test system performance, and optimize aircraft operations [17].

III.2.7 DT in Healthcare

In healthcare, DTs are employed to develop real-time, dynamic models of patients, providing valuable insights that support personalized treatments and predictive diagnostics. These virtual representations are continuously updated with real-time data from the patient, enabling healthcare professionals to monitor physiological conditions more accurately and in a non-invasive manner. For instance, in cardiology departments, DTs can be used to create highly detailed simulations of a patient's cardiovascular system. These models allow doctors to analyze various treatment options, such as medication adjustments or surgical interventions, and predict patient-specific outcomes with greater precision, ultimately enhancing the decision-making process for individualized care. By running simulations within the DT environment, cardiologists can anticipate potential complications, assess risks, and refine treatment plans without directly impacting the patient[78].

Beyond patient care, hospitals and medical facilities leverage DT technology for the efficient management of medical equipment. DTs can monitor the status and performance of various devices, such as MRI (Magnetic Resonance Imaging) machines, ventilators, and other critical systems, ensuring they function optimally and without interruption. Predictive analytics generated from these digital models help anticipate equipment failures, schedule preventive maintenance, and avoid costly breakdowns. This proactive approach minimizes downtime,

enhances resource management, and optimizes the overall operational efficiency of healthcare systems[78].

III.2.7.1 Technologies & tools of DT for healthcare sector

DTs in the healthcare sector rely on a suite of advanced technologies and tools that enable real-time patient modeling, predictive analytics, and personalized treatment planning. These technologies help create precise, dynamic models of patients, healthcare systems, and medical equipment, leading to better diagnosis, treatment, and operational efficiency as show in *FigureIII.1*.

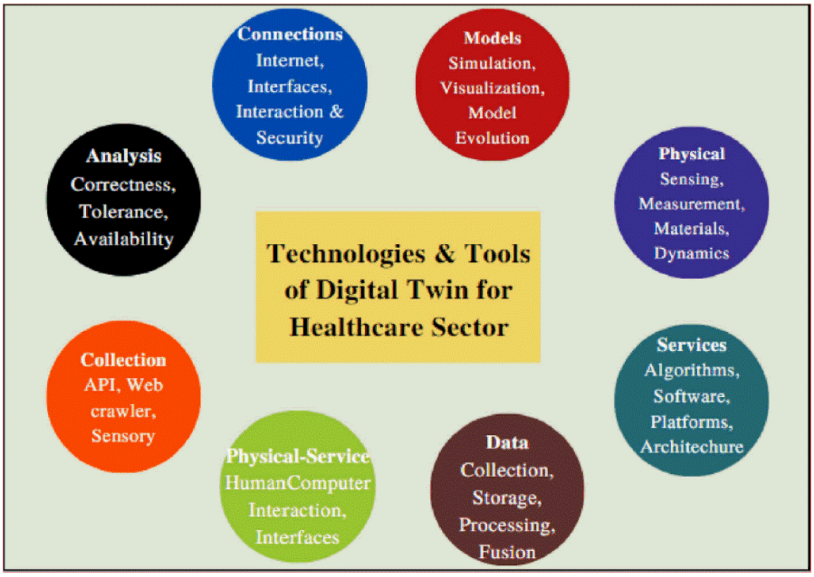


Figure III.1 Technologies & tools of DT for healthcare sector[6]

Internet of Things, which allows the seamless integration of wearable devices and medical sensors. IoT devices, such as smartwatches, glucose monitors, ECG sensors, and SpO_2 monitors, continuously collect real-time data on various physiological parameters. This data feeds into the DT models, facilitating dynamic, real-time simulations of a patient's health status[79]. Through the collection of this continuous data stream, healthcare professionals can gain valuable insights into patient behavior and disease progression, thus allowing for timely and accurate interventions.

cloud computing and **edge computing**. As IoT devices generate vast amounts of data, cloud platforms provide scalable storage and computational power to handle this data effectively. These cloud services facilitate complex computational tasks such as predictive analytics and data fusion, making it easier to manage large-scale health data repositories.

edge computing reduces latency by processing data locally, closer to the patient, rather than relying solely on cloud-based solutions. This real-time data processing capability is crucial in medical scenarios where immediate decisions are required, such as monitoring critical patients or detecting anomalies in medical equipment performance [80].

Edge computing also enhances privacy by minimizing the transmission of sensitive patient data, as only aggregated or critical information is sent to the cloud for further analysis.

AI and ML algorithms form the analytical backbone of DT systems in healthcare. AI enhances the predictive capabilities of DTs by analyzing historical and real-time data, identifying patterns, and forecasting potential future events. For example, AI models can analyze years of patient data to predict the likelihood of heart failure or detect early signs of complications in diabetic patients. ML models are also pivotal in optimizing treatment plans by simulating how different interventions might impact a patient's specific condition. These technologies not only allow for more precise diagnosis but also enable adaptive and personalized treatment strategies, tailored to the unique physiological profile of each patient[35]. The ability to simulate "what-if" scenarios empowers healthcare providers to explore various treatment pathways, assess their potential outcomes, and make data-driven decisions that enhance patient care.

3D modeling and simulation software in healthcare DTs allows for a highly detailed visualization of patient anatomy and the simulation of medical procedures. In surgical planning, for example, a DT of a patient's organs can be used to map out a surgery before it takes place, enabling surgeons to anticipate potential complications and optimize the procedure[81]. These 3D models are created by integrating data from imaging technologies such as MRI and CT (Computed Tomography) scans with patient-specific physiological data. This holistic view of the patient's condition enhances precision and improves the success rates of complex surgical interventions.

big data analytics with DT systems plays an essential role in managing the extensive datasets generated by electronic health records (EHRs), wearable devices, and imaging systems. With the vast amount of data being collected, advanced data analytics platforms are used to extract meaningful insights that support medical decision-making.

federated learning hospitals and healthcare systems can train ML models on decentralized patient data without directly accessing it, ensuring privacy and data security while still leveraging the full potential of AI-driven insights. This distributed approach allows multiple healthcare facilities to collaborate in developing robust, large-scale models for disease detection and management without compromising patient confidentiality[72].

5G technology further complements DT systems by enabling high-speed, low-latency communication between IoT devices, cloud servers, and medical professionals. This connectivity ensures that critical patient data can be transferred and processed in real-time, facilitating timely interventions and continuous monitoring of patient health, particularly for those in remote locations or requiring telemedicine services.

augmented reality and **virtual reality** applications in medical training and patient education, where DTs can be used to simulate surgeries, anatomy, and medical procedures[71].

In addition to patient-specific applications, DTs are being used for monitoring and managing the operational efficiency of medical equipment within healthcare facilities. Predictive maintenance, driven by AI and IoT data, allows hospitals to monitor the performance of critical equipment such as MRI machines, ventilators, and surgical tools. By predicting when equipment is likely to fail, hospitals can schedule maintenance before breakdowns occur, thereby minimizing downtime and ensuring optimal resource management[80]. This technology significantly enhances the reliability of medical devices and helps to avoid disruptions that could negatively impact patient care.

Blockchain technology is also emerging as a key enabler of DT systems in healthcare by addressing the challenges of data security and integrity. Given the sensitivity of health data, blockchain's decentralized and immutable nature ensures that patient information remains secure and tamper-proof. Blockchain also facilitates the safe sharing of medical data across different healthcare providers and systems, ensuring that the DT model of a patient remains accurate and up to date[82]. This transparency is crucial for building trust between healthcare providers, patients, and third-party entities involved in the healthcare ecosystem.

III.2.7.2 DT Health modeling process

The DT health modeling process as shown in Figure III.*2* involves creating a virtual replica of a patient or healthcare system that mirrors real-time physical states and conditions. This simulation aims to enhance diagnostics, personalize treatments, and optimize operational efficiency.

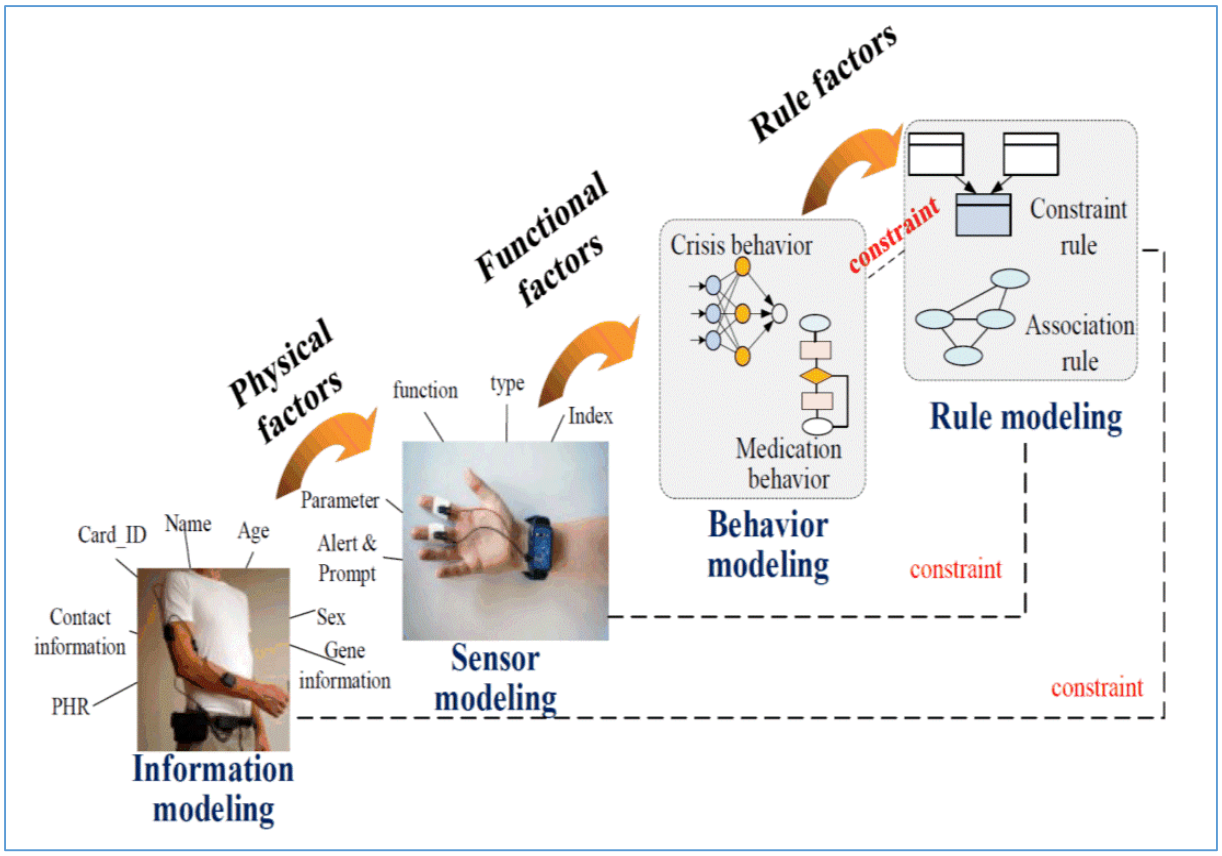


Figure III.2 DT Health modeling process[83]

1. **Data Collection and Integration**

The process begins with real-time data collection from patient sensors, electronic health records (EHRs), and medical devices. Data includes vital signs, lab results, imaging, and historical health data. IoT-enabled sensors such as wearable ECG monitors and glucose sensors collect continuous health metrics, while historical data from EHRs establishes baseline health conditions. This data integration is essential to accurately reflect the patient's physiological state[68][78].

2. **Modeling and Simulation**

Once the data is collected, a DT model is constructed using a combination of physics-based simulations and AI algorithms. For example, in cardiology, models simulate heart behavior, blood flow, and responses to treatment, while in oncology, DTs may model tumor growth and reactions to therapies. These simulations enable healthcare professionals to test treatment scenarios without affecting the patient, improving precision medicine and reducing risks[84][85].

3. **Real-Time Synchronization**

A critical aspect of DTs is their ability to synchronize with the physical entity they represent in real time. Data from monitoring devices continuously updates the DT, ensuring the virtual model remains a true reflection of the patient's current state. This dynamic feedback loop allows healthcare providers to track disease progression and make timely interventions[15][86].

4. **Personalized Diagnostics and Treatment Simulations**

DTs are used to personalize treatment by simulating various interventions and predicting outcomes. For instance, a DT can simulate how a heart responds to a new medication or how a cancerous tumor reacts to radiation. This enables doctors to tailor treatment plans specifically to the patient's needs, optimizing outcomes and minimizing side effects[77]. In chronic disease management, DTs can help predict future health challenges by identifying patterns that may indicate disease exacerbation[87].

5. **Predictive Analytics and Decision Support**

DTs leverage predictive analytics to forecast potential health risks or complications. ML models analyze patient data to detect trends and anomalies that might indicate disease progression or future critical events. This information supports proactive healthcare, enabling timely interventions that prevent emergencies such as heart attacks or strokes[78]. The DT also serves as a decision support tool, recommending treatments or lifestyle changes based on simulation results[68].

6. **Feedback and Continuous Improvement**

As the DT continuously interacts with real-world data, it learns and refines its models, becoming more accurate over time. This continuous improvement is crucial for maintaining the DT’s reliability and precision in simulating increasingly complex medical scenarios[15]. Additionally, new data sources, such as updated imaging scans or additional sensor data, can be integrated into the DT to enhance its predictive capabilities[84].

7. **Application in Equipment and Healthcare Operations**

In addition to patient care, DTs are utilized for equipment monitoring and operational management in hospitals. DTs can track the performance of medical devices, such as MRI machines and ventilators, predicting when maintenance is required and preventing unexpected breakdowns. This helps optimize the workflow and resource management in healthcare facilities, ensuring continuous and efficient operation [7][85].

III.2.7.3 Overview of Digital Twin Elements

The digital twin development process entails constructing unique virtual models that share core foundational features. [88][89], as shown in the Figure III.3.

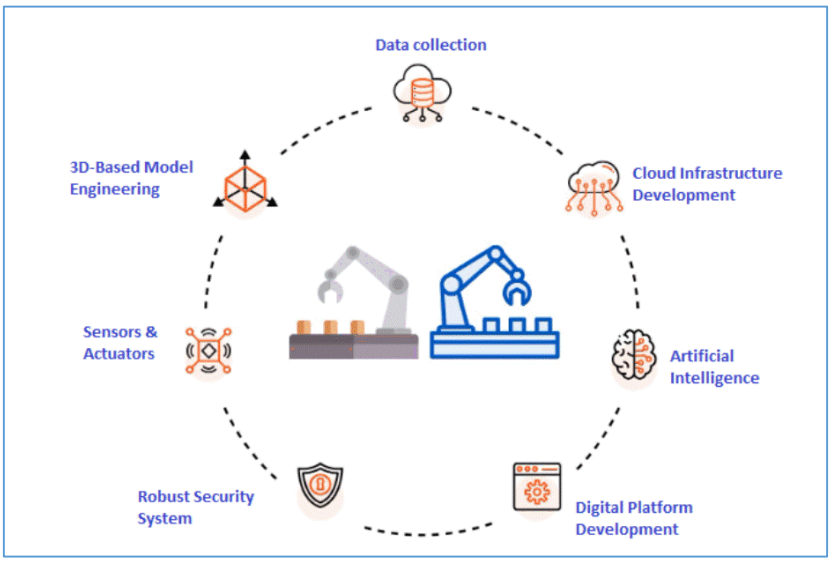


Figure III.3 Digital twin elements

- **Data collection**

Some components are responsible for collecting real-world data, while others focus on analyzing, predicting behavior, or presenting insights in an intuitive manner

- **3D-Based Model Engineering**

This component creates a detailed virtual replica based on data obtained from a physical object. Businesses utilize 3D modeling and engineering tools to examine objects or processes, predict their performance, and detect potential issues before implementing solutions in reality.

- **Cloud Infrastructure Development**

Cloud platforms provide storage for the data gathered through sensors. These platforms enable users to access and interact with the virtual model remotely, facilitating seamless connectivity and real-time information sharing over the Internet.

- **Artificial Intelligence**

AI plays a pivotal role in interpreting and analyzing the data generated by the digital twin. It aids in decision-making, forecasting future scenarios, detecting trends, and identifying anomalies as they occur.

- **Digital Platform Development**

These platforms act as interactive spaces where engineers monitor, analyze, and interact with digital twin simulations. They include cloud-based platforms, mobile and web applications, visualization tools, and specialized management systems.

- **Robust Security System**

Given the sensitivity of the data contained in digital twins, robust cybersecurity measures are critical. This involves ensuring data protection from unauthorized access, encryption of transmitted data, and adherence to privacy regulations. Effective strategies include fault prevention and system integrity management.

- **Sensors & Actuators**

Sensors gather real-world data such as temperature, humidity, motion, location, or vibration and convert it into digital signals. This information serves as the foundation for creating an accurate virtual representation of physical objects or systems.

III.2.7.4 Key Features and Capabilities of a Digital Twin

Before designing a digital twin, it's essential to understand its key features and capabilities[90][91], as illustrated in the Figure III.4.

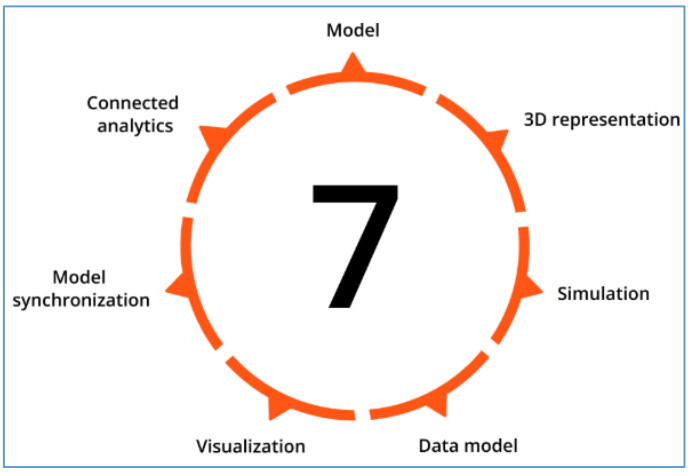


Figure III.4 Digital twin features Capabilities

- **Model**

A digital twin replicates the properties and characteristics of a physical object. This feature allows users to create virtual replicas within a built environment to observe and track their behavior.

- **3D representation**

  This feature offers an exact visual representation of the physical object, delivering an almost lifelike experience. It simplifies the interpretation of analytic data through realistic models.

- **Simulation**

  Simulation tools place the virtual model in a controlled digital environment. By altering environmental parameters, the software can evaluate how the object behaves under different conditions.

- **Data model**

  A digital twin enables real-time visualization of the relationships between various components of a physical device or system. It provides labeled data and ensures a clear understanding of operations and workflows.

- **Visualization**

  Users can view digital twin models on multiple devices, including desktops and mobile platforms. These tools provide immediate insights into the system's performance and functionality.

- **Model synchronization**

  This feature ensures the digital model stays aligned with real-world parameters. Advanced software allows for real-time synchronization, reflecting any physical changes directly in the virtual representation.

- **Connected analytics**

  Digital twins leverage machine learning and computational algorithms to deliver actionable insights into the performance and behavior of devices or systems, based on measured properties.

III.2.7.5 Conceptual Framework and Interactions of Digital Twin Systems

A digital twin (DT) serves as a virtual model of a physical object or process, spanning potentially its entire life cycle. This virtual representation reflects the real-time status of the physical counterpart and maintains a record of historical data. Furthermore, the DT can predict future performance and implement control adjustments to enhance overall operations.

Figure III.5 illustrates a conceptual model of a general DT, showcasing interactions between the virtual and physical environments and an operator.

encompass the following key tasks:

- Task 1: Collecting data from the physical entity to the virtual model. This involves sensors embedded in the physical entity transmitting data to the virtual environment using a specified protocol and frequency.
- Task 2: Conducting virtual simulations or optimization processes to improve the performance of the physical entity or minimize the risk of malfunctions or failures.
- Task 3: Implementing corrective actions on the physical system by transmitting data to its actuators through a predefined protocol.

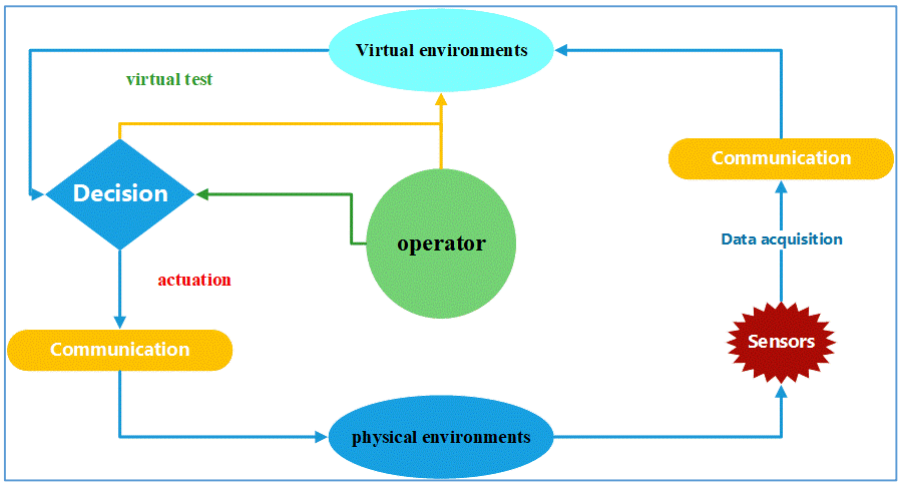


Figure III.5 Health modeling process

III.3 Internet of Things

The IoT connects a vast array of devices, enabling seamless communication and data exchange, which is crucial for creating smarter systems and processes across industries.

III.3.1 Definitions

The IoT refers to a vast network of interconnected devices that communicate with one another and exchange data over the internet. These devices are embedded with various sensors, software, and other technologies that enable them to collect, analyze, and transmit data in real-time. The proliferation of IoT has led to the emergence of smart homes, intelligent transportation systems, and automated industrial processes, among many other applications.

IoT devices range from everyday household items, such as smart thermostats and wearable fitness trackers, to complex industrial machines equipped with sensors that monitor performance and operational conditions. The ability of these devices to gather and share data is fundamental to creating efficient systems that can adapt and respond to changing conditions. This data is crucial for the development of DTs, as it provides the real-time information necessary to create accurate digital replicas of physical systems[92].

Furthermore, the integration of IoT with cloud computing and advanced analytics enhances the capability of these devices, allowing for sophisticated data processing and decision-making. By harnessing the power of IoT, organizations can gain valuable insights into their operations, improve efficiency, reduce costs, and create more resilient systems. The synergy between IoT and DT technology exemplifies how interconnected devices can revolutionize industries and foster innovation[93] [73].

III.3.2 Development and History of IoT

The concept of the IoT emerged in the late 1990s, spurred by advancements in wireless communication technologies that allowed devices to communicate and share data seamlessly. The term "Internet of Things" was coined by Kevin Ashton in 1999 during a presentation at Procter & Gamble, where he emphasized the potential of connecting everyday objects to the internet for improved supply chain management and data analysis. This foundational idea laid the groundwork for what would become a transformative technological movement.

In the early 2000s, IoT began to gain traction as more devices were equipped with sensors and internet connectivity. This period saw the development of early applications, such as RFID (Radio Frequency Identification) tags that enabled the tracking of inventory in retail

environments. As the technology matured, the potential for IoT expanded dramatically, encompassing a wide range of applications from smart home devices, like thermostats and security systems, to industrial sensors used in manufacturing and logistics.

The rapid growth of IoT has been fueled by several factors, including the proliferation of mobile devices, the advent of cloud computing, and advancements in data analytics. By the 2010s, IoT had become integral to various sectors, facilitating data-driven decision-making and enabling real-time system monitoring. The ability to collect, analyze, and act upon vast amounts of data has empowered organizations to optimize operations, enhance customer experiences, and drive innovation [94].

Today, IoT continues to evolve, with emerging technologies such as 5G connectivity, edge computing, and AI further enhancing its capabilities. The integration of these technologies is enabling more sophisticated applications, including smart cities, autonomous vehicles, and advanced healthcare solutions, solidifying IoT's position as a cornerstone of the digital transformation across industries [95][96].

the Table III.1 illustrating the Historical Key Milestones of IoT from 1990 to 2023.[87]

Table III.1 IoT Key Milestones and Developments

Year	Key Milestones and Developments
1990	Wireless communication for M2M began. John Romkey created a toaster that could be controlled via the Internet.
1994	IEEE Spectrum magazine described a futuristic concept of integrating and automating everything via the Internet.
1995	Siemens introduced the first cellular module designed for M2M communication.
1999	Kevin Ashton coined the term "Internet of Things" in a presentation at Procter & Gamble.
2010	IoT gained mainstream attention, with Google’s Street View raising public awareness of connected devices.
2011	Gartner included the "Internet of Things" in its "hype-cycle for emerging technologies."
2012	LeWeb organized a conference on IoT, and the concept was increasingly featured in popular magazines like *Forbes*.
2013	IDC predicted that IoT could grow into an $8.9 trillion market by 2020.

2014	IoT saw a surge in popularity and began to become a tangible concept in the market.
2015	Google acquired Nest Labs for $3.2 billion. IoT was the main theme at the Consumer Electronics Show (CES) in Las Vegas.
2016	Amazon launched AWS IoT Core, furthering the adoption of IoT.
2017	Global IoT devices surpassed 8.4 billion, with major investments from companies like Amazon, Google, and Apple in voice-activated smart home devices.
2018	The European Union's General Data Protection Regulation (GDPR) was enacted, affecting IoT devices that handle personal data. Blockchain was explored as a potential solution for securing IoT data. The number of IoT devices grew to approximately 11 billion.
2019	The rise of 5G networks boosted the development of Industrial IoT (IIoT).
2020	IoT connections increased significantly, with more than half of activities linked to IoT devices.
2021	The number of active IoT devices exceeded 13 billion.
2022	The World Economic Forum recognized IoT as one of the top three technological advancements with the most significant impact.
2023	IoT devices were expected to surpass 15 billion, with strong momentum in the transportation and energy sectors.

III.3.3 Applications of IoT

The applications of the IoT are vast and span numerous industries as show Figure III.*6***,** revolutionizing how organizations operate and interact with their environments. In healthcare, IoT-enabled devices, such as wearable sensors and smart medical devices, play a crucial role in monitoring patients' vital signs in real-time. These devices continuously collect data, which is then fed into DT models to facilitate predictive analytics. By analyzing this data, healthcare providers can anticipate health issues, personalize treatment plans, and improve patient outcomes, ultimately leading to more efficient and effective care delivery[77].



Figure III.6 Application scenarios of the IoT [97]

In the manufacturing sector, IoT sensors are integrated into production lines to continuously monitor equipment performance. This real-time data collection enables predictive maintenance, allowing organizations to identify potential issues before they lead to equipment failures. By leveraging IoT technology, manufacturers can significantly reduce downtime, optimize production schedules, and enhance overall operational efficiency. For instance, companies like General Electric have successfully implemented IoT solutions to monitor gas turbines, resulting in lower operational costs and improved reliability [10].

Additionally, IoT has transformative applications in smart cities, where it enhances urban infrastructure and improves the quality of life for residents. Smart traffic management systems utilize IoT sensors to monitor vehicle flow and congestion, enabling more efficient traffic patterns and reducing travel times. Similarly, IoT-enabled waste management systems can optimize collection routes based on real-time data about bin fill levels, leading to more efficient resource use and reduced operational costs.

In agriculture, IoT devices are employed for precision farming, allowing farmers to monitor soil conditions, weather patterns, and crop health. This data-driven approach facilitates informed decision-making, improving yields while minimizing resource consumption. As IoT technology continues to evolve, its potential applications will expand even further, driving innovation across multiple sectors and fostering a more connected and efficient world [98][99].

III.4 Deep Learning

Deep Learning has transformed the landscape of artificial intelligence by enabling machines to process and understand complex data through advanced neural network architectures.

III.4.1 DL Definitions

DL, a subset of AI and ML as show in Figure III.*7*, has emerged as a revolutionary paradigm in the field of data analysis and interpretation. Rooted in the principles of neural networks, DL architectures are designed to model complex patterns and representations in vast amounts of data [100]. Unlike traditional ML techniques, which often rely on handcrafted features, DL algorithms autonomously learn hierarchical feature representations from raw data, allowing for more accurate and robust predictions across a wide range of applications [101].

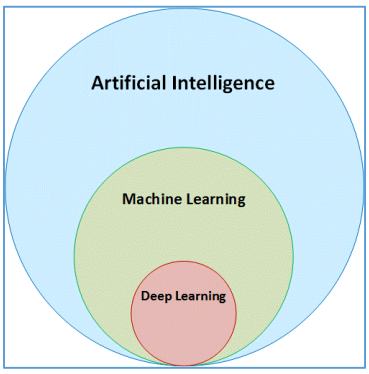


Figure III.7 The relation Between AI,ML &DL

The rapid advancement of computational power, coupled with the availability of large-scale datasets, has significantly fueled the growth of DL in recent years. As a result, DL has been successfully applied in diverse domains such as image and speech recognition, natural language processing, and autonomous systems [102],[103][104]. The ability of DL models to achieve state-of-the-art performance in tasks that were previously deemed challenging or infeasible has garnered immense interest from researchers and practitioners alike.

Furthermore, DL continues to evolve with the development of novel architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs), each tailored to specific types of data and applications[105],[106],[107]. These advancements have not only enhanced the capabilities of DL but have also opened new avenues for interdisciplinary research, integrating insights from neuroscience, cognitive science, and computer science.

Despite its successes, DL also presents challenges that warrant ongoing investigation. Issues such as model interpretability, data bias, and the need for substantial labeled datasets pose

significant hurdles to its widespread adoption [108],[109]. As the field matures, addressing these challenges will be crucial for ensuring the ethical deployment and scalability of DL solutions in real-world applications.

In summary, DL represents a transformative force in the realm of AI, offering unprecedented opportunities for innovation and discovery across various sectors. As researchers continue to explore its potential, the implications of DL for technology, society, and the future of work are profound and far-reaching.

III.4.2 Development and History of DL

The concept of neural networks, which form the foundation of DL, has its roots in the 1940s, with early models like the perceptron proposed by Frank Rosenblatt. However, significant advancements in the field did not occur until the late 20th century, primarily due to the development of backpropagation algorithms. This pivotal breakthrough allowed for more efficient training of multi-layer neural networks, enabling them to learn complex patterns in data. Despite these advancements, the widespread adoption of DL was limited by the computational resources available at the time.

The modern resurgence of DL began in the 2010s, driven by several key factors. One of the most significant was the advent of big data, which provided vast amounts of training data necessary for developing robust DL models. Simultaneously, advances in Graphics Processing Units (GPUs) allowed for the parallel processing of large datasets, significantly reducing the time required for training deep neural networks. This combination of large datasets and powerful computational tools led to remarkable breakthroughs in various applications, including image and speech recognition, natural language processing, and game playing.

Today, DL is widely used across multiple industries, revolutionizing sectors such as healthcare, finance, autonomous systems, and entertainment. In healthcare, for example, DL models analyze medical images for diagnosis and treatment planning, while in autonomous systems, they enable vehicles to perceive and respond to their environments in real-time. The continuous evolution of DL techniques, including the development of architectures like CNNs and RNNs, further enhances its applicability and effectiveness in addressing complex problems [100],[106].

III.4.3 DL Architectures

DL comprises various architectures, each tailored to solve different types of tasks, including image recognition, sequential data processing, and generative models. The following sections outline the major architectures that underpin DL applications.

III.4.3.1 Feedforward Neural Networks (FNNs)

FNNs represent the simplest form of artificial neural networks, where information moves unidirectional from input to output through one or more hidden layers. In FNNs, there are no cycles or loops, ensuring that the flow of data remains forward through the network. Each neuron in a hidden layer performs a weighted sum of inputs followed by the application of a non-linear activation function, Figure III.8 present the feedforward neural network architecture.

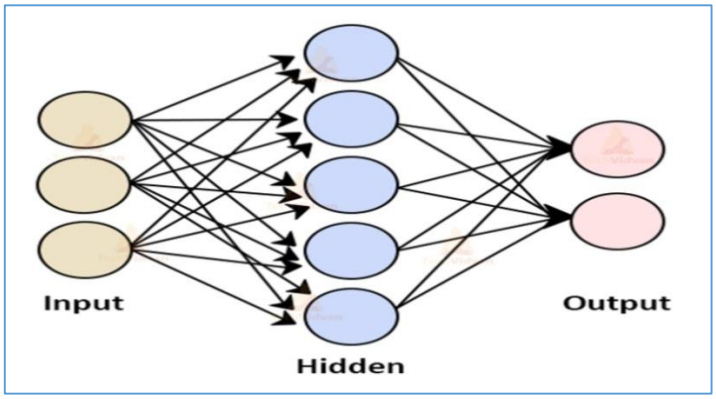


Figure III.8 Feedforward Neural Networks

The equation governing the operation of a neuron in an FNN is as follows:

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j \tag{3.1}$$

Where:

- x_i epresents the input,
- w_{ij} denotes the weights between the input and neuron ij,
- b_j is the bias term,
- z_j is the weighted sum.

The weighted sum is passed through an activation function, such as the sigmoid function:

$$a_j = \sigma(z_j) = \frac{1}{1 + e^{-z_j}} \tag{3.2}$$

This basic architecture is useful for simpler classification and regression tasks but is limited when processing more complex data due to the absence of spatial and temporal hierarchies in its structure [107].

III.4.3.2 Convolutional Neural Networks

CNNs are designed specifically for tasks involving grid-like data structures, such as images. CNNs employ convolutional layers that apply a set of filters (kernels) to input data to detect local patterns, such as edges, textures, and more abstract features at deeper layers. This architecture excels in computer vision tasks due to its ability to capture hierarchical spatial features. The in Figure III.*9* present an example of CNN.

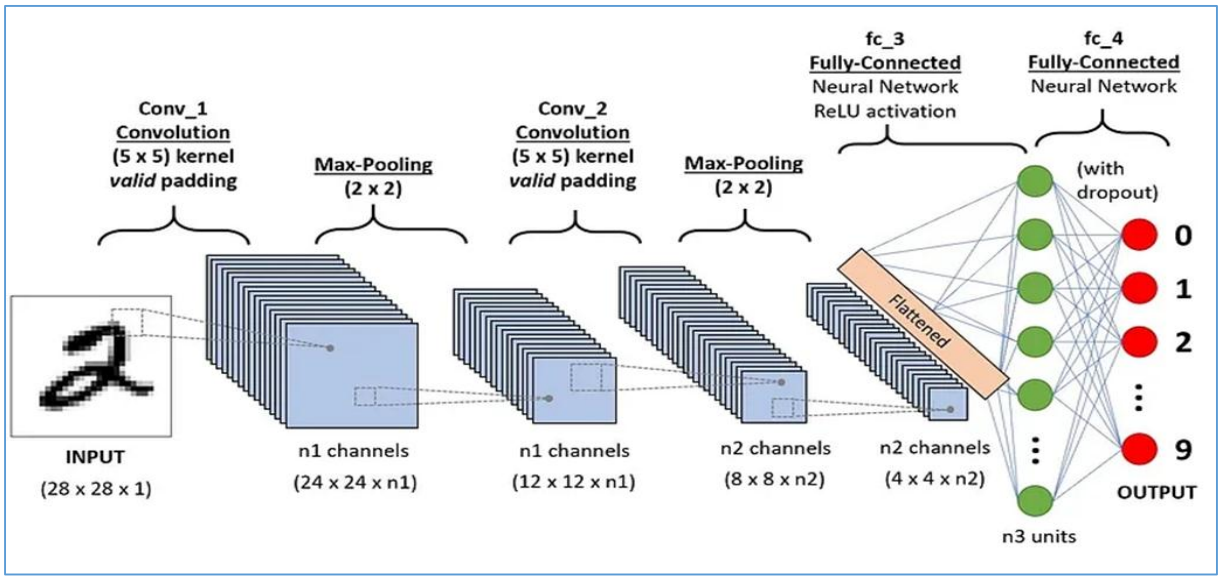


Figure III.9 Convolutional Neural Networks example[43]

The convolution operation in a CNN is defined as:

$$a_{ij}^{(l)} = \sigma \sum_{k=1}^{K} W_k^{(l)} * a^{(l-1)} + b^{(l)} \tag{3.3}$$

Where:

$a^{(l-1)}$ represents the input activations from the previous layer,

$W_k^{(l)}$ is the kernel or filter at layer l,

$*$ is the convolution operator,

$b^{(l)}$ is the bias term,

σ is an activation function (e.g., ReLU).

CNNs have been integral in advancing the field of image recognition, as exemplified by the success of models such as AlexNet and VGGNet in the ImageNet competition [100].

III.4.3.3 Recurrent Neural Networks (RNNs)

RNNs extend the concept of feedforward networks by introducing loops within the architecture, allowing information from previous time steps to influence current input processing. This makes RNNs particularly well-suited for tasks involving sequential data, such as time series analysis or natural language processing, the RNN architecture is showing in FigureIII.10.

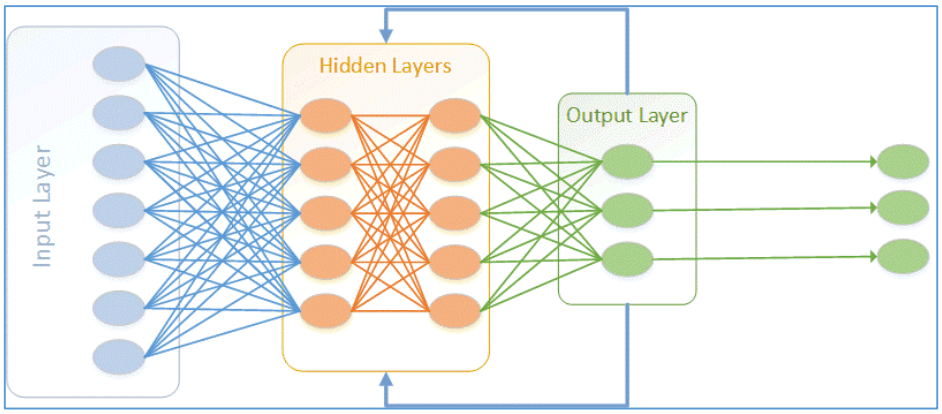


Figure III.10 Recurrent Neural Networks architecture

The hidden state of an RNN at time step t is given by:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + \mathrm{b}) \quad (3.4)$$

Where:

h_t tht is the hidden state at time t,

h_{t-1} represents the hidden state from the previous time step,

x_t is the input at time t,

W_h and W_x are weight matrices,

b is the bias,

σ is the activation function.

Although traditional RNNs struggle with long-term dependencies due to issues such as vanishing gradients, architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have been developed to mitigate these challenges [110].

III.4.3.4 DL Applications

DL has demonstrated exceptional capabilities across a wide range of applications, reshaping industries from healthcare to autonomous systems.

- **Healthcare**

DL is revolutionizing healthcare through its application in medical imaging, predictive diagnostics, and drug discovery. CNNs, in particular, have shown proficiency in analyzing medical images such as X-rays, MRIs, and CT scans for disease detection and classification. For instance [111], demonstrated the efficacy of CNNs in classifying skin cancer at a level comparable to dermatologists.

- **Autonomous Systems**

DL is a cornerstone in the development of autonomous systems, particularly self-driving cars. CNNs are used for real-time object detection and classification from camera and LIDAR inputs, while RNNs or Transformer-based architectures interpret sequential driving scenarios. The ability of DL models to perceive the environment and make decisions has been key to advancements in this field[112].

III.4.4 DL Challenges and Limitations

Despite its success, DL is not without limitations. The development of DL systems is still hampered by several challenges, including the following:

III.4.4.1 Data Requirements

DL models often require vast amounts of labeled data for training. This requirement can be problematic in fields where labeled data is scarce or difficult to obtain, such as in medical research. As a result, many DL models rely on transfer learning or self-supervised learning techniques to reduce data dependence[100].

The objective function for a DL model trained on a labeled dataset:

$D = \{(x_1 + y_1), \dots\dots\dots\dots, (x_n + y_n)\}$ can be written as:

$$L = \sum_{i=1}^{n} L\big(y_i, f(x_i\,;\,\theta)\big) \tag{3.5}$$

Where:

$f(x_i\,;\theta)$ is the neural network with parameters θ.

L is the loss function that measures the prediction error.

III.4.4.2 Overfitting

Overfitting is a persistent challenge in DL, where a model performs well on the training data but fails to generalize to unseen data. This problem is particularly prevalent in models with a high number of parameters relative to the amount of training data. Techniques such as dropout, regularization, and cross-validation are often employed to combat overfitting [113].

III.4.4.3 Measures to assess the performance DL model

This section introduces metrics used to assess the performance of the classifier in accurately predicting image class labels. These metrics include overall accuracy (recognition rate), sensitivity (recall), specificity, precision, and the F-measure.

Table III.2 provides detailed formulas for calculating these metrics. To better understand the classifier's effectiveness, we apply it to a labeled test dataset, where *P* represents the number of positive images, and *N* corresponds to the number of negative images.

Precision stands out as a key metric, often used more broadly to describe the predictive capabilities of a classifier.

Table III. 2 measures evaluation

Measure	Formula
recognition rate	$\frac{TP+TN}{P+N}$
Error rate	$\frac{TP+FN}{P+N}$
Recall	$\frac{TP}{P}$
Specificity	$\frac{TN}{N}$
Precision	$\frac{TP}{TP+FP}$
F, F-measure, harmonic mean of precision and recall	$\frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$

III.4.5 Recent Advances in DL

Recent years have seen numerous innovations in DL that have pushed the boundaries of what these models can achieve. Key advancements include self-supervised learning, transfer learning, and reinforcement learning.

III.4.5.1 Self-Supervised Learning

Self-supervised learning is a paradigm that reduces reliance on labeled data by using the structure of the data itself to generate labels like in Figure III.*11*. This approach has gained popularity in domains like natural language processing, where models like BERT (Bidirectional Encoder Representations from Transformers) use masked language modeling tasks to learn without human supervision [114].

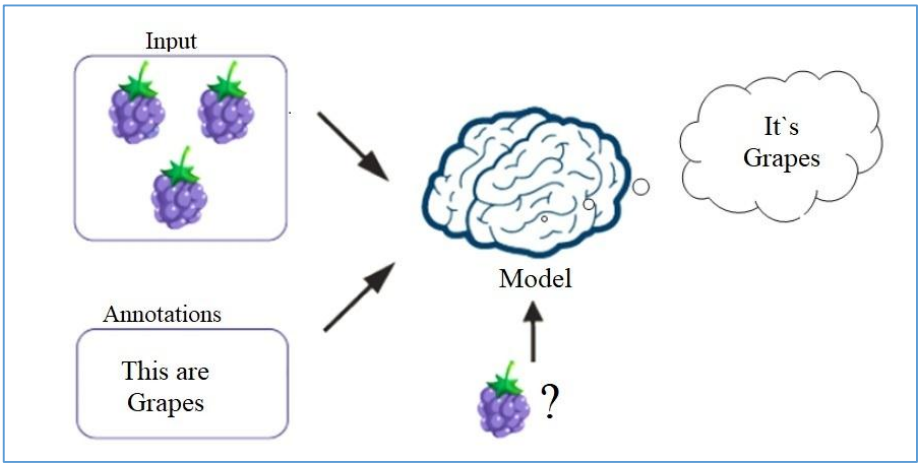


Figure III.11 Self-Supervised Learning

III.4.5.2 Transfer Learning

Transfer learning has been widely adopted in DL to address the problem of data scarcity. In this approach, models pre-trained on large datasets are fine-tuned for specific tasks with smaller, task-specific datasets. This technique has been especially impactful in computer vision [115].as in Figure III.*12* .

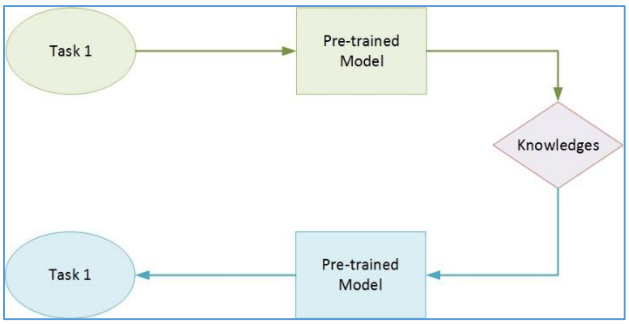


Figure III.12 Transfer learning diagram

III.4.5.3 Edge AI

With the advent of more powerful edge computing devices presented in Figure III.*13*, the deployment of DL models on devices such as smartphones, IoT devices, and autonomous drones is becoming more feasible. This trend, known as Edge AI**,** reduces the need for cloud-based computing by enabling inference directly on the device [116].

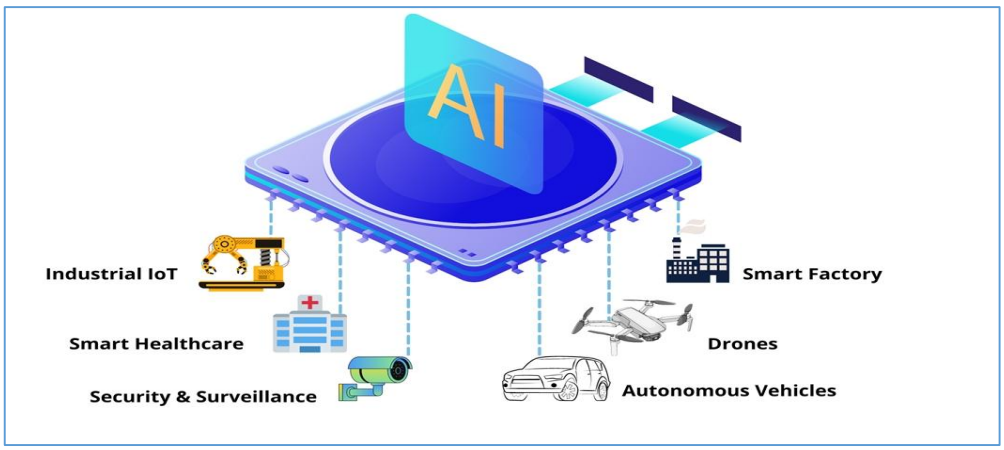


Figure III.13 Edge of AI

III.5 Hardware and Software Tools

The creation of our advanced health monitoring system necessitates a diverse array of hardware and software tools. In this chapter, we will explore these components in detail. As presented in FigureIII.14 our system is structured around five key elements: the data acquisition unit, the DL models for ECG analysis, the IoT-based monitoring framework, the communication infrastructure, and the user interface for real-time visualization. Each of these components plays a critical role in ensuring efficient real-time monitoring and analysis of patient health, leveraging the latest advancements in technology to enhance healthcare delivery.

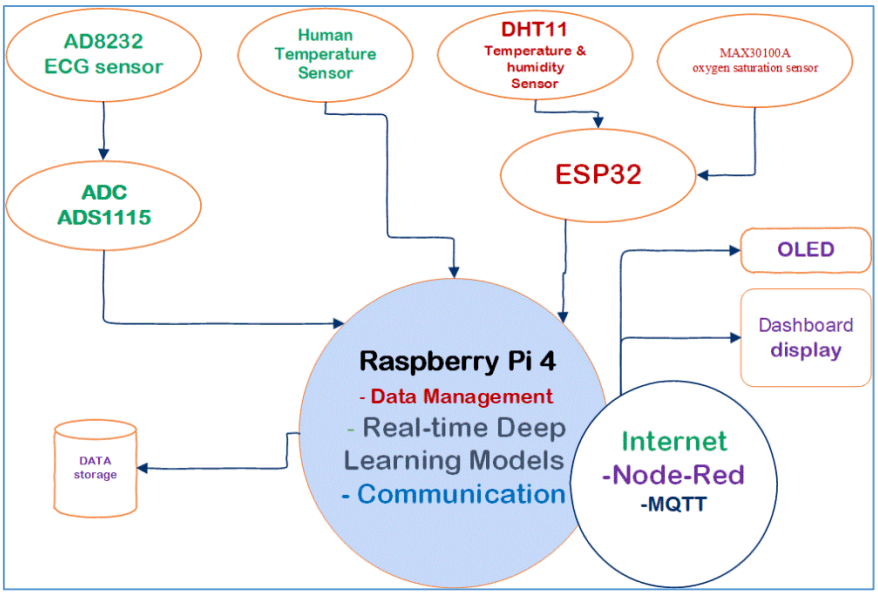


Figure III.14 The health monitoring system tools

III.5.1 Hardware Used

III.5.1.1 Processing Unit

The Raspberry Pi and ESP32 were selected as the processing units because they best meet the requirements of our system under development. The Raspberry Pi offers robust processing capabilities and connectivity options, while the ESP32 provides efficient data handling and integration with various sensors, making them complementary components in our design

III.5.1.1.1 Raspberry Pi

The Raspberry Pi is a versatile mini-computer featuring an ARM processor, created by the Raspberry Pi Foundation in the UK to enhance computer science education. Designed as an accessible tool for learning programming, it supports various languages, including Python and Scratch. Its ability to interface with external hardware and run multiple open-source operating systems—such as GNU/Linux, Raspbian, and Debian—makes it an ideal choice for both educational purposes and practical applications. Since the release of its first model, the Raspberry Pi B, in February 2012 [117][118], several generations have emerged, each offering improved performance and capabilities.

- **Presentation of Raspberry Pi 4 B**

The Raspberry Pi 4 Model B (Pi4B) is the first of a new generation of Raspberry Pi computers supporting more RAM and with significantly enhanced CPU, GPU and I/O performance in a similar form power factor, envelope and cost as the previous generation Raspberry Pi 3B+.

The Pi4B is available with 1, 2, 4, or 8 gigabytes of LPDDR4 SDRAM as show in FigureIII.15 .[119]

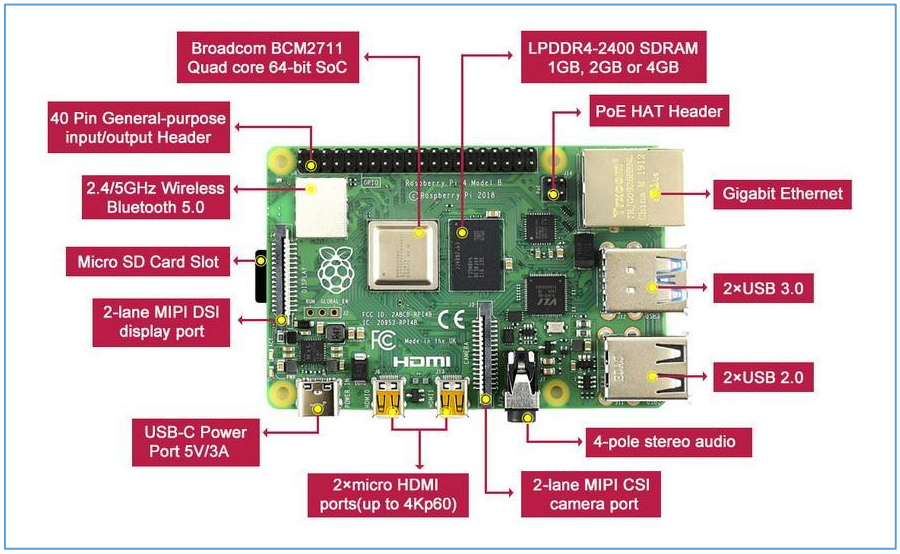


Figure III.15 Raspberry Pi 4B presentation [120]

- **Hardware**

• Quad core 64-bit ARM-Cortex A72 running at 1.5GHz
• 1, 2 and 4 Gigabyte LPDDR4 RAM options
• H.265 (HEVC) hardware decode (up to 4Kp60)
• H.264 hardware decode (up to 1080p60)
• Video Core VI 3D Graphics
• Supports dual HDMI display output up to 4Kp60

- **Interfaces**

• 802.11 b/g/n/ac Wireless LAN
• Bluetooth 5.0 with BLE
• 1x SD Card
• 2x micro-HDMI ports supporting dual displays up to 4Kp60 resolution
• 2x USB2 ports
• 2x USB3 ports
• 1x Gigabit Ethernet port (supports PoE with add-on PoE HAT)
• 1x Raspberry Pi camera port (2-lane MIPI CSI)
• 1x Raspberry Pi display port (2-lane MIPI DSI)
• 28x user GPIO supporting various interface options:
– Up to 6x UART

– Up to 6x I2C

– Up to 5x SPI

– 1x SDIO interface

– 1x DPI (Parallel RGB Display)

– 1x PCM

– Up to 2x PWM channels

– Up to 3x GPCLK outputs

- **Software**

• ARMv8 Instruction Set

• Mature Linux software stack

• Actively developed and maintained

- **GPIO Interface**

The Pi4B makes 28 BCM2711 GPIOs available via a standard Raspberry Pi 40-pin header as show in FigureIII.16 . This header is backwards compatible with all previous Raspberry Pi boards with a 40-way header.

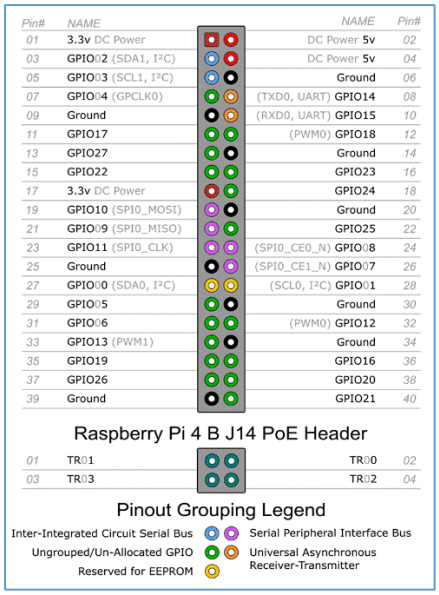


Figure III.16 Raspberry Pi 4 B Pinout

III.5.1.1.2 ESP32

ESP32 is the most integrated solution for Wi-Fi + Bluetooth applications in the industry with less than 10 external components. ESP32 integrates the antenna switch, RF balun, power

amplifier, low noise receive amplifier, filters, and power management modules. As such, the entire solution occupies minimal Printed Circuit Board (PCB)area as presented in FigureIII.17. ESP32 uses CMOS for single-chip fully-integrated radio and baseband, and also integrates advanced calibration circuitries that allow the solution to dynamically adjust itself to remove external circuit imperfections or adjust to changes in external conditions.[121].

- **ADC (Analogue-to-Digital Converter):** converts analogue signals to digital values for processing.
- **Processor:** Dual-core XTensa LX7 microprocessor, capable of running up to 240 MHz
- **Memory:** Comes with 512 KB of internal SRAM.
- **I/O Peripherals Support:** Includes SPI, I2S, I2C, PWM, RMT, ADC, UART, SD/MMC host, and TWAI™ for versatile hardware interfacing.
- **GPIOs:** Features 45 programmable GPIOs.
- **Storage:** Includes an 8 MB flash memory and supports larger, high-speed octal SPI flash and PSRAM.
- **Cache:** Configurable data and instruction cache.
- **AI Acceleration Support:** Offers AI acceleration for neural network computing and signal processing, accessible through ESP-DSP and ESP-NN libraries. [122]

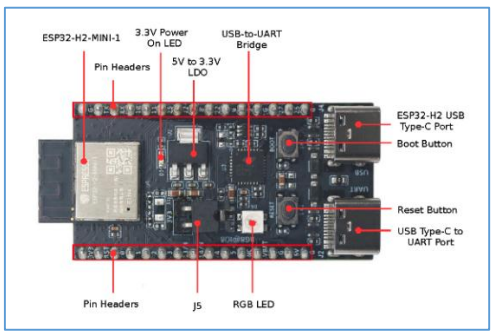


Figure III.17 ESP32 [123]

III.5.1.2 Sensors

III.5.1.2.1 ECG Sensor AD8232

The AD8232 is a highly specialized analog front-end chip designed for low-power HR and ECG monitoring applications. This single-lead ECG sensor is ideal for wearable health devices, offering a compact and efficient solution for acquiring bio-potential signals like heartbeats. It

excels in environments where noise, such as motion artifacts or poor electrode contact, can interfere with accurate data collection. The AD8232 filters and amplifies weak ECG signals, making them suitable for further processing in systems like microcontrollers or digital signal processors. Its low power consumption and ability to reject common-mode noise make it particularly suitable for battery-powered, portable health monitoring devices. These features position the AD8232 as a go-to choice for developers and engineers working on cutting-edge fitness and healthcare technologies, the parts of AD8232 presented in FigureIII.18 are:

- Power Input Pins (3.3, GND)
- Electrode pad connector pins (RA, LA, RL, 3.5 mm female jack)
- Data output pin (Output)
- Leads off detection output pins (LO-, LO+)
- Shutdown control pin(~SND)
- LED

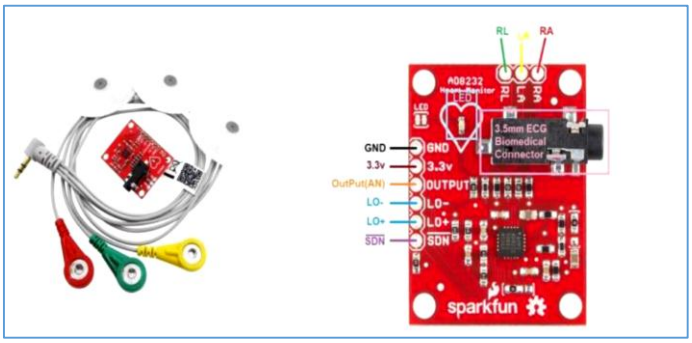


Figure III.18 ECG sensor AD8232[124]

III.5.1.2.1.1Oxygen saturation sensor MAX30100A

The MAX30100A show in FigureIII.19 is an integrated pulse oximeter and HR sensor solution designed for wearable health and fitness devices. It combines two LEDs (red and infrared), a photodetector, optimized optics, and low-noise analog signal processing to detect pulse and oxygen saturation (SpO_2) levels. Its small size and low power consumption make it ideal for battery-operated devices, such as smartwatches and fitness bands.

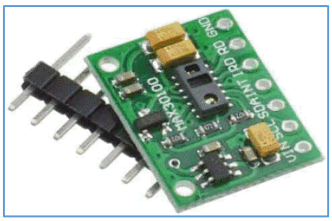


Figure III.19 MAX3010A SpO2 Sensor

III.5.1.2.1.2Human body temperature sensor

A human body temperature sensor is a device designed to measure the body's temperature. These sensors are commonly used in healthcare, fitness, and wearable devices to provide continuous or on-demand monitoring of a person's temperature its shown in FigureIII.20 .



Figure III. 20 Human Body Temperature Sensor

III.5.1.2.1.3Environment sensor DHT11

- The DHT11 is a low-cost digital temperature and humidity sensor, commonly used in various electronics projects for monitoring environmental conditions. It is popular in DIY, hobbyist, and IoT projects due to its ease of use and reliable performance in measuring both temperature and humidity its presented in FigureIII.21.
- Operating Voltage: 3.5V to 5.5V
- Temperature Accuracy: Measures temperature from 0°C to 50°C with an accuracy of ±2°C.
- Humidity Accuracy: Measures relative humidity from 20% to 90% with an accuracy of ±5%.
- Sampling Rate: 1 Hz (one reading per second) .

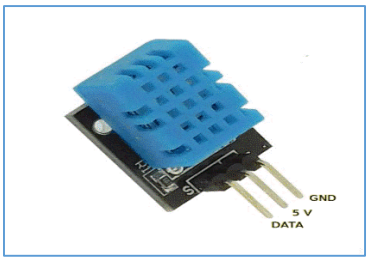


Figure III.21 Temperature and Humidity sensor DHT11

III.5.1.2.2 Analog to Digital Converter ADS1115

The **ADS1115** is a high-precision, low-power 16-bit analog-to-digital converter (ADC) designed by Texas Instruments. It is widely used in applications requiring precise analog measurements due to its versatility and ease of use. The ADS1115 presented in FigureIII.22 is often paired with microcontrollers like Arduino and Raspberry Pi for projects requiring multiple analog inputs, such as sensor reading, data acquisition, and industrial monitoring systems[124].

16-bit Resolution: Provides highly accurate digital readings of analog signals with 16-bit resolution.

4-Channel Input: The ADS1115 has four single-ended or two differential inputs, allowing multiple sensors or input sources to be connected.

Programmable Gain Amplifier (PGA): Includes an onboard PGA with selectable gain settings, enabling measurement of smaller signals with higher precision.

I²C Interface: Uses an I²C interface for communication, making it easy to connect with microcontrollers.

Low Power: Optimized for low-power operation, making it suitable for battery-powered devices.

Data Rate: Adjustable data rates from 8 to 860 samples per second (SPS), balancing between speed and accuracy.

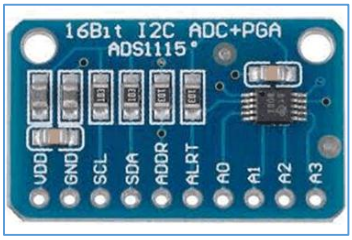


Figure III.22 Analog to Digital Converter ADS1115

III.5.1.2.3 Oled display

An OLED (Organic Light Emitting Diode) display is a flat light-emitting technology that differs from traditional LCDs in its ability to emit light without the need for a backlight. OLED displays are widely used in modern devices like smartphones, wearables, and display modules due to their high contrast ratios, faster response times, and lower power consumption. In maker projects, small OLED presented in FigureIII.23 modules are popular for displaying information in embedded systems, such as Arduino or Raspberry Pi projects.

- **I²C (Inter-Integrated Circuit)**

A simple two-wire protocol that allows communication between the microcontroller and the OLED module. Commonly used in projects where fewer GPIO pins are available.

- **SPI (Serial Peripheral Interface)**

A faster communication protocol compared to I²C but requires more pins.



Figure III.23 Oled Display

III.5.1.2.4 Power and Battery EB615268VU

The EB615268VU in FigureIII.24 is a specific lithium-ion rechargeable battery model that is commonly used in mobile phones and other portable devices. This model is typically found in older devices and may not be as widely available today. Below are some general specifications and details about this type of battery:

Battery Type: Lithium-ion rechargeable battery.

Nominal Voltage: 3.7V, typical for lithium-ion cells.

Capacity: Often around 1500mAh to 1700mAh, though the exact value can vary depending on the specific model and manufacturer.



Figure III. 24 Lithium Battery EB615268VU

III.5.2 Software Used

III.5.2.1 python

Python is a high-level, interpreted programming language that has become one of the most widely used languages due to its simplicity, readability, and vast ecosystem of libraries. Created by Guido van Rossum and first released in 1991, Python was designed with an emphasis on code readability, allowing developers to express concepts in fewer lines of code compared to other languages like C++ or Java. Its clean syntax, using indentation to define code blocks, makes it especially attractive to beginners and professionals alike. This structure helps in maintaining and debugging code, fostering collaboration in large-scale software development projects.

Python supports multiple programming paradigms, including procedural, object-oriented, and functional programming, making it a versatile tool across domains. It has been adopted for various applications, from web development (with frameworks like Django and Flask) to scientific computing, data analysis, ML, and AI (with libraries such as NumPy, Pandas, TensorFlow, and PyTorch). The language’s large standard library, often described as "batteries included," provides tools for tasks such as file handling, regular expressions, web services, and much more, reducing the need for external dependencies.

Python's dynamic typing and built-in memory management, handled by a garbage collector, simplify development by reducing boilerplate code and allowing developers to focus on

problem-solving. Its flexibility and ease of integration with other languages (like C, C++, and Java) make Python an ideal tool for system integration. Additionally, Python's growing use in automation, scripting, and rapid prototyping has made it a go-to language in industries ranging from finance to healthcare.

Python's strong, open-source community has been a key driver of its success, continuously developing new libraries and frameworks that extend its capabilities. The language is widely supported on various platforms, including Windows, macOS, and Linux, ensuring accessibility for developers worldwide. Its application in emerging fields like AI, ML, and data science has solidified its importance in modern technology. Consequently, Python continues to dominate rankings as one of the most popular and in-demand programming languages today [125],[126],[127] ([8] .

III.5.2.2 Google Colab (Colaboratory)

Google Colab is a free, cloud-based platform developed by Google that allows users to write and execute Python code directly in a web browser. It is widely used by data scientists, ML practitioners, and educators due to its ability to provide powerful computational resources, such as GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units), at no cost. Colab operates similarly to Jupyter Notebooks, enabling users to create notebooks that combine code execution with narrative, rich text, equations, and visualizations. This feature is especially beneficial for sharing research, tutorials, and collaborative projects.

One of the major benefits of Google Colab is its ease of collaboration. Multiple users can work on the same notebook simultaneously, which makes it ideal for team-based projects and educational environments. The platform supports numerous popular libraries, such as TensorFlow, PyTorch, Keras, NumPy, Pandas, and Matplotlib, which are essential for ML, data analysis, and scientific computing. Additionally, Colab simplifies the process of loading data from external sources, such as Google Drive or cloud storage, enhancing its utility in data-intensive tasks.

Google Colab eliminates the need for a local development environment, allowing users to begin coding by simply logging into a Google account as shown in figureIII.25. This makes it particularly advantageous for beginners or individuals without high-performance hardware, as it provides access to advanced resources. The platform also offers Colab Pro, a paid version that extends runtime, provides faster GPUs, and allocates more memory, making it suitable for more demanding ML tasks, such as DL model training on large datasets.

Because of its open-source nature and integration with Google's ecosystem (e.g., Drive, Big Query), Colab is widely adopted in both academia and industry. It has become a crucial tool in the modern data science and ML pipeline, removing barriers to entry and promoting collaboration across distributed teams[128] .

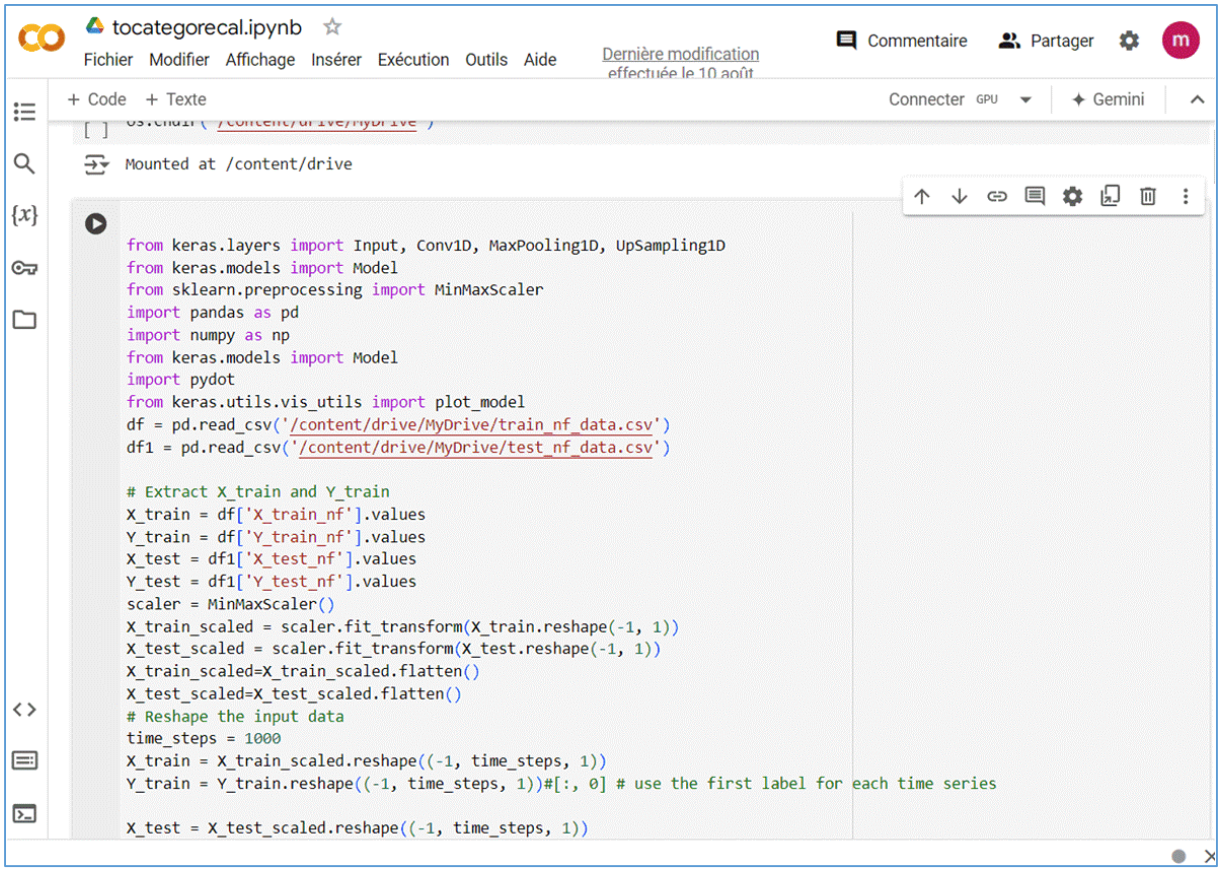


Figure III.25 google colab platform

III.5.2.3 C/C++ (Arduino IDE Framework) for ESP32

The ESP32 microcontroller has emerged as a leading choice for IoT applications, thanks to its robust features, including dual-core processing, integrated Wi-Fi, and Bluetooth capabilities. When programmed in C/C++ using the Arduino framework, developers can fully exploit these features while benefiting from the intuitive and user-friendly environment provided by the Arduino IDE presented in FigureIII.26. The Arduino framework streamlines the programming process by offering a rich set of libraries that abstract complex hardware interactions, enabling developers to focus on application logic rather than low-level programming details. For example, the WiFi.h library allows for straightforward management of Wi-Fi connections, enabling the ESP32 to act as both a client and an access point, facilitating data transfer to and from cloud services or local networks with minimal coding effort [129] .

the ESP32's event-driven architecture and multi-threading capabilities make it particularly suitable for real-time applications. This is especially important in scenarios where multiple sensors need to report data simultaneously or when a device must respond to various events, such as user inputs or sensor readings. With the Arduino framework, developers can efficiently handle external events without blocking the main execution flow, which enhances responsiveness in applications like smart home automation systems where rapid reactions to sensor data are essential (Hercog et al., 2022).

Additionally, the extensive library support within the Arduino ecosystem accelerates development. Libraries like Bluetooth Serial and Webserver simplify the integration of Bluetooth communication and web server functionality, enabling seamless interactions between devices, smartphones, or web clients. This is particularly advantageous in healthcare applications, where real-time data exchange between wearable devices and mobile applications is crucial for continuous monitoring and timely intervention[130].

Furthermore, the ESP32’s ability to support Over-the-Air (OTA) updates allows developers to remotely update firmware without requiring physical access to the device. This feature is vital for maintaining IoT deployments, especially in remote or difficult-to-reach environments, ensuring that devices are always up to date with the latest features and security patches [131].

The strong community support around the Arduino ecosystem further enriches the development process. With numerous forums, tutorials, and resources available, both novice and experienced developers can easily find guidance, reducing the learning curve associated with embedded systems programming. This combination of powerful hardware capabilities, ease of programming, and extensive library support makes the ESP32 an ideal platform for IoT applications, from simple projects to complex systems[130,131].

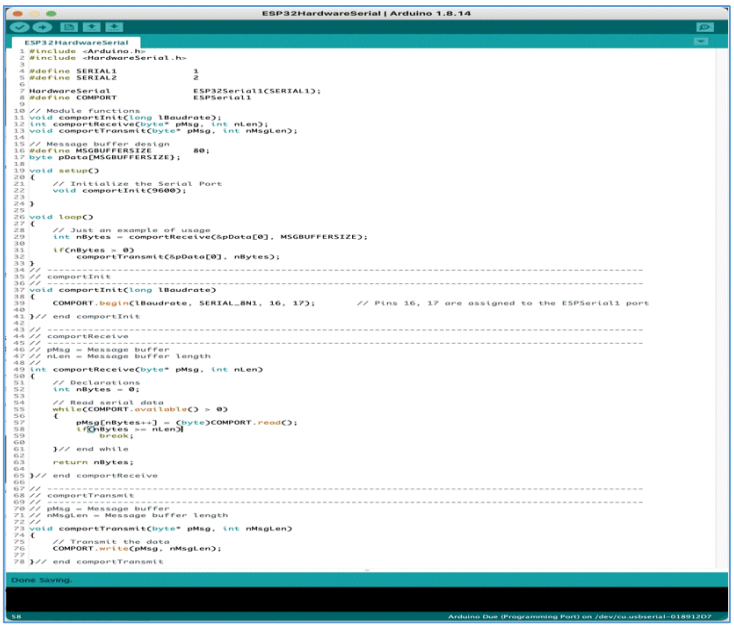


Figure III.26 Arduino IDE platform

III.5.3 Node-RED Server

Node-RED is a powerful tool that operates as a server-side application, enabling developers to create and manage data flows in an intuitive, graphical manner. Developed by IBM in 2013 as part of its efforts to advance the IoT, Node-RED runs on Node.js, which allows it to efficiently handle asynchronous events and real-time data processing[132] . The Node-RED server facilitates the integration of various devices, APIs, and services, making it an ideal choice for building IoT applications and automating workflows. Users can deploy flows that process real-time data from diverse sources, such as sensors and databases, while interacting with cloud services or local devices through a visual interface. Its architecture supports event driven programming, enabling seamless communication and data exchange across multiple components in an application [133]

Moreover, Node-RED's extensibility through custom nodes and a rich library of pre-built nodes fosters rapid development and enhances its capabilities, making it a favored platform for both developers and non-developers alike seeking to implement complex automation tasks efficiently [134].

III.5.3.1 Node-RED Editor

The Node-RED editor is a user-friendly interface that facilitates the creation and management of data flows, consisting of four key components as shown in FigureIII.27. At the top is the header, which provides access to essential features such as saving, deploying, and managing flows. On the left side, the palette contains a diverse collection of nodes that users can drag and

drop into their workspace, enabling various functions like input/output operations and data processing. The main workspace is situated in the center, where users visually arrange and connect nodes to create their desired workflows. Finally, the sidebar on the right offers additional options for managing nodes, viewing information, and accessing debugging tools, making the overall experience intuitive and efficient for both beginners and experienced developers.

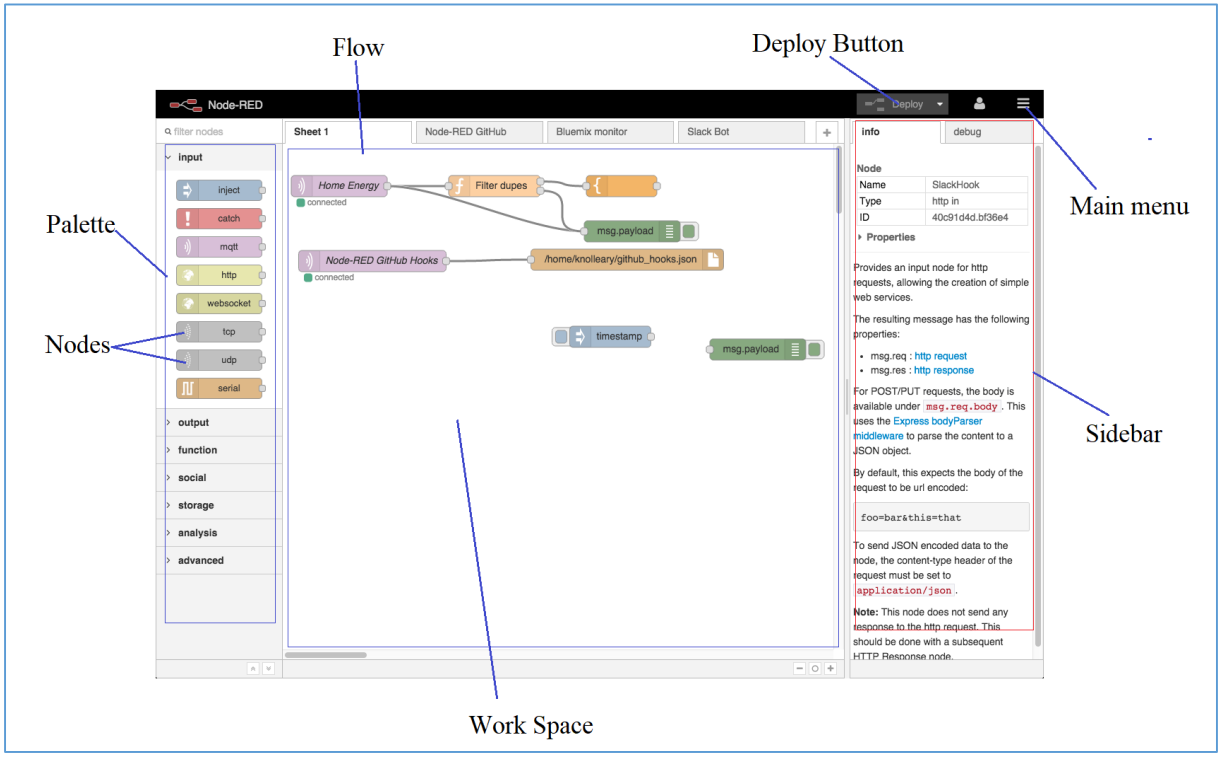


Figure III.27 Node-red editor

III.5.3.1.1 Header

The **header** of the Node-RED editor is located at the top of the interface and serves as the main navigation and control area. It includes several critical features:

- **Menu Options**: Users can access various functionalities, including managing flows, importing and exporting configurations, and accessing the settings menu.
- **Deploy Button**: A prominent button that allows users to deploy their changes to the running Node-RED instance, ensuring that any modifications made in the workspace take effect.
- **Search Functionality**: An integrated search bar for quickly locating nodes or searching through flows, improving usability in larger projects.

- **User Management**: Options for managing user accounts and permissions, especially in collaborative environments.

III.5.3.1.2 Palette

The **palette** in Node-RED is a crucial component that displays all the installed nodes available for building flows. Users can utilize the **palette manager** to install additional nodes, thereby enhancing the platform's capabilities. FigureIII.28 showcases some of the various modules included in Node-RED, such as:

- **Dashboard**: This module provides a suite of nodes, including text displays, gauges, graphs, and LEDs, enabling users to create dynamic dashboards for visualizing real-time data from different services.
- **Input/Outputs**: This category features nodes designed for sending and receiving data across various protocols, including serial, MQTT, and HTTP, facilitating effective communication with external systems.
- **Function**: Containing a range of processing nodes, this module includes simple options like delay nodes, more complex nodes such as switches, and programmable function nodes that can be tailored to fit specific programming needs.
- **Storage**: Nodes within this module are used to read from and write to files or databases, such as files and MySQL, simplifying data management tasks.
- **Social**: The "social media" nodes enable interactions with platforms like email, Twitter, and Facebook, allowing users to send and receive emails, notifications, and tweets, integrating social features into their applications.

Nodes are created upon deploying a flow, allowing them to send and receive messages while the flow is active. They are automatically removed when the next flow is deployed. Each node consists of an HTML file, which defines its visual representation and specifies the number of inputs and outputs, and a JavaScript file, which governs the node's functionality. This architecture supports a diverse and customizable ecosystem within Node-RED, making it an adaptable tool for various applications.

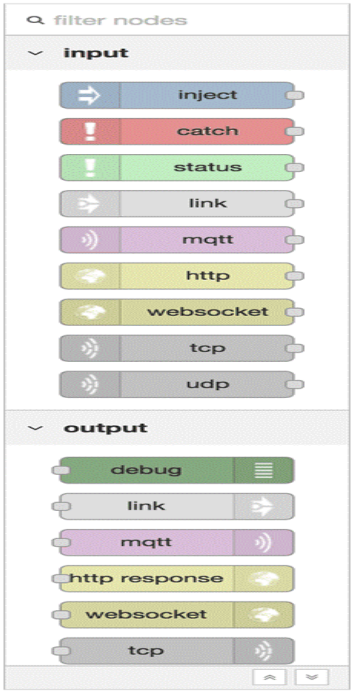


Figure III.28 Node-red palette

III.5.3.2 Main Workspace

The **main workspace** is the central area where users design and configure their data flows. Its features include:

- **Visual Flow Representation**: Users can connect nodes using wires, visually representing the flow of data and control between different components. This allows for an intuitive understanding of how data is processed.
- **Node Configuration**: Clicking on a node opens its configuration panel, where users can set parameters, define properties, and specify behaviors to customize how the node operates.
- **Zoom and Pan**: The workspace supports zooming in and out and panning across larger flows, making it easier to navigate complex applications with many interconnected nodes.

III.5.3.3 Sidebar

The sidebar in Node-RED is a valuable feature that offers various panels containing useful tools for the editor. Its components include:

- **Information Panel:** This section displays detailed information about the currently selected node, providing a summary of its properties and helpful descriptions to assist users in understanding how to configure it effectively.

- **Debug Panel:** This panel shows messages sent to debug nodes within the flow, along with logging information from the execution process. This functionality is crucial for troubleshooting and monitoring the behavior of flows in real time.
- **Configuration Nodes Panel:** This area presents a list of all configuration nodes organized by their scope, allowing users to easily access and manage these nodes as needed.

  Context Panel: This panel displays the content of the context data storage, providing insight into the data being stored and manipulated within the flows.

Additionally, some nodes, such as those in the node-red-dashboard module, can provide their own custom sidebar, enhancing the functionality and user experience. The sidebar thus plays a key role in managing nodes, debugging flows, and maintaining an organized workspace, making it an essential tool for developers working in Node-RED.

III.5.3.3.1 Some Available Nodes in Node-RED

Node-RED offers a diverse range of nodes that cater to various functionalities, allowing users to build complex workflows with ease. Here are some notable categories and examples of available nodes as shown in FigureIII.29:

- **Input Nodes**: These nodes facilitate the collection of data from external sources. Examples include:
  - **HTTP In**: Receives HTTP requests, allowing integration with web applications.
  - **MQTT In**: Subscribes to MQTT topics to receive messages from IoT devices.
- **Output Nodes**: Used to send data to various destinations, such as:
  - **HTTP Response**: Sends responses back to HTTP requests.
  - **MQTT Out**: Publishes messages to MQTT topics, enabling communication with other devices.
- **Processing Nodes**: These nodes perform data manipulation or analysis. Examples include:
  - **Function Node**: Allows users to write custom JavaScript code to process incoming messages.
  - **Switch Node**: Routes messages based on specific criteria, enabling conditional logic in flows.

- **Storage Nodes**: Designed for managing data storage, such as:
  - **File Node**: Reads from or writes to files on the file system.
  - **MySQL Node**: Interacts with MySQL databases for data retrieval and storage.
- **Social Media Nodes**: Enable interactions with social platforms, such as:
  - **Email Node**: Sends and receives emails, allowing for communication through email services.
  - **Twitter Node**: Posts tweets or retrieves tweets from specific users or hashtags.
- **Dashboard Nodes**: These nodes help create user interfaces for displaying data visually. Examples include:
  - **Chart Node**: Visualizes data trends over time.
  - **Gauge Node**: Displays real-time metrics in a visual gauge format.

By leveraging these nodes and their functionalities, users can create robust applications that integrate various data sources and services, making Node-RED a powerful tool for IoT and automation projects.

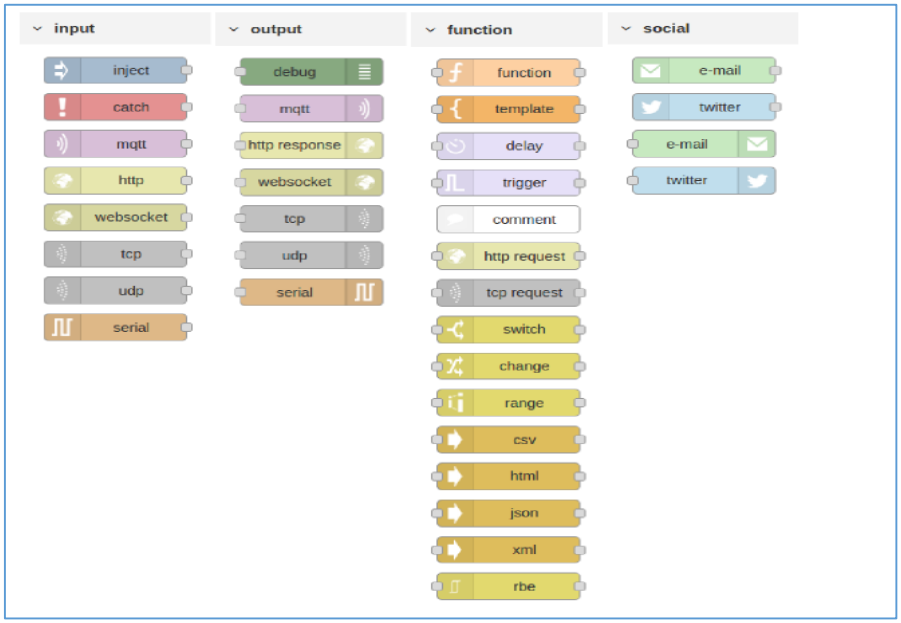


Figure III.29 Some Available Nodes in Node-RED Editor

III.5.3.4 Node-RED Dashboard

The **Node-RED Dashboard** is a powerful set of nodes that allows users to create web-based user interfaces for their applications. It provides a range of customizable UI components that can be easily integrated into Node-RED flows, enabling real-time data visualization and interaction. Here's a detailed overview of the Node-RED Dashboard presented in FigureIII.30:

1. **User Interface Components**: The Dashboard includes a variety of pre-built UI widgets, such as:
    - **Text**: Display static or dynamic text.
    - **Charts**: Visualize data trends over time using line charts, bar charts, or pie charts.
    - **Gauges**: Represent real-time metrics visually with analog or digital gauges.
    - **Buttons**: Allow users to trigger actions within the flow.
    - **Sliders and Input Fields**: Enable user input for controlling devices or adjusting settings.
2. **Responsive Design**: The Dashboard is built to be responsive, adapting to different screen sizes and devices, which makes it suitable for mobile and desktop use.
3. **Customizable Layout**: Users can arrange and style their dashboard components using a grid layout, making it easy to create organized and visually appealing interfaces.
4. **Real-Time Updates**: The Dashboard supports real-time data updates, meaning that any changes in the underlying Node-RED flow can be instantly reflected in the UI, allowing for dynamic monitoring and control of applications.
5. **User Authentication**: Built-in options for user authentication help secure dashboards, allowing only authorized users to access sensitive data and control functionalities.



Figure III.30 Node-RED Dashboard

III.6 conclusion

In summary, the convergence of DT, IoT and DL technologies represents a significant leap forward in how industries approach real-time monitoring, data analysis, and decision-making. These interconnected systems offer unprecedented opportunities for enhancing operational efficiency, enabling predictive maintenance, and driving innovation through intelligent automation. By harnessing the power of IoT for data collection, leveraging DL models for pattern recognition and decision-making, and utilizing DTs as virtual replicas of physical entities, industries are equipped to create more adaptive and resilient environments.

This chapter has explored the fundamental definitions, historical evolution, and diverse use cases of DT, IoT, and DL across various sectors, demonstrating their vital role in the ongoing digital transformation. The future promises even greater integration and advancements, paving the way for smarter healthcare systems, more efficient manufacturing processes, and more responsive urban infrastructures. As these technologies continue to evolve, their synergy will further enhance capabilities across sectors, driving new levels of optimization and intelligence in the connected world.

Chapter IV

A Concept of Operation Room Digital Twin

IV.1 Introduction

In modern surgical rooms, precision and real-time decision-making are critical to ensuring successful outcomes. The concept of the DT, which refers to a virtual model of a physical system or process, is being increasingly adopted in healthcare to enhance these capabilities. By creating a real-time digital counterpart of surgical rooms, including the medical instruments and equipment used during operations, healthcare professionals can improve both planning and execution of surgeries.

A DT of a surgical room allows for the integration and synchronization of advanced medical devices with real-time data, offering predictive insights, continuous monitoring, and more efficient surgical workflows. Key surgical instruments, from robotic surgical systems to monitoring devices, can now communicate with the digital environment through embedded sensors and IoT-enabled systems. This real-time data is used to mirror the physical behavior of each instrument, enabling greater accuracy and control in the operating room.

In this chapter, we will explore the types of surgical instruments used in operating rooms, how they communicate with the digital infrastructure, and the steps involved in creating a DT that includes these instruments. By understanding the integration of these devices into a DT, we gain insight into how data-driven decisions and predictive models can improve surgical procedures and patient outcomes, the Figure IV.*1* present a real operation room.



Figure IV.1 real operation room from Medea Hospital

IV.2 Types of Surgical Instruments and Their Role in the Operating Room

Surgical instruments are at the heart of any procedure in the operating room. These instruments range from basic tools to highly sophisticated devices that assist in complex operations. Each plays a vital role in ensuring precision and efficiency during surgery. In the context of a DT, understanding the functions and data that these instruments generate is essential for creating accurate digital replicas and improving operational workflows. Below is an overview of the various types of surgical instruments and how they contribute to the functioning of a surgical room.

IV.2.1 Surgical Lighting

Surgical lighting is a critical element in the operating room, providing the necessary illumination for surgeons to perform precise operations. Effective lighting ensures even brightness across the operating field with minimal shadows and heat, which is essential for the success of surgical procedures as present in FigureIV.2.

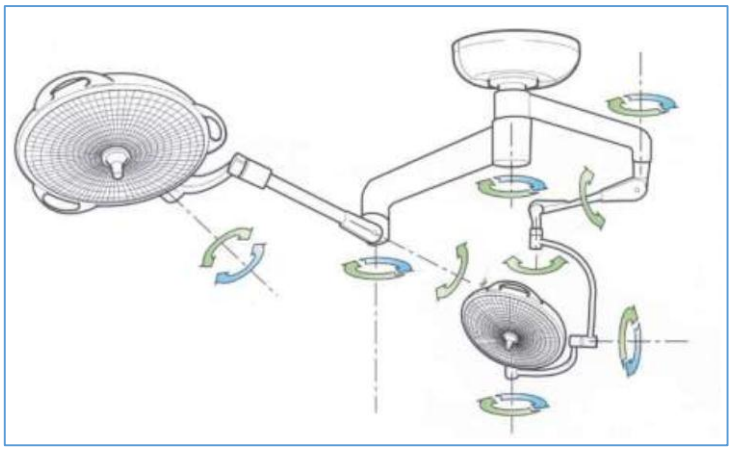


Figure IV.2 Surgical Lighting System

In a DT, the surgical lighting setup is digitally replicated, allowing for real-time adjustments based on data collected from sensors in the lights. These sensors monitor brightness, shadowing, and heat levels, feeding this information into the DT as shown in FigureIV.3. The system can then automatically adjust the lighting to maintain optimal conditions throughout the surgery.

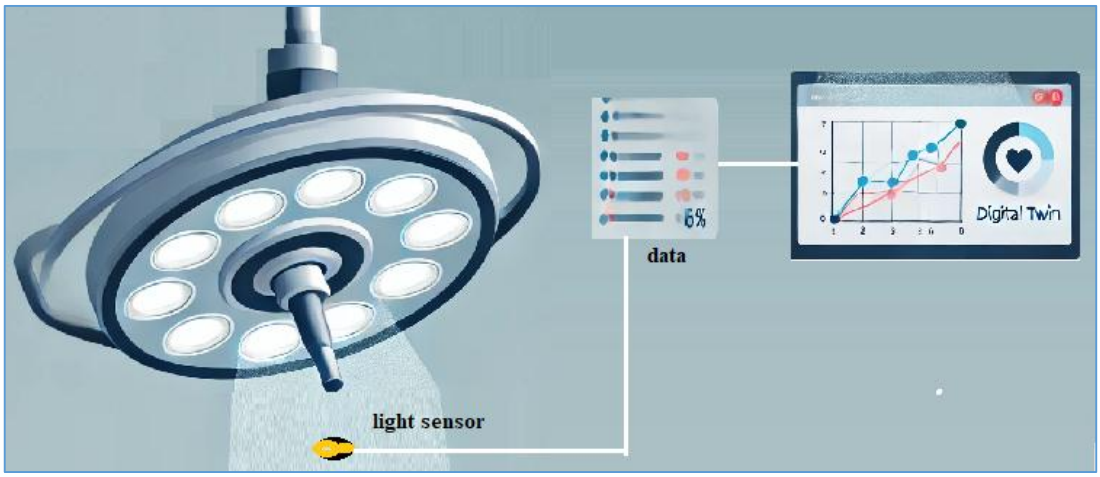


Figure IV.3 Lighting Sensors and Control in DT

By using the DT, surgeons receive instant feedback about the lighting quality and can adjust it remotely when needed. The system also uses historical data to predict potential lighting system issues, enabling preventive maintenance before any failures occur.

IV.2.2 Medical Gases and Their Role in Surgery

Medical gases are essential for both anesthesia and certain surgical procedures. The distribution, monitoring, and regulation of these gases in the operating room must be precise to ensure patient safety and the effectiveness of the surgery as present in FigureIV.4. In a DT system for a surgical room, medical gases such as oxygen, nitrous oxide (N_2 O), and carbon dioxide (CO_2) can be tracked and controlled in real-time, providing both anesthetic support and facilitating

surgical operations. The integration of these gases into the digital environment enables continuous monitoring, predictive alerts, and optimization of gas delivery systems.

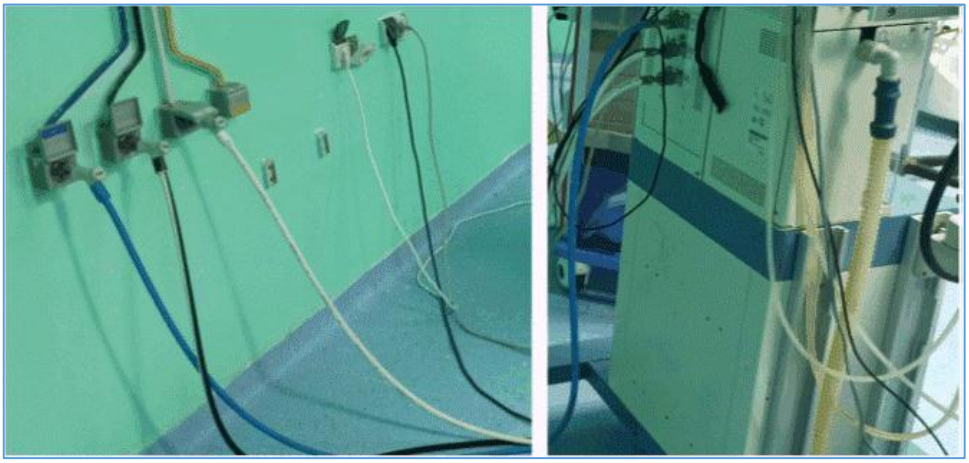


Figure IV.4 gases distribution in hospital

IV.2.2.1 Types of Medical Gases Used in Surgery

The following gases are commonly used in compliance with ISO 7396-1:2016 for medical gas pipeline systems:

Oxygen (O_2): Essential for maintaining adequate oxygenation of the patient's blood. Oxygen is supplied through the pipeline system at pressures typically regulated around 4 to 5 bar, in accordance with standard guidelines.

Nitrous Oxide (N_2 O): Used primarily as an anesthetic, often delivered in combination with oxygen. Pressure ranges typically hover around 4 to 4.5 bar for safe delivery.

Compressed Medical Air: Used to power pneumatic surgical tools and assist in patient ventilation. It is typically delivered at pressures between 4.5 and 10 bar, depending on the application.

Carbon Dioxide (CO_2): Employed in laparoscopic and other minimally invasive surgeries to create space by insufflating the body cavity. CO_2 is supplied at varying pressures depending on the requirements of the procedure, usually between 3 and 7 bar.

Vacuum Systems: Used to extract gases, fluids, or secretions from the patient during surgery. Vacuum pressure in medical gas systems is typically set below 60 kPa (absolute pressure) in compliance with ISO standards.

Argon, Nitrogen, Helium: These gases are less commonly used but serve specific purposes in cryosurgery and other advanced treatments, delivered in controlled mixtures depending on the procedure's needs, The Table IV.1 present the main medical fluids and there characteristic.

Table IV.1 The main medical fluids, their chemical code, their color and their pressure

Gas	Chemical Code	Color	Typical Pressure
Oxygen	O_2	White	4.8 bar
Nitrous Oxide	N_2 O	Blue	4 to 4.5 bar
Medical Air	-	Yellow	5 to 10 bar
Vacuum	-	-	≤60 kPa (absolute pressure)
Carbon Dioxide	CO_2	-	3 to 7 bar

IV.2.2.2 Integration of Medical Gases into the DT

In compliance with ISO 7396-1:2016, the integration of medical gases into the DT system includes the following critical aspects:

- **Gas Flow Regulation:** ISO standards mandate that medical gas systems must have precise flow meters and regulators. By integrating these into a DT, the flow of gases such as oxygen and nitrous oxide can be monitored in real-time. Any deviation from the prescribed flow rates triggers alerts, ensuring patient safety.
- **Pressure Monitoring:** The pressures within medical gas systems must stay within defined ranges to ensure safety and efficacy. A DT can simulate and continuously monitor these pressure levels, ensuring compliance with ISO safety regulations. The system can automatically adjust pressure to avoid unsafe conditions.
- **Safety Mechanisms:** ISO 7396-1:2016 requires the use of safety valves and fail-safe mechanisms to prevent over-pressurization. These mechanisms can be modeled within the DT, ensuring that any deviations outside of the recommended operational ranges are immediately addressed.

IV.2.2.3 Monitoring and Predictive Maintenance

In addition to real-time control, the DT can track the long-term performance of medical gas systems. This data can help predict when maintenance is required on regulators, valves, or other parts of the system, reducing the risk of equipment failure during surgery.

The DT allows for predictive analytics based on historical data to ensure that gas supplies and delivery systems are functioning optimally, minimizing the risk of interruptions during critical procedures.

IV.2.2.4 Sensors for Medical Gases in a DT

1. **Flow Sensors**:
    - **Purpose**: Measure the flow rate of gases (e.g., oxygen, nitrous oxide, carbon dioxide) to ensure that the correct amount is delivered.
    - **Example**: Mass flow meters or ultrasonic flow sensors.
2. **Pressure Sensors:**
    - **Purpose**: Monitor the pressure in gas lines to ensure it remains within safe operational limits.
    - **Example**: Piezoelectric or strain gauge pressure sensors that can detect pressure changes and provide real-time feedback to the DT.
3. **Temperature Sensors**:
    - **Purpose**: Ensure that gases like CO_2 (used in laparoscopic surgery) or gases for cryosurgery are maintained at the correct temperature.
    - **Example**: Thermocouples or RTD (Resistance Temperature Detectors).
4. **Gas Composition Sensors:**
    - **Purpose**: Analyze the composition of gas mixtures to ensure the right concentrations of gases are being delivered, especially during anesthesia.
    - **Example**: Infrared gas analyzers or electrochemical gas sensors.
5. **Oxygen Saturation Sensors (O_2 Sensors):**
    - **Purpose**: Measure the concentration of oxygen in the pipeline or at the delivery point to ensure adequate oxygen levels are provided during surgery.
    - **Example**: Galvanic or zirconia oxygen sensors.
6. **Leak Detection Sensors:**
    - **Purpose**: Detect any gas leaks in the system that could pose a risk to safety.
    - **Example**: Infrared or ultrasonic leak detectors.
7. **Flow Valve Position Sensors:**
    - **Purpose**: Monitor the position of flow control valves to ensure they are operating correctly and adjusting the gas flow as needed.
    - **Example**: Potentiometers or magnetic position sensors.

IV.2.2.5 Actuators for Medical Gases in a DT

1. **Flow Control Valves (Automatic or Servo-Valves):**
    - **Purpose**: Actuate to adjust the flow of medical gases in response to sensor input, maintaining optimal flow rates for different procedures.
    - **Example**: Electromagnetic or pneumatic actuators controlling precision flow valves.
2. **Pressure Regulators (Smart Regulators):**
    - **Purpose**: Automatically adjust the pressure in gas pipelines based on feedback from pressure sensors to ensure safe delivery of gases.
    - **Example**: Electromechanical or pneumatic pressure regulators.
3. **Temperature Control Systems:**
    - **Purpose**: Adjust the temperature of gases, especially in applications such as cryosurgery or heated surgical tools.
    - **Example**: Electric heaters or coolers with integrated thermal control systems.
4. **Shut-off Valves (Safety Actuators):**
    - **Purpose**: Actuate in emergency situations to stop the flow of gases if unsafe conditions (e.g., high pressure or leakage) are detected.
    - **Example**: Solenoid actuated shut-off valves.
5. **Mixing Systems (Gas Blenders):**
    - **Purpose**: Control the ratio of gases (e.g., oxygen and nitrous oxide) to deliver precise mixtures for anesthesia or other medical applications.
    - **Example**: Motorized gas mixing valves with actuators.

IV.2.3 System Integration in the DT

The sensors continuously monitor real-time conditions (pressure, flow, temperature, composition), while actuators adjust gas delivery based on this data. The DT simulates the behavior of the physical system, predicts potential issues, and helps optimize operations by making necessary adjustments automatically.

For example, if a pressure sensor detects a drop in the oxygen line, the DT can alert the system to increase flow or engage a backup supply. Similarly, if the temperature in a CO_2 line rises above the safe range, the actuator adjusts the cooling system to compensate, ensuring safety and efficiency in surgical procedures.

IV.3 Medical instruments

IV.3.1 Anesthesia Machines

Anesthesia machines deliver controlled mixtures of gases (such as oxygen, nitrous oxide, and anesthetic agents) to keep patients unconscious and pain-free during surgery as shown in Figure IV.5. A DT can simulate and monitor the anesthesia process, ensuring precise dosage and the timely delivery of gases, while also tracking patient vitals for safety.



Figure IV.5 Anesthesia machine

IV.3.1.1 Sensors

- **Gas Flow Sensors:** Monitor the flow rate of anesthesia gases and ensure the correct delivery based on the patient's needs.
- **Pressure Sensors:** Ensure that gas is delivered at the correct pressure to avoid complications such as barotrauma.
- **Patient Oxygen Saturation Sensors (SpO_2):** Continuously measure the oxygen levels in the patient's blood to ensure they remain within a safe range during surgery.

IV.3.1.2 Actuators

- **Flow Control Valves:** Automatically adjust the flow of gases based on real-time sensor input.
- **Vaporizer Control:** Adjusts the concentration of anesthetic agents in the gas mixture.

- **Alarms and Notifications:** Activated when sensor data indicates unsafe conditions (e.g., low oxygen saturation, high pressure).

IV.3.1.3 DT Integration

A DT of an anesthesia machine can provide real-time simulations of gas delivery and patient responses. It allows for continuous monitoring of gas levels and flow rates, while also predicting potential failures or issues with the machine. Additionally, the DT can simulate patient-specific anesthetic needs, allowing for personalized anesthesia plans based on prior data.

IV.3.2 Patient Monitoring Systems

IV.3.2.1 Purpose

Patient monitoring systems track vital signs such as HR, blood pressure, and oxygen levels during surgery. Integrating these systems into a DT ensures real-time monitoring and alerts for abnormal conditions.

IV.3.2.2 Sensors

- **ECG Sensors:** Track HR and rhythm, detecting abnormalities such as arrhythmias.
- **Pulse Oximeters:** Monitor oxygen saturation levels in the blood.
- **Blood Pressure Sensors:** Measure the patient's blood pressure throughout the procedure.

IV.3.2.3 Actuators

- **Alarm Systems:** Alert the surgical team when vitals deviate from safe ranges.
- **Automated Adjustments:** Integration with anesthesia or ventilator systems to automatically adjust oxygen delivery, anesthesia dosage, or other parameters.

IV.3.2.4 DT Integration

In a DT, patient vitals can be continuously simulated and tracked. The system provides real-time feedback and predictive analytics, warning the surgical team of potential complications before they occur. Historical data can also be used to tailor the monitoring to specific patient profiles, improving outcomes.

IV.3.3 Infusion Pumps

Infusion pumps presented in FigureIV.6 deliver precise doses of medications or fluids to the patient during surgery. A DT can simulate and monitor dosage rates, ensuring that medication is delivered accurately.

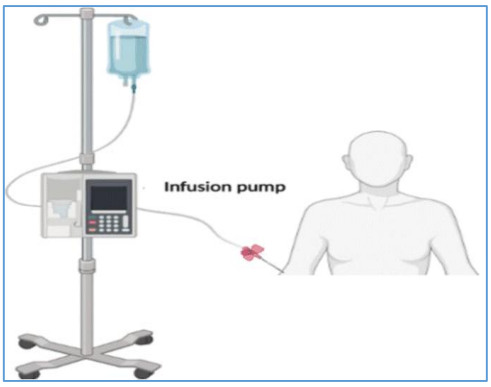


Figure IV.6 Infusion pumps

IV.3.3.1 Sensors

- **Flow Rate Sensors:** Measure the rate of medication delivery.
- **Occlusion Sensors:** Detect blockages in the infusion line.
- **Pressure Sensors:** Monitor the pressure in the delivery system to avoid over-infusion.

IV.3.3.2 Actuators

- **Pump Controls:** Adjust the rate of fluid or medication delivery based on real-time feedback.
- **Alarms:** Triggered by blockages, incorrect dosage rates, or equipment malfunctions.

IV.3.3.3 DT Integration

The DT monitors and simulates the infusion process, providing real-time adjustments to maintain optimal dosage. It can predict blockages and potential equipment failure, minimizing interruptions during surgery.

IV.3.4 Electrosurgical Units (ESUs)

ESUs use high-frequency electrical currents to cut tissue or coagulate blood during surgery as present in FigureIV.7. A DT can monitor energy delivery and simulate tissue interactions to optimize surgical outcomes.



Figure IV. 7 Electrosurgical Units (ESUs)

IV.3.4.1 Sensors

- **Energy Output Sensors:** Measure the electrical energy delivered to tissues.
- **Tissue Impedance Sensors:** Monitor the resistance of tissues to ensure that the energy is being delivered safely and effectively.

IV.3.4.2 Actuators

- **Energy Control Units:** Adjust the power output based on real-time feedback from the sensors to avoid excessive tissue damage or insufficient coagulation.

IV.3.4.3 DT Integration

The DT models tissue interactions in real-time, ensuring that energy levels are optimized for the procedure. The system also tracks the usage of the ESU to predict when maintenance or recalibration may be necessary.

IV.3.5 Imaging Systems (X-rays, MRI, CT Scanners)

Imaging systems provide visual insight into the patient's body during surgery. The DT can simulate the optimal angles and conditions for capturing images, ensuring better surgical guidance.

IV.3.5.1 Sensors

- **Position Sensors:** Track the angle and movement of the imaging devices.
- **Radiation Dose Sensors:** Monitor the amount of radiation delivered during imaging.

IV.3.5.2 Actuators

- **Positioning Actuators:** Adjust the angle and position of the imaging device based on real-time feedback to capture optimal images.
- **Exposure Control:** Regulates radiation levels to ensure patient safety.

IV.3.5.3 DT Integration

The DT simulates the imaging process, optimizing device placement for each specific patient. It also tracks radiation exposure to ensure safety and improve image quality for better surgical decision-making.

IV.3.6 Surgical Robots in a DT System

Surgical robots are highly advanced machines that assist surgeons in performing delicate, minimally invasive procedures. These robots can enhance precision, flexibility, and control

beyond the limits of human capability. They are used in various fields, such as urology, gynecology, and cardiology, to handle complex surgeries with greater accuracy. A DT of a surgical robot replicates the physical robot in a virtual environment, tracking its movements in real time and allowing for predictive maintenance and simulations before, during, or after surgeries.

IV.3.6.1 Sensors

Surgical robots are equipped with a range of sensors that feed data into the DT. Key sensors include

- **Position Sensors:** Track the exact location and movement of the robotic arms to ensure precision in the surgical field. These sensors help the DT replicate the robot's movements in real-time, allowing for monitoring and adjustments.
- **Force Sensors:** Measure the amount of force applied by the robotic instruments on tissues. This data can help prevent excessive force that might damage delicate tissues.
- **Torque Sensors:** Monitor the rotational force applied by the robotic joints and motors, ensuring smooth and controlled movements.
- **Camera and Optical Sensors:** Some robots include integrated cameras that provide visual feedback to the surgeon and the DT. These sensors help enhance accuracy during surgery and allow for visual simulations in the virtual environment.

IV.3.6.2 Actuators

Actuators control the movement of the surgical robot’s arms and instruments. These include:

- **Servo Motors:** These are precision actuators that control the joints and movement of the robotic arms. The DT can monitor the status of these motors in real-time and predict when maintenance or calibration is required.
- **Pneumatic Actuators:** Used in some robotic systems for specific movements that require compressed air, these actuators allow for fast and powerful actions, such as grasping or manipulating tissues.
- **Haptic Feedback Actuators:** Provide tactile feedback to the surgeon based on sensor data, allowing them to "feel" the resistance of tissues and organs through the robotic system.

IV.3.6.3 DT Integration

The DT system for surgical robots creates a real-time virtual model of the robot’s movements and interactions during surgery. Data from the sensors is continuously fed into the DT, where

it is processed and analyzed. This allows the DT to mirror the robot's actions and predict potential mechanical issues, such as joint wear or motor failure.

Additionally, the DT can simulate procedures, helping surgeons plan operations in advance. By running simulations with virtual patients, the robot's movements can be optimized for the unique anatomy of each patient, reducing the risk of complications.

IV.3.6.4 Applications

- **Preoperative Planning:** Surgeons can simulate the surgery in the DT before the actual procedure, allowing them to perfect their approach and avoid potential complications.
- **Intraoperative Monitoring:** During the surgery, the DT provides real-time feedback on the robot's performance, alerting the surgical team to any deviations or risks.
- **Postoperative Analysis:** After the surgery, the DT records all data, enabling analysis for quality control, training, or future procedure planning.
- **Predictive Maintenance:** The DT can predict when parts of the robot need servicing or replacement, reducing downtime and avoiding malfunctions during surgery.

IV.3.7 Surgical Microscopes

Surgical microscopes provide high magnification and illumination for precision surgery. The DT can help adjust the focus and magnification dynamically during the procedure.

IV.3.7.1 Sensors

- **Magnification Level Sensors:** Track the current magnification setting.
- **Focus Sensors:** Monitor the focus position to maintain clarity.

IV.3.7.2 Actuators

- **Zoom and Focus Controls:** Automatically adjust the microscope's settings based on real-time feedback and surgical needs.

IV.3.7.3 DT Integration

The DT optimizes the magnification and focus of the microscope based on the surgeon's actions and the patient's anatomy, ensuring a clear and precise view during surgery.

IV.3.8 Patient Monitoring via Cameras

Cameras can be used in the operating room to monitor the patient's physical condition beyond vital signs, allowing the DT to create a visual record of patient positioning, skin color, movement, and other visual indicators of health during the surgery.

It can also be used to monitor the actions and movements of the medical staff during surgery. This data can be used to optimize workflows, ensure adherence to protocols, and monitor for any deviations that could impact patient safety.

IV.3.8.1 Sensors:

- **High-Definition Cameras:** Capture detailed images or video of the patient in real-time, providing visual feedback for the DT. This information can be used to track the patient's condition and ensure proper positioning during surgery.
- **Thermal Cameras:** Monitor the patient's body temperature distribution, helping detect potential complications like inflammation or poor circulation in real-time.
- **Motion Tracking Cameras:** Capture the movements of the surgical team and medical staff in the operating room. These cameras can track the positioning and actions of each person, ensuring that sterile protocols are followed and minimizing the risk of contamination.
- **Facial Recognition and Gesture Recognition Cameras:** Identify individual staff members and monitor their interactions with the surgical equipment. These cameras can recognize specific gestures or interactions that are critical for maintaining safety and procedure flow.

The This Table IV.*2* concisely organizes the key elements of patient and medical staff monitoring within the DT system

Table IV. 2 key elements of patient and medical staff monitoring within the DT system

Category	Purpose	Sensors	Digital Twin Integration
Patient Monitoring	Monitor the patient's physical condition, posture, and indicators such as skin color and body temperature during surgery	High-Definition Cameras Thermal Cameras	Combines visual data with other sensor data (e.g., vitals) to monitor patient positioning and detect potential issues in real-time.
Medical Staff Monitoring	Track the movements and actions of the surgical team to ensure workflow efficiency and adherence to safety protocols	Motion Tracking Cameras Facial & Gesture Recognition Cameras	Tracks staff movements and interactions, optimizing workflows and ensuring compliance with sterile procedures for safety.
Combined Monitoring	Provide a holistic view of the operating room, tracking both patient condition and staff interactions	HD Cameras, Thermal Cameras Motion & Gesture Recognition Cameras	Creates a comprehensive simulation of the operating room, improving patient safety, workflow efficiency, and protocol adherence.

IV.3.8.2 DT Integration:

In the DT, the visual data from these cameras is combined with other sensor data to create a more comprehensive model of the patient's condition. This integration helps ensure that the surgical team can detect subtle signs of distress or improper positioning that might not be reflected in vital signs alone. Additionally, thermal imaging data can provide insights into areas of concern, such as detecting possible signs of infection early by identifying abnormal temperature patterns.

The DT for medical staff monitoring creates a virtual model of the operating room environment, tracking the movements and actions of each staff member. This data can help identify bottlenecks, inefficiencies, or risks in the workflow, allowing for optimizations to improve the overall efficiency and safety of the surgery. By monitoring staff adherence to safety protocols, the DT can also alert the team to potential breaches in procedure, ensuring a higher level of safety and hygiene.

IV.4 Communication

for the DT system, focusing on whether systems communicate directly or require intermediary controllers like microcontrollers, FPGAs, or Raspberry Pi.

IV.4.1 Direct Communication Systems

These systems have built-in communication capabilities and can send data directly to the DT without needing additional controllers.

IV.4.1.1 Patient Monitoring Systems

- Components: ECG sensors, pulse oximeters, blood pressure monitors.
- Communication: Bluetooth, Wi-Fi, Zigbee.
- Explanation: Modern patient monitoring systems come with integrated wireless communication modules. Data on patient vitals is transmitted directly to the DT over hospital networks (e.g., Wi-Fi or Bluetooth), without requiring intermediary devices.

IV.4.1.2 Imaging Systems (X-ray, MRI, CT Scanners)

- Components: Position sensors, radiation dose sensors, imaging control systems.
- Communication: Ethernet, Fiber Optic.
- Explanation: Imaging systems are equipped with built-in high-speed communication capabilities (Ethernet or Fiber Optic), allowing direct transmission of large image files to the DT for analysis and integration into simulations.

IV.4.1.3 Ventilators

- Components: Airflow sensors, oxygen sensors, pressure sensors, actuators (valves).
- Communication: Wi-Fi, Ethernet.
- Explanation: Ventilators in modern hospitals are networked and can transmit data on air pressure, oxygen levels, and airflow directly to the DT, allowing for real-time monitoring and adjustments.

IV.4.1.4 Anesthesia Machines

- Components: Gas flow sensors, pressure sensors, actuators (valves, vaporizers).
- Communication: Ethernet, CAN Bus.
- Explanation: Anesthesia machines can communicate directly with the DT via Ethernet or CAN Bus to provide continuous data on gas delivery and patient status without the need for additional controllers.

IV.4.2 Indirect Communication Systems (with Controllers)

These systems require intermediary controllers to manage sensor data and control actuators before communicating with the DT.

IV.4.2.1 Surgical Robots

- Components: Robotic arms, position sensors, force sensors, actuators (servo motors).
- Controller: FPGA or Real-Time Controller Board.
- Explanation: Surgical robots rely on real-time control from an FPGA or similar controller. Sensor data is processed locally by the controller, which then sends the processed data to the DT via Ethernet or Fiber Optic networks.

IV.4.2.2 Infusion Pumps

- Components: Flow rate sensors, pressure sensors, occlusion sensors, actuators (pump controls).
- Controller: Microcontroller (e.g., STM32, Arduino).
- Explanation: Microcontrollers handle the control of flow rates and pump operations. They collect data from sensors, process it, and then send it to the DT via Ethernet or Wi-Fi for continuous monitoring.

IV.4.2.3 Electrosurgical Units (ESUs)

- Components: Energy output sensors, tissue impedance sensors, actuators (energy control units).
- Controller: FPGA or Microcontroller.
- Explanation: ESUs require precise energy control based on real-time data. An FPGA or microcontroller processes the sensor data and controls the energy output, transmitting the processed data to the DT for further analysis.

IV.4.2.4 Surgical Microscopes

- Components: Magnification sensors, focus sensors, actuators (zoom and focus controls).
- Controller: Microcontroller or Raspberry Pi.
- Explanation: The microcontroller or Raspberry Pi adjusts the microscope's zoom and focus in response to sensor data. This data is then transmitted to the DT via Wi-Fi or Ethernet for real-time feedback and adjustments during surgery.

IV.4.2.5 Suction Systems

- Components: Flow rate sensors, pressure sensors, actuators (suction controls).
- Controller : Micro-Controller (e.g Arduino).
- Explanation: Microcontrollers control the suction system, adjusting power based on sensor input. The microcontroller sends performance data to the DT for optimization and monitoring via Ethernet or CAN Bus.

IV.4.2.6 Sterilization Units

- Components: Temperature sensors, humidity sensors, actuators (sterilization cycle controllers).
- Controller: Microcontroller or Raspberry Pi.
- Explanation: Sterilization units require a microcontroller to manage temperature and humidity levels during sterilization cycles. Data is sent to the DT via CAN Bus or Zigbee to ensure proper tracking of sterilization procedures.

IV.4.3 Hybrid Communication Systems

Some systems can operate either with direct communication or with controllers, depending on the hospital's infrastructure and the system’s complexity.
Sterilization Units and Infusion Pumps can either send data directly to the DT if they have built-in communication capabilities, or they may use a microcontroller to manage local data processing before sending it.

IV.5 The proposed Digital Twin

The proposed DT system for the operating room is designed to create a real-time, virtual replica of critical medical devices such as infusion pumps, anesthesia machines, cameras, and alarm systems. By integrating sensors and actuators with communication protocols like Wi-Fi, Ethernet, and CAN Bus, the DT system mirrors the operation of these devices, allowing for predictive maintenance, enhanced monitoring, and seamless control during surgical procedures. The proposed DT is presented in the diagram of Figure IV.*8*.

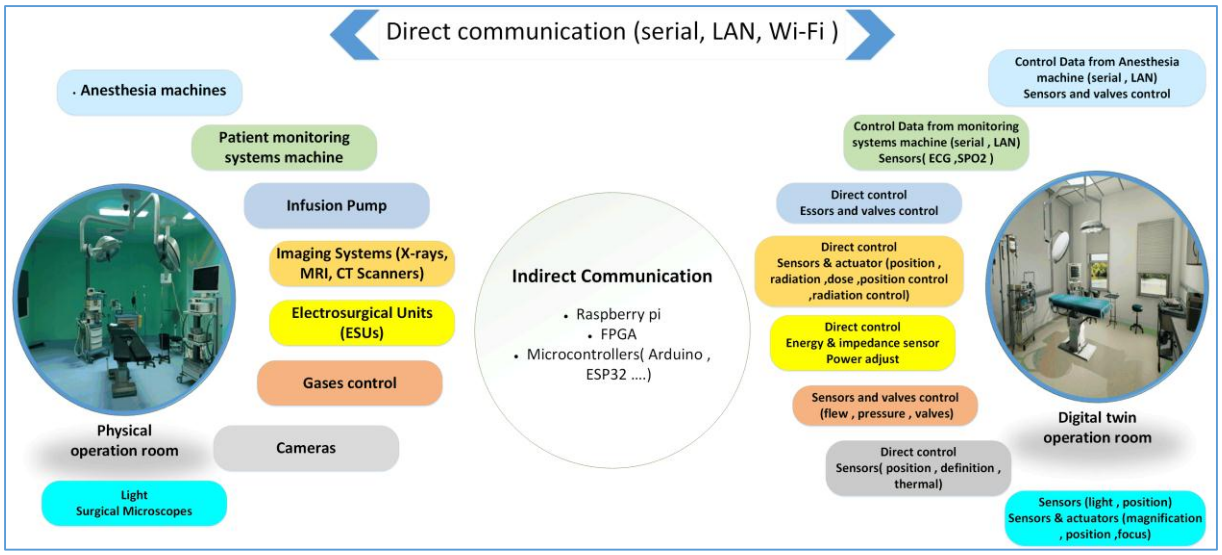


Figure IV.8 operation room DT

IV.6 Conclusion

the implementation of a DT system in the operating room represents a significant advancement in medical technology. By creating a real-time virtual counterpart of essential surgical instruments, the system enhances the precision, safety, and efficiency of medical procedures. The integration of communication protocols and real-time data from sensors and actuators allows for predictive maintenance and immediate adjustments, ensuring that medical teams can focus on patient care while minimizing the risk of equipment failure. This innovative approach offers transformative potential in improving surgical outcomes, optimizing workflows, and setting new standards for patient safety and care in modern healthcare.

Chapter V

The Proposed Framework: Integrating IoT and Deep Learning for Healthcare Systems

V.1 Introduction

In recent years, the integration of AI and IoT in healthcare has gained significant traction, particularly in the areas of real-time patient monitoring and diagnostics. This chapter outlines the development and practical implementation of a cutting-edge AI-driven IoT system designed for real-time ECG analysis and comprehensive patient health monitoring. The motivation behind the development of this system is driven by the increasing demand for efficient, non-invasive, and real-time healthcare solutions to address the growing prevalence of CVDs.

CVDs remain a leading cause of mortality worldwide, accounting for over 17 million deaths annually. ECG monitoring, a non-invasive diagnostic tool, plays a pivotal role in detecting heart-related anomalies, such as arrhythmias and myocardial infarctions. Traditionally, ECG interpretation has relied heavily on manual analysis by healthcare professionals, which is not only time-consuming but also subject to human error. The increasing complexity of ECG signals and the volume of patient data necessitates more accurate and automated systems. This has led to the exploration of AI and IoT technologies as potential solutions to improve both diagnostic accuracy and real-time monitoring capabilities [1][2].

With the advent of DL algorithms, particularly CNNs, the automatic detection and classification of heart conditions from ECG data have improved significantly. Coupled with IoT technologies, these systems enable real-time data collection, remote monitoring, and rapid diagnosis, offering a more scalable and accessible healthcare solution. By integrating IoT devices with AI-driven analytics, healthcare providers can monitor patients' vital signs continuously, allowing for earlier detection of abnormalities and reducing the risk of delayed interventions.

V.1.1 Objectives

The system described in this chapter aims to provide a comprehensive real-time monitoring solution that incorporates both hardware (sensors and microcontrollers) and software (DL models and IoT protocols). The specific objectives include:

- Real-time ECG Monitoring

Capturing and analyzing ECG signals in real-time using IoT-connected sensors to provide continuous cardiac monitoring.

- Automated Heart Condition Detection

Utilizing DL algorithms to classify ECG signals into categories such as arrhythmias, congestive heart failure, and normal sinus rhythm, ensuring faster and more accurate diagnoses.

- Remote Healthcare Solutions

Allowing healthcare professionals to remotely monitor patient data via secure web interfaces, reducing the need for in-person visits and enabling timely interventions.

- Scalability and Adaptability

Designing a system that is not only scalable but also adaptable to various healthcare environments, from hospitals to home care, making advanced healthcare accessible to a wider range of patients.

V.1.2 Challenges and Solutions

The development of this system presented several challenges that needed to be addressed to ensure its effectiveness in practical healthcare settings. These challenges include.

- Data Transmission and Latency

Achieving real-time monitoring requires low-latency data transmission. This was addressed by utilizing the MQTT protocol, which is optimized for low-bandwidth communication, ensuring that data is transmitted in real-time without significant delays [135].

- Accuracy of AI Models

Training DL models to accurately classify heart conditions is crucial. Data augmentation techniques and advanced model architectures such as CNNs were employed to achieve high accuracy in detecting abnormalities in ECG signals [136][10].

- Integration of Multiple Sensors

Combining ECG, SpO_2, and temperature sensors into a unified system while ensuring synchronization of data was another key challenge. The system design carefully integrates these components to ensure that healthcare providers receive a comprehensive view of the patient's health[137][138] .

- Data Privacy and Security

Given the sensitive nature of health data, ensuring its security during transmission and storage was critical. Encryption techniques and secure communication protocols were implemented to safeguard patient information [139].

V.2 System Architecture

The system comprises four primary modules, each module is responsible for a specific task in the overall operation of the healthcare monitoring system. Figure V.*1* provides a high-level overview of the system architecture.

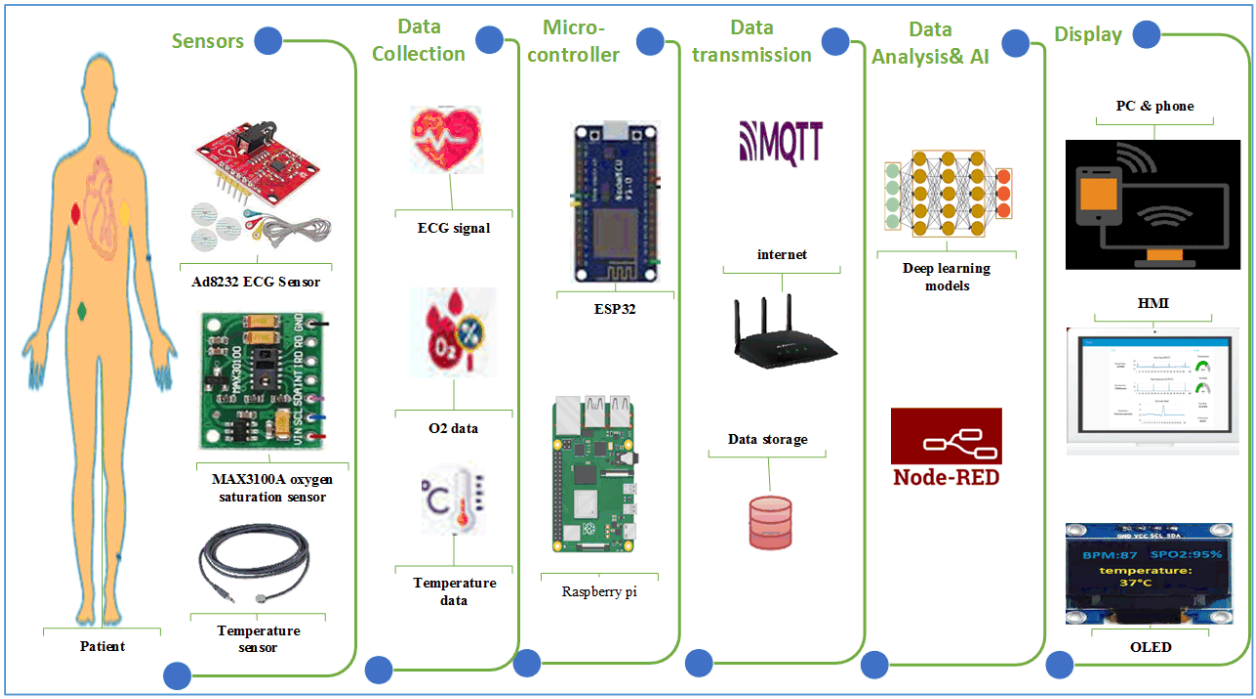


Figure V.1 System setup Architecture presentation

1. **Data Acquisition**: This module captures real-time physiological data from the patient using various sensors, such as ECG, SpO_2, and temperature sensors.
2. **Data Processing**: DL models are applied to the transmitted data to classify and analyze the ECG signals.
3. **Data Transmission**: Using the MQTT protocol, the acquired data is securely transmitted to the cloud for real-time analysis.
4. **UI/Visualization**: The processed data is visualized in a user-friendly interface using Node-RED, enabling healthcare professionals to monitor the patient's condition in real-time

V.2.1 Data Transmission

All the gathered data is sent to a cloud server using the MQTT protocol, which guarantees both efficient and dependable data transmission. Once received, the data is processed through Node-RED workflows for detailed analysis and visualization. This method ensures the system can scale and adapt to different data loads, while also preserving the security and confidentiality of sensitive health information during the transfer process. Data Processing

V.2.2 Data analysis and visualization

In the Node-RED environment, ECG data is processed through two simultaneous pathways:

V.2.2.1 ECG Signal Peak Detection for HR Analysis

This method involves utilizing a peak detection algorithm to accurately identify the significant peaks within the ECG signal, which are crucial markers of the heart's electrical activity. By isolating these peaks, typically corresponding to the QRS complex, the process enables precise calculation of HR and rhythm. Accurate peak detection is essential not only for HR determination but also for diagnosing potential irregularities, such as arrhythmias or abnormal heart patterns. Moreover, this technique serves as a foundation for more advanced ECG signal analysis, improving the overall reliability of cardiovascular diagnostics.

V.2.2.2 Cardiovascular Disease Classification

In this step, a classification model is employed to categorize the ECG data into various disease types, which is vital for accurate medical diagnostics. The model analyzes patterns within the ECG signals, distinguishing between normal and abnormal heart activities, and classifies them according to specific cardiovascular conditions such as arrhythmias, myocardial infarction, or ischemia.

Following the peak detection process, the outputs are integrated with additional health data such as oxygen saturation and body temperature, resulting in a comprehensive health assessment. Key metrics like oxygen levels, temperature, and HR are derived, while the system simultaneously provides detailed classification results. This allows for the identification of potential diseases, with the ECG waveform visually displaying the detected peaks, further enhancing the accuracy and clarity of the diagnostic information provided to healthcare professionals.

V.2.3 Integrated User Interface with Local and Remote Access

Patient health data and diagnostics are presented through two primary methods, ensuring accessibility and efficiency in healthcare delivery.

V.2.3.1 Local Patient Monitoring

On-site monitoring is facilitated through a Human Machine Interface (HMI) or an LCD display connected to a Raspberry Pi system. This setup enables local healthcare professionals to access real-time patient information, including ECG signals, detected peaks, disease classification, and vital health metrics. The intuitive display allows for quick assessment and immediate medical response when needed, ensuring that healthcare providers can take swift action based on accurate and update information.

V.2.3.2 Remote Patient Monitoring

Secure remote access is offered across various devices such as computers, smartphones, and tablets, enabling off-site medical personnel to monitor patient data from anywhere. Through authenticated accounts, remote healthcare professionals can log in to view real-time and historical health data, ensuring continuous monitoring of patients' conditions, even outside the clinical setting. This functionality is especially beneficial for critical or long-term patients who require ongoing observation.

The dual-access system enhances the ability to respond promptly to medical emergencies while maintaining strict safeguards around patient privacy and data security. This combination of on-site and remote access promotes a more flexible and responsive healthcare environment.

V.2.4 System Architecture and Workflow Integration

The system operates as a fully integrated framework, facilitating the seamless transmission of data from sensors to analysis models and finally to visualization platforms. This unified design ensures:

- Continuous real-time monitoring of vital health metrics
- Rapid and accurate disease diagnosis
- Efficient communication between local and remote healthcare professionals

By leveraging advanced IoT protocols and cloud computing technologies, the system guarantees that crucial health data is securely transmitted, processed, and accessed with minimal delay. While the primary focus of this research is not on the specifics of data security,

the system's architecture is built with the capability to support robust security measures, safeguarding sensitive patient information throughout its entire lifecycle from acquisition to storage and access.

V.3 DL Models

V.3.1 DL model for ECG peak detection

This DL model is designed specifically to detect and accurately locate peak amplitude points within the ECG signal waveform. These peaks represent crucial markers in the cardiac cycle, corresponding to electrical impulses that govern the heart's function. The model’s primary goal is to precisely identify the highest amplitude values, or peaks, which are essential for evaluating cardiac activity, determining HR, and detecting any potential irregularities or abnormalities in heart rhythm.

By leveraging the power of DL, the model is capable of learning complex patterns in ECG signals, leading to improved accuracy in peak detection compared to traditional methods. This enhanced precision plays a critical role in diagnosing conditions such as arrhythmias and other CVDs, making it an invaluable tool in modern healthcare.

V.3.1.1 ECG Analysis Using MIT-BIH Arrhythmia Dataset

The success of any ML project hinges on the quality and relevance of the dataset used for training and testing. For this DL model, the MIT-BIH Arrhythmia Database serves as the foundational dataset. This database provides a diverse and extensive collection of ECG recordings, each sample meticulously annotated to reflect various cardiac events, such as arrhythmias and other irregularities. Its richness ensures that the model can learn to detect critical features, including peaks in ECG signals, which are vital for analyzing HR and identifying QRS complexes.

The MIT-BIH dataset's comprehensiveness enables the model to develop a robust understanding of both normal and abnormal heart rhythms, improving its ability to generalize across different patient cases. To provide further insights into the dataset, Figure V.2 presents the distribution of peak counts per sample, shedding light on the variability in ECG signal patterns across the dataset.

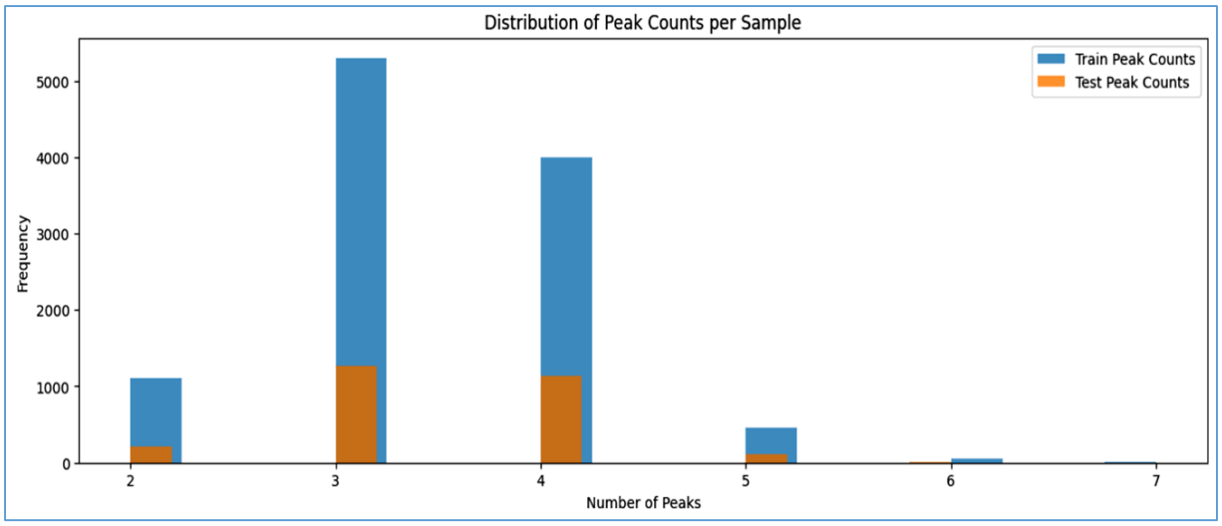


Figure V.2 Dataset distribution of the peak counts

Additionally, Figure V.*3* visualizes ECG signals from both the training and test sets, showing how the DL model detects peaks in raw data. These visualizations demonstrate the model's ability to process complex ECG signals, further highlighting the importance of the MIT-BIH dataset in building an accurate and reliable peak detection model.

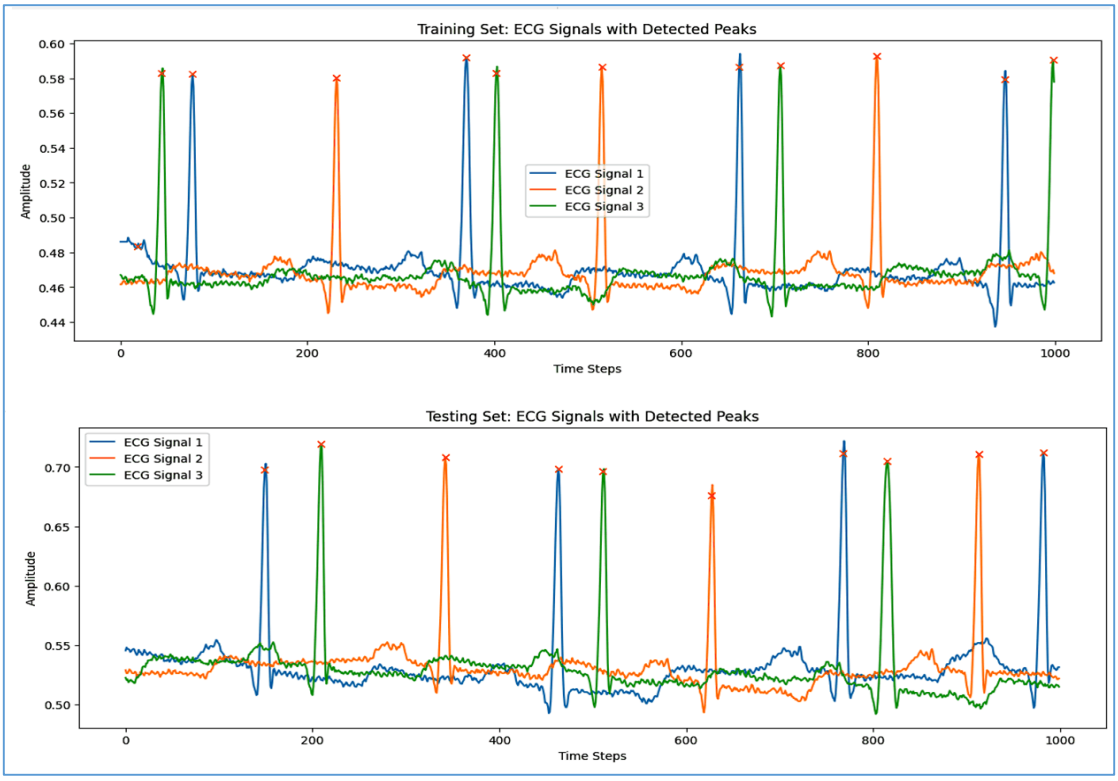


Figure V.3 Dataset presentation with Peak Marker

V.3.1.2 DL Architecture for Peak Detection in ECG Signal

Accurately detecting peaks in ECG signals is crucial for a wide range of cardiac analyses. Among these peaks, the R-peak is particularly important, as it serves as a key indicator of HR, aids in assessing the QRS complex duration, and is instrumental in identifying abnormalities such as arrhythmias. Precise detection of these peaks is essential for clinical diagnosis, allowing healthcare professionals to make informed decisions based on reliable data.

Our peak detection model is based on a combination of CNNs and upsampling techniques, designed specifically to extract relevant features from the ECG signal and detect peaks with high precision. The architecture of the model consists of the following essential layers:

1. Input Layer: The model receives ECG signal segments as inputs, represented as sequences of voltage values.
2. Convolutional Layers: A series of convolutional layers with increasing abstraction levels aim to capture the underlying patterns in the ECG signal. These layers help the model learn relevant features associated with peaks.
3. Max Pooling Layers: These layers downsample the input, focusing on retaining the most essential information while reducing computational complexity.
4. Upsampling Layers: Following the convolutional layers, the model employs upsampling layers to reconstruct the original signal dimensions while preserving learned features.
5. Convolutional and Sigmoid Layers: The model concludes with convolutional layers followed by a sigmoid activation function.

Each convolutional layer enhances the model's ability to discern key features at multiple scales, improving its precision in detecting the defining elements of the ECG signal. As a result, the model is capable of capturing both subtle and prominent patterns that correspond to peaks, ensuring reliable detection across various patient conditions, this model architecture is showing in Figure V.*4*.

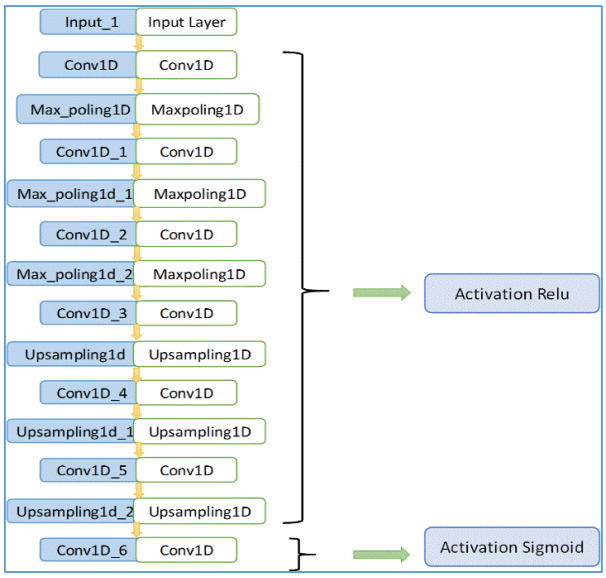


Figure V.4 peak detection model architecture

The primary objective of this phase is to assess the model's performance in conditions that closely replicate real-world scenarios. During training, the model rigorously learns to identify patterns within ECG segments that are indicative of peaks, with a specific focus on minimizing the binary cross-entropy loss between the predicted peaks and the actual peaks annotated in the ECG data. This meticulous training process results in a model that can accurately detect peaks in ECG signals, a critical capability that unlocks numerous applications in healthcare.

One of the immediate applications of this trained peak detection model is the calculation of HR. By accurately detecting the R peaks, which correspond to the heart's contractions, the model enables real-time HR monitoring. This functionality is crucial for assessing a patient's cardiac health, tracking HR fluctuations, and gaining valuable insights into physiological responses under various conditions.

The model's exceptional performance is reflected in its outstanding accuracy metrics. Following extensive evaluation, the model achieved an accuracy of approximately **99.93%**, with a validation accuracy of **99.87%**. These results underscore the model's ability to discern complex features within ECG signals, capturing not only the prominent peaks but also subtle indications of peaks that may otherwise be overlooked. This level of precision ensures a comprehensive analysis of the ECG signal, making the model a reliable tool in both diagnostic and monitoring applications, as demonstrated in Figure V.5

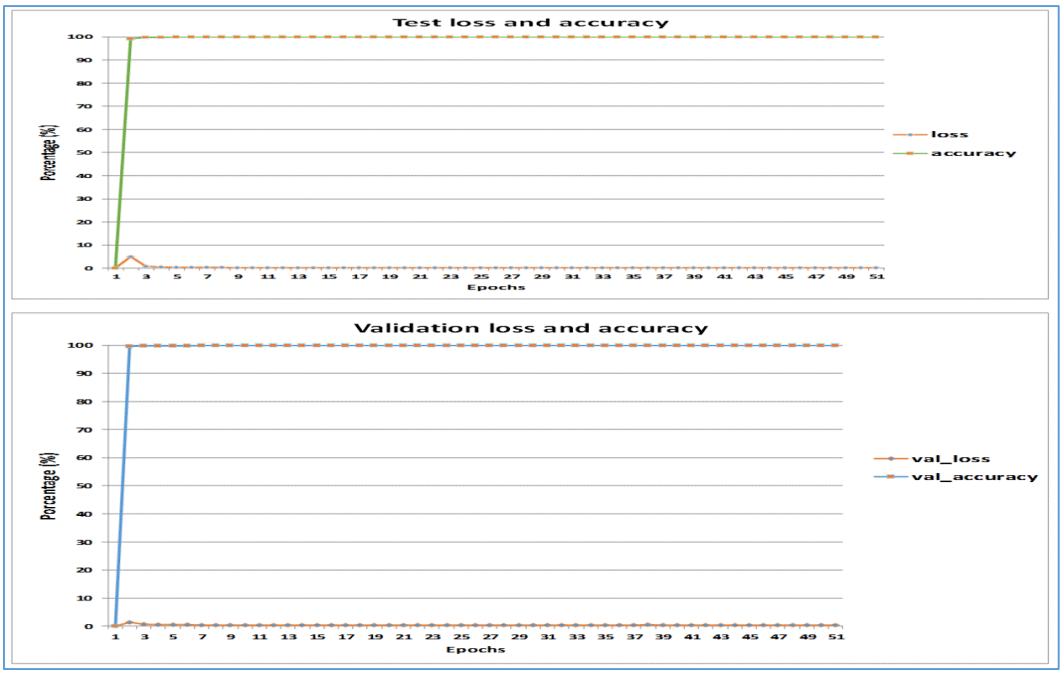


Figure V.5 Test and Validation Loss Over Training Epochs for the Peak Detection Model

Accuracy is a common evaluation metric in DL methods. It is calculated as the ratio of correctly predicted instances to the total number of instances, and its formula is:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5.1)$$

Where:

- TP = True Positives (correct predicted positive cases)
- TN = True Negatives (correct predicted negatives cases)
- FP = False Positives (incorrectly predicted positive cases)
- FN = False Negatives (incorrectly predicted negatives cases)

This remarkable accuracy highlights the model's ability to detect intricate features within the ECG signal, even capturing the faintest indications of peaks. It is crucial to emphasize that this high accuracy is not a product of overfitting to the training data. Extensive measures have been taken to ensure the model's robustness and generalizability. When evaluated on novel, unseen ECG data, the model continues to demonstrate consistently high performance, validating its ability to adapt to variations in different ECG recordings and effectively generalize its peak detection capabilities.

One of the immediate and practical applications of accurate peak detection is the calculation of HR. By precisely identifying the R peaks, which correspond to the heart's contractions, the model enables real-time HR computation. This functionality is essential for evaluating a patient's cardiac health, monitoring HR fluctuations over time, and providing valuable insights into physiological responses to various conditions.

V.3.2 DL model for ECG classification

Building on the success and high accuracy of our peak detection model, we now transition to the next phase of our research: developing an advanced DL model for ECG classification. This phase extends the scope of our work beyond merely identifying peaks, allowing for a more comprehensive analysis of cardiac health.

The classification model aims to categorize ECG signals into distinct cardiac conditions, such as arrhythmias, ischemia, or other cardiovascular abnormalities. By incorporating sophisticated neural network architectures, the model is designed to recognize subtle patterns and deviations in the ECG waveform that are indicative of specific heart conditions. This enables healthcare providers to not only monitor the heart's activity in real time but also to automatically detect and classify potential abnormalities, making it a powerful diagnostic tool.

The development of this classification model enhances the overall system's ability to deliver actionable insights, paving the way for earlier diagnosis, improved patient outcomes, and personalized treatment plans based on precise ECG analysis.

V.3.2.1 Comprehensive ECG Signal Database for Classification

The dataset utilized in this study plays a pivotal role in the development of DL models aimed at classifying cardiac heartbeat signals. It is a rich and diverse resource, derived from two renowned sources: the MIT-BIH Arrhythmia Dataset [140] and the PTB Diagnostic ECG Database[26][141] my paper ref]. The combination of these two datasets results in a comprehensive collection of ECG signals, essential for conducting thorough and detailed cardiac signal analysis.

This amalgamated dataset consists of **87,554 samples** in the training set and **21,892 samples** in the test set, providing a significant volume of data for both model training and evaluation. Each ECG signal in the dataset corresponds to a unique heartbeat pattern, encompassing a wide variety of conditions, including normal heartbeats, various arrhythmias, and myocardial infarctions. The diversity of heartbeat patterns ensures that the dataset can support a range of tasks, such as arrhythmia classification, anomaly detection, and general cardiovascular condition analysis.

Preprocessing and segmentation techniques have been applied to the ECG signals to ensure that individual heartbeats are carefully isolated and prepared for model analysis. These steps significantly

enhance the clarity and quality of the data, facilitating the development of precise and effective classification models.

This dataset, due to its diversity and meticulous preparation, is a valuable tool for researchers and data scientists aiming to advance the field of cardiac signal analysis. Ultimately, the insights gained from models trained on this data can lead to improved diagnosis and monitoring of heart-related conditions, contributing to more personalized and timely healthcare interventions.

V.3.2.1.1 Initial Data Loading and Preparation

The first step in the data analysis process involves loading the two key datasets, mitbih-train.csv and mitbih-test.csv, into pandas Data Frames. These CSV files contain the raw ECG data, with each row representing a distinct heartbeat signal. By using pandas, a powerful Python library for data manipulation, the ECG data is efficiently organized into a structured format that is easy to work with.

The loading of these CSV files is a critical step, as it ensures that the heartbeat signals are properly formatted for further preprocessing and analysis. The structure of the Data Frames allows for seamless data exploration, manipulation, and visualization, which are essential for training the DL classification models. Each row includes essential features such as the voltage values over time, which define the ECG waveform, and labels that categorize the heartbeat patterns.

Once loaded, the data can be preprocessed, segmented, and fed into the DL model, setting the stage for the subsequent stages of classification and evaluation.

V.3.2.1.2 Data Exploration and Over-view

After loading the data, the next step involves conducting an exploratory analysis to gain a better understanding of the dataset's structure and characteristics. This analysis begins by examining the dimensions of both the training and test sets. The results reveal that the training set consists of 87,554 samples, each comprising 188 distinct features, while the test set contains 21,892 samples with the same number of features.

These features represent the various data points captured from the ECG signals, such as voltage values over time, which are crucial for analyzing the heartbeat patterns. The exploratory phase provides insights into the overall composition of the dataset, helping identify any potential inconsistencies or patterns that may influence the performance of the DL model.

By assessing the shape and characteristics of the data, researchers can better understand the volume and complexity of the information, paving the way for further preprocessing steps such

as normalization, segmentation, and feature extraction, which are essential for the accurate classification of ECG signals.

V.3.2.1.3 Distribution of Heartbeat Classes

To better understand the distribution of heartbeat classes within both the training and test datasets, the code performs an analysis that quantifies the frequency of each class. These classes, represented by the values 0.0, 1.0, 2.0, 3.0, and 4.0, are found in the last column (column 187) of each dataset and correspond to different types of heartbeats or cardiac conditions.

This enumeration allows for the identification of how many samples belong to each class, which is crucial for understanding the balance or potential imbalance within the dataset. A well balanced dataset, where all classes have a similar number of samples, typically allows for more reliable and unbiased training of the classification model. Conversely, if certain classes are underrepresented, the model may struggle to accurately classify those types, leading to biased predictions.

Understanding the class distribution is essential for implementing strategies such as class weighting, oversampling, or understanding to address any imbalances that could affect model performance. The analysis of class distribution ultimately helps ensure that the classification model is both fair and effective across all heartbeat types.

V.3.2.1.4 Graphical Analysis of Class Distribution

To facilitate a clearer understanding of the class distribution within the dataset, the code generates a pie chart as a visual representation of the distribution of heartbeat classes in the training set. This graphical depiction provides an immediate, concise overview of the proportion of each class, making it easier to identify any imbalances that may exist across the different heartbeat types.

By visually illustrating the relative frequencies of each class, the pie chart simplifies the process of detecting whether certain classes are underrepresented or overrepresented, which could impact the performance of the classification model. As shown in Figure V.*6*, this visual tool helps inform decisions about potential adjustments, such as rebalancing the dataset or applying specific techniques like class weighting to ensure fair and accurate model training.

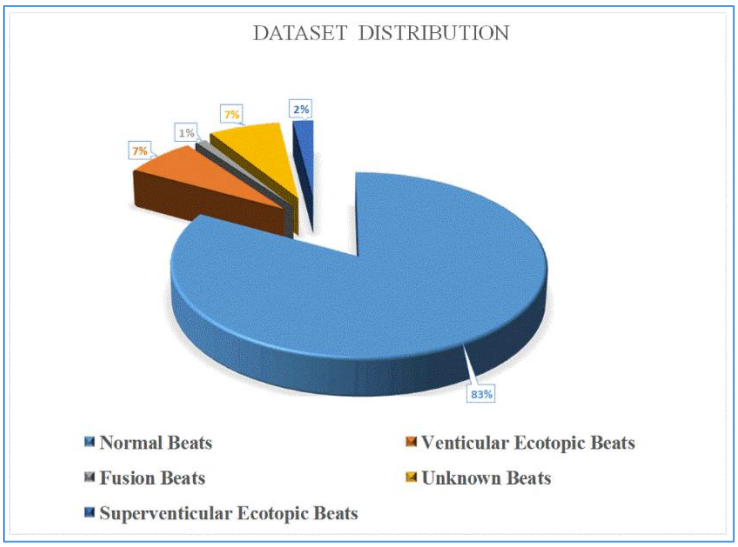


Figure V.6 Graphical presentation of Dataset class distribution

The t-SNE and PCA plots provide valuable insights into the distribution of the five ECG classes in the dataset. These visualizations reveal significant overlap between the classes, indicating that the current feature set does not fully distinguish the classes in a two-dimensional space. While certain clusters, such as those representing Normal Beats, are somewhat distinct, the overall overlap suggests that simpler models may struggle to classify the ECG signals accurately.

This overlap underscores the importance of advanced feature engineering and the potential necessity of using more sophisticated ML models. Enhancing class reparability through improved features or utilizing DL architectures may help achieve better classification performance. The observed patterns, as shown in Figure V.*7*, highlight the limitations of current features and the opportunity for further refinement in the model development process.

The ROC curve for the multi-class classification model provides a visual representation of the model's performance across the five ECG classes. Each curve corresponds to a specific class, illustrating the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity). The AUC (Area Under the Curve) values for each class further quantify the model's ability to distinguish between the different classes [142][143].

A higher AUC value suggests better classification performance for that particular class, with values closer to 1 indicating near-perfect discrimination between positive and negative instances. As shown in Figure V.*8*, the ROC curves and AUC values offer a clear measure of how well the model performs in distinguishing each class, providing essential insights into areas that may require further refinement for improved classification accuracy.

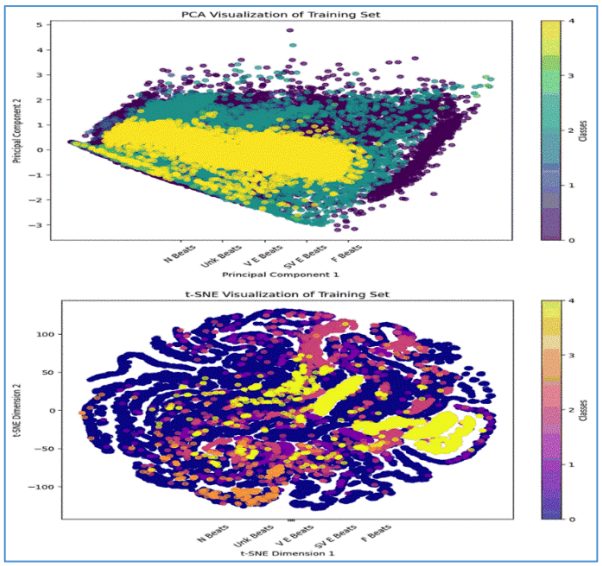


Figure V.7 t-SNE and PCA visualization

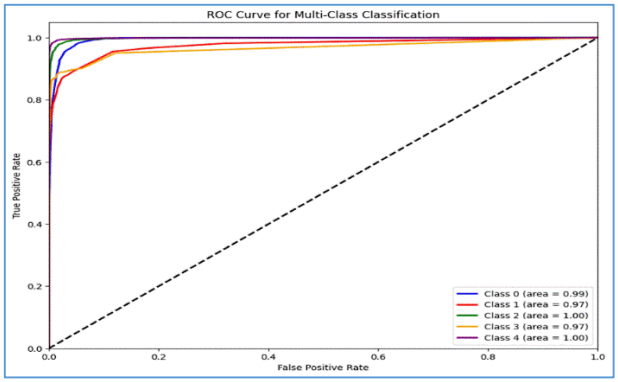


Figure V.8 ROC curve for the multi-class classification

V.3.2.1.5 Resampling dataset for Balanced Classes

To address class imbalance, the code implements a resampling procedure aimed at creating balanced subsets for each class (0, 1, 2, 3, and 4). This balance is achieved through a combination of up-sampling the minority classes and down-sampling the majority class. For example, the largest class (class 0) is reduced to contain 20,000 samples, while the minority classes (classes 1, 2, 3, and 4) are increased via up-sampling to match this new size.

This careful resampling ensures a more equitable distribution of data across all classes, which is essential for training ML models without bias toward any particular class. Once the resampling process is complete, the code selects random samples from each class within the training dataset using the group by function, creating a new data frame labeled 'classes.' These selected samples serve as valuable resources for further analysis, visualization, and, more

importantly, for gaining insights into the distinct characteristics of each heartbeat class, as shown in Figure V.*9*.

This process not only improves the fairness of model training but also enhances the model's ability to accurately classify all heartbeat types, leading to more reliable and generalizable results.

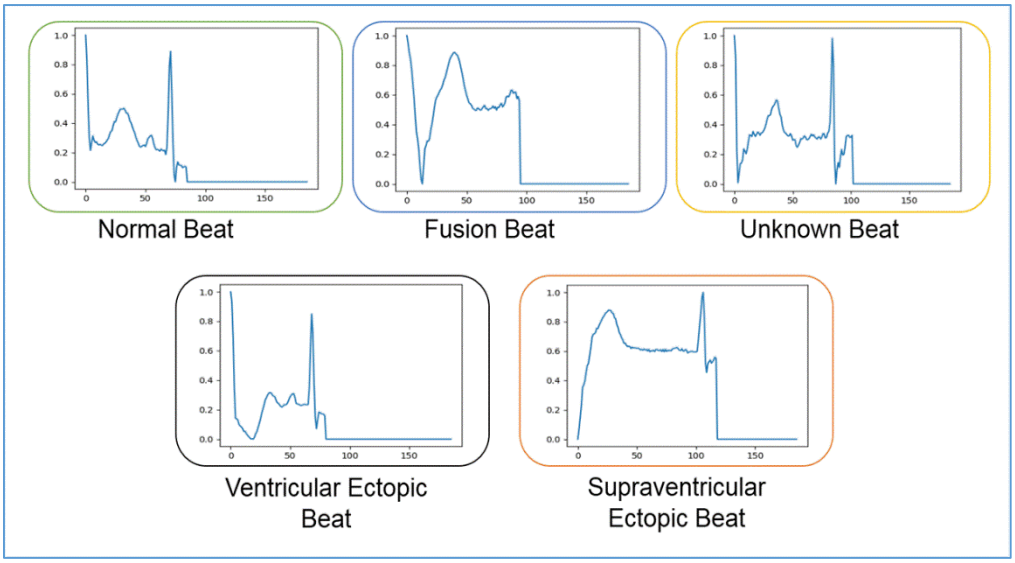


Figure V.9 Presentation of Dataset Classes in the ECG signal

The dataset, sourced from the Kaggle repository [144], offers researchers and data scientists a valuable resource for advancing cardiac signal analysis and improving the diagnosis and monitoring of heart-related conditions.

V.3.2.2 Architecture of an Hybrid CNN-RNN Model for ECG Classification

Our classification model is meticulously designed to handle the complexity of ECG signals. As illustrated in Figure V.*10*, the model leverages DL techniques by combining CNNs and RNNs to capture both spatial and sequential features inherent in ECG data. This fusion of spatial and temporal analysis allows the model to extract critical insights from the entire ECG waveform, enabling a comprehensive understanding of the underlying cardiac dynamics.

The architecture is divided into two major branches: one dedicated to processing the ECG signals using CNNs and the other using RNNs. These branches are then integrated into a unified model for disease class prediction.

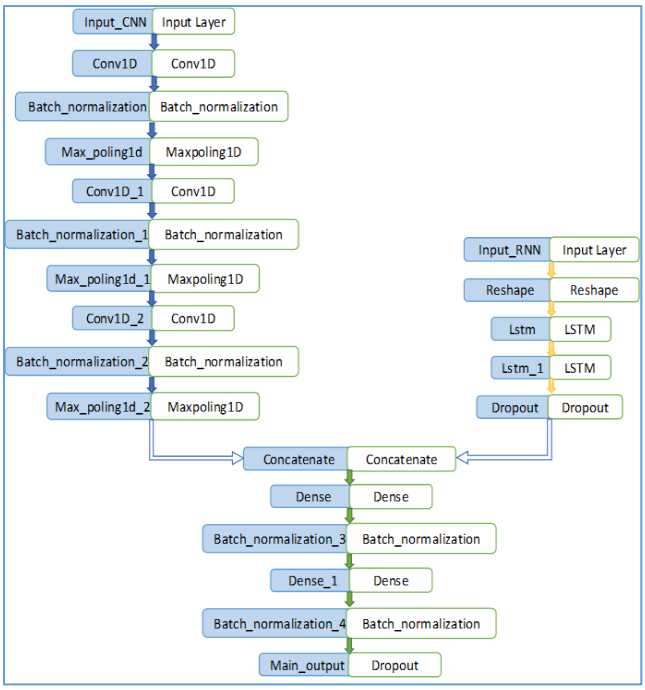


Figure V.10 classification model architecture

- CNN Branch:

The CNN branch processes the ECG data by applying convolutional layers to capture spatial features. To stabilize training and enhance convergence, batch normalization is applied after each convolutional layer. Max pooling layers are used for down-sampling, helping to retain essential features while reducing the data's dimensionality. The output from the CNN branch is then transformed into a 1D vector using a flatten layer, preparing it for further processing.

- RNN Branch:

The RNN branch focuses on the temporal aspects of ECG data. Initially, the data is reshaped to prepare it for processing by Long Short-Term Memory (LSTM) layers. The LSTM layers are critical for capturing the temporal dependencies within the sequential data, such as heartbeat intervals and rhythms. Dropout is employed within the RNN branch to mitigate overfitting and improve generalization.

- Combining CNN and RNN:

After processing by the CNN and RNN branches, their outputs are concatenated to form a combined feature vector that captures both spatial and temporal information from the ECG signals. This combined vector enables the model to integrate both aspects of the data for more accurate predictions.

- Dense Layers and Output:

The concatenated feature vector is passed through dense layers with batch normalization, allowing the model to extract high-level features. Finally, the output layer uses a softmax activation function to predict the probability of each disease class, providing the final classification for each input.

This model architecture, by combining CNN and RNN techniques, ensures a robust and holistic approach to ECG classification, effectively handling the spatial and sequential characteristics of the data for improved diagnostic accuracy.

V.3.2.3 Model Training, Evaluation, and Performance Discussion

During the model training and evaluation process, our primary focus was on developing and accessing a robust classification model for ECG signal analysis. Several key components contributed significantly to the success of this phase:

- Optimization and Loss Function

The model was compiled using the Adam optimizer, a widely-used optimization algorithm for neural networks. Adam dynamically adapts the learning rate throughout training, enhancing the model's ability to converge towards optimal solutions. Additionally, we utilized the categorical cross-entropy loss function, which is particularly well-suited for multi-class classification problems. This loss function measures the discrepancy between the predicted and actual class labels, allowing the model to refine its predictions more effectively.

- Learning Rate Adaptation

A crucial aspect of the training process was the implementation of a learning rate scheduler, which adjusts the learning rate dynamically as training progresses. This adaptation ensures that the model converges efficiently to an optimal solution, while preventing common issues such as overshooting or being stuck in local minima. As the model moves closer to convergence, the learning rate decreases, allowing for finer adjustments to the weights and parameters.

- Training Data

The model was trained on the provided training dataset, consisting of ECG signals and their corresponding class labels. Over a specified number of epochs, the model gradually refines its internal parameters based on the input data, learning to make increasingly accurate predictions. The iterative nature of the training process allows the model to continuously improve its classification abilities.

Figure V.*11* presents a visual representation of the model's training and evaluation results. This figure illustrates the convergence of the loss function towards zero and the increase in accuracy towards one, highlighting the model's steady improvement during training. These graphs serve as valuable tools for understanding the model's performance and ensuring that it is learning effectively.

One particularly insightful aspect of the evaluation process is the use of a confusion matrix, which provides a detailed assessment of the model's classification accuracy across different classes. Figure V.*12* depicts the confusion matrix for select classes, offering a more granular view of the model's performance. This matrix helps identify areas where the model excels and where it may struggle, allowing for targeted improvements in future iterations.

Overall, the combination of the Adam optimizer, dynamic learning rate adaptation, and the use of categorical cross-entropy has resulted in a highly effective classification model capable of accurately distinguishing between multiple classes of ECG signals.

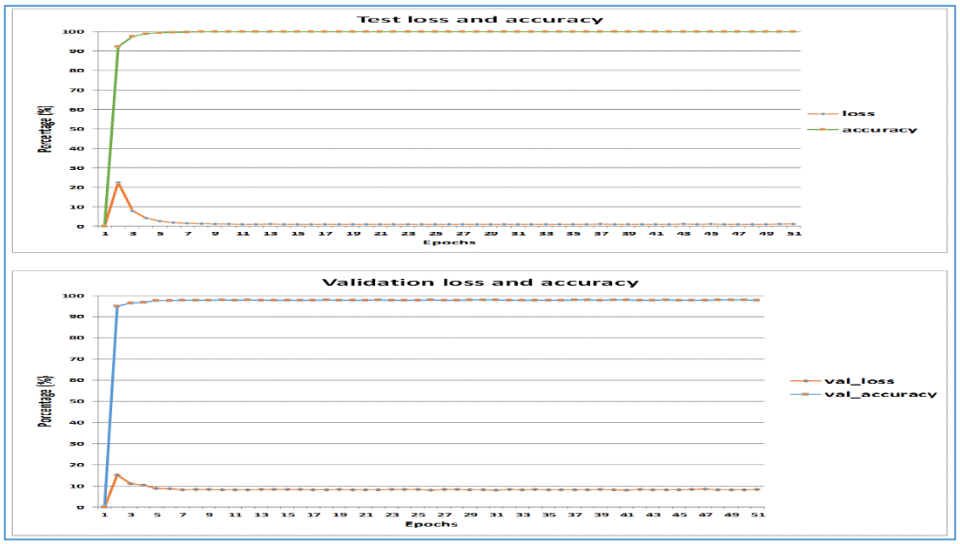


Figure V.11 classification model result

- Class-Specific confusion matrices

In Figure V.*12*, we present the class-specific confusion matrices, which provide a more detailed analysis of the model's performance for each individual class. These matrices are invaluable for understanding how well the model distinguishes between the five different classes, offering a deeper look into its classification accuracy within each category. Each subfigure illustrates the model's ability to correctly predict class labels, allowing us to identify where the model excels and where it may encounter difficulties.

By carefully examining these class-specific confusion matrices, we can gain important insights into the strengths and limitations of the classification model. This granular evaluation helps us pinpoint areas for improvement, enabling further refinement and optimization of the model. Such optimizations are crucial for ensuring more accurate and reliable multi-class classification, which is particularly important in healthcare applications where diagnostic accuracy can have a significant impact on patient outcomes.

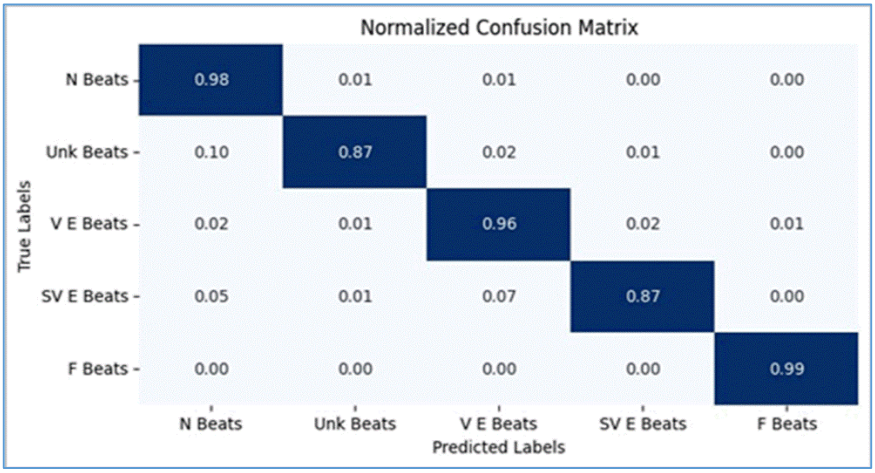


Figure V.12 Confusion matrix validation

V.4 Embedded health monitoring system setup

In the world of IoT, the rapid and efficient processing of data is critical, especially in real-time health monitoring. This chapter outlines the detailed implementation of an advanced health monitoring platform that leverages the power of Node-RED and MQTT protocols to optimize the speed of ECG data analysis and improve overall system performance.

- Sensors and Micro-Controller Integration

At the core of our health monitoring system is the seamless integration of cutting-edge sensors and micro-controllers. By utilizing sensors such as the ECG sensor AD8232, the SpO_2 sensor MAX30100A, and the temperature sensor DHT11, we ensure comprehensive data collection for a holistic evaluation of patient health.

ECG Sensor (AD8232): Interfaced with the ESP32 micro-controller, this sensor provides real-time ECG data, delivering critical insights into the patient's cardiac health.

SpO_2 and Temperature Sensors: Connected to a Raspberry Pi, these sensors allow continuous monitoring of oxygen saturation and body temperature, offering an all-encompassing view of a patient's vital signs.

The ESP32 and Raspberry Pi micro-controllers act as central hubs in the system, managing the data collection and transmission processes. This setup ensures that critical health data is continuously available for real-time analysis and display. To further improve system flexibility and portability, the platform is designed to run on battery power, making it suitable for mobile healthcare applications.

- Data Transmission and Cloud Integration

Patient data collected from the sensors is transmitted to a cloud server where it is stored for future use. This data is integrated into Node-RED flows via the MQTT protocol, ensuring seamless and efficient communication between devices. The implementation of this embedded system, as shown in Figure V.*13*, supports battery operation, creating a portable and flexible health monitoring solution that enables continuous and accurate assessment of patient health, proactive interventions, and mobile use.

By combining advanced sensors, micro-controller integration, cloud-based data storage, and battery support, this platform offers a scalable, reliable, and highly portable health monitoring solution. This comprehensive setup enhances the ability to monitor patient health in real time and respond to medical needs swiftly and effectively.

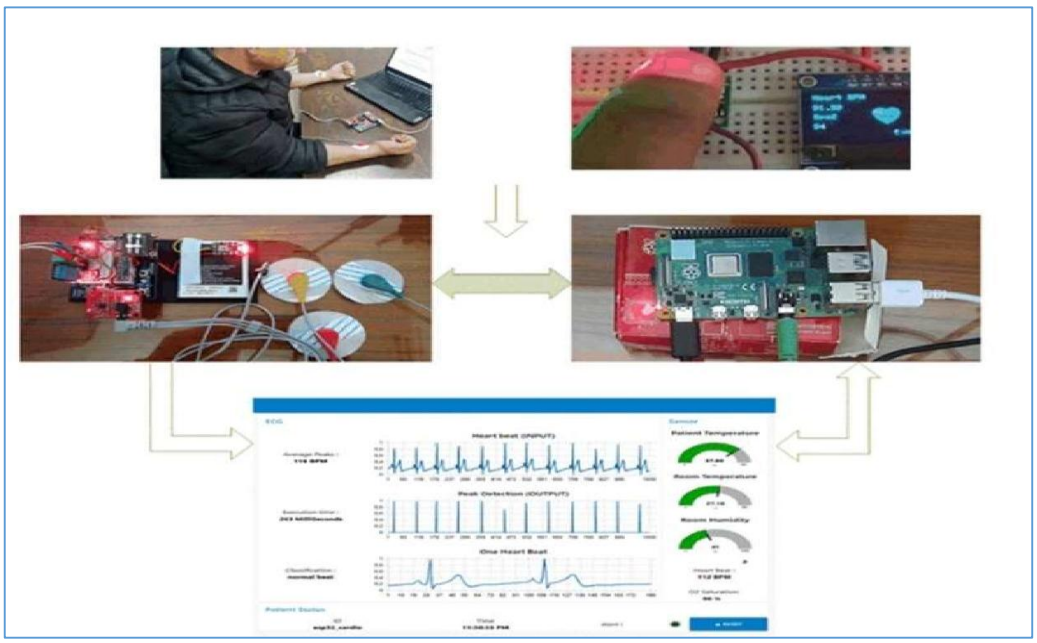


Figure V.13 Hardware implementation of the Health Monitoring System

V.4.1 IoT Architecture

V.4.1.1 Real-Time ECG Data Streaming and Analysis via IoT

To facilitate seamless integration of the ECG peak detection model with real-time data streaming, we implemented an IoT architecture using Node-RED and MQTT protocols. This architecture enables continuous data flow from the ECG sensor to the classification model, allowing for real-time analysis and visualization of patient data.

The Node-RED platform offers a user-friendly visual programming interface, simplifying the creation of complex IoT workflows. This platform allows the design and implementation of data pipelines that handle the continuous transmission and processing of ECG signals. The ECG data is captured, processed, and routed through various nodes to the peak detection model in real time.

MQTT, a lightweight messaging protocol designed for minimal bandwidth usage, ensures efficient communication between devices and the cloud server. It manages the secure and fast transmission of ECG data from the sensors to the server, facilitating near-instantaneous feedback for real-time monitoring and analysis.

This combination of Node-RED and MQTT provides a scalable and robust framework that supports the real-time processing needs of the ECG peak detection model. By enabling continuous data flow and immediate analysis, the system ensures timely insights into cardiac health, making it ideal for critical healthcare applications.

V.4.1.2 Comprehensive Node-RED Integration for Health Monitoring

The Node-RED workflow for our health monitoring system consists of three main components: data acquisition, model integration, and visualization.

- Data Acquisition

The first component involves the collection of ECG data from various sensors. Node-RED facilitates the continuous streaming of data using MQTT to receive real-time ECG signals from the sensors. This step ensures that the system captures vital health metrics efficiently and reliably, forming the foundation for subsequent analysis.

- Model Integration

Once the data is acquired, it is fed into the ECG peak detection model. Node-RED acts as a conduit, seamlessly connecting the incoming data streams to the analytical model. This

integration allows the system to process the ECG signals in real time, identifying peaks and extracting relevant features necessary for cardiac health assessment.

- Visualization

The final component of the Node-RED workflow is visualization. The processed data, including detected peaks and other critical metrics, is presented in an intuitive and user-friendly dashboard. Node-RED offers various visualization nodes that enable the display of ECG waveforms, peak detection results, and real-time patient health information. This visualization is crucial for healthcare professionals to monitor patients effectively and make informed decisions based on the analyzed data.

By combining these three components within the Node-RED framework, we create a cohesive and efficient workflow that supports real-time health monitoring and enhances the overall functionality of the embedded system.

V.4.2 Models integrated into Node-Red

Our health monitoring platform seamlessly integrates two TensorFlow models into the Node-RED environment. These models, which have been meticulously trained and fine-tuned for ECG peak detection and ECG pattern classification, have been converted to TensorFlow.js. This conversion allows for efficient utilization of the models within Node-RED, enabling real-time data analysis and visualization.

By leveraging TensorFlow.js, we can run the models directly in the browser or on a server, facilitating fast inference without the need for extensive backend processing. This capability enhances the responsiveness of the health monitoring system, allowing for immediate feedback based on incoming ECG data.

The integration of these models into Node-RED enables healthcare professionals to monitor patients' cardiac health dynamically. The ECG peak detection model identifies critical features, such as R-peaks, while the classification model categorizes the detected patterns, providing insights into potential arrhythmias and other cardiovascular conditions.

Overall, the incorporation of these TensorFlow models into Node-RED significantly enhances the functionality of our health monitoring platform, facilitating efficient real-time analysis and visualization of ECG data.

V.4.2.1 Peak detection model Over-view

The ECG data is processed by the Peak Detection Model, which has been meticulously trained to accurately predict the locations of peaks within the ECG signal. This model plays a crucial role in providing insights into cardiac activity by identifying key features such as R-peaks. Additionally, it calculates the HR based on the detected peaks, further enriching the information available to healthcare professionals for assessing patient health.

V.4.2.2 Classification model Functionality

Simultaneously, the ECG data is analyzed by our Classification Model, a TensorFlow powered algorithm proficient in distinguishing between normal and pathological ECG patterns. This model classifies the ECG signals into relevant categories, enabling healthcare professionals to identify potential arrhythmias and other cardiovascular conditions effectively.

The integration of both the peak detection and classification models empowers healthcare professionals with comprehensive insights into the patient's cardiac health, all within the Node-RED environment. This dual model approach ensures that critical data is analyzed in real time, facilitating timely and informed decision making. The flow of this work is illustrated in FigureV.*14*.

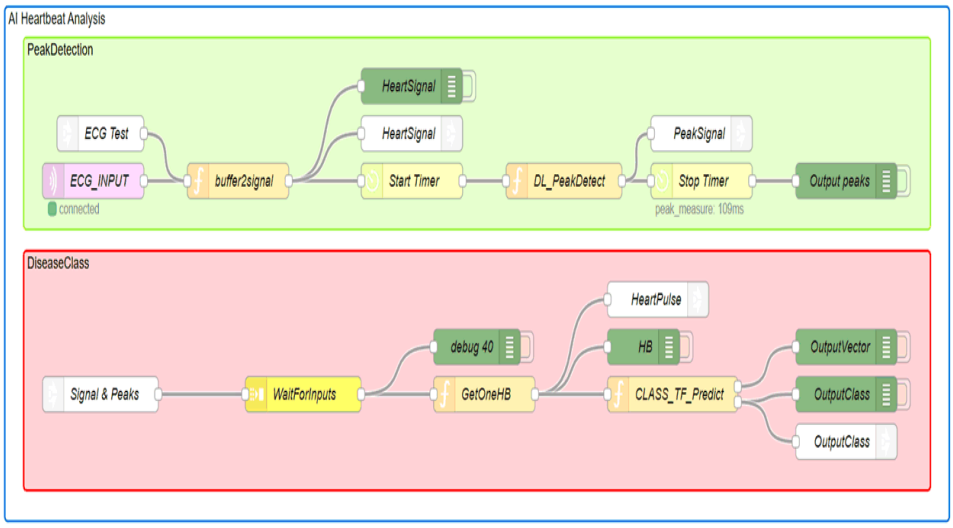


Figure V.14 Node-RED DL models integration

V.4.2.3 Sensors Sensor Integration Process in Node-RED

The integration process involves developing intuitive and interconnected flows within Node-RED to link the ECG sensor AD8232, the SpO_2 sensor MAX30100A, and the temperature

sensor DHT11. Through the use of custom Node-RED nodes and configurations, we establish a cohesive network that efficiently processes real-time data from these sensors.

- The ECG sensor provides vital information regarding the patient's cardiac activity, allowing for continuous monitoring of heart health.
- The SpO_2 sensor contributes essential data on oxygen saturation levels, an important indicator of respiratory health.
- The temperature sensor offers insights into ambient conditions, which can impact patient comfort and well-being.

These sensor inputs are meticulously integrated into Node-RED flows, ensuring a synchronized and coherent stream of health data. By leveraging the MQTT protocol, the consolidated sensor data is efficiently transmitted to the cloud for secure storage and advanced analysis.

The flexibility and visual simplicity of Node-RED make it an effective tool for orchestrating sensor integration. This capability enables our health monitoring platform to deliver accurate and timely health insights, enhancing the overall quality of patient care. As depicted in FigureV.*15*, the integration process showcases the seamless flow of data from multiple sensors, underscoring the robustness of the system.

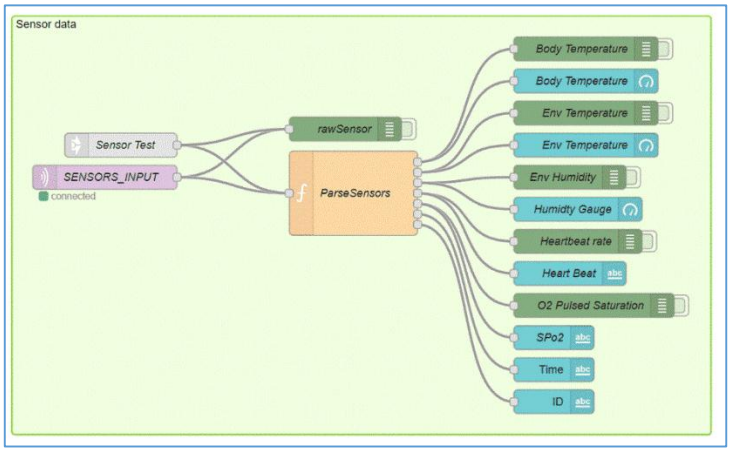


Figure V.15 Node-RED sensors integration

V.4.2.4 Node-RED Alert System for Patient Emergencies

To enhance user experience and facilitate immediate responses in critical situations, our health monitoring system incorporates a patient triggered alert notification flow, as illustrated in Figure V.*16.* a dedicated alert button is integrated into the system, empowering patients to initiate an alert when they sense a medical emergency or experience discomfort.

Upon pressing the alert button, Node-RED seamlessly generates a notification that is promptly dispatched to the attending medical professionals. This real-time alerting system ensures that healthcare providers receive timely notifications, enabling them to take swift and decisive actions.

The integration of this patient initiated alert feature significantly enhances the responsiveness of our health monitoring platform. It emphasizes patient empowerment by giving individuals control over their health monitoring process and facilitates rapid medical interventions when needed. By incorporating this functionality, we ensure that patients can communicate their needs effectively, ultimately improving overall health outcomes.

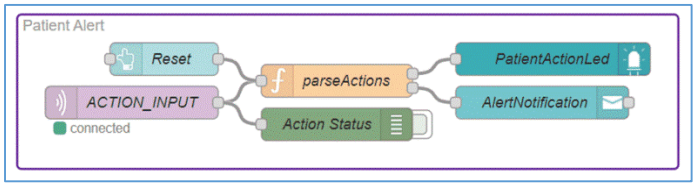


Figure V.16 Node-RED patient alert

V.4.2.5 Node-RED Doctor Account Management and Security

In our Node-RED dashboard, we have implemented a secure and personalized account system for doctors to ensure confidentiality and restricted access to patient data. Each authorized doctor is assigned unique login credentials, which adds an essential layer of authentication to prevent unauthorized access.

This secure login mechanism is designed to protect sensitive patient information, allowing only authorized personnel to view and manage health data. The system requires doctors to authenticate their identities before accessing the dashboard, thereby safeguarding patient privacy and ensuring compliance with healthcare regulations.

As illustrated in Figure V.*17*, the login interface is user-friendly, facilitating easy access for authorized doctors while maintaining stringent security protocols. This approach enhances the overall integrity of the health monitoring platform, ensuring that only qualified healthcare professionals can interact with patient data and contribute to their care.

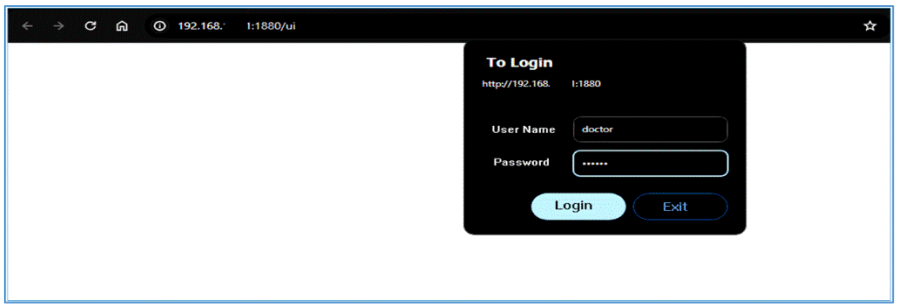


Figure V.17 Node-RED login interface

V.4.2.6 Node-RED Visualization Tools in Health Monitoring Platform

In the visualization component of our health monitoring platform, we offer healthcare professionals a comprehensive view of critical cardiac information in real time. This feature enables clinicians to monitor key metrics, such as ECG waveforms, HR, oxygen saturation, and temperature, all within a single interface.

As illustrated in Figure V.*18*, the corresponding Node-RED flow effectively organizes and displays this data, ensuring that healthcare providers can access essential information quickly and intuitively. The visual representations not only enhance understanding but also facilitate timely decision making and intervention based on the patient's current health status.

By integrating real-time visualization into the health monitoring system, we empower healthcare professionals to respond proactively to changes in patient conditions, ultimately improving the quality of care provided.

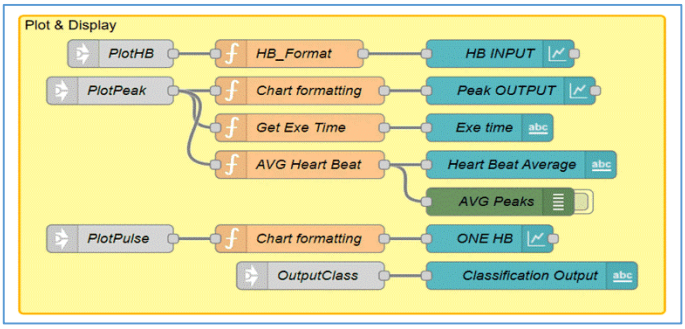


Figure V.18 Node-RED display block

V.4.3 Visualization

V.4.3.1 Real-time Display of ECG Signals on Node-RED

The real-time ECG signal, transmitted from the sensor via the MQTT protocol, is displayed on the Node-RED dashboard. This continuous stream of data enables healthcare professionals to

immediately assess the patient's cardiac activity, providing critical insights necessary for timely interventions.

The dashboard visualizes the ECG waveform in real time, allowing clinicians to monitor key indicators of heart health, such as rhythm and rate, as they occur. This immediate access to live data is crucial for detecting anomalies, facilitating prompt decision making, and enhancing overall patient care.

By integrating real-time ECG monitoring into the health platform, we ensure that healthcare providers are equipped with the information they need to respond effectively to any changes in a patient's condition.

V.4.3.2 Visualization of Predicted ECG Peak Markers

The locations of ECG peaks, as identified by our Peak Detection Model, are superimposed onto the ECG waveform displayed on the dashboard. These predicted peak markers provide valuable visual cues, enhancing the interpretation of the ECG signal.

By clearly indicating the positions of key features, such as R-peaks, the markers facilitate quick and accurate assessments of cardiac function. Healthcare professionals can easily identify critical points in the ECG, allowing for more effective monitoring and analysis of the patient's heart health. This integration of visual markers not only streamlines the diagnostic process but also improves the overall usability of the monitoring platform.

V.4.3.3 Real-Time HR Monitoring on Dashboard

The HR, calculated in real-time based on the positions of the ECG peaks, is prominently displayed on the dashboard. This vital metric provides healthcare professionals with immediate insights into the patient's cardiac rhythm and overall heart health.

By offering real-time HR data, the dashboard enables clinicians to monitor fluctuations and detect any irregularities in the patient's heartbeat. This functionality is crucial for timely assessments and interventions, as it allows healthcare providers to respond quickly to changes in cardiac activity. The clear presentation of HR information enhances the usability of the monitoring system, facilitating informed decision making in patient care.

V.4.3.4 Continuous QRS Complex Monitoring and Classification

In our system, we continuously monitor the ECG signal and extract one QRS complex at a time. Following the extraction, our Classification Model is applied to each QRS complex, enabling the identification and classification of specific cardiac patterns.

This dynamic display of QRS complexes, along with their corresponding classifications, equips healthcare providers with critical information for assessing the patient's cardiac condition. By distinguishing between normal and pathological patterns, clinicians can quickly identify any abnormalities that may require intervention.

This real-time monitoring and classification of QRS complexes enhance the overall diagnostic capabilities of the health monitoring platform, facilitating timely and informed decision making in patient care.

V.4.3.5 SpO_2 Level monitoring

The SpO_2 sensor (MAX30100A) continuously collects data and transmits it to the Node-RED dashboard, where it is integrated for easy access. This integration allows healthcare providers to view oxygen saturation levels alongside other critical health metrics, offering a holistic perspective on the patient's condition. Real-time SpO_2 monitoring enables quick evaluations of respiratory health, which is vital for timely medical interventions.

V.4.3.6 Patient temperature monitoring

In our system, a high precision temperature sensor specifically designed for human monitoring continuously tracks the patient's body temperature. This sensor provides accurate measurements that are crucial for detecting any significant changes in the patient's status. Each temperature reading is recorded with a timestamp and associated with the patient's unique ID, creating a detailed timeline of health events. When the monitoring system detects critical conditions, an alert LED lights up, signaling healthcare staff for immediate action. Additionally, a reset button is included for convenience, allowing staff to easily reset the monitoring parameters as needed. This comprehensive visualization interface within Node-RED equips healthcare professionals with real-time insights into vital signs, facilitating swift decision making and timely interventions.

V.4.3.7 Environment Temperature and humidity monitoring

The DHT11 sensor measures both temperature and humidity, transmitting this environmental data to Node-RED for display on the dashboard. By incorporating this additional information, healthcare providers gain a more complete understanding of the patient's environment, which can significantly influence health outcomes. This holistic approach to monitoring supports better informed clinical decisions.

V.4.3.8 Patient Identification and Alert System

Every patient is assigned a unique identification (ID) number that is linked to their vital signs and health data within the system. This ensures accurate tracking and association of recorded metrics with the correct patient, providing a comprehensive overview of their health status. The alert system further enhances patient safety by notifying healthcare professionals immediately when critical changes occur, enabling prompt responses to any urgent situations.

V.4.4 Final Node-RED dashboard

The Node-RED dashboard is designed to provide a user-friendly interface specifically tailored for healthcare professionals, enabling comprehensive monitoring and analysis of patient data. Within this dashboard, practitioners can view a wide array of vital parameters in real time, including visual representations of the heartbeat signal, average peaks, and results from peak detection algorithms.

The interface showcases detailed visualizations of the QRS complex, along with its corresponding classifications, facilitating in depth cardiac assessments. Essential physiological metrics, such as HR, oxygen saturation, and patient temperature, are prominently displayed for quick reference. Additionally, environmental factors, including room temperature and humidity, are integrated into the dashboard to provide contextual insights that can affect patient care.

Importantly, the dashboard features patient identification and timestamp information, along with LED alerts that notify healthcare staff of critical events requiring immediate attention. A reset button is also included to ensure the interface remains functional and ready for subsequent use.

This comprehensive range of features empowers healthcare practitioners to make informed decisions regarding medical interventions while ensuring continuous monitoring of the patient's health status. An example of the final visualization is presented in Figure V.*19*



Figure V.19 Final Dashboard Presentation

V.5 Performance Evaluation

V.5.1 Response Time Estimation for Real-Time ECG Monitoring

In our real-time ECG monitoring system, we utilize the AD8232 ECG sensor for signal conditioning, the ADS1115 ADC converter for high-resolution digital conversion, and the Raspberry Pi 4B, which is equipped with a Quad-core Cortex-A72 processor and wireless connectivity, for data processing and management.

To estimate the system's real-time response time, we consider several components of the data flow. The ADC conversion on the ADS1115, operating at a rate of 250 samples per second (SPS), takes approximately 4 ms per sample. Data processing, which includes data handling and preprocessing, adds an additional 1 to 10 ms. Finally, DL inference on the Raspberry Pi 4B typically requires about 50 to 150 ms per batch.

As a result, the total response time for the system ranges from 55 to 164 ms, with an average response time around 100 to 150 ms. This variability depends on factors such as the complexity of the DL model and the specific preprocessing steps applied to the ECG data. This response time is crucial for ensuring timely and effective monitoring of patient cardiac health in real-time scenarios.

V.5.2 Comparison with our result and related work

The *Table V.1* illustrate the most advantages and drawbacks between our paper and important related work

Table V. 1 Comparison of our result and related work

	Method	**Accuracy & Results**	**Advantages**	**Drawbacks**
Islam et al., 2020[139]	Development of a smart healthcare monitoring system in an IoT environment utilizing five sensors: heart rate, body temperature, room temperature, CO and CO2 sensors.	Limit (<5%) for each case.	Real-time healthcare monitoring, use of IoT.	No AI or DL.
Mary et al., 2023 [145]	Development of an IoT based ECG monitoring system utilizing a heart rate sensor and classification using Adaptive Deep Neural Networks (ADNN).	Accuracy of 98.1%.	IoT Cloud based Health Monitoring System; ECG dataset; use of ADNN.	Based just on the classification (no ECG analysis), uses just 2 classes (normal, abnormal).
Zhang et al., 2023 [137]	Development of ECG classification based on CNN in IoT healthcare systems.	The average F1-score reached 84.3%.	ECG classification, use of CNN, use of IoT.	The accuracy is not the same for the classes, no ECG analysis, healthcare system with just ECG sensor.
Debnath et al., 2022 [146]	Design and implementation of a real-time remote patient monitoring (IoT) technology and biomedical sensors.	-	Real-time monitoring; multi-sensors; comparison with medical instruments.	No ECG analysis, no AI or DL.
our Research	Integrated healthcare system using ESP32, Raspberry Pi, Node-RED, MQTT, and deep learning models trained on MIT-BIH dataset.	Accuracy of approximately 99%.	Real-time ECG analysis; comprehensive patient monitoring; uses multiple sensors (ECG, SpO2, temperature); advanced IoT infrastructure; high accuracy deep learning models.	Doesn`t focus on security

V.6 Conclusion

This chapter has detailed the development and implementation of a cutting-edge AI-driven IoT system designed for real-time ECG analysis and comprehensive patient health monitoring. By integrating advanced technologies such as DL algorithms, IoT devices, and robust data transmission protocols, our system addresses the pressing need for efficient, non-invasive healthcare solutions, particularly in the realm of cardiovascular disease monitoring.

The utilization of the AD8232 ECG sensor, ADS1115 ADC converter, and Raspberry Pi 4B has facilitated the accurate acquisition, processing, and visualization of critical cardiac data. The seamless integration of various physiological sensors, including SpO_2 and temperature

monitors, provides healthcare professionals with a holistic view of patient health, enabling timely and informed decision-making.

Through rigorous training and evaluation of our DL models, we achieved remarkable accuracy in detecting and classifying heart conditions, thus enhancing diagnostic capabilities. The incorporation of a user-friendly Node-RED dashboard allows for real-time visualization of vital parameters and alerts, improving the responsiveness of healthcare interventions.

Despite the challenges faced during development such as data transmission latency, model accuracy, and data security effective solutions were implemented to ensure the system's reliability and performance. The findings presented in this chapter demonstrate the potential of AI and IoT technologies to transform healthcare delivery, offering scalable and adaptable solutions suitable for diverse clinical environments.

Overall, the advancements showcased in this chapter lay the groundwork for future innovations in real-time health monitoring, ultimately contributing to improved patient outcomes and enhanced healthcare practices.

Chapter VI

General Conclusion and Perspectives

VI.1 General Conclusion

This work aimed to develop a comprehensive IoT-based healthcare monitoring system that integrates DL models for ECG peak detection and classification in real-time, with the additional integration of DT technology for surgical environments. The primary objectives were to design a system capable of accurately detecting R-R peaks, classifying ECG signals into multiple cardiac conditions, and connecting the system to a DT of the operating room for enhanced decision-making.

The results showed that the system successfully achieved the objectives, demonstrating an accuracy of 99% in ECG peak detection and classification. The IoT-driven healthcare system integrated sensors such as ECG, SpO2, and temperature to continuously collect patient data, which was processed using DL algorithms to provide real-time, actionable insights. The system's performance was validated through simulations in real-time scenarios, highlighting its potential to significantly reduce response times and improve clinical decision-making in surgical settings.

Answering the research questions posed, the study showed that the integration of IoT and DL can indeed enhance real-time ECG analysis and patient monitoring in surgical environments. Additionally, the connection of the system to a DT of the operating room proved to be an effective tool for real-time surgical decision-making, enabling surgeons to visualize and predict outcomes during surgeries. By integrating these technologies, the system provides a dynamic, virtual representation of the operating room, where real-time data is continuously updated and used for predictive analytics, offering significant value in optimizing surgical procedures.

The main contributions include:

1. The development of an IoT-based system for continuous ECG analysis and patient monitoring.
2. The integration of DL algorithms for peak detection and signal classification of ECG data.

3. The implementation of DT technology to simulate and visualize the operating room environment in real-time, offering a novel approach to surgical decision-making and patient safety.

However, the study has several limitations that must be addressed in future work. First, while the system demonstrated high accuracy in detecting and classifying ECG signals, the models need to be further refined to handle more complex cases, such as multi-condition diagnosis or dynamic adjustments based on evolving patient data. Additionally, while the IoT infrastructure is designed to integrate diverse data sources, issues related to data integration, latency, and system interoperability remain challenges that need to be resolved to ensure seamless communication between devices and platforms. Data privacy and security concerns also need further attention to ensure the system complies with healthcare regulations and patient confidentiality.

VI.2 Perspectives

Looking ahead, there are several key areas for future research:

1. Model Refinement: Improving the DL to handle more complex scenarios, including multi-condition diagnoses, and enhancing their adaptability to a wide range of patient profiles.
2. Scalability: Expanding the system's capabilities to be used in broader healthcare environments such as emergency departments, or chronic disease management, where continuous, real-time monitoring is equally critical.
3. Data Integration and Interoperability: Addressing the challenge of integrating various medical data sources into a cohesive system without latency or data loss, particularly as more devices are added to the network.
4. Security and Privacy: Strengthening the security protocols to ensure that IoT-based healthcare systems are fully compliant with privacy standards and regulations, ensuring patient data is protected in real time.

In conclusion, this research contributes to the development of an advanced IoT-based healthcare monitoring system that integrates Deep Learning for real-time ECG analysis and continuous patient monitoring in surgical environments. The system utilizes IoT technologies to collect and analyze patient data in real time, significantly enhancing decision-making, surgical precision, and patient safety. Through the use of Node-RED, the system is designed to interface with Digital Twin (DT) technology, enabling the real-time simulation of the surgical environment. This integration allows for dynamic monitoring, where data from the IoT sensors

can be visualized and analyzed in a virtual model of the operating room, offering valuable insights for surgical teams. As healthcare continues to evolve, the findings of this research provide a foundation for creating intelligent, real-time healthcare systems that improve both clinical efficiency and patient outcomes.

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