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Tomato Plant disease detection and classification using leaf images based deep learning

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Presented by:

OUZDADI Kaouthar

BENHADJI Asma

Proposed and supervised by:

Dr. CHOUCHANE Ammar

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بسم الله الرحمن الرحيم

Dedication

To those who are not matched by anyone in the world , to those who have made a great deal, and have given what cannot be returned ,to you these words, my dear father and mother , I dedicate this research to you ,you have been my best supporter throughout my academic career.To my real life support my brothers Mohamed, Toumi, Abdou, Khaled, Redhouane,their spouses and children , to my second mother Fatma and my sisters Anfel , words cannot describe you. To my sisters who were not born to my mother but have become my family Hasina, Asma, Zola, Meriem, Chaima and Safia ,my dear partner Asma . I stand in this beautiful moment thanks to you.In the latter special dedication to my little Riadh pray for him to heal

OUZDADI Kaouthar

I dedicate this work to my parents who gave me all the love.appreciation and encouragement to reach this day: To my dear mother Your endless encouragement and natural nurturing has been my guiding light. Your belief in my abilities fueled my determination to overcome any obstacle that came my way. Dad, your wisdom and guidance is invaluable. Your unwavering belief in my potential has inspired me to reach for the stars and to settle for nothing less than excellence. Husband, your unwavering support, patience and understanding have been my constant source of motivation. To my dear daughters, Enas and Alaa, to my brothers Youssef, Mohammed and Yassin , to my partner Amel. I dedicate my final education project to each of you as a token of my deepest appreciation. This achievement would not have been possible without your love, sacrifice, and unwavering support. Thank you for being my pillars of strength and for always standing by my side. With all my love and gratitude.

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Abstract

Tomato plant diseases detection and classification using leaf images based deep learning revolves around the field of plant pathology and agriculture. The focus is on developing effective methods that leverage deep learning algorithms to enable early and accurate identification of plant diseases. Deep learning has exhibited great potential in precisely recognizing and classifying diverse types of plant diseases using leaf images. This has the capacity to significantly impact agriculture and enhance food security. By devising efficient deep learning-based approaches, this study aims to contribute substantially to the advancement of plant disease detection and classification, promoting sustainable practices in agriculture. In this work, we investigate a hybrid system that use a powerful machine learning algorithm named exponential discriminant analyses (EDA) with transfer learning process based on recent and the powerful deep nets including, Resnet50, Darknet53, Densenet201and Efficientnetb0. Our system is evaluated on two challenging datasets, Plantvillage, and Taiwan tomato leaves with 18,340 and 14,531 tomato images respectively. The experimental results show high competitiveness of the proposed method.

Keywords:. Plant disease detection, Deep learning, Transfer learning,Exponential discriminant analyses, Leaf images.

Resumé

La détection et la classification des maladies des plants de tomate se font avec l'utilisation des images de feuilles basent sur le domaine de la pathologie végétale et de l'agriculture. On met en évidence sur le développement de méthodes efficaces qui exploitent les algorithmes d'apprentissage profond afin de permettre une identification précoce et précise des maladies des plantes. L'apprentissage profond a montré un grand potentiel dans la reconnaissance et la classification précise de différents types de maladies des plantes en utilisant des images de feuilles. Cela peut avoir un impact significatif sur l'agriculture et promouvoir la sécurité alimentaire. En élaborant des approches efficaces basées sur l'apprentissage profond, cette étude vise à contribuer de manière substantielle à l'avancement de la détection et de la classification des maladies des plantes, en favorisant des pratiques durables en agriculture. Dans ce travail, nous étudions un système hybride qui utilise un puissant algorithme d'apprentissage automatique appelé analyses discriminantes exponentielles (EDA) avec un processus de transfert d'apprentissage basé sur des réseaux profonds récents et puissants, notamment Resnet50, Darknet53, Densenet201 et Efficientnetb0. Notre système est évalué sur deux bases de données complexes, Plant village et les feuilles de tomate de Taïwan, avec respectivement 18 340 et 14 531 images de tomates. Les résultats expérimentaux montrent une compétitivité élevée de la méthode proposée.

Mot clés :Détection des maladies des plants ,Apprentissage profond, Transfert d'apprentissage ,Analyses discriminantes exponentielles , Images de feuilles.

ملخص

يتم كشف وتصنيف أمراض نبات الطماطم باستعمال صور أوراقها وذلك بالاعتماد على التعلم العميق في مجال علم أمراض النباتات والزراعة ويُسلطُ الضوء على تطوير سُبل فعالة للكشف المكبر والدقيق لهذه الامراض بالاستعانة بخوارزميات التعليم الدقيق. وقد قدم هذا الاخير العديد من الإمكانيات في هذا المجال. ويمكن لذلك أن يؤثر بشكل كبير على الزراعة وتعزيز الامن الغذائي من خلال دراسة فعالة قائمة على هذا النوع من التعلم التي تهدف الى تقدم هذا المجال وتعزيز الممارسات المستدامة في الزراعة.في عملنا هذا نتطلع الى دراسة نظام متكامل يستخدم خوارزمية تعلم آلي قوية تسمى تحليلات التمييز الأسي (EDA) مع عملية نقل التعلم باستعمال شبكات عميقة حديثة وقوية بما في ذلك,

Resnet50, Darknet53, Densenet201وEfficientnetb0 ويتم تقييمه على مجموعتي بيانات صعبتين taiwanو plantvillage بواسطة اوراق الطماطم 18,340 و14,531 صورة للطماطم على التوالي.تظهر النتائج التجريبية تنافسية عالية للأساليب المقترحة.

الكلمات المفتاحية: كشف امراض النباتات، التعلم العميق،نقل التعلم، تحليلات التمييز الاسي، صور الاوراق.

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Lists of Acronym

ACC	Accuracy
CNN	Convolutional Neural Network
DL	Deep Learning
KNN	K Nearest Neighbors
LDA	Linear Discriminant Analysis
PCA	Principal Component Analysis
ReLu	Rectified Linear Unit
GLCM	Gray-level co-occurrence matrix
ML	Machine Learning
AI	ArtificialIntelligence
ANI	Artificial Narrow Intelligence
AGI	Artificial General Intelligence
ASI	Artificial Superintelligence
ANN	Artificialneural network
BPNN	Back propagation neural network
SaaS	Software as a service
IoT	Internet of thing
SVM	Support vector machines
EDA	Exponential Discriminant Analysis

General Introduction

The theme of tomato plant diseases and plant disease detection and classification using leaf images based deep learning revolves around the field of plant pathology and agriculture. It focuses on developing efficient methods for early detection and identification of plant diseases using deep learning, which has shown great promise in accurately identifying and classifying different types of plant diseases based on leaf images. This has the potential to significantly impact agriculture and food security.Traditional methods of detecting and classifying tomato plant diseases can be time-consuming, costly, and often inaccurate. This can lead to significant yield losses and economic damage for farmers and gardeners. Early detection of plant diseases is crucial in preventing the spread of the disease and minimizing crop losses. Therefore, there is a need for more efficient and accurate methods of detecting and classifying plant diseases,how could that be.

Among the modalities in the system of classification Plant disase ,the "Plant disease detectionand classification using leaf images based deep learning" by the fact that it is permanent and unique. Researchers are still trying to develop detection and classification systems through mathematical tools usually complex to discriminate between classes.

The objective followed in this dissertation proposes an approach to improve the performance of the Plant disease detection and classification system by using several methods with a set of operations. For this purpose, we have made the combination between different methods of extraction of deep features , which allowed us to obtain a better adaptation for the realization of an Plant disease detection and classification system and the improvement of its robustness.

This dissertation contains a general introduction in which we discuss the problem ofplant disease detection and classification, we also emphasize our modest contribution to this vast field that has motivated a large number of researchers over the past ten years.

The contributions of our work are :

- Development of an Intelligent System for Tomato Plant Disease based on Leaf Images, the goal is to create an automated and efficient solution for disease detection in tomato plants.
- Explores the use of four popularPretrained CNN Deep Models (Resnet50, Darknet53, Densenet201, and Efficientnetb0), to leverage the powerful feature extraction capabilities of these models for more then10 tomato plant disease recognition.
- Fusion of Extracted Features, we focuse on combining the extracted features from the four pretrained CNN models, in order to leverage the complementary information provided by each model and enhance the overall performance of disease recognition.a more robust and

discriminative representation is expected, leading to improved accuracy in disease classification.

- The proposed approach is evaluated on two challenging datasets: Plantvillage and Taiwan tomato dataset.The datasets provide a diverse range of tomato plant images with various disease instances.By testing the oursystem on these datasets, the effectiveness and generalizability, and the robustness of the proposed approach are assessed, providing insights into its real-world applicability

Four main chapters are presented in this work as follows:

Chapter I: In this first chapter we give an overview of the plant disease detection and classification from images by presenting some definitions and terminology necessary to understand this topic.

Chapter II: In this chapter we introduce the available public databases and some related works. we also discuss the plant disease detection and classification approches such as Artificial intelligence,Supervised learning, deep learning and transfer learning

Chapter III: This chapter is dedicated to the design of the proposed solution, we explain the different steps used for the implementation of our system Features extraction using deep (Darknet53, Densenet20, ResNet-50, and EfficientNet-b0) and Subspace projection and Dimensionality reduction using powerfull technique named EDA, The experimental results are presented and discussed in this chapter.We study the task of plant disease detection and

classification using several experiments.

Chapter I:

Generalities of plant Disease detection

I.1 Introduction

Since cultivation plays a significant part in the economies of States, they are subjected to a variety of obstacles, including plant diseases that represent a threat to agriculture, making it important to handle them and understand the amount and severity of their occurrence.by improving agriculture and incorporating cutting-edge technology into it, such as smart agriculture systems, these illnesses can be prevented. You will observe this in thischapter.

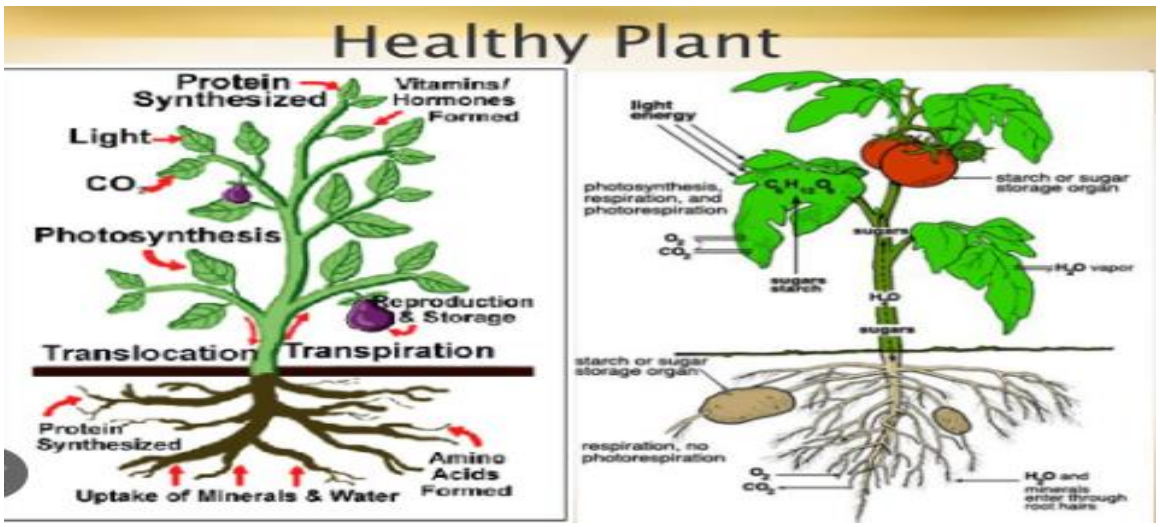
I.2 Plant pathology

The Concept of disease , in general, is a defect in the structure or function of an organism, and it can also be said that it is a change in the biological system at the molecular or cellular level[1].

Plant pathology considered as a branch of science,it is also called "phytopathology",plant pathology is a study include diagnosis and the nature of disease and treatment of affected plant**.** Plant pathology is the scientific study of plant disease caused by pathogens(infectious and non infectious disease)and environmental condition (physiological factors). This science includes many areas such as knowledge of botany,microbiology, crop scienc,ecology, genetics,biochimestry, molecular biology[2].The major goals of plantpathology:

- To study biotic (living),mesobiotic and abiotic(non living) and environmental causes of disease or disorders.
- To study the mechanisms of disease development by pathogens.
- To study the plant pathogen intraction in relation to environment.
- To develop methods of management of plant disease[3].

We give an example of the healthy plant in FigureI.1.



FigureI.1: Healthy plant.

I.3 Diagnosis of plant disease

Plant disease is an abnormal physiological process that causes an abnormality in plant structure, growth, or function by a causative agent, exposing the plant to continuous disturbance. Plant diseases can also be classified into infectious and non-infectious, according to their causes, as they are represented by fungi, bacteria, viruses, nematodes or parasitic flowering plants, temperature extremes and unfavorable relationships between moisture, oxygen, and toxic substances in the soil and atmosphere.Figure I.2illustratedvarious type of plant [4].



Figure I.2: Various types of plant disease.

I.3.1 Disease triangle

When it comes to plant diseases, there are some conditions that must be met before a disease can develop. This is frequently condensed in a diagram known as the disease triangle (Figure I.3) . According to the disease triangle, three beneficial conditions must exist together in order for a disease

to exist. These three include a disease-causing pathogen, a plant that can serve as a host, and favorable environmental factors[5].



Figure I.3: Disease triangle**.**

I.3.2 Classification of plant disease

Plant diseases are classified on the basis of various parameters:

I.3.2.1 Pathogens

Pathogens are microorganisms that can cause diseases in plants. These can include viruses, bacteria, fungi, and other organisms that can damage or destroy their host.It can be represented in the FigureI.4 below [6]:

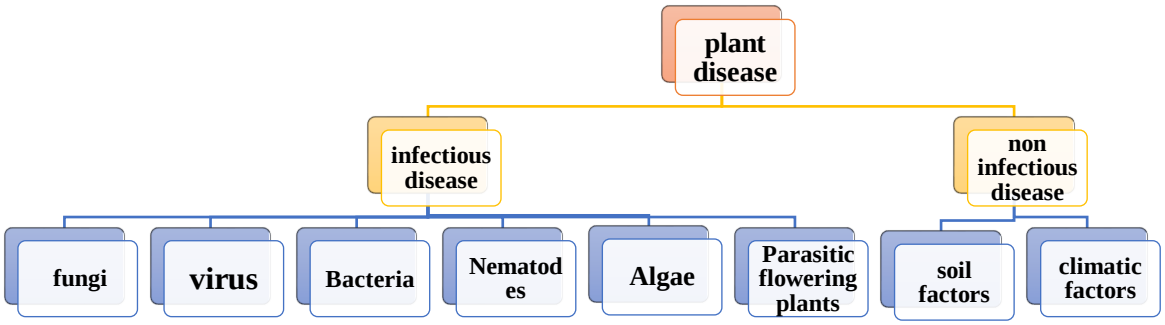


Figure I.4: Illustration to classify plant diseases according to their causes.

I.3.2.2 Plant diseases according to crop types

The prevalence of plant diseases varies by crop type, with some crops being more susceptible to certain diseases than others.among them:

- Diseases of field crops (wheat and barley).
- Diseases of vegetable crops (tomato, eggplant).
- Fruit diseases.
- Forest tree diseases(timber).

- Diseases of flowers and ornamentals[7].

I.3.2.3 Plant disease according symptoms

Diagnosing plant diseases based on their symptoms is a crucial step in effective disease management. Identifying symptoms can help farmers quickly pinpoint the underlying disease and implement appropriate control measures. among these listed symptoms:

- **Rust:** Rust diseases are a group of fungal diseases that occur as a result of fungal rust, so that the leaves are greatly affected, and sometimes they appear on the stems and even flowers and fruits the color of rust varies due to the multiplicity of fungi [8].
- **Smuts:**It is caused by the fungus Ustilaginales.
- **Rots:**caused by bacteria and fungi [9].
- **Blight:**Blight is a term used to describe a number of plant diseases that cause abrupt and severe yellowing, browning, spotting, wilting, or death of leaves, flowers, fruit, or other plant [10].
- **Leaf spot: "Xanthomonas"** compestris frequently causes bacterial leaf spot [9].
- **Canker:**Canker disease usually affects fruit trees including apple, peach, and pears as well as ornamental woody plants, forest trees, and some other types of trees. It results in dieback of twigs and branches, slows tree growth, degrades the quality of lumber, and severely lowers fruit tree yields [11].
- **Wilt:** Wilt is a fungal disease caused by the following fungi **"Verticillium", "Fusarium ", Ceratocystis"[12]**.
- **Powderymildew:** It is a fungus-related disease that affects leaves and stems, and sometimes seen in flowers and fruits [13].
- **Downy mildew:** A fungus-like organism called an "**Oomycete**" is the source of a leaf disease known as downy mildew [14].In Figure I.5 we see some example of plant disease according symptoms.



Figure I.5: (a) Early blight,**(b)** Rustdidease,**(c)** Rot,**(d)** Environmental factors.

I.4 Plant disease detection

The process of screening, diagnosing, and subsequently following the development of a sickness or condition and the efficacy of a treatment is known as disease detection and monitoring. It is typically used for chronic conditions, although it can be used for any condition that needs ongoing treatment.Thetraditional method being followed for this supervision is eye observation which is more time-consuming, expensive and alot of expertise is required [15].

Detecting plant diseases and pests is a key area of research in the science of machine vision. It is a technique that gathers plant photos using machine vision equipment and uses those images to determine whether or not they contain pests and diseases[16].

As seen in Figure I.6 there are fundamentally four stages to the plant disease detection procedure.

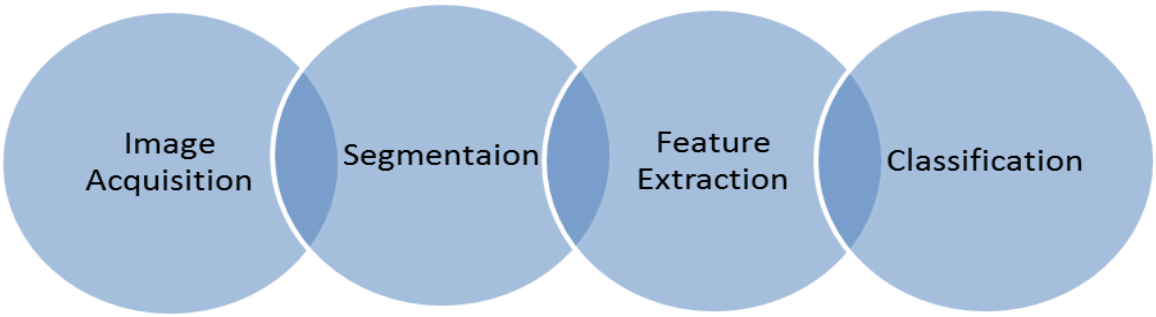


Figure I.6: Phases of plant disease detection system.

I.4.1 Image Acquisition

Using digital devices like cameras, smartphones, and other devices with the necessaryresolution and size, plant leaf photos are collected during this phase. Moreover, photos from the webcan be used.

The application system developer is solely responsible for creating the picture database. The image database is what makes the classifier in the final stage of the detection system more effective[17].

I.4.2 Segmentation

Segmentation refers to the division of a picture into multiple components. components with comparable or identical characteristics. There are several ways for segmentation, including k-means clustering, converting RGB to HIS model, and Otsu approach.

- **Segmentation using Boundary and spot detection algorithm**

  The RGB picture is transformed into the HIS model for segmentation. this technique aids in locating the leaf's diseased area.the boundary algorithm is used, and the connection of the eight pixels is examined, for boundary detection.

- **Masking of green pixels**

Masking is the process of setting a pixel's value in a picture to zero or another value.So the leaf's healthy area is represented by the green area. All those variables are set to zero when a green pixel's intensity exceeds the one before it. pixels with zero values are removed after masking. In masking, the H and S plane value and value of 1, which is assigned to a specific region, are used to identify the diseased portion of the leaf. The remaining regions are assigned a value of 0. A binary image simply consists of zeros and ones as a consequence. Thus, it is possible to remove the leaf's sick portion**.**

- **Threshold based segmentation**

This technique divides input photos into groups depending on how similar their tonal or grayscale values are. This technique was typically applied to dark objects against bright backgrounds or light things against dark backgrounds. The threshold-based method will select an appropriate threshold value T to categorize the pixels in the image into different groups and distinguish objects from the background. The only values in a binary image are ones and zeros. The original RGB color image is then multiplied by this binary image. The diseased area is removed in this manner.

I.4.3 Feature extraction

The technique of converting the raw data into numerical features that can be manipulated while retaining the information in the original data set is known as feature extraction.

- **GLCM(Gray-level co-occurrence matrix)**

It is a statistical technique for determining texture that takes into account a spatial relationship with the pixel. The matrix is then used to extract the statistical traits. From a given image, characteristics such as color, texture, morphology, homogeneity, contrast, correlation, and energy are retrieved. The respected image is then given some value by this extracted characteristic. Moreover, it may be used to find sick plant regions.

- **Shape features**

Based on the geometry of the leaves, there are numerous aspects. Using the Euclidean distance, one may determine the leaf's length.

- **Venation**

The veins on the leaves can be used to identify them more easily. Every species of plant has its own veins. By utilizing morphological techniques, these can be extracted. As a result, the backdrop part's information is removed, leaving only the vein pattern visible.

I.4.4 Classification

The goal of classification phase is determine if the input image is healthy or diseased**.**

- **Using ANN**

The neural network is used to categorize the database. When classifying data, these feature vectors are viewed as ANN neurons. The weighted sum of the inputs provided determines the output.

- **K-means clustering**

Clustering by k-means is used for partitioning. In essence, K- denotes the use of clustering to divide an object's set of features into K different classes. The squares of the distances between the object and the relevant clusters are used to minimize this classification.

- **Otsu Threshold Algorithm**

By setting all pixels below a certain threshold to zero and all pixels above the threshold to one, thresholding is a technique used to construct binary pictures from grey level images.

- **SVM (Support Vector Machine)**

is a supervised learning technique built on kernels that is used as a classification tool. The training procedure maximizes the space between the training data and the class boundary in this case. Support vectors, which are the result and depend on training data, are used. It works well in high-dimensional spaces, when there are more dimensions than training data.

- **Back Propogation**

In a recurrent network, the BPNN algorithm is utilized. Once they have been trained, the neural weights can be fixed and utilized to determine output values for fresh query images that are not yet in the learning database [18].

I.5 Importance and objectives of plant disease detection

In the real world of agricultural production, plant disease identification is crucial. It ensures that the agricultural planting's normal operation and successful harvest occur by carefully examining the plant's development and overall health[19].we explained the plant disease detection in Figure I.7.The key goals are:

- To develop a system that can accurately identify crop disease and pest.
- Establish a pesticide database for the appropriate disease and pest.
- To offer a cure for the condition that has been identified [20].

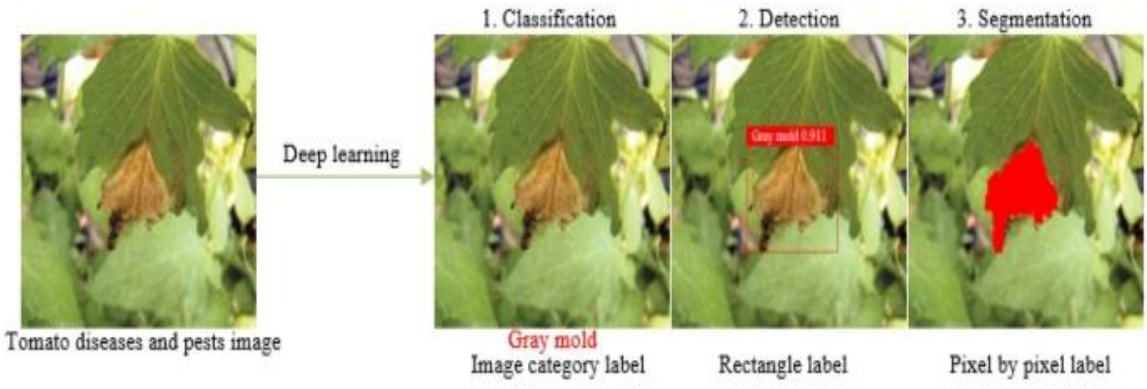


Figure I.7:plant disease detection.

I.6 Advantages and disadvantages of plant disease detection

While there are several advantages to using plant disease detection such as high prediction accuracy and reliable operation even when training examples contain errors. there are also potential disadvantages to consider. For example,require extensive training and challenging to comprehend learnt function [18].in Table I.1 we mention that .

Table I.1:advantages and disadvantages of plant disease detection.

Advantages	Disadvantages
• Early detection • Improved management • Precision agriculture • Increased productivity • Cost-effective	• Cost of implementation • Technical expertise • False positives and negatives • Limited accessibility

Rapidly evolving pathogens: Plant pathogens can rapidly evolve and develop resistance to treatment methods. Some detection technologies may not keep pace with the evolving pathogens, making it challenging to detect newly emerged diseases or strains. Continuous research and development efforts are required to ensure the effectiveness of disease detection methods against emerging pathogens.

I.8 Smart agriculture system

I.8.1 Artificial intelligence agriculture

AI is vast area of computer science that concerned with building intelligent machines that can do tasks that would typically need human intellect.Agriculture is one of the oldest professions in the world, it has a great impact on the economy. But it faces several effects, which makes it difficult for farmers to make judgments about which crop is harvested, so we had to develop traditional agriculture using modern technology,with AI, through to DL (deep learning),ML (machine learning) and ANN (artificial neural network)[21].

I.8.2 Smart agriculture technologies

The main goal of smart farming is to improve farm productivity through the use of hardware and software. Using IoT, drones, robotics, and artificial intelligence, smartfarming focuses on managing farms, plantations, and all related farming activities to find apath to predictable farm output. In order to manage farm operations, smart farming focuseson using data collected from many sources. The ability to collect data and interpret it ishow smart agriculture technologies set themselves apart. IoT hardware and SaaS(Software as a service) are used in "smart farming" to collect data and provide actionable insights for managing all agricultural operations.

- **IoT in Agriculture**

In order to increase productivity and predictability, IoT in agriculture uses sensors, drones,and robots that are linked to the internet and work automatically or semi-automatically toexecute tasks and collect data. Agriculture automation and robots, sometimes referred to asagri-bots, are beginning to get the attention of farmers due to rising labor needs and shortages worldwide. Due to a lack of workers. Agri-bots have gained in popularity as aresult of recent developments in sensor and AI technologies that allow robots to learn fromtheir environment.

- **Smart Greenhouses**

By generating a self-sustaining microclimate ideal for crop production, smart greenhousesare transforming the agricultural production. Farmers may gather real-time data that maximizes efficiency and enhances yields using precision irrigation, temperaturemanagement, lighting modification, and other methods in controlled surroundings without worrying about unexpected weather or predators.

- **Semi-automatic robots**

Robots with arms that can identify weeds and spray pesticides on the damaged plants canprevent major harm and lower the cost of pesticides overall. These machines can also be employed for lifting and harvesting. Heavy farming equipment may be operated from the comfort of homes using phone displays, and GPS can constantly track its where abouts.

- **Drones**

Drones are used in agriculture to image, map, and survey farms. They are providwithsensors and cameras. They may be remotely controlled, or they can fly alone using flight plans that are controlled by agricultural software and GPS in their embedded systems. Information about crop health, irrigation, spraying, planting, soil and field, plant counts and yield prediction, among other topics, may be gleaned from the drone data.

- **Smart remote sensing**

Agricultural sensors like weather stations are used for remote sensing to collect data,which is subsequently sent to analytical instruments for processing. They keep an eye outfor variations in temperature, light, humidity, form, and size of the crops. The informationgathered by sensors about humidity, temperature, moisture precipitation, and dewdetection aids in forecasting the weather on farms so that appropriate crops may becultivated. In order to modify the quantity of water required for irrigation and choose themost advantageous kind of cultivation, the examinationof the soil quality helps to identifythe nutrient value and drier parts of farms, soil drainage capacity, or acidity**.**

- **Computer imaging**

The usage of sensor cameras placed at various locations around the farm or camera-equipped drones is necessary for computer imaging. They digitally process thephotographs they take in order to extract valuable insights from them. They are used forproduce sorting and grading after harvest as well as quality control, disease detection,irrigation monitoring, and crop grading. To control the quality of image processing usingmachine learning, the size, shape, color, and growth of standing crops are identified bycomparing photos from a database with photographs of those crops[22].

I.8.3 Advantages and disadvantages of smart agriculture

Plant disease detection offers numerous advantages in terms of early detection, improved management, and increased productivity. However, it is essential to address the disadvantages such as cost, technical expertise, and accessibility to ensure effective implementation and widespread adoption of these detection technologies[23].we will explain it in Table I.2.

Table I.2: Advantages and disadvantages of smart agriculture.

Advantages	Disadvantages
• Increased efficiency • Precision farming • Resource conservation • Early detection of problems • Data-driven decision making	• Initial investment and maintenance costs • Technical expertise and training • Connectivity and infrastructure challenges • Data privacy and cybersecurity risks • Dependence on technology

I.8.4 Differences between traditional and smart agriculture

Traditional agriculture relies on manual labor and experience-based decision-making, while smart agriculture uses advanced technologies.Table I.3 clarify the difference between them [24].

Table I.3: Differences between traditional and smart agriculture.

Traditional	Smart

• the region uses the same set of crop growing techniques, many of which arenot scientific. • application of insecticides and fertilizerswithout precision across the entire field. • Separate manual management of both field and financial data results in mistakesand data loss. • It is not able to geotag or detect zones. • no accurate weather prediction techniques. • Farmers use traditional tools, whichmakes the operation tedious and time-consuming.	• Every farm is examined to determine thebest crop kinds and input needs for efficiency and profitability. • Early detection and input applicationsolely in the afflicted area reducesexpenditures. • Centrally located on a digital platform isall farm data. • uses satellite imagery to identify thevarious farming zones. • realistic projections of the weather tomaximize resource use and reduce losses. • Task automation boosts output, efficiency,and cost-effectiveness.

I.10 Conclusion

In this chapter, we provide an overview of plant diseases, including the different reasons for disease classification. We have introduced the basics of smart farming. We also briefly discussed the basic ways that leaf and plant disease detection algorithms learn.

ChapterII:

Plant disease detection: Algorithm and Method

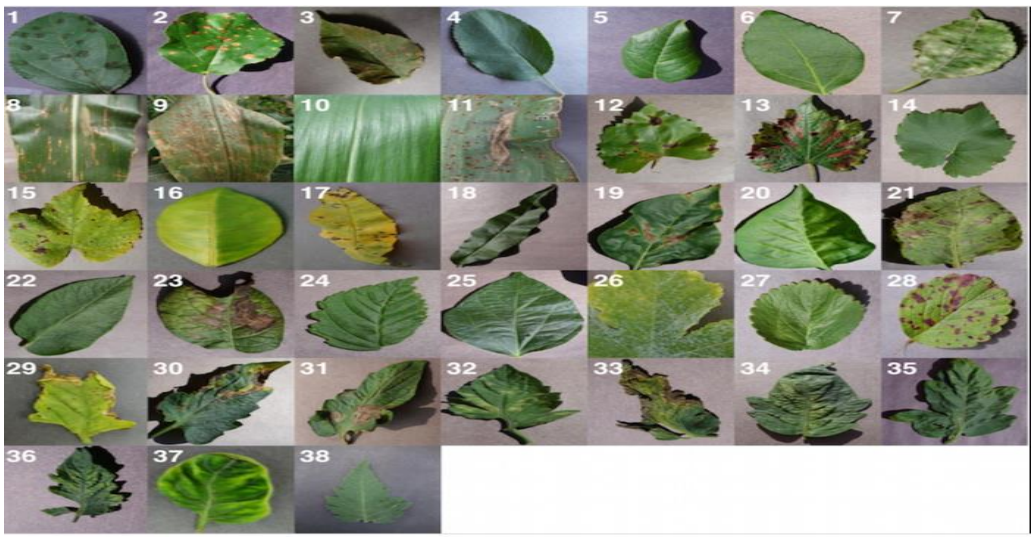
II.1 Introduction

provides an overview of plant disease detection algorithms and methods. It discusses the PlantVillage dataset, related terminology, and the application of AI and ML in disease detection. The chapter covers supervised and unsupervised learning, DL with CNNs, and the concept of transfer learning. It sets the foundation for subsequent chapters, summarizing the key aspects of plant disease detection techniques.

II.2 Plant disease dataset

- **Plantvillage**

was developed to offer effective ways to find 39 different plant diseases. It has 61,486 pictures of backgrounds and leaves from plants. It was made using six different augmentation strategies to produce more varied datasets with various environmental factors. Scaling, rotation, noise injection, gamma correction, picture flipping, and PCA color augmentation were some of the augmentations used in this process.we exemplified of leaf images from the plantvillage dataset [24].we exampled in FigureII.1 leaf images from the plant village dataset andmention their title in Table II.1.



FigureII.1: example of leaf images from the plantvillage dataset.reapresenting every crop –disease pair used.

Table II.1: Titles of images.

Number of image	Title of image
(1)	Apple Scab, Venturiainaequalis
(2)	Apple Black Rot, Botryosphaeriaobtusa
(3)	Apple Cedar Rust, Gymnosporangiumjuniperi-virginianae
(4)	Apple healthy
(5)	Blueberry healthy
(6)	Cherry healthy
(7)	Cherry Powdery Mildew, Podoshaera clandestine
(8)	Corn Gray Leaf Spot, Cercosporazeae-maydis
(9)	Corn Common Rust, Pucciniasorghi
(10)	Corn healthy
(11)	Corn Northern Leaf Blight, Exserohilumturcicum
(12)	Grape Black Rot, Guignardiabidwellii
(13)	Grape Black Measles (Esca), Phaeomoniellaaleophilum, Phaeomoniellachlamydospora
(14)	Grape Healthy
(15)	Grape Leaf Blight, Pseudocercosporavitis
(16)	Orange Huanglongbing (Citrus Greening), CandidatusLiberibacter spp
(17)	Peach Bacterial Spot, Xanthomonascampestris
(18)	Peach healthy
(19)	Bell Pepper Bacterial Spot, Xanthomonascampestris
(20)	Bell Pepper healthy
(21)	Potato Early Blight, Alternariasolani
(22)	Potato healthy
(23)	Potato Late Blight, Phytophthorainfestans
(24)	Raspberry healthy
(25)	Soybean healthy
(26)	Squash Powdery Mildew, Erysiphecichoracearum
(27)	Strawberry Healthy
(28)	Strawberry Leaf Scorch, Diplocarponearlianum
(29)	Tomato Bacterial Spot, Xanthomonascampestrispv. vesicatoria
(30)	Tomato Early Blight, Alternariasolani

(31)	Tomato Late Blight, Phytophthorainfestans
(32)	Tomato Leaf Mold, Passalorafulva
(33)	Tomato Septoria Leaf Spot, Septorialycopersici
(34)	Tomato Two Spotted Spider Mite, Tetranychusurticae
(35)	Tomato Target Spot, Corynesporacassiicola
(36)	Tomato Mosaic Virus
(37)	Tomato Yellow Leaf Curl Virus
(38)	Tomato healthy

The process of diagnosing the part of the tomato plant that is infected, noting differences like brown or black patches and holes on the plant, and then hunting for insects can all help to identify tomato plant diseases.

Tomatoes and similar vegetables like potatoes cannot be grown more than once on the same farm in a single season.

three-year span . Any member of the grass family, such as wheat, corn, rice, sugarcane, etc., should ideally be planted before tomatoes in order to maintain the soil's fertility.

Two categories can be made out of the tomato issues: the 16 diseases caused by bacteria, fungi, or poor cultivation practices, and the five additional diseases caused by insects. The bacteria produces a severe type ofBacterial wilt is a devastating disease caused by the bacteria Ralstonia solanacearum. This bacterium has a long lifespan in soil and can enter roots through wounds created naturally during the formation of secondary roots, wounds created artificially during cultivation or transplanting, or even by insects.

Disease development is favored by high temperatures and moisture levels. The bacteria swiftly spread inside the plant's water-conducting tissue, filling it with slime. While the leaves may continue to be green. An infected plant stem appears brown in a cross section with yellowish stuff pouring out of it.

- After examining the photos of the leaves, they have presented a fresh technique in their research to diagnose the disease in tomato crops.they created a Convolution Neural Network model to categorize the photos after obtaining the dataset. The effectiveness of the model has been examined in relation to a number of characteristics, including training accuracy, validation accuracy, testing accuracy, and the number of trainable parameters. structured as follows: talks about the literature review of the available techniques. presents a discussion of the dataset. presents the experimental design .

The Plant Village dataset was used to extract images of tomato disease. Images of crops like tomatoes, potatoes, grapes, apples, corn, blueberries, soybeans, and strawberries are included in the dataset.The crop we chose as our goal was tomato the Figure II.2of several tomato classes [25]:

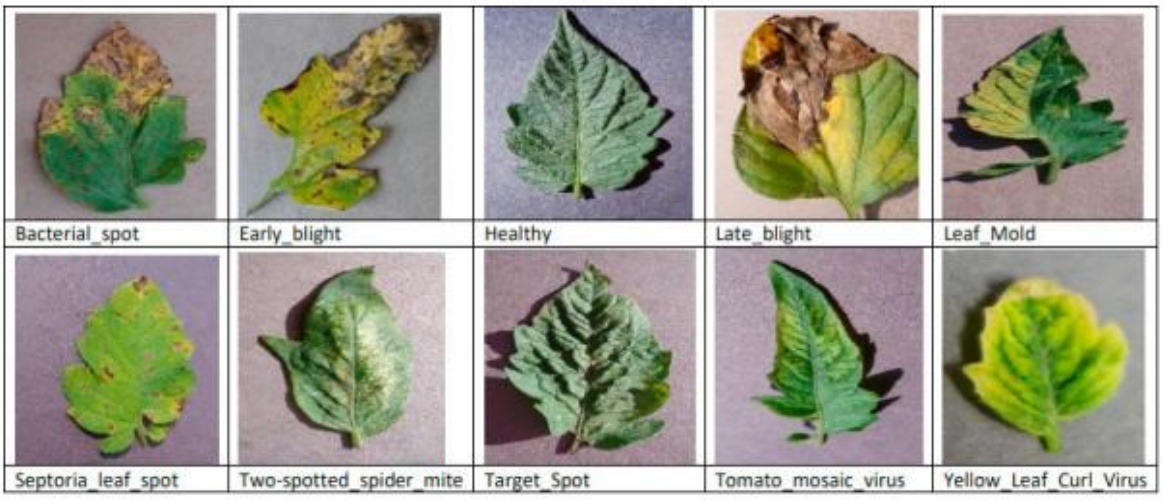


Figure II.2:image of various diseases of tomato.

- **Taiwan**

Taiwan tomato leaves database has the images challenged by changing brightness, multi-leaf, background clutter, shadow on the leaves, low quality of the image, and different textures in the farm conditions Figure II.3. Taiwan tomato leaves database had six classes (five disease classes and one healthy class). Based on the results, healthy, Late Blight, Bacterial Spot classes were common in both databases. The images of both databases were resized to 256 ×256, and the augmented images of both databases were used[26].

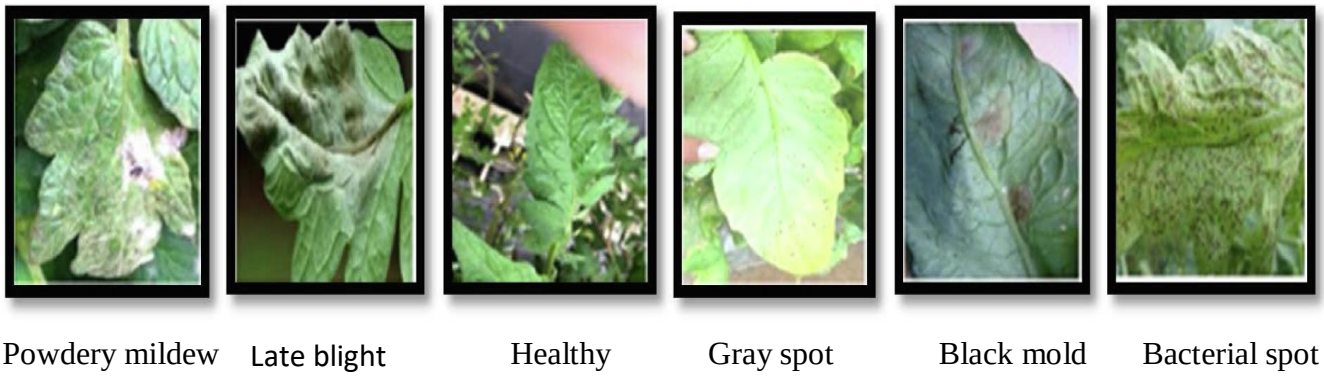


Figure II.3: Sample images Taiwan tomato leaves Dataset with different challenges.

II.3 Related words

Thermal Imaging for Stress and Disease Monitoring: Thermal imaging has proven effective in detecting temperature variations associated with plant stress and disease. Mahlein et al. (2012) utilized thermal imaging cameras to monitor the spatial distribution of sugar beet diseases, such as Cercospora leaf spot and powdery mildew. The research highlighted the potential of thermal imaging as a non-contact and rapid screening method for identifying infected plants in the field[27].

Multi-sensor Fusion for Enhanced Detection: Integrating multiple sensing technologies can enhance the accuracy and reliability of plant disease detection. Zheng et al. (2014) combined visible light imaging and fluorescence spectroscopy to develop a multi-sensor fusion system for identifying citrus Huanglongbing disease. Their results demonstrated the advantage of integrating complementary data from different sensors, leading to improved disease detection performance[28].

Image-based Plant Disease Recognition: Image analysis has become a prominent tool in plant disease detection due to its non-destructive nature and potential for automated and rapid screening. For instance, Mohanty et al. (2016) developed a deep learning model, known as PlantVillage, for the identification of various crop diseases using leaf images. Their approach achieved high accuracy in detecting diseases such as tomato early blight, soybean leaf blight, and corn common rust, showcasing the potential of image-based recognition methods[29].

Deep Learning Approaches for Disease Classification: Deep learning algorithms have shown promising results in classifying plant diseases from images. Sladojevic et al. (2016) applied convolutional neural networks (CNNs) to distinguish between healthy and infected grapevine leaves affected by downy mildew disease. Their study demonstrated the capability of CNNs to learn discriminative features and accurately classify disease conditions[30].

Mobile Applications for On-field Disease Detection: Mobile applications utilizing image analysis have gained popularity for on-field disease detection. Cruz et al. (2020) developed a smartphone application, PlantMD, for identifying common diseases in tomato plants based on leaf images captured in the field. Their research demonstrated the feasibility of using mobile devices as cost-effective and accessible tools for real-time disease monitoring[31].

In summary, image-based plant disease detection techniques, including deep learning, hyperspectral imaging, thermal imaging, multi-sensor fusion, and mobile applications, have showcased their potential in accurate and efficient disease identification. These approaches contribute to the development of non-invasive, rapid, and scalable solutions for plant disease management and crop protection.

II.4 Artificial intelligence (AI)

Artificial intelligence is the simulation of human intellectual functions by technology, so that it is a branch of computer science[32]. AI combines Deep Learning and Machine Learning [33].

It is the science of creating intelligent machines, particularly intelligent computer software [34]. Artificial intelligence is formed up of the two words artificial and intelligence, which relate to things manufactured by humans and the capacity for independent thought, respectively. As a result, artificial intelligence is "thinking power made by human"[35]. Artificial intelligence has advanced significantly in the fields of industry, military, space, informatics, and health[36]. With the use of sophisticated algorithms, quick, repeated processing, and vast amounts of data, AI enables software to automatically learn from patterns or features in the data. Artificial intelligence is important because

- AI automates data-driven repetitive learning and discovery.
- AI gives made things intelligence.
- AI adjusts using algorithms for progressive learning.
- AI examines a wider range of data.
- AI reaches astonishing precision.
- AI makes the most of data [37].

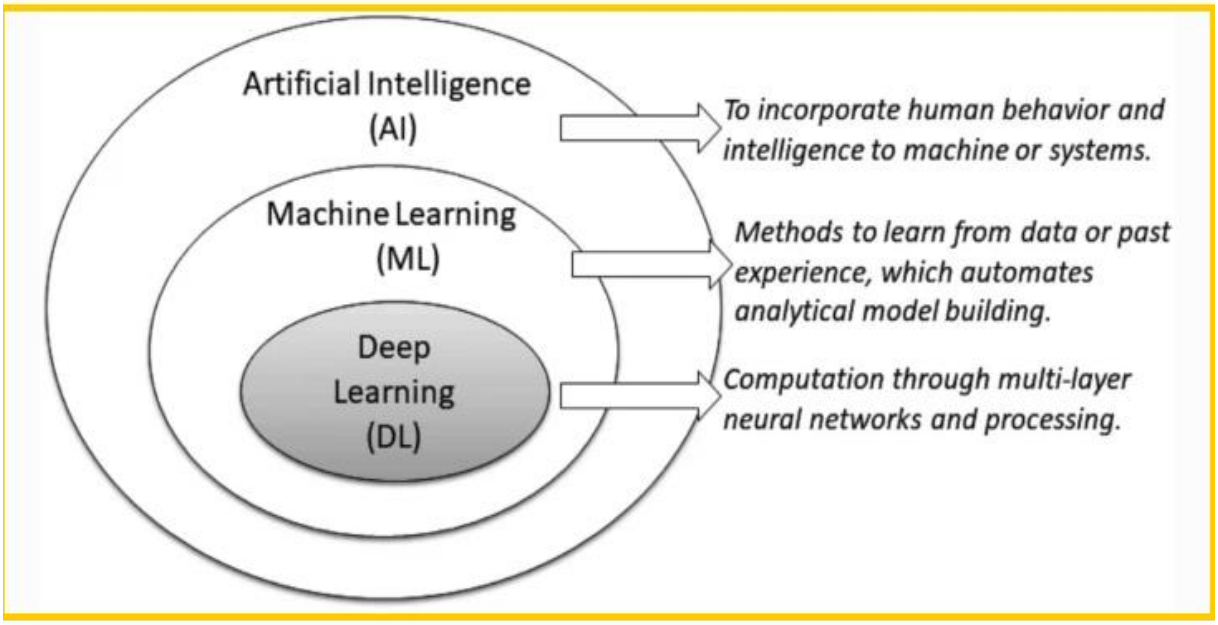


Figure II.4: The position of deep learning (DL), comparing with machine learning (ML) and artificial intelligence (AI).

II.5 Machine learning

Machine learning is a subfield of artificial intelligence broadly defined as the ability of a machine toimitator the behavior of an intelligent human. ML means that the performance of computer

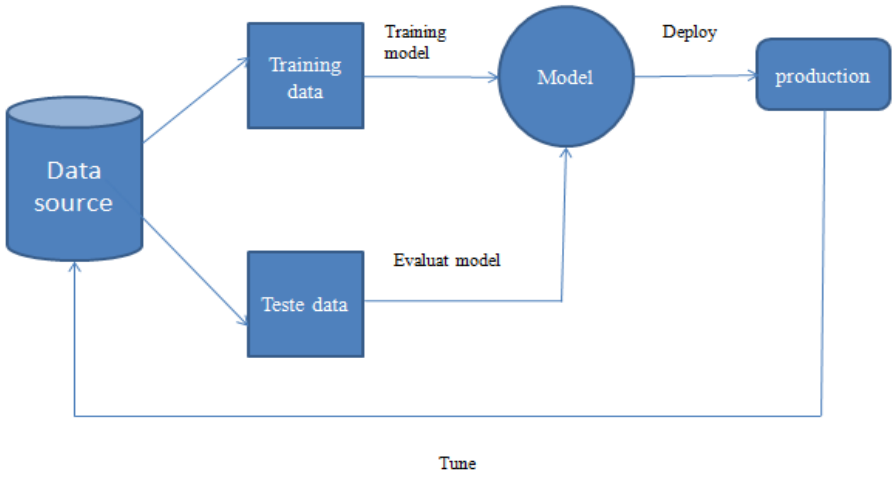
programsimproves with experience with a class of tasks and performance measures. As such, it targets to automatethe task of building analytical models to perform cognitive tasks like as object recognition or naturallanguage translation[38]. This is achieved by employing algorithms that iteratively learn from problem-specific training data, enabling computers to find hidden insights and complex patterns. ML has showngoodapplicability, especially for tasks involving high-dimensional data, such as classification andregression. It can help make reliable and repeatable decisions by learning from previous calculations andextracting patterns from vast databases. For this reason, ML algorithms are successfully applied in manyfields, suchlike fraud detection, speech and image recognition, or natural language processing (NLP)[39] .

Table II.2:machine learning types.

Machine Learning		
Supervised learning		**Unsupervised learning**
Classification model	**Regression model**	**Clustering**
Support-vector machines	Linear regression	Connectivity-based clustering
Discriminant analysis	Logistic regression	Distribution- based clustering
Naïve Bayes	SVR, GPR	Density-based clustering
Nearest neighbor	Ensemble methods	Centroid-based clustering
Neural networks	Decision trees	Fuzzy clustering

II.5.1 Supervised learning

The machine learning task of supervised learning is to train a function that translates an input to anoutput using examples of input-output pairs. It uses labelled training data composed of a collection oftraining examples to infer a function. Algorithms that require outside help arethose that fall under thecategory of supervised machine learning. Train and test datasets are created from the input dataset. Theoutput variable in the train dataset has to be predicted or classified. Every algorithm extracts some sort ofpatterns from the training dataset and use them to predict or classify the test dataset.FigureII.5 provides theworkflow for supervised machine learning methods.



FigureII.5: Supervised learning workful.

II.5.1.1Regression

Regression is the process of estimating an output value based on a variety of inputs. The output value for classification is discrete, but the output value for regression is continuous. Regression comes in two types: multivariate regression, which estimates several output values, and univariate regression, which estimates just one output value. The approximate nonlinear function and time series prediction are two common examples of regression. The purpose of this section is to functionally describe the regression.

Let's talk about the sort of regression where only one output variable is provided, called univariate regression. A classic example of a univariate regression is the nonlinear function approximation, which estimates a single output variable from a single input variable. Time series prediction, also known as univariate regression, is the prediction of a single future measure by examiningpast measures and present measures. In this type of regression, the input data, which is provided as an input vector, generates many output values. The practice of predicting several future measures by examining previous and current measures is known as multivariate time series prediction[40].Figure II.6 provides a functional illustration of univariate and multivariate regression.

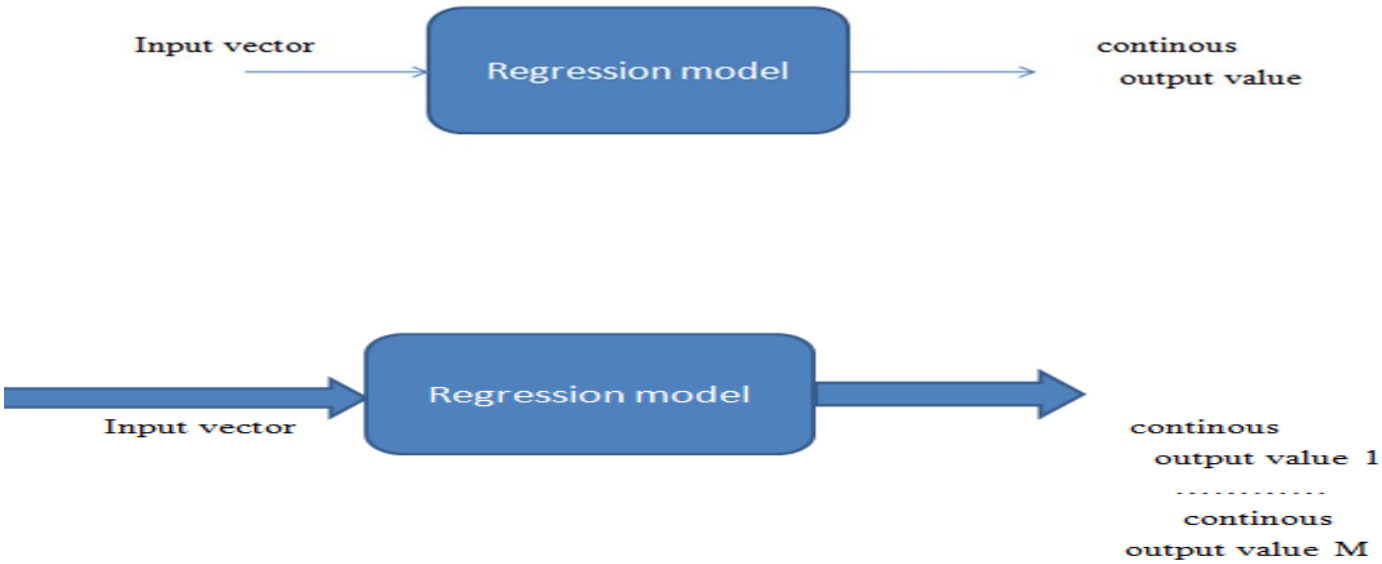


Figure II.6: (a) univariate regression ,**(b)**multivariate regression.

❖ **Decision tree**

A decision tree is a graph that displays options and results as a tree. The edges of the graph indicatethe conditions or rules for making decisions, but the nodes in the graph represent an event or a choice.There are nodes and branches in every tree. Each node represents a set of characteristics that needs to becategorized, and each branch indicates a possible value for the node. This is explained in Figure II.7.

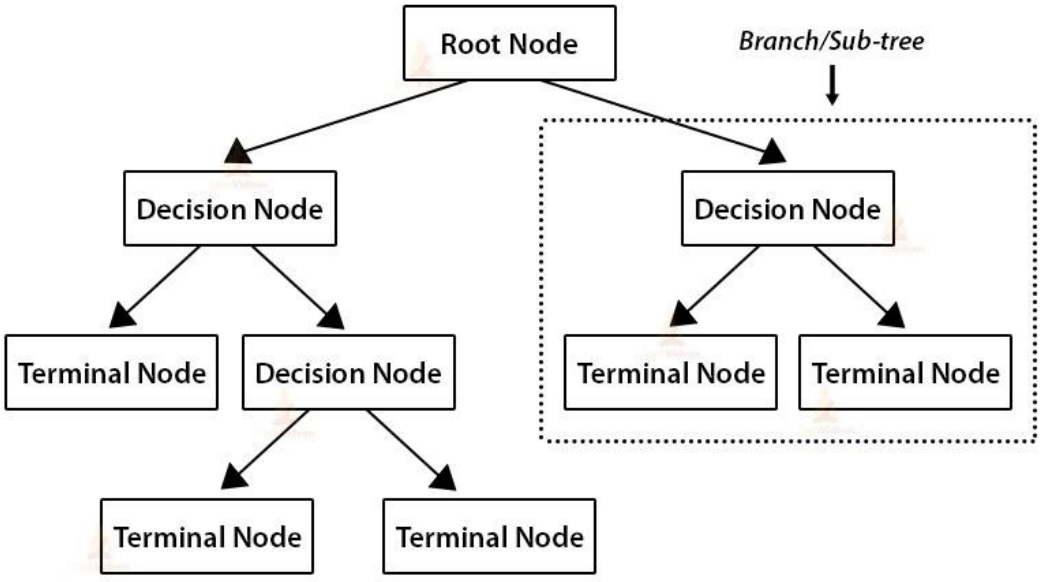


Figure II.7: decision tree.

❖ **Navie Bayes**

It is a classification method built on the Bayes Theorem and predicated on the idea of predictorindependence. A Naive Bayes classifier, to put it simply, believes that the existence of one feature in aclass is unrelated to the presence of any other feature. Nave Bayes is primarily used in the textcategorization sector. It is mostly used for classification and clustering applications based on theconditional probability of happening.

II.5.1.2 Classification

The classification is defined as the process of assigning one or some among the predefined categories.

❖ **Support Vector Machine (SVM)**

Support Vector Machine (SVM) is another popular modern machine learning approach. Support-vector machines in machine learning are supervised learning models with related learning algorithms thatexamine data used for regression and classification analyses. SVMs can effectively do non-linearclassification in addition to linear classification by automatically translating their inputs into featurespaces with high dimensions. This technique is known as the kernel trick. It essentially draws linesbetween the classes. The margins are drawn to have the shortest possible distance between them and theclasses, which minimizes classification error. This is explained in Figure II.8 .

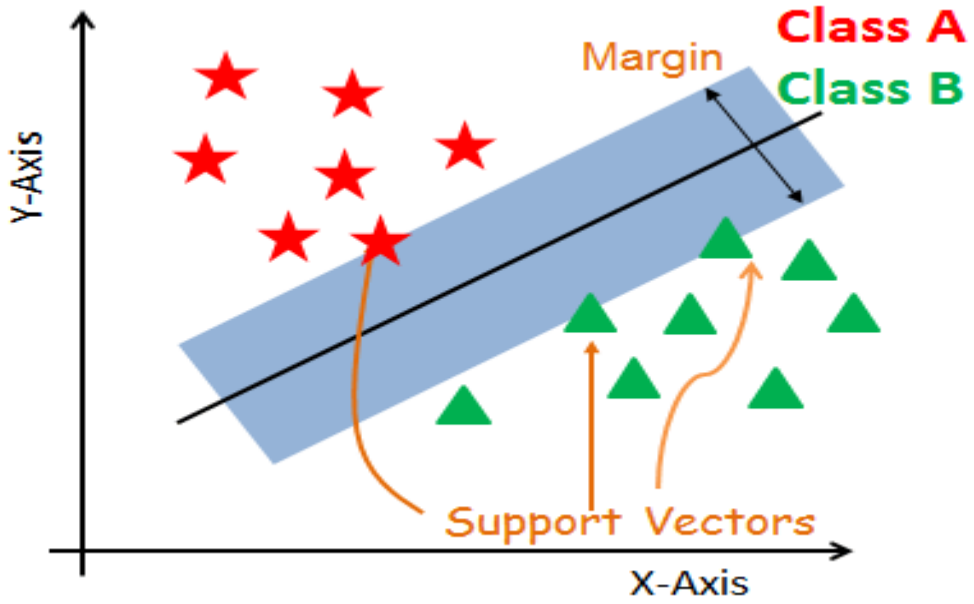


Figure II.8: support vector machine.

❖ **LinearDiscriminant Analysis (LDA)**

This method serves to minimize intra-class variability and maximize inter-class variability. The projection matrix (A) of this method is obtained by solving the following eigenvalue problem[41].Eq II.1

$$S_b U = S_w \lambda \quad \textbf{Eq II.1}$$

Where Sb and Sw are respectively the inter-class variability matrix and the intra-class variability matrix.Eq II.2 and Eq II.3

$$S_b = \sum_{s=1}^{S} (\omega_s - \bar{\omega})\,(\omega_s - \bar{\omega})^T \quad \textbf{Eq II.2}$$

$$\boldsymbol{S_\omega = \sum_{S=1}^{S} \frac{1}{\eta_S} \sum_{i=1}^{\eta_1} (\omega_i^s - \overline{\omega_s})(\omega_i^s - \overline{\omega_s})^T} \quad \textbf{Eq II.3}$$

where N is the total number of sessions.

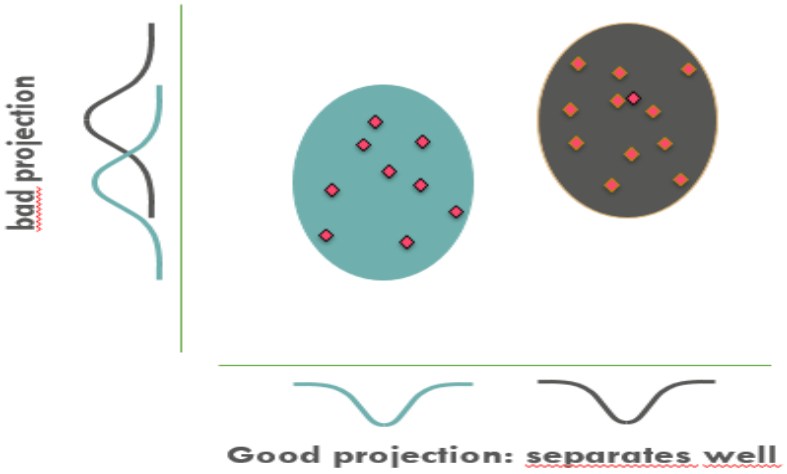


Figure II.9: Maximize component axes for class separation.

II.5.2 Unsupervised Learning

These are known as unsupervised learning since in contrast to supervised learning more than there is no right answer and there is no teacher. The algorithms are left to find and display the interesting structure in the data on their own. Few features are learned from the data by the unsupervised learning algorithms. When new data is introduced, it recognizes the class of the data using the previously learned features. It is mostly used for feature reduction and clustering.

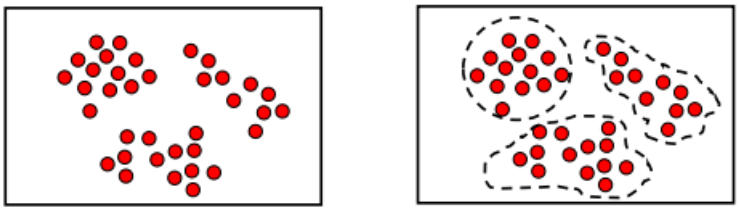


Figure II.10: Unsupervised Learning.

❖ **Principal Component Analysis (PCA)**

A Principal Component Analysis (PCA) allows to define, from a training dataset, a subspace allowing to simultaneously keep the discriminating information and to remove the secondary (non informative) information.

This method consists in finding a new base of the data space whose vectors are orthogonal to each other. The first of these vectors corresponds to the maximum variance direction of the training data. The other components are determined by the orthogonality constraint between the vectors while respecting a maximum variance direction. Thus instead of storing an image vector of size Resolution N, we store a vector of size R ≤ M number of training images. In the PCA approach illumination normalization is always essential.

PCA is a fast, simple and popular technique in pattern identification, it is one of the best techniques. PCA projections are optimal for the reconstruction of a reduced dimensional base[42]

Method

1. Select Data Matrix, X^T mean zero.
2. Calculate the average.

   $\Psi = \frac{1}{N}\sum_{i=1}^{N} X_i$ **Eq II.4**
3. Subtract the mean of the distribution from the data set.

   $X_i = X^T - \Psi$ **Eq II.5**
4. Calculate the covariance matrix XX^T.

   $C = \sum_{i=1}^{N} X_i X_i^T$ **Eq II.6**
5. Calculate the eigenvalues and eigenvectors V of the covariance matrix.

   For $i = 1 \ldots . . N$
6. Commander les vecteurs propres $V_i (i = 1 \ldots . N)$ by their corresponding eigenvalues λ_i,by decreasing order.
7. Keep only the eigenvectors with the most important eigenvalues (the main components);

   $k(k \ll N)X^K = V^K . X$ **Eq II.7**
8. Solve for PCA.

   $\lambda V_{X^T} = C_X V_{X^T}$ **Eq II.8**

PCA is the simplest of the true multivariate eigenvector analysis. Often, its functioning can be consideredas revealing the internal structure of the data in order to better explain the variance in the data.

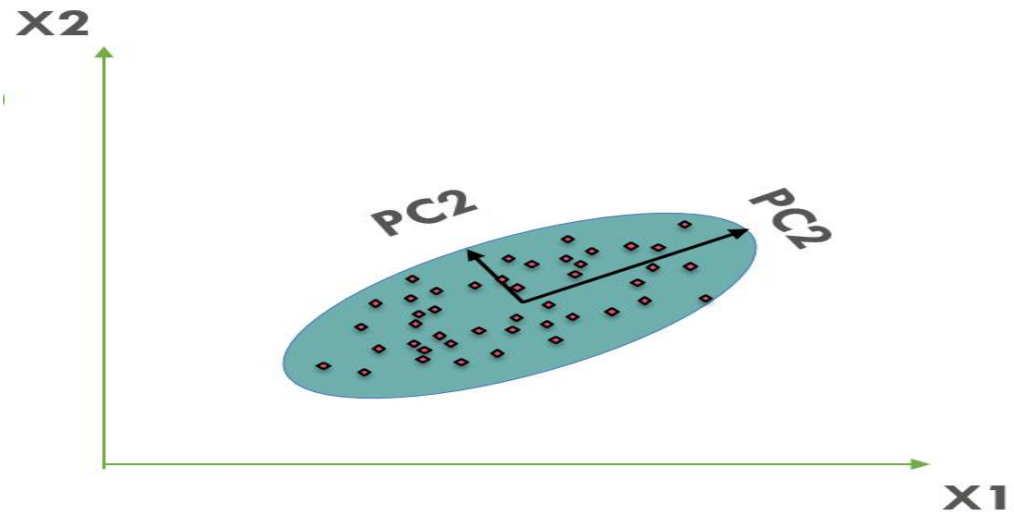


Figure II.11: Principal Component Analysis.

❖ **K-Means Clustering**

The main idea is to define k centers, one for each cluster. These centers should be placed in a cunning way because different location causes different results. So, the better choice is to place them as much as possible far away from each other. K-means is one of the simplest unsupervised learning algorithms that solves the well-known clustering problem. In Figure II.12 we see the different between after and before k-means[43].

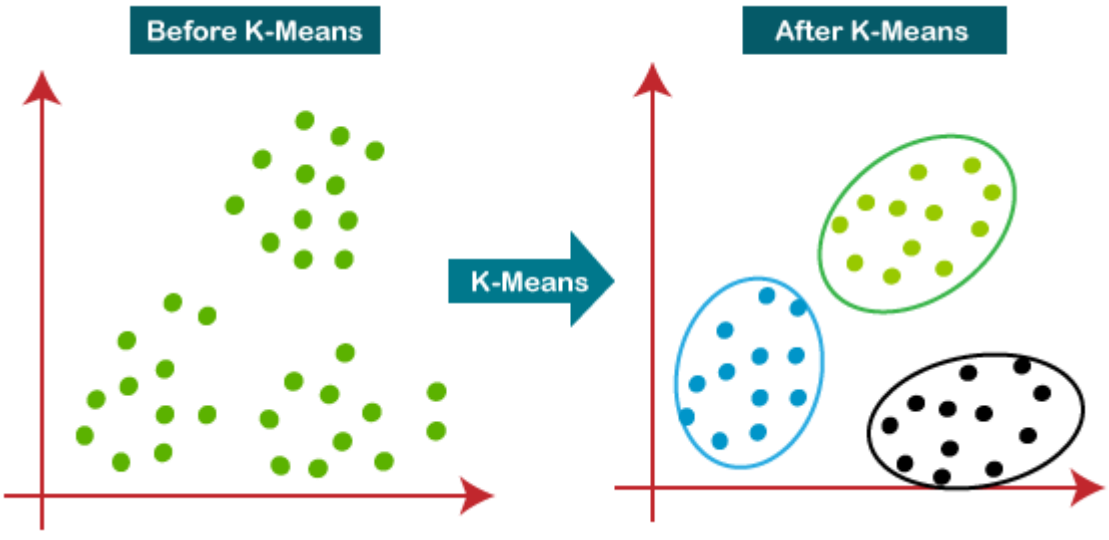


Figure II.12:k-means clustering.

II.6 Deep learning

Deep learning is a subset of machine learning and one of the most sophisticated technologies in artificial intelligence, this is basically a neural network made up of three or more layers [44].Figure II.4 An illustration of the position of deep learning (DL), comparing with machine learning (ML) and artificial intelligence (AI)[45].

Artificial neural networks, also known as deep learning neural networks, make an effort to imitate the human brain through the use of data inputs, weights, and bias. Together, these components accurately identify, categorize, and characterize items in the data.

Deep neural networks are made up of many layers of interconnected nodes, each of which improves upon the prediction or categorization made by the one underneath it. Forward propagation refers to the movement of calculations through the network. A deep neural network's visible layers are its input and output layers. The deep learning model ingests the data for processing in the input layer, and the final prediction or classification is performed in the output layer Figure II.13 is a simple representation of neural network[46].

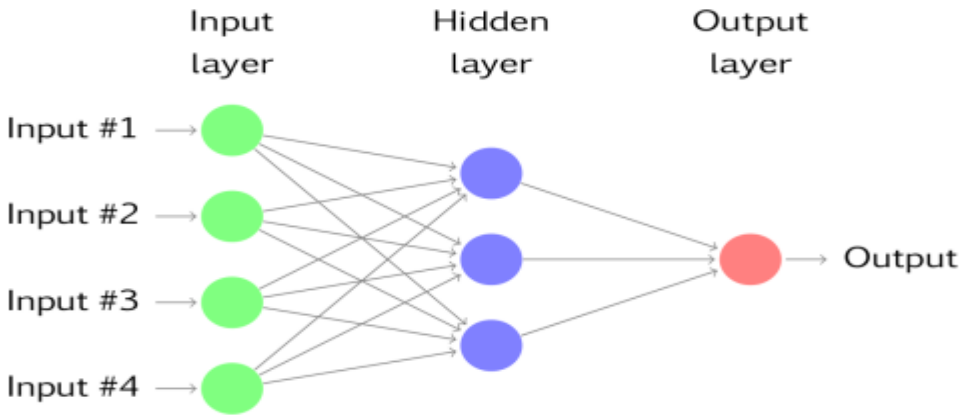


Figure II.13: simple neural network.

- **The input layer:** The number of neurons in this layer corresponds to the number of inputs in the network.
- **Hidden layers:** An arbitrary number of layers with an arbitrary number of neurons, the hidden neurons are located between the input neurons and the output neurons.
- **The output layer:** This is the last layer of the network, it calculates the final probabilities using the logistic activation function (binary classification) or the softmax function (multi-class classification), A loss function (loss function) is associated with this layer to calculate the classification error, it is generally the cross entropy (cross binary entropy), the number of neurons in the layer of output is the number of network output values.

Each layer receives data as input and returns it transformed. For this, it calculates a linear combination and then possibly applies a non-linear function, called the activation function. The coefficients of the linear combination define the parameters (or weights) of the layer. There are several types of architecture for neural networks:

• **Multi-layer perceptrons:** which are the oldest and simplest.

• **Recurrent neural networks(RNN):** used for sequential data such as textor time series.

• **CNN:** Particularly suitable for processingpictures.

In our project we are interested in the convolutional neural network which will be described in detail in the next section.

II.6.1 CNN

is a subset of machine learning. It is one of the many different kinds of artificial neural networks that are applied to numerous applications and data types. Specifically used for image recognition and other tasks involving the processing of pixel data, CNNs are a type of network design for deep learning algorithms[47].

Although there are different kinds of deep learning neural networks, CNNs are the preferred network architecture for detecting and classifying objects. They are therefore ideally suited for computer vision tasks and for applications where accurate object recognition is crucial, such autonomous vehicles and facial recognition [48].

Figure II.14 represent a picture of CNN to identify the image of dog

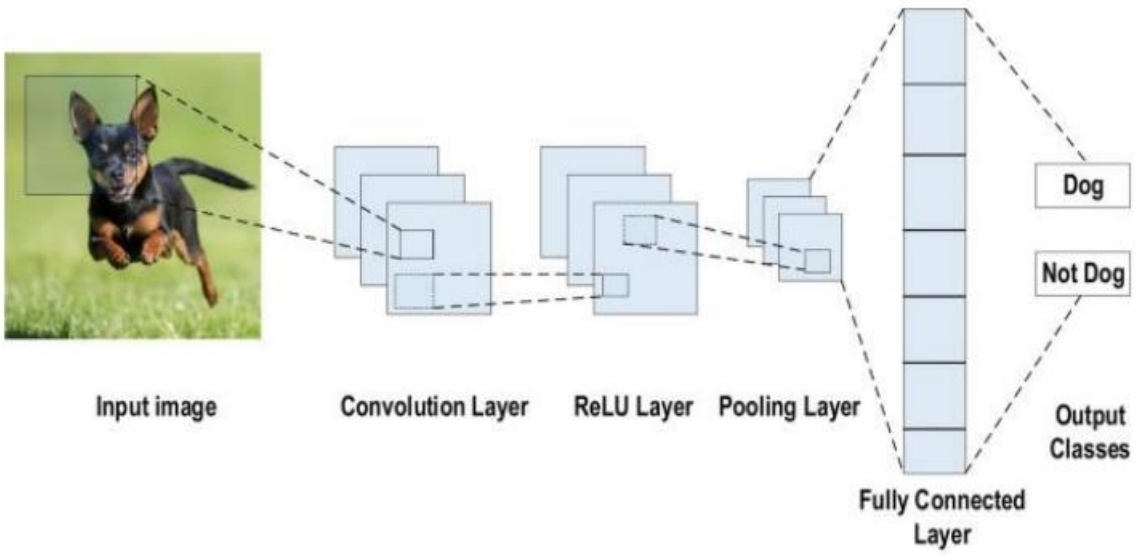


Figure II.14: Convolutional Neural Network to identify the image of a dog.

CNN normally consists of four different layer types: fully linked, convolution, and pooling layers. The first two layers, convolution and pooling, extract features, while the third layer, fully connected, transfers the extracted features to the output [49]. additionally, it automatically and adaptively learns spatial hierarchies of data using a backpropagation technique [48].

- **Convolution layer**

Is the key element of any CNN architecture. It has a number of convolutional kernels, also known as filters, that are convolved with the input image (N-dimensional metrics) to produce an output feature map. The following picture represents example of convolution layer.

The next Figure II.15 it's the 5x5 image, where each pixel's value is either 0 or 1. A filter matrix with a 3x3 dimension is also present.

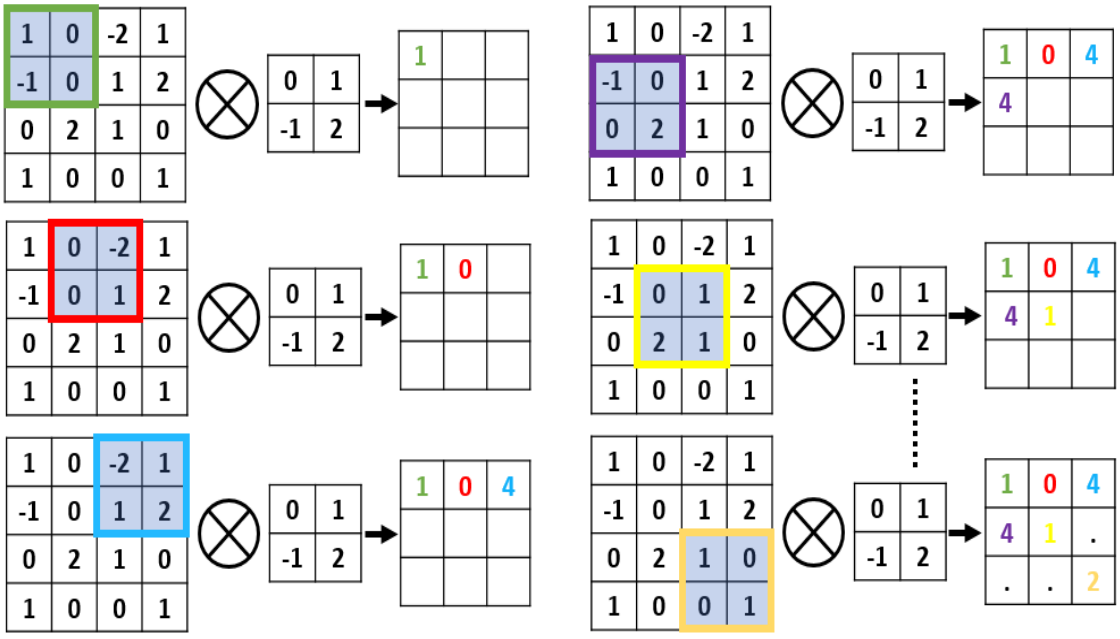


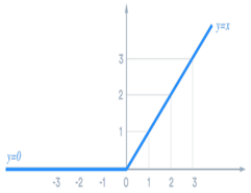
Figure II.15: The primary calculations executed at each step of convolutional layer.

- **ReLU layer**

The rectified linear unit is referred to as ReLU. The next step is to transfer the feature maps to a ReLU layer after they have been retrieved.

ReLU executes an operation element-by-element, setting all the negative pixels to 0. The result is a corrected feature map, and it gives the network non-linearity. The graph in Figure II.16 of a ReLU function is shown below[50].

-55	67	40	-33	43	-6
-2	45	-55	34	99	12
13	13	0	-56	33	13
5	-99	94	-65	1	-51
-9	1	7	8	22	-70
-8	-78	-44	18	09	10



0	67	40	0	43	0
0	45	0	34	99	12
13	13	0	0	33	13
5	0	94	0	1	0
0	1	7	8	22	0
0	0	0	18	09	10

Figure II.16: The graph of ReLU function.

- **Pooling layer**

pooling is a method for generalizing features retrieved by convolutional filters and assisting the network in identifying characteristics regardless of where they appear in the image ,The pooling process' fundamental steps are quite similar to those of the convolution operation. You pick a filter and move it over the output feature map of the convolutional layer that came before. The most popular filter size is 2 ×2,There are various methods for pooling. The two most popular methods are average pooling and maximum pooling [51]. Figure II.17 show an example of 2×2max pooling.

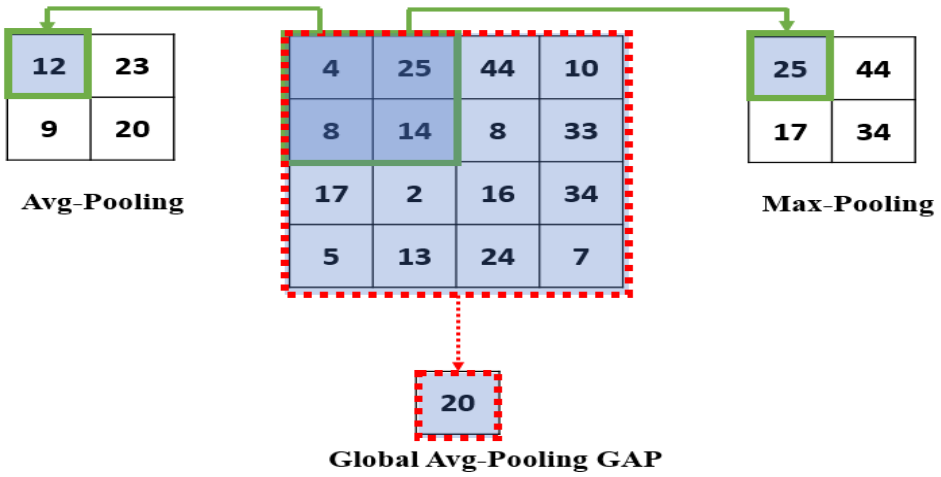


Figure II.17: Example of 2×2 max pooling.

- **Fully connected layer**

The CNN's FC layer is where image classification based on the features gathered from the preceding layers takes place. Fully connected in this context refers to the connection of every input or node from one layer to every activation unit or node in the subsequent layer [52]. Figure II.18 show an example of fully connected layer.

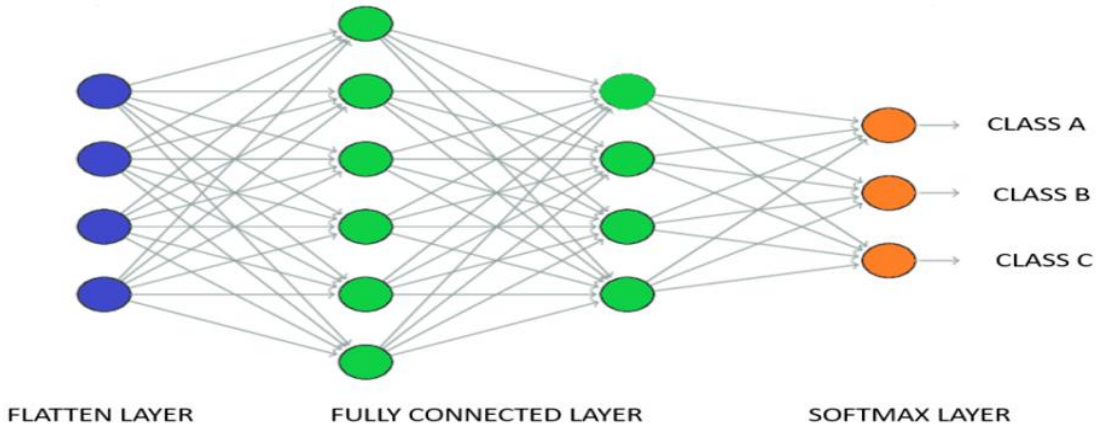


Figure II.18: Fully connected layer.

- **Pretrained model**

Deep features are extracted by CNN which have significantly improved the state of the art in many applications, this success would not have been possible without the availability of the ImageNet organisation of large labelled datasets which have been used to learn high quality features[53]**.** We cite some deep learning models that can be used :

VGG CNN

A CNN model among the most known feature extractors can be used. This network is revolutionary in its inherent simplicity and structure, it uses a very deep architecture with very small convolutional kernels (3x3) with a stride of 1 pixel, this model has been trained on 2.6 million images of 2622 different celebrities[54].

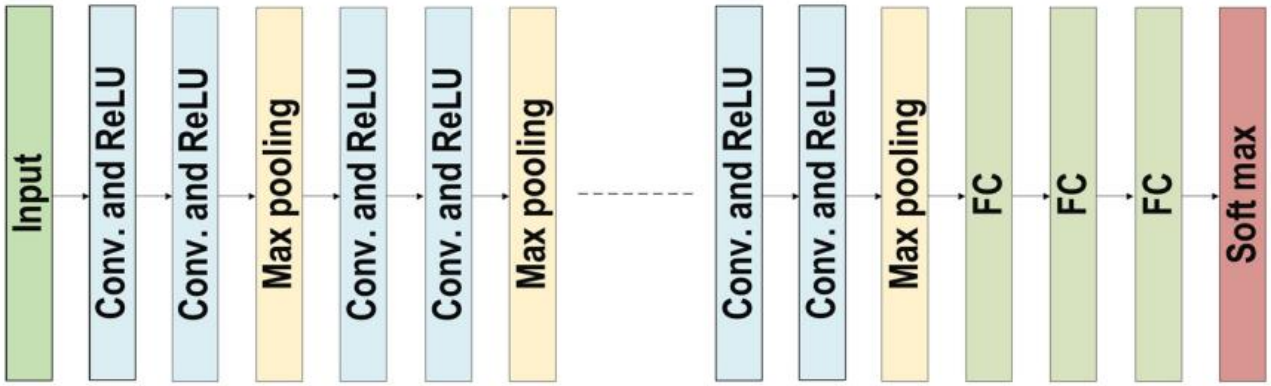


Fig II.19: The architecture of VGG

Resnet : The abbreviation for residual network. It is a type of deep neural network with a different network topology than VGG, the main idea of this network is the residual block. The network allows

the development of extremely deep neural networks, which can contain 100 or more layers in order to extract the best possible features, with several architecture: resnet-22, resnet-50, resnet101, resnet-150, etc…[55].

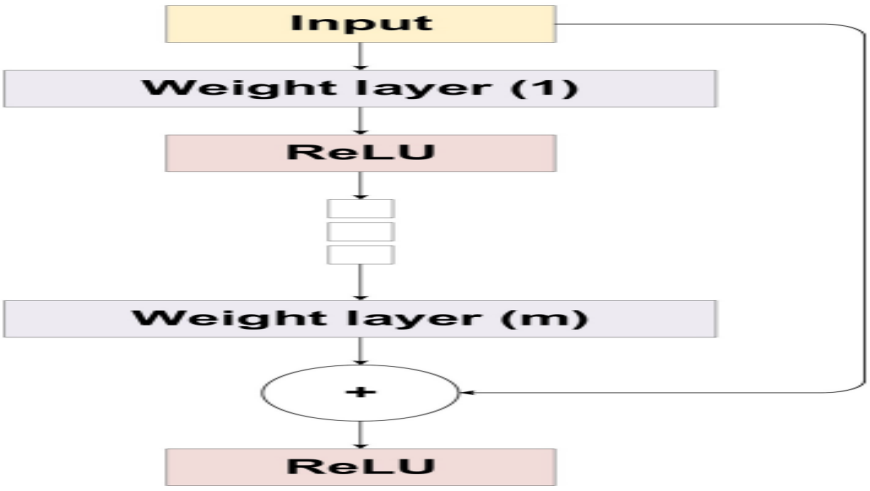


Fig II.20: The block diagram for ResNet

Alex Net

CNN gained popularity thanks to the deep learning architecture called AlexNet. It was created by Geoff Hinton, Ilya Sutskever, and Alex Krizhevsky. The ImageNet Large Scale Visual Recognition Challenge was won using the first large-scale CNN, AlexNet. The AlexNet architecture produced state-of-the-art results at the time it was published and was created to be utilized with large-scale image datasets. The five convolutional layers that make up AlexNet include two dropout layers, three fully connected layers, and one max-pooling layer. Relu is the activation function utilized in all levels.This is shown inFigure II.20 [56].

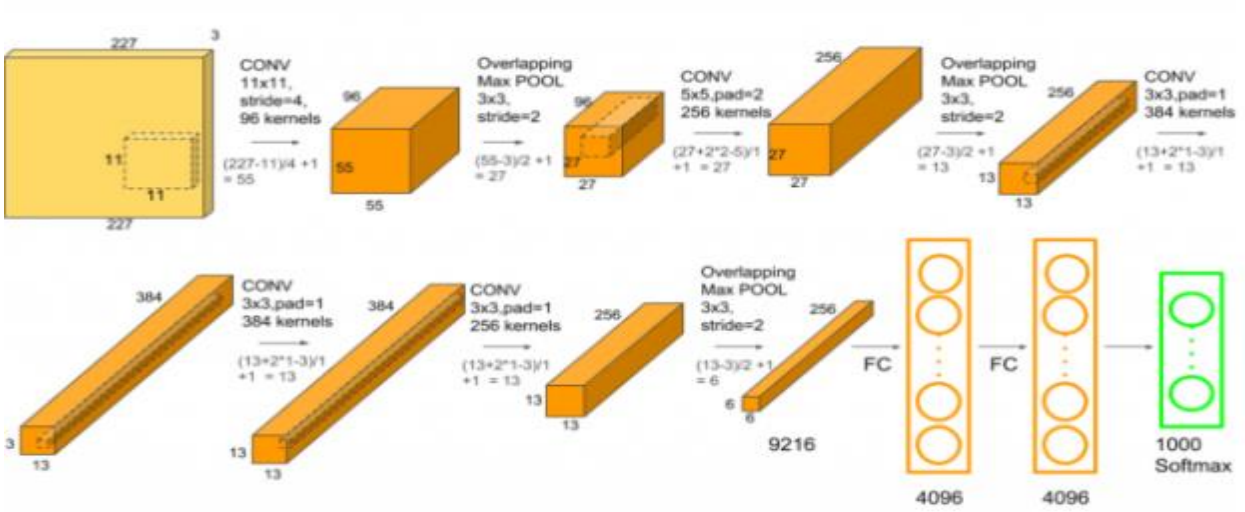


Figure II.21: AlexNet architecture.

DarkNet53

Having 53 layers total, DarkNet-53 is a convolutional neural network. A pretrained version of the network that has been trained on more than a million photos is available for loading from the ImageNet database. The pretrained network is capable of classifying photos into 1000 different object categories, including keyboard, mouse, pencil, and numerous animal images.[57]

Layer	Filters size	Repeat	Output size
Image			416 × 416
Conv	32 3 × 3/1	1	416 × 416
Conv	64 3 × 3/2	1	208 × 208
Conv Conv Residual	32 1 × 1/1 64 3 × 3/1	Conv Conv Residual × 1	208 × 208 208 × 208 208 × 208
Conv	128 3 × 3/2	1	104 × 104
Conv Conv Residual	64 1 × 1/1 128 3 × 3/1	Conv Conv Residual × 2	104 × 104 104 × 104 104 × 104
Conv	256 3 × 3/2	1	52 × 52
Conv Conv Residual	128 1 × 1/1 256 3 × 3/1	Conv Conv Residual × 8	52 × 52 52 × 52 52 × 52
Conv	512 3 × 3/2	1	26 × 26
Conv Conv Residual	256 1 × 1/1 512 3 × 3/1	Conv Conv Residual × 8	26 × 26 26 × 26 26 × 26
Conv	1024 3 × 3/2	1	13 × 13
Conv Conv Residual	512 1 × 1/1 1024 3 × 3/1	Conv Conv Residual × 4	13 × 13 13 × 13 13 × 13

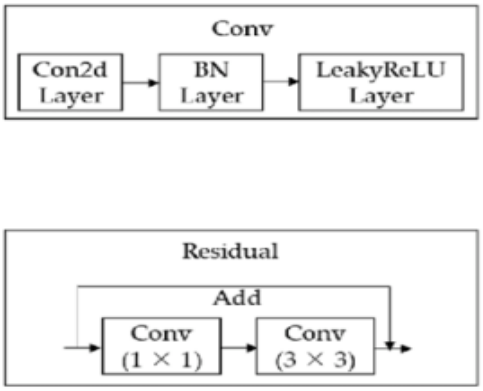


Figure II.22:structure of the Darknet53 convolutional network.

DenseNet201

The DenseNet architecture employs a straightforward connectivity pattern that connects all layers directly to one another in a feed-forward fashion, meaning that each layer receives additional inputs from all preceding layers and passes its own feature-maps to all subsequent layers, in order to maximize the information flow between the layers in the network. This architecture allows for with the help of DenseNet, the vanishing gradient problem is mitigated, feature propagation is strengthened, feature reuse is encouraged, and the overall number of parameters is significantly reduced. Therefore, DenseNet-201 was used in this study.[58]

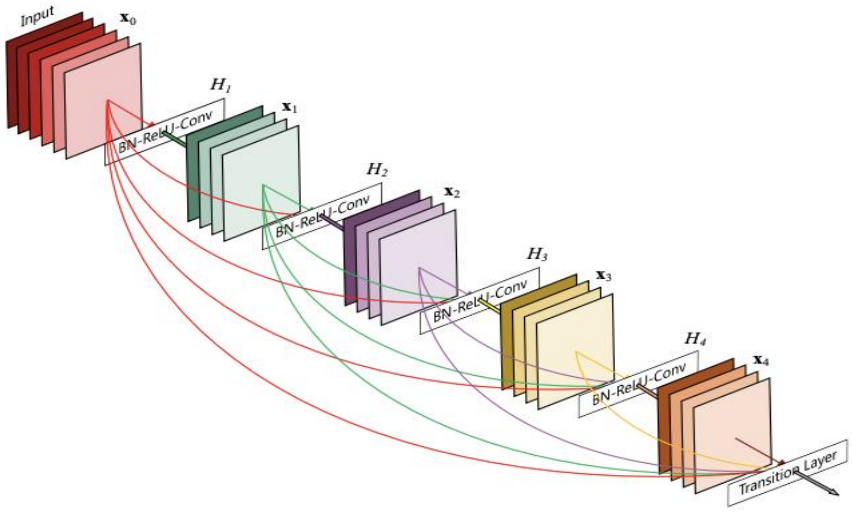


Figure II.23: Avisualization of the DenseNet-201 architecture.

EfficientNetb0

EfficientNetB0 model has been used, with a previous transfer learning process. To reduce overfitting by lowering the quantity of parameters a global_average_pooling2d layer was added. The EfficientNet algorithms are built with highly effective but simple compound scaling techniques. The method allows to scale up from baseline convolutional network to any required resource limitations whilst retaining model performance, acquired from transfer learning from external datasets[59].

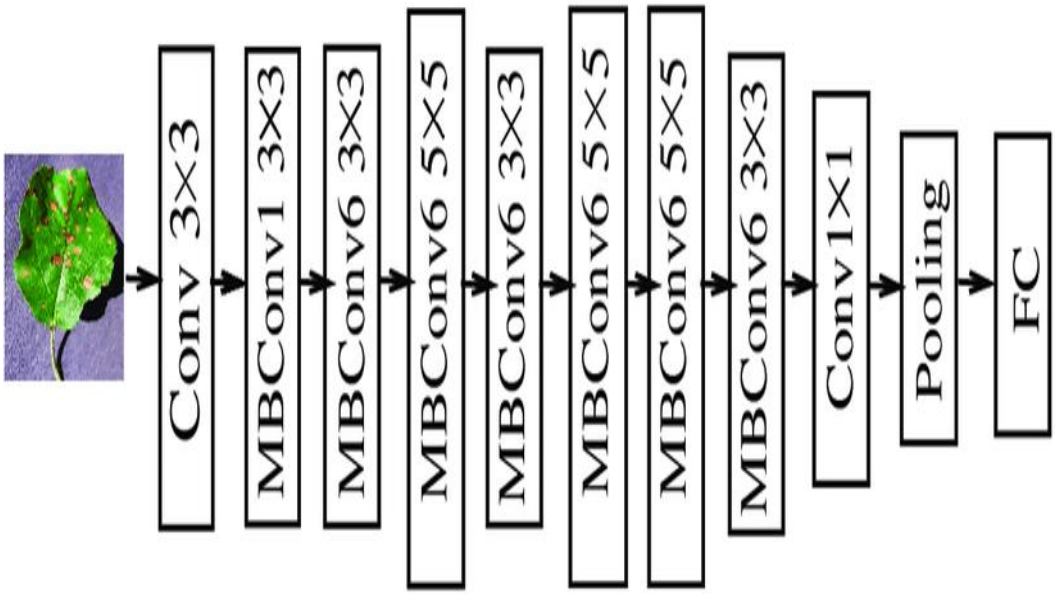


Figure II.24: Basic block diagram of EfficientNet model.

II.7 Transfer learning

Transfer learning, in other words, is a machine learning technique where we use a previously trained model as the foundation for a model on a new problem[60].

Reduced training time, enhanced neural network performance (in most cases), and the lack of a significant amount of data are three of transfer learning's most significant benefits.

Transfer learning is useful in situations when it is not always possible to get the large amounts of data required to train a neural network from scratch[61].

To get beyond the constraints of conventional machine learning models, deep learning experts invented transfer learning[62].Figure II.25 is A brief representation of transfer learning with the data set image.

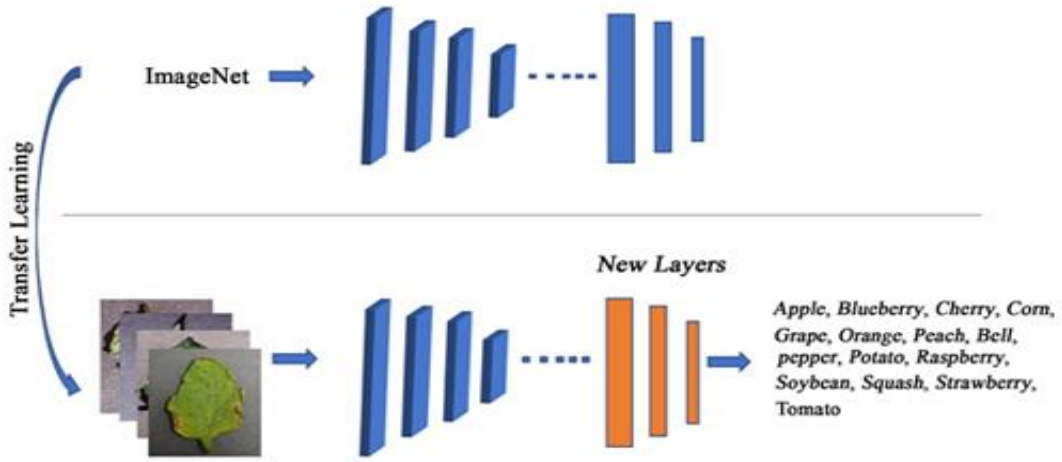


Figure II.25: Transfer learning with data set image.

We have six steps to implement transfer learning:

- Obtain the pre-trained model
- Create base model
- Freeze layers so don’t change during training:TheFigure II.26 below shows this

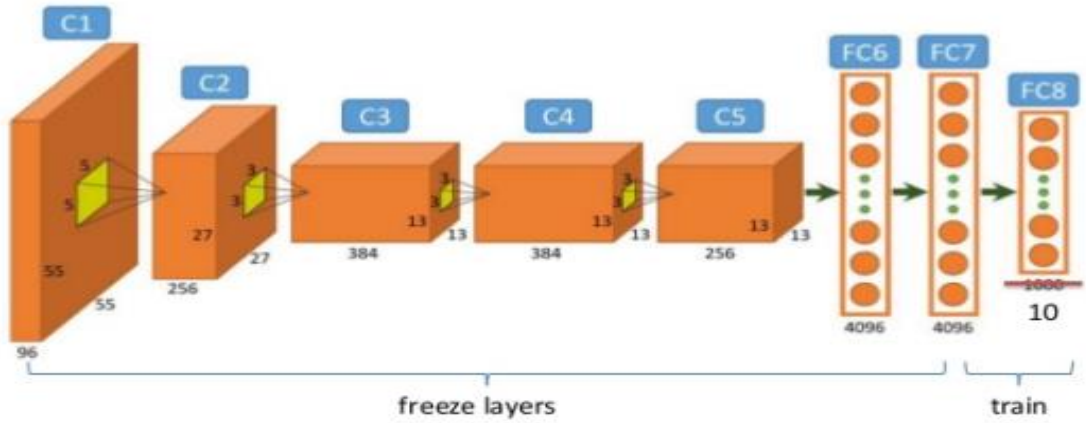


Figure II.26: Freeze layers example.

- Adding new trainable layers
- Training the new layers on the dataset
- Improve the model via fine-tuning [63].

II.8 Conclusion

In this chapter, we made an introduction to artificial intelligence, and also referred to its branches of machine learning and deep learning with many algorithms, PlantVillage is the most famous and widely used database for comparing different algorithms., and also talked about CNN, which is one of the most famous deep neural networks. networks. This works well in machine learning tasks ,especially in programs that work with image data .

ChapterIII:

IMPLEMENTATIONS AND RESULTS

III.1 Introduction

Tomato is an economically important crop; however, it is highly susceptible to various diseases. The objective of this study is to diagnose tomato leaf diseases by classifying images of healthy and unhealthy tomato leaves. To achieve this, we employ four pre-trained CNNs: DarkNet53, DenseNet201, ResNet50, and EfficientNetB0. These CNN models are utilized to train on two different databases, namely PlantVillage and Taiwan dataset.

In our work, we introduce a novel method called EDA for both dimensionality reduction and classification purposes. EDA enables us to effectively analyze and process the data, reducing its dimensionality while retaining the relevant information. The matching process is assured by cos-similarity measure. By utilizing this approach, we aim to enhance the accuracy and efficiency of disease diagnosis in tomato plants**.**

III.2 Environment used

The programming language used in this work is MATLAB, emulated by the programming environment of the same name (in our case MATLAB 2012a). Matlab allows for the simple and fast implementation of algorithms, the implementation of tasks requiring high computing power, the manipulation and display of curves, and the creation of graphical interfaces. The experiments were carried out on a PC with an Intel(R) Core(TM) i5-3210M 2.5GHz with Turbo Boost up to 3.1GHz.

III.3 Proposed solution and protocol

The importance of robust image features in classification and detection of Plant disease is widely acknowledged.The feature extraction stage consists of extracting a certain number of features from images by certain methods explained later in this chapter. The dimensionality reduction stage is about reducing the dimensions of the collected data to be used without complications inside the learning algorithm. The training stage is responsible for learning the discriminative features for each images in the datasets. The testing stage estimates the performance of the training stage by testing plant images. The Matching stage determines classification of the plant images by comparing their feature vectors using cosine similarity metric.

The figure III.1 represents our architecture for Plant disease and classification system. Each part is discussed in details in the next sections.

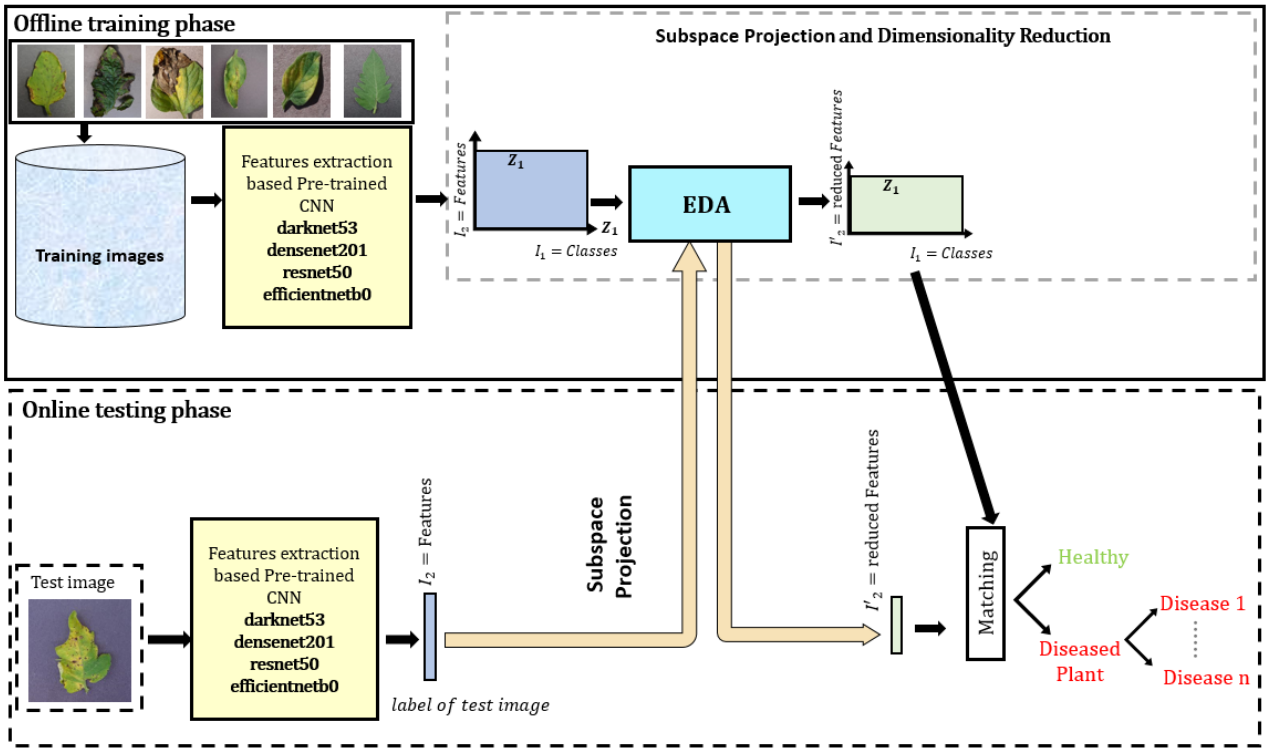


Fig III.1: global system shematic.

III.3.1 Features extraction using deep features based on CNNs

We extract four different types of features based on CNNs to accurately describe plant images. We take them out of the original plant image, which is 224 x 224 x 3. We extract features from the Darknet53, Densenet201, ResNet-50, and EfficientNet-b0 network using. There are 1×1000 dimensions for each feature vector.

III.3.2 Subspace projection andDimensionality reduction

The extracted features from the Darknet53, Densenet20, ResNet-50, and EfficientNet-b0 approaches are concatenated to create the feature vector. The primary issue with features vectors is their high dimensionality. It is necessary to project the feature vector onto a lower space that only contains discriminant data as a result. Additionally, the computation time can be shortened, and the output classifiers require less storage space. The potential for information loss is dimensionality reduction's biggest disadvantage. When done incorrectly, dimensionality reduction might eliminate important data instead of only irrelevant data. For various purposes, data scientists use a variety of dimensionality reduction techniques, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), TeSNE, and Exponential Discriminant Analysis (EDA). In our work we use subspace projection exponential Discriminant Analysis technique (EDA) proposed by abdlmalik et al. in[64]. In terms of dimensionality reduction, this new method outperformed earlier ones The algorithm forExponential Discriminant Analysis (EDA).

EDA is a technique used in pattern recognition and classification tasks. It's goal to get over the issue of small sample sizes without removing the discriminant data from the LDA null space,and to solve a large-scale eigenproblem .we use the EDA (Exponential Discriminant Analysis) method for dimensionality reduction and classification of these characteristic vectors.To extract discriminant information contained in the null space of Sw, the eigenvector matrix of Sw is replaced by exp(wi) and the eigenvector of Sb by exp(bi). EDA leads to the projection matrix that comprises the leading eigenvectors of Eq III.3[64].

$$\text{Sw}=\sum_{i=1}^{M}\sum_{j=1}^{ni}(W_{ij}-m_i)(W_{ij}-m_i)^T \quad \textbf{eq III.1}$$

$$Sb = \sum_{i=1}^{M} n_i\,(m_i\text{-m})(m_i\text{-}m)^T \quad \textbf{eq III.2}$$

Where: Wij is the jth of the samples in the class,

$\bar{mi}$ is the average of the samples in class i,

$\bar{m}$ is the mean of all samples,

ni is the number of samples in the class i.[65]

$$\left(exp((Sw)^{-1})exp(Sb)\right) \quad \textbf{eq III.3}$$

In the Linear Discriminant Analysis (LDA), the class label of each sample must be known. The definition for Sw et Sb which directly exploit the weak side-information. More precisely, the image pairs of the same class are directly used to compute the within-class scatter matrix and the image pairs of different classes are used to calculate between-class scatter matrix. Let (Eq III.4 as a set of same class image and Eq III.5 as a set of defferent class image) :

$$S_{class} = \{(x_i, x_j): l(x_i) = l(x_j)\} \quad \textbf{eq III.4}$$

$$D_{class} = \{(x_a, x_b): l(x_a) = l(x_b)\} \quad \textbf{eq III.5}$$

III.4.3 Matching

To compare between two images pair, we used the reduced features projected through the EDA space which are concatenated to form one feature vector. Then, we applied cosine similarity[66]for each pair test of the two images, so a match score is done. Cosine similarity between two vectors **A** and **B** is defined in Eq III.6

$$\textbf{similarity} = \cos(\theta) = \frac{A\cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} AiBi}{\sqrt{\sum_{i=1}^{n} Ai^2}\sqrt{\sum_{i=1}^{n} Bi^2}} \quad \textbf{Eq III.6}$$

by merging the reduced features projected through the EDA space, we formed a unified feature vector. Utilizing cosine similarity, as defined in Equation previous , we calculated the match score for each test image pair, enabling us to assess their similarity effectively.

III.5 Experiments and results

III.5.1 Experiments on TaiwanData set

In Table III.1, we present the results of our experiments on the TaiwanData dataset. The following table includes various methods such as darknet53, densenet201, resnet50, and efficientnetb0 demonstrate distinct performance scores across the thresholds.Combinations of models, including darknet53+efficientnetb0, exhibit consistent high performance. However, the last row, representing the efficientnetb0+darknet53+resnet50+densenet201 combination, shows varying scores across different thresholds, indicating some fluctuations in its performance. Overall, this table provides valuable insights into the performance of different models and their combinations on the TaiwanData dataset, aiding in model selection and understanding their efficacy.

Table III.1: results of our experiments on TaiwanData dataset.

method / **N-LDA**	**100**	**200**	**300**	**400**	**500**	**600**	**700**	**800**	**900**
Darknet53	93.78	**93.98**	93.98	93.98	93.98	93.98	93.98	93.98	93.68
Densenet201	**95.79**	95.79	95.79	95.79	95.79	95.79	95.79	95.79	95.79
Resnet50	95.09	95.09	95.19	**95.29**	95.29	95.09	95.09	95.09	95.09
Efficientnetb0	95.89	**96.09**	95.89	95.89	95.89	95.89	95.89	95.89	95.89
Darknet53+Densenet201	95.89	**95.89**	95.89	95.89	95.79	95.89	95.89	95.89	95.89
Darknet53+Resnet50	96.39	96.19	**96.39**	96.19	96.29	96.19	96.19	96.19	96.19
Darknet53+Efficientnetb0	97.79	97.89	97.99	98.19	98.09	98.19	98.19	98.19	**98.29**
Densenet201+ Resnet50	96.29	96.79	96.49	96.59	**96.79**	96.79	96.69	96.79	96.79
Densenet201+Efficientnetb0	**97.59**	97.49	97.49	97.39	97.39	97.39	97.39	97.39	97.39
Resnet50+ Efficientnetb0	97.89	**97.99**	97.99	97.99	98.09	98.09	97.89	97.89	97.89
Darknet53+Densenet201+ Resnet50	96.89	97.19	97.09	97.19	97.19	97.19	**97.29**	97.19	97.19
Darknet53+Densenet201+ Efficientnetb0	**97.89**	97.89	97.89	97.79	97.89	97.79	97.79	97.89	97.89
Efficientnetb0+Densenet201 + Resnet50	97.99	98.09	98.09	98.09	**98.29**	98.29	98.29	98.29	98.29
Efficientnetb0+Darknet53+ Resnet50	97.99	**98.29**	98.29	98.29	98.92	98.29	98.19	98.19	98.19
Efficientnetb0+Darknet53+ Resnet50+ Densenet201	62.22	61.92	62.02	61.62	62.12	61.92	62.12	62.62	**63.22**

III.5.2 Experiments on PlantVillage Data set

In Table III.2, we present the results of our experiments on the PlantVillage dataset. The table includes various methods such as darknet53, densenet201, resnet50, and efficientnetb0 demonstrate distinct performance scores across the thresholds. Combinations of models, including darknet53+efficientnetb0, exhibit consistent high performance. However, the last row, representing the efficientnetb0+darknet53+resnet50+densenet201 combination, shows varying scores across different thresholds, indicating some fluctuations in its performance. Overall, this table provides valuable insights into the performance of different models and their combinations on the PlantVillage dataset, aiding in model selection and understanding their efficacy.

Table III.2: results of our experiments on PlantVillage dataset.

Method / **N-LDA**	**100**	**200**	**300**	**400**	**500**	**600**	**700**	**800**	**900**
Darknet53	95.63	95.69	95.66	95.69	95.69	**95.83**	95.77	95.69	95.74
Densenet201	97.13	97.22	97.22	97.22	97.24	**97.27**	97.27	97.27	97.24
Resnet50	96.19	**96.33**	96.27	96.30	96.19	96.24	96.19	96.24	96.22
Efficientnetb0	95.69	95.69	**95.80**	95.80	95.74	95.74	95.77	95.77	95.74
Darknet53+Densenet201	97.00	97.05	97.05	97.05	**97.05**	97.05	96.99	96.99	96.99
Darknet53+Resnet50	97.19	97.16	97.22	97.24	97.27	97.24	97.24	97.27	**97.30**
Darknet53+Efficientnetb0	97.30	97.44	97.47	97.49	97.44	97.44	97.41	97.44	**97.49**
Densenet201+ Resnet50	97.22	97.41	97.30	97.30	97.36	97.33	97.36	97.36	**97.52**
Densenet201+Efficientnetb0	97.44	97.58	97.49	97.41	97.52	97.52	97.49	97.52	**97.66**
Resnet50+ Efficientnetb0	97.27	97.36	97.30	**97.38**	97.38	97.36	97.22	97.24	97.27
Darknet53+Densenet201+ Resnet50	97.63	97.69	97.66	97.66	97.66	97.66	97.66	97.66	**97.77**
Darknet53+Densenet201+ Efficientnetb0	98.02	97.97	97.94	97.94	97.94	97.94	97.17	97.17	**98.08**
Efficientnetb0+Ensenet201+ Resnet50	97.69	97.69	97.72	97.72	97.74	97.72	97.69	97.69	**97.77**
Efficientnetb0+Darknet53+ Resnet50	**98.02**	97.97	97.97	97.99	97.94	97.94	97.91	97.91	97.97
Efficientnetb0+Darknet53+ Resnet50+ Densenet201	97.81	**97.91**	97.91	97.91	97.91	97.91	97.91	97.91	97.88

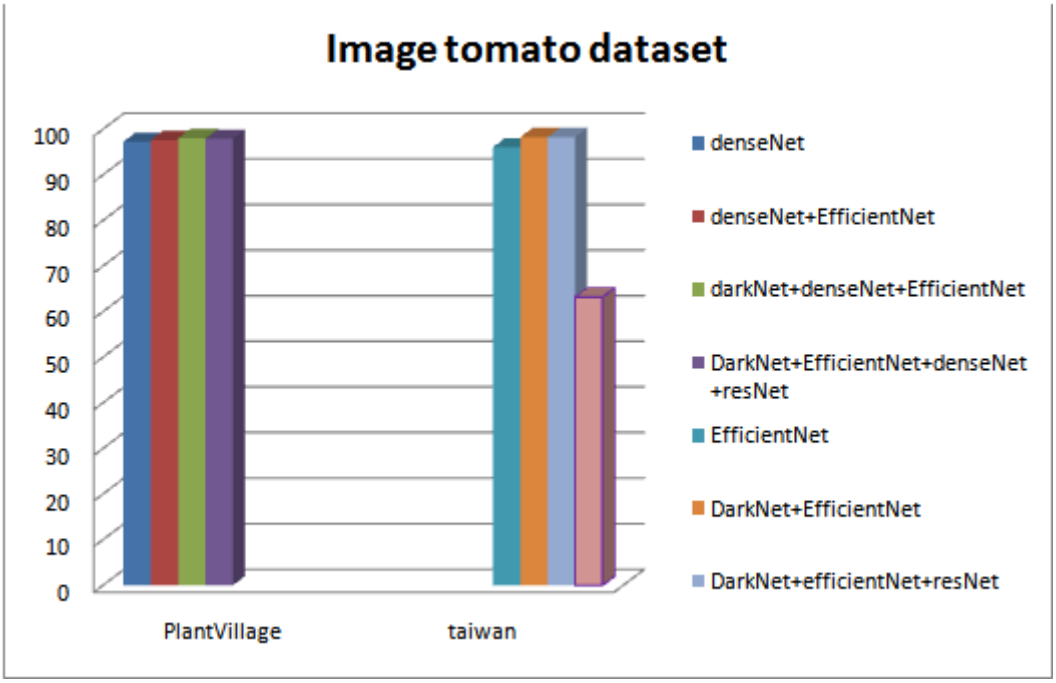


Fig III.2:bar curve of experiments on PlantVillage and taiwan dataset.

III.5 Discussion

The experiments that we conducted using the proposed approach feature extraction representations from plant images using four types of features based on CNN (Darknet53, Densenet20, ResNet-50, and EfficientNet-b0) on two datasets (**Taiwan** and PlantVillage **Dataset**) These features captured important visual patterns and characteristics related to plant diseases. By comparing the performance of the four CNN models on the two datasets, we gained insights into their strengths and weaknesses, We conclude the following:

- **The powerful of deep features**

when it comes to tomato leaf disease analysis, harnessing the power of deep features through deep learning models allows for more accurate and comprehensive understanding and diagnosis of diseases affecting tomato plants. The deep features capture crucial information from images, enabling effective disease identification, classification, and subsequent decision-making in agriculture and plant pathology**.**

- **The benefit of the concatenation of deep features**

By combining deep features from multiple CNN models, such as the concatenation of Darknet53 with Densenet201 or ResNet-50, improved classification performance was achieved. The fusion of diverse deep features enhanced the overall representation capability, leading to more accurate and robust plant disease detection.

- **The powerful of EDA technique in our system**

the powerful use of EDA techniques in our system offers benefits such as improved data understanding, data quality assessment, feature selection and engineering, anomaly detection, insights for model selection and tuning, and effective visual communication. By leveraging these advantages, we can develop a robust and reliable system that effectively utilizes the available data and delivers accurate results and valuable insights.

- **Effect of N_LDA number**

The variation of the N_LDA parameter within the range of 100 to 900 had a significant impact on the classification performance. As the value of N_LDA increased, the accuracy of plant disease classification generally improved. However, it is important to note that beyond a certain point, further increases in N_LDA did not yield significant improvements in performance, suggesting the presence of a saturation point.

III.5 Comparison of the state of the art

The table presents a comparison of the accuracy results from different experiments conducted in different years: Based on the information in the table, the proposed model in 2023 achieved an accuracy of 98.08% for Plant Village, while the model used in Taiwan achieved an accuracy of 98.29% while in 2020, it achieved an accuracy of 98.29%. CNN has an accuracy of 91.20%, and in 2021 the merger of DenseNet and C-GAN results in an accuracy of 97.11% in Plantvillage. The algorithm used in Taiwan, ResNet50, achieved an accuracy of 85.8%. In 2022, the Wave-like Automatic Encoder (WAE) achieved an accuracy of 98.1% in Plantvillage, while Densenet201 in Taiwan achieved an accuracy of 61.35%.

It should be noted that our proposed model is superior to other experiments and achieves a higher accuracy rate.

Tab III.3: Comparison of the proposed model accuracy with other models.

years	Algorithm	Plantvillage(%)	Algorithm	Taiwan(%)
2020	CNN network[67]	**91.20%**	-	-
2021	DenseNet,C-GAN[67]	**97.11%**	ResNet50[68]	**85.8%**
2022	Wavelet-likeAuto-Encoder(WAE)[69]	**98.1%**	Densenet201[70]	**61.35 %**
Ours 2023	Darknet53+Densenet201+ Efficientnetb0	**98.08%**	Efficientnetb0+Densenet201+ Resnet50	**98.29%**

III.6 Conclusion

In this chapter, we have presented an effective method for the detection and classification of plant diseases. We have outlined the structure that represents this method, which includes various stages such as feature extraction, dimensional reduction using EDA technology, training, testing, and matching. Furthermore, we have evaluated the accuracy results of four popular models, namely Darknet, EfficientNet, ResNet, and DenseNet, on two different datasets: PlantVillage and Taiwan dataset.

General conclusion

plant disease detection and classification using leaf image based on deep learning is a field developed to advance agriculture and enhance food security. The aim is to create efficient processes that make use of deep learning algorithms to enable early and accurate detection of plant diseases, by leveraging models like Darknet53, Densenet201, ResNet-50, and EfficientNet-b0, along with techniques like subspace projection and dimensionality reduction using EDA, the system achieved robustness and improved performance. The experimental results presented in Chapter III demonstrated the effectiveness of the system, with evaluation metrics indicating high accuracy and precision. The availability of comprehensive datasets and thorough training processes contributed to reliable and accurate results. The research contributes to the field of plant pathology and agriculture, offering insights into the potential of deep learning for disease detection and highlighting areas for future exploration. Overall, this dissertation's findings have implications for plant disease management, agricultural practices, and food security. By improving early detection and classification of plant diseases, the proposed system can help minimize crop losses and enhance agricultural productivity. Further research can focus on addressing challenges related to dataset diversity and real-world generalization to further enhance the system's capabilities.

The perspectives of this work revolve around two main points:

- Expansion to Other Crop Diseases: Our thesis focuses on tomato leaves, but expanding the smart system is a potential area to include diseases in other crops. By adapting the current framework and training it in data sets for different crops, a wider impact and practical application can be provided by creating a more diverse and comprehensive system for disease detection.

- Development of a Mobile Application: the development of a mobile application for disease detection and diagnosis will enable farmers, agricultural professionals, to easily capture leaf images and receive instant disease identification and recommendations. The application can leverage the trained model and integrate with a user-friendly interface, providing a convenient tool for on-the-spot disease diagnosis, monitoring, and timely treatment suggestions.

The proposed system showed promising results in accurately identifying and classifying different diseases, offering a more efficient and accurate approach compared to traditional methods

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