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Ministry of Higher Education and Scientific Research
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THEME

Oligonychus detection Using YOLO ALGORITHM

Academic Year: 2022/2023

Acknowledgment

First of all, I would like to thank Allah for all the blessings and favors. Then I would like to thank my family and friends for the needed support they gave me during my thesis journey, I would like to thank my father for being a source of inspiration to me. I would like to express my sincere gratitude to our supervisor Dr Belhadj Morad for guiding us through the process of writing this thesis, and helping us in every possible way. I am also grateful to the jury for honoring us with their presence, and accepting to evaluate our thesis, without forgetting all of my teachers who have helped me during my years in collage, especially Dr AMER Khadija, thank you. Finally, it wouldn't be an acknowledgment without mentioning my partner who is like a brother to me, the one who never says "no" to anyone, Yacine, thank you for being such a gentil soul.

Acknowledgment

Firstly, I want to express my sincere thanks to Allah. Your guidance, blessings, and constant presence have been the foundation of my journey and the source of my strength. I would also like to show my deepest gratitude to my family. Their love, support, and belief in me have been crucial to my accomplishments. To my parents, thank you for teaching me the values of hard work and determination. Your unwavering encouragement and sacrifices have shaped me into the person I am today. I am also thankful for the friendship and support of my dear friend, Benali Mohammed Anis. Your friendship has been a source of strength and motivation throughout my journey. To all my friends, mentors, and teachers, thank you for your guidance and wisdom. Your support and dedication have played a significant role in my growth and development. Lastly, I want to express my gratitude to all those who have impacted my life in some way. Your kindness, gestures, and presence have made a lasting impression on me. I am humbled and grateful for the love and support I have received. As I step into the next phase of my life, I carry with me the lessons, memories, and relationships that have shaped me. I am truly fortunate to have such an amazing support system, and I will always be thankful for the role each of you has played in my journey. I would also like to extend my appreciation to my supervisor, Belhadj Morad, for his guidance and support throughout this endeavor.

Abstract

Olygonichus is a widespread crop disease causing concern for farmers globally. Traditional methods have proven ineffective, but recent advances in AI and drone technology offer promise in controlling it.
This discussion focuses on employing AI-powered drones for Olygonichus disease management, potentially boosting crop yields and food security.
The YOLO Algorithm is used for accurate disease detection. With this algorithm, drones can both identify and treat Olygonichus disease:
1. Identification: Trained on images of affected crops, the YOLO algorithm enables drones to swiftly recognize Olygonichus disease. It marks affected areas by drawing boxes around them.
2. Treatment: Equipped with specialized tools, drones can administer targeted treatments to afflicted crops. For instance, they can carry sprayers to apply pesticides directly to affected plants. This precise targeting reduces the need for broad treatment and minimizes harm to unaffected crops.
By merging the YOLO algorithm's identification capabilities with the treatment delivery potential of drones, farmers can efficiently manage Olygonichus disease. This targeted approach safeguards overall crop yield and enhances food security.
Key terms: YOLO, Olygonichus, CNN, Deep learning, Computer vision.

Résume

L'Olygonichus est une maladie généralisée des cultures qui préoccupe les agriculteurs du monde entier. Les méthodes traditionnelles se sont avérées inefficaces, mais les progrès récents de l'IA et de la technologie des drones sont prometteurs. Cette discussion se concentre sur l'utilisation de drones alimentés par l'IA pour la gestion de la maladie d'Olygonichus, ce qui pourrait améliorer les rendements des cultures et la sécurité alimentaire.
L'algorithme YOLO est utilisé pour la détection précise des maladies. Avec cet algorithme, les drones peuvent à la fois identifier et traiter la maladie d'Olygonichus :
1. Identification : Formé sur des images de cultures touchées, l'algorithme YOLO permet aux drones de reconnaître rapidement la maladie d'Olygonichus. Il marque les zones touchées en dessinant des boîtes autour d'elles.
2. Traitement : Équipés d'outils spécialisés, les drones peuvent administrer des traitements ciblés aux cultures touchées. Par exemple, ils peuvent transporter des pulvérisateurs pour appliquer des pesticides directement sur les plantes touchées. Ce ciblage précis réduit la nécessité d'un traitement général et minimise les dommages aux cultures non touchées.
En fusionnant les capacités d'identification de l'algorithme YOLO avec le potentiel de traitement des drones, les agriculteurs peuvent gérer efficacement la maladie d'Olygonichus. Cette approche ciblée protège le rendement global des cultures et améliore la sécurité alimentaire.
Mot clé : YOLO, Olygonichus , CNN, apprentissage en profondeur, vision par ordinateur.

الملخص

حلم الغبار هو مرض محاصيل واسع الانتشار يثير قلق المزارعين على مستوى العالم. أثبتت الأساليب التقليدية أنها غير فعالة، لكن التطورات الأخيرة في تكنولوجيا الذكاء الاصطناعي والطائرات بدون طيار تبشر بالخير في التحكم فيها. تركز هذه المناقشة على استخدام طائرات بدون طيار تعمل بالذكاء الاصطناعي لإدارة مرض اوليگنځهس، مما قد يعزز غلة المحاصيل والأمن الغذائي.

تستخدم خوارزمية يوبو للكشف الدقيق عن الأمراض. باستخدام هذه الخوارزمية، يمكن للطائرات بدون طيار تحديد وعلاج مرض اوليگنځهس:

١. التعرف: تمكّن خوارزمية يوبو، التي تم تدريبها على صور المحاصيل المتضررة، الطائرات بدون طيار من التعرف بسرعة على مرض اوليگنځهس. إنه يميز المناطق المتضررة من خلال رسم صناديق حولها.

٢. العلاج: مجهزة بأدوات متخصصة، يمكن للطائرات بدون طيار إدارة العلاجات المستهدفة للمحاصيل المصابة. على سبيل المثال، يمكنهم حمل الرشاشات لتطبيق المبيدات مباشرة على النباتات المتضررة. هذا الاستهداف الدقيق يقلل من الحاجة إلى علاج واسع ويقلل من الضرر الذي يلحق بالمحاصيل غير المتأثرة.

من خلال دمج قدرات تحديد خوارزمية يوبو مع إمكانية تقديم العلاج للطائرات بدون طيار، يمكن للمزارعين إدارة مرض اوليگنځهس بكفاءة. ويضمن هذا النهج المستهدف مجمل غلة المحاصيل ويعزز الأمن الغذائي.

الكلمات المفتاحية : يوبو ، حلم الغبار ، ث ، تعلم العميق ، الرؤية الحاسوبية .

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General introduction

Smart agriculture using artificial intelligence (AI) is a rapidly growing field that is transforming the way we approach farming. One critical application of AI in agriculture is its use in tackling palm diseases, which have a significant impact on the global date producing. Diseases such as Boufaroua pest (known as Acarus) have been responsible for the destruction of millions of palm trees worldwide, resulting in substantial economic losses for farmers. To address this challenge, we are turning to AI-powered technologies, such as unmanned aerial vehicles (UAVs) and image processing, to detect and diagnose palm diseases in a timely and accurate manner. These tools enable farmers to make data-driven decisions that can help them prevent or mitigate the spread of disease, improve crop yields, and enhance the economic viability of their farms. As such, the integration of AI in agriculture presents a promising avenue for combating palm diseases, promoting sustainable farming practices, and improving the livelihoods of farmers.

Problematic

Despite the farmers and agricultural institutions efforts to preserve crops and provide the necessary conditions for them, pests can still infect them and cause significant losses. One of the most prominent pests that affects date palms is the Boufaroua pest (known as Acarus), which infects the fruits and reduces their quality to the point where they become unsuitable for consumption. As a result, the crop is lost due to the speed of its spread, and chemical treatment is harmful to humans. Other methods of control are also ineffective.

Motivations

Regarding the massive improvement ; Artificial intelligence has given the agrecultural field over the past few years, we were motivated by the potential of the use of Machine Learning in the early detection and classification of the Boufaroua pest (known as Acarus), and the huge impact it has on overcoming the burdens and difficulties existing in the agrecultural field.

Contributions

In our research, we made a significant contribution to the field by focusing on the recognition of Olygonychus disease effects on date fruit using the YOLO algorithm. By leveraging the power of deep learning, we aimed to enhance the accuracy and efficiency of disease detection and classification in date fruit. Through extensive experimentation and analysis, we explored the performance of the YOLO algorithm in accurately identifying and categorizing Olygonichus diseases affecting date fruit. By fine-tuning the model and utilizing different Hyper parameters , we aimed to optimize the detection process.

Chapter 1

Work-Background

1.1 Introduction:

Artificial intelligence can play an important role in detecting diseases in agriculture thanks to its ability to analyze large amounts of data and detect different models and classifications. It can also diagnose diseases by analysing images taken from plant crops and trees to detect signs of specific diseases. Deep AI-based models are trained to distinguish sound papers from those with diseases and determine the type and severity of infection.

1.2 Palm Tree :

1.2.1 History of the palm tree:

Scientists disagree on the origin of the date palm. Some believe it originated in the Arabian Gulf, while others believe it originated in a dry, semi-hot region stretching from Senegal to India. The oldest evidence of date palm cultivation is in Iraq, dating back to over 4,000 years ago. [1]

1.2.2 Geographical distribution of the world's date production :

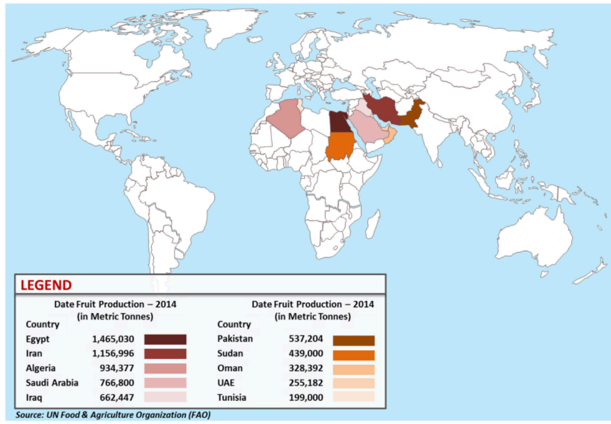

Figure 1.1: WORLD MAP OF THE TOP TEN DATE FRUIT PRODUCING COUNTRIES IN 2014.

1.2.3 Date Palms:Cultivation, Economic Significance, and Nutritional Value:

Date palms are special trees that are known for their valuable fruit, called dates. They have been grown for a long time and are important for the economy in many places. To grow date palms, people need to take care of them. These trees like to grow in hot and dry areas with soil that drains well. They need a lot of sunlight. Date palms have male and female trees, and their flowers get pollinated by the wind or insects. Date palms are very valuable for making money. The dates they produce are in high demand and are used for eating fresh or cooking. Dates are full of good things for our bodies, like fiber and important minerals. Many countries rely on date farming to provide jobs and help their agriculture.

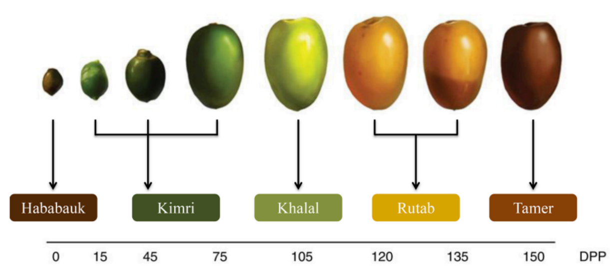

Figure 1.2: THE FIVE GROWTH STAGES OF A DATE FRUIT BY DAYS POST POLLINATION (DPP)

1.2.4 Oligonychus afrasiaticus:

In the most arid regions of North Africa and the Middle East, the date palm mite (DPM), Oligonychus afrasiaticus (McGregor) (Acari: Tetranychidae), In locally called “Boufaroua”(figure1), is a serious pest of date palms. By eating and forming webs on date fruits and reducing their quality and yield, it causes significant economic losses. The most remarkable damage was observed on the commercially valuable Deglet-Nour date variety.

Figure 1.3: NAKED EYE OLIGONYCHUS AFRASIATICUS

In recent years, the Algerian government has invested in the modernization of the date industry, with a focus on increasing production and improving the quality of Algerian dates and this is the statistic of the financial circumstance .

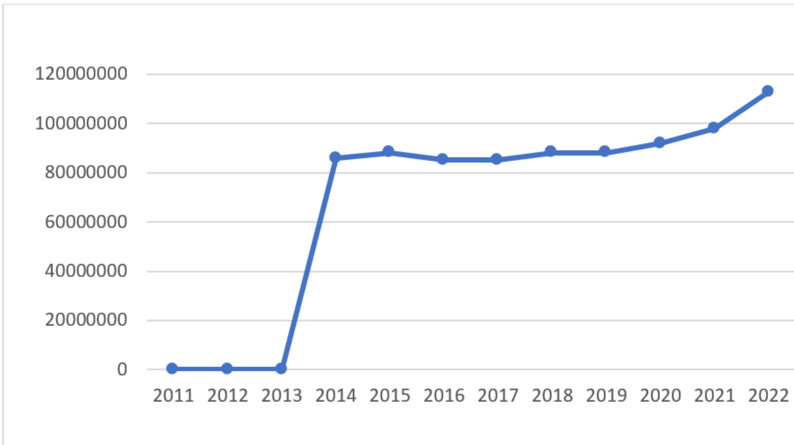

Figure 1.4: financial circustance

Descreption of Oligonychus afrasiaticus

The date dust mite passes through four distinct developmental stages, notably egg, larva, nymph, and adult:

- The adult (figure 1.3) has an almost glabrous body, oval in shape slightly flattened on the dorsal side with 04 pairs of legs. Its color varies from greenish yellow to pink. This mite practically invisible to the naked eye, has a dimension of the order of 0.22 -0.44 mm long and 0.17-0.20 mm wide, It exhibits sexual dimorphism with the end of the body being round in the female and somewhat tapering in the male .

- The egg (figure 1.3) is spherical in shape measuring 0.1 mm in diameter, pink, red or yellow in color. The female can lay 50 to 100 eggs.

- The six-legged larvae (figure 1.3) are smaller (0.15 - 0.20 mm) as compared to the nymphs and adults. Oligonychus afrasiaticus has color morphs and the larvae may assume orange, yellowish white or yellow color and 03 pairs of legs.

- The nymphs possess 4 pairs of legs and their colors range from light yellow to light orange. They resemble adults morphologically; however, they are usually smaller.[2]

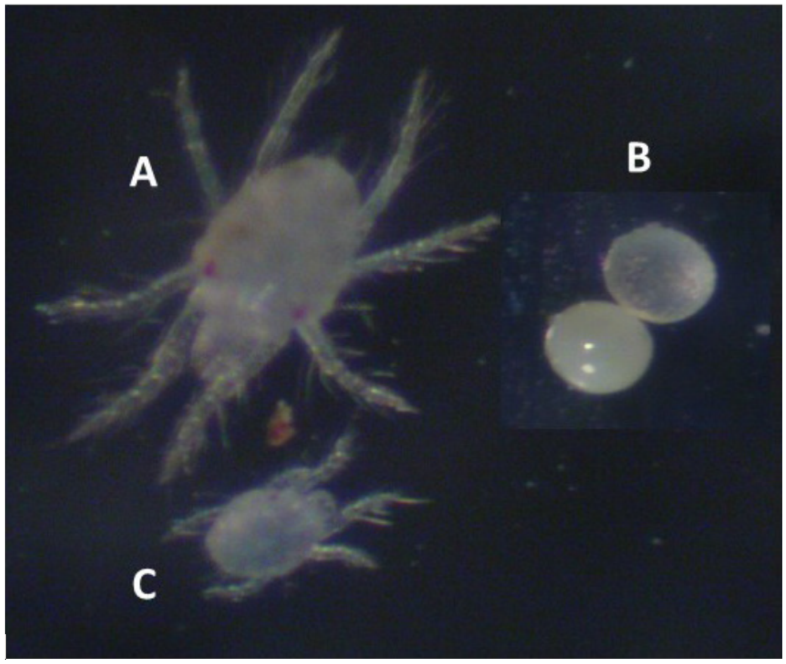

Figure 1.5: Old world date palm dust mite, Oligonychus afrasiaticus, different life stages; (A) adult, (B) egg and (C) larva

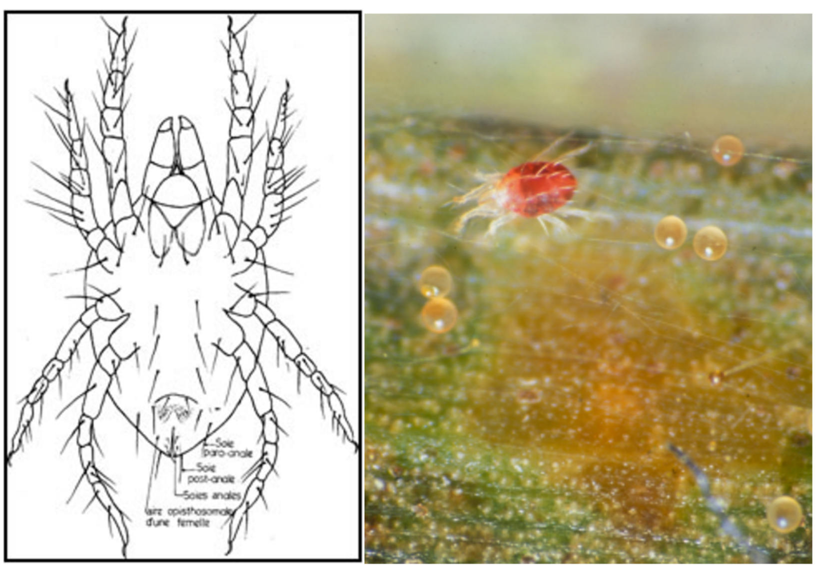

Figure 1.6: Microscopic Oligonychus afrasiaticus

Cycle life of Oligonychus afrasiaticus

Albufurwa spends the winter in the form of adult females in the heart of the palm tree between the fiber and anguish. These females appear between mid and end of June, feeding on soft fronds first and then turning into fruits.
Females begin to lay eggs on the fruit bunch (shamrakh) as well as on the silk tissue secreted by the protonymph and deutonymph and adults, One female dust spider lays 6-23 eggs and averages about 13 eggs throughout her lifetime,eggs hatch after 2 - 4 days, give small larvae, about 0.14 mm long, light green in color - and have three pairs of legs, These larvae feed by sucking plant sap from fruits or plant tissues For a period ranging from 20 to 3 days.
And then these larvae inhabit for a period ranging from 12 to 24 hours, where they shed after that the protonymph with a yellow or green color, which is characterized by the presence of four pairs of legs and is larger than the larva and it is possible to distinguish between the male and the female in this stage.

Figure 1.7: the date palm scale

This spider reproduces sexually where virginal (unfertilized) females lay eggs that produce only males. Adults leave the branch at full maturity of the fruits heading to the heart of the palm where they feed on the new fronds until October, Then it enters the winter sleep phase when temperatures drop and spends the winter period in most cases on the fronds surrounding the heart of the palm or on the grasses in the fields, When temperatures rise, the wicker attacks and then the fruits again.

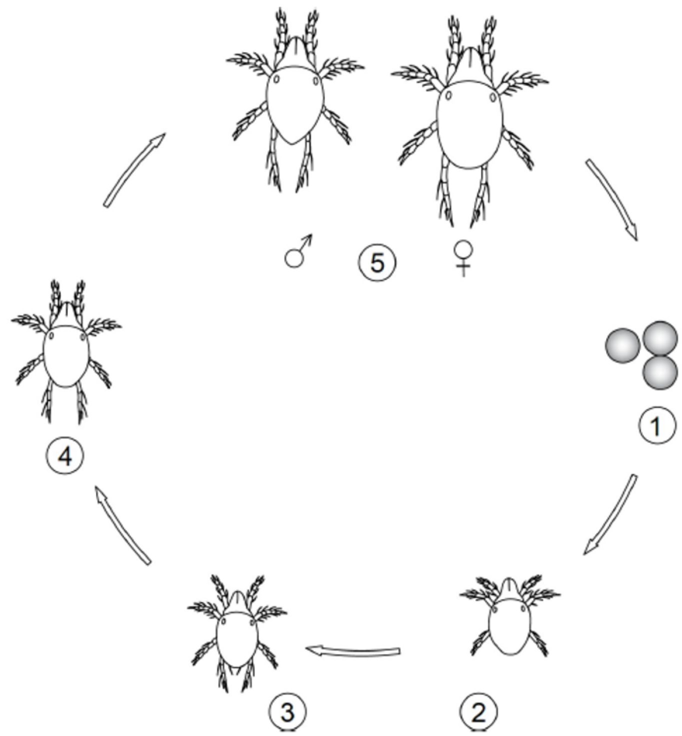

Figure 1.8: Life cycle of the date dust mite, Oligonychus afrasiaticus; (1) egg, (2) larva, (3) protonymph,(4) deutonymph, and (5) adult

Spread and infection

The incidence of this pest increases on palm trees scattered in the streets, where they are considered as windbreaks that trap the pests they carry, including the dust spider, and then multiply and are carried by the wind to other trees, and so on, and it also spreads through its attachment to the legs of insects and birds.

1.3 Artificial intelligent:

It is a branch of computer science that is interested in developing systems and software capable of simulating human intelligence and carrying out tasks that are considered smart in digital environments. AI relies on leveraging technologies such as machine learning, pattern recognition, natural language interaction, sound and image processing

1.4 Machine Learning:

Is a part of artificial intelligence, is the study of computer algorithms that can improve automatically through experience and by the usage of some data. Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, speech recognition, and computer vision.

1.4.1 Type Machine Learning :

Machine learning approaches are traditionally divided into four broad categories:

Supervised Learning:

Supervised learning algorithms build a mathematical model of a set of data that contains both the inputs and the desired outputs. The data is known as training data, and consists of a set of training examples. Each training example has one or more inputs and the desired output, also known as a supervisory signal. Examples of supervised learning algorithms:

- SVM (Support Vector Machine)
- Random forest

Unsupervised Learning:

Unsupervised learning algorithms take a set of data that contains only inputs, and find structure in the data, The algorithms, therefore, learn from test data that has not been labeled, classified or categorized. Instead of responding to feedback. Examples of unsupervised learning algorithms:

- KNN (The k-nearest neighbors algorithm).
- K-means clustering.

Semi-supervised Learning:

Semi-supervised learning falls between unsupervised learning (without any labeled training data) and supervised learning (with completely labeled training data). Some of the training examples are missing training labels.

Reinforcement Learning:

Reinforcement learning is the learning of a mapping from situations to actions so as to maximize a scalar reward or reinforcement signal. The learner is not told which action to take, as in most forms of machine learning, but instead must discover which actions yield the highest reward by trying them

1.5 Deep Learning:

Deep learning is a subset class of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain far from matching its ability, allowing it to "learn" from large amounts of data. [3] [4]

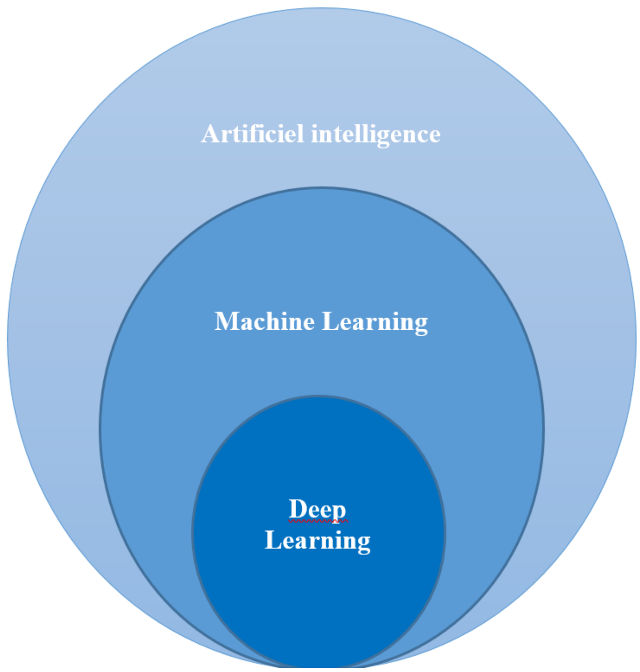

Figure 1.9: RELATIONSHIP BETWEEN THE AI AND ML AND DL

1.6 Digital Imaging:

A digital image is an image composed of pixels, each with finite, discrete quantities of numeric representation for its intensity or gray level. Digital image has two types

- Vector
- Raster

1.6.1 Pixel

A pixel is the smallest unit of a digital image or graphic that can be displayed and represented on a digital display device.

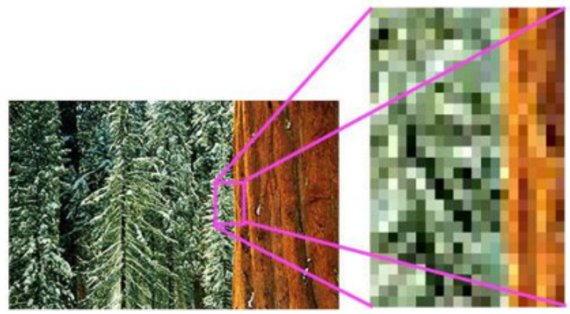

Figure 1.10: PIXEL

1.6.2 Characteristics

The General characteristics of any image are:

Dimension

The size of an image can also be described as its dimension. Usually, it is given in pixels in the format width x height.

Résolution

Resolution refers to the smallest size an object or detail can be represented in an image. Higher resolution means that pixel sizes are smaller, providing more detail.

Histogram

An image histogram is a graphical representation of the number of pixels in an image as a function of their intensity.

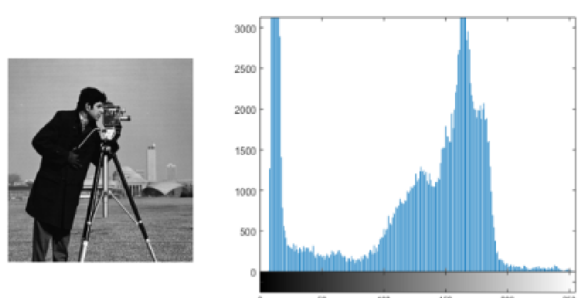

Figure 1.11: HISTOGRAM

Color image

A color image is a picture displayed in color by a computerized device on an attached or separate display screen.

1.7 Computer vision

Computer vision is a predominant and versatile field in the current era and various researchers in this field are carrying out lots of research. Computer vision instructs machines to understand, grasp, and analyze a high-level understanding of visual contents. Its subfields include scene or object recognition, object detection, video tracking, object segmentation, pose and motion estimation, scene modeling, and image restoration [5] . In this review, we focus on the object detection and its relevant subfields such as object localization and segmentation, one of the most important and popular tasks of computer vision. The common deep learning models can be utilized for any computer vision task includes Convolution Neural Network (CNN), Deep Belief Networks (DBN), Deep Boltzmann Machines (DBM), Restricted Boltzmann Machines (RBM), and Stacked Autoencoders.[5]

1.8 Conclusion

In this chapter, we presented the different basics that we should know to start our work on detecting and classifying Oligonychus disease using deep learning. We started by getting to know Oligonychus disease and what is artificial intelligence, and identifying the digital image. we presented a sub class of AI called Machine learning and the deference between the ML and the deep learning. Next, in the next chapter we will focus more on the different methods we have proposed for the detection and classification of Oligonychus disease

Chapter 2

Proposed method

2.1 Introduction

Object detection is an important task in many popular fields such as medical diagnosis, robot navigation, automatic driving, augmented reality and so on. In these complex scenarios, object detection methods based on deep learning approach, such as Region-based Convolutional Neural Networks (R-CNN) , Spatial Pyramid Pooling Networks (SPPNet), fast R-CNN, faster R-CNN , Region-based Fully Convolutional Networks (R-FCN) , Feature Pyramid Networks (FPN) , and You Only Look Once (YOLO) [6] show greater advantages than traditional methods. YOLO is one of the fastest object detection methods with good real-time performance and high accuracy ,various applications have utilized YOLOs for object detection and recognition in various context and performed tremendously well in comparison with their counterparts two stage detectors. This motivates us to write a specific review on YOLO and their architectural successors by presenting their design details, optimizations proposed in the successors, tough competition to two stage object detectors, etc. This section presents the brief introduction of deep learning and computer vision, object detection and related terminologies, challenges, stages and their role in the implementation of any object detection algorithm, brief evolution of various object detection algorithms, popular datasets utilized, and the major contributions of the review.

2.2 Proposed methods

2.2.1 Contribution 1: The use of Yolo

We used transfer learning with YOLOv8 to achieve the best accuracy rate. We experimented with different hyper-parameters, such as the number of epochs, learning rate, and batch size. Here is a more detailed explanation of each hyper-parameter:

- Number of epochs: This is the number of times the model is trained on the entire dataset. A higher number of epochs will generally lead to a more accurate model, but it will also take longer to train.
- Learning rate: these hyper-parameter controls how much the model's weights are updated during training. A higher learning rate will cause the model to learn faster, but it may also cause the model to over-fit the training data.
- Batch size: This is the number of data points that are used to update the model's weights during training. A larger batch size will generally lead to more accurate model, but it will also require more memory and computational resources.

By experimenting with different-hyper parameters, we were able to achieve a high accuracy rate with YOLOv8.

2.3 Convolutional neural network (CNN)

Convolutional Neural Networks (CNNs) are a class of deep neural networks that are specifically designed for processing structured grid-like data, such as images. CNNs are inspired by the organization and functionality of the visual cortex in animals, and they excel at extracting hierarchical features and patterns from input data. By employing convolutional layers, pooling layers, and fully connected layers, CNNs can automatically learn and classify complex patterns and objects in images.[7] [8]

2.3.1 Applications of CNNs

Image Classification

CNNs have been applied in image classification for a long time [9] [10]. Compared with other methods,CNNs can achieve better classification accuracy on large scale datasets [11] [12] [13] due to their capability of joint feature and classifier learning.

Object detection

Object detection is a computer vision task that involves identifying and locating objects in images or videos. It is an important part of many applications, such as surveillance, self-driving cars, or robotics. Object detection algorithms can be divided into two main categories: single-shot detectors and two-stage detectors.

2.3.2 Layers of CNNs

CNNs use a series of layers to extract features from the input data. This allows them to learn hierarchical representations of the data, which can be used to classify images or identify objects within them

Convolutional Layers

Convolutional layers are the heart of a Convolutional Neural Network. They work by convolving the input data with a set of learnable filters, which are small matrices that slide over the input image to extract local features. Each filter produces a feature map, which highlights a specific aspect of the input data, such as edges or corners.

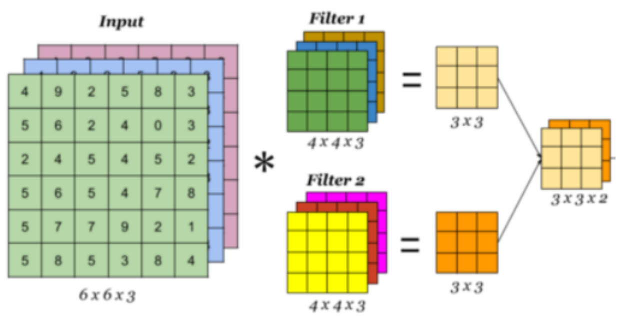

Figure 2.1: CONVOLUTIONAL LAYER

Batch normalization Layer

Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch.

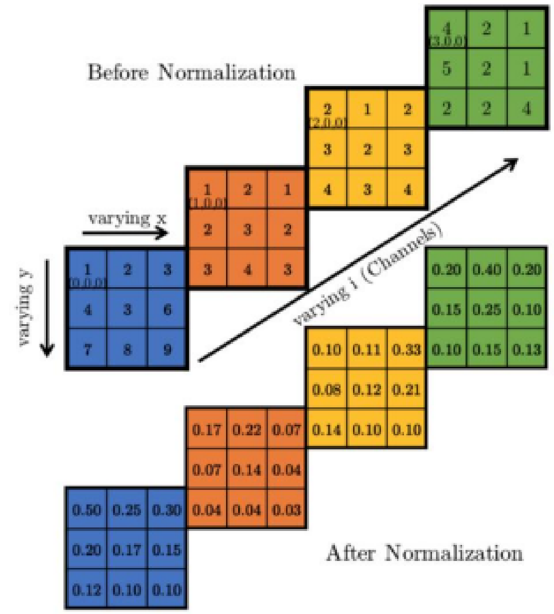

Figure 2.2: BATCH NORMALIZATION EXAMPLE

Pooling layers

Pooling layers are used to downsample the feature maps produced by the convolutional layers, reducing their dimensionality while preserving the most important information. There are several types of pooling that can be used in a CNN, including max pooling and average pooling. Max pooling works by taking the maximum value within a small region of the feature map.

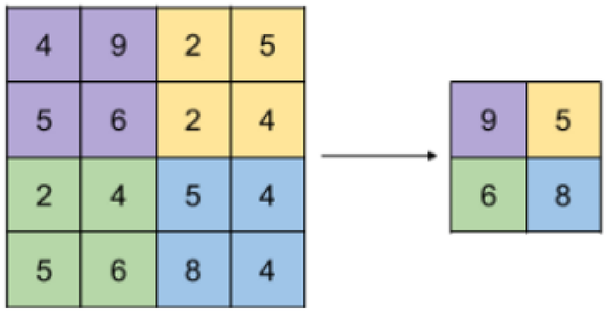

Figure 2.3: MAX POOLING LAYER EXEMPLE

Concatenate layer

In convolutional neural networks (CNNs), a concatenate layer is used to merge the feature maps from different paths or branches of the network. This operation is also known as concatenation or feature map concatenation.

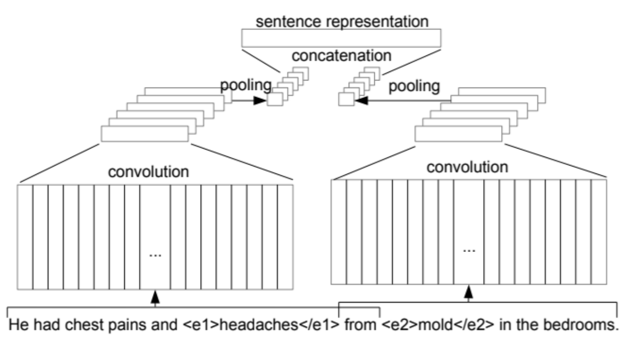

Figure 1: CNN with extended contexts

Figure 2.4: CONCATENATE LAYER EXEMPLE

2.3.3 Activations functions of CNNs

In CNN, activation functions are applied to the output of each layer to insert non-linear into the network. This is important because it allows the network to know more complex relationships between input data and output labels. There are many different activation functions that can be used in CNNs. In the YOLO version used in our subject use ACTIVATION FUNCTION SELU

Scaled Exponential Linear Unit (SELU)

SELU was defined in self-normalizing networks and takes care of internal normalization which means each layer preserves the mean and variance from the previous layers. SELU enables this normalization by adjusting the mean and variance.
SELU has both positive and negative values to shift the mean, which was impossible for ReLU activation function as it cannot output negative values.

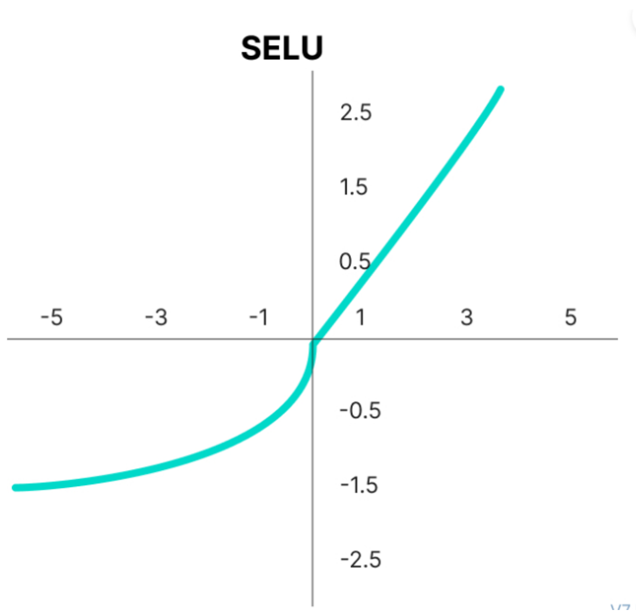

Figure 2.5: SELU ACTIVATION FUNCTION

Mathematically it can be represented as:

Equation 1 SELU

$$f(\alpha, x) = \lambda \begin{cases} \alpha\left(e^{x}-1\right) & for\ x<0 \\ x & for\ x \geq 0 \end{cases}$$

2.4 You only look once (YOLO)

YOLO is a deep learning algorithm that uses a convolutional neural network (CNN) to detect objects in images. It works by dividing the image into a grid and predicting bounding boxes and class probabilities for each grid cell.
YOLO is fast and accurate, as it only requires a single forward pass through

the network to make predictions. This makes it ideal for real-time applications such as Oligonychus detection.

2.4.1 The Evolution of the YOLO Object Detection Algorithm

You Only Look Once (YOLO) is a viral and widely used algorithm [14]. YOLO is famous for its object detection characteristic. In 2015, Redmon et al. gave the introduction of the first YOLO version [14] . In the past years, scholars have published several YOLO subsequent versions described as YOLO V2, YOLO V3, YOLO V4, and YOLO V5 [15] [16]. There are a few revised-limited versions, such as YOLO-LITE [17] [18] . This research paper only focused on the five main YOLO versions.

2.4.2 The YOLO we used

We chose the YOLOv8 architecture under the assumption that it would provide us the highest probability of success given the task. YOLOv8 is assumed the new state-of-the-art due to its lower inference speed on the dataset.

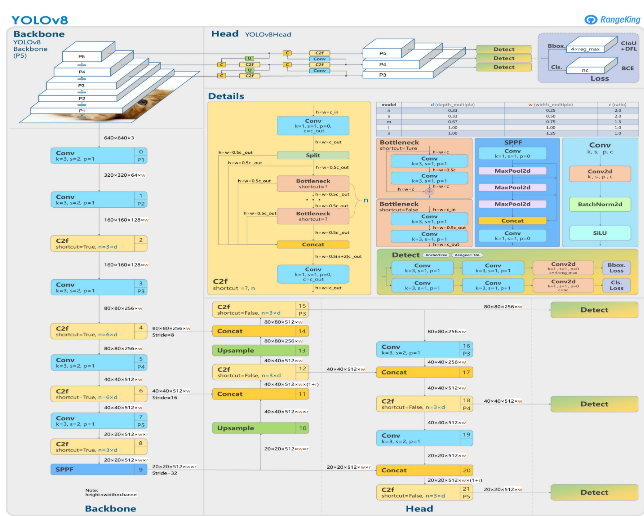

Figure 2.6: YOLOV8 ARCHITECTURE

2.4.3 Loss function used

The generalized loss function and weight update procedure can be defined as follows:

$$\mathcal{L}\left(\Theta\right)=\frac{\lambda_{box}}{N_{pos}}\ \mathcal{L}_{box}\left(\Theta\right)+\frac{\lambda_{box}}{N_{pos}}\ \mathcal{L}_{cls}\left(\Theta\right)+\frac{\lambda_{dfl}}{N_{pos}}\ \mathcal{L}_{dfl}\left(\Theta\right)+\emptyset\ \left\|\Theta\right\|_2^2$$

$$V^t=\beta V^{t-1}+\nabla_\theta\ \mathcal{L}\left(\Theta^{t-1}\right)$$

$$\Theta^t=\Theta^{t-1}-\mathfrak{y}V^t$$

Where 1 is the generalized loss function incorporating the individual loss weights and a regularization term with weight decay θ, 2 is the velocity term with momentum β, and 3 which is the weight update rule and η is the learning rate. The specific YOLOv8 loss function can be defined as:

$$=\frac{\lambda_{box}}{N_{pos}}\sum_{x,y}1\ c_{x,y}^{*}\left[1-q_{x,y}+\frac{\left\|b_{x,y}\ -\hat{b}_{x,y}\right\|_2^2}{\rho^2}+\alpha_{x,y}\upsilon_{x,y}\right]+\frac{\lambda_{cls}}{N_{pos}}\sum_{w,y}\sum_{c\in classes}\mathcal{Y}_c\log\left(\hat{y}_c\right)+\left(1-y_c\right)\log\left(1-\hat{y}_c\right)$$

Where:

$$q_{x,y}=IoU_{x,y}=\frac{\widehat{\beta}_{x,y}\bigcap\ \beta_{x,y}}{\widehat{\beta}_{x,y}\bigcup\beta_{x,y}}$$

$$\upsilon_{x,y}=\frac{4}{\pi^2}(\arctan\left(\frac{w_{x,y}}{h_{x,y}}\right)-\arctan\left(\frac{\hat{w}_{x,y}}{\hat{h}_{x,y}}\right)$$

$$\alpha_{x,y}=\frac{\upsilon}{1-q_{x,y}}$$

$$\hat{y}_c=\sigma\left(.\right)$$

$$\hat{q}_{x,y}=softmax\left(.\right)$$

and:

- N_{pos} is the total number of cells containing an object.
- 1 $c_{x,y}^{*}$is an indicator function for the cells containing an object.
- $\beta_{x,y}$ is a tuple that represents the ground truth bounding box consisting of

(xcoord,ycoord, width, height).
• $\widehat{\beta}_{x,y}$ is the respective cell's predicted box.
$b_{x,y}$ is a tuple that represents the central point of the ground truth bounding box. • y_c is the ground truth label for class c (not grid cell c) for each individual grid cell (x,y) in the input, regardless if an object is present.
• $q_{(x,y)-1}$ are the nearest predicted boxes IoUs (left and right) $\in c^*_{x,y}$
• $w_{x,y}$ and $h_{x,y}$ are the respective boxes width and height.
• ρ is the diagonal length of the smallest enclosing box covering the predicted and ground truth boxes.
Each cell then determines its best candidate for predicting the bounding box of the object. This loss function includes the CIoU (complete IoU) loss proposed by Zheng et al.[6] as the box loss, the standard binary cross entropy for multi-label classification as the classification loss (allowing each cell to predict more than 1 class), and the distribution focal loss proposed by Li et al.[12] as the 3rd term.

2.4.4 The flowchart of our proposed method

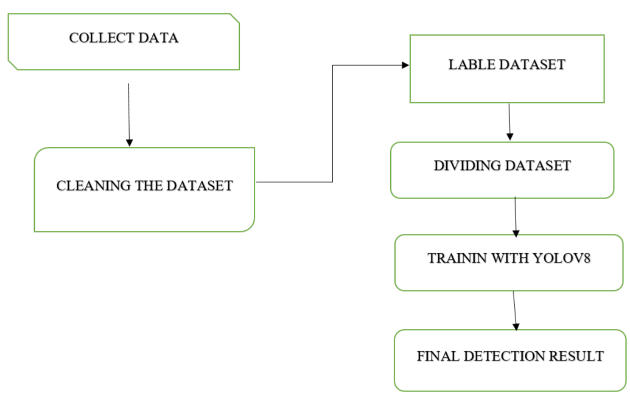

Figure 2.7: The flowchart of our proposed method

2.5 Conclusion

From the latest work with the CNN and YOLO, we got many results some positive and some negative, which we will see in details in the next chapter. We will devout the next chapter to the details of experimental results, with a description of the DATA used as well and the materials, followed by a discussion of the acquired results for our contribution

Chapter 3

Results and discussions

3.1 Introduction

In this chapter, we evaluate how well our method works for detecting Oligonychus using the YOLOv8 algorithm. We start by explaining the dataset we used and the materials we used for our experiments. Then, we present the results for our contribution and discuss how well they performed. We consider things like accuracy, precision, recall, and how fast the algorithm runs. By doing this evaluation, we show how effective the YOLOv8 algorithm is in finding Oligonychous. This chapter is important because it gives valuable information about our approach and its success

3.2 Dataset

A dataset is a collection of structured or unstructured data that is organized and used for analysis, research or training machine learning models. In our subject ("Oligonychus Disease"), we needed an accurate data set, which is why we collected a number of images of dates, including sick and unsick. We also based on Internet sources to collect data, the data set is classified into two categories: sick and unsick date images. Images can lead to remarkable results in the classification, detection and fragmentation of bubbling disease when combined with machine learning.

Table 3.1: DATASETS CLASS AND COUNTITY.

CLASS	TRAIN	TEST	VALIDATE
infested	200	40	40
UNINFECTED	200	40	40

Figure 3.1: UNIFECTED DATASET

Figure 3.2: infested DATASET

3.2.1 Labelled Dataset

Labeling the Dataset Using ”labelimg” In this project, the dataset was labeled using a program called ”labelimg.” Witch is made by python ,This program was utilized to annotate and mark the regions of object on the images.The labeling process involved the following steps:
1. Installation and Setup: The ”labelimg” program was installed and configured on the system. This program provides a user-friendly graphical interface for efficient and accurate labeling.

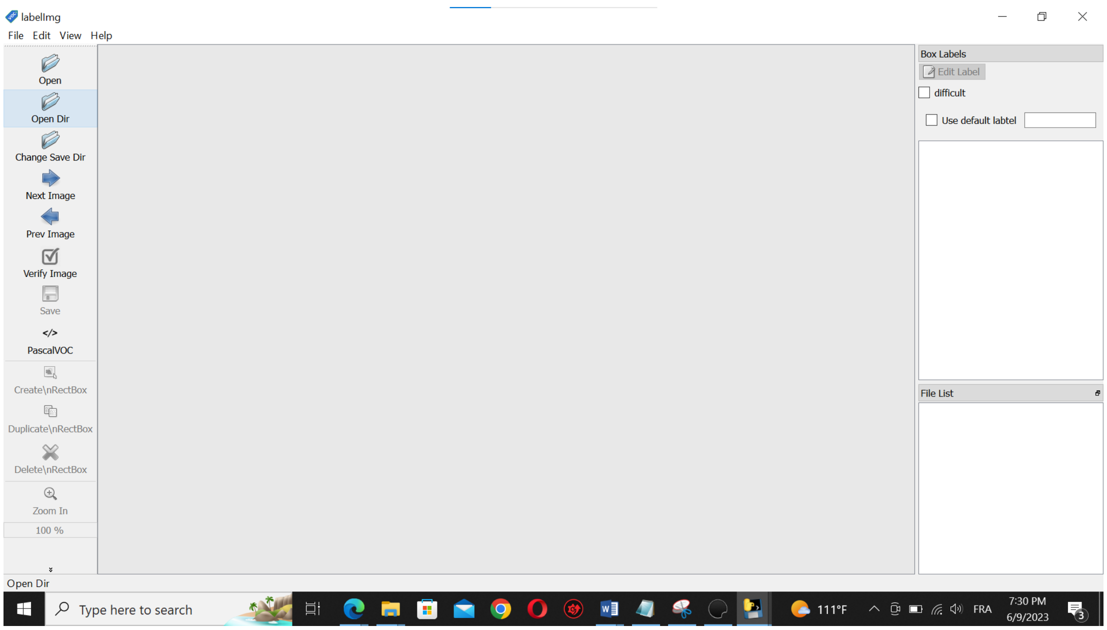

Figure 3.3: INTERFACE OF LABELIMG

2. Loading and Displaying Images: The palm tree images were loaded into the ”labeling” program, which allowed for easy viewing and navigation through the dataset.

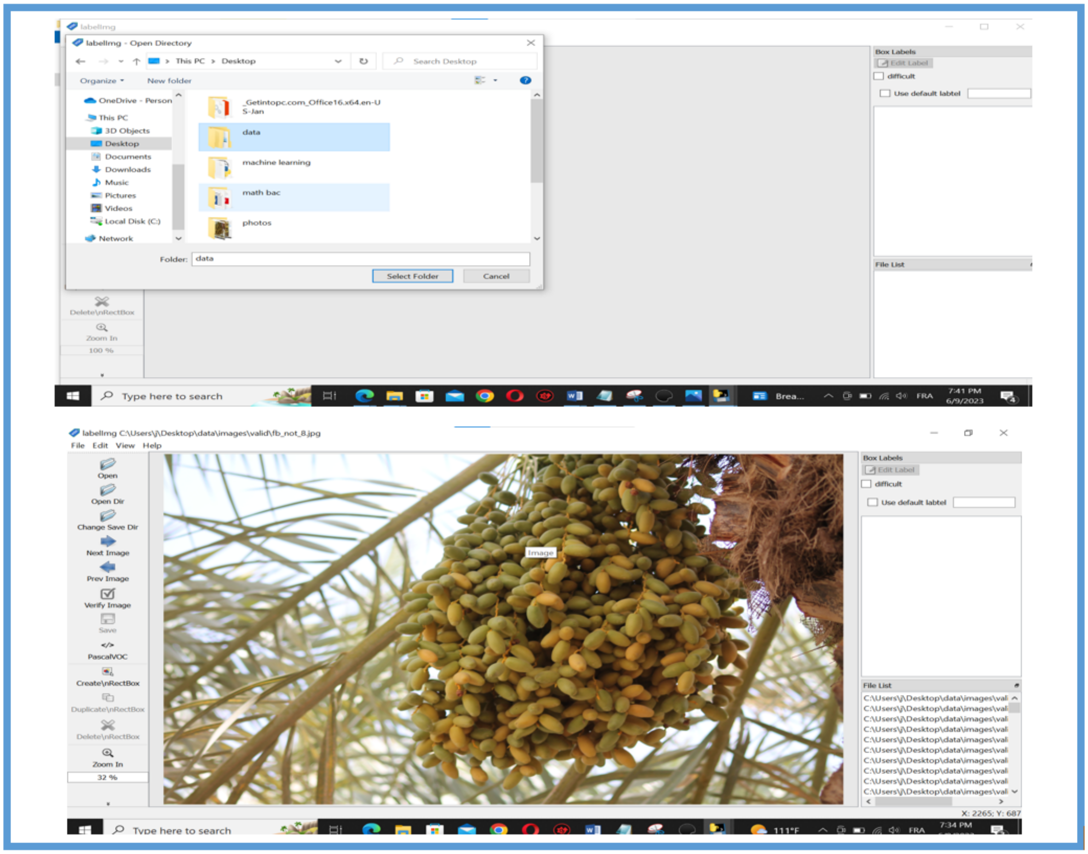

Figure 3.4: LOADING IMAGE

3. Annotation Process: Using the provided tools and functionalities, we manually marked effected date fruit as well as uninfected date fruit by drawing bounding boxes around the objects. These bounding boxes precisely delineated the boundaries of the disease for training the YOLOv8 algorithm. The usage of "labelimg" provided a convenient and efficient solution for dataset labeling. It allowed for precise identification of uninfected and infested date fruit By utilizing this labeling program and following the described process, I ensured accurate annotations, which are essential for training the YOLOv8 algorithm effectively. This labeled dataset serves as a valuable resource for training and evaluating the disease detection model, contributing to the success of this project.

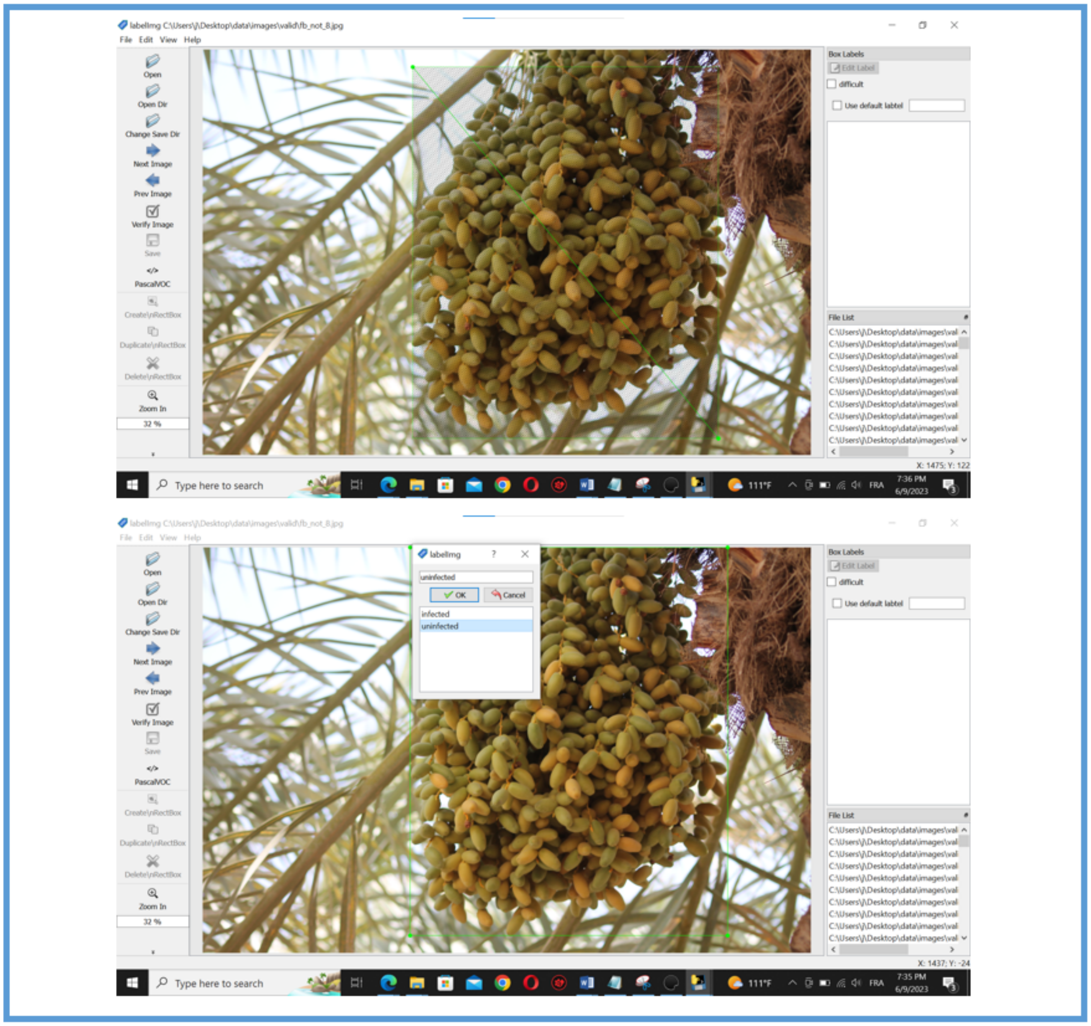

Figure 3.5: ANNOTATION IMAGE

3.3 Materials

- PYCHARM
- PYTHON
- ULTRALYTICS
- OPENCV-PYTHON
- CVZONE

- LABELIMG

3.4 Hardware

All the executions were performed on two different laptops, it is based on regular Jupyter Notebook. The used hardwares have the following specifications:

1. HP ELITEBOOK 830 G5

- Intel®core TM i5-7200U CPU @2.50GHz
- 8GO RAM
- Intel ® HD Graphics 620

1. LENOVO THINKPAD T470P

- Intel®core TM i5-7440HQ CPU @2.80GHz
- 8GO RAM
- NVIDIA GFORCE 940MX

3.5 Results and Discussions

3.5.1 Processing

We started by choosing a hundred epochs of training and splitting the dataset into two parts. We used 90During the process, we tried different values for certain settings like the number of training rounds, the learning rate, and the batch size. After several attempts, we settled on the following settings: a learning rate of 0.012, a batch size of 16, and a total of 100 training epochs.
Using these chosen settings, we ran the training process again to teach our model from the data. The result we obtained reflects our efforts in carefully selecting and fine-tuning these settings to achieve the best performance

3.5.2 Results

CONFUSION MATRIX : This is the confusion matrix of our model

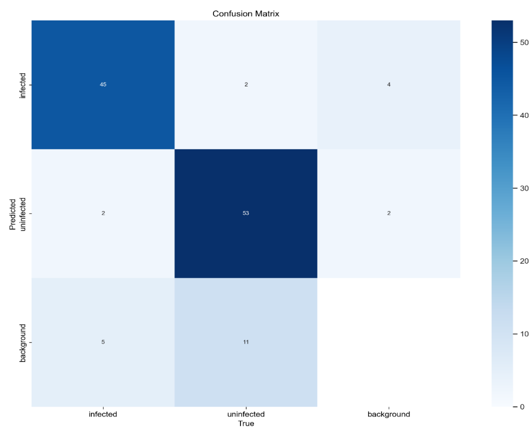

Figure 3.6: CONFUSION MATRIX

Based on the obtained outcome, we were able to quantify the accuracy, precision, and recall metrics.
Overall Accuracy :

$$OverallAccuracy = \frac{Truepositive + TrueNegative}{Allthenumberofconfusionmatrix}$$

$$OverallAccuracy = \frac{98}{124} = 79\%$$

Precision :

$$Precision = \frac{Truepositive}{TruePositive + FalsePositive}$$

$$Precision = \frac{98}{98 + 7} = 87\%$$

Recall Or sensitivity :

$$Recall = \frac{Truepositive}{TruePositive + FalseNegative}$$

$$Recall = \frac{45}{45 + 13} = 77\%$$

F1-Score :

$$F1 - Score = \frac{2PrecisionRecall}{Precision + Recall}$$

$$F1 - Score = 81\%$$

The develop of box_loss and cls_loss during the train : As we can notice the curves of loss_box and cls_loss go down which is good result

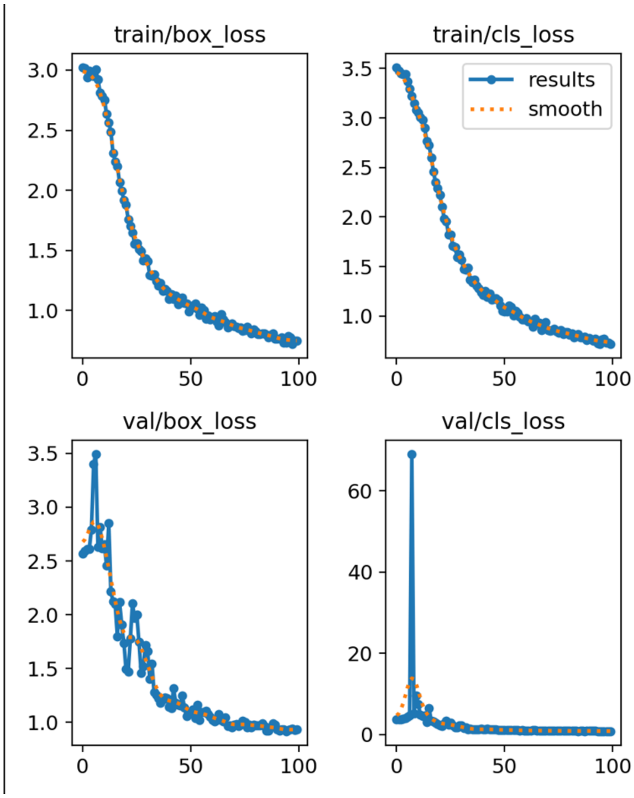

Figure 3.7: CURVES OF BOX_LOSS AND CLS_LOSS

Images Predicted by our model

Figure 3.8: PREDICTED IMAGES

3.5.3 Discussions

We conducted a lot of training sessions and discovered that the model described in this chapter is the most accurate one. It could have been even more accurate if we had a bigger dataset, but we had to work with what was available to us. Despite this limitation, we put in a lot of effort to optimize the model's performance using the resources we had. We carefully analyzed the results of each training session and made adjustments to improve the accuracy. Although we would have liked to have more data, we worked diligently to make the most of what we had

3.6 Conclusion

We began by describing the dataset we used and then examined the materials in detail. Our main contribution involved utilizing the YOLO algorithm with different settings, known as hyperparameters. Initially, we tried using the default hyperparameters, even though the training process took a long time. Unfortunately, we didn't achieve the desired outcome.
To improve the results, we made several changes to the hyperparameters and tested them extensively. We repeated this process multiple times, ensuring each adjustment was carefully assessed. The goal was to find the best combination of settings that would give us the optimal result we were aiming for.

General Conclusion

The use of artificial intelligence (AI) algorithms in plant health has gained significant attention. We did the application of the YOLOv8 algorithm for the detection of Oligonychos disease, a specific affliction affecting palm trees. AI algorithms, such as YOLOv8, have demonstrated promising results across various domains. Our research aims to investigate the effectiveness of the YOLOv8 algorithm in early detection and classification of Oligonychos disease in palm trees. We conducted experiments using a palm tree-specific dataset and implemented the YOLOv8 algorithm accordingly. The training process proved to be time-consuming, requiring substantial computational resources. Throughout our research, we encountered obstacles related to resource limitations, particularly concerning the availability of suitable hardware. Additionally, we faced challenges in comprehending certain AI concepts. Nonetheless, we firmly believe that the field of AI in plant health is still evolving, and with advancements in technology, these limitations will diminish in the future. In conclusion, our study highlights the potential of the YOLOv8 algorithm for detecting Oligonychos disease in palm trees. We anticipate that further research and technological advancements will continue to enhance the accuracy and efficiency of AI-based methods in plant health monitoring and disease detection

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