People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research
Mohamed El Bachir El Ibrahimi University of Bordj Bou Arreridj
Faculty of Mathematics and Computer Science
Department of Computer Science

DISSERTATION

Presented in fulfillment of the requirements for the degree of

Master in Computer Science

Specialty: Networking & Multimedia

THEME

Detection of predatory insects that attack bees in beehives using deep models

Presented by:

Ouali Meriem

Publicly defended on: 11/06/2025

In front of the jury composed of:

President: Dr.Charikhi Mourad

Examiner: Dr.Saifi Abdelhamid

Supervisor: Dr.Foudhil Belhadj

2024/2025

Dedication

I dedicate my work:

To my dear parents, who have always encouraged me and never left my side.

To my family members, who were there for me when I needed them.

To my supervisor, Dr. Belhadj Foudhil, for sharing his knowledge and advice with me.

To my friends, thank you for your love and support.

To everyone who helped me, I genuinely appreciate your help.

Acknowledgments

First, I thank God for giving me the patience and determination to complete this work.

I am grateful to my supervisor, Dr. Belhadj Foudhil, for his help during this project.

I would also like to thank the jury members for their time and expertise in evaluating my work.

I am grateful to all the professors in the Computer Science department for sharing their knowledge with all the students, myself included.

Finally, I thank all the people who have supported me during this project.

Abstract

Bees play an important role in many fields,not just in agriculture.However,in the past years the number of bees has experienced a serious decrease.There are many factors that contributed in that,among the main ones being predatory insects that kill bees and destroy their hives.This thesis aims to develop a YOLO model capable of detecting those insects.The model is intended to be deployed in a real time intelligent insect detection system that comes with a 360-degree rotating camera.Only the design is covered in this study not real-world deployment.By using deep learning techniques,this work seeks to help in creating an automated and efficient monitoring system to protect honey bees.

Keywords: bees protection, artificial intelligence, convolutional neural network, insect detection,YOLO model, automated monitoring.

Résumé

Les abeilles jouent un rôle important dans de nombreux domaines, pas seulement dans l'agriculture.Cependant, au cours des dernières années, le nombre d'abeilles a connu une sérieuse diminution.Il y a de nombreux facteurs qui ont contribué à cela, parmi les principaux étant les insectes prédateurs qui tuent les abeilles et détruisent leurs ruches.Ce mémoire vise à développer un modèle YOLO capable de détecter ces insectes. Le modèle est destiné à être déployé dans un système intelligent de détection d'insectes en temps réel qui est équipé d'une caméra rotative à 360 degrés.Seule la conception est abordée dans cette étude, et non la mise en œuvre réelle.En utilisant des techniques d'apprentissage profond, ce travail cherche à contribuer à la création d'un système de surveillance automatisé et efficace pour protéger les abeilles.

Mots-clés : protection des abeilles, intelligence artificielle, réseau de neurones convolutifs, détection d'insectes, modèle YOLO, surveillance automatisée.

ملخص

يلعب النحل دورًا مهمًا في العديد من المجالات، وليس فقط في الزراعة. إلا أن عدد النحل قد شهد انخفاضًا كبيرًا في السنوات الأخيرة. هناك العديد من العوامل التي ساهمت في ذلك، غير أن من أبرزها الحشرات المفترسة التي تقتل النحل وتدمر خلاياه. يهدف هذا البحث إلى تطوير نموذج YOLO قادر على اكتشاف هذه الحشرات. النموذج مُصمم ليُستخدم في نظام ذكي لرصد الحشرات في الوقت الحقيقي، مزود بكاميرا دوّارة بزاوية 360 درجة. مع ذلك، تقتصر هذه الدراسة على تصميم النظام دون تنفيذه في الواقع. من خلال تقنيات التعلم العميق، يسعى هذا العمل إلى المساهمة في إنشاء نظام مراقبة آلي وفعال لحماية النحل.

الكلمات المفتاحية: حماية النحل، الذكاء الاصطناعي، الشبكات العصبية الالتفافية، اكتشاف الحشرات، نموذج YOLO، المراقبة الآلية.

Table of Contents

List of Abbreviations

AI Artificial Intelligence

YOLO You Only Look Once

IoT Internet of Things

ML Machine Learning

DL Deep Learning

GPU Graphics Processing Unit

CNN Convolutional Neural Network

ReLU Rectified Linear Unit

List of Figures

List of Tables

General Introduction

Artificial Intelligence, Machine Learning and Deep Learning have proven to be efficient in multiple sectors.In agriculure,specifically in apiculture and beekeeping. These technologies have been used for various tasks like: invasive insect detection, example: hornets and wasps, early disease identification such as:varroa mites, which are considered one of the most threatening enemies of bees worldwide. There are also systems for tracking bees to check for any abnormalities.Other systems are used for monitoring environmental changes that affect honey bees (temperature,humidity,etc). These technologies use various tools to accomplish great results ,this tools include: cameras ,sensors and of course,one of the most used technologies, deep learning models (YOLO and its many versions).

The number of diseased bees is increasing rapidly because they are under threat from various enemies such as predatory insects, diseases and parasites, etc.This affects not only the apiculture sector but also the economy and the balance of ecosystems. Beekeepers throughout history have tried many methods to eliminate these threats, but their methods consume a lot of time, require heavy labor work, and eventually did not succeed in protecting the bees and their hives.

My target in this thesis is to apply technologies like Artificial Intelligence and Deep Learning, specifically the YOLO model,to develop a system capable of detecting invasive insects of bees in real time with minimal human intervention. My proposed system reduces the pressure of manual inspections for beekeepers while protecting the bees from dangers.

To accomplish this, the thesis is organized into three chapters:

Chapter one: In this chapter, I discuss the beekeeping state, the various threats honeybees face, and the solutions for these threats, specifically the role of technologies like Artificial

Intelligence, Machine Learning, and deep learning to create smart automated solutions.

Chapter two: This chapter presents the technologies used to create these intelligent systems and proposes the design of a real time intelligent predatory insect detection system.

Chapter three: In this chapter, I explain the implementation steps and the results of the trained insect detection model.

In the end, this thesis concludes with a general conclusion.

Chapter 1

Beekeeping Threats and Existing Solutions

1.1 Introduction

This chapter discusses the importance of bees and the problem of increasing bee population mortality,globally and in Algeria.It covers the types of honeybees in Algeria, the various threats they face and the existing solutions to protect them.Also,it mentions existing studies and real world implementations of beekeeping systems using technologies like AI and deep learning.

1.2 The Importance of Bees and the Decline of Bee Populations in Algeria

Bees play a crucial role in many fields: in agriculture, they transfer pollen between flowers that is necessary for their reproduction and results in making food like seeds, vegetables, and fruits needed for human survival.This process is called pollination and bees are considered one of the most important pollinators on the planet.A study showed that 75% of the world's most important food crops depend on pollinators.In the economy, bee pollination was valued at hundreds of billions of US dollars every year which is very high.This proves that any decrease in bee numbers would affect not only agriculture but also the economy, worldwide food supply and ecological balance[1][2].

However, reports from several parts of the world have confirmed a rapidly increasing bee loss.In the United States, between 2023 and 2024, it was confirmed that American honey bee colonies experienced a 55.1% loss, which is the highest loss in the past 14 years[3].The causes of these losses include:climate changes, overuse of pesticides, pathogens (Deformed Wing Virus), parasites (varroa mites) and invasive insects[4].

Algerian beekeepers also suffered huge colony losses. Reports confirmed that these losses are only increasing due to multiple factors: unexpected climate changes such as extreme heatwaves, the lack of forage (nectar), etc.But also, humans added to the problem, as confirmed in a study done in the Ziban region of Algeria, where beekeepers showed a lack of proper training and beekeeping knowledge, the overuse of pesticides, and limited bee health care.

Despite all these challenges, the Algerian authorities did not take proper measures to solve this problem, which puts the apiculture sector in great danger[5].

Several strategies were created to minimize honey bee loss, among which: reducing the use of pesticides that affect the bees and ensuring good communication between the government and the beekeepers to find the best approaches [6][7].

1.3 Bee Populations in Algeria

1.3.1 Apis mellifera intermissa (Tellian Honey Bee)

This honey bee is found in the north ,it is a small ,dark colored bee ,known to be aggressive and can cope well with climate changes[8].

1.3.2 Apis mellifera sahariensis (Saharan Honey Bee)

It is a yellow-colored honey bee, and just like its name implies,it exists in the southern desert oases.It is less aggressive than A. m. intermissa, and can live in dry and very hot areas[8][9].

Tellian Honey Bee

Saharan Honey Bee

Figure 1.1: Types of bees in Algeria

1.4 Threats to beekeeping in Algeria

According to reports from beekeepers in Algeria and ceratin articles,beeekeeping faces many threats from predatory insects and also from other non insect threats that kill bees or disturb their activities.

1.4.1 Predatory insects

While there is no specific informations available on the internet about the types of insects that attack honey bees in Algeria, the most well known among algerian beekeepers are:

1.4.1.1 Wasps (Vespula spp.)

These insects kill bees and steal the results of their hard work, including honey, brood, and pollen.Not only do wasps kill honey bees, but they also reduce their food resources, which threatens the life of the bees and the entire beehive.

1.4.1.2 Hornets (Vespa spp.)

Considered a major threat to bees.They are famous for being very aggressive causing severe damage to beehives. Hornets kill honey bees to feed on their larvae.

Wasp

Hornet

Figure 1.2: Predatory insects that attack bees in Algeria

1.4.2 Other non insect threats to bees and beehives

1.4.2.1 Diseases

- **Nosema Disease:** Research on Algerian apiaries shows that 108 out of 164 colonies from different parts of the country were indeed infected with Nosema[10].

- **American Foulbrood (AFB):** The presence of Paenibacillus larvae, the causative agent of American Foulbrood (AFB), has been confirmed in five regions: Algiers, Boumerdes, Blida, Bouira, and Tipaza.It was discovered that several factors contributed to the spread of this disease, such as transhumance, sailing bees in swarms,which spreads the infections faster,and most importantly, insufficient beehive hygiene measures by beekeepers[11].

1.4.2.2 Parasitic Mites

- **Varroa Destructor:** This study shows how widespread this parasitic mite is in Algeria. Research confirmed that all Apis mellifera intermissa colonies (118 colonies) from the north to south of the country, as well as all Apis mellifera sahariensis colonies (12 colonies), were 100% infected[9].

1.4.2.3 Viral Infections

- **Deformed Wing Virus (DWV):** DWV is a virus that affects honey bees by causing wing deformities, making flying difficult.It is commonly spread by the Varroa mite.The study showed that all the tested bee colonies (100% of bee colonies) were infected with this virus[9].

- **Black Queen Cell Virus (BQCV):** Test results show that 100% of the colonies had BQCV. This harmful virus causes the queen bee larvae death, which leads to lower reproductive rates[9].
- **Sacbrood Virus (SBV):** This virus reduces the number of new adult bees by infecting bee larvae, causing them to die before maturing.According to the study, 100% of the bees tested positive for SBV[9].

1.4.2.4 Animal Predators

- **Birds:** Certain birds like bee eater (Meropis Apiaster) in Algeria attack bees during flight.
- **Mammals:** Small mammals, such as mice,consume honey, nectar and pollen and cause damage to the hive.

1.5 Existing Solutions for Hive Protection

1.5.1 Traditional Methods

In order to protect bees from pests and diseases, beekeepers used multiple traditional methods:

1.5.1.1 Physical Barriers

Beekeepers in order to protect bees from various threats like: termites, roaches, earwigs, praying mantids, and lice, placed single colonies on stands or benches covered with oil or sticky barriers. Regular beehive monitory is nessecary to protect the bees from any threats[12].

Figure 1.3: Beehive placed above a stand to protect from invasive insects

1.5.1.2 Manual Removal

In underdeveloped parts of the world like: Asia and Africa, where there is limited access to chemicals, beekeepers are forced to use traditional methods that are time consuming such as: manual removal of invaders (beetles), killing them by flapping, crushing, baiting or manually extracting them from the hives using hive tools just like in the case of wax moths[13].

1.5.1.3 Chemical Repellents and Pesticides

The use of pesticides is a very common and effective practice to kill pests, but it is harmful to bees.That's why they have been replaced by natural repellents,plant based essential oils, which are effective against predatory insects (beetles and wax moths) including neem,thyme and citronella[13].

Figure 1.4: Beekeeper applying Pesticides

1.5.2 Modern Technological Solutions

In order to help solve the challenges that beekeepers encounter in beekeeping, AI was applied for various uses like automating hive monitoring and detecting predatory insects.This makes beekeeping easier for beekeepers because it reduces labor work and consumes less time, which results in protecting the bees and their hives, leading to a high production rate.To do this, AI has the ability to analyze data such as: images and sensors to perform monitoring in real time[14][15].

1.5.2.1 The Uses of AI in Beekeeping

AI has made several contributions in the field of apiculture among which:

- Hive monitoring

- Detection of diseases (varroa mites) and invasive insects (wasps and hornets)
- Climate changes tracking(temperature,humidity)
- Bee distribution management[14][15].

1.5.2.2 Hive Monitoring using Machine Learning

Machine learning uses mainly three strategies :

- **Supervised Learning:** uses classification, regression and algorithms like: Random Forest ,Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) , examples of use: honey harvest prediction, disease(Varroa destructor) and pest detection[14].
- **Unsupervised Learning:** It looks for relations between data that has no outputs.It is applied in clustering(grouping) bees that have similar patterns like:the same disease symptoms and behavior [14].
- **Reinforcement Learning (RL):** RL is a technique that learns by interacting with the surrounding environment using real-time footage(videos). It applies deep models like:CNN and RNN (Recurrent Neural Network)[14].

1.5.2.3 Applications of AI in Beehive Management

In order to aid beekeeping, researchers have developed automated real-time monitoring systems for hives that benefit from cameras and sensors.An example of this is temperature sensors that detect when the temperature is too cold and automatically turn on the heat[14].

1.6 Studies and Real World Solutions

1.6.1 Insect Detection Systems Using Deep Learning

There are several articles that explore the use of deep learning models including: CNN and YOLO (YOLOv3, YOLOv8, etc) to protect bees from predatory insects.For example ,an article talks about an automatic YOLOv5 pest detetction system that detects then classifies insects that ruin crops[16].Another study showed how to develop a system to detect Vespa Velutina (Asian hornet) using YOLOv5s and comes in the form of a mobile ,capable of sending alerts in real time[17].

This articles prove that deep models specifically the YOLO model can efficiently be applied to do beehive monitoring.

1.6.2 Beehive Surveillance Systems Using Both AI and IoT

This studies show how to combine between AI and IoT to create smart beehive systems:

This article presents 'IntelliBeeHive',which is a multi purpose monitoring system to detect varroa mites, track honeybee movements and monitor pollen collection.It is based on YOLOv7-tiny ,this system acheived a 96.28% accuracy[18].

This paper explains a ResNet system to count the number of bees,and can be used to study phenomenas like Colony Collapse Disorder (CCD) and bee health, with an accuracy of 93% [19].

Kontogiannis proposed a method to track phenomenas that cause bee mortality (swarming, Colony Collapse Disorder (CCD), etc) using deep learning models implemented in the Bee Smart Detector[20].

1.6.3 Real World Implementations

Many intelligent hive surveillance systems have been designed,among them is:

The device called 'Wyze Cam' uses a 360 degree rotating camera to provide 24/7 surveillance. Beekeepers have used it for beehive monitoring, and many gave positive feedback about its performance[21].

BeeMate utilizes HD cameras to detect parasites and predatory insects, along with sensors such as temperature sensors and sound sensors to detect any abnormalities in the hives. It also performs bee counting and stores all the collected data so that beekeepers can make use of it to protect their bees [22].

Such systems can be used as inspiration to create more advanced and precise monitoring systems.

1.7 Limitations of existing solutions

The existing insect detection and beehive surveillance systems have shown good results,still they have certain limitations.YOLO model sometimes can struggle to detect tiny insects in complex environments.Intelligent devices like IntelliBeeHive and Wyze Cam often depend on a stable internet connection and constant power supply, which are not always available in remote areas.These systems mostly are used only for monitoring,but they don't always help beekeepers take quick action, like stopping swarms or responding to diseases in real time.The high cost for the setup and maintenance of systems.

1.8 Conclusion

This chapter explained the important role of honey bees, the threats they face in Algeria, and the existing strategies to protect them,traditional and modern,and showed how inconvenient traditional methods are in beehive protection.It also explored the techniques that can be applied to build efficient smart beehive monitoring systems.

Chapter 2

Design of a Smart Insect Detection System

2.1 Introduction

This chapter is divided into two parts. In the first part ,I present the main technologies that I used to create my insect detection system, including Artificial Intelligence and Deep Learning. In the second part, I discuss the design of my real time smart monitoring system that uses the YOLO model for insect detection.The system's architecture and implementation are explored, along with the role that every component plays.

2.2 Technologies for developing smart detection systems

Technologies like artificial intelligence, machine learning, and deep learning are used to develop automated and intelligent systems for the detection of invasive insects that kill honey-bees.

2.2.1 Artificial Intelligence (AI)

Artificial Intelligence (AI) means the ability of machines to think and act like humans. It has various applications in many domains including reasoning, problem solving and decision making , which is one of the most important functions of AI [23].

2.2.1.1 Machine Learning (ML)

ML is a branch of AI that allows machines to process and learn from datasets without being explicitly programmed. ML has three types: supervised learning, unsupervised learning and reinforcement learning. In apiculture, ML is used in pest and disease identification, monitoring bee behavior and tracking environmental changes that affect honey bee health[14].

2.2.1.2 Deep Learning (DL)

Deep Learning (DL) has the ability to process large datasets, like:images and video.It applies neural network architectures to extract patterns to allow the system to learn from them. In apiculture, the Convolutional Neural Network (CNN) model is widely used to detect and classify insects and parasites (Varroa mites) that cause severe harm to bees and bee colonies,all of that in real time [14][24].

2.2.2 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN) is a type of deep learning model.In this project ,CNNs play an important role in the detection of predatory insects that attack bees,they extract features from images in this case predatory insects features and are widely used for for object detection and image classification. CNN uses multiple layers[25]:

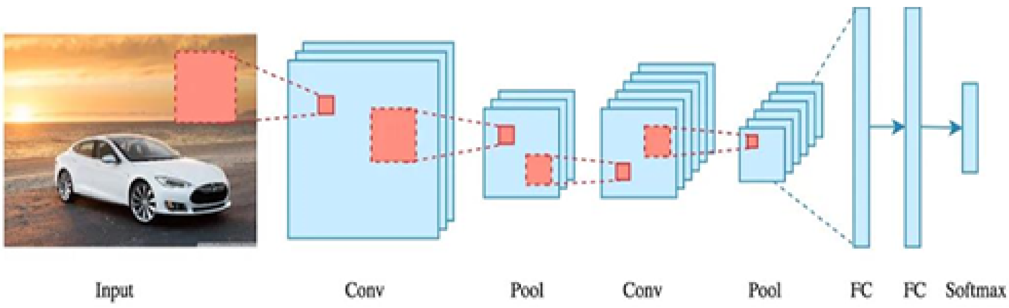

Figure 2.1: Convolutional Neural Network (CNN)

2.2.2.1 Convolutional Layer

The convolutional layer applies filters (matrices of numbers) to the image.When these filters move across the input image, they create feature maps that show the locations of the features detected in the image.Each filter is responsible for detecting a specific feature, such as shapes[26].

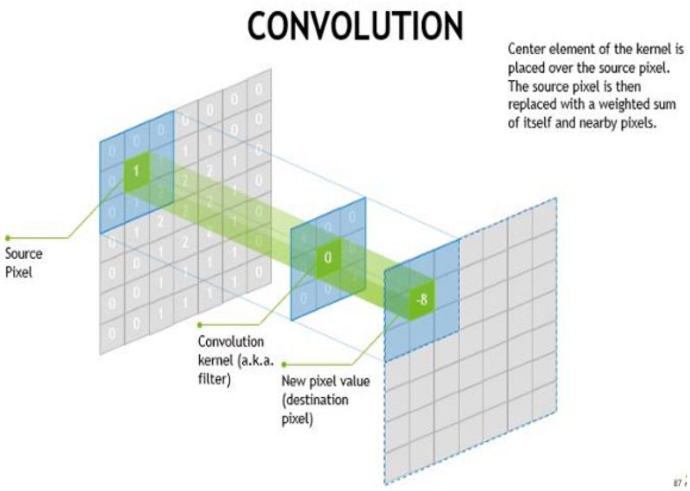

Figure 2.2: Convolutional Layer

2.2.2.2 Activation Function

In this step, a non-linear activation function (a mathematical operation) such as ReLU (Rectified Linear Unit) is applied to the feature maps. It works by removing all negative values and setting them to zero, while keeping the positive values the same.This allows the model to be non linear which helps the network to learn from complex shapes.ReLU is very applied because it's fast, simple to use and helps the network learn better and faster[27].

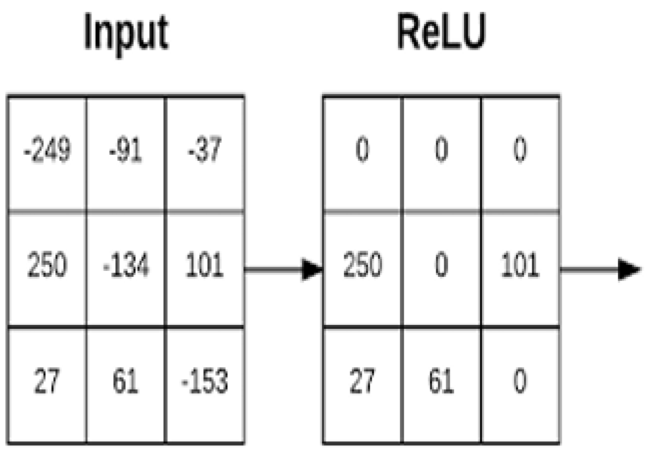

Figure 2.3: Activation Function (ReLU)

2.2.2.3 Pooling Layers

Pooling layers reduce the size of feature maps. They do this by applying filters that perform aggregation functions,these functions take the maximum or the average value in the input feature map, then put the results in a new output matrix[28].

The most used types of pooling are:

- **Max Pooling:** It selects the maximum value each time it moves through the image and places it in a new matrix. This process allows the network to keep the most important features from the input image[28].

- **Average Pooling:** It keeps the average value in the window and places it in the output matrix, this aids to store general features,unlike max pooling which focuses on the stronger ones[28].

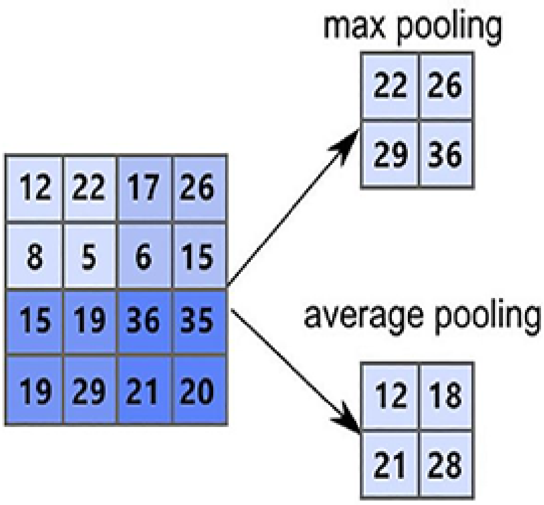

Figure 2.4: Pooling Layers

2.2.2.4 Fully Connected Layer (FC Layer)

This layer multiplies the input vector by a weight matrix and then applies an activation function such as softmax.It connects every neuron to all neurons in the previous layer,which allows the model to learn from the features extracted earlier.Since it is placed at the end of the network,it combines the learned information and performs the final classification[29].

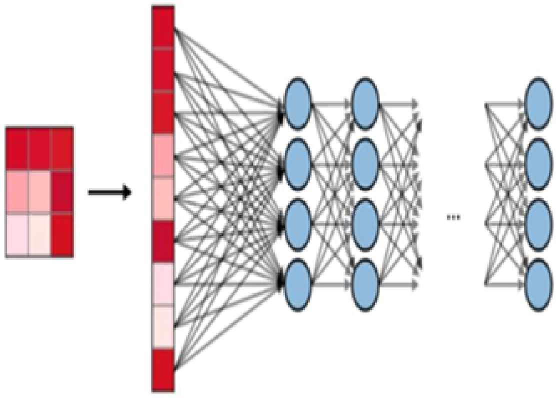

Figure 2.5: Fully Connected Layer (FC Layer)

2.2.3 YOLO (You Only Look Once) as a deep learning framework

YOLO (You Only Look Once) is the main deep learning model used in this project.It is an object detection algorithm that can locate and classify objects in an image.It processes the image and performs detection in a single step, without needing to go over the image multiple times.YOLO is known for being very fast, precise, easy to use and it performs better than older techniques such as DPM and R-CNN[30].

2.2.3.1 YOLO Architecture

YOLO is the core technology for developing the insect detection model.It is considered extremely fast and highly suitable for real-time detection [30].

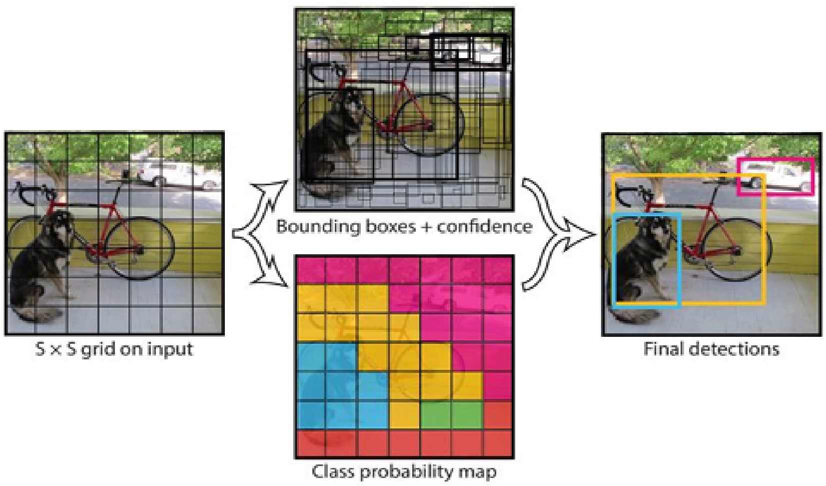

Figure 2.6: YOLO for Object Detection

a. Image Resizing and Grid Division : YOLO resizes the input image and then divides it to an S × S grid.When the center of an object is located in a grid cell,that cell detects that object[30].

b. Bounding Box Prediction : Every grid cell starts making multiple predictions, each one is represented by a bounding box(B bounding boxes).Each bounding box have 4 coordinates:coordinates of the center of the box that are relative to the cell (x,y),and coordinates of the width and height of the bounding box, which are relative to the full image (w,h). To evaluate the results of the predicted boxes,YOLO uses an objectness score (a number to show how confident the model is of the presence of an object inside of it).In the end,anchor boxes are used to help achieve a more accurate detection [30].

c. Class Prediction : The grid cells predict the class probabilities(C).

The class score formula:

$$\text{Class score} = \text{Class probability} \times \text{Objectness score}$$

The class score shows the probability of a class existing in the box and how well the bounding box fits the object [30].

d. Predictions Filtering : To reduce incorrect predictions, YOLO applies a threshold for example:0.3 and compares it to the bounding box confidence. It only keeps the bounding boxes with confidence equal to or greater than the threshold.

e. Applying Non Maximum Suppression (NMS) : NMS is applied to keep only the bounding box that has the highest confidence among all boxes and remove the other boxes so each object has only one bounding box [30].

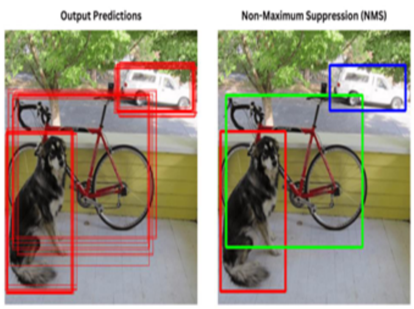

Figure 2.7: Non-Maximum Suppression (NMS)

2.2.3.2 YOLO for Object Detection (Insect Detection)

YOLO model has proven to be able to detect small and tiny objects even when they move fast. It can perform real time detection that is efficient ,rapid and accuracte.YOLO also has the ability to differentiate between insects that look alike, which is very important for this insect detection project.It also can perform well outdoors [31][32].

2.2.3.3 Insect Detection using YOLOv11m

Various YOLO versions have been used for insect detection such as :YOLOv3, YOLOv5 and YOLOv8. The reason I chose YOLOv11 for predatory insect detection is because it is more accurate than previous versions.Especially,YOLOv11m (medium) is selected because it combines between speed ,precision and also being the lightest among YOLOv11 versions (yolov11l ,yolov11s ,etc).Yet, YOLOv11m is not suitable for direct implementation on embedded devices like cameras,because it is large in size,requires a large amount of memory (RAM) and takes longer to process data which must be done in real time. In order to use YOLOv11m it has to be converted to a more lightweight format like ONNX,that is faster,smaller in size and suitable to deploy in embeeded devices[31][33][34][35].

2.3 The design of an intelligent beehive surveillance system

In this part I present my proposed architecture and real world implementation for the invasive insect detection system :

2.3.1 The architecture of the system

The figure below demonstrates the stages in the predatory insect detection system.The system has two phases:

Model development phase: For the data acquisition,I used labeled images of wasps and other elements such as bees,hornets, backgrounds and humans.The next step is training the deep learning model ,which is done in two steps:

Training: The model learns the important features of wasps like:color and size, and how to differentiate between them and non wasps.

Validation: To make sure that the model does not overfit to training images,I evaluated it on new images to see if it generalizes well on them.

My resulting model is used for testing on real world scenarios.

Real World Deployment Phase: In the deployment phase, my trained model is integrated into a real time monitoring system for invasive insect detection of honeybees. A camera captures real time footage,then sends it to the trained model to perform the insect detection.The system checks if an invasive insect is present in the output image:

If YES → Send ALERT , If NO → No alert is sent

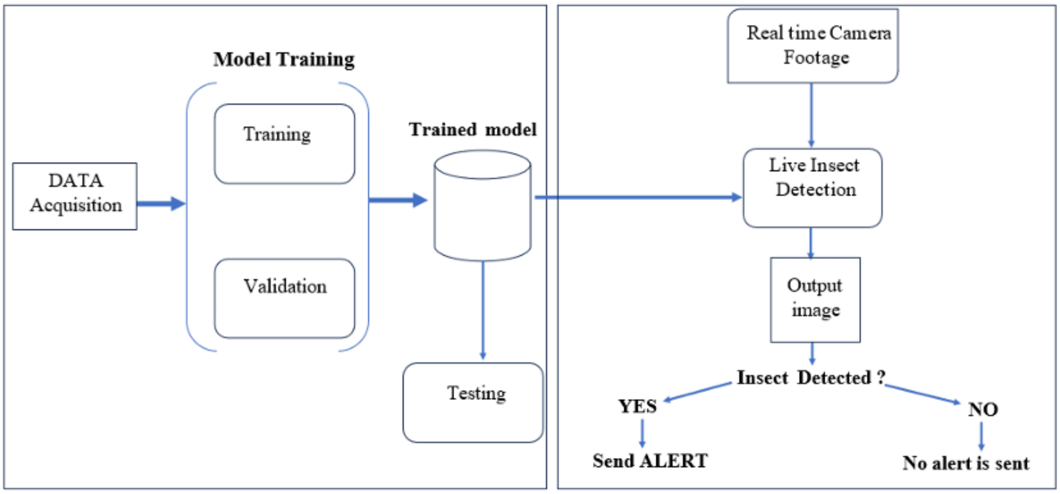

Figure 2.8: Architecture of the proposed system for bees protection

2.3.2 A Schematic Implementation for the Intelligent Beehive System

The figure explains how my proposed system detects predatory insects of bees in real time and with high effectiveness:

When the 360 degree rotating camera detects motion using the motion sensors, it sends the footage directly to the processing unit then the YOLOv11m model performs insect detection.If a predatory insect is detected, alerts are sent immediately to the beekeepers using Wi-Fi, Bluetooth or LTE. All of this happens in real time to ensure immediate beekeepers intervention and protection of the bees.My system guarantees 24/7 beehive monitoring,it uses a solar panel as an energy source during the day and a backup battery at night.

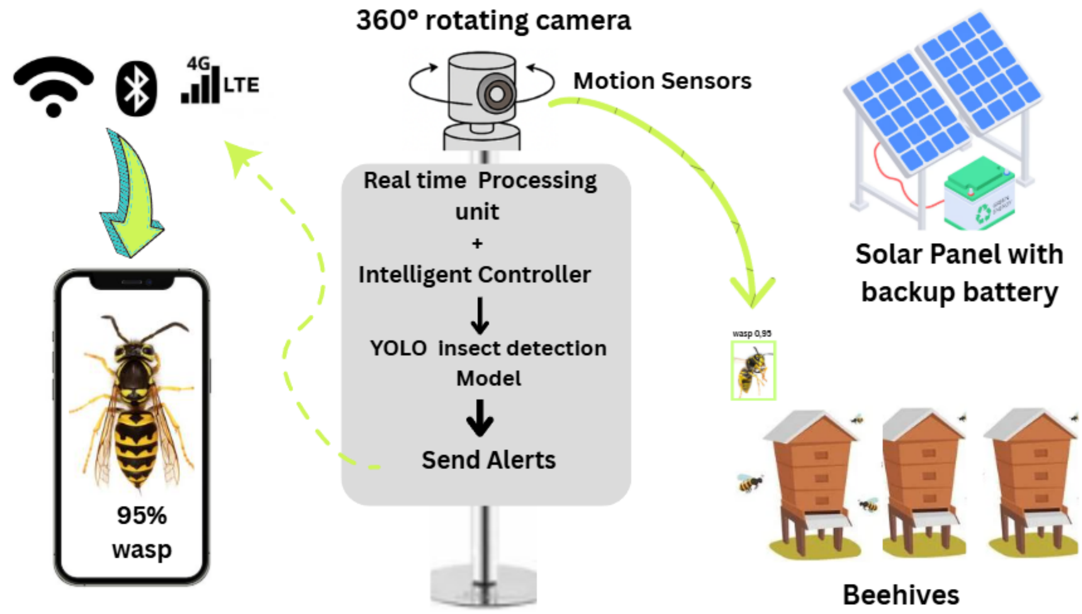

Figure 2.9: A proposed implementation for the system

2.3.2.1 Roles of the System Components

a. Camera

In this system,I propose that the camera is placed above a pole near the beehives and has several features: a 360 degree rotation technique that allows it to capture real-time footage from all directions, ensuring maximum detection of harmful insects.The camera is weatherproof to preserve it since it is placed outdoors. It includes color infrared lights for monitoring during the nighttime and in low-light conditions,that's how the system can provide 24 hour surveillance. The camera also has motion sensors that detect any motion around the hives and then automatically turn on the camera[36][37].

Figure 2.10: Example of a 360-degree weatherproof camera

b. Real time Processing

All the recordings from the camera go directly to the processing unit example :NVIDIA Jetson Nano.First,it analyzes the images and performs insect detection using the YOLO model.It does not only detects harmful insects but also classifies them (wasps, hornets,etc.) without confusing them with bees or other non-threatening insects or animals.Then, it sends alerts to beekeepers so that they can eliminate those insects.

Figure 2.11: NVIDIA Jetson Nano Processing Unit for insect detection

c. YOLO model

My model is designed to detect and then classify predatory insects that kill bees and cause damage to beehives.It has the ability to differentiate these insects from other harmless ones,for example: ladybugs, flies, butterflies, and of course,bees.In order to accomplish real world detection, the images used in the dataset for training the YOLOv11 model consist of various scenarios that can be encountered in real life:

- Single predatory insect images
- Multiple predatory insect images
- Predatory insects with bees
- Bees
- Other harmless insects (flies,ladybugs,etc)
- Other images to reduce false positives,such as: humans, backgrounds (flowers,trees)and objects

d. Power source

In terms of the power source, I chose a solar panel with a battery for backup. During the day,the solar panel captures sunlight and transforms it into electrical energy,that is used as a source of power for the smart system .The excess electricity is stored in the battery. At night, solar panels cannot function without sunlight,the battery provides the energy.My used technique is co low-cost because it reduces electricity usage and ensures consistent 24/7 monitoring [38].

Figure 2.12: Solar panels with battery backup for 24/7 beehive monitoring

e. Connectivity

I ensured to add connectivity tools such as Wi-Fi, Bluetooth, and LTE to send alerts to beekeepers in real time if invasive insects are detected, they also allow storing surveillance footage (videos).

f. Protective casing

To protect the components of the system from external factors such as water,I decided to use a trusted enclosure consisting of : An IP67 waterproof casing,which is easy to install.The camera is equipped with an anti-glare lens made from polycarbonate to protect against sun rays[39].

Figure 2.13: Example of efficient weatherproof casing

2.4 Conclusion

In this chapter I presented the technologies used in building hive surveillance systems, as well as a proposed design for an intelligent, automated and real time predatory insect detection system. Both the architecture and the real world implementation are explained, with the detailed role of each component.The objective of this chapter is to suggest a solution to more effective automated beehive surveillance using deep learning models.

Chapter 3

Implementation and results

3.1 Introduction

In this final chapter, I started with a presentation of the tools used.After that, I explained in details the implementation method of the deep learning model based on YOLOv11m for predatory insect detection and the evaluation of its effectiveness in real world scenarios, according to various criteria, in order to improve the model's performance in terms of both time and efficiency. Finally, I presented the results of testing on various images and discussed these results.

3.2 Tools

3.2.1 Programming Language PYTHON

Python is a high-level programming language used in many fields, such as machine learning, data analysis and deep learning, It is considered simple, easy to read, has open source features and a large number of libraries. This makes it a suitable choice for deploying insect detection systems like my proposed system using YOLO model [40].

3.2.2 GOOGLE COLAB

Google Colab is a free cloud service offered by Google. It provides a Jupyter Notebook that can be used for writing and executing Python code.Commonly used for deep learning and data analysis projects.It has various features that makes a great user experience,those features include:integration with Google Drive,different types of acceleration (GPU,TPU). Google Colab was chosen to do the training for the dataset using YOLO[41].

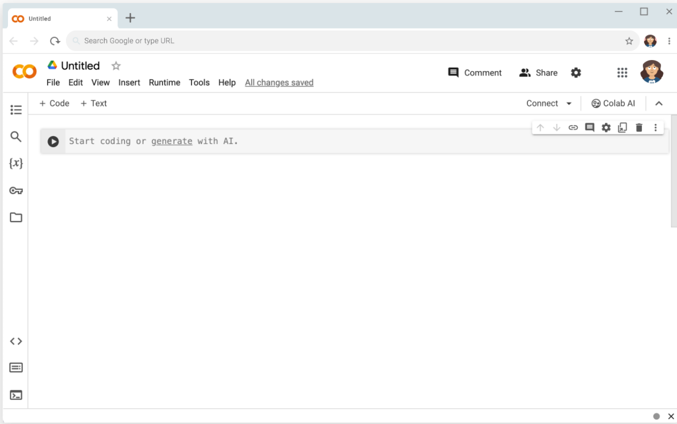

Figure 3.1: Interface of Google Colab

3.2.3 ROBOFLOW

Roboflow is a platform that is widely used in machine learning projects and research. It allows for many tasks: uploading,annotating,training,augmentation and offers various export methods,including YOLO and its many versions (YOLOv8, YOLOv11,etc)[42].

3.3 Implementation

In order to achieve accurate insect detection, the implementation process went through several steps, each step is explained in details.

3.3.1 Methodology

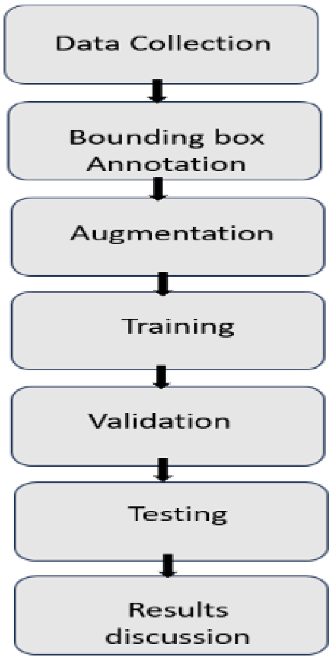

Figure 3.2: Implementation process

3.3.2 Data Collection

Due to the lack of information about the types of predatory insects that attack honey bees in Algeria and the limited available datasets.I had to choose a specific insect to do detection.The insect chosen was the wasp, because it was the one that I confirmed its existance in Algeria, and there were some datasets available for it.However, since the number of wasp datasets was still not enough,I decided to create my own dataset.

I collected images from the following sources:

https://universe.roboflow.com/vespula-vulgarish6jkz/vespulavulgaris/dataset/1

https://universe.roboflow.com/sai-1voka/new-q5ji6/dataset/1

Additionally, I added images from iNaturalist, a famous site used by researchers to collect insect images for their datasets. To ensure that the model performs well in real world detection, I focused on including images from different scenarios:

- Single wasp images

- Multiple wasps in the same image
- Wasps with bees

I also added negative images.These are images that are not labeled because they don't have wasps.Including negative images is extremely important to help the model learn how to differentiate between wasps and bees, harmless insects, and other elements such as animals,humans and backgrounds (flowers,leaves,grass,etc).

The dataset was split as follows: 95% for training and 5% for validation.The test was done later on new images and videos.

The link to the wasp dataset:

https://universe.roboflow.com/meriem-klpeb/waspdetection/dataset/13

The link to the full dataset with negative images:

https://drive.google.com/file/d/1wviqEKtOeQo3Z166eXbMwdVNVCWqZ8tU/view ?usp=sharing

The dataset is structured as follows:

Category	**Original Images**	**After Augmentation**	**Training (95%)**	**Validation (5%)**
Wasps	4946	9384	8876	508
Bees	3583	–	3404	179
Other Insects	2026	–	1925	101
Backgrounds	1463	–	1390	73
Animals	400	–	380	20
Objects	208	–	198	10
Humans	300	–	285	15

Table 3.1: Detailed Dataset Split

Split	Wasp Images	Negative Images	Total Images
Training (95%)	8876	7582	16458
Validation (5%)	508	398	906
Total	9384	7980	17364

Table 3.2: Total Dataset Count

3.3.3 Data augmentation

Data augmentation is a widely used method that aims to create more diverse images in the training set by applying certain transformations, such as rotation, cropping, and flipping,to the dataset. This helps the model learn better with new unseen cases. In this project,because the insects are small and hard to detect, and the image quality varies,I tested several augmentation techniques and in the end chose only light ones that keep the wasp images realistic and clear enough (not too dark or too blurry) so the model can detect the wasps.

1. Horizontal Flip:flips the original image horizantally.

Example:

Figure 3.3: Applying Horizontal Flip

2. Brightness (Between 0% and +15%): increases the original image's brightness to maximum 15%.

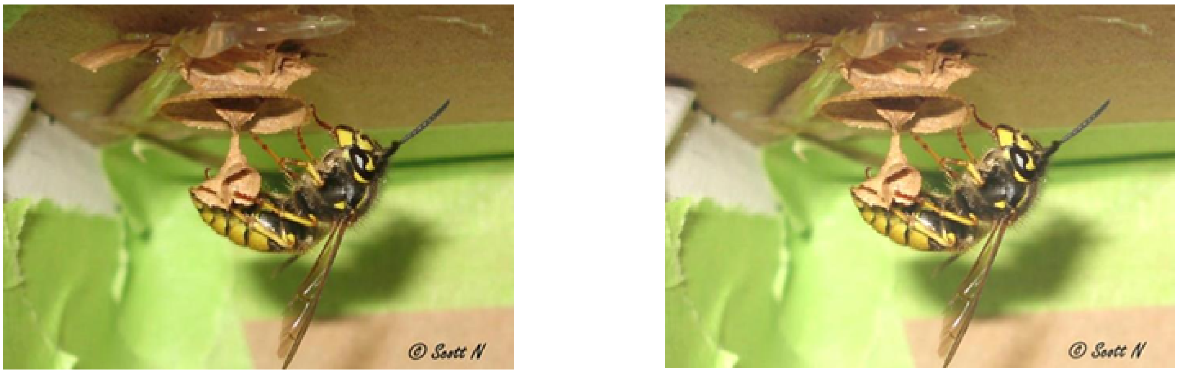

Figure 3.4: Applying Brightness (Between 0% and +15%)

3.Blur(Up to 1px): applies Gaussian blur to maximum 1 px to the input image.

Example:

Figure 3.5: Applying Blur(Up to 1px)

3.3.4 Data annotation

The annotation of wasp images was done on the Roboflow platform. The annotations focused on the most important characteristic of the wasp which is the body but some parts of the the wings and antennae were cut off because wasps have long wings and attennae and including them in the bounding box means also adding more background that can affect the detection process.So, only the body and small parts of the wings and antennae were included.

Figure 3.6: Example of an annotated wasp image

3.3.5 Training

The training was done in Colab, specifically Colab Pro, which offers fast GPUs (A100) and more execution time compared to the Colab Free Plan.The YOLOv11m model was trained using a total of 15,537 images.

The link of the source code:

https://colab.research.google.com/drive/1MZa2w44TrJafA2cXMQPKuYRvtcdYlnba?usp=sharing

3.3.5.1 Training Code Implementation

```
[ ] # Checking GPU
    !nvidia-smi
```

Afficher la sortie masquée

```
[ ] # Installing YOLO
    !pip install ultralytics
```

Afficher la sortie masquée

```
[ ] # Importing
    import ultralytics
    ultralytics.checks()
```

Afficher la sortie masquée

```
[ ] from ultralytics import YOLO
    from IPython.display import Image
```

```
[ ] from google.colab import drive
```

```
[ ] from google.colab import drive
    drive.mount('/content/drive')

    # Extracting the ZIP file
    !unzip -q "/content/drive/MyDrive/WaspDetection.yolov11.zip" -d "/content"

    # Setting the dataset path
    dataset_path = "/content/WaspDetection.v13i.yolov11"
```

```
# Training the model
!yolo task=detect mode=train \
    data={dataset_path}/data.yaml \
    model="yolo11m.pt" \
    epochs=100 batch=16 imgsz=640 multi_scale=True \
    dropout=0.05 cos_lr=True lr0=0.002 momentum=0.94 \
    weight_decay=0.0008  workers=2 patience=20 \
    optimizer=AdamW warmup_epochs=3 warmup_bias_lr=0.1
```

3.3.5.2 Training results

This table is a comparison between Epoch 1 and Epoch 65 (the best epoch). The results show that mAP, precision(P), and recall(R) values have increased significantly, while the box loss value has decreased, meaning the model's detection accuracy for wasp images has improved. Although I set the training to run for 100 epochs, it was stopped early at epoch 85 because I used Early Stopping,that stops the training if no improvements were noticed after 20 consecutive epochs.The best performance was recorded at epoch 65 and the weights were saved in best.pt file.

Metric	**Epoch 1 (First Epoch)**	**Epoch 65 (Best Epoch)**
Box Loss	1.843	0.9832
mAP@50	0.383	0.993
mAP@50:95	0.145	0.721
Precision (P)	0.423	0.978
Recall (R)	0.481	0.979

Table 3.3: Training performance

3.3.6 Validation

Evaluating the performance of the YOLOv11m based model is essential to test its effectivness and precision in real scenarios.The most common validations metrics include:

3.3.6.1 Evaluation Metrics

1. Confusion Matrix

A confusion matrix is a table used to evaluate the performance of the model.The way it works is by comparing the model's predictions with the true results .An example for wasp detection would be:

- **True Positives (TP):** The model correctly detected wasps.
- **False Positives (FP):** The model incorrectly detected other elements (e.g., other insects) as wasps (false detection).
- **False Negatives (FN):** The model failed to detect wasps in the image.
- **True Negatives (TN):** The model did not mistake other elements such as : bees, background,etc,as wasps[43].

2. Presicion(P) Represents the percentage of correct positive detections out of the total positive predictions. It shows the score of true positive predictions out of all the positive predictions[44].

The Formula:

$$\text{Precision} = \frac{TP}{TP+FP}$$

TP (True Positives) ,FP (False Positives)

3.Recall(R)

Represents the percentage of correct positive detections out of all the actual positives. It shows the score of true positive predictions out of all the actual positives in the dataset [43].

The Formula:

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. F1 Score

Merges between precision and recall into a new metric, which makes it suitable for measuring imbalanced datasets performance [43]. It is calculated like this:

$$F1 \text{ Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.Intersection over Union (IoU)

It calculates the overlap between the bounding box and the real bounding box to check how close the prediction is to the correct case[45].

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

6.Mean Average Precision (mAP)

mAP measures the average precision (AP) of every class to see how accurate the predictions are. Its value is between 0 and 1.

mAP@0.5: Calculates the average precision at a 0.5 IoU threshold.
mAP@0.5 to 0.95: Calculates the average precision from 0.5 to 0.95 IoU thresholds[44].

3.3.6.2 Evaluation Code

```
# Validate the model
!yolo task=detect mode=val \
    model="/content/runs/detect/train/weights/best.pt" \
    data={dataset_path}/data.yaml \
    imgsz=640 conf=0.5 \
    save=True save_json=True save_conf=True
```

3.3.6.3 Evaluation Results

Metric	Validation Result
mAP@50	0.984
mAP@50-95	0.737
Precision (P)	0.992
Recall (R)	0.969

Table 3.4: Validation Results

3.3.7 Testing

3.3.7.1 Testing Code

```
!yolo task=detect mode=predict model="/content/runs/detect/train/weights/best.pt"
source="/content/BEEHIVES.PNG" imgsz=640 conf=0.5 save=True
```

3.3.7.2 Testing results

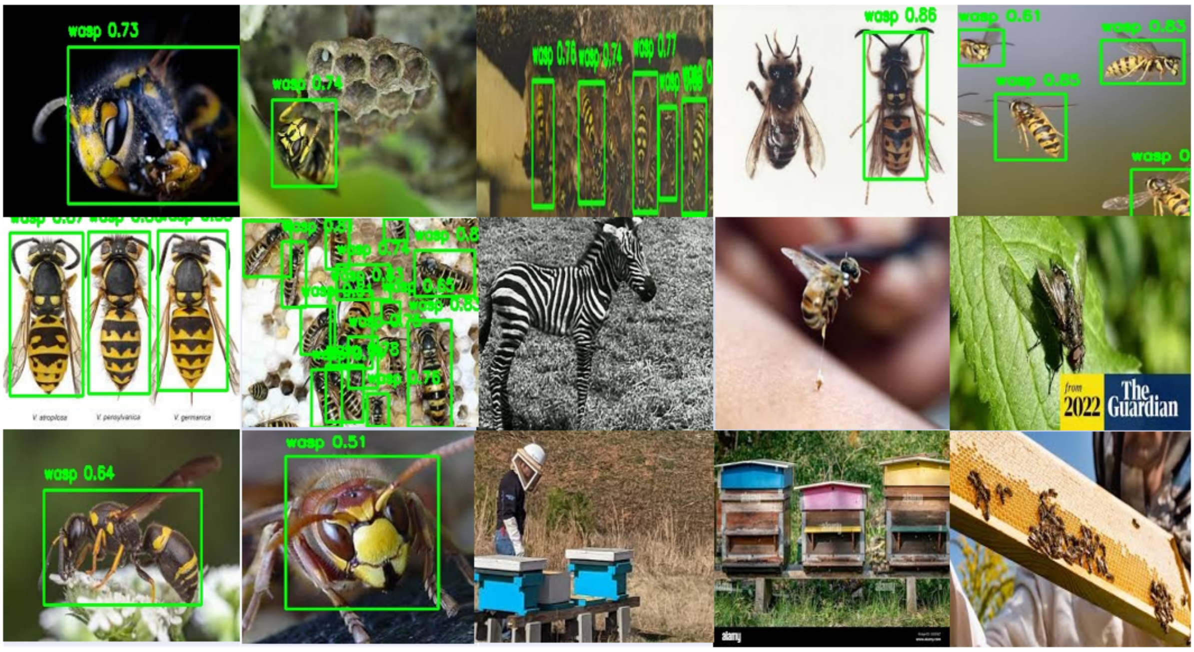

Figure 3.7: The results of the testing

3.3.7.3 Result discussion

The results showed that the YOLOv11m based model was capable of detecting wasps even under challenging conditions, such as low quality and blurry images. It was also effective in differentiating wasps from other items including humans, animals, objects, backgrounds, and other insects.The use of a confidence threshold equal to 0.5,helped reduce false positives,particularly in cases of insects with similar appearance such as hornets. However, the model sometimes struggled with insects that closely look like wasps specifically insects that resembele wasps in terms of shape ,color or size.

The following figure shows a comparison between wasps and some of their look alike insects:

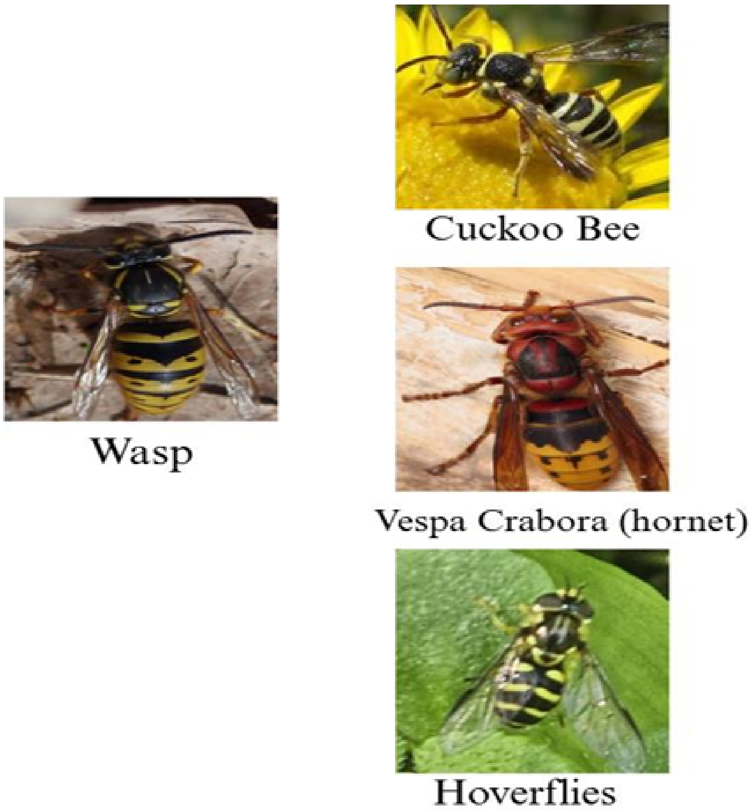

Figure 3.8: Comparison between wasps and some of their look alike insects

3.4 Conclusion

In this chapter,I explored the key concepts and tools used in the development,then went on to show the detailed implementation steps of a YOLOv11m based model for predatory insect detection,specifically wasps. The results demonstrate that the trained YOLO model achieved very high validation performance, with a precision of 0.992, recall of 0.969, mAP@50 of 0.984, and mAP@50-95 of 0.737. The test results also indicate strong performance on wasp images with high accuracy, as well as on negative images. However, the model sometimes makes errors, particularly with insects that share similar appearances with wasps. Regardless, the model showed great potential and can be further improved to achieve even better results.

General Conclusion

The issue of dying bees is considered a major global crisis due to the essential roles that bees play. In Algeria specifically, beekeeping is a very important sector that impacts both food supply and the economy. So, it was necessary to study the bee population and investigate the various causes of honeybee mortality, including predatory insects that kill bees and destroy their hives.Additionally, it was crucial to evaluate the existing solutions,the traditional and technological ones for this threats.

The researches confirmed the lack of effective solutions against invasive insects, Which led to look more in depth to create an efficient solution for this danger in Algeria.The first step was to understand the technologies used in this systems,including Artificial Intelligence (AI), deep learning, Convolutional Neural Networks (CNN), and the YOLO model. The next step was to propose a solution inspired by existing systems and studies: the design of a real-time, automated, and accurate predatory insect detection system based on the YOLOv11m model,that combines between accuracy and performance to detect small and fast moving insects.

The trained model showed great results in detecting wasps, a well known threat to honey bees in Algeria. It performed well on wasp images and negative images, even with images of look alike insects of wasps. The model proved to be very good at detecting wasps in various image qualities and different scenarios: single wasp images, multiple wasp images, and wasps with bees. It was able to differentiate between wasps and all other elements: animals, humans,objects and backgrounds (trees, flowers, leaves, etc).Some misclassifications were noticed due to the extreme similarity in size, shape or color, which confused the model. In terms of negative images, adding more insects that look like wasps, such as hornets, which confused the model, could enhance its accuracy. Apart from that, the model presented strong potential and can be further improved to perform higher detection quality.

Suggested improvements include :

- Searching for more real wasp images instead of relying only on augmentation to help the model learn from various real world cases.
- Focusing on including more images of difficult scenarios such as those with many wasps, wasps with bees and blurry images to help the model learn to detect wasps more accurately even in harsh conditions.
- Including other predatory insects that attack bees in Algeria by interviewing Algerian beekeepers about the specific types of invasive insects and adding them to the dataset.
- In terms of negative images, adding more insects that look like wasps, such as hornets, which confused the model.
- Testing other deep learning models to find the most suitable one for insect detection, such as Faster R-CNN (Region-based Convolutional Neural Network), RetinaNet, DETR (DEtection TRansformer)and others.

In conclusion, this thesis presented a promising idea for an intelligent surveillance system for beehives that can be more improved to include other threats to honeybees and increase its accuracy to develop a system that is more efficient, automated, and works in real time. With further enhancements, such a system with high level performance could be used not just by Algerian beekeepers but by all beekeepers in the world.

References

[1] Food and Agriculture Organization of the United Nations (FAO), “Why we need bees for a nutritious future,” 2023. [Online]. Available: https://www.fao.org/newsroom/story/Why-we-need-bees-for-a-nutritious-future/en.

[2] World Economic Forum, “Why protecting pollinators is essential to securing our food systems,” 2019. [Online]. Available: https://www.weforum.org/stories/2019/12/protect-pollinators-food-security-biodiversity-agriculture.

[3] Auburn University College of Agriculture, “National survey indicates highest bee colony losses in 14 years,” 2024. [Online]. Available: https://agriculture.auburn.edu/news/national-survey-indicates-highest-bee-colony-losses-in-14-years/.

[4] Pollinator.org, “Threats to pollinators,” [Online]. Available: https://www.pollinator.org/threats.

[5] S. Hitouche, M. R. Messak, I. A. Imane, and M. Lazereg, “Challenges of beekeeping in arid regions: A case study from the ziban region, algeria,” Sustainable Environment and Climate Change, vol. 8, no. 4, pp. 191–204, 2024. [Online]. Available: https://armgpublishing.com/journals/sec/volume-8-issue-4/article-13/.

[6] Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, “The assessment report on pollinators, pollination and food production,” 2016. [Online]. Available: https://zenodo.org/records/3402857.

[7] U.S. Environmental Protection Agency (EPA), “Tools and strategies for pollinator protection,” 2025. [Online]. Available: https://www.epa.gov/pollinator-protection/tools-and-strategies-pollinator-protection.

[8] G. Salvatore, A. C. B. Amar, K. Canale-Tabet, R. Fridi, N. T. Aoul, S. Saci, E. Labarthe, V. Palombo, M. D'Andrea, A. Vignal, and P. Faux, "Natural clines and human management impact the genetic structure of algerian honey bee populations," *Genetics Selection Evolution*, vol. 55, no. 1, p. 94, 2023. [Online]. Available: https://doi.org/10.1186/s12711-023-00864-5.

[9] N. Adjlane, B. Dainat, L. Gauthier, and V. Dietemann, "Atypical viral and parasitic pattern in algerian honey bee subspecies apis mellifera intermissa and a. m. sahariensis," *Apidologie*, vol. 47, no. 5, pp. 631–641, 2017. [Online]. Available: https://hal.science/hal-01532357v1.

[10] M. Chahbar, S. B. S. Gaouar, T. Hakim, and N. Adidou, "First spatial distribution of nosemosis (nosema sp.) infected local bee, apis mellifera intermissa in algeria," *Egyptian Journal of Pest Control*, vol. 26, no. 2, pp. 189–194, 2016.

[11] N. Adjlane and N. Haddad, "Prévalence et répartition de la bactérie *Paenibacillus larvae* (agent causal de la loque américaine) au niveau de quelques ruchers de la région centre d'algérie en 2019," *Revue Nature et Technologie*, vol. 13, no. 2, pp. 85–93, 2021.

[12] M. Sarwar, "Insect pests of honey bees and choosing of the right management strategic plan," *International Journal of Entomology Research*, vol. 1, no. 2, pp. 16–22, 2016.

[13] R. K. Gupta, W. Reybroeck, J. W. van Veen, and A. Gupta, Eds., *Beekeeping for Poverty Alleviation and Livelihood Security*. Springer, 2014.

[14] S. Dimitrijević and N. Zogović. Machine learning advances in beekeeping. ICIST. 2022. [Online]. Available: https://www.researchgate.net/publication/363924735_Machine_Learning_Advances_in_Beekeeping.

[15] P. K. Astuti, B. Hegedus, A. Oleksa, Z. Bagi, and S. Kusza, "Buzzing with intelligence: Current issues in apiculture and the role of artificial intelligence (ai) to tackle it," *Insects*, vol. 15, no. 6, p. 418, 2024. [Online]. Available: https://www.mdpi.com/2075-4450/15/6/418

[16] I. Ahmad, Y. Yang, Y. Yue, C. Ye, M. Hassan, X. Cheng, Y. Wu, and Y. Zhang, "Deep learning based detector yolov5 for identifying insect pests," *Agronomy*, vol. 12, no. 19,

2022. [Online]. Available: https://www.mdpi.com/2076-3417/12/19/10167.

[17] M. S. Jeon, Y. Jeong, J. Lee, S.-H. Yu, S. Kim, D. Kim, K.-C. Kim, S. Lee, C.-W. Lee, and I. Choi, "Deep learning-based portable image analysis system for real-time detection of vespa velutina," *Applied Sciences*, vol. 13, no. 13, 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/13/7414

[18] C. I. Narcia-Macias, J. Guardado, J. Rodriguez, J. Rampersad-Ammons, E. Enriquez, and D. C. Kim. Intellibeehive: An automated honey bee, pollen, and varroa destructor monitoring system. [Online]. Available: https://scholarworks.utrgv.edu/cs_fac/130/.

[19] S. Bilik, I. Janakova, A. Ligocki, D. Ficek, and K. Horak, "Computer vision approaches for automated bee counting application," [Online]. Available: https://www.researchgate.net/publication/381404416_Computer_Vision_Approaches_for_Automated_Bee_Counting_Application.

[20] S. Kontogiannis, "Beehive smart detector device for the detection of critical conditions that utilize edge device computations and deep learning inferences," *Sensors*, vol. 24, no. 16, pp. 1–19, 2024. [Online]. Available: https://doi.org/10.3390/s24165444.

[21] Wyze cam for beehive monitoring. [Online]. Available: https://wyze.com/.

[22] "Beemate smart beehive," [Online]. Available: https://beemate.ai/.

[23] IBM, "Artificial intelligence," IBM Think, 2024. [Online]. Available: https://www.ibm.com/think/topics/artificial-intelligence.

[24] G. Voudiotis, A. Moraiti, and S. Kontogiannis, "Deep learning beehive monitoring system for early detection of the varroa mite," *Signals*, vol. 3, no. 3, pp. 506–523, 2022. [Online]. Available: https://doi.org/10.3390/signals3030030

[25] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Liu, X. Wang, and G. Wang, "Recent advances in convolutional neural networks," 2015. [Online]. Available: https://www.researchgate.net/publication/288060170.

[26] S. Dutta, "Exploring filters and feature maps in convolutional neural networks (cnns)," Medium, 2021. [Online]. Available: https://medium.com/@sanjay_dutta/exploring-filters-and-feature-maps-in-convolutional-neural-networks-cnns-b9ec65eb98b4

[27] K. Anupam, "How relu includes non-linearity in neural networks," Medium, 2020. [Online]. Available: https://medium.com/@kumaranupam2020/how-relu-includes-non-linearity-in-neural-network-b9f03fbcbac9

[28] A. Jain, "Pooling and their types in cnn," Medium, 2020. [Online]. Available: https://medium.com/@abhishekjainindore24/pooling-and-their-types-in-cnn-4a4b8a7a4611

[29] D. Unzueta, "Fully connected layer vs. convolutional layer: Explained," Built In, 2025. [Online]. Available: https://builtin.com/machine-learning/fully-connected-layer

[30] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[31] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," *arXiv preprint arXiv:2004.10934*, 2020.[Online]. Available: https://arxiv.org/abs/2004.10934.

[32] Y. Li, Q. Li, J. Pan, Y. Zhou, H. Zhu, H. Wei, and C. Liu, "Yolo-based real-time detection of small and tiny objects in high-resolution uav images," *Remote Sensing*, vol. 16, no. 16, p. 3057, 2024. [Online]. Available: https://doi.org/10.3390/rs16163057

[33] Ultralytics, "Deploying ultralytics yolov11 on rockchip for efficient edge ai," 2024. [Online]. Available: https://www.ultralytics.com/blog/deploy-ultralytics-yolo11-on-rockship-for-efficient-edge-ai.

[34] Ultralyticsc, "Ultralytics/YOLO11. Hugging Face," 2024. [Online]. Available: https://huggingface.co/Ultralytics/YOLO11.

[35] Globant, "Deploying machine learning models on iot devices using onnx," 2023. [Online]. Available: https://medium.com/globant/deploy-machine-learning-models-on-iot-devices-using-onnx-dc34cd854e27.

[36] Reolink, "Beehive camera: How to monitor beehives with security cameras," [Online]. Available: https://reolink.com/blog/beehive-camera/.

[37] Excelite, "Polycarbonate camera dome," [Online]. Available: https://exceliteplas.com/application/polycarbonate-camera-dome/.

[38] SolarClue, "Off-grid solar 24/7," [Online]. Available: https://blog.solarclue.com/blog/off-grid-solar-24-7/.

[39] P and C Today, "Outdoor enclosures help protect bees with housing for hive monitoring device," [Online]. Available: https://www.pandct.com/news/outdoor-enclosures-help-protect-bees-with-housing-for-hive-monitoring-device.

[40] Python Software Foundation, "About python," [Online]. Available: https://www.python.org/about/.

[41] E. Bisong, "Google colaboratory," in *Building Machine Learning and Deep Learning Models on Google Cloud Platform*. Apress, 2019, pp. 59–64, [Online]. Available: https://doi.org/10.1007/978-1-4842-4470-8_7.

[42] Roboflow, "Roboflow: Organize, label, train, and deploy computer vision models," 2023, [Online]. Available: https://roboflow.com.

[43] GeeksforGeeks, "Understanding the confusion matrix in machine learning," [Online]. Available: https://www.geeksforgeeks.org/confusion-matrix-machine-learning/.

[44] Roboflow, "What is mean average precision (map) and how does it work?" [Online]. Available: https://blog.roboflow.com/mean-average-precision/.

[45] B. on Computer Science, "Ml and map in object detection," [Online]. Available: https://www.baeldung.com/cs/ml-map-object-detection.