Technische Universität Clausthal

Master's Thesis

Different Stages of Maturity Detection of Oyster Mushrooms from Images Using Machine Learning

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Abstract

Gourmet mushrooms are seen in the wild and cultivated indoors in a controlled environment, and their maturity identification is labour-intensive. Oyster mushrooms are one of them, adapted for this thesis. Manually looking at the mushrooms for maturity detection is impossible throughout the year in central Europe. So, oyster mushrooms are grown inside the grow chambers in a controlled environment with attached cameras sending pictures hourly. A literature review was conducted to check which methodology can be adapted to solve this problem. Machine learning was one of the methodologies adopted in similar cases; hence, it is chosen here. The oyster mushrooms' image data set was not publicly available; hence, images from the grow chambers were annotated manually. The images were annotated for the model YOLO version 8, adapted for this thesis, which is faster and accurate than other machine learning models for object detection. 572 images of oyster mushrooms were annotated with 1,948 instances of different classes and split into a .8:.2 ratio for training and validation. The images and the annotations were fed into three scales of the YOLOv8 model for training, and they achieved training accuracy of 83.83%, 90.6% and 84.36% on average for YOLOv8 nano, YOLOv8 small and YOLOv8 medium, respectively. These images are also trained and tested on a laboratory platform and tested on Raspberry Pi to incorporate IoT.

Zusammenfassung

Gourmet-Pilze kommen in freier Wildbahn vor und werden in kontrollierten Innenräumen kultiviert. Die Bestimmung ihres Reifegrads ist arbeitsintensiv. Austernpilze sind einer davon, der für diese Arbeit angepasst wurde. Eine manuelle Untersuchung der Pilze zur Reifeerkennung ist in Mitteleuropa das ganze Jahr über unmöglich. Daher werden Austernpilze in den Wachstumskammern in einer kontrollierten Umgebung gezüchtet, wobei angeschlossene Kameras stündlich Bilder senden. Es wurde eine Literaturrecherche durchgeführt, um zu prüfen, welche Methodik zur Lösung dieses Problems angepasst werden kann. Maschinelles Lernen war eine der Methoden, die in ähnlichen Fällen angewendet wurden; daher wird es hier ausgewählt. Der Bilddatensatz der Austernpilze war nicht öffentlich verfügbar; Daher wurden die Bilder aus den Wachstumskammern manuell mit Anmerkungen versehen. Die Bilder wurden für das für diese Arbeit angepasste Modell YOLO Version 8 annotiert, das schneller und genauer ist als andere maschinelle Lernmodelle zur Objekterkennung. 572 Bilder von Austernpilzen wurden mit 1.948 Instanzen verschiedener Klassen annotiert und für Training und Validierung in ein Verhältnis von 0,8:0,2 aufgeteilt. Die Bilder und Anmerkungen wurden zum Training in drei Skalen des YOLOv8-Modells eingespeist und erreichten eine Trainingsgenauigkeit von durchschnittlich 83,83 %, 90,6 % und 84,36% für YOLOv8 nano, YOLOv8 small und YOLOv8 medium. Diese Bilder werden auch auf einer Laborplattform trainiert und getestet und auf Raspberry Pi getestet, um IoT einzubinden.

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Contents

List of Abbreviations

AI .... Artificial Intelligence

YOLO .... You only look once

SSD .... Single short multi-box Detector

VGG .... Visual Geometry Group

CNN .... Convolutional neural network

RGB .... Red Green Blue

ANN .... Artificial neural network

CVAT .... Computer Vision Annotation Tool

YAML .... Yet Another Markup Language

MATLAB ..... Matrix Laboratory

ML .... Machine Learning

DL .... Deep Learning

ReLU .... Rectified Linear Unit

RCNN .... Region-Based Convolutional Neural Network

Chapter 1

Introduction

Gourmet mushrooms are tasty and in high demand. Gourmet mushrooms like oysters, mushrooms, shiitake and king oysters are widely seen in markets where skilled humans must look into it to identify the maturity of mushrooms, which is a time-consuming task [1]. Due to economic factors and growing environments, the farmers are losing hundreds of millions yearly because they cannot harvest the right matured ones [2]. The maturity detection of gourmet mushrooms can be automate to save time and money by adopting AI methods. For now, oyster mushrooms are adopted for this thesis as they are easy to grow with little care. For this thesis, the oyster mushroom is grown in indoor champers with a controlled environment as depicted in Figure 1.1.

FIGURE 1.1: Mushroom Grow Champers in DIGIT lab Goslar, Germany (Source: [3])

1.1 Cultivation of Oyster Mushrooms

The mycelium, which is the fungal culture of the mushrooms, is used to grow the mushrooms on a large scale. The mycelium propagation of oyster mushrooms is bought from farmers and online markets. The mycelium is transferred to the substrate. Wheat was used as the primary substrate, the medium for propagating the mycelium and kept in the grow chambers for growth and fruiting. Once they start to pop out from the expected opening from the grow pods, they are observed closely and harvested by gently twisting them [4]. The grow pods used here are reusable plastic buckets. The chances of contamination and bacterial yellowing of oyster mushrooms is high when not correctly observed [4]. To monitor the growth of the indoor oyster mushrooms, cameras at different angles are fixed inside the champers in Figure 1.1.

Reusable plastic grow pods were used to reduce the amount of plastic waste produced. Proper holes were used on the sides of the boxes for the fruiting. The grow pods were stacked on each other to reduce the space by replicating vertical farming, which is self-described in Figure 1.2.

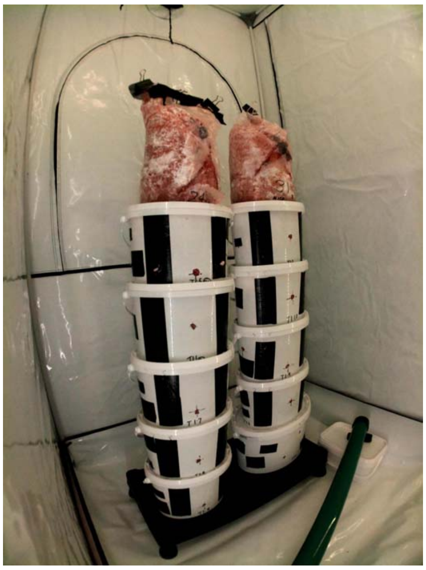


Figure 1.2: Mushroom Grow pods stacked facing cameras inside grow chambers (Source: [3])

This thesis aims to automate the identification of the different maturity stage of oyster mushrooms from images collected from the grow chambers Figure 1.1. This experimental set-up was carried out in DIGIT, Goslar, Germany. Figure 1.3 shows an example of oyster mushrooms during harvesting from the grow chamber Figure 1.1. The grow pods with matured mushrooms on the top bucket and the over-matured oyster mushrooms at the bottom bucket.

FIGURE 1.3: A sample of oyster mushrooms during harvesting from chambers(Source: [3])

1.2 Existing Body of Knowledge

This section describes what already exists in the maturity identification of the crops and other mushrooms from images for building this thesis. A scientific literature review is significant for understanding what others have done regarding the maturity identification of different crops and mushrooms. Automated harvesting in agriculture has a significant role when considering labour effort. When automation is incorporated, the human effort and harvesting costs are reduced. Section 1.2.1 describes the existing automated ready-to-harvest stages of different crops, followed by Section 1.2.2 specifically describes mushrooms and Section 1.2.3, the detected gap that contributes to the base of this thesis.

1.2.1 Maturity Detection of Different Crops

Mark Antony et al. [5] have used image-processing techniques to find the maturity of different fruits from images and assess whether they are ready to harvest. The convolutional neural network, abbreviated to CNN, was used to determine the maturity of the fruits. Images of bananas, mango and calamansi (Philippine lime) are classified into pre-matured, matured and over-matured stages. Images were taken and fed into the CNN from the daily video recording of the fruits' growth stages. The images coming from the convolutional layer are fed into the max pool layer [5]. The images were also converted into a greyscale for better results. One of the results of this study was that Red, Green and Blue (RGB) images were predicted more accurately than grey-scale images [5]. The bananas were predicted with an accuracy of 97% for RGB images, and calamansi were predicted with an accuracy of 87% for grey scale images. Mangoes have a lower prediction percentage.

K.Raut et.al [6] used artificial neural networks and image analysis software like matrix laboratory (MATLAB) to determine the maturity of fruits like cherries and strawberries by analyzing the colour images. The fruits were classified as pre-matured, early-matured, mature, and over-matured. The input RGB images are fed into the Red and Green channels, followed by the Red and Green mask and features of the fruits are extracted. Image augmentation is done to each input image for feature extraction that can extract the colour features of the cherry and strawberry [6]. The feature extraction is done to reduce the image size to feed into the feed-forward network. Moreover, clustering is done to classify the good and bad fruits [6]. 17 and 26 samples of cherry and strawberry were used to train and test. The artificial neural network (ANN) [7] architecture used has 24 input neurons and 48 hidden layers, and the architecture could predict early matured, pre-mature, pre-over-matured, and over-matured cherries and strawberries. Maturity analysis using image processing using MATLAB predicted 63% and 60% for cherry and strawberry fruit, respectively, for different maturity stages for the fruits [6].

1.2.2 Maturity Detection of Mushrooms

This section explicitly dives through the works on oyster mushrooms' maturity identification. Michael B. Crowe [8] from Arizona, United States, a famous mushroom farmer, has experienced cultivating large-scale gourmet mushrooms, manually looking with bare eyes and gently twisting the matured ones from the grow pods for selling. Taking this into account, automated maturity identification can be made to reduce the time and reduce skilled labour, which consumes time[9].

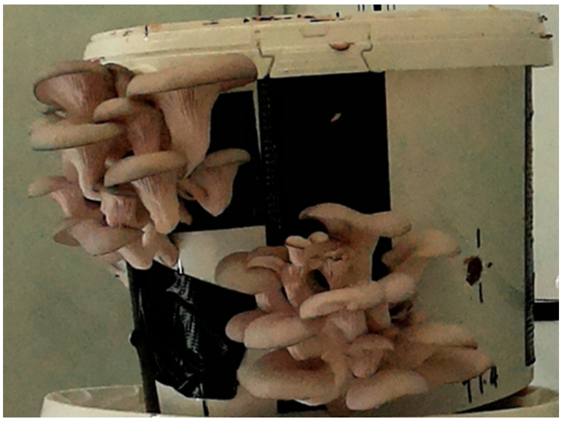


FIGURE 1.4: A sample of matured mushrooms from growing pods.(Source: [3])

Yang Qian et al. [1] have proposed a deep learning technique called Single Shot Multi-Box Detector (SSD) method, which is used for object detection from the images. The study contributes to oyster mushroom identification from the images so the robot arm can locate and harvest the matured ones. The SSD method is first applied to the images of the oyster mushrooms to extract the features. The number of images used for training, validation and testing was 4000, 3000 and 300, respectively [1]. The images are collected from the greenhouse at different times and in light. Rectangle boxes are drawn around the mushrooms called anchor boxes and converted to their pixel values. These values are fed to the SSD methods. The SSD method is trained with a learning rate of 0.001 and a batch size of 60; the model is saved every 10 minutes during training [1]. Three-dimensional positional technology is for localizing where the mushrooms in the 3D space for the robot to pick them up accurately. The model attains a 0.951 F1 score in detecting the mushrooms and an average 3D localization error of 2.43mm [1]. Figure 1.5 shows an example of how mushroom grow pods are arranged and anchor box around them.

FIGURE 1.5: Oyster mushrooms images from the greenhouse.(Source: [1])

Hashim et al. [10] proposed a grading system for grey oyster mushrooms for farmers to export to supermarkets. Depending upon the colour, size, and damage conditions of the grey oyster mushrooms, the mushrooms are graded into grades 1,2 and 3, where grade 1 is best quality, grade 2 is acceptable quality and grade 3 is not acceptable for sale [10]. For this intra-class classification, deep learning is utilized. Visual Geometry Group with 16 (vgg16) layers is one of the CNN networks used in this study [10]. A total of 540 images were used to train the network and 60 for testing. The image size of 224 x 224 pixels is set as per the requirement of vgg 16, with a batch size of 6 [10]. The model achieves an accuracy of 96.6% for ten epochs. Figure 1.6 is an example of oyster mushrooms images used for training.

1.2.3 Contribution - Detecting a Gap

As Section 1.2.2 states, the maturity of oyster mushrooms is detected using various methods. Section 1.2.2 discussed the oyster mushroom study, but the image data set

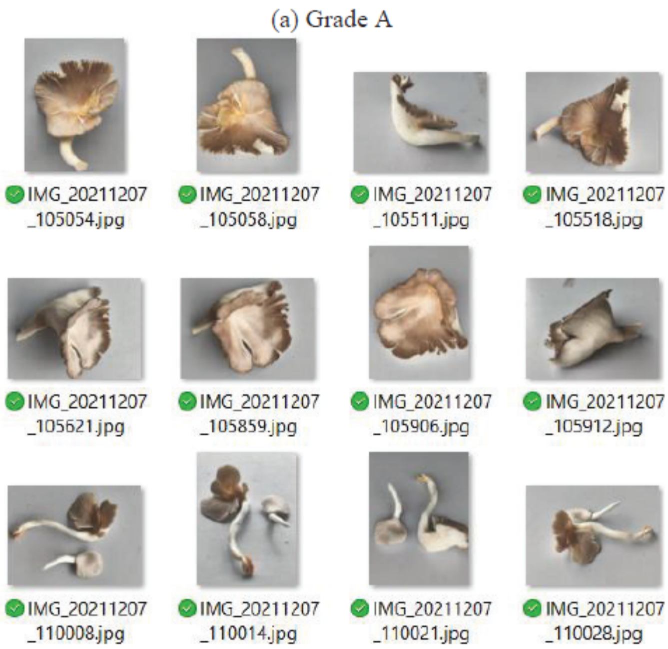


FIGURE 1.6: Oyster mushrooms image data set used for training vgg16.(Source: [10])

was publicly unavailable. Moreover, the images are not applicable in this context. Cultivating and harvesting the oyster mushroom is a labour-intensive task that needs to be automated. This thesis aims to automate the maturity detection of the oyster mushroom that grows in grow pods in indoor chambers with a controlled environment. The data set was prepared for this thesis because the oyster mushrooms different growth stage images are not publicly available. This thesis first specifies the scientific ways to do a literature review to know the existing body of knowledge. It is, furthermore, finding a method that can accurately identify the matured oyster mushroom from the not-ready and overdue oyster mushrooms.

1.3 Research Questions

This thesis aims to fill the gap detected in Section 1.2.3. The goal of the main research question is to fill the gap, and it is as follows: **RQ: How to Detect the Maturity of the Oyster Mushrooms from Images Grown in Indoor Chambers?**
The main research question is subdivided into three sub-research questions to answer in a more formal and structured manner. The sub-research question is as follows:

- **RQ-1: How to review the literature for an existing methodology for maturity detection of the oyster mushroom from the images?**

- **RQ-2: How to prepare the image data set for maturity detection of oyster mushrooms?**
- **RQ-3: How to develop a model for object detection and classification?**

The RQ1, RQ2, and RQ3 are answered in a way that systematic and structured ways that contribute to the main research question. The RQ1 describes how to conduct a literature review in the field of computer science that can lead to finding an answer to the defined problem. This answer leads to choosing a model that can accurately predict the oyster mushrooms from the images. For predicting the mushrooms, how to prepare the images will be answered in RQ2. In the end, RQ3 is answered on how to develop the model for mushroom detection from the images prepared in RQ2. Answering the sub-research questions contribute to answering the main research question of this thesis.

1.4 Research Methodology

This section describes the methodology selected for answering the research question stated in Section 1.3. This thesis aims to automate the maturity detection of the oyster mushrooms from the images, which includes preparing the images and developing the model that can predict the matured mushrooms from the images; the design science paradigm [11] is suitable for this thesis and adopted here. The following section describes the process of conducting the design science and is followed by the section on how this thesis sticks to this paradigm to answer the research question stated in Section 1.3.

1.4.1 Design Science Research - Theory

Hevner et al. [11] define that "the design-science paradigm seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artefacts". "In the design-science paradigm, knowledge and understanding of a problem domain and its solution are achieved by building and applying the designed artefact" [11]. Design science is fundamentally a problem-solving skill [11]. "It seeks to create innovations that define the ideas, practices, technical capabilities, and products through which the analysis, design, implementation, management, and use of information systems can be effectively and efficiently accomplished" [11]. Hevner et al. [11] state that IT artefacts are defined as a construct (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems). "These concrete prescriptions enable IT researchers and practitioners to understand and address the problems inherent in developing and successfully implementing information systems within organizations" [11].

The following section describes how the design science research is conducted in this thesis [11].

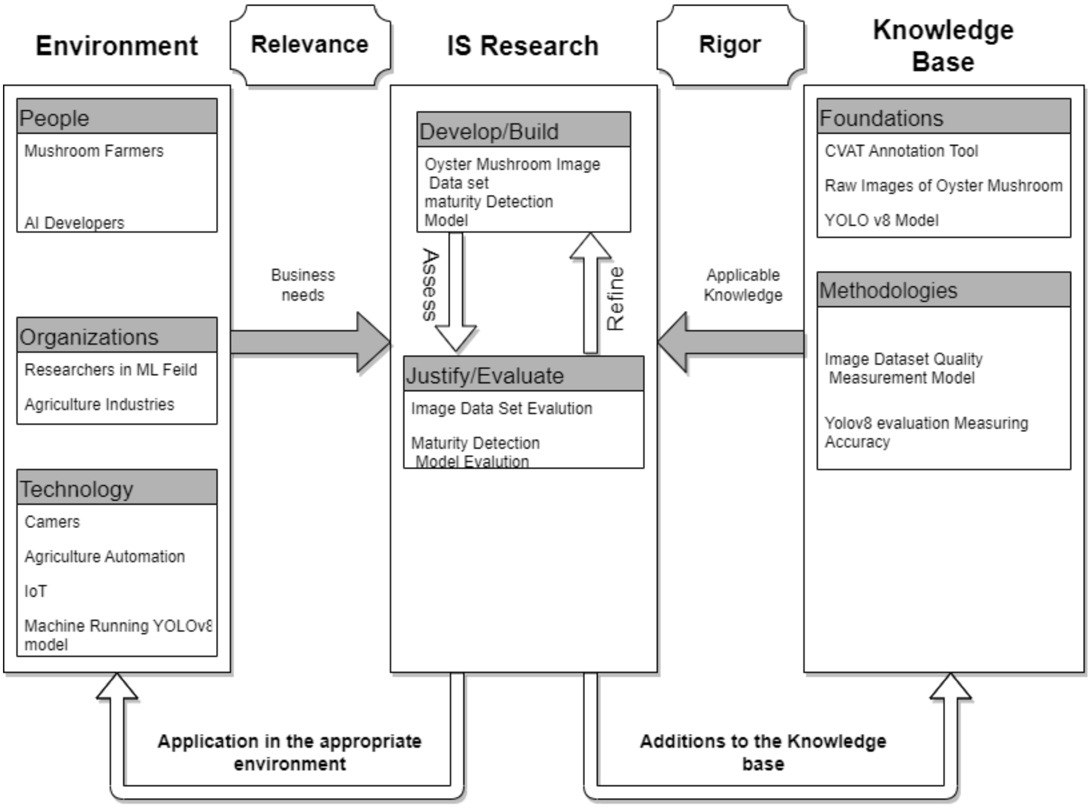


FIGURE 1.7: Design Science Research - Framework (Source: [11])

The new artefacts created by the design science framework for this thesis can be found in Figure 1.7. "The environment defines the problem space in which the phenomena of interest reside" [11] . In this thesis, the environment is farmers and the AI developers who cultivate oyster mushrooms and must harvest them manually. The IS research is composed of two phases: development and justification. In the development phase, the artefacts created here are the image data set and the model that detects the maturity of the oyster mushrooms created; in the evaluation phase, the newly created artefacts are evaluated using the design evaluation methodologies stated in the [12] for the data set , for evaluating the model created for maturity detection, Chapter 6 describe the methods. The artefacts were created to contribute to the knowledge base, which consists of two parts: foundations and methodologies. The literature review was done to find the references that can lead to the solution to the problem identified. The methodology to evaluate the artefacts created is defined in the methodology section of this thesis data analysis and model validation are applicable. How well the model is good at detecting the maturity of oyster mushrooms from images and the image data set created provides an excellent solution to this thesis.

1.4.2 Design Science Research - Guidelines

This section describes the guidelines for practising design science research, Hevner et al.[11] "state that design science is an inherent problem-solving process". The artefacts are created by following these guidelines. The guidelines are integrated into the table below.

Guideline	Description
Guideline 1: Design as an Artifact	Design-science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.
Guideline 2: Problem Relevance	The objective of design-science research is to develop technology-based solutions to important and relevant business problems.
Guideline 3: Design Evaluation	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.
Guideline 4: Research Contributions	Effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.
Guideline 5: Research Rigor	Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Guideline 6: Design as a Search Process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Guideline 7: Communication of Research	Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.

TABLE 1.1: Design Science Research - Guidelines (Source: [11])

The application of these guidelines to this thesis is as follows.

1.4.2.1 Guideline 1: Design as an artefact

The created artefacts lead to closing the gaps that are described in Section 1.3. The artefacts created here are the image data set of the oyster mushroom that grows in indoor chambers in DIGIT, Goslar ,Germany and the developed model that takes the images to predict the correct maturity of the oyster mushrooms.

1. Observational	Case Study: Study artifact in depth in business environment
	Field Study: Monitor use of artifact in multiple projects
2. Analytical	Static Analysis: Examine structure of artifact for static qualities (e.g., complexity)
	Architecture Analysis: Study fit of artifact into technical IS architecture
	Optimization: Demonstrate inherent optimal properties of artifact or provide optimality bounds on artifact behavior
	Dynamic Analysis: Study artifact in use for dynamic qualities (e.g., performance)
3. Experimental	Controlled Experiment: Study artifact in controlled environment for qualities (e.g., usability)
	Simulation – Execute artifact with artificial data
4. Testing	Functional (Black Box) Testing: Execute artifact interfaces to discover failures and identify defects
	Structural (White Box) Testing: Perform coverage testing of some metric (e.g., execution paths) in the artifact implementation
5. Descriptive	Informed Argument: Use information from the knowledge base (e.g., relevant research) to build a convincing argument for the artifact's utility
	Scenarios: Construct detailed scenarios around the artifact to demonstrate its utility

Table 1.2: Design Science Research - Evaluation Methods (Source: [11])

1.4.2.2 Guideline 2: Problem Relevance

The problem described here is to identify whether the oyster mushrooms growing in indoor chambers are ready to harvest or precisely at what growth stage the mushrooms can be harvested to rely on something other than human experts to harvest them. By automating the maturity identification of the gourmet mushrooms, the time consumed for making a decision can reduce the labour effort.

1.4.2.3 Guideline 3: Design Evaluation

The artefacts created to address the problem of this thesis are evaluated not only by analytical methodology but also by other evaluation methodologies. The accuracy of the model, losses and other parameters of the model are also evaluated. To evaluate the artefacts created, the design evaluation methods are used, and they are explained in the table below. The oyster mushroom data set was evaluated by following the steps from the scientific work [12]. Moreover, the model created for the oyster mushroom maturity identification is evaluated by testing the model on unseen images of oyster mushrooms.

1.4.2.4 Research Contribution

This thesis mainly contributes to two artefacts. The image data set of oyster mushrooms that are prepared for the model selected in research question one, and the model developed that detects the maturity of the oyster mushrooms from the images captured by the camera inside the grow chambers.

1.4.2.5 Research Rigor

The methodology to conduct research is stated here to address the problem of knowing how others have done to identify the maturity of crops. Systematic steps were conducted for a literature review, from formulating a research question to deriving the solution. The solution was also obtained by taking guidance from an external guide that works on the same topic. The solution methodology latest version of YOLO [13], was adapted after analysis with other scientific approaches. The methodology YOLO [14] has three different platforms that can be performed on the images: Object detection, segmentation and classification. Basic machine learning methods perform the object detection method, and the hyperparameters are trained on the coco data set [15]; training was done on the custom data set.

1.4.2.6 Design as a Search Process

This thesis aims to automate the identification of the maturity of oyster mushrooms using machine learning methods. To conclude, conducting different steps derived from the research question stated in Section 1.3. These steps involve research for an optimal solution.

1.4.2.7 Communication of Research

The image data set used in this thesis and the Literature review is publicly available through the personal GitHub [16] platform. The model used for this thesis is published on the academic platform. The work presented in this thesis could pave the way for future studies. Other models that could perform better than this can also be adapted to work on this image data set created.

1.5 Thesis Structure

The structure of this thesis is explained in this section. Chapter 2 describes the existing body in a more described way, how others identify the maturity of the mushrooms and the methods or algorithms used to distinguish the different maturity stages. Chapter 3 describes the systematic steps to conduct a literature review to interpret how the computer science field defines the problem and derive a conclusion. Moreover, what are the inclusion and exclusion criteria for selecting the scientific works that optimally answer the research question; Chapter 4 is the preparation of the images to feed into the model that can detect the mushrooms from the images. Chapter 5 is based on the previous chapter that develops the model setting parameters as the data set is fed into the model for mushroom detection and how different varieties of the model performed to the data set prepared in Chapter 4. In Chapter 6, the primary evaluation is done by comparing the model with the existing aspects, and the model's accuracy is noted. Chapter 7 concludes the thesis and provides the outlook and future work.

Chapter 2

Presuppositions

This chapter presents the presuppositions and prerequisites to wrap the concepts that need to have while continuing to read this thesis. Section 2.1 describes the technologies that determine the maturity of crops and mushrooms to know what others have done in similar situations. Following by, Section 2.2 describes the basic methodology needed to conduct the scientific literature review. Finally, in Section 2.3, the prerequisites to understanding the machine learning model to predict the maturity of the oyster mushrooms from the image data set.

2.1 Overview-Why Oyster Mushrooms?

Gourmet mushrooms are edible fungi suitable for a wide range of age groups. Gourmet mushrooms are highly in food culture [2] [17]. However, the cultivation and harvesting of gourmet mushrooms is labour-intense task that consumes more time and money then production cost [18]. Harvesting the right matured mushrooms can bring profit to the farmers. This exists for the button mushrooms [19]. This is different regarding gourmet mushrooms, which grow in batches as shown in Figure 1.4. Among different gourmet mushroom, oyster mushrooms are widely cultivated as they can grow throughout the year in a controlled environment [17]. Furthermore, in large-scale cultivation, checking the maturity of the oyster mushrooms with bare eyes and harvesting by gently twisting them needs skilled labour [17]. This thesis investigates how to automate the different stages of maturity detection of the oyster mushrooms as they have different growth patterns than button mushrooms.

2.2 Reviewing the Literature

Silva et al. [20] propose how to do a systematic literature review to figure out the state of the art. This methodology guides the computer science field to conduct a step-by-step from the initial steps to find the solution to a problem from the existing body of knowledge. This helps anyone that takes initial steps in research. Before conducting a literature review, it is crucial to know whether any study exists regarding the current field [21]. The research is done to know the existing body of knowledge and to understand the state of the art to come up with the solution to the research problem that was found [20].
The primary and foremost part of conducting the literature review is to define the research question. This makes the researcher understand what he/she needs to look for to figure out. After defining the main research question, extract the initial keywords. Search strings are formed using the conjunction "AND" and "OR". The search strings are executed in the search engines from the field of computer science to obtain the scientific work that contributes to the study. Once the search string execution returns the results, then comes the paper refinement stage; by examining the scientific papers returned, the search string returned which returned did not make sense to the study is removed or calibrated and parsed or removed.
Furthermore, the other works are downloaded and saved. Analyzing the scientific papers' abstract, introduction and conclusion, closely related to the research questions, are selected to answer the main research question. The answer to the research question is obtained after consulting a guide who works in the same research area. Listed are the main steps to conduct the systematic literature review adopted from [20]:

- **Defining the main research questions of the literature review.**
- **Defining keywords.**
- **Defining search string.**
- **Defining search engines.**
- **String refinement.**
- **Search string execution.**
- **Download and store search results.**
- **Define inclusion and exclusion criteria.**
- **Selection of papers - First stage - Analysis by title and abstract.**

- **Selection of papers - Second stage - Analysis by Introduction and Conclusion.**
- **Selection of papers - Third stage - Complete reading and quality checklist.**
- **Extraction of answers related to research questions.**

2.3 Machine Learning Basics

This section brushes up the terms like machine learning (ML) and deep learning (DL) that readers possess; moreover, it gives an insight into the further understanding of this thesis. The basic concepts of these sections are taken from the textbook "The Deep Learning" [22].

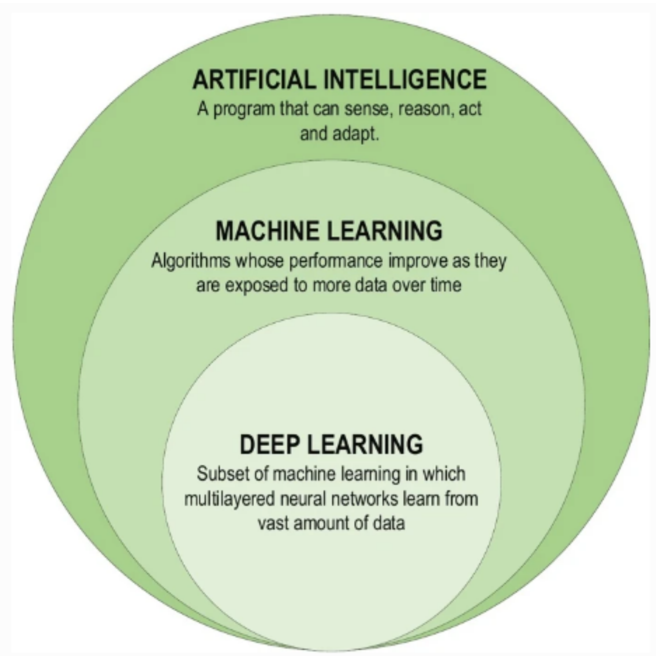


FIGURE 2.1: Deep learning a subset of Artificial Intelligence (Source:[23])

AI can solve problems that it experiences from the data fed into it. The data can be in any form, such as images, audio, text etc. The machine analysis the data and try to learn the concepts by building a hierarchical structure. Building these concepts on top of each other creates a layer-like system that is deep; this brings an idea called deep learning, which is the subset of artificial intelligence and machine learning [22].

2.3.1 Supervised Learning

Supervised learning is the machine learning paradigm that takes the input and associates some values that are related to these input values [24]. That is, input x, along with its associated values, the output value y is challenging to obtain. In any case, the supervised algorithm can group the output into different categories. In other words, the technique deals with labelled data. The advantage of this paradigm is the output data is obtained or generated to the prior knowledge, and the results are compared with the available inputs. Supervised learning is also called learning from examples [25] [24]. Figure 2.2 depicts supervised learning in a structured manner.

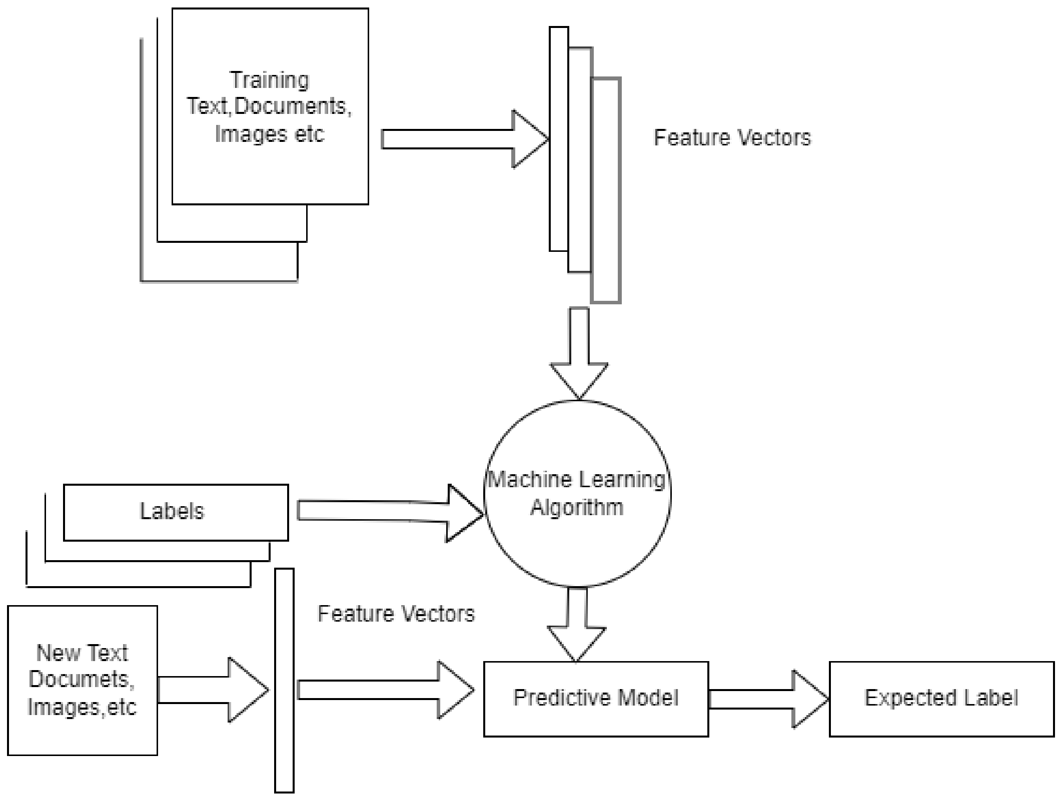


FIGURE 2.2: Supervised Learning paradigm
(Adapted from:[24])

2.3.2 Unsupervised Learning

Unsupervised learning is a different machine learning paradigm that takes the input x only [24]. No description of the input values is taken. The critical difference between supervised and unsupervised learning is that there is no objective to learn; the data is not labelled into any categories. So there is no human effort to label the data, or the labels are unavailable [25]. "The data is learned to recognize the pattern to derive rules from it" [24].

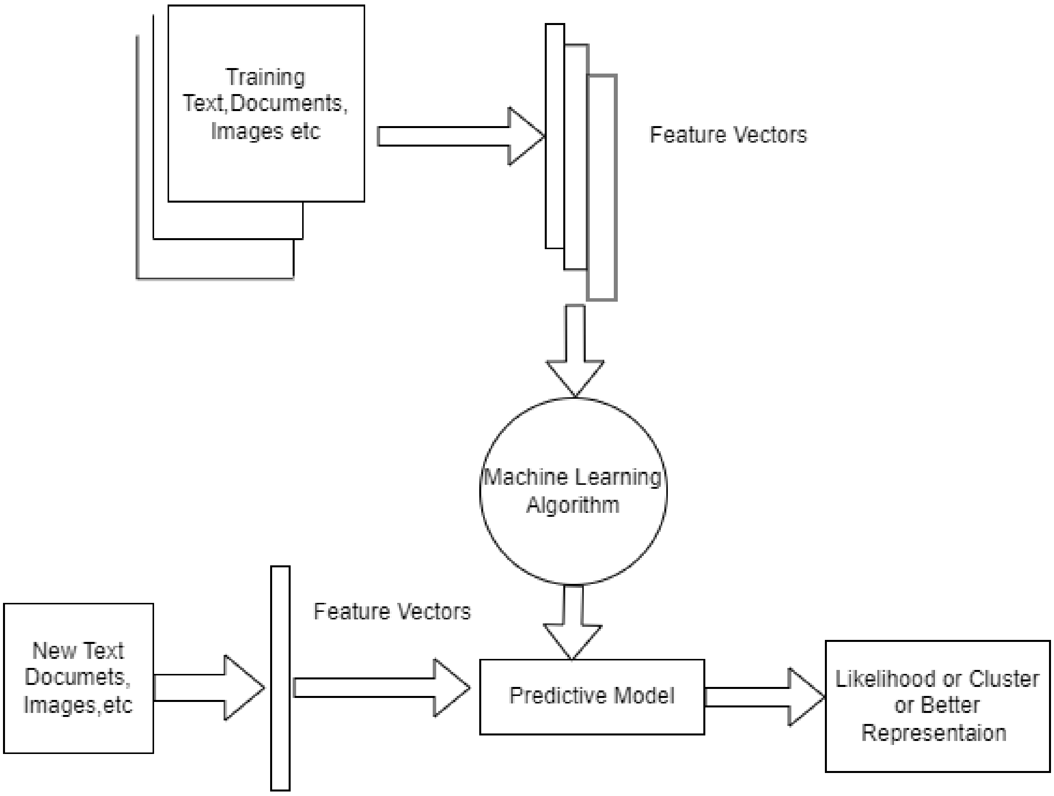


FIGURE 2.3: Unsupervised Learning Paradigm
(Adapted from:[24])

2.4 Maturity Detection Using ML

As this thesis aims to detect the three classes of oyster mushrooms from the images, labelling the images of oyster mushrooms is essential. Images and labels can be used to identify the maturity of the oyster mushroom, here supervised learning paradigm 2.3.1 can be adopted. The images need to be labelled to prepare the images for the training, as the oyster mushroom images are not publicly available [26]. The images taken from the cameras from Chambers 1.1 are manually labelled for supervised learning using the online web-based annotation tool CVAT [27]. The preparation of the oyster mushroom data set for supervised learning is discussed detailed in Chapter 4.

2.5 Neural Networks

As there are many ways to detect objects in computer science, the literature review in Section 2.2 was done to understand which method is suited for detecting the different maturity stages of oyster mushrooms; machine learning is a subset of the artificial intelligence field that understands and builds methods that make the machine learn from the data fed into it and make predictions once to the unknown data which, image recognition is a widespread application that can extract the features or identify the objects from the digital images [24]. Many various methodologies can detect objects from images or videos. Each model differs by accuracy, speed, real-time object detection, classification and segmentation. The deep learning network has different convolutional neural networks (CNN) types. They are discussed here in deep as this thesis detects the maturity of the mushrooms using CNN networks [22].

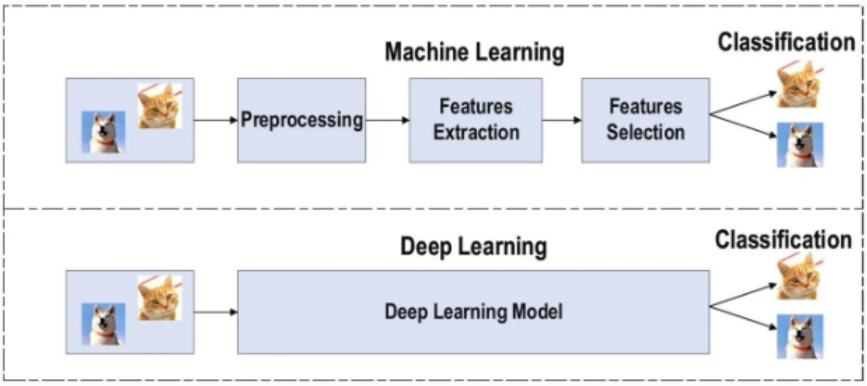


FIGURE 2.4: Object Detection differs from Machine Learning (Source:[23])

2.5.1 CNN

Compared to other neural networks, CNN [28] [29] [30] have fewer connections and parameters and is much easier to train the data set. This network is used in speech recognition, image analysis and many other fields. The architecture of CNN is similar to the basic structure of the neurons passing signals in the human body [28]. The CNN has three main layers: convolutional, pooling, and fully connected [29]. The convolutional layer extracts the features of the input data [28]. In this thesis aspects, the images are the input and the features of the images extracted by the neurons. All the neurons are connected. The information of one neuron is processed and fed into the next neuron, exactly like the human body. The extracted features from each neuron form a feature map. The features are added together after the mathematical operation called convolution. After convolving, an activation function is applied to the learned features [31]. The activation function is responsible to decide the neuron should be activated or not [31]. The weight is added up together with the neuron weight and passed to the next neuron [31]. The next step is pooling, as it reduces the resolution of the feature map. Pooling is placed in between two convolution layers [32]. Figure 2.4 shows how the object detection differs from traditional machine learning algorithms. Figure 2.5 gives a simple understandings of how CNN takes an image and predicts the object.

The ReLU layer mentioned in Figure 2.5 is the commonly used activation function. The functionality of the activation function is to map the input to the output so that

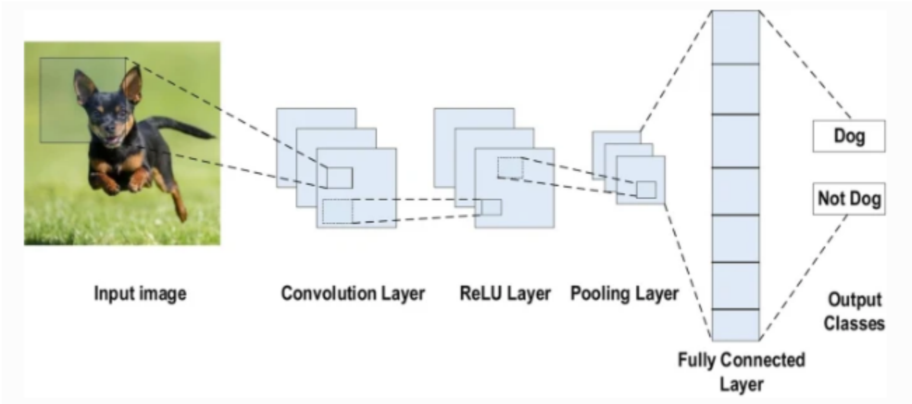


FIGURE 2.5: Simple understanding of CNN working (Source:[23])

it achieves non-linearity. The mapping is obtained by adding the weights and adding them. The activation function changes the whole value to a positive number [23] [31]. CNN have a significant role in the field of literature [28]. In recent years, R-CNN [33], YOLO [14] [34] and SDD [35] are some CNN networks used for object detection. Each network has its different computational power and accuracy rate. The literature review described in Chapter 3 details which method is adopted in this thesis.

2.5.2 Object Detection Methods

Object detection [36], image classification, and object tracking are some of the applications of the CNN network. Object detection differs from other computer tasks as they have to localize where the object in the video frame or image is. The sliding window-based approach was present in the past to determine whether an object was present or not in the image; these approaches consumed high computational power [37]. The object detector method is treated as a regression problem [37]. Text detection and audio detection are out of the scope of this thesis. Hence it is not discussed here.

Chapter 3

Reviewing the existing literature

This chapter deals with how to conduct a literature review to derive a conclusion to the research questions stated in Section 1.3. The steps from formalizing a research question to deriving the conclusion followed from the scientific work. The steps involved from stating the problem to deriving the conclusion and implementing the steps included in this thesis. Evaluating the literature review is excluded from this thesis's scope..

3.1 Introduction

The aim of Chapter 3 is to derive the solution to the research question stated in Chapter 1. In order to answer the research question **RQ1.How to review the literature for an existing methodology for maturity detection of the oyster mushrooms from the images?** as stated in Section 1.3, it is subdivided into three subsections to answer RQ1 more sophisticatedly and structured.

- **RQ1.1: What are the preliminary steps for conducting research?**
- **RQ1.2: What is the methodology for selecting scientific papers to derive a conclusion?**
- **RQ1.3: What are the results of the literature review?**

Answers to these questions are discussed detailed in each sub-sections of this chapter. The first Section 3.2, of this Chapter 3 aims to answer the first sub-research question RQ1.1 which is how to formulate a research question for conducting a literature review in computer science for a beginner who needs more experience in this field. The following Section 3.3 describe the methodologies to follows to derive the answer to the research question defined in Chapter 1. The answer to the main research question is the basis for the following chapters that can identify the oyster mushroom's maturity from the image described in Section 3.4. These results are derived by the comparative study of the other methods used to identify the maturity of crops, precisely mushrooms and this chapter is summarized in Section 3.5, followed by a conclusion in Section 3.6.

3.2 Preliminary Steps of Literature Review

L.S.Silva et al. describe in [38] the systematic steps to conduct the literature review in computer science and corresponding fields. The base of these steps is taken from the [39]. The steps described in [38] are more objective for users who have a first hand in handling research. The practical guide to conducting the literature review follows step by step.

3.2.1 Defining the main Research Question

The first and foremost step to conducting research is formulating a research question. By defining the research question, the author determines what needs to be done by doing the research. The question was formulated using the "HOW" question. The formulated question is as follows:
How to detect the different growth stages (not matured,matured,over matured) of oyster mushrooms' from the digital photos collected from the fixed cameras inside the growing chambers?

3.2.2 Defining Keywords

L.S.Silva et al. state that [38] there are several ways to extract the keyword for defining the search string. The primary way to define the search string is by analyzing the research question in 3.2.1. The other method is to use the scientific papers from the area of the study additionally find the new word and synonyms of the word found.

3.2.2.1 First Keywords

By analyzing the research questions defined in Section 3.2.1, the keywords extracted are:

AI, image processing, oyster mushroom cultivation, mushrooms, image measurement, image analyzing, optimal growth, mushroom harvesting, mushroom cultivation, oyster mushroom classification, segmentation.

3.2.2.2 New Words and Synonyms

Some scientific papers from the interested area are selected to extract new words and synonyms. The scientific papers selected and the new words and synonyms are described in this section. One of the scientific papers selected was " Development of a Mushroom Growth Measurement System Applying Deep Learning for Image Recognition" [19]. Additionally, the new keywords and synonyms found are as follows:

Image Measurement, measurement period, monitoring, temperature sensors, IoT, convolutional neural network, mushroom size, growth conditions of the crop, growth status, growth rate, microclimate control, captured image size, image processing technology, image recognition technology, size classification of mushroom, identification results, image localization, mushroom cap size.

"Deep learning based research on quality classification of shiitake mushrooms" [40] was the other scientific paper that was selected, and the new words and synonyms are as follows:

Classification and detection, channel pruning mechanism, pruned model, identification and quality inspection, feature extraction, defect detection, surface texture, computer vision technology, detection technology, deep learning, spectral analysis, grading mushroom, quality classification networks, spectral characteristics/problems, generalization ability of network model, data marking tool-labelling images

"A novel image measurement algorithm for common mushroom caps based on convolutional neural network" [41] is one of the other papers selected for this purpose.

Measure diameter of cluster mushroom, microclimate data, image measurement system, size of mushroom caps, generate growth rate, mushroom cap, identification, innovate score-punishment (SP)algorithm, circle hough transform(Open CV implementation), state of the crop, computer vision technology, Image measurement system, circle diameter of mushroom, YOLO Algorithm, Identify small-medium-large images, fine-grained features, feature extraction, calculate number of pixel (prior circle in addition to *pixel) fine-tuning.*

”Recursive-YOLOv5 Network for Edible Mushroom Detection in Scenes With Vertical Stick Placement” [2] was selected after the previous one.

Mushroom detection, optimal picking cycle, ripe edible mushroom, object detection algorithm, growth status, recursive YOLOv5, edible mushroom recognition algorithm, automatic recognition of ripe mushroom, target tracking, behavioural recognition, physique recognition, semantic segmentation, image segmentation, foreign object occlusion, target overlap, image distortion, target detection networks, adaptive anchor algorithm.

”Image Analysis of Mushroom Types Classification by Convolution Neural Networks” [42] is the next scientific paper selected.

poisonous substances, classification of types of mushrooms, CNN, characteristics of mushrooms, recognition and classification of mushrooms, mould plant(mushroom), opening cap level, nondestructive technique (recognize mushroom fragrance), useful groups and harmful groups (classification) by CNN tensor flow.

3.2.3 Defining Search String

After extracting the new word and synonyms, the keywords are separated, the separated word is taken, and its synonyms are concatenated using **OR** connector. These synonyms are concatenated using the **AND** to end the string.This can be formulated as follows:

(inspection OR evaluated OR classify OR classification OR selected OR categorized OR calculated OR optimize OR results OR conditions OR Validate) ***AND*** *(texture OR pattern OR features OR characteristics OR types OR quality)* ***AND*** *(methods OR tools OR function OR algorithms OR models OR technologies OR system Or assessment OR identification)* ***AND****(learn Or learning OR prediction OR tuning OR policy OR study)****AND****(extract OR simplify OR enhanced OR sampling OR remove OR reduce OR verify OR target)* ***AND****(product OR crop OR mushroom cap)****AND****(growth rate OR harvested time OR stage OR size OR cycle OR region)*

After this step the search string is executed in the search engines from the computer science fields, which contribute to this research.

3.2.4 Defining Search Engines

The readings were done from the search engines defined below:

- IEEE Xplore
- Science Direct(Elsevier)
- Springer
- ACM
- Google Scholar
- Google

3.2.5 String Refinement

These strings were parsed(also changed in the order of appearances) to obtain relevant scientific works. They are:
Mushroom image classification -pattern classifier - image recognition mushrooms-image analysis- quality classification - methods to classify-deep learning based mushroom classification-nutritional mushroom classifier-harvest time of oyster mushrooms-image segmentation-instance segmentation-maturity identification.
The search strings that do not contribute to the study were removed.

3.2.6 Search String Execution

The date of the execution and number of articles returned (from a similar date) are updated on a spreadsheet a database for scientific papers is created. The search strings used, articles returned, and date of executions are arranged in Table 3.1. The search strings contributing to the study were saved. The search strings that did not give relevant outputs are removed.

3.2.7 Downloading and Storing Search Results

The search strings are executed, downloaded, and files are stored in .bib file format. The scientific papers contribute to this research and are downloaded from the search engines defined in 3.2.4 are stored.

Search Strings used	Search Engine	Date of execution
Quality classification of edible mushrooms	IEEE Xplore	15-09-2022
Methods to classify mushrooms	IEEE Xplore	26-09-2022
Harvest time of mushroom	IEEE Xplore	29-09-2022
Identification of maturity of oyster mushrooms	Google Scholar/Springer	24-09-2022
Identification of maturity of oyster mushrooms	Science Direct	29-09-2022
Oyster mushroom maturity identification using deep learning	Google Scholar/MDPI	24-09-2022
Instance segmentation for oyster mushroom classification	IEEE Xplore	27-09-2022
Image analysis of mushrooms	ACM	24-09-2022
Segmentation for oyster mushroom classification	IEEE Xplore	27-12-2022

TABLE 3.1: Search string execution

From reference [43] to [65] the scientific papers showing similar study patterns were downloaded from different search engines and saved.

3.3 Methodologies of Selecting the Scientific Paper

After downloading and storing the scientific papers, the next stage is defined by several specific criteria. The main selection criteria are by observing the main research question defined in Section 3.2.1. Restriction by English language, restriction by primary articles such as surveys, excluding other systematic reviews.

3.3.1 Initial Stage-Selection of Papers

The scientific papers that are downloaded after executing the search string are analyzed and imported into a worksheet additionally saved in personal google drive. In this stage, the title and abstract of the papers are observed. The worksheet was created to include the status of the papers, which can be included, excluded and doubtful. These criteria were determined by the selection criteria discussed in Section 3.3. The scientific papers with the status" doubtful" were discussed with this thesis's examiners, and they were made sure that they could not be included.

3.3.2 Final Stage-Selection of Papers

In this stage, the introduction and conclusion of the scientific papers are analyzed as an intermediate stage of the selection criteria to refine the selection. The quality of the papers is checked by the researcher who works in the same field, and they make sure the papers go to the final stage. In the final stage, the quality papers are deleted or removed from the worksheet. Moreover, at this stage, the advisor has a significant role in selecting the papers, leading to the answer to the problem defined. From the papers cited above, the papers that contribute to the study are selected, and they are:

[1], [2], [10], [40], [51], [54], [63] and [41] were selected by analyzing the title, abstract, introduction and conclusion. Language English was set as a restriction.

After checking the quality of the papers in addition to the data set used [1], [2], [10], [40], [63] are selected to derive the answer to the research question.

3.3.3 Extraction of the Answer

In this stage, the answer to the research question or, in other words, the problem defined should be derived. The worksheet that stores the scientific papers' detailed description is assigned an ID; these ID numbers can be used to refer to the papers in future. The artefacts of each paper are different, and obtaining an answer from those is a critical task. Following the guide from the experienced researchers is taken as per stated by L.S.Silva et al. in [38].
Machine learning is one methodology that can work on large amounts of data that can learn from the data fed into it and apply it to real-world data.
After analyzing the final stage, papers were sorted out to identify the maturity of the mushrooms using machine learning methods to sort this problem. Deep learning is a subset of machine learning that uses images and videos, analyzes them, and gives the output [22]. Versions of YOLO [14], (Recursive-YOLO5, YOLOv5) [66], SSD [35], VGG16 [10] were some of them used in these similar works. This can be adopted in this situation as these methods show more than 90% accuracy in detect objects.
Mask R-CNN [67] and YOLACT [68] are some of the other methods which can be used to detect object if the noise in the image is higher.

3.4 Results of the Literature Review

The following Section answers **RQ1.1: How to review literature for maturity detection of the oyster mushroom from the images?**
The machine learning algorithms can locate the mushrooms in the images and can learn from them. The objects in the images are located by obtaining the x and y coordinates of the images [69]; the whole image is processed differently by different algorithms. The main algorithms that classify the oyster mushrooms from the digital images and how they work are discussed in the following subsections.

3.4.1 YOLO - You Only Look Once

The YOLO [14] [69] [70] is based on CNN. YOLO is the most used algorithm to detect and localize objects from the images. It is faster and more accurate than SSD [35] [69]. This method inputs the picture into the image size is reduced to small grids anchor boxes and calculates class proximity grids. The size of the image is reduced to small grids; in conclusion, the image significantly differs from the original and training images. Non-existing positions in the images cannot be learned. The method should learn (train) images that is appropriate to the YOLO's characteristics. When the size of the image is reduced [14], resulting in a difference in ratio to the original image can cause poor performance of YOLO.

3.4.2 SSD - Single Short multi-box Detector

Single short multi-box detection algorithms are similar to the YOLO based on CNN and can detect objects and localize the position faster [35]. SSD, as the name implies, divide the image into multiple boxes called feature map and identify the presence of objects inside the boxes based on CNN. The accuracy outperforms other CNN methods, even with a small image input size. In other words, besides the limitation to the accuracy when considering large-sized images, this method is faster in detection. The anchor box, which is centred on each feature point grid, determines the object's presence [35].

3.4.3 VGG-16 - Visual Geometry Group

The visual geometry group [71] with 16 layers takes the input images to the pre-trained network model. 16 refers to the number of layers [71]. Each layer supports object detection and claims an accuracy of about 92.7% with a 3x3 kernel size. The 16-layer neural network takes the weight, bias, and related training procedure to the neural network. As there are more layers, this increases the time to train the parameters.

3.5 Summary

The answer to the research question RQ1 is defined in Section 3.1. The research question defined is phrased in 3.2.1, and the steps to answers to the research question is derived in Sections 3.2.2 to 3.3.3. The final results of the research question are stated in 3.4.

3.6 Conclusion

A comparative study was done to understand the performance of algorithms to detect the oyster mushroom growing in the indoor chambers. The YOLO method is accurate moreover faster than other methods [72]. Multiple versions of YOLO guarantee better performance than the older versions when taking the different features of the images. YOLO is also efficient when analyzing images from video streams [73]; when it comes to small images, YOLO can not identify them accurately compared to SSD. VGG 16 is the base of SSD, and the image is divided into boxes regarding speed and accuracy. This method can also be used to detect oyster mushrooms [74]. Out of these algorithms, variations of YOLO, such as YOLACT ++ and Mask R-CNN, can also propose object detection as their identification rate is reasonable even when the noise probability is higher.

Chapter 4

Image Data set Preparation of Oyster Mushrooms

In this chapter, the image data set preparation for the model, which is derived in Chapter 3 Section 3.6, is explained in detail. The images of oyster mushrooms can be used to identify the different stages of maturity using the latest version of the YOLO model [14]. The images that have growth stages of oyster mushrooms are classified into three different stages such as not matured, matured and overdue. These images are prepared as the model YOLO takes as input for analyzing the images for the object detection.

4.1 Introduction

The aim of Chapter 4 is to answer the research question RQ2: **How to prepare the image data set of oyster mushrooms for maturity identification?** as stated in Section 1.3 in Chapter 1. To answer the RQ2 in more sophisticated and structured way, it is sub divided into three subsections:

- **RQ2.1: What model is used for detecting the maturity of the oyster mushrooms from the images?**
- **RQ2.2: What classifications are given to the mushrooms in the images?**
- **RQ2.3: What annotation tool can be used to classify the mushrooms for object detection?**

Answers to these questions are discussed detailed in each section of this chapter. The first Section 4.2 of this chapter aims to answer first sub-research question RQ2.1 that is the basic understanding of the machine learning model YOLO, followed by its latest version used in this thesis. The following Section 4.3 describe the different classes assigned to the mushrooms that distinguish the ready-to-harvest mushroom from not-matured and overdue. Section 4.4 describes the annotation methodology to prepare the images for maturity identification. Section 4.5 discussed the findings and followed by the conclusion in Section 4.6.

4.2 Model for Maturity Detection of Oyster Mushrooms

This section aims to answer the sub-research question **RQ2.1: What model used for detecting the maturity of the oyster mushrooms from the images?**

At the end of Chapter 3, the solution for the main research question mentioned in Section 3.2.1 is defined. The scientific literature review done in Chapter 3 states that the machine learning methodologies can significantly use when it comes to analyzing images and videos. As concluded in Section 3.6, YOLO [14] is one of the most widely-used solution for the maturity detection of the oyster mushrooms. The latest version of the model YOLO can be used more than other methods for maturity detection of the oyster mushrooms.

YOLO model is one of the deep learning methods for image processing [69]; it describes that images can be trained not only to identify whether the object is present in the picture or not but also the position of the object located in the entire image which can separate it from the other objects of the same image by the bounding boxes [14]. The YOLO [14]method spatially classifies objects using the bounding boxes [14]. Compared with the latest YOLO variants, version 8 is adapted for this thesis, which is more accurate and faster than other older versions [13] [75].

4.2.1 Characteristics of the YOLO Model

By the name itself, the model looks once through the entire image or video frame and predicts whether the object is present or not, moreover, the position of objects with respect to the other objects in the image. The state-of-the-art object detector YOLO [14] is accurate and faster in detecting what the objects are in the image when compared to other CNN-based models [69] [72] [73]. The YOLO network is faster because it takes 45 frames per second and can process images at a rate of 45 frames per second when running on Titan X GPU[14]. The latest versions of YOLO can process even 150 +

frames per second, which makes the model even faster. When comparing to Faster R-CNN YOLO model makes fewer background mistakes [14].
"The YOLO divides the whole input image into the S x S grids"; if the image's center falls into the corresponding grid, that grid is responsible for the prediction of the object [14].

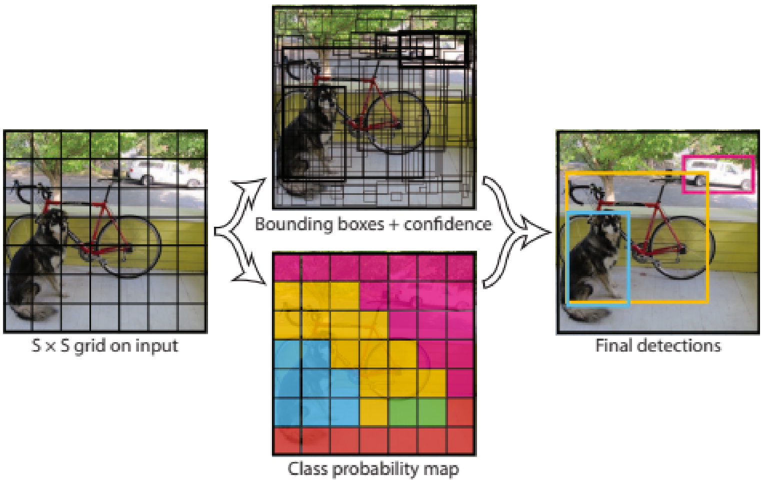


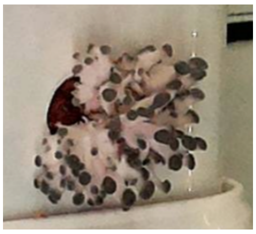
FIGURE 4.1: Working of base YOLO network (Source:[14])

Figure 4.1 describes the working of YOLO. Each grid cell predicts the bounding boxes and the confidence of the prediction [14]. The confidence score shows how confident the model predicts that the object is in the bounding box [14]. Each bounding box detects each object, and multiple bounding boxes can detect multiple objects from a single image, as in Figure 4.1, the bicycle, dog and car score more confidently than other bounding boxes. The network passes over the image or video frame once and detects whether the object is present. Unlike other CNN networks, the YOLO network divides the task into two. The first task divides the object into a grid and identifies whether it is there; the second is classifying it precisely like a human looking once and understanding the object [75].

4.3 Mushrooms Classes

This section answers the second sub-research question **RQ2.2: What classifications are given to the mushrooms in the images?**
There are two types of region-based methods, one-stage and two-stage methods [76]. The one-stage methods are region-free and use bounding boxes to predict the objects in the images. YOLO and the later versions of YOLO are examples of single stages [76]. They have better computational efficiency and high-speed prediction by calculating the bounding box regression when compared to other methods. The idea of annotating the

images is to determine the location of the objects in the images and predict which class they belong to [76]. As the model is selected, the oyster mushroom images collected from the grow chambers must be prepared for the model YOLO version 8. The model takes the bounding boxes and the information about each image in the text file format. The bounding boxes [77]give the idea of localizing the objects; here, the object is the oyster mushrooms of various maturity. The four coordinates of the bounding box are (x,y,w and h), where (x,y) is the centre coordinates of the box 'w' is the width and 'h' is the height of the box[78].



(a) pinning stage

(b) matured

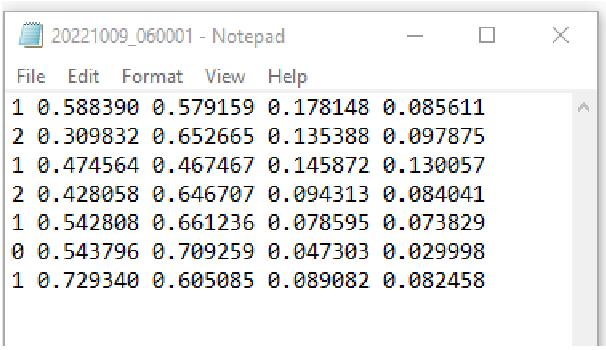
(c) right matured

(d) overdue

FIGURE 4.2: The different growth stages of the oyster mushrooms

Annotated data is the prerequisite for training the machine learning models; labelling them is to give meaningful features to them [36]. Figure 4.2 depicts different growth stage of the mushroom from pinning to overdue. From now, three major maturity stages of the oyster mushrooms are considered for this thesis, **not matured**, **matured** and **overdue** [36]. As shown in Figure 4.4, the green rectangle is the mushroom which is matured; the pink rectangles are overdue and the orange rectangle is not matured.

For the preparation of mushroom images, the three stages of the mushrooms are classified as **class 0** as not matured, **class 1** as matured and **class 2** as overdue, which depicts in Figure 4.3. The first number gives the class number of the oyster mushroom followed by (x,y) coordinates of the bounding box and w and h values. **Class 1** is the right matured


20221009_060001 - Notepad

File Edit Format View Help

```
1 0.588390 0.579159 0.178148 0.085611
2 0.309832 0.652665 0.135388 0.097875
1 0.474564 0.467467 0.145872 0.130057
2 0.428058 0.646707 0.094313 0.084041
1 0.542808 0.661236 0.078595 0.073829
0 0.543796 0.709259 0.047303 0.029998
1 0.729340 0.605085 0.089082 0.082458
```

FIGURE 4.3: Different Class representation of a single image after annotation

one that can be harvested and ready to consume. **Class 0** is not ready in CVAT [27] means not matured stage and **Class 2** is in the overdue stage.

4.4 Annotation for Image Data Set

This section aims to answer the sub-research question **RQ2.3: What annotation tool can be used to classify the mushrooms for object detection?**
Since one of the artefacts created here is the oyster mushroom data set which is mentioned in Section 1.4.2.1, the images are manually annotated using the online open-source web-based annotation tool called CVAT [27]. Annotation plays a major role in preparing the data. The model comes across in Chapter 3; YOLOv8 takes pictures and the corresponding text file for training the model. Figure 4.4 shows the bounding boxes that is available in the CVAT tool used in this thesis.

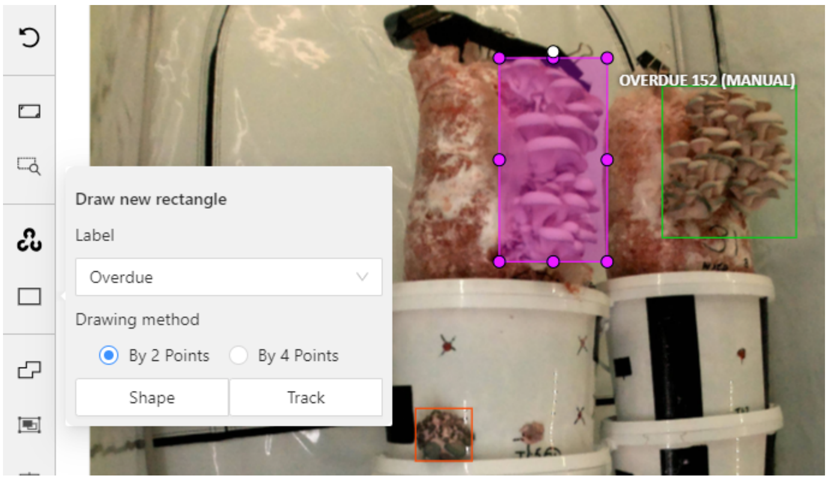


FIGURE 4.4: User interface of CVAT for drawing bounding boxes around the oyster mushroom (Source:[27])

After annotating of the oyster mushrooms images, the annotations are downloaded as text files; each image has a corresponding text file. The text files and images are stored in a folder and split into training and validation sets later. The machine learning annotation formats are also available in CVAT. The YOLOv8 model takes the images and bounding boxes, for example, deep learning model called Mask R-CNN [67] the objects can be annotated by drawing polygons around the objects using CVAT. The polygon annotation cannot be saves as text file , other format is adopted such as COCO json. After the annotation of the oyster mushrooms images, the annotations are downloaded as text files; each image contains each text file. The text files and the image files should match the name for training.

FIGURE 4.5: The annotated image of oyster mushrooms from a different angle (Source:[27])

The bounding boxes [77] are the rectangle boxes in the CVAT that draw around the objects to locate where the object is. The box specifies the x and y coordinates of the total image from the corner and the bounding box's height and width concerning the image's center[69].

For obtaining better results, some key factors need to be kept in mind. The training and recognition image ratio shows the model performance [69]. The difference in the ratio is less gives a better model. For YOLO the training ratio is the image resolution regardless of the original size of the image. The model reduces it to 416 x 416 pixels. which is the ratio of width and height of the image. Distorted images give a higher ratio, and they show low performance. For good accuracy of model YOLOv8, the training images should be pre-processed as follows [69]:

- " The accuracy of the model YOLO can be increased by making the same training and detection image ratio" [69].
- " The proportion of the area occupied by the object in the image must be similar in the training and detection images"[69].

The images collected from the grow chamber is annotated. 572 images oyster mushrooms images with different maturity of mushrooms are annotated as **class 0** as matured, **class**

1 as matured and **class 2** as overdue. There were 641 **not matured** class instances which are called **not ready** in CVAT. Similarly, 648 **matured** as **ready** and 659 were **overdue**.

A total of 572 images of the oyster mushrooms were annotated instances, with

Classes	Number of instances
Not Ready	641
Ready	648
Overdue	659
Total	1948

Table 4.1: Number of instances of oyster mushrooms used for training

The annotated images are trained on YOLOv8 nano for 20 to 150 epochs model on intel Core i5 HP laptop with 8.00 GB RAM and the quality of the image data set is observed. The annotated instances are not distributed equally on the data set, hence the oyster mushroom data set is fixes by removing the annotations. The bounding boxes which are not closer to the flush is also re-annotated such a way that the there is no free space between the box and mushroom flush.

4.5 Summary

This chapter answers the research question RQ2 defined in Section 1.3. The model used to detect the maturity of the oyster mushrooms is YOLOv8, which is defined in Section 4.2, followed by the characteristics of the model is explained. Section 4.3 explains the classes given to the oyster mushroom that distinguishes the matured mushroom from the other classes, such as not matured and overdue. Last Section 4.4 describes the annotation tool used to prepare the data set and how the images are prepared.

4.6 Conclusion

The oyster mushroom image data set is prepared for the model chosen for this thesis, YOLOv8. The model takes the bounding box coordinates for extracting the features for training. The bounding box coordinates are downloaded in the text format where each image have its corresponding text files; the CVAT online open-source web-based annotation tool is used to prepare the data set. The oyster mushrooms are classified as **class 0**, not matured; **class 1**, as matured and **class 2**, as overdue.

Chapter 5

Developing and Deploying the Maturity Detection Model

This chapter explains how to develop a model that can detect the different stages of maturity of oyster mushrooms from the images prepared in Chapter 4. The working of the model, how the images are trained to identify the different maturity of the oyster mushrooms; moreover, different scales of YOLOv8 to obtain better results are discussed here.

5.1 Introduction

The main objective of this chapter is to answer the research question, **RQ3 "How to develop the YOLOv8 model for object detection and classification?"** which is formulated in Section 1.3. Like the previous chapters, it is subdivided into three sub-research questions to answer the main research question in a sophisticated and structured manner.

- **RQ3.1: What is the architecture of the model?**
- **RQ3.2: What are the processing steps to train the model?**
- **RQ3.3: What are the optimization parameters of the model?**

The answers to the sub-research questions describe this chapter. Section 5.2 describes the model's architecture and how the images are fed into the model for maturity detection. The layers in the model and how they are analyzed in the images detect the objects for different-sized models; here, the object is oyster mushrooms. Section 5.3 describes the processing steps for training the model to detect the oyster mushrooms, mainly focusing on splitting the image data set into a train and validation set created in Chapter 4. Section 5.4 describes how the model is optimized for the best results. This chapter is concluded in Section 5.5.

5.2 Introduction to YOLOv8

This section describes the model's architecture, which takes the images as input and analyses them to locate and identify the oyster mushrooms from the images. Section 5.2.2 describes the basics of the object detection model YOLOv8 architecture. Following that, Section 5.3, the model describes how the bounding boxes are taken to locate and classify the objects for the model and how to implement them to detect the oyster mushrooms.

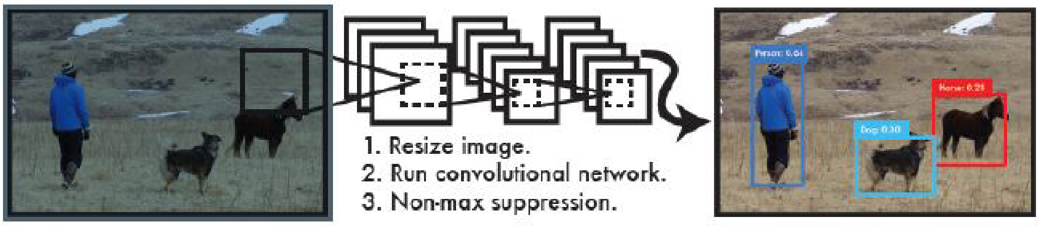


FIGURE 5.1: Base YOLO detection mechanism (Source:[14])

Figure 5.1 depicts an example of how images are fed into the YOLO model. The image is resized, a single convolutional network is run through it and the thresholds the detection by the model's confidence [14]. As in Figure 5.1, the model predicts the man, a dog and hours and the percentage of confidence in detecting those objects in the image. YOLO scan the entire image once and predict the bounding boxes and the classes of the candidate box [14]. Using a single CNN network, it can predicts multiple bounding boxes from a single image, exactly like how humans look and understand at single glance.

5.2.1 The Model YOLOv8

Like the base YOLO model, version 8, abbreviated to YOLOv8, takes the entire image and predicts the bounding box, the confidence score, and class probabilities. As the model's various versions are available, version 8 is the latest and faster than the others [75]. The YOLOv8 was released on January 2023 by Ultralytics [13]. YOLOv8 is anchor free and trained at 640 pixel resolutions. The model consists of five different sized versions like YOLOv8n(nano), YOLOv8s(small), YOLOv8m(medium), YOLOv8n(large) and YOLOv8x(extra large)[13]. The models are used for object detection, segmentation and classification. The segmentation module of YOLOv8 called YOLOv8-Seg; In this

thesis only the object detection is focusing [13].
For this thesis, the nano, small and medium models are chosen to train the images of the oyster mushrooms prepared in Chapter 4.

5.2.2 Architecture of the model YOLOv8

YOLOv8 uses an single CNN for object detection and much faster than existing models. The base of AI is data. To train the YOLOv8 model images of the oyster mushrooms are prepared in Chapter 4, and the text files corresponding to each image file are fed into the model and trained various sizes of the model. The architecture of the model is as follows [79]. The model has three parts; they are: **Backbone**, **Neck** and **Head** [79]. The backbone is the CNN layer that integrates the image features; the neck is a combination of layers that combine the image features from the backbone and forward to the head for the prediction. The backbone compresses all the features of the input image, called feature extraction. Feature extraction is carried out to generalize the same features of the same objects in the input. It can be scaled to various sizes. The head is responsible for localization and classification [75]. The complete and final detection is in the head section [13] [75]. Figure 5.2 depicts the working of the YOLOv8 model described in [75]. The image is taken as 640 x 640 pixels compressed and features extracted by two consecutive convolutional layers, which increases the detection accuracy. The anchor-free model independently takes each object in the image and processes it for object detection, classification and segmentation tasks [75]. In this network, the sigmoid activation function calculates the probabilities of the bounding boxes containing the object [75].
For calculating the bounding box loss and the class probabilities the YOLOv8 uses the DFL [80] and binary cross-entropy functions. The model can train on GPU, CPU and edge devices like Raspberry Pi.

5.3 Pre-processing steps for Training the YOLOv8

The Pre-processing steps involve image data set preparation. Images are annotated correctly, ensuring the bounding box is close to the oyster mushrooms and have no blank space between them. The size of the images for training and validation are the same. YOLOv8 resizes the images to 640 x 640 pixels[13].

The model's complexity and performance can be assessed when training a model. Moreover, the image data set is divided into two sets: the training set and the validation set

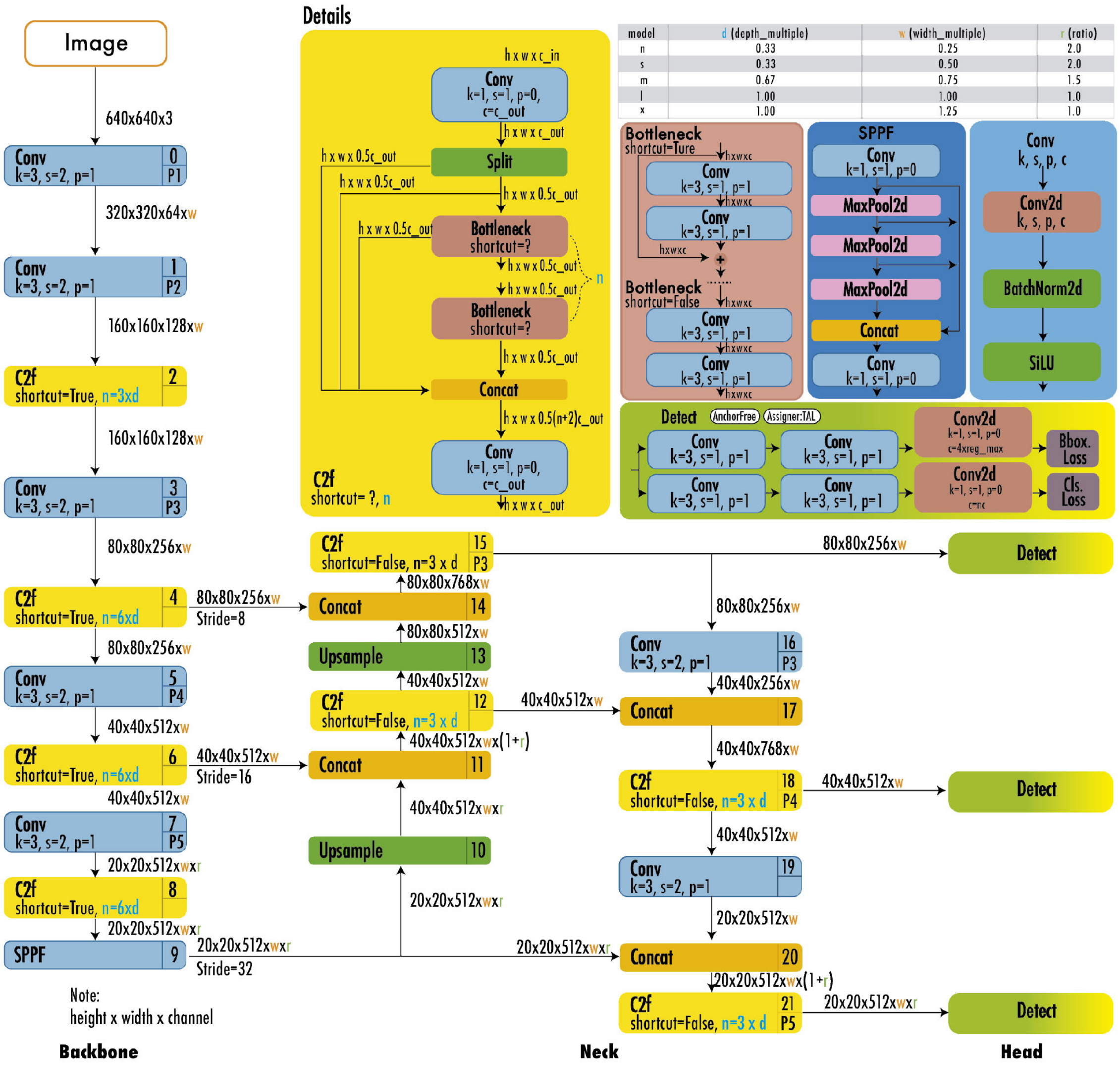


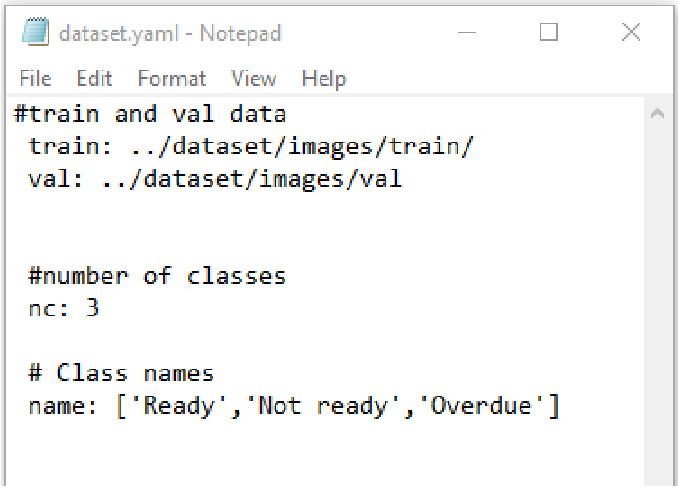
FIGURE 5.2: Architecture of YOLOv8 (Source:[75])

[22]. The first part is for the training of the set, and the second part is to select the complexity of the model [22].

A validation set can be used to get the exact accuracy of the model. The test set is a set of images that used to detect the data's accuracy that the model has not seen before. Often in machine learning aspects, the training set is about 80%, and 20% of the set will be a validation set [22]. This is because there should be enough data to train the model to learn and to make a reliable estimate of the model's performance [22].

The YOLOv8 model is pre-trained on the COCO data set [15] [13]. To train the model YOLOv8 on the images of oyster mushrooms' prepared in Chapter 4, '.yaml' files and images must be fed into the model. The yaml file is to define data configuration. In this thesis, the yaml file consists of the path to the files containing the images and annotation files and also the class information used for this thesis. The main classes used here are

class 0: not Matured, **class 1: Matured** and **class 2: Overdue**. Figure 5.3 shows a version of the yaml file for training the oyster mushrooms data set. Ultralytics [13] has included a list of package dependencies as requirement file for training the data in a Python environment with essential requirements PyTorch at least 1.7.




```
#train and val data
 train: ../dataset/images/train/
 val: ../dataset/images/val


 #number of classes
 nc: 3

 # Class names
 name: ['Ready','Not ready','Overdue']
```

FIGURE 5.3: An example of yaml file used for training

For training the model, the various scales of YOLOv8 were selected as mentioned in 5.2.1; the nano, small and medium models were trained for more epochs where the early stopping is turned on to avoid over fitting.

As per the size, the YOLOv8 model has nano, small and medium, these models were trained for several epochs, and the results were analyzed. The early stopping was active, so the epochs automatically stopped once the model stopped learning new features. After training 20 epochs with 150 images, the model was tested on a small oyster mushrooms image data set (10 images) on the model nano. The issues were analyzed and fixed; the bounding boxes should be close to the object, and there should be no extra space between the object and the bounding box. Like any other object detection model, the accuracy of the model's accuracy is calculated in Chapter 6 using a confusion matrix.

5.3.1 YOLOv8-nano

The YOLOv8 nano model was trained by setting the arguments [13]. The epoch reached 323; the model stopped training as the model could not observe any improvement; this was achieved because the early stopping was activated. The model took 20 hours and 48 minutes to train on the CPU with a speed of 0.9ms per image. The precision-recall (PR)curve obtained while training shows all classes achieve .924 of mAP @ 0.5 thresholds. The F1 score of the training data set is given in Figure 5.4. The F1 score gives the model accuracy; when looking at the curves, the F1 score for model nano is

.88, where the F1 score lies between 0 and 1, and the model shows better accuracy when the value is near 1. Figure 5.4, is the F1 graph obtained for model nano while training set.

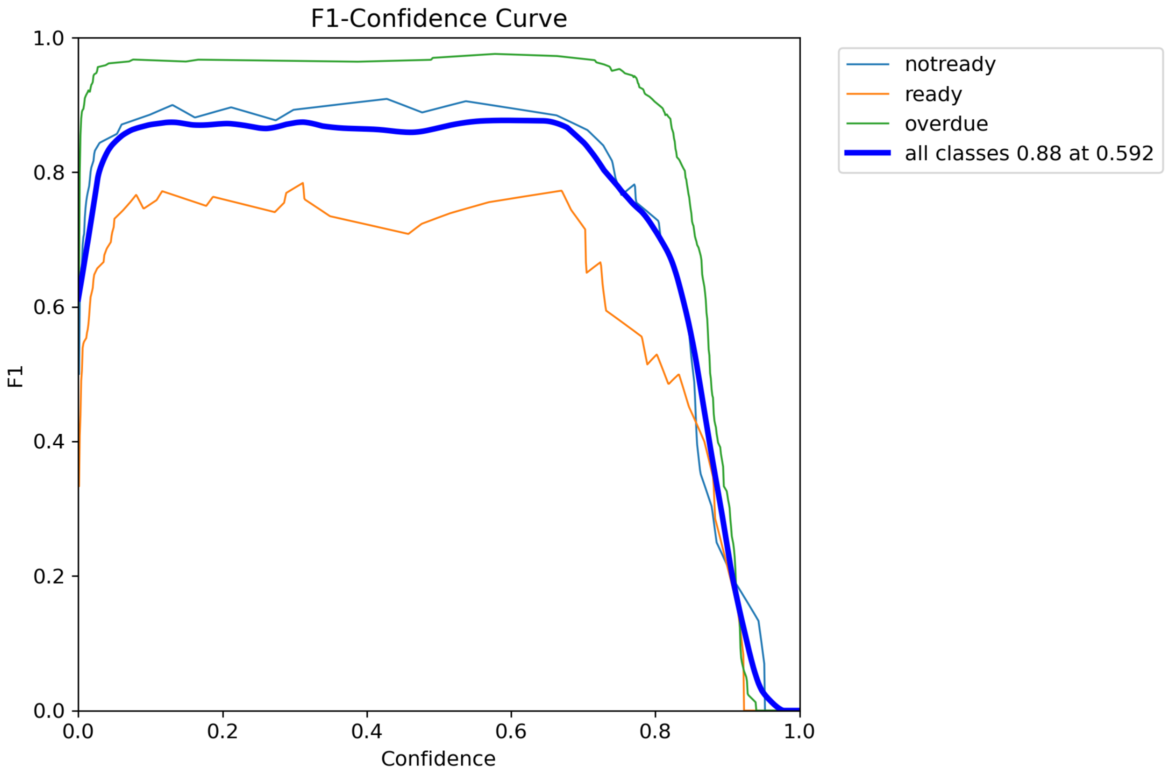


FIGURE 5.4: F1 curve of YOLOv8 nano

5.3.2 YOLOv8-small

Similar to the nano model, the model small was trained; at 250 epochs, the model stopped training, and the model achieved .910 mAP @ 0.5. Similarly, the model did not complete the epochs assigned to it and stopped early. Figure 5.5 depicts the results as a PR curve for the model YOLOv8s. The F1 score for model small is .86.

5.3.3 YOLOv8-medium

The medium model was trained similarly to other models, and it completed 265 epochs in 40 hours and 32 minutes and achieve .907 mAP @ 0.5 threshold. The model medium took 0.7 ms speed per image for detection. The F1 score for medium model is .85. Figure 5.6 shows the F1 curve for Yolov8 medium.

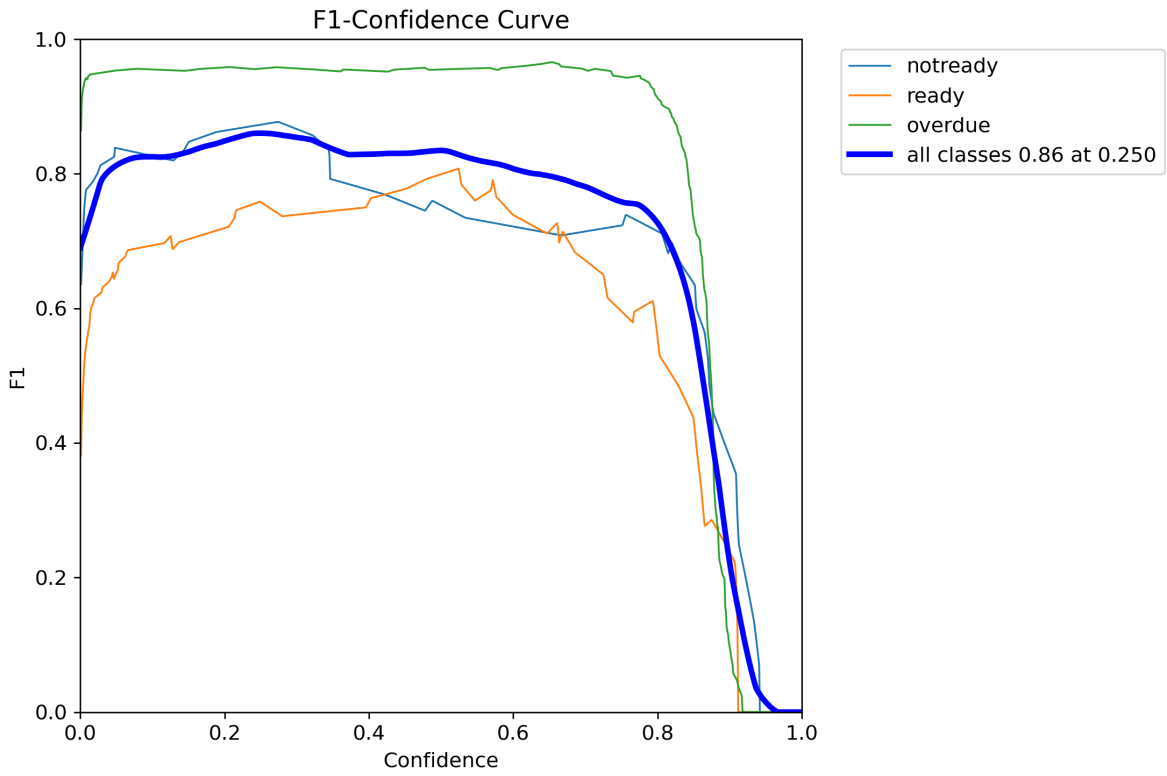


FIGURE 5.5: F1 curve of YOLOv8 small

5.4 Optimizing YOLOv8

This section discussed model optimization of the model nano, small and medium. The parameters of the machine learning model need to be optimized to obtain better results. There are several optimizers to adjust the parameters of different models. The model parameters are optimized to get lower error rates. The training of model YOLOv8 encloses various parameters. The parameters used in the COCO data set [15] are used here similarly. These parameters can be set to enhance the results. The batch size, learning rate, and weight decay are some of the significant parameters.
The data set configuration file recommended for YOLOv8 is a yaml file. The yaml file is created by following the documentation depicted in [13]. The "YOLOv8n.pt" was used to train the model nano similarly YOLOv8s.pt, YOLOv8m.pt for the other two. The models take a few arguments to train the image data set of oyster mushrooms. They are mentioned in 5.3.1, 5.3.2 and 5.3.3.

The patience argument was activated for early stopping so that the model does not over fit, meaning the model cannot make decision as it learns all the features. The batch size is set to 16, which is the number of samples that are processed before it is updated, which is dissimilar to the number of epochs, which is the number of complete passes through the entire training data set. CPU was chosen as the device for training here.

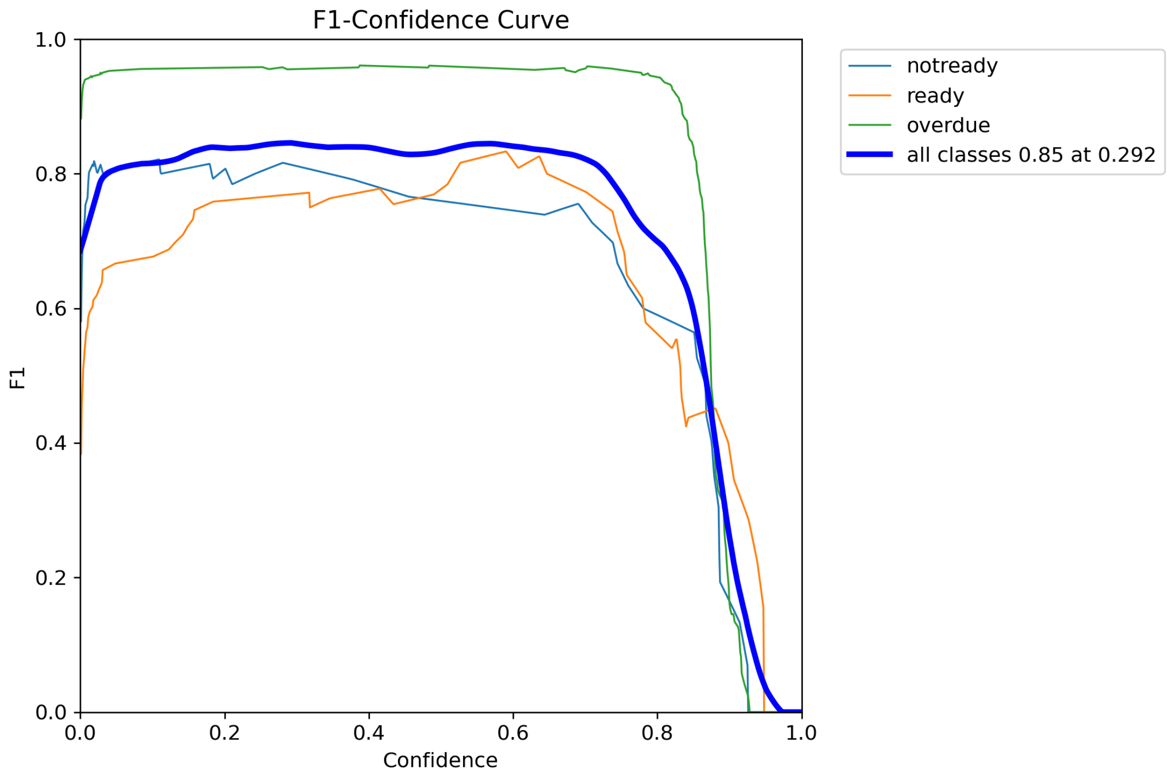


FIGURE 5.6: F1 curve of YOLOv8 medium

The training was done on a 64-bit Windows 10 operating system with Intel core i7 CPU with 16 GB RAM. The optimizer used here was 'AdamW'. The learning rate was 0.01, which was not changed for any models.

5.5 Conclusion

The model YOLOv8n,s and m was trained following the documentation on the official website of Ultralytics [13]. The model parameters were set in a way that the number of classes trained for these models produced the best results. The three classes not matured, matured and overdue were classified using the bounding boxes, and the class instances were balanced. This was an iteration process. The performance of the model is evaluated in Chapter 6.

Chapter 6

Evaluation

This chapter evaluates the artefacts created in this thesis. The image data set created in Chapter 4 and the maturity detection model chosen in Chapter 5 is used to predict the maturity of oyster mushrooms from the images. The quality of the annotation and image data set used the model's accuracy to predict the model. The first section defines the evaluation of the image data set, and the second section evaluates the model that predicts the maturity of oyster mushrooms. The nano, small, and medium scales of YOLOv8 models are tested separately to determine which model is better for detecting oyster mushroom maturity from images. The evaluation of reviewing the literature in Chapter 3 is out of the scope of this thesis and hence eliminated.

6.1 Introduction

The basis of artificial intelligence is data. Data in this thesis is digital images of oyster mushrooms collected from the oyster mushroom grow chambers. The images and annotated text files are evaluated together by following the specific methodology. The model is evaluated by testing the trained model on a data set that the model has not seen before. Section 6.2 gives detailed steps to evaluate the oyster mushroom image data set; Section 6.3 describes the evaluation methods for the maturity detection model. Section 6.6 concludes this chapter.

6.2 Evaluation of the Oyster Mushroom Image Data Set

Y.Gong et al. [12], describes the importance of evaluating the data set. The accuracy and quality of the model for training rely on the data set. The evaluation of the image data set is done in different ways. For this thesis, the methodology depicted in [12] is followed. The proposed data set quality measurement model and the nine evaluation metrics are executed in this section. The labels of the images play a key role in the evaluation process. The quality of the image data set is processed along with corresponding labels. The evaluation metrics executed here are [12]:

- **Label File Integrity**
- **Image File Integrity**
- **Label Category Validity**
- **Label Category Uniqueness**
- **Label Category Accuracy**
- **Label Category Integrity**
- **Label Category Imbalance**
- **Label Box Accuracy**
- **Image Parameter Rationality**

6.2.1 Label File Integrity

Along with the images, the images' labels are considered for evaluation. In this evaluation, the label files are missing for any of the images, which indicates the annotation information of the image is missing .xml files are recommended here. However, .txt files for each annotated image are downloaded from CVAT and used for this thesis. If the images have any missing labels, then the annotation information is lacking.

$$X = \frac{A}{B} \tag{6.1}$$

Where A is the number of images without labels and *B is the total number of images* [12]. Here, the number of images without the labels is zero; then, the value of $X = 0$.

6.2.2 Image File Integrity

This metric checks the images that are missing corresponding to the annotation file. The images that are annotated are extracted and saved separately.

$$X = \frac{A}{B} \tag{6.2}$$

Where A is the total number of text files without the images, and *B is the total number of text files* [12]. Here also, the text files without images are zero; again, $X = 0$.

6.2.3 Label Category Validity

As the name implies, the category of the label is not within the category range N. The label categories in the label files are not matured, matured and overdue. All the images of oyster mushrooms are under this category. No other miscategories happened here. Hence the metric is again zero here.

$$X = \frac{A}{B} \tag{6.3}$$

Where A is the number of records whose label category is not in the range N, Where N is the category range which is 3, and *B is the total number of image records* [12]. The annotated labels come under the oyster mushroom classes category, so the images all come under these classes. Here $X = 0$, as no other category is present here.

6.2.4 Label Category Uniqueness

This metric defined the uniqueness of the labels in the data set; this is applicable only when there are multiple labels. There are three different label categories, as defined in Table 4.1; as in equation 6.4, *A is the number of records with various labels* , and *B is the total number of image records*[12].

$$X_c = \frac{A_c}{B} \tag{6.4}$$

Where the value for c is 0,1, and 2 for **not matured**, **matured** and **overdue** respectively and *B = 572 for all classes.* The values for *X_0 = 641/572* , *X_1 = 648/572* and

$X\_2 = 659/572$ which is *1.12, 1.3, and 1.15* respectively. This values are evaluated with the threshold value in the Table 6.1

6.2.5 Label Category Accuracy

The label category does not match the label object; the object cannot conform to the label is belongs to them; for example, a cat is labelled as a dog which is the incorrect label.

$$X = \frac{A}{B} \tag{6.5}$$

Where A is the number of records with incorrect labeling, and *B is the total number of records* [12].

6.2.6 Label Category Integrity

This metric informs the missing labelled information, labels give the idea about the object in the image, but the information about the labels is unavailable and missing.

$$X = \frac{A}{B} \tag{6.6}$$

A is the total number of records lacking label information, and *B is the number of images*[12]. The oyster mushrooms' image data set in Chapter 4 here lacks complete label information. The description about the labels are not available, so this evaluation is not applicable.

6.2.7 Label Category Imbalance

This metric gives the difference in the data of each category, counting the label category and the difference between the number of categories in the image data set [12].

$$X = \frac{\sum_i^N |x - \bar{x}|}{N} \tag{6.7}$$

X is defined as the count of each category, and *N is defined as the total number of images in the data set*[12]. This evaluation is applied to the complete data set before splitting into training and validation sets, as the number of classes is three; the values for the **not matured**, **matured** and **overdue** are 0.0145, 0.00232 and 0.0169, respectively. These values are compared with the threshold values given in Table 6.1.

6.2.8 Label Box Accuracy

This metric is defined as x and y coordinates representation, not a box. The coordinates are x,y x_min, y_min, x_max and y_max. There are main errors if the image object of the box does not match the box. The box should be with the annotation category, which indicates the accuracy of the annotation [12].

$$X = \frac{E1 + E2 + E3}{T} \tag{6.8}$$

E1 is the error one when x_min and y_min is greater than x_max and y_max, E2 is error two when the four data are missing, and E3 is error three when the object of the box is wrong. [12] *T is the sum of the image records* [12].This evaluation is not applied to the oyster mushrooms' data set. The labels contain the bounding box coordinates, and the bounding box values are the (x,y) coordinate, which gives the box's center and the image's width and height [12]. This information is not lacking for any objects as they are generated and checked manually.

6.2.9 Image Parameter Rationality

This metric is defined by checking the parameter of the labels of the images are reasonable, including the number of channels. There is only annotation information, but no image exists. Usually the channel numbers will be fixed and it will takes the values 2,3 or 4.

$$X = \frac{A + B}{T} \tag{6.9}$$

Where *A is the total number of objects with the wrong image channel number, B iterates each label to check the missing images,* and only labels exist [12]. Moreover, t is the total number of images. This evaluation is also not applicable to this thesis as the information about the labels are not stored, hence excluded.

6.2.10 Evaluation of metrics

The values of the "Label Category Uniqueness" gives a value that is greater than the threshold value given in Table 6.1, so the evaluation report for this image data set modifies the data set. Hence the other metrics, such as "Label Category Imbalance" and "Label Category Accuracy", are not calculated as one metric that gives the modification result of the data set.

Evaluation metrics	metrics result	Evaluation threshold
Label File Integrity	Label File Missing Rate	<=0.1%
image File Integrity	Image File Missing Rate	<=0.1%
Label Category Validity	Label Category Invalid Rate	<=0.1%
Label Category Uniqueness	Label Category Non-Unique Rate	<=0.1%
Label Category Accuracy	Label Error Rate	<=0.1%
Label Category Integrity	Label Category Information Missing Rate	<=0.1%
Label Category Imbalance	Label Imbalance Rate	<=0.1%
Label Box Accuracy	Box Error Rate	<=0.1%
Image Parameter Rationality	Unreasonable Parameter Rate	<=0.1%

FIGURE 6.1: Threshold values for the evaluation metrics(Source:[12])

The image are re-annotated for training, the class distribution to each of the instances are not balanced. The overdue class has more instances. This issue was solved by removing more overdue instances. The images that doesn't have all classes labels were also removed.

6.3 Evaluation of the YOLOv8 model for Oyster Mushroom Detection

6.3.1 Confusion Matrix

The model is evaluated by comparing the confusion matrix normalized while training the different scales of YOLOv8 [81]. The model's nano, small and medium are tested on the same test set to compare the results. The size of the model influences the training time and results. The accuracy of the model is calculated using the confusion matrix [81]. The accuracy of the model is calculated using Equation 6.10 [81].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.10}$$

Where TP, TN, FP, and FN are true positive, true negative, false positive and false negative, respectively [81]. These are commonly used in machine learning methods to evaluate the performance of the model [81]. Calculating the accuracy of the models from the confusion matrices obtained while training the model Figure 6.2 evaluated, Equation 6.10 is executed, and the results are depicted in Table 6.1.

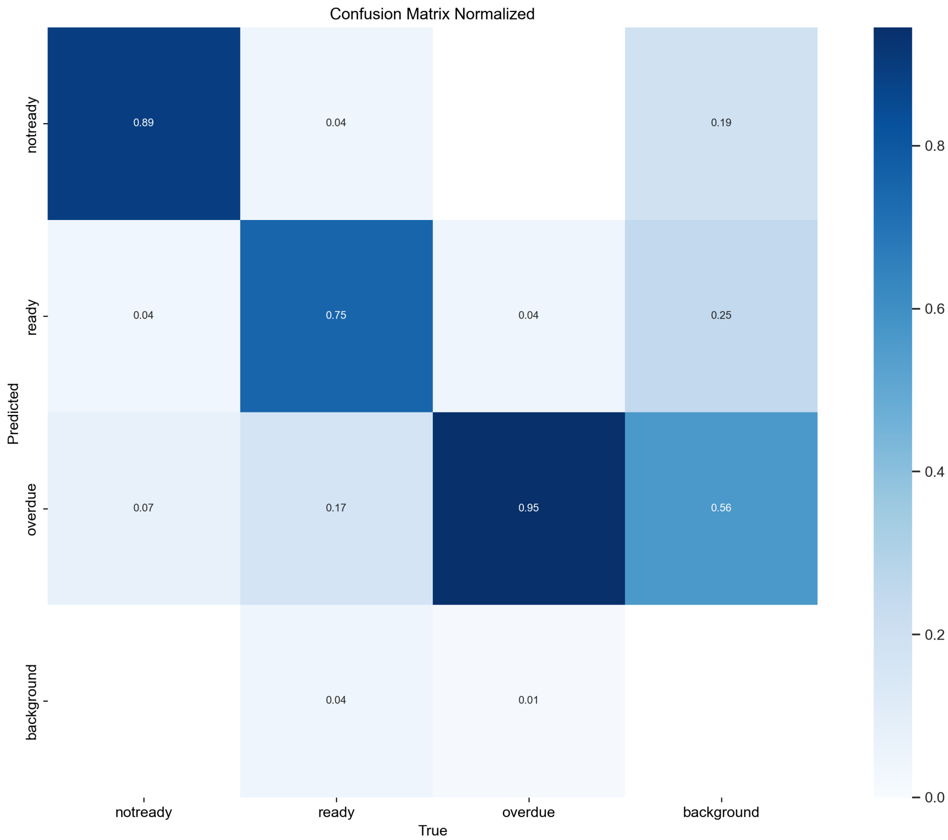


FIGURE 6.2: Confusion matrix for the model nano

Model	Not Matured	Matured	overdue
Nano	91.5%	81.3%	78.7%
Small	92.4%	84.4%	95.0%
Medium	89.4%	83.2%	80.5%

TABLE 6.1: Accuracy of different models over the three classes

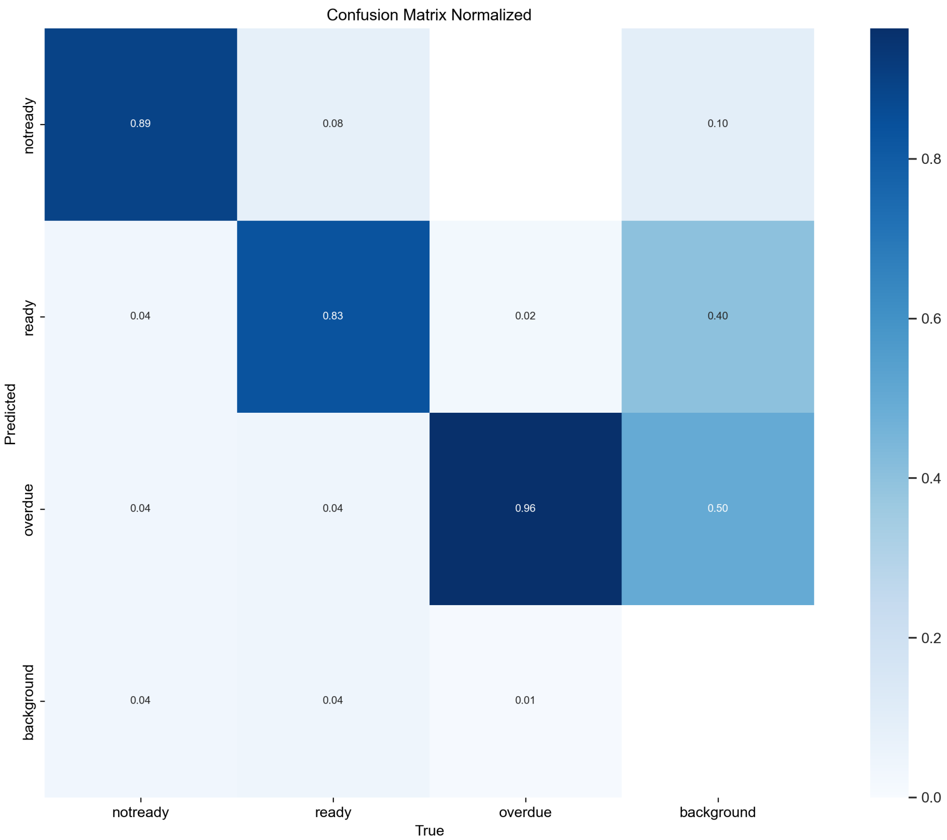


FIGURE 6.3: Confusion matrix for the model small

6.3.2 Precision-Recall

Another evaluation criterion of the model is calculating the precision and recall values. The precision gives the number of true positive predictions divided by true positive and false negative, and the recall provides the proportion of the actual positive to the true positive and false negative [81]. It also indicates correctly identifying all relevant instances in the data set [81]. The precision and recall are calculated using Equations 6.11 [81] and 6.12 [81], respectively, and the models are evaluated by Mean Average Precision(mAP) at the threshold of 0.5 [81]; the values are depicted in Table 6.2 .

$$Precision = \frac{TP}{TP + FP} \tag{6.11}$$

$$Recall = \frac{TP}{TP + FN} \tag{6.12}$$

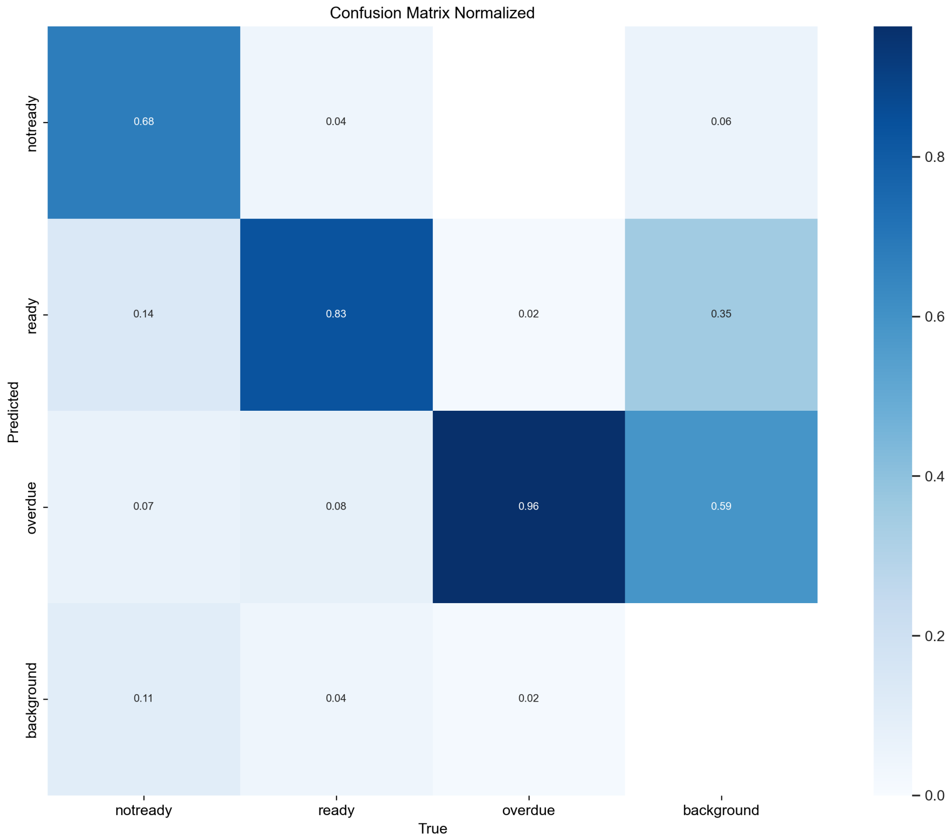


FIGURE 6.4: Confusion matrix for the model medium

Model	Precision	Recall	mAP@.5
Nano	.79	.89	.924
Small	.71	.75	.910
Medium	.83	.88	.907

TABLE 6.2: Precision and Recall values of three models

6.4 Evaluation on Edge Device - Raspberry Pi

This section discusses implementing maturity detection on edge devices. The Raspberry Pi [82]is connected to a keyboard, mouse and monitor; it works as a small computer. The YOLOv8 model is tested on Raspberry Pi[82] using transfer learning. As the Raspberry Pi is a small-sized mini-computer; it is impossible to train a complete model from scratch. Raspberry Pi takes the best values that are trained and tested on the device. The OS of Raspberry Pi is 64-bit with a 2 GB RAM installed. The testing images are saved on the local storage of the Raspberry Pi. Figure 6.8 shows the basic model of Raspberry Pi used. the average time taken by the Raspberry Pi to detect an image is 2.35 sec, 4.05 sec and 6.84 sec for model nano, small and medium respectively.

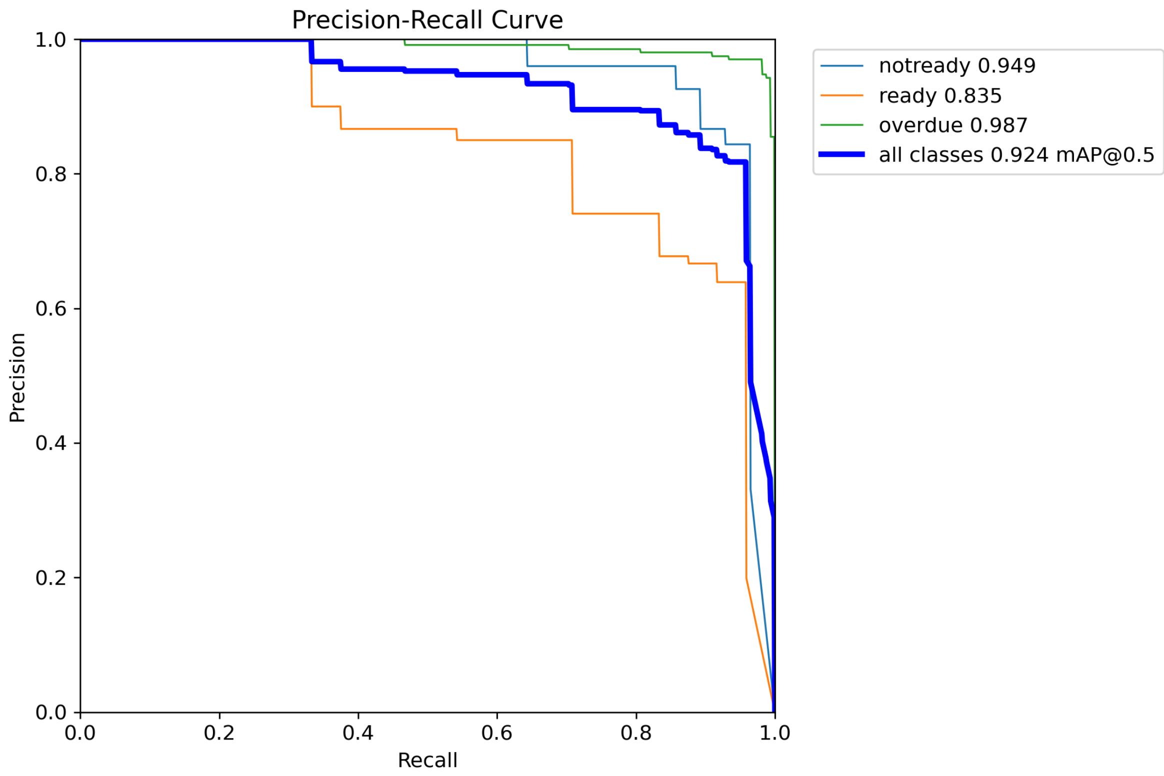


FIGURE 6.5: PR curve obtained for the model nano

All the models are tested on the same data set, and the results are noted. For a comparison study of the time taken by different models to predict the correctness of the data, the mean is taken for 10 iterations and a box plot for model nano, small and medium is plotted. Figure 6.9 shows that the time taken for the model medium is larger than any of the other plots.

6.5 Test Results

Figure 6.10 gives some of the oyster mushroom tested images from different angles that were not in the training and validation set. The test was carried out on the same images on all models. Figure (a) is the tested image on the YOLOv8 nano model with a correct prediction of the not-matured mushrooms. Figure (b) is the image that tested on the medium model and detected all the overdue oyster mushrooms. Figure(c) is the detection on the model small detect the not matured oyster mushrooms. However, Figure(d) gives the wrong prediction that made a detection where there is no mushroom body.

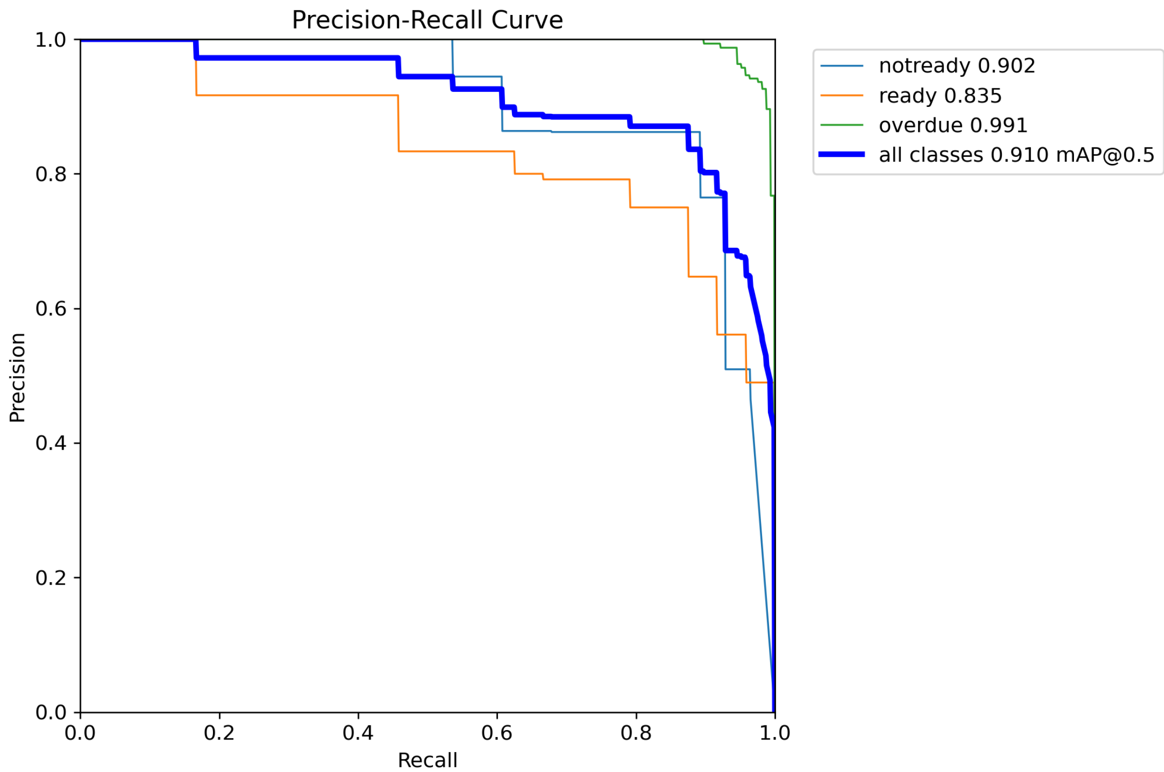


FIGURE 6.6: PR curve obtained for the model small

6.6 Conclusion

The evaluation for the oyster mushroom data set prepared in Chapter 4 and the maturity detection model for the oyster mushrooms are evaluated; The image data set needs to be modified to get better results as they lack uniqueness in the label category. The various scales of the model are calculated for the accuracy as depicted in Table 6.1. The YOLOv8 model performs well over the classes, which is above 80%. The model medium is good for predicting the model's maturity, as the precision and recall values are .83 and .88, respectively.

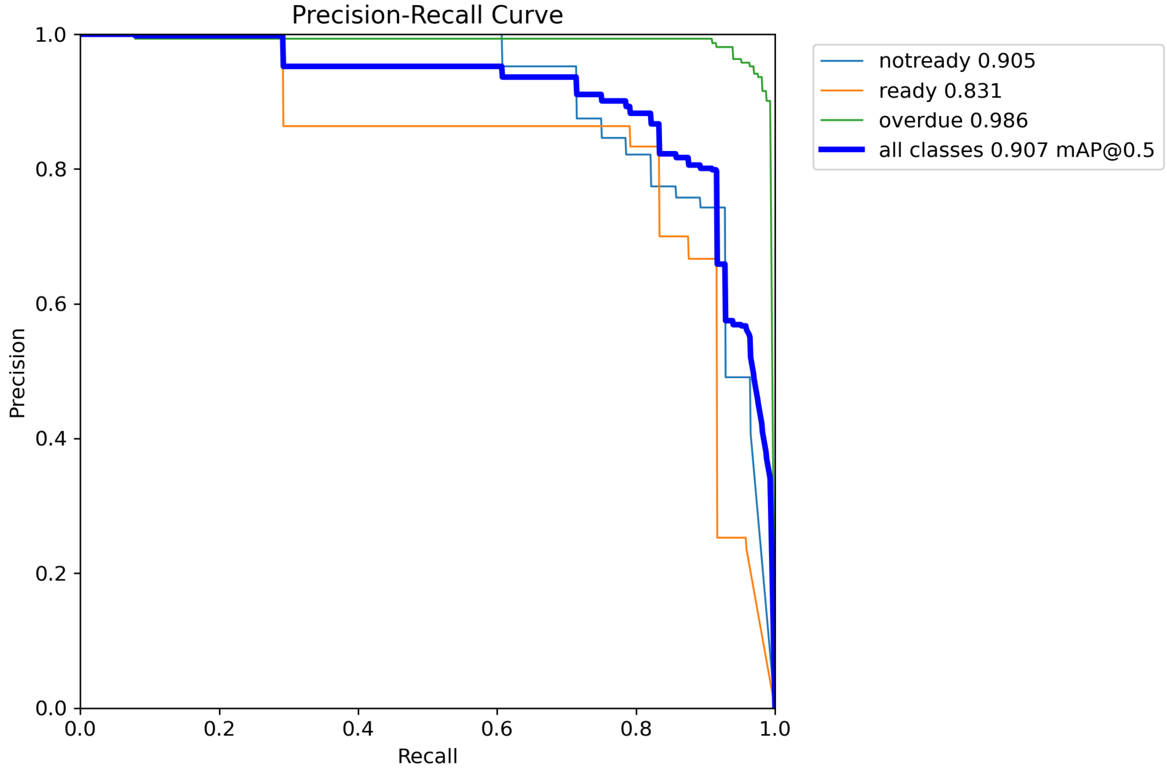


FIGURE 6.7: PR curve obtained for the model

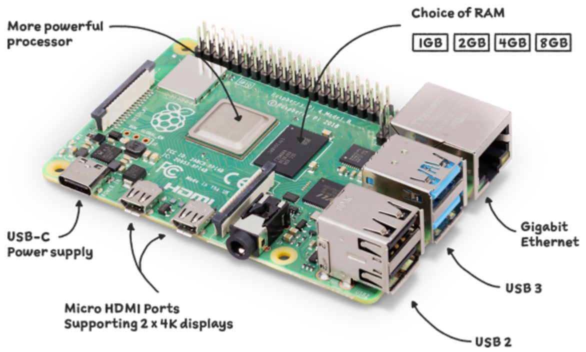


FIGURE 6.8: Threshold values for the evaluation metrics(Source:[82])

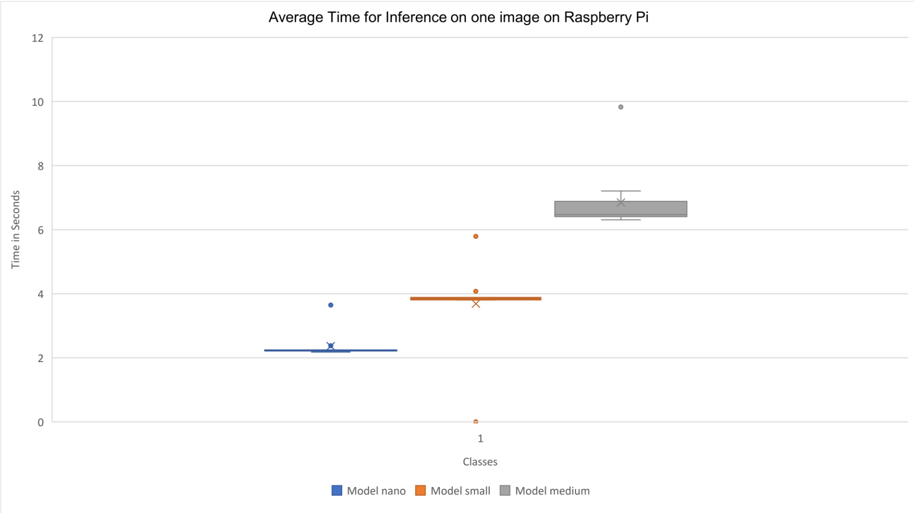
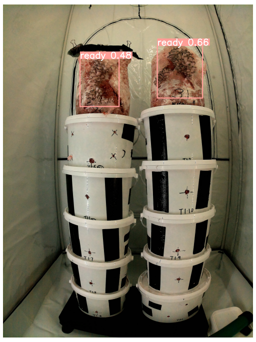


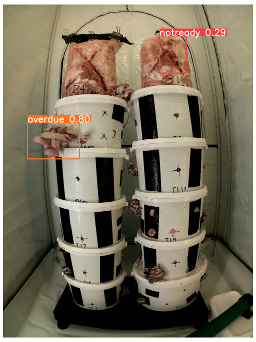
FIGURE 6.9: Box plot representation of average time required for inferences on one image on nano, small and medium models



(a) Model Nano

(b) Model Medium

(c) Model Small



(d) Wrong detection-model small

FIGURE 6.10: The different growth stages of the oyster mushrooms

Chapter 7

Conclusion and Future Work

This chapter concludes the works presented in this thesis. The research questions answered in each chapter are summarized, and the answer to the main research question is answered here, followed by the limitations and the possibility of future work.

7.1 Introduction

This thesis uses machine learning to investigate the maturity detection of oyster mushrooms from images. The first step was conducting a literature review to know the existing body of knowledge on identifying the maturity of crops. This study was adopted to check the maturity detection of the oyster mushroom. The conclusion of the literature review leads to selecting the machine learning model to detect the maturity of the oyster mushrooms growing in indoor chambers. The deep learning techniques that emerge these days are optimal for analyzing the images and locating and classifying the objects from the images. This thesis adopted the deep learning model, CNN-based YOLOv8, widely used in many applications. The latest YOLO, YOLOv8, is more accurate and faster in detecting and localizing objects. The various models of YOLOv8 were used on the same data set. The images of oyster mushrooms were prepared as the YOLO method accepts. CVAT online annotation tool was used for annotating the oyster mushroom; each image has its corresponding individual text file with the bounding box coordinates and the class number. The different scales of model YOLOv8 were trained with the image data set prepared. The results are compared using regular machine learning methodologies. Moreover, they are compared with each other to determine which model can be used to assess the maturity of the oyster mushrooms.

7.2 Answering the Research Questions

The main research question of this thesis, defined in Chapter 1, **" How to identify the maturity of the oyster mushroom from the images?"** is divided into three sub-research questions. **RQ1: How to review the literature for an existing methodology for maturity detection of the oyster mushroom from the images? RQ2: How to prepare the image data set for maturity detection of oyster mushrooms?** And **RQ3: How to develop the YOLOv8 model for object detection and classification?** The sub-research questions are answered more sophisticatedly and structured in Sections 7.2.1, 7.2.2 and 7.2.3, respectively.

7.2.1 RQ1: How to review the literature for an existing methodology for maturity detection of the oyster mushroom from the images?

The literature review was conducted in a way that contributed to the main research question. The scientific papers that show a similar pattern were downloaded and stored. The scientific works that contribute to the works are analyzed, and the rest are eliminated. The works that show a similar pattern were machine learning methodologies, specifically deep learning methods that can analyze the images and locate the objects from an image. The YOLOv8 was adopted from several methodologies due to its accuracy and speed than the other methodologies.

7.2.2 RQ2: How to prepare the image data set for maturity detection of oyster mushrooms?

The images of oyster mushrooms collected from the grow chambers are prepared in the way that the YOLO model takes. Annotations are made around the mushroom's whole body. Bounding boxes were used to locate the oyster mushrooms; each image has a corresponding text file that gives the details of the oyster mushrooms, the x, and y coordinates, which indicate the image's centre and the width and height of the image. Three classes were given to the oyster mushrooms, **class 0** as not matured, **class 1** as matured and **class 2** as overdue.

7.2.3 RQ3: How to develop a model for object detection and classification?

The latest model of the YOLOv8 is used to identify the maturity of the oyster mushroom. The model takes the oyster mushroom images and the yaml file with the path and configuration of the image data set. The image data set is split into training and validation sets. A total of 572 images were used with 1,948 instances of three classes. The batch size for training was 16 as default on the CPU device. All three models were trained on the same data set. The confusion matrix obtained for each model belongs to the bounding box prediction in terms of TP, TN, FP and FN are calculated.

7.3 Limitations

Numerous limitations came up when doing this thesis. The model was trained on the CPU as the personal GPU ran out after 20 epochs. If the GPU is used, the time taken to train all three models can be considerably reduced. The image data set was another limitation, as the images were unclear, and the class instance distributions were not balanced. The annotations were done by manually as the knowledge about the maturity classification of matured to overdue was limited. The total number of trained images was 458; more training images can result in better results. Only three classes of labels of the oyster mushrooms were considered, as it limits the stage of pinning and intermediate matured oyster mushrooms being ignored. Only bounding box annotation is considered in this thesis, as segmentation and classification are ignored. This can be improved as it can detect only the mushroom flushes.

7.4 Future Work

An improved oyster mushroom image data set with segmentation is a possible maturity detection study. The maturity detection can be extended to other models that work with bounding boxes. This thesis can be improved by improving the quality of the oyster mushroom image data set and the annotations. The maturity detection can be incorporated with human-machine interaction by sending it to a robot arm for harvesting the matured oyster mushrooms for large-scale production. Furthermore, this model can cooperate with other crops for automated maturity detection and harvesting.

Bibliography

[1] Y. Qian, R. Jiacheng, W. Pengbo, Y. Zhan, and G. Changxing, "Real-time detection and localization using SSD method for oyster mushroom picking robot", in *2020 IEEE International Conference on Real-time Computing and Robotics (RCAR)*, IEEE, 2020, pp. 158–163.

[2] B. Wei, Y. Zhang, Y. Pu, *et al.*, "Recursive-YOLOv5 Network for Edible Mushroom Detection in Scenes With Vertical Stick Placement", *IEEE Access*, vol. 10, pp. 40 093–40 108, 2022.

[3] E. official webpage. "ETCT LAB". https://etce-lab.com/index.php/mushr-a-smart-automated-and-scalable-indoor-harvesting-system-for-gourmet-mushrooms. (1-January-2023), (visited on 04/25/2023).

[4] N. Ejigu, B. Sitotaw, S. Girmay, and H. Assaye, "Evaluation of oyster mushroom (Pleurotus ostreatus) production using water hyacinth (Eichhornia crassipes) biomass supplemented with agricultural wastes", *International Journal of Food Science*, vol. 2022, 2022.

[5] M. A. Ayllon, M. J. Cruz, J. J. Mendoza, and M. C. Tomas, "Detection of overall fruit maturity of local fruits using convolutional neural networks through image processing", in *Proceedings of the 2nd International Conference on Computing and Big Data*, 2019, pp. 145–148.

[6] K. Raut and V. Bora, "Assessment of fruit maturity using digital image processing", *International Journal of Science Technology and Engineering*, vol. 3, no. 1, pp. 273–279, 2016.

[7] J. Zupan, "Introduction to artificial neural network (ANN) methods: what they are and how to use them", *Acta Chimica Slovenica*, vol. 41, pp. 327–327, 1994.

[8] M. B. Crowe. "Southwest Mushrooms". https://southwestmushrooms.com/en-de. (1-October-2022), (visited on 04/25/2023).

[9] N. P. M. Illo and M. A. L. Orobia, "Development of Oyster Mushroom Siopao", *Sustainable Development*, vol. 10, no. 1, pp. 75–78, 2022.

[10] N. M. Z. Hashim, M. D. Shaharudin, A. Jaafar, *et al.*, “Grey Oyster Mushroom Classification toward a Smart Mushroom Grading System for Agricultural Factory”, in *2022 2nd International Conference on Intelligent Technologies (CONIT)*, IEEE, 2022, pp. 1–6.

[11] A. R. Hevner, S. T. March, J. Park, and S. Ram, “Design Science in Information Systems Research”, *MIS quarterly*, vol. 28, no. 1, pp. 75–105, 2004.

[12] Y. Gong, Y. Xue, Q. Dong, *et al.*, “Quality Evaluation of Image Dataset based on Label File”, in *2021 8th International Conference on Dependable Systems and Their Applications (DSA)*, IEEE, 2021, pp. 639–646.

[13] J. Q. Glenn Jocher Ayush Chaurasia, “YOLO by Ultralytics”, version 8.0.0, 2023-1-10. [Online]. Available: %5Curl%7Bhttps://github.com/ultralytics/ultralytics/tree/main%7D (visited on 04/21/2023).

[14] 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*, 2016, pp. 779–788.

[15] T.-Y. Lin, M. Maire, S. Belongie, *et al.*, “Microsoft coco: Common objects in context”, in *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, Springer, 2014, pp. 740–755.

[16] A. M. .-G. personal page. “MSAthira”. https://github.com/MSAthira/Documentation_yolo/tree/master/thesis_benjamin_athira. (1-January-2023), (visited on 04/25/2023).

[17] J. Nongthombam, A. Kumar, B. Ladli, M. Madhushekhar, and S. Patidar, “A review on study of growth and cultivation of oyster mushroom”, *Plant Cell Biotechnology and Molecular Biology*, vol. 22, no. 5&6, pp. 55–65, 2021.

[18] M. Huang, L. He, D. Choi, J. Pecchia, and Y. Li, “Picking dynamic analysis for robotic harvesting of Agaricus bisporus mushrooms”, *Computers and Electronics in Agriculture*, vol. 185, p. 106 145, 2021.

[19] C.-P. Lu, J.-J. Liaw, T.-C. Wu, and T.-F. Hung, “Development of a mushroom growth measurement system applying deep learning for image recognition”, *Agronomy*, vol. 9, no. 1, p. 32, 2019.

[20] R. Silva and F. Neiva, “Systematic literature review in computer science—a practical guide.(2016)”,

[21] A. Carrera-Rivera, W. Ochoa-Agurto, F. Larrinaga, and G. Lasa, “How-to conduct a systematic literature review: A quick guide for computer science research”, *MethodsX*, p. 101 895, 2022.

[22] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org.

[23] J. Nongthombam, A. Kumar, B. Ladli, M. Madhushekhar, and S. Patidar, "A review on study of growth and cultivation of oyster mushroom", *Plant Cell Biotechnology and Molecular Biology*, vol. 22, no. 5&6, pp. 55–65, 2021.

[24] J. Alzubi, A. Nayyar, and A. Kumar, "Machine learning from theory to algorithms: an overview", in *Journal of physics: conference series*, IOP Publishing, vol. 1142, 2018, p. 012 012.

[25] L. Alzubaidi, J. Zhang, A. J. Humaidi, *et al.*, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions", *Journal of big Data*, vol. 8, pp. 1–74, 2021.

[26] A. Sujatanagarjuna, S. Kia, D. F. Briechle, and B. Leiding, "MushR: A Smart, Automated, and Scalable Indoor Harvesting System for Gourmet Mushrooms", *Agriculture*, vol. 13, no. 8, p. 1533, 2023.

[27] C. Documentaion. "CVAT annotation tool". https://opencv.github.io/cvat/docs/. (12-April-2023), (visited on 05/29/2023).

[28] J. Wu, "Introduction to convolutional neural networks", *National Key Lab for Novel Software Technology. Nanjing University. China*, vol. 5, no. 23, p. 495, 2017.

[29] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network", in *2017 international conference on engineering and technology (ICET)*, Ieee, 2017, pp. 1–6.

[30] R. Chauhan, K. K. Ghanshala, and R. Joshi, "Convolutional neural network (CNN) for image detection and recognition", in *2018 first international conference on secure cyber computing and communication (ICSCCC)*, IEEE, 2018, pp. 278–282.

[31] P. Ramachandran, B. Zoph, and Q. V. Le, "Searching for activation functions", *arXiv preprint arXiv:1710.05941*, 2017.

[32] J. Gu, Z. Wang, J. Kuen, *et al.*, "Recent advances in convolutional neural networks", *Pattern recognition*, vol. 77, pp. 354–377, 2018.

[33] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation", in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2014, pp. 580–587.

[34] X. Han, J. Chang, and K. Wang, "You only look once: unified, real-time object detection", *Procedia Computer Science*, vol. 183, no. 1, pp. 61–72, 2021.

[35] W. Liu, D. Anguelov, D. Erhan, *et al.*, "Ssd: Single shot multibox detector", in *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14*, Springer, 2016, pp. 21–37.

[36] Y. Amit, P. Felzenszwalb, and R. Girshick, "Object detection", *Computer Vision: A Reference Guide*, pp. 1–9, 2020.

[37] R. Vaillant, C. Monrocq, and Y. Le Cun, "Original approach for the localisation of objects in images", *IEE Proceedings-Vision, Image and Signal Processing*, vol. 141, no. 4, pp. 245–250, 1994.

[38] F. Weidt and R. Silva, "Systematic literature review in computer science-a practical guide", *Relatórios Técnicos Do DCC/UFJF*, vol. 1, no. 8, 2016.

[39] S. Keele *et al.*, *Guidelines for performing systematic literature reviews in software engineering*, 2007.

[40] Q. Liu, M. Fang, Y. Li, and M. Gao, "Deep learning based research on quality classification of shiitake mushrooms", *LWT*, vol. 168, p. 113 902, 2022.

[41] C.-P. Lu and J.-J. Liaw, "A novel image measurement algorithm for common mushroom caps based on convolutional neural network", *Computers and electronics in agriculture*, vol. 171, p. 105 336, 2020.

[42] J. Preechasuk, O. Chaowalit, F. Pensiri, and P. Visutsak, "Image analysis of mushroom types classification by convolution neural networks", pp. 82–88, 2019.

[43] M. A. Islam, M. A. Islam, M. S. U. Miah, and A. Bhowmik, "An automated monitoring and environmental control system for laboratory-scale cultivation of oyster mushrooms using the Internet of Agricultural Thing (IoAT)", pp. 207–212, 2022.

[44] J. Wieme, K. Mollazade, I. Malounas, *et al.*, "Application of hyperspectral imaging systems and artificial intelligence for quality assessment of fruit, vegetables and mushrooms: A review", *Biosystems Engineering*, vol. 222, pp. 156–176, 2022.

[45] M. Kudo and J. Sklansky, "Comparison of algorithms that select features for pattern classifiers", *Pattern recognition*, vol. 33, no. 1, pp. 25–41, 2000.

[46] J. F. Tude vizhanoyo, "Enhancing colour differences in images of diseased mushrooms", *Computers and Electronics in Agriculture*, vol. 26, no. 2, pp. 187–198, 2000.

[47] H. Rahman, M. O. Faruq, T. B. A. Hai, *et al.*, "IoT enabled mushroom farm automation with Machine Learning to classify toxic mushrooms in Bangladesh", *Journal of Agriculture and Food Research*, vol. 7, p. 100 267, 2022.

[48] A. Mukherjee, T. Sarkar, K. Chatterjee, *et al.*, "Development of artificial vision system for quality assessment of oyster mushrooms", *Food Analytical Methods*, vol. 15, no. 6, pp. 1663–1676, 2022.

[49] T. Sarkar, A. Mukherjee, K. Chatterjee, *et al.*, "Comparative analysis of statistical and supervised learning models for freshness assessment of oyster mushrooms", *Food Analytical Methods*, vol. 15, no. 4, pp. 917–939, 2022.

[50] P. Van Loon, A. Sonnenberg, H. Swinkels, L. Van Griensven, and G. Van der Heijden, "Objective measurement of developmental stage of white button mushrooms (Agaricus bisporus)", *Mushroom Science*, vol. 14, pp. 703–708, 1995.

[51] C.-H. Lee, D. Choi, J. Pecchia, L. He, and P. Heinemann, "Development of a mushroom harvesting assistance system using computer vision", in *2019 ASABE Annual International Meeting*, American Society of Agricultural and Biological Engineers, 2019, p. 1.

[52] M. Ahmed, N. Abdullah, K. U. Ahmed, and M. Bhuyan, "Yield and nutritional composition of oyster mushroom strains newly introduced in Bangladesh", *Pesquisa Agropecuária Brasileira*, vol. 48, pp. 197–202, 2013.

[53] D. Royse, T. Rhodes, S. Ohga, and J. Sanchez, "Yield, mushroom size and time to production of Pleurotus cornucopiae (oyster mushroom) grown on switch grass substrate spawned and supplemented at various rates", *Bioresource Technology*, vol. 91, no. 1, pp. 85–91, 2004.

[54] W. Ketwongsa, S. Boonlue, and U. Kokaew, "A New Deep Learning Model for the Classification of Poisonous and Edible Mushrooms Based on Improved AlexNet Convolutional Neural Network", *Applied Sciences*, vol. 12, no. 7, p. 3409, 2022.

[55] A. Wibowo, Y. Rahayu, A. Riyanto, and T. Hidayatulloh, "Classification algorithm for edible mushroom identification", in *2018 International Conference on Information and Communications Technology (ICOIACT)*, IEEE, 2018, pp. 250–253.

[56] P. Tongcham, P. Supa, P. Pornwongthong, and P. Prasitmeeboon, "Mushroom spawn quality classification with machine learning", *Computers and Electronics in Agriculture*, vol. 179, p. 105 865, 2020.

[57] D. Sahu and R. M. Potdar, "Defect identification and maturity detection of mango fruits using image analysis", *American Journal of Artificial Intelligence*, vol. 1, no. 1, pp. 5–14, 2017.

[58] D. Surya Prabha and J. Satheesh Kumar, "Assessment of banana fruit maturity by image processing technique", *Journal of food science and technology*, vol. 52, no. 3, pp. 1316–1327, 2015.

[59] V. M. Lomte, S. Sabale, R. Shirgaonkar, P. Nagathan, and P. Pawar, "Fruit Counting and Maturity Detection using Image Processing: A Survey",

[60] L. Raja Sekar, N. Ambika, V. Divya, and T. Kowsalya, "Fruit classification system using computer vision: a review", *International Journal of Trend in Research and Development (IJTRD), ISSN*, pp. 2394–9333, 2018.

[61] N. Zahan, M. Z. Hasan, M. A. Malek, and S. S. Reya, "A Deep Learning-Based Approach for Edible, Inedible and Poisonous Mushroom Classification", in *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*, IEEE, 2021, pp. 440–444.

[62] Y. Onishi, T. Yoshida, H. Kurita, T. Fukao, H. Arihara, and A. Iwai, "An automated fruit harvesting robot by using deep learning", *Robomech Journal*, vol. 6, no. 1, pp. 1–8, 2019.

[63] J. Rong, P. Wang, Q. Yang, and F. Huang, "A field-tested harvesting robot for oyster mushroom in greenhouse", *Agronomy*, vol. 11, no. 6, p. 1210, 2021.

[64] J.-E. Dong, J. Zhang, Z.-T. Zuo, and Y.-Z. Wang, "Deep learning for species identification of bolete mushrooms with two-dimensional correlation spectral (2DCOS) images", *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 249, p. 119 211, 2021.

[65] R. Rahmat, T. Aruan, S. Purnamawati, S. Faza, T. Lini, *et al.*, "Fungus image identification using K-Nearest Neighbor", in *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, vol. 420, 2018, p. 012 097.

[66] M. Horvat and G. Gledec, "A comparative study of YOLOv5 models performance for image localization and classification", in *Central European Conference on Information and Intelligent Systems*, Faculty of Organization and Informatics Varazdin, 2022, pp. 349–356.

[67] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask r-cnn", in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 2961–2969.

[68] D. Bolya, C. Zhou, F. Xiao, and Y. J. Lee, "Yolact: Real-time instance segmentation", in *Proceedings of the IEEE/CVF international conference on computer vision*, 2019, pp. 9157–9166.

[69] H.-J. Jeong, K.-S. Park, and Y.-G. Ha, "Image preprocessing for efficient training of YOLO deep learning networks", in *2018 IEEE International Conference on Big Data and Smart Computing (BigComp)*, IEEE, 2018, pp. 635–637.

[70] D.-J. Shin and J.-J. Kim, "A deep learning framework performance evaluation to use yolo in nvidia jetson platform", *Applied Sciences*, vol. 12, no. 8, p. 3734, 2022.

[71] H. Qassim, A. Verma, and D. Feinzimer, "Compressed residual-VGG16 CNN model for big data places image recognition", in *2018 IEEE 8th annual computing and communication workshop and conference (CCWC)*, IEEE, 2018, pp. 169–175.

[72] J.-a. Kim, J.-Y. Sung, and S.-h. Park, "Comparison of Faster-RCNN, YOLO, and SSD for real-time vehicle type recognition", in *2020 IEEE international conference on consumer electronics-Asia (ICCE-Asia)*, IEEE, 2020, pp. 1–4.

[73] S. Srivastava, A. V. Divekar, C. Anilkumar, I. Naik, V. Kulkarni, and V. Pattabiraman, "Comparative analysis of deep learning image detection algorithms", *Journal of Big Data*, vol. 8, no. 1, pp. 1–27, 2021.

[74] L. Tan, T. Huangfu, L. Wu, and W. Chen, "Comparison of YOLO v3, Faster R-CNN, and SSD for Real-Time Pill Identification", 2021.

[75] J. Terven and D. Cordova-Esparza, "A comprehensive review of YOLO: From YOLOv1 to YOLOv8 and beyond", *arXiv preprint arXiv:2304.00501*, 2023.

[76] X. Qian, S. Lin, G. Cheng, X. Yao, H. Ren, and W. Wang, "Object detection in remote sensing images based on improved bounding box regression and multi-level features fusion", *Remote Sensing*, vol. 12, no. 1, p. 143, 2020.

[77] J. Yu, Y. Jiang, Z. Wang, Z. Cao, and T. Huang, "Unitbox: An advanced object detection network", in *Proceedings of the 24th ACM international conference on Multimedia*, 2016, pp. 516–520.

[78] Y. Yao, G. Cheng, G. Wang, *et al.*, "On improving bounding box representations for oriented object detection", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–11, 2022.

[79] H. Lou, X. Duan, J. Guo, *et al.*, "DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor", *Electronics*, vol. 12, no. 10, p. 2323, 2023.

[80] X. Li, W. Wang, L. Wu, *et al.*, "Generalized focal loss: Learning qualified and distributed bounding boxes for dense object detection", *Advances in Neural Information Processing Systems*, vol. 33, pp. 21 002–21 012, 2020.

[81] D. Witten and G. James, *An introduction to statistical learning with applications in R.* springer publication, 2013.

[82] R. official webpage. "raspberrypi setup". https://www.raspberrypi.com/products/raspberry-pi-4-model-b/. (1-January-2023), (visited on 07/25/2023).

Declaration of Authorship

I Athira Mavoomkuttathil Sivachandran, hereby certify that I have written the work independently and have not used any other sources or aids than those specified and that all parts of this work that have been taken literally or analogously from other sources have been identified as such and that the work is in the same or a similar form has not yet been submitted to any other examination body.
Furthermore, I declare that I agree with the public availability of my thesis in the institute and university library.

Date: 6-9-2023

Signed: