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PFA Report

Synthesis Project

Title

Intelligent Agricultural Monitoring System

realised by :

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Presented on 17/05/2024 to the jury :

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Résumé

La convergence de l'IoT et de l'IA révolutionne l'agriculture. Notre Système de Surveillance Agricole Intelligent s'attaque à la détection précoce des anomalies chez les oliviers en utilisant des algorithmes avancés de vision par ordinateur. En intégrant les bibliothèques PyTorch et OpenCV avec le modèle YOLOv8, nous permettons l'identification en temps réel des maladies, des ravageurs et des carences nutritionnelles. Ce système offre aux cultivateurs d'oliviers un outil proactif pour optimiser la santé et le rendement des cultures dans des conditions environnementales diverses.

Mots clés : IoT, IA, agriculture, détection d'anomalies, vision par ordinateur, PyTorch, OpenCV, YOLOv8.

Abstract

Agriculture is being revolutionized by IoT and AI convergence. Our Intelligent Agricultural Monitoring System uses cutting-edge computer vision techniques to address early anomaly identification in olive plants. The YOLOv8 model is integrated with the PyTorch and OpenCV libraries to allow real-time identification of pests, illnesses, and nutrient deficits. With the help of this system, olive producers can maximize crop health and productivity under a variety of environmental circumstances in a proactive manner.

Key words : IoT, AI, agriculture, anomaly detection, computer vision, PyTorch, OpenCV, YOLOv8

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Dedication

The most significant individuals in my life, who have helped me along the way at every turn, are the ones I would like to dedicate this report to. First and foremost, to my cherished father, who instilled in me the importance of diligence, tenacity, and commitment. May God's heaven provide him eternal serenity.

Secondly, to my mom, who has always been my pillar of support and inspiration. I appreciate your unwavering belief in me and your encouragement to follow my aspirations. I am appreciative of everything you have done for me.

In addition, I would like to dedicate my report to my friends Wassim, Amine, Roua, and Ines, as well as my family, who have supported me through good times and bad. Walid is my project partner. I appreciate everything you have done to help with this endeavor; your love, encouragement, and support have been priceless.

Thanks

I extend my heartfelt gratitude to my dear friends and my family, whose unwavering support and encouragement propelled me forward during the pursuit of this project. Their belief in my capabilities and constant motivation were invaluable throughout this journey. I also express my deepest appreciation to my partner Yosri, whose dedication and collaboration were instrumental in achieving the remarkable results of this project. Furthermore, I am immensely thankful to our supervisor Mme Emna for their guidance, patience, and unwavering support throughout the realization of our project. Their expertise and mentorship have been indispensable in shaping the success of our endeavor.

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Abbreviations List

AI: Artificial Intelligence

ANN: Artificial Neural Network

CNN: Convolutional Neural Network

CNTK: Microsoft Cognitive Toolkit

DCNN: Deep Convolutional Neural Network

DFL: Dynamic Focus Loss

DSI: Display Serial Interface

FAIR: Facebook's AI Research

FOV: Field Of View

GNN: Graph Neural Network

GPIOS: General Purpose Input /Output

GPU: Graphic Processor Unit

HD: High Definition

HDMI: High-Definition Multimedia Interface

IoT: Internet of Things

ILSVRC: ImageNet Large Scale Visual Recognition Challenge

IRTF: Infrared Spectroscopy with Fourier Transform

IOU: Intersection Over Union

K: Potassium

LCD: Liquid Crystal Display

mAp: Average precision mean

ML: Machine Learning

MSE: Mean Squared Error

N: Nitrogen

NLP: Natural Language Processing

OpenCV: Open Source Computer Vision Library

OS: Operating System

P: Phosphorus

PC: Personal Computer

RAM: Random Access Memory

ReLU: Rectified Linear Unit

ResNet: Residual Network

RNN: Recurrent Neural Network

SoC: System on Chip

SVM: Support Vector Machine

TPU: Tensor Processing Unit

USB: Universal Serial Bus

UVC: USB Video Class

VGG: Visual Geometry Group

YOLO: You Only Look Once

GENERAL INTRODUCTION

The ability of robots to carry out tasks requiring cognitive capacities akin to those of humans has altered the way we tackle difficult tasks thanks to artificial intelligence (AI). In this study, we use the YOLO v8 model for image identification and classification in order to apply artificial intelligence to the detection of anomalies in olive leaves. In order to discover and categorize anomalies in olive leaves, the project places a strong emphasis on the integration of artificial intelligence technologies, notably in object identification and picture classification. This application of AI not only increases the precision and effectiveness of anomaly detection, but also shows how AI has the ability to revolutionize agricultural quality assurance and monitoring. With the use of cutting-edge AI models, we hope to enhance anomaly detection, facilitate improved agricultural management, and guarantee healthier olive production.

Chapter 1: Context of the project

1. Introduction

This chapter provides a thorough analysis of Tunisia's agricultural economy, with a special emphasis on the olive business. After applying our research on existence, we will perform a thorough analysis of its current status, and in the end, we will provide our model as a strong answer to the problems facing the industry.

2. General context of Tunisia’s Olive industry

2.1 Olive production

The olive industry in Tunisia has seen substantial change in this year. Twenty percent of the world's olive groves are found in Tunisia, which also produces the most olives, with six percent of the global total. The olive tree is highly valued on a social, cultural, and economic level. Covering thousands of hectares, olive groves are a vital source of income for many rural communities. Tunisian agricultural culture is firmly anchored in the practice of olive surveillance. It is predicated on inherited knowledge that entails careful monitoring of fruit maturation, meteorological patterns, and other environmental elements. Ensuring a high-quality crop and preserving Tunisian olive oil's reputation in both domestic and international markets depend heavily on this monitoring. Farmers support the integrity and sustainability of Tunisia's olive oil business by maintaining these principles.

2.1 Statistics

Tunisia has seen a steady increase in olive production during the last two decades. The introduction of newer, more productive olive types, improvements in cultivation techniques, and the growing demand for olives and olive oil are some of the reasons for this growth. We can represent the statistics of olive production in Figure 1

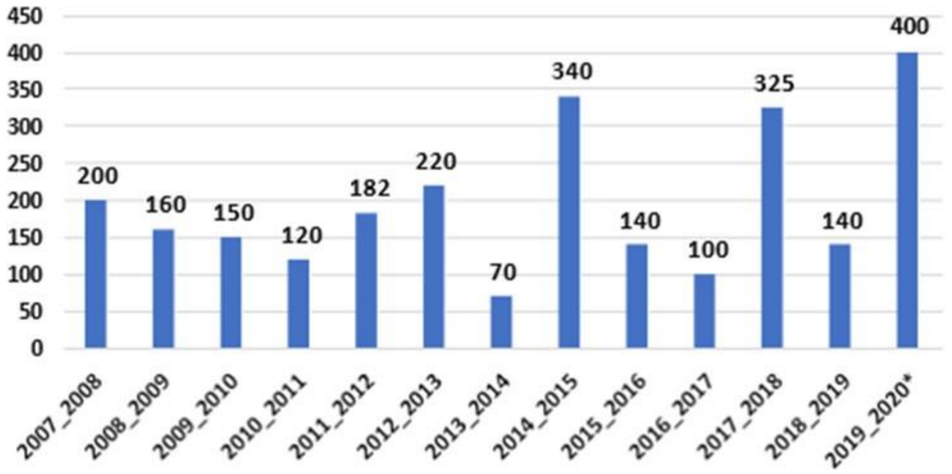

Figure 1: Evolution of national olive oil production (in 1000 tons) [1]

The figure shows the Tunisia's overall increasing trend in olive production during the time under study. There have, nevertheless, been variations from year to year. From 2007 to 2011, production decreased gradually, reaching 120,000 tons in that year. After that, it increased from 2011 to 2013 before recording a drop in production to 70.000 tons in 2014. It also have reached the highest peak in 2020 with 400.000 tons of production.

3. Study of existance

3.1 Olive tree treatment for monitoring

3.1.1 Classical methods

a) Insecticide and fungicide spraying

The application of chemical agents intended to prevent and minimize the effects of fungal diseases and insect pests on olive trees is known as insecticide and fungicide spraying (Figure

2). Usually, sprayers specialized tools that evenly apply chemicals to the foliage, branches, and trunk of tree which are used in conjunction with this procedure. Although these chemicals are useful in controlling pests and diseases, there is growing awareness of the possible negative effects that their indiscriminate use may have on the environment and human health. As a result, a research is being done on more sustainable and alternative approaches to managing pests and diseases in olive farming.

Figure 2: Insecticide and fungicide spraying [2]

b) Regular pruning of trees

Pruning olive trees on a regular basis entails removing some branches, shoots, and foliage to preserve the tree's productivity, health, and form. This procedure aids in the removal of unhealthy or dead wood, enhances airflow and solar penetration within the canopy, and encourages the development of the new growth. By focusing the tree's energy on fruit-bearing branches and reducing extra vegetative growth, pruning also promotes fruit output, as shown in Figure 3.

Figure 3: Regular pruning of trees [3]

c) Soil amendment with natural or chemical fertilizers

The process of adding nutrients to the soil to increase its fertility and supply necessary elements for olive tree growth and development is known as soil amendment (Figure 4). This can be accomplished using chemical fertilizers that provide particular quantities of potassium (K), phosphorus (P), nitrogen (N), and other micronutrients, or with natural fertilizers like compost, manure, or organic waste. By boosting nutrient cycling, microbial activity, and soil structure, natural fertilizers support soil health and sustainability. Fertilizer rates must be applied carefully and monitored to avoid nutrient imbalances, reduce environmental effect, and promote healthy tree growth and fruit output.

Figure 4: Soil amendment [4]

3.1.2 Modern methods

Modern methods of monitoring olive trees and detecting anomalies on olives greatly benefit from technological advances, particularly with the emergence of computer vision.

The health of olive trees can be monitored more quickly, accurately, and non-invasively with current technologies than with classical methods, which can be time-consuming and prone to human error.

There are some modern methods utilized for modelling such as:

a) Use of drones

Using computer vision software and high-resolution cameras, drones are used in this way to monitor olive groves (Figure 5). At precise altitudes, the drones fly over the fields to take close-up pictures of the olive trees and their fruits. The computer vision software examines the high-resolution images produced by the cameras to look for anomalies, such as symptoms of pests, plant diseases, water stress, or other problems related to the health of the crop. This technique has the benefit of quickly and effectively covering huge amounts of land, enabling growers to identify possible issues early and implement the necessary remedial measures.

Figure 5: Drone equipped for monitoring olive trees [5]

b) Use of IoT sensors

This method relies on installing IoT (Internet of Things) sensors in olive orchards to monitor various environmental and agronomic parameters in real-time (Figure 6). These sensors are strategically positioned throughout the orchard to measure variables such as soil moisture, ambient temperature, light intensity, soil electrical conductivity, and other relevant parameters. The data collected by these sensors is transmitted to a central platform wirelessly, where it is analysed using advanced algorithms. This analysis helps to detect trends, patterns, and potential anomalies, providing growers with valuable insights into the health status of their olive trees and the actions to take to optimize yield and quality.

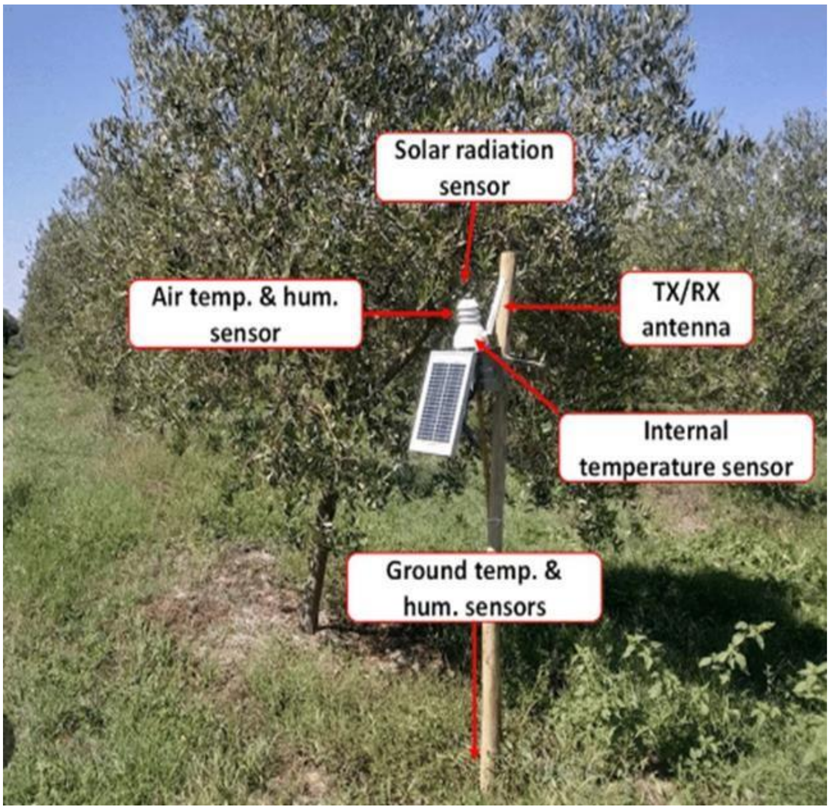

Figure 6: Sensors' integration in olive trees [6]

3.2 Previous work of the subject

In the area of precision agriculture for olive growing, notable instances include:

3.2.1 OliveScan

OliveScan remote sensing and monitoring solution is especially designed especially for olive groves. It offers producers high-resolution photos of their olive trees by utilizing drones in the air and satellite imagery. With the use of these photos, farmers can keep an eye on the condition of their trees, spot possible illnesses early on, and evaluate the viability and prospective production of their crops. Olive growers may run their groves more profitably and efficiently by using OliveScan to help them make educated decisions. This solution is shown in Figure 7

Figure 7: OliveScan [7]

3.2.2 GreenCode.Ai

GreenCode.Ai (Figure 8) is committed to creating innovative technology solutions for the agricultural industry, with an emphasis on crop monitoring, which includes olive trees. They provide a broad range of tools, including sophisticated data analytics software, sensor-based monitoring systems, and remote sensing platforms, as part of their package of services and solutions. By giving farmers access to real-time crop analytics, these solutions are intended to empower farmers and help them successfully optimize their operations and maximize yields.

Figure 8: GreenCode.Ai icon [8]

3.2.3 Vinsight

Vinsight (Figure 9) is specialized in developing agricultural monitoring systems with artificial intelligence that are specifically designed for olive groves, orchards, and vineyards. Their creative technology analyzes sensor data gathered from the field as well as aerial photos using machine learning algorithms. Vinsight analyzes this data and offers growers tips and actionable insights to improve crop management techniques. Vinsight's cutting edge monitoring technologies assist olive growers in making well-informed decisions that enhance the productivity and health of their olive harvests, whether it be pinpointing stress spots within the grove or streamlining watering schedules.

Figure 9: Vinsight [9]

4. Problem statement

There are various drawbacks to the traditional olive monitoring techniques. First of all, because they are frequently manual and prone to human error, they may take longer to identify problems and produce wrong decisions. Furthermore, these techniques could not be accurate enough to identify irregularities early on, endangering the wellbeing of olive trees and the caliber of the crop. They can also be labor-intensive and demand a large amount of human resources.

While they provide cutting-edge solutions for olive monitoring, currently available services like OliveScan, Vinsight, and GreenCode.Ai also have drawbacks. Even while these services make use of cutting-edge technologies like computer vision and data analytics, they can be expensive to implement and call for sophisticated infrastructure. Additionally, they might not be customized to meet the unique requirements of olive growers, and also the features of the orchard and the surrounding environment can affect how effective they are.

5. Proposed solution

5.1 Our mission

The goal of our suggested model, an Intelligent Olive Monitoring System, is to transform olive farming methods by using real-time monitoring and early anomaly identification in olive groves. Through the promotion of sustainable agricultural techniques, this system seeks to raise olive yield and quality, optimize resource consumption, and improve crop management.
An inventive and customized method for identifying irrigualtions in olives is provided by our own intelligent agricultural monitoring service which provides a promising alternative by offering early detection of olive anomalies, rapid response, and autonomous decision-making. Our technology has the ability to identify three different kinds of olive anomalies in real time using computer vision and artificial intelligence. Additionally, the system is capable of independently deciding which detections to make and initiating preventive measures, which improve the olive tree health, increases the productivity in a cost-effective manner and ensures the health and quality of crops.

5.2 Operating principle

The operating principle of the intelligent olive monitoring system can be divided into 5 phases: anomaly detection, data analysis, anomaly identification, treatment recommendation and medication distribution.
First, the service uses cameras with high quality to keep an eye on olive groves all the time. These cameras are intended to identify early indicators of irregularities, like color shifts, questionable areas, or deformed leaves. An artificial intelligence system receives the photos taken by the cameras and uses them to examine the visual traits of olive leaves. Then, using a reference database that includes details on prevalent olive leaf diseases, this method compare

these properties. Data analysis enables the technology to precisely detect irregularities in the olive leaves. The service use algorithms to decide the proper preventive treatment when the abnormality has been recognized. To correct nutritional deficiencies, this can entail using particular insecticides, modifying irrigation, or adding fertilizers.

Finally, the service accurately applies the prescribed medicaments to the impacted olive groveareas using automated machines.

6. Conclusion

The olive monitoring system, which uses computer vision technology to boost yields, reduce costs, and improve operational efficiency, has the potential to revolutionize olive farming operations. Rapid advancement in this technology is being fueled by increased interest, despite obstacles including crop variances and environmental conditions. In the upcoming chapter we will go deeper into the software algorithms, as well as the overall AI context and detection models that drive these systems.

Chapter 2: General Concepts

1. Introduction

In this chapter, we explore how AI is applied in various domains, from identifying objects in images to classifying and categorizing visual content into predefined classes. We delve into the techniques that facilitate these processes and discuss their practical applications across different industries, demonstrating AI's transformative impact on modern life and business operations.

2. Artificiel Intelligence

Artificial Intelligence encompasses a suite of technologies that empower machines to perceive, understand, act, and learn with levels of intelligence comparable to human capacities. This diverse field includes various branches such as machine learning and natural language processing, each progressing on its unique trajectory. By integrating these technologies with data analytics and automation, businesses can enhance operations and achieve strategic objectives. This might manifest in improved customer service, optimized supply chains, or more efficient data management.

2.1. Narrow AI (also known as "Weak" AI)

Most AI applications that we come across on a regular basis are classified as narrow AI. These systems are made to perform a single task or a group of related tasks with a high level of skills. Applications for weather forecasting, digital assistants, and specific business analytics tools are few examples. These systems have a major impact on economic sectors by improving efficiency and streamlining operations, although having a narrow operating scope. Global industry transformation by narrow AI is continuing to

change how we work and engage with technology on a daily basis.

2.2. General AI (also known as "Strong" AI)

General artificial intelligence, which stands in stark contrast to narrow AI, is a higher level of intelligence that is frequently portrayed in science fiction. It talks about robots with broad cognitive abilities comparable to human intelligence, meaning they can think abstractly, behave strategically, and accomplish a variety of jobs. Even while robots are now quite good at certain jobs, such data analysis and logical processing, the idea of general artificial intelligence is still speculative in its entirety.

2.3. Object detection

The artificial intelligence method of object detection involves locating items in digital photos or movies. Thanks to this technology, machines can now automatically identify and find different items by differentiating them from their surroundings. They are widely used in many useful applications, including controlling traffic systems, improving security systems, and enabling autonomous vehicles to navigate. Systems that need to have a thorough awareness of their environment in order to interact intelligently with it and make decisions based on visual inputs which must be able to recognize things with accuracy. This feature is essential for developing AI applications across multiple industries that are more aware and responsive, as illustrated in Figure 10.

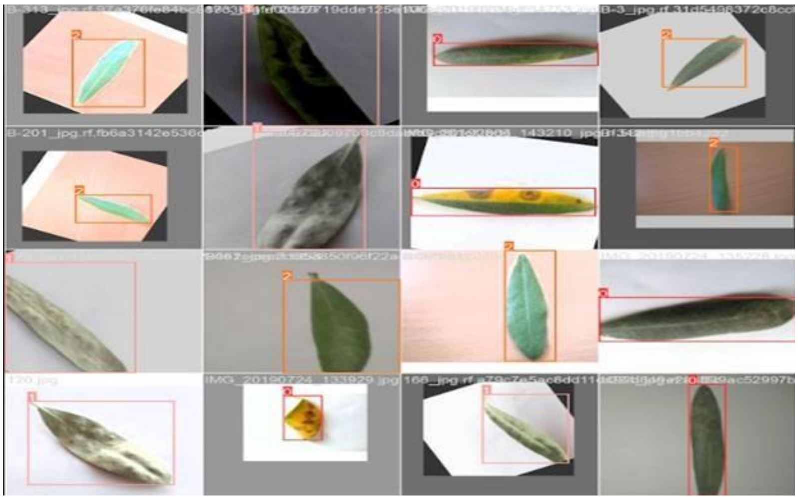

Figure 10 : Object detection

2.4. Image classification

Image classification is a core process in computer vision that involves categorizing images into predefined classes based on their visual content. This process is fundamental in various applications, especially in healthcare, where it supports tasks like disease diagnosis and medical imaging analysis. The classification of images can be broadly categorized into three types:

2.4.1. Binary Classification

Binary classification is the simplest form of image classification where each image is classified into one of two distinct categories. This method is particularly useful for tasks that require a yes/no decision. For example, in medical diagnostics, binary classification can be employed to determine whether an image shows signs of a specific disease or not.

2.4.2. Multi-Class-Classification

Multi-class classification involves assigning an image to one of several categories. This differs from binary classification by allowing more than two possible outcomes. In healthcare, multi-class classification might be used to categorize different types of cells in a sample under a microscope, each type representing a different category.

2.4.3. Multi-Label-Classification

Multi-label classification extends the capabilities of traditional models by allowing a single image to be categorized into two or more classes simultaneously. This approach is suitable for more complex scenarios where an image might exhibit attributes that span multiple categories. For example, a single medical image could show multiple symptoms that need to be identified and classified into various disease categories, as shown in Figure 11.

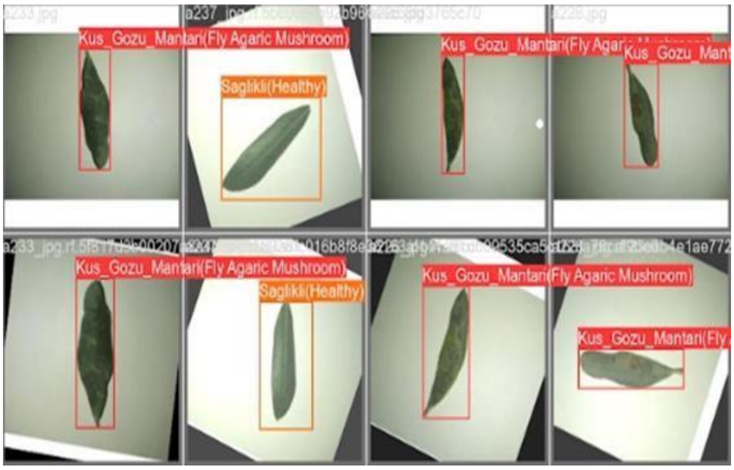

Figure 11 : Image classification

2.5. Techniques of image classification

Image classification is a key technique in computer vision that assigns images to predefined categories or labels using various machine learning and deep learning algorithms. This process is fundamental in numerous applications, including medical diagnosis, object recognition, and more.

2.5.1. Classification with Classical Methods of Machine Learning

Classical machine learning methods use statistical approaches to categorize images:

Naive Bayes: This algorithm applies Bayes' theorem with the assumption that all features are independent. It is effective for large datasets and is used in text categorization, spam filtering, sentiment analysis, and medical diagnosis.

Regression Trees: Used primarily for regression problems, these trees predict continuous values by making binary decisions that split the data into progressively smaller subsets until reaching predictions.

SVM (Support Vector Machines): SVMs are utilized for classification, regression, and outlier detection. They work by finding a hyperplane that maximizes the margin between two data classes, creating an optimal separation with the greatest distance to the nearest points of any class.

2.5.2. Classification Using Deep Learning Network

Deep learning offers advanced methods for image classification with improved accuracy and speed:

DC-N (Deep Convolutional Neural Networks): These networks have transformed image classification with their ability to learn hierarchical feature representations. The convolutional layers extract complex patterns and features from images, which are essential for tasks like object detection and segmentation.

VGG (Visual Geometry Group Network): Known for its depth, the VGG architecture uses multiple convolutional layers to achieve high accuracy in image recognition tasks by progressively extracting and refining features from the input data.

ResNet (Residual Network): This architecture introduced a novel approach of using skip connections to allow signals to bypass layers, enhancing gradient flow and enabling the training of very deep networks without performance degradation.

These classifications and methods demonstrate the breadth of machine learning's application in image analysis, each contributing uniquely to advancements in technology and industry practices.

2.6. Application

Image classification extends its utility beyond the typical sectors, finding its role in more specialized applications

2.6.1. Traffic and Transportation System

In the realm of traffic management, image classification is used to monitor and control traffic flow, detect congestion, and improve overall road safety. This technology is capable of analysing video feeds to detect anomalies in traffic patterns, which can be crucial for timely interventions to prevent congestion and accidents classification program.

2.6.2. Security Enhancements

Face recognition technologies are widely adopted in security systems for identity verification, enhancing the safety of public spaces and secure facilities. By identifying individuals accurately and swiftly, this technology helps in mitigating potential security threats and ensuring the integrity of restricted areas.

2.6.3. Pharmaceutical Quality Control

In the pharmaceutical industry, image classification is vital for ensuring the safety and efficacy of drug distribution. This technology is primarily used in quality control processes during the production of pills and capsules. It helps identify and verify any physical irregularities in size, shape, and color, ensuring that only products meeting high-quality standards are distributed to consumers. This rigorous inspection helps maintain the integrity and correctness of medications, significantly enhancing patient safety and compliance with healthcare regulations.

3. Foundational Principles of Artificial Neural Networks

Artificial Neural Networks (ANNs) represent a branch of artificial intelligence designed to replicate the architectural and functional aspects of neural networks observed in human brains. Composed of interconnected elements known as artificial neurons, ANNs process information through these units. Each artificial neuron gathers inputs from multiple other neurons and generates an output. This output is then transmitted to subsequent neurons or to the ANN's final output layer, ultimately yielding the intended outcome.

3.1. Configuration of Artificial Neural Network

ANNs are organized into layers made up of interconnected nodes that sequentially process information.

There are three types of layers in a Neural Network:

- **The Input Layer:** Receives raw data which is then processed in subsequent layers.
- **The Hidden layers:** Intermediate layers where most data processing occurs, transforming inputs into something the output layer can us which is the output layer is the final layer of an ANN and produces the network's prediction (Figure 12).
- **Output Layer:** The final layer produces the network's output. The output layer transforms the information from the hidden layers into a format that fits the problem's requirements, such as a probability vector in classification tasks, showing the likelihood of the input belonging to a certain class (Figure12).

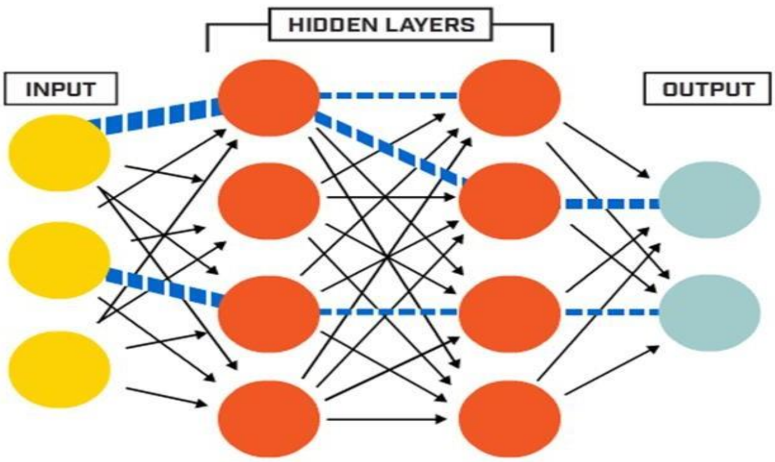

Figure 12: Layers of an Artificial Neural Network [10]

3.2. Perceptron

A key element of neural networks, the perceptron serves as a binary classifier. It produces a single binary output by processing several input signals, and it is the foundation of more intricate neural network structures, as shown in Figure 13.

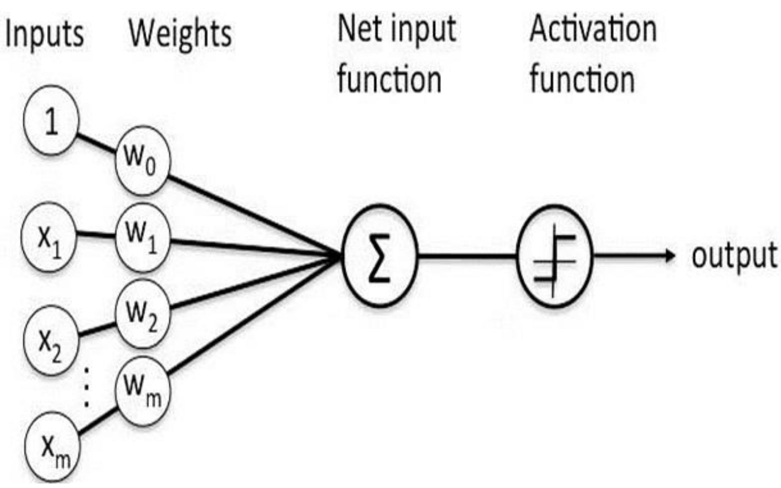

Figure 13: Perceptron [11]

3.3. Activation functions

In artificial neural networks (ANNs), activation functions aid in identifying the output layer, neuronal signal, or neural model output. They give the network non-linear characteristics, which are essential for deciphering intricate data patterns. Important activation mechanisms consist of:

- **Sigmoid Activation function**: Maps inputs to a probability between 0 and 1, useful in binary classification. The issue with the sigmoid activation function is the vanishing gradient problem, which occurs when the function's gradient becomes extremely small for very high or very low input values. This can significantly slow down the learning process, as it affects the update of weights during training, as shown in Figure 14

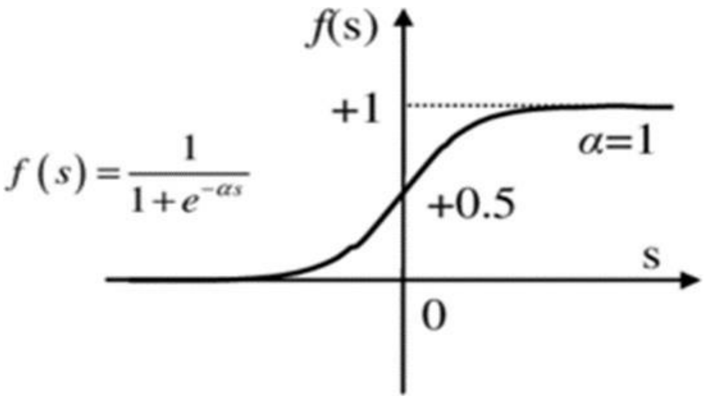

Figure 14: Sigmoid Activation function [12]

- **Tanh Activation Function**: Outputs values between -1 and 1, making it useful when the model needs to normalize the output, as shown in Figure 15.

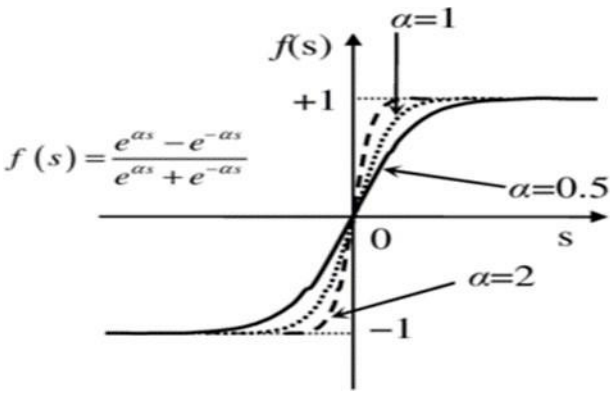

Figure 15: Tanh Activation function [12]

- **ReLU Activation Function**: Helps with faster and effective training by outputting the input directly if positive; otherwise, it will output zero, as illustrated in Figure 16.

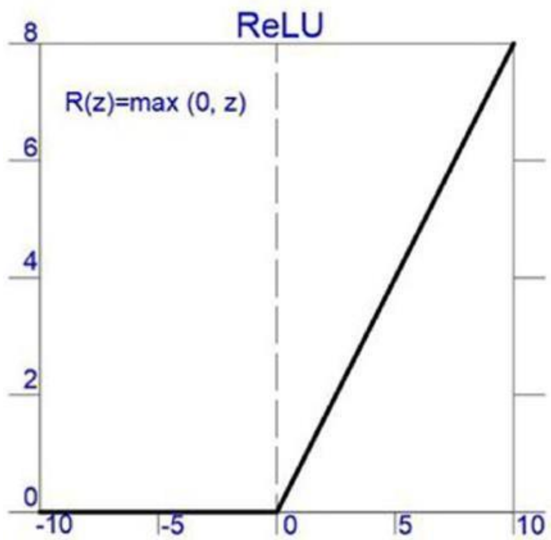

Figure 16: ReLU Activation Function [13]

3.4. Loss Function

Helps with faster and effective training by outputting the input directly if positive; otherwise, it will converge to a zero as an output. A loss function is a mathematical function that measures the difference between predicted and actual values of an output variable.

3.5. Mean Squared Error Function

Mean Squared Error (MSE) is a widely used metric in regression analysis. It calculates the average of the squares of the differences between predicted values and actual observations. The MSE is defined by the equation MSE = Σ(yi − pi)**2 (2)

Where yi represents the observed value at the i_th position, pi is the predicted counterpart for yi and n denotes the total number of observations.

4. Types of Neural Nets Learning

4.1. Supervised Learning

Supervised learning involves training a machine learning algorithm using data that has already been labeled. The primary aim of this approach is to train the algorithm to generate precise predictions or judgements when presented with new, unknown data.

4.2. Unsupervised Learning

Unsupervised learning works with unlabeled data and aims to discover underlying patterns or structures in the data. Unlike supervised learning, where the algorithm learns from predefined inputs and outputs, unsupervised learning does not have this guidance, focusing instead on identifying intrinsic relationships within the data.

5. Different Types of Neural Networks in Deep Learning

5.1. Recurrent Neural Networks RNN

Recurrent Neural Networks (RNNs) are a type of neural networks specifically engineered for handling data sequences by using feedback loops within the network's architecture, as depicted in Figure 17. These networks are particularly effective at managing data that evolves over time, such as audio tracks, video feeds, or speech recordings. What sets RNNs apart is their ability to maintain a memory state that holds past input information. This capability enables the network to generate predictions that consider previous data, thereby recognizing long-term patterns in sequences. In contrast to traditional feedforward networks that treat each input separately without acknowledging order, RNNs excel in tasks where understanding temporal dynamics is crucial. They have found increasing use in fields like natural language processing and anomaly detection, among others.

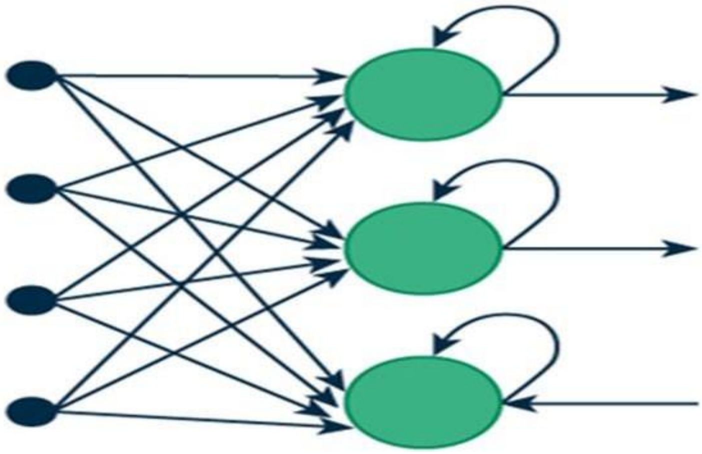

Figure 17: RNN structure [15]

5.2. Graph Neural Networks GNN

Graph Neural Networks (GNNs) have recently seen a surge in popularity, largely due to their capability to handle complex data represented in the form of graphs. Graphs, as depicted in Figure 18, consist of nodes and edges that map out the relationships among various entities. GNNs are explicitly designed to analyze such data structures, which enables them to excel at tasks like node classification, link prediction, and developing recommendation systems. A distinct advantage of GNNs compared to conventional neural networks is their ability to integrate information from the entire network's topology during processing. This integration helps GNNs to more effectively comprehend the interactions among nodes within larger networks, leading to more precise predictions and improved performance across a variety of tasks, as shown in Figure 18.

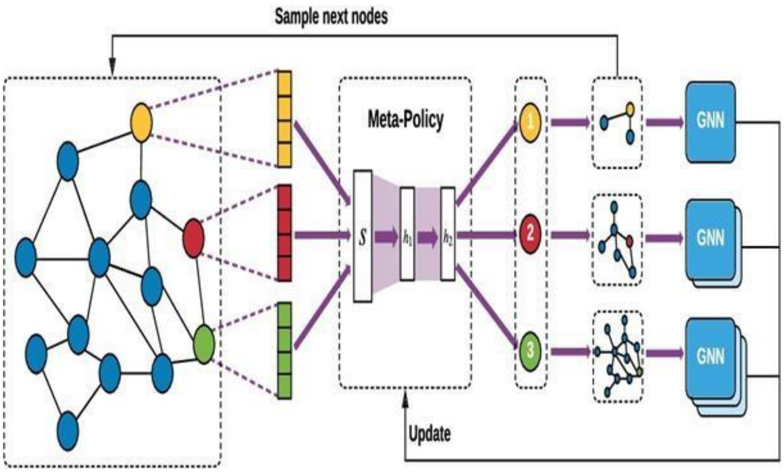

Figure 18 : GNN structure [16]

5.3. Convolutional neural network

A convolutional neural network (CNN), depicted in Figure 19, is a type of deep learning model extensively utilized in computer vision. This advanced model features multiple layers of neurons that connect in a way that allows the network to autonomously detect patterns and characteristics within images. CNNs perform convolutions, which are mathematical operations, across these layers to efficiently categorize and recognize complex visual information. Their high level of accuracy is supported by the capability to learn from extensive datasets and the advancements in computing hardware, such as GPUs and TPUs. These features make CNNs a critical tool in various image analysis applications, including object detection, segmentation, and medical imaging diagnostics.

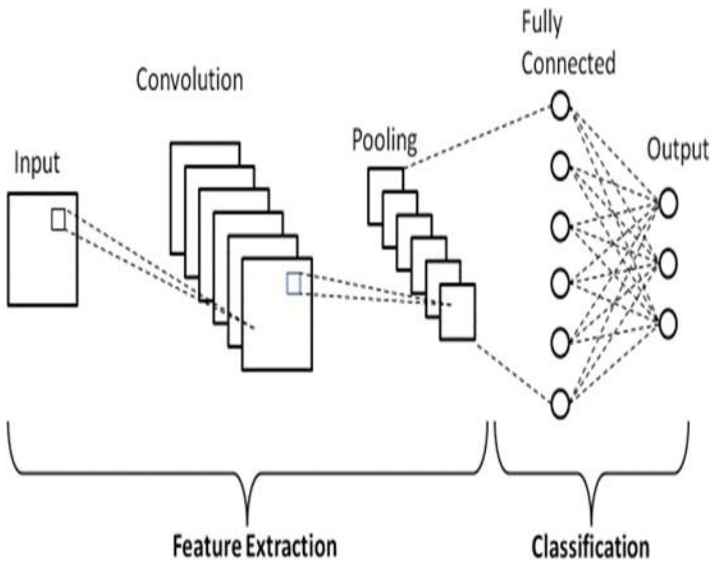

Figure 19 : CNN structure [17]

6. Predefined models

6.1. ResNet

ResNet, short for Residual Network, introduced by Microsoft Research in 2015, revolutionized deep learning by enabling the training of networks with substantially greater depth than was previously possible. Its defining feature is the introduction of "residual blocks" with skip connections that allow inputs to bypass one or more layers. ResNet was designed to solve the vanishing gradient problem by facilitating the flow of the gradient through the network, which makes deep networks easier to optimize and enhances performance significantly. The model's effectiveness was proven when it won the 2015 ImageNet competition with a record-breaking low error rate. ResNet architectures come in various depths, including ResNet-50, ResNet-101, and ResNet-152, making them adaptable to a wide range of applications in computer vision.

6.2. VGGNet

VGGNet, introduced by the Visual Graphics Group at Oxford in 2014, is a deep convolutional neural network known for its simplicity and depth, which features consecutive convolutional layers followed by max-pooling layers, culminating in three fully connected layers. It is widely recognized for its use in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) where it achieved top accuracy with a significantly deeper architecture than previous models.

The VGGNet models, especially VGG16 and VGG19 (indicating the number of layers), are highly regarded for their high performance in extracting features for image recognition tasks. Their uniform architecture facilitates easy scaling and integration into different applications, though it is computationally intensive due to the high number of parameters.

6.3. YOLOv8

6.3.1. Basic Understanding

YOLO (You Only Look Once) is one of the fundamental networks in deep learning that is used to carry out tasks including object detection, picture recognition, and classification. Figure 20 below illustrates a simple YOLO model.

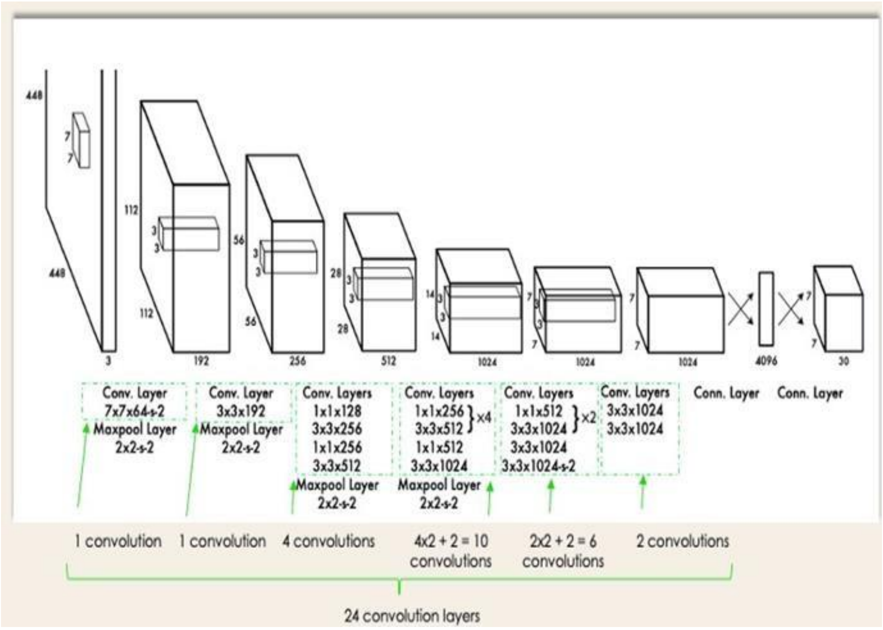

Figure 20: Basic YOLO model [18]

Here's how the architecture functions:

- Before the input image is processed by the convolutional network, it is resized to 448 by 448.
- To produce a cuboidal output, a 3x3 convolution is applied after a 1x1 convolution to lower the number of channels.

- With the exception of the final layer, which employs a linear activation function, the underlying activation function is ReLU.

Some other methods, such dropout and batch normalization, regularize the model and keep it from overfitting, respectively.

6.3.2. YOLO Object Detection

The algorithm operates using the four strategies listed below: Residual blocks, bounding box regression, intersection Over Unions or IOU and Non-Maximum Suppression.

a) Residual blocks

In the first phase, the original image is divided into NxN grid cells of equal shape (the image on the right shows N as 4 in our example). The task assigned to each grid cell is to locate the object it covers, forecast its class, and provide the probability and confidence value for that class, as illustrated in Figure 21.

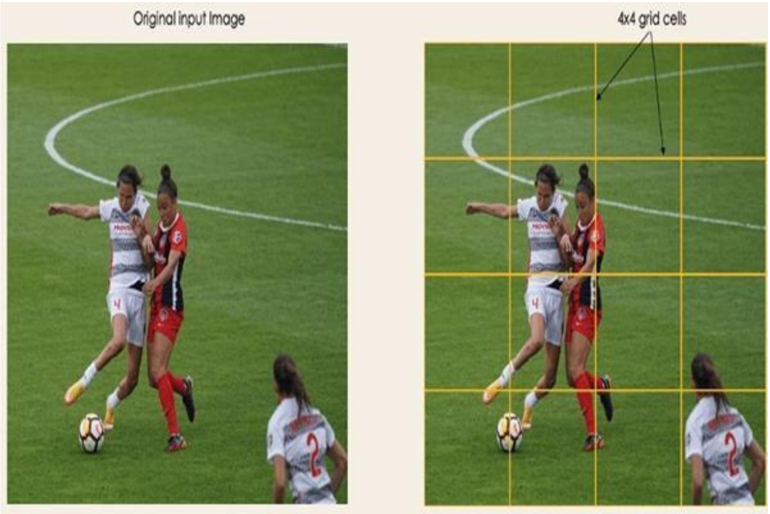

Figure 21 : Basic YOLO model [18]

b) Bounding box regression

Finding the bounding boxes which shown in Figure 22, match the rectangles indicating each object in the image, is the next step. Bounding boxes can be added to an image in an equal number as the number of items it contains.

Y is the final vector representation for each bounding box. YOLO uses a single regression module to determine the properties of these bounding boxes.

Y = [c1, c2, bh, bw, pc, bx, by]. (3)

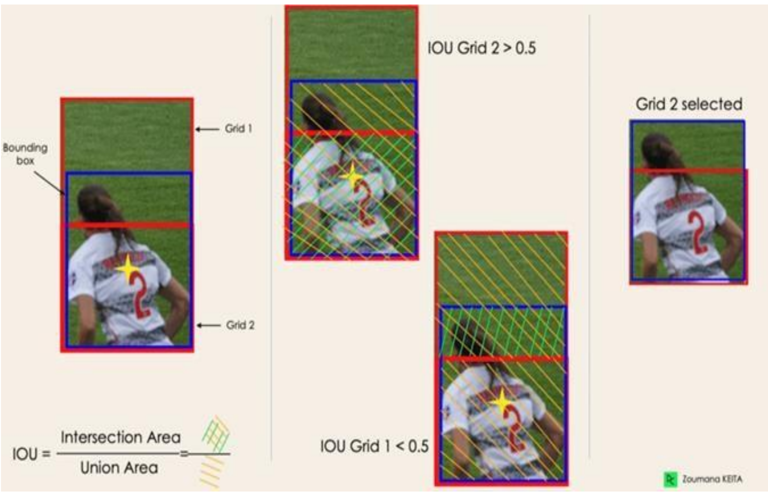

Figure 22: Bounding box regression [18]

This is particularly crucial while the model is being trained:

- Pc represents the probability score of the grid that contains an object. For example, the probability score for each of the red grids will be greater than zero. Since there is a zero (insignificant) probability for each yellow cell, the graphic on the right is a simplified version.
- The bounding box's center's x and y coordinates with respect to the surrounding grid cell are denoted by the variables bx and by.
- The bounding box's height and width in relation to the surrounding grid cell are represented by the values bh and bw.
- The two classes Player and Ball are represented by c1 and c2. As many classes as you use case calls for are possible.

This coordinates are shown in Figure 23.

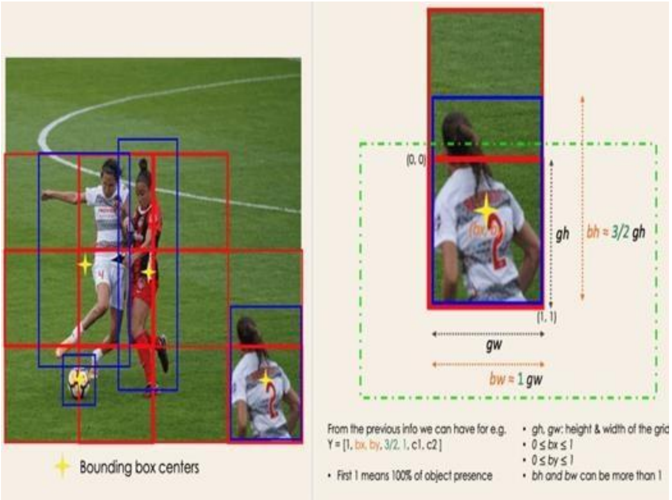

Figure 23: Box coordinates [18]

c) Intersection Over Union or IOU

The majority of the time, even though not all of them are significant, a single object in an image can have several grid box possibilities for prediction. The IOU, which has a value between 0 and 1, aims to eliminate these grid boxes and retain just the ones that are pertinent. This is the reasoning for it:

- The IOU selection threshold is set by the user and can be, for example, 0.5.
- Next, YOLO divides the intersection area by the union area to find each grid cell's IOU.
- Lastly, it takes into account grid cells with an IOU > threshold and disregards the forecast of grid cells with an IOU ≤ threshold.

An example of using the grid selection process on the bottom left object is shown in Figure 24 below. It is evident that only "Grid 2" was ultimately chosen out of the two grid possibilities that the object initially possessed.

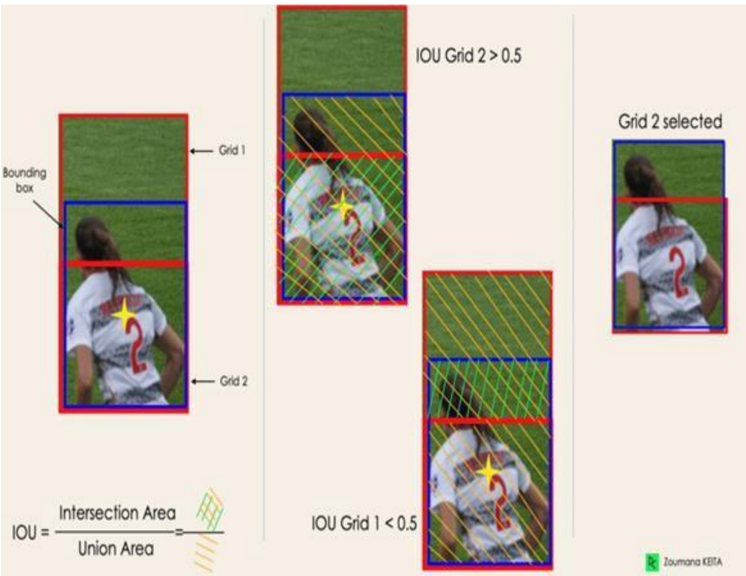

Figure 24: The IOU [18]

d) Non-Maximum Suppresion

An object may have several boxes with IOU beyond the threshold, and leaving all those boxes could include noise, therefore setting a threshold for the IOU is not necessarily sufficient. This is the point where we can apply NMS to retain only the boxes that have the highest detection probability score.

7. Conclusion

As a conclusion, AI's foundational principles and advanced technologies are revolutionizing how industries tackle challenges, proving that this field will continue to redefine our approach to complex problems. In the next chapter, we will talk about the realization of our project including the implementation and results.

Chapter 3: Realisation of the system

1. Introduction

This chapter explores the fundamental elements of our research, explaining the methodical methodology used in dataset creation, the careful choice and setup of hardware and software, and the integration of these efforts into concrete results and their practical implementation.

2. Presentation of the dataset

2.1 The study of the olive leaves anomalies

Three anomalies that we are interested about finding in olive leaves for our project are as follows:

2.1.1 Kus_Gozu_Mantari (Fly Agaric Mushroom)

This abnormality could appear on the olive leaf as a speckled or circular discoloration that resembles the Fly Agaric Mushroom's cap. The distinctive red top of this mushroom has white markings on it.

This anomaly's existence might point to an olive tree fungal infection. Given that the Fly Agaric Mushroom is toxic, its presence on the leaf may indicate that the tree is being attacked by fungus,as illustrated in Figure 25.

Figure 25: Kus_Gozu Mantari [18]

2.1.2. Pas_Akari (Foot Candle)

Pas_Akari, also known as the "foot" of the candle, is the form or arrangement of candle flames at the bottom of the candle. It can also refer to a certain pattern or appearance on the olive leaf. This abnormality may be a sign of stress or injury to the leaves, possibly brought on by changes in temperature, exposure to the sun, or a lack of nutrients. The erratic pattern that resembles candle flames may represent localized stress on the tissue of the leaf, as shown in Figure 26.

Figure 26: Pas_Akari [18]

2.1.3 Saglikli (Healthy)

This indicates that the olive leaf appears to be normal and free of any obvious defects. It would seem to be a typical leaf with no abnormal discolorations or marks.

A "healthy" leaf is not an oddity in the conventional sense, but it provides a standard against which to measure others. It shows the ideal growing environment for the olive tree, which includes enough nutrients, a sufficient supply of water, and defense against pests and illnesses, as illustrated in Figure 27.

Figure 27: Saglikli [18]

2.2 Data preparation

The following procedures have been used to construct our dataset: data collection, data splitting, data labelling , data processing, and data augmentation.

2.2.1 Data collection

Any machine learning research needs data collecting, thus we used Kaggle to find our datasets We have assembled a dataset of high-resolution photos of several abnormalities in olive leaves, on this platform which were obtained via drones and ground-based sensors. Important metadata, including time stamps and geographic positions, is also included in Kaggle datasets [18]. This dataset serves as the basis for further analysis and model building with the goal of precisely identifying and categorizing anomalies in olive leaves, hence supporting sustainable practices in olive production.

2.2.1 Data splitting

A critical phase in machine learning is data splitting, which is necessary to assess model performance and avoid overfitting. Usually, the datasets are separated into testing, validation, and training sets. In our instance, we divided our dataset effectively using the Scikit-Learn module. To ensure a balanced representation of normal and anomalous olive leaf photos in each set, we partitioned the dataset into training and testing subsets using algorithms such as train_ test_ split. A validation set was also produced in order to assess training performance and adjust model hyperparameters. The foundation for precise anomaly identification in olive leaves was established by this methodical splitting technique, which enabled strong model evaluation and generalization.

2.2.2 Data labelling

An important component of supervised learning is data labeling, which is the process of annotating datasets with pertinent labels to make model training easier. Data labeling guarantees that models can correctly identify between several classes or categories within the data in the larger context of machine learning. We labeled our dataset carefully using the CVAT.ai platform [19] by showing the anomaly's presence in each image. In addition to producing the ground truth labels required for model training, this laborious labeling method helped to build a comprehensive dataset for olive leaf anomaly detection. We ensured the integrity and correctness of my dataset by utilizing CVAT.ai's labeling capabilities, which laid a strong foundation for creating efficient anomaly detection models in olive farming.

2.2.3 Data processing

Data processing, which includes operations like normalization, augmentation, and feature extraction, is essential to getting datasets ready for machine learning tasks. Data processing often seeks to convert unprocessed data into a format that may be used for model evaluation and training. We processed our dataset's photos by scaling, normalizing, and enhancing them effectively using the PyTorch framework . A wide range of data processing tools and utilities, such as data loaders and transformations made especially for working with picture data, are offered by this framework. Furthermore, PyTorch's integration with GPU acceleration made it possible to handle big image datasets quickly and in parallel, guaranteeing optimal performance for model training.

3. Hardware and software tools

3.1 Hardware tools

We will supply the hardware tools in this section.

3.1.1 Raspberry pi

A keyboard, mouse, and computer monitor can be readily attached to the little Raspberry Pi single-board computer. It is the perfect tool for anyone interested in learning to program because it supports a wide range of programming languages, including C, C++, Python, and more. The Raspberry Pi has also been utilized in many digital maker projects and offers a variety of input/output capabilities that allow it to communicate with the outside world. We used the Raspberry Pi 4 Model B for our project. This model is the newest in the RaspberryPi 4 series and comes with a potent 64-bit quad-core processor clocked at 1.5GHz, dual-band wireless LAN, faster Ethernet, Bluetooth 5.0, BLE, and support for Power-over-Ethernet, as seen in Figure 28.

Figure 28: Raspberry Pi 4 Model B [20]

These are the standard components of a Raspberry Pi board:

• **SoC**: an integrated circuit comprising a variety of computer components, such as RAM, CPU, and memory RAM which is 4GB.

• **DSI display connector**: this is where an LCD screen is connected.

• **GPIOS**: these are the pins that link electronic equipment. Forty pins make up the Raspberry Pi B.

• **HDMI port**: for connecting a TV or monitor.

• **Ethernet port**: This port connects the device to the rest of the network and is a typical 10/100 Mbit/s Ethernet port.

• **USB ports**: Keyboards and mice and other devices are connected to standard USB 2.0 connectors. There are four USB ports on the Raspberry Pi B+ model.

•**Audio port**: a speaker connection 3.5mm jack.

•**Micro-USB power connector**: it is used to power the Raspberry Pi.

• **USB and Ethernet interface chip**

• **Camera connector**: makes it possible to take pictures and record videos.

The operating system is stored in a micro-SD card slot on the other side of the board. Our demands are best served by the Raspberry Pi, which has 128,000 times more RAM and a clock speed that is 40 times quicker than the Arduino. Compared to the STM32, it is far more powerful and capable of handling several jobs.

Additionally, compared to STM32 and Arduino, the Raspberry Pi offers more connections (HDMI, Ethernet port, USB port, etc.).

3.1.2 Redragon Streaming Webcam HITMAN GW800

In our project, we used the Redragon camera. It has a ton of capabilities that help users record video and take high-quality pictures while live broadcasting. With its Full HD 1080p recording capability and 30 frames per second frame rate, the HITMAN GW800 provides vivid and detailed images for live videos. The webcam's focusing feature guarantees crisp images even when the user is moving, as in Figure 29.

Figure 29: Webcam HITMAN GW800 [21]

Its caracteristics:

- Resolution:1080p
- Pixel size: 3.0 µm * 3.0 µm
- Field of View (FOV): D = 72°
- Automatic control for saturation, contrast, sharpness, white balance, and exposure.
- Supports Win XP (SP2, SP3), VISTA, Win 7, 8, 10, Linux, or OS with UVC driver.

3.2 Software tools

3.1.1. Raspberry pi OS

An operating system based on Linux that was created especially for the Raspberry Pi is called Raspbian or Raspberry Pi OS. It is fully equipped with all the functions and tools needed for regular use. Linux which has a sizable collection of more than 35,000 packages, has been tailored to function flawlessly with the Raspberry Pi, as shown in Figure 30.

Figure 30: Raspberry Pi Os interface [22]

3.1.2. OpenCV (Open Source Computer Vision Library)

It is a free and open-source software library for machine learning and computer vision. It has many features for processing photos and movies, including the ability to detect objects, identify faces, segment images, and extract features. Written in C++, OpenCV may be used with a number of programming languages by using its bindings, such as Python, Java, and MATLAB.

It finds extensive application in domains such as robots, augmented reality, healthcare, and the automobile sector.

3.1.3. PyTorch

Facebook's AI Research lab (FAIR) created the open-source deep learning framework PyTorch. Because it offers a dynamic and adaptable computational graph structure, research and quick prototyping benefit greatly from its use. Compared to static computation networks used by frameworks such as TensorFlow, PyTorch provides dynamic computation graphs, providing greater flexibility in model development and debugging. For applications like computer vision, reinforcement learning, and natural language processing, it also offers a vast ecosystem.

3.1.4. Keras

Python-based Keras is an open-source neural network library. Its user-friendly, modular, and extendable design makes it possible to quickly experiment with deep neural networks. Building and training neural networks is made easier with Keras' high-level API, which hides a lot of the intricate details of lower-level processes. It is compatible with running atop different deep learning frameworks, including Theano, Microsoft Cognitive Toolkit (CNTK), and TensorFlow. For applications including picture categorization, sequence modeling, and generative modeling, Keras is frequently utilized in research as well as in production settings.

4. Results and implementation

4.1 Training

We integrated our YOLOv8 model with our own data games to get precise results that were tailored to our particular needs.

4.1.1. Cellular distribution

The Figure 31 represents the distribution of cells across various sizes within distinct groups. Each dot on the scatter plot represents an individual cell, with its width and height indicated on the horizontal and vertical axes respectively. Groupings are denoted such as

Kus_Gozu_Mantari (Fly Agaric Mushroom) with the red color, Pas Akari (Foot Candle) with the pink color, and Saglikli (Healthy) with the orange color. The intensity of color corresponds to the density of cells at specific sizes within each group; darker shades indicate a higher concentration of cells.

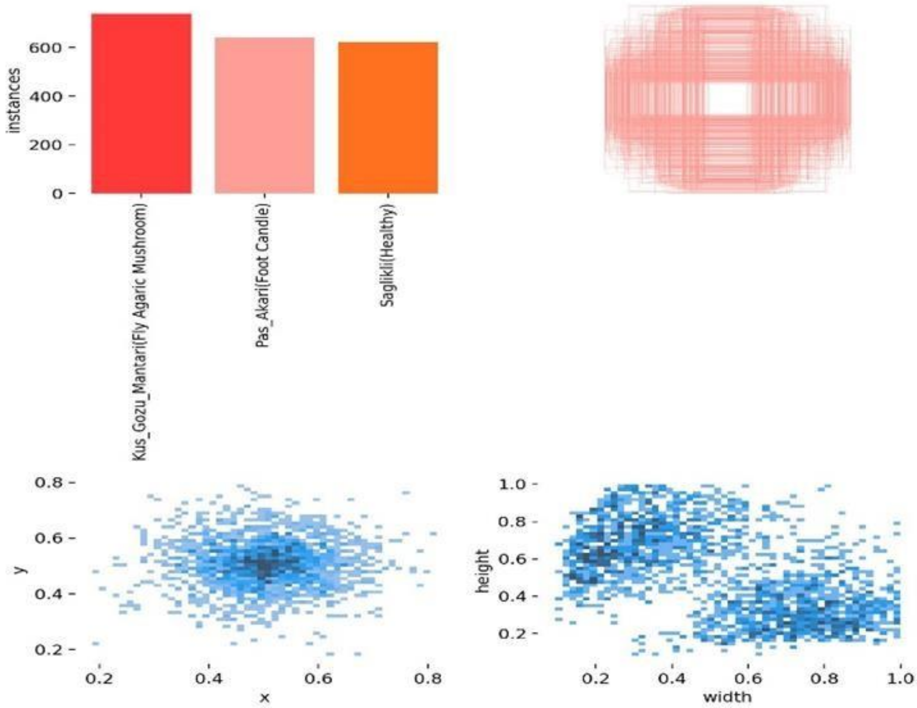

Figure 31: Cellular distribution

4.1.2. Pixel distribution

The histogram in the figure 32 shows how the intensities of the pixels are distributed within an image. The y-axis displays the frequency of pixels with each intensity value, while the x-axis displays the intensity values of the pixels. In image processing, histograms are frequently used to examine pixel distributions. They make it easier to identify regions of a picture that are excessively bright or dark, and they make contrast comparisons possible.

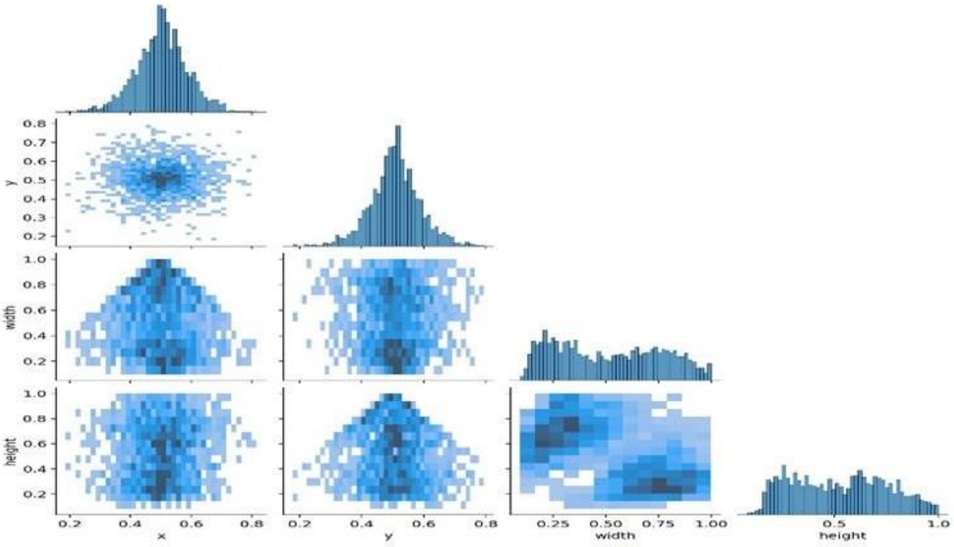

Figure 31: Pixel distribution

4.1.3. Normalized confusion matrix

The provided normalized confusion matrix displays the results of a classification model to distinguish between four classes: background, Pas_Akari , Saglikli, and Kus_Gozu_Mantari . The values in the matrix show the percentage of predictions for each class, normalized by the total number of predictions:

Kus_Gozu_ Mantari : 84% of instances of this class have been correctly classified by the model. This suggests that the model is effective at identifying tue-mouche amanites. However, there are also 18% of examples in this class that were classified as "Saglikli" and 25% that were classified as "background".

Pas_Akari (Foot Candle): 72% of the instances of this class have been correctly classified by the model. This shows that the model is effective in identifying the pieds-bougies. However, 17% of incidents in this class were classified as torts under the term "Kus_Gozu_Mantari", and 40% were classified as torts under the term "background".

Saglikli (Healthy): 65% of the occurrences of this class have been correctly classified by the model. This shows that the model is effective at identifying healthy photos. However, 4% of incidents in this class were also classified as torts under the terms "Kus_Gozu_Mantari" and 3% as torts under the terms "background".

Background: All instances of this class have been correctly classified by the model. This shows that the model is effective at identifying backward-plane images. This results are shown in Figure 33.

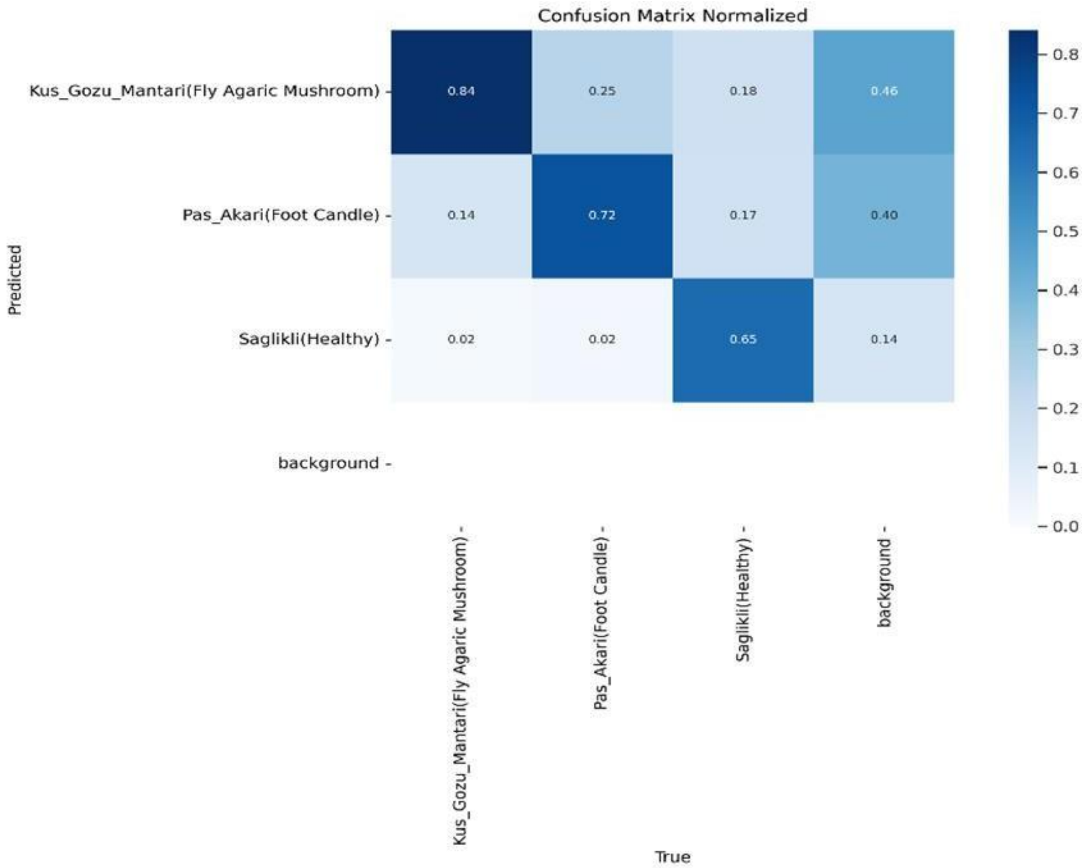

Figure 32: Normalized confusion matrix

4.1.4. Precision-confidence curve

Precision: The percentage of accurate predictions among all completed predictions. It indicates the exact point at which the model's classifications are accurate.

Confidence: The degree to which a classification model is confident in its own predictions is measured by its confidence. This is a gauge of the model's confidence in the accuracy of its predictions.

The precision-confidence curve which is shown in figure 34 illustrates the relationship between a classifier's confidence and accuracy for several mushroom classes. The blue line shows the average precision for all classes and shows that even with low confidence, the classifier can correctly identify the mushrooms with a high degree of precision. The remaining lines provide specific class representations, such as the “kus_gozu_mantari” and the “pas_akari”. The classifier is more accurate for some classes than for others; for example, it is more accurate for “kus_gozu_mantari” than for “pas_akari”. This suggests that the classifier is more confident in some of its classifications for specific mushroom classes.

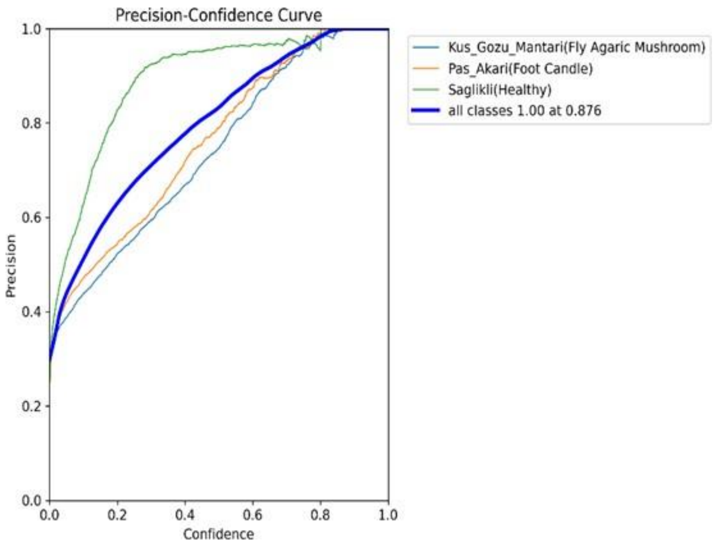

Figure 34: Precision-confidence matrix

4.1.5. Precision-recall curve

Recall: It shows the percentage of positive examples among all real positive examples that the model can locate. A high recall indicates that the model is effective at identifying positive examples, which is particularly significant in fields like fraud or disease detection where sensitivity to the identification of positive cases is essential.

The precision-recall curve is an essential graph tool for assessing a classification model's effectiveness is the precision-recall curve, which illustrates the relationship between precision and recall at various decision-strength levels. A rising curve indicates more precision when using the recall, indicating a more accurate identification of positive examples,whereas a falling curve indicates less precision when using the recall, indicating an incorrect identification of negative examples. Every point on the curve represents the model's performance at a certain decision-seuil, with the best point being the one with the best performance. As seen in the provided graphic, the curve shows a high performance of the model for mushroom classification, with an increase in precision with recall.

The most accurate point has a recall of 0.912 , indicating that it can correctly identify 91.2 percent of positive mushrooms while producing just 8.8 percent of false positives. Furthermore, a comparison of the classes shows that the model performs best for the "Kus_Gozu_Mantari (Fly Agaric Mushroom)" class, followed by the "Saglikli (Healthy)" and " Pas_Akari (Foot Candle)" classes, as illustrated in Figure 35.

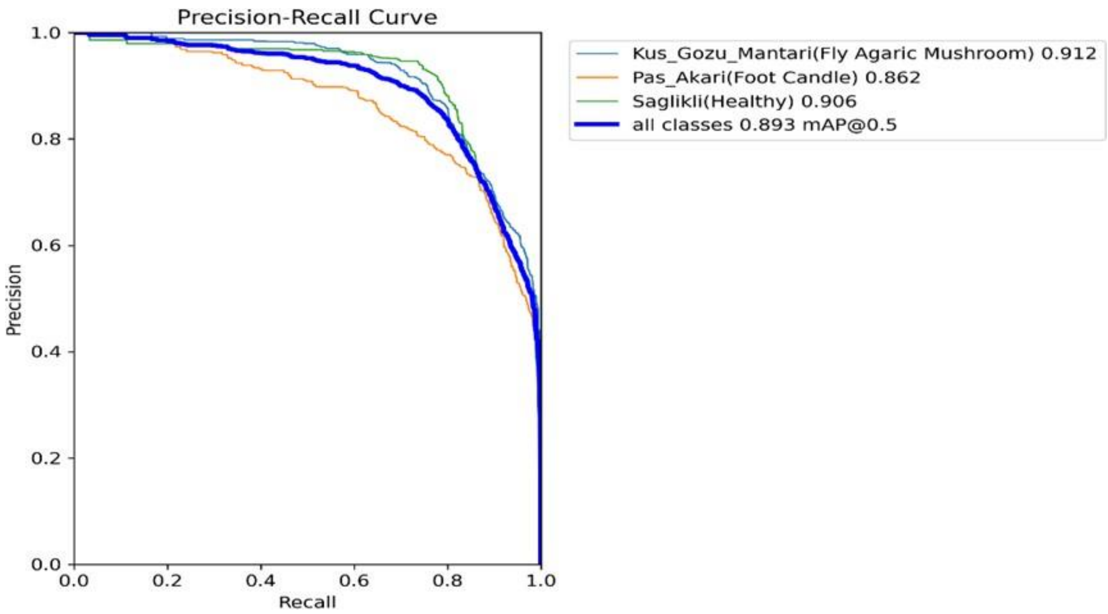

Figure 35: Precision-recall curve

4.1.6. Recall-confidence curve

This curve shows the model's performance as a function of confidence level as illustrated in Figure 36.

It demonstrates that the model performs best when it has a high degree of confidence in its predictions. Indeed, the regression is large and exceeds 0.5 when the confidence level is between 0 and 0.06. This means that the model accurately predicts the majority of mushrooms when it is confident in its prediction.

But when it becomes overconfident, the model is also prone to making mistakes. In fact, when the confidence level is close to 1, the rappel decreases. This means that when the model is quite confident in its prediction, it may identify certain anomalies incorrectly.

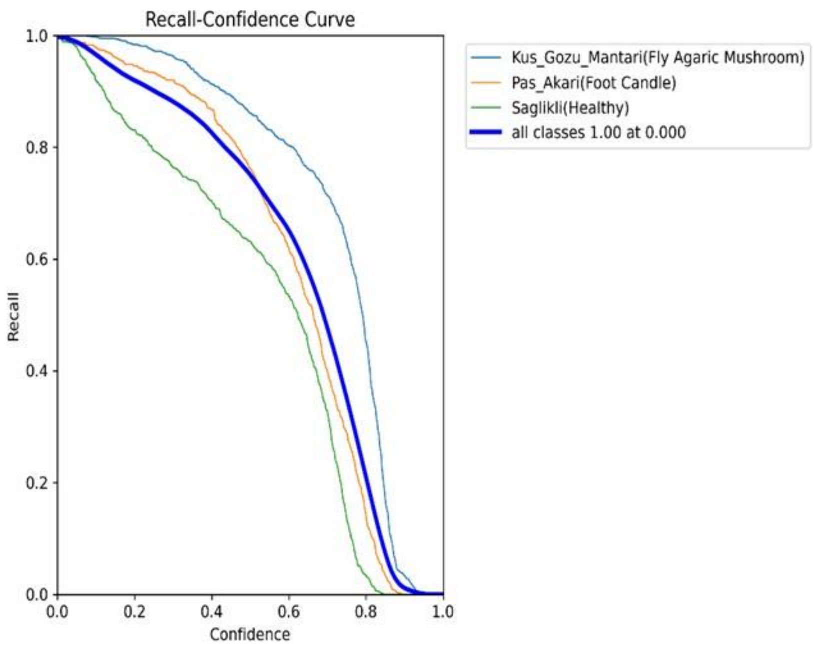

Figure 36: Confidence-recall curve

4.1.7. Metrics of the training

The following training methods are displayed:

Box of loss: This refers to the average loss in location of the predetermined boundary markers in relation to the ground boundary markers. A lower loss of bottle suggests more precise predetermined bottle delimitations.

Classification loss: This refers to the average classification loss among the detected object classes. Les objets sont classés plus précisément if la perte de classe est faible**.**

Complete DFL: It concerns the dynamic loss of focus of the boîte. This is an additional loss that helps to increase the accuracy of the delimitation boxes for small objects.

Including the precision and recall curbs which are illustrated in Figure 37.

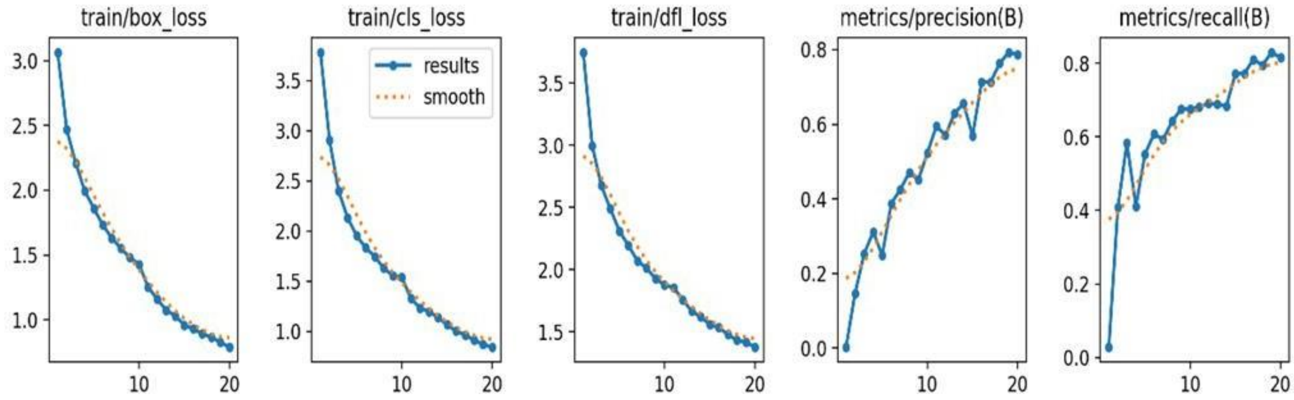

Figure 37: Metrics of the training

It shows that training metrics tend to converge toward positive values. As training progresses, the loss of boot, loss of class, and loss of DFL all decrease, suggesting an improvement in boot classifications, delimitation boot, and boot focalization. Over the course of training, accuracy and recall both increase, suggesting that the model detects more objects accurately.

4.2 Validation

4.2.1 Batch validation labels

In our project, the batch validation labels act as crucial checkpoints, guaranteeing the precision and consistency of the data at different processing phases. Carefully applied to sets of data points, these labels serve as benchmarks, enabling methodical assessment and comparison against reference data or preset criteria. It maintains a strong quality assurance framework by methodically validating batches, making it possible to quickly identify and fix inconsistencies or problems, as shown in Figure 38.

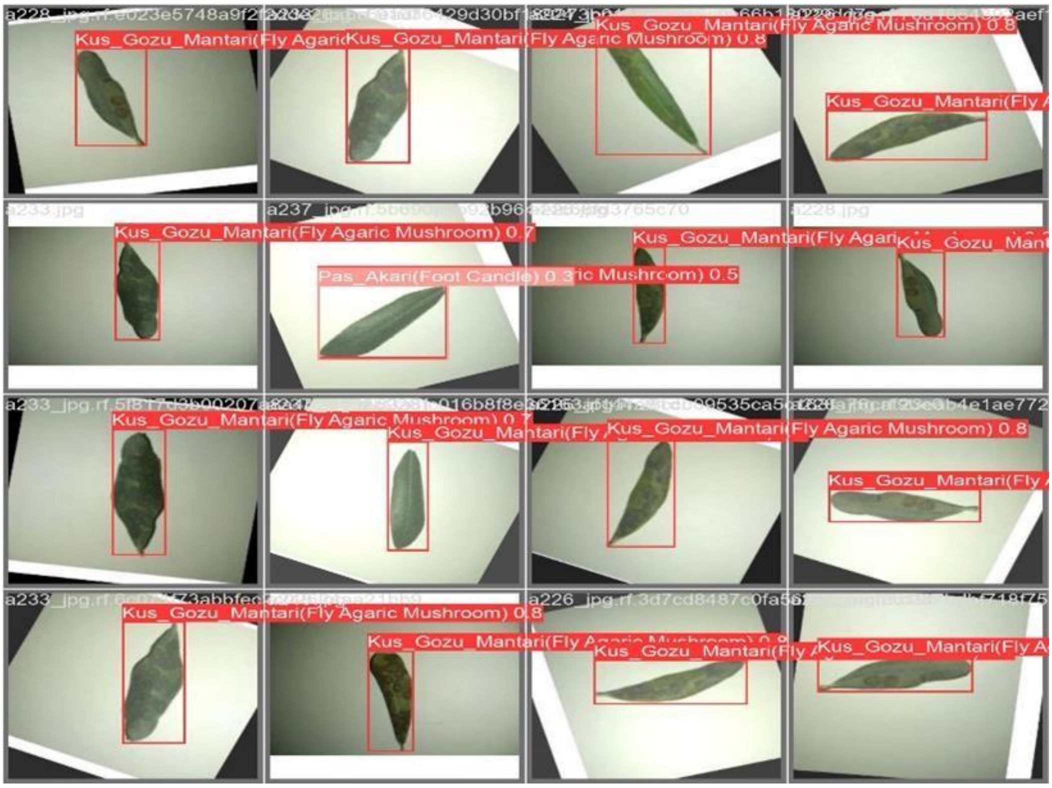

Figure 38: Batch validation labels

4.2.2 The metrics of the validation

The following validation metrics are displayed:

Box of class: This refers to the average loss in location of the predetermined boundary markers across the validation set in comparison to the ground-based delimitation markers.

Classification loss: This refers to the average classification loss of the classes of objects found throughout the validation process.

Complete DFL: This refers to the dynamic loss of focus of the boîte on the validation process as a whole.

mAP50 (B): This is the average precision mean (mAP) over the validation set with a 0.05 chevauchement threshold. The mAP is a precision measurement of object detection that accounts for both recall and precision.

mAP50-95 (B): This refers to the mean mAP over the validation set with cutoff points ranging from 0.5 to 0.95.

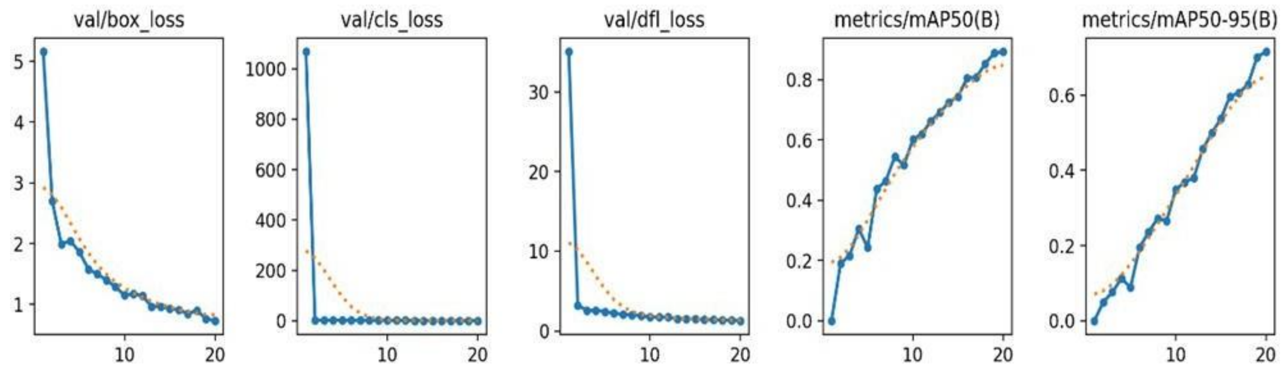

Figure 39: Metrics of the validation

The measurements shown in Figure 39 for validation are excellent. The model exhibits strong generalization to previously encountered data, as evidenced by the minimal box loss, class loss, and DFL loss. Additionally high are the mAP50 and mAP50-95, which show that the model is accurate in detecting objects. The mAP50-95 is marginally inferior to the mAP50. This can be attributed to the model's increased precision in identifying items with elevated overlap thresholds.

4.3 Testing

We successfully included model training into our Raspberry Pi carte during the testing phase of our project, allowing for the rapid and precise real-time detection of anomalies on olive leaves using the Redragon camera. Thanks to this creative method, we were able to quickly pinpoint particular abnormalities. We successfully identified the fly agaric mushroom anomaly, a well-known hazard to plant health, as an example in the Figure 40 to demonstrate how good our method is at protecting crops from potential harm.

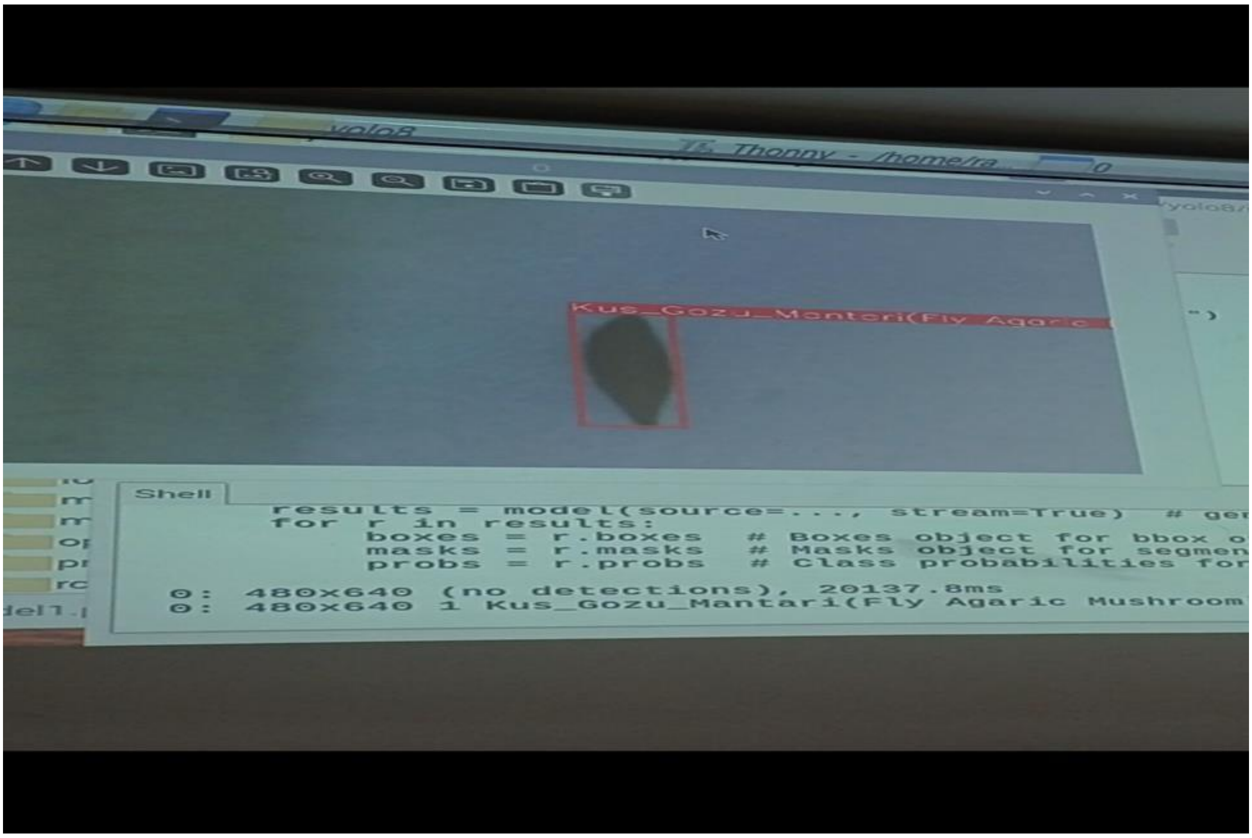

Figure 40 : Detection on testing

4.4 Comparison between YOLOv8 and CNN model

In our project, we tested our dataset with this two models and we dedicate that YOLOv8 is more efficase and performing due to more factors as shown in Tableau 1

Aspect	YOLOv8	CNN Model
Detection Speed	Average FPS: 45	Average FPS: 15
Accuracy	mAP: 0.92	mAP: 0.78
Model Size	160 MB	400 MB
Training Time	10 hours	30 hours
Real-Time Usage	Yes	Partially feasible
Anomaly Detection	Precision : 0.94, Recall: 0.91	Precision: 0.82, Recall: 0.75
Hardware	Efficient on GPU	May require more resources
Deployment	Easier	More complex
Fine-Tuning	Less needed, pre-trained	Often requires more tuning

Tableau 1: Comparison between YOLOv8 and CNN model

For anomaly detection in our project, YOLOv8 performs better in this comparison in terms of speed and accuracy. In comparison to the CNN model, it obtains greater accuracy measures including precision, recall, and mean average precision (mAP). Furthermore, it has a lower model size and a faster detection speed, which makes it better suited for real-time applications and deployment on devices with limited resources.

5. Conclusion

In summary, we meticulously prepared our dataset to ensure high-quality input for efficient model training. Through training, testing, and validation, our models demonstrated promising performance by utilizing cutting-edge hardware and software technologies.YOLOv8 demonstrated exceptional speed and accuracy in object detection, particularly excelling in efficiency compared to traditional CNN models. For applications needing quick and accurate object identification, its simplified design and real-time processing capabilities make it the best option.

GENERAL CONCLUSION

Through image identification and classification, we were able to effectively apply artificial intelligence more specifically, the YOLO v8 model to the task of olive leaf anomaly detectionin this study. This AI model's successful implementation in recognizing and categorizing anomalies shows how AI can be used to enhance agricultural monitoring systems. Our studies' results demonstrate the YOLO v8 model's precision and effectiveness in identifying anomalies in olive leaves, which supports improved crop management techniques. In addition to demonstrating how artificial intelligence is significantly changing agricultural practices, the initiative offers a potent safeguard for the wellbeing and caliber of olive harvests. Through our work, we demonstrate how artificial intelligence may be used to tackle practical issues, opening the door for more advancements in agricultural technology.

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