REVOLUTIONIZING AGRICULTURE: UNVEILING YOLOV-8-POWERED MULTI-LABLED SEEDS SEGMENTATION

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Revolutionizing Agriculture: Unveiling YOLOv8-Powered Multi-Labeled Seeds Segmentation**", submitted by **Hafiz Al Fahim** and **Md. Abid Hasan** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **13th July, 2024.**

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We hereby declare that this project has been done by us under the supervision of **Dr. Md. Monzur Morshed, Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

There is a wide range of dry seeds in the world. The quality of seeds significantly impacts crop production. Hence, seed classification is vital for both marketing and production, serving as the foundation for sustainable principles in agriculture systems. The primary objective of this study is a method for extracting multiple seeds from a single image by segmenting them. Thus, a multi-label segmentation and detection system was developed to distinguish 18 different varieties of seeds with similar features. For the training model, images of 100 seeds of 18 varieties were taken with a high-resolution camera. In the initial stage, images undergo augmentation and feature extraction processes. Resulting a total of 1029 by 18 shapes of labels. The initial phase was focused on processing data and extracting the valuable features from it. For segmentation and detection, the model YOLOv8 was applied. Also, to compare the performance of our custom train YOLOv8 model we trained a vanilla YOLOv5. Our breakthrough YOLOv8 model achieved an impressive 99% confidence level for select classes in our private dataset, with an overall average detection rate of 94.5%. Whereas the YOLOv5 conducted an overall detection rate of 94.7%.

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ANN	Artificial Neural Network
YOLO	You Only Look Once
ML	Machine Learning
AI	Artificial Intelligence
CSV	Comma Separated Values

CHAPTER 1
INTRODUCTION

1.1 Overview

In the field of contemporary agriculture, tackling the complex task of identifying and categorizing seeds with many labels is a crucial undertaking. The objective of this project is to develop a novel technique that can accurately identify different types of seeds in a picture, even when there are several instances of the different seed type present. This work directly addresses the challenging problems of unbalanced class distributions, inter-class similarity, and overlapping seeds in the context of agricultural applications. It represents a substantial advancement in using the capabilities of deep learning. Several essential reasons highlight the importance and immediacy of this effort. Although there is a huge variety of seeds globally, just 18 examples are usually chosen for examination, revealing a significant difference in our understanding of this crucial element of agriculture. In addition, the restricted availability of datasets exacerbates this difficulty, serving as an obstacle to advancement in this critical area of research. Moreover, the advancement of multi-label solutions shows great potential for transforming different deep learning applications, namely in the fields of computer vision and picture classification. By improving and perfecting these solutions, we can successfully fulfill the growing need for accurate and efficient seed classification tools, thereby driving progress in agriculture operations and other fields. By conducting this study our targeted achievements will be given below.

• Compile a diverse seed image dataset representative of various varieties to address accessibility gaps in seed segmentation data.

• Explore and select optimal feature extraction techniques tailored for multi-label seed segmentation, enhancing classification accuracy and efficiency.

• Build a resilient multi-label segmentation system capable of accurately segmented seed images with multiple labels, addressing complexities in seed detection.

• Thoroughly evaluate the effectiveness and target areas for development of the created system by using appropriate metrics.

• Investigate and implement solutions for challenges like class imbalance and overlapping seeds to ensure the reliability and robustness of the system.

The best models can be selected and their performance optimized with the use of this knowledge in future research endeavors. This work represents a first step toward creating a multi-label development and research environment that is more diverse and inclusive.

1.2 Background and Present State

Agriculture is the backbone of many economies and basis of food security worldwide. In this backdrop, for the last few years, technological advancement has taken the center stage in changing agriculture from mechanization to precision farming. Of late, one area that has witnessed plenty of developments is the application of computer vision and machine learning techniques in agricultural processes. Here, it presents innovative solutions for the problems associated with crop monitoring, disease detection, and yield prediction.

Advanced techniques in computer vision have been applied to many challenging issues in agriculture. One such challenge is the accurate segmentation of seeds within agricultural images for seed counting, quality assessment, and yield estimation. The traditional approaches to seed segmentation are not very effective and efficient with respect to the diversity in types of seeds and changing environmental factors. Recent years have provided robust models that have deeply gone into the area of deep learning, especially YOLOv8—"You Only Look Once" version 8. Real-time object detection was the major deployed use of YOLOv8, which has also shown bright prospects in agriculture. Building on this, recently, YOLOv8 has been used to explore multi-labeled seed segmentation. This can be used in detection in images, not only for the seeds but also further classification according to their size, shape, and even health status. The application of YOLOv8 in seed segmentation is therefore very paradigmatic for both automation and precision farming. This technology can readily create a revolution in workflows of seed processing by providing farmers and researchers with more informed and timely insight into seed populations and their qualities. In addition, the automation of seed segmentation by YOLOv8 will undertake a much-needed reduction of labor costs by improving operational efficiency in agriculture. YOLOv8-driven multi-labeled seeds segmentation holds great potential to take agriculture to another level by opening the way toward the resolution of existing challenges in the analysis of seeds and reaching more sustainable and productive agricultural practices in the future.

1.3 Problem Statement

We have a primary dataset that consists of seed images, each of which has numerous seeds from different classes in it. There are eighteen different seed classes in the dataset, and each seed may belong to more than one class. In this study, the main challenge is accurately classifying seeds in photos with many occurrences, where each seed can be in different classes. This is a tough case since traditional multi-label classification algorithms typically assume one instance per image.

1.4 Objectives

This project is motivated by numerous factors that highlight how important it is to develop multi-label solutions for multi-instance images. First and foremost, just 18 cases are selected from the world's approximately trillion varieties of seeds. While it may seem insignificant in contrast, there is a significant discrepancy in the dataset's accessibility.

Second, multi-label creation is crucial to many deep learning applications, such as computer vision and image categorization. We may increase the effectiveness of these apps by building more exact and efficient solutions that match the increasing need for seed categorization.

Last but not least, to extract the diversity from an image, we also study several multi-class models in conjunction with multi-label classification. The best models can be selected and their performance optimized with the use of this knowledge in future research endeavors. This work represents a first step toward creating a multi-label development and research environment that is more diverse and inclusive.

1.5 Scope and Limitations

The preparation of seed images and data collection are included in the project scope. Investigating and choosing appropriate feature extraction methods for the images can also be helpful. Additionally, it will support creating and using a multi-label categorization system. The evaluation of the model's performance will be verified using the relevant measures. The last and most important step in this section is researching solutions for problems like class imbalance and overlapping seeds.

1.6 Report Organization

Chapter 1 provides an introduction to our research, outlining its objectives, motivations, and the financial analysis conducted. We delve into the foundational aspects that set the stage for our investigation into multi-label seeds classification and segmentation. Chapter This chapter establishes a theoretical framework essential for comparing existing models with our novel approach. In Chapter 3, we detail our research methodology, encompassing the data collection procedures, model architecture, and hardware specifications.

Chapter 4 presents the experimental results obtained from our proposed model. Accompanied by detailed statistical analyses. This empirical evidence forms the basis for evaluating the efficacy and performance of our research.

Chapter 5 explores the societal impact of our work, focusing on the ethical considerations and how our findings contribute to advancements in agriculture and societal betterment. Finally, Chapter 6 consolidates our study with a summary of key findings, conclusions drawn from our analysis, and suggestions for future research directions. This concluding chapter encapsulates the entirety of our research journey and outlines pathways for further improvements.

1.7 Summary

This study explores the field of multi-label seed classification, a frontier in computer vision where the identification of the several roles that a single seed may play becomes paramount. See a picture full of seeds, each with the capacity to be a member of several classes. The study's goal is to come up with a model that may resolve this complicated puzzle and show all the seeds. There is so much practical usefulness in this research. Imagine bringing about a revolution in agriculture via the unmatched accuracy of seed classification. Imagine automating seed classification and easily sorting different kinds of seeds for effective packing and delivery. By pushing the limits of technology, this research seeks to enable a variety of disciplines, including seed classification in agriculture.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Before exploring the intricacies of YOLOv8-powered multi-labeled seed segmentation in agriculture, it's crucial to establish a solid grasp of key concepts and terminologies shaping this field. YOLOv8, short for "You Only Look Once version 8," is an advanced object detection algorithm renowned for its exceptional speed and accuracy in identifying objects within images. Multi-labeled seeds segmentation involves the process of identifying and delineating multiple types or varieties of seeds within an image, playing a pivotal role in seed classification and crop management practices. Precision agriculture, a cornerstone of modern farming methodologies, leverages cutting-edge technologies like remote sensing, GPS, and machine learning to optimize resource allocation, enhance crop yields, and minimize environmental impact. Object detection, a fundamental task within computer vision, revolves around the identification and localization of objects within images or videos, providing precise bounding boxes around detected objects for further analysis. Machine learning, a key driver of technological advancements, encompasses the development of algorithms and models capable of learning from data to make predictions or decisions without explicit programming. Lastly, computer vision focuses on enabling computers to interpret and understand visual information from the real world, spanning tasks such as image classification, object detection, and scene understanding. These terminologies collectively provide a foundational framework for understanding and discussing the implementation and implications of YOLOv8-powered multi-labeled seeds segmentation in agricultural contexts.

2.2 Related works

This study attempts to address the problem of previous methodologies' low accuracy in categorizing seed varieties. The scientists proposed a two-step process: first, they used a convolutional neural network to extract visual properties from seed images, and then they fed those features into several classifiers. An artificial neural network and CNN worked together to achieve an astounding 98.1% accuracy rate. This demonstrates how deep learning has the potential to provide accurate and effective seed type identification, which is a crucial ability for enhancing agricultural practices and preserving seed purity [1].

The main goal of this study is to use machine vision and multivariate analysis to sort different types of paddy seeds into groups based on how pure they are. Three kinds of paddy seeds were used to take pictures with an RGB camera. It was possible to pull out

20 important traits from 375 images of paddy seeds using an image processing program. To find out how to separate different types of paddy seeds, variance modeling and the analysis of principal components were used. Using the PLS-DA, SVM-C, and KNN methods, classification models for different types of paddy seeds were created. It was discovered that morphological picture features were more important than color and texture features. Using these features together, the accuracy was 83.8%, 93.9%, and 87.2%. It is possible to do this with the SVM-C method and certain color, shape, and texture traits [2].

Unlabeled data helps multi-label tasks such as document and picture classification, but noise gets in the way of these tasks. A method called MLSTE is suggested in this study. It uses nearest neighbor editing to help choose reliable data and better labels. This makes things work better. Think of it as hardworking data without labels librarian that improves the accuracy of categorization for real-world uses [31].

This study addresses tasks in which a hierarchy of labels may be present on data points. While other approaches overlook this hierarchy, Fully Associative Ensemble Learning (FAEL) makes use of it to improve accuracy. FAEL approaches the link between a class's sub-labels and anticipated label as a multi-variable regression problem, using binary restrictions and kernel methods to capture intricate correlations. Experiments demonstrate that FAEL performs better than baselines on gene, picture, and large-scale visual identification datasets with both DAG and tree hierarchies. To put it briefly, the hierarchy structure is embraced in order to improve multi-label classification accuracy [3].

In this study, scientific advances have been driven for millennia by pattern identification, or the search for patterns in data. This field aims at automatically revealing the inherent order in data, from Kepler's celestial laws, which originated from Tycho Brahe's observations, to the regularities in the spectrum of atoms that guide quantum physics. Pattern recognition uses computer algorithms to find these patterns and then use them to improve science by using them for data classification and other tasks [26].

In the past few years, there have been big steps forward in the field of classification using multiple labels. For example, the label-based power set approach has become a more useful method. With this framework, label combinations are used as class values, which makes classification faster and better. When tested against other, better models, the suggested one shows comparable precision and scalability, showing that this method could be used to get around the heavy computational needs present in current meta-label methods for multi-label classification [14].

The study created an algorithm for digital image analysis that can tell the difference between six types of rice seeds in Zhejiang Province. For discriminant analysis, the method used color and shape features. The model was put to the test on a test dataset and got scores of 90.00%, 88.00%, 95.00%, 82.00%, 74.00%, and 80.00% for each type [8].

Hierarchical classification is an example of multi-label classification in which instances can be linked to more than one label, which is arranged in a set way. But not having enough data is a common issue in automated classification, especially when the classification is hierarchical. The goal of this study is to create SSHC which can learn from both labeled and unlabeled data, work with both tree and DAG types, and guess label paths that have one or more nodes. An initial SSHC constructed using local information was created. It uses unlabeled data to train a hierarchical classifier by giving them fake labels. Early tests on a part of the FunCat datasets are encouraging, as the SSHC-BLI performs better than a supervised hierarchical classifier that was only trained on labeled instances [6].

The study looks into different ways to do Multi-Label Classification in datasets with more than one label. This is done to fix the problem of class imbalance. Multi-label datasets have problems with multi-label data analytics because the samples and labels are not spread out evenly. The study gives an in-depth look at the most recent and best MLC methods, covering things like how to deal with uneven multi-label datasets, how to evaluate them, and how to compare them. The study also talks about the pros and cons of current methods, which will help guide future studies in this area. The results will help make MLC more accurate in datasets with more than one label [12].

Label powerset (LP) is a way to learn with more than one label. It treats each pair of labels in the set used for training as a separate class value. It does have trouble with a lot of labels and instructional examples in application domains, though. RAkEL (RAndom k labELsets) is an idea to fix this problem. It splits the first set of labels into small, random groups called labelsets [19].

Deep learning has emerged as a promising method for classifying seed defects, overcoming the limitations of traditional machine learning methods. By incorporating convolutional neural networks (CNNs) and transfer learning, researchers have significantly improved the accuracy of seed classification compared to traditional machine learning algorithms. Because the method for deep learning got more accurate as the network got deeper, making it suitable for automated seed manufacturing. This end-to-end network can significantly enhance the efficiency of seed classification [11].
The Convolutional Neural Network is used in the study to classify images of Jasmine Rice seeds sprouting with more than one label. There are three groups in the dataset: excellent, decent, and poor. The training set has 970 pictures, and the validation set has 194 pictures. The accuracy of the model is good enough, with precision, recall, and Fl-scores of 0.80, 1.00, and 0.89 for great growth, 0.83, 0.83, and 0.83 for excellent growth, and 0.87, 0.93 for bad germination [13].

Multi-label classification is important for many reasons. Based on the Multi-Branch Neural Network Model (MBNN), this paper presents a new architecture. In this design, Convolutional Neural Networks are used to encode data from several semi-parallel smaller networks or layers in a way that keeps them separate. The work makes small changes to current Multitask Learning architectures by creating two new designs that use neural network feature extractors that have already been trained. The multi-branch neural network design works better than simple multi- label classification methods. Among deep neural networks, the "network with multi-features" gets the best classification score. f1-scores of 88.81%, 88.64%, and 88.81% for the Pascal VOC 2007 dataset, Nuswide, and Pascal VOC 2012 datasets, in that order [9].

Hierarchical multi-label classification (HMC) involves categorizing instances into multiple classes arranged in a hierarchical structure. This article explores decision tree induction methods for HMC and their use in functional genomics. There are two methods used: single HMC trees (SC) and hierarchical single-label classification (HSC). SC sets up individual single-label classification tasks for each class, whereas HSC considers class dependencies. Classes can be organized in a tree structure with a maximum of one parent or a DAG structure with multiple parents. HMC and HSC are suitable for this environment. We used MIPS's tree structure and Gene Ontology DAG structure to show that HMC trees were better than HSC and SC trees at making predictions, modeling size, and induction time across 24 yeast data sets. Thus, the HMC tree is a good choice for tasks that need models that are easy to understand [7].

The proposed safe rice variety classification system combines hyperspectral imagery and deep CNN to gather complementary space and spectral data from rice seeds. A deep CNN is used to identify rice varieties from acquired spatio-spectral data. This method generates spatio-spectral characteristics from raw sensor data, unlike current techniques that require manual feature engineering. The proposed method outperformed commonly used support vector machine-based methods by up to 11.9% in total classification accuracy using two rice datasets. Trust between rice buyers and sellers is essential for effective farming and distribution of rice varieties [15].

2.3 Comparison between existing work

In this section, we conduct a comparative analysis to evaluate the effectiveness and efficiency of YOLOv8-powered multi-labeled seeds segmentation in agriculture compared to traditional methods.

Traditional seed segmentation methods often rely on manual labor or simplistic image processing techniques, which may result in inaccuracies and inefficiencies. In contrast, YOLOv8 offers unparalleled precision and speed in identifying and segmenting objects within images, making it a promising solution for improving seed segmentation processes.

Through our comparative analysis, we aim to assess several key factors, including accuracy, efficiency, scalability, and adaptability across different agricultural contexts and crop varieties. By comparing the performance of YOLOv8 with traditional methods, we can determine the extent to which YOLOv8 enhances seed segmentation accuracy and efficiency.

Additionally, we explore the potential impact of YOLOv8-powered segmentation on precision agriculture practices, such as seed spacing optimization, plant health monitoring, and yield prediction. By evaluating the effectiveness of YOLOv8 in these applications, we can assess its overall contribution to improving agricultural productivity and sustainability.

Furthermore, we consider user perceptions and acceptance of YOLOv8-powered technologies, as well as the socio-economic and environmental implications of widespread adoption. Understanding these factors is essential for identifying barriers to adoption and developing strategies to promote the successful implementation of YOLOv8 in agricultural settings.

In summary, our comparative analysis aims to provide insights into the strengths and limitations of YOLOv8-powered multi-labeled seeds segmentation and its potential to revolutionize agriculture. By synthesizing our findings, we can offer recommendations for optimizing the deployment and utilization of YOLOv8 in agricultural practices, ultimately driving innovation and sustainability in the agricultural sector.

Based on the relevant literature, Table [2.3.1] compares the most effective algorithms and their respective efficiencies.

Table 2.3.1: Comparative Analysis.

Study	CNN Model	Accuracy
Shima J. et al. [1]	CNN, ANN, kNN, SVM, LDA, boosted tree, bagged tree	CNN, ANN = 98.1%
Nadia A. et al [2]	PLS-DA, SVM-C and KNN	PLS-DA= 83.8% SVM-C=93.9% KNN=87.2%
Gulzar et al [4]	SVM, NIR, LR, RF, LeNet and ResNet	ResNet = 86.08%
Somsawut N. et al [13]	CNN	CNN=89%

2.4 Open issues

The scope of the problem addressed in this study revolves around the challenges and limitations encountered in traditional seed segmentation methods within the agricultural sector. Traditional approaches to seed segmentation often involve manual labor or simplistic image processing techniques, which can lead to inaccuracies, inefficiencies, and limited scalability. These methods may struggle to accommodate the diverse range of seed varieties and agricultural contexts, hindering precision agriculture practices and impeding efforts to optimize crop management and yield prediction. Furthermore, the scope encompasses the potential of YOLOv8-powered multi-labeled seeds segmentation to overcome these challenges and revolutionize agricultural practices. By leveraging advanced object detection algorithms like YOLOv8, there is an opportunity to enhance the accuracy, efficiency, and scalability of seed segmentation processes. YOLOv8 offers unparalleled precision in identifying and delineating multiple types of seeds within images, thereby facilitating more accurate seed classification, quality assessment, and crop monitoring.

Additionally, the scope extends to the broader implications of adopting YOLOv8-powered segmentation technologies in agriculture. This includes assessing the impact on precision agriculture practices, user acceptance and perceptions, socio-economic dynamics, and environmental sustainability. By understanding the scope of these implications, stakeholders can better evaluate the feasibility and benefits of integrating

YOLOv8 into agricultural workflows and drive innovation in the agricultural sector.

In summary, the scope of the problem encompasses the challenges and limitations of traditional seed segmentation methods in agriculture, the potential of YOLOv8-powered multi-labeled seeds segmentation to address these challenges, and the broader implications of adopting this technology for agricultural productivity, sustainability, and innovation.

2.5 Summary

We used Google Scholar and other academic publishers to find primary studies on affinity analysis, deep learning, and image processing. Key phrases were used to locate literature on affinity analysis, multi-label classification, and machine learning approaches. The selection of authentic research papers was crucial for generating a survey report, as not all articles are of the highest quality. We found some papers about multi-labeled classification and seed classification by using different machine learning algorithms. After assessment, all research that has been done on multi-label classification so far has focused on identifying a single object, leaving a significant gap in the field of knowledge. The researchers used multi-class classifications in their own investigation to overcome this problem. This creative method addresses a significant gap in the field by accurately identifying particular objects among an overwhelming number of other objects.

CHAPTER 3
METHODOLOGY

3.1 Overview

In computer vision, Multi-label Seed Segmentation” remains an intriguing problem. This work focuses on creating a strong system that can reveal the varied types of seeds within a single image. See a picture full of seeds, each with the capacity to fall under more than one class. Our goal is to present a segmentation model that solves this complex riddle and distinguishes the numerous seeds in a single image.

We divide the subjects into both functional and non-functional ones to perform this study. We concentrate on accurately identifying several seed kinds in a single image during the functional phase. Additionally, we must allocate some work to each seed's pertinent label. Subsequently, it is necessary to examine resilient performance across unbalanced datasets.

We will concentrate on effectiveness, adaptability, and explain ability throughout the non-functional phase. We shall concentrate on the improved processing in the efficiency section. In the scaling phase, there will also be the capability to manage extensive datasets and a wide range of seed kinds. Finally, the explain ability section will wrap up with knowledge of the model of decision-making for openness and confidence.

3.2 Proposed Methodology

The suggested methodologies are broken down into several sections to carry out this study.

- Data Collection: To do this, we must first get the data and then process it to make it as efficient as possible.
- Class Distribution: After collecting the data, we distributed the seeds classes in 18 categories.
- Data Processing: After finishing of phase 2 we will dive into the processing part which is visualized in phase 3 of the fig [3.2.1].
- Model Training: After processing and labeling the data, we will build a model for multi-label segmentation and classification.
- Model Evaluation: In final stage, we will use multi-label classification measures, such as hamming loss, accuracy, recall, f1-score, and others, to train the model and assess its performance.

Our suggested technique is fully visualized, and it is displayed in Fig [3.2.1].

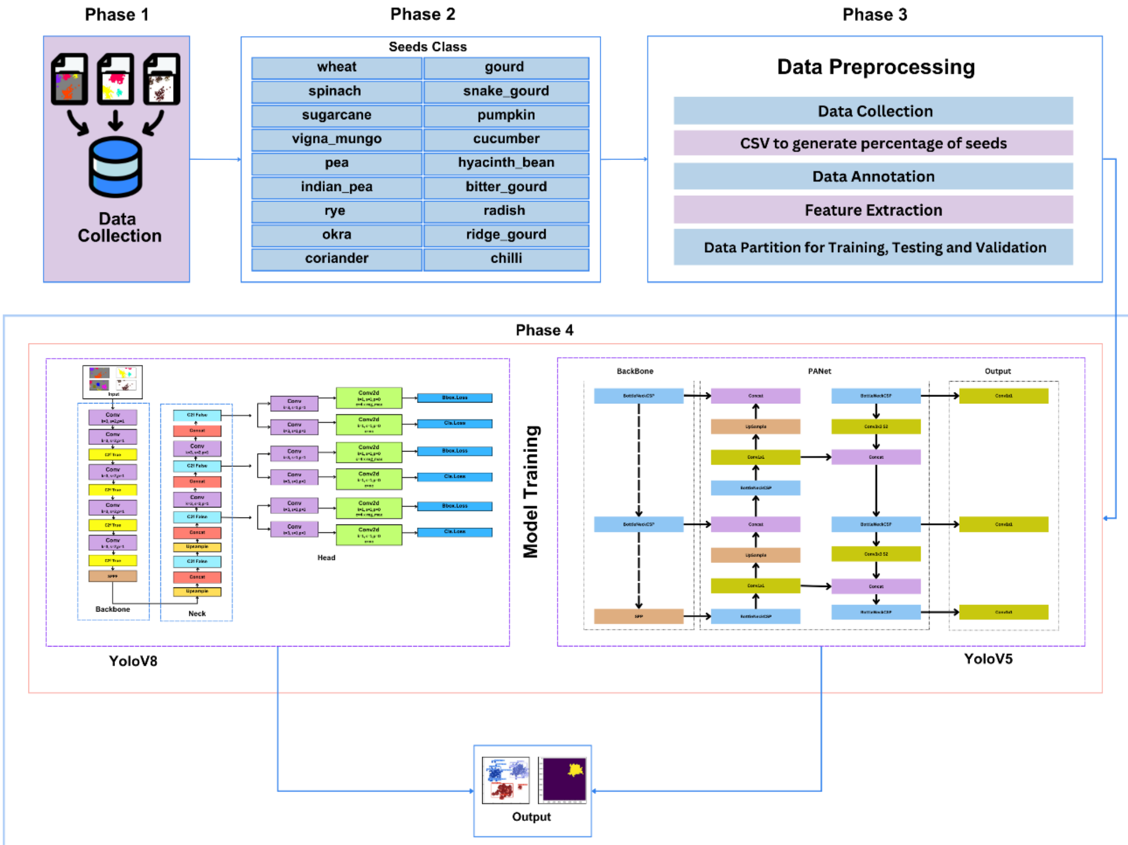

Figure 3.2.1: Proposed Workflow

Data Collection: For this study, we started by taking 100 images of seeds from the local market using a 48- megapixel Samsung smartphone camera that included 18 different classes. A single picture in the initial dataset has several classes. Once the first stage is over, we reformat the image to be 3 by 3 and have a resolution of 224 by 224. By applying data augmentation techniques, we can create nine more pictures from a single photograph. We first raise the data from 100 to 1030 by doing this. In Fig. [3.2.1], the related labels, such as formation of datasets and structure, were displayed. Also, the multi label and single label data are putted in side by side for the easy understanding of differences between both.

Single-Label

Multi-Label

Figure 3.2.2: Some Raw Image of Datasets.

The dataset was created by authors. Thus, the contain images are not available in the internet. PI chart in Fig [3.2.3] shows the amount of raw data and it's containing labels of each 18 classes of seeds and their percentage which helps to understand the quantity more precisely.

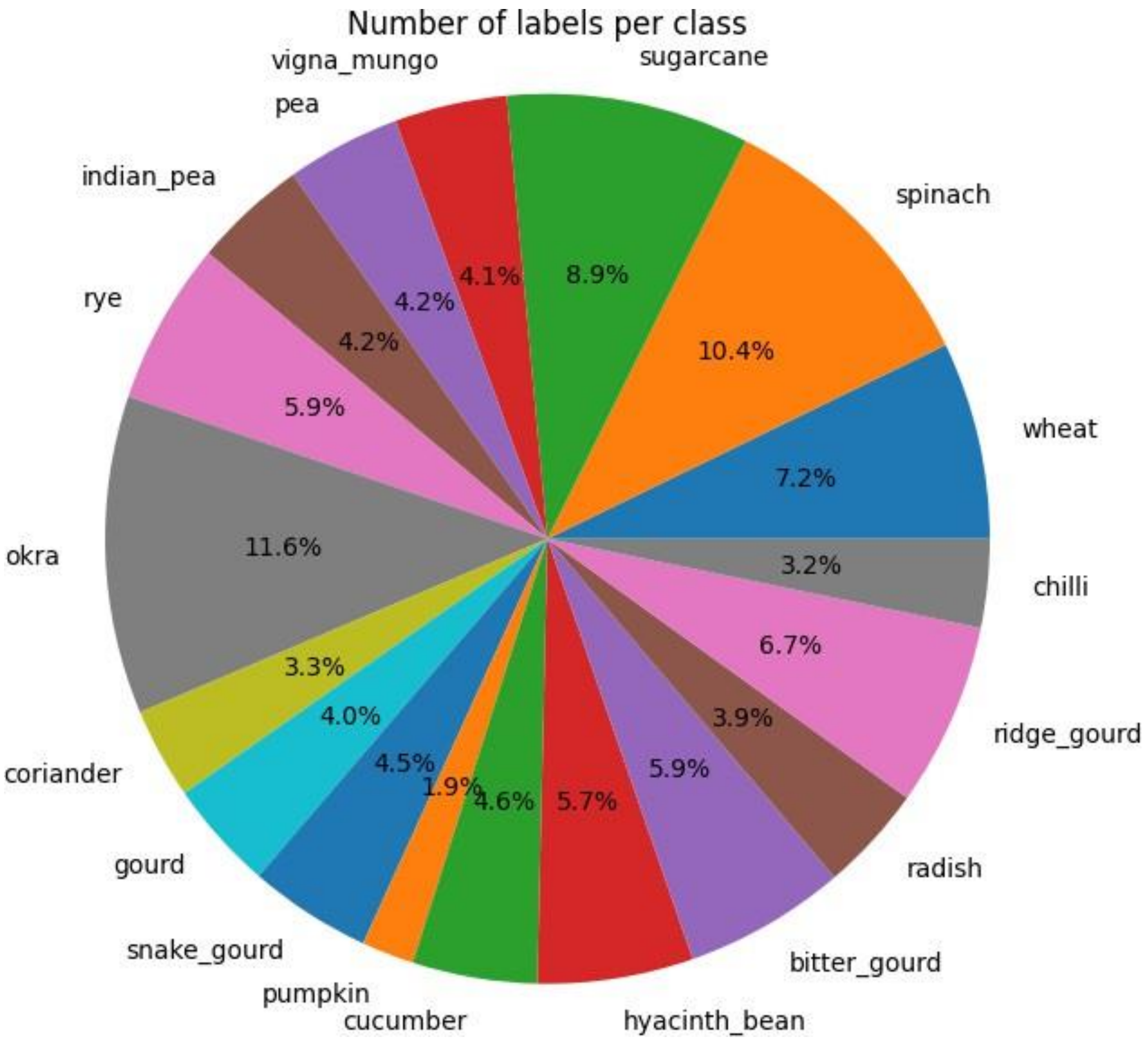

Figure 3.2.3: Visualization of class quantity.

3.3 Hardware / Software Requirement

In order to properly execute the technique, several prerequisites must be adhered to. The implementation requirements cover the software and hardware components, in addition to concerns for data gathering and model assessment.

Hardware and Software Requirements:

Datasets: 1030 primary images of seeds.

Computing Infrastructure: Cloud-based VMs with GPUs.

Software: Grammarly, VsCode.

Frameworks, libraries and packages: Yolo, Numpy, Matplot, Ultralytics

Development Tools: Git, GitHub, Google Docs. Google Colab, RoboFlow.

Computing Resources: Workstations with GPUs, cloud storage.

Literature: Research papers, journals, online libraries.

3.4 Project Management and Financial Analysis

To conduct this study hassle-free and timely, we followed a scheduled timeline. This study is currently in its initial stages. We are working on this research and building a model using free software. But we plan to make the model into a product in the future. At that time, we will have a proper budget for the project, and we may use premium software subscriptions. Also, Fig [3.4.1] and Fig [3.4.2] show the entire scheduled timeline.

WBS NUMBER	TASK TITLE	TASK OWNER	START DATE	DUE DATE	DURATION	PCT OF TASK COMPLETE
0	**Contents**					
	Project Charter		10-12-2023	10-12-2023	0	100%
	Abstract		10-12-2023	13-12-2023	4	100%
1	**CHAPTER 1: INTRODUCTION**					
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4.1	Project Objectives		30-12-2023	30-10-2023	0	100%
4.2	Quality Deliverables		31-12-2023	31-12-2023	0	60%
4.3	Chart Tracking		02-01-2024	08-01-2024	6	100%
4.4	Chart Updates		03-01-2024	08-01-2024	5	90%
4.5	Project Performance		04-01-2024	07-01-2024	3	60%
4.7	Checkup		07-01-2024	08-01-2024	1	100%
4.8	Final Changes		07-01-2024	10-01-2024	3	60%

Figure 3.4.1: Finalizing every section and advancing this study.

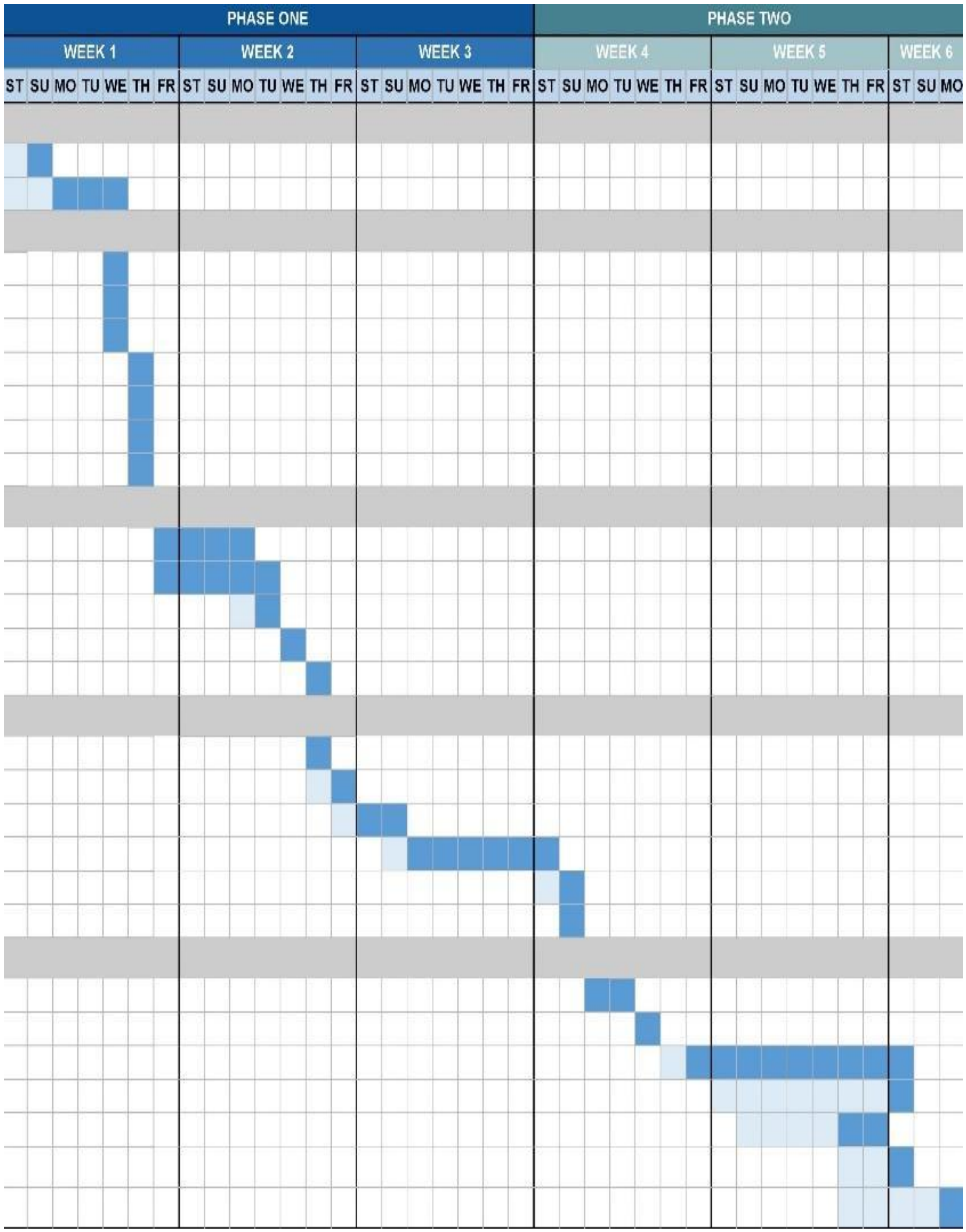

Figure 3.4.2: Finalizing every section and advancing this study.

3.5 Summary

The overall methodology chapter explores the challenging task of multi-label seed classification as it relates to computer vision. The main objective was to build a robust system that could correctly identify different types of seeds from a single picture. The suggested method includes a full process of collecting data, processing it, and extracting features. It also uses advanced multi-label classification algorithms to test how well the models work. In terms of functional requirements, the study places importance on enhancing seed identification and addressing the challenges posed by imbalanced datasets. On the non-functional front, the focus lies on enhancing the scalability, scalability, and portability of the system. The data collection phase entails the creation of images, augmented to 1030, reformatted to a 3 by 3 layout, and represented in a binary CSV file. The project management approach follows a predetermined schedule and uses free software solutions to develop a unique model and allocate resources effectively in the future. Overall, the study highlights a methodical and effective approach to multi-label seed classification in computer vision applications.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In computer vision, Multi-label Seed Segmentation" remains an intriguing problem. This work focuses on creating a strong system that can reveal the varied types of seeds within a single image. See a picture full of seeds, each with the capacity to fall under more than one class. Our goal is to present a segmentation model that solves this complex riddle and distinguishes the numerous seeds in a single image. We divide the subjects into both functional and non-functional ones to perform this study. We concentrate on accurately identifying several seed kinds in a single image during the functional phase. Additionally, we must allocate some work to each seed's pertinent label. Subsequently, it is necessary to examine resilient performance across unbalanced datasets. We will concentrate on effectiveness, adaptability, and explain ability throughout the non-functional phase. We shall concentrate on the improved processing in the efficiency section. In the scaling phase, there will also be the capability to manage extensive datasets and a wide range of seed kinds. Finally, the explain ability section will wrap up with knowledge of the model of decision-making for openness and confidence.

4.2 Train Model

Deep neural networks get optimal performance when the amount of data is higher. The first stage of the proposed workflow is the augmentation of the original images and raised the data quantity. In below there is a description of the experimental design:

Image Augmentation:

Image enhancement is used in this stage. Picture augmentation adds fresh data to an existing dataset while preserving its label data. A bigger data set improves model generalization, creation it more lenient to unknown inputs. Data augmentation helped us reach training data objectives. Nevertheless, brightness, contrast, saturation, scaling, cropping, flipping, and revolution were utilized to improve color and position. Data augmentation included random horizontal and vertical rotation, without any effects. Each original picture was improved 10 times.

Figure 4.2.1: Augmented Images

Image Annotation:

During the second stage of the process, we employ Roboflow for manually annotating our picture data. The seed class annotation process, supported by Roboflow, provides an efficient method for organizing and identifying our seed-related information to feed our deep learning model. Through the utilization of Roboflow's user-friendly interface and robust annotation capabilities, we are able to precisely and efficiently describe and categorize different sorts of seed classes with accuracy. Through careful annotation, every individual seed instance is tagged with pertinent metadata, including seed category, dimension, hue, and shape, which offers significant context to help train our deep learning models.

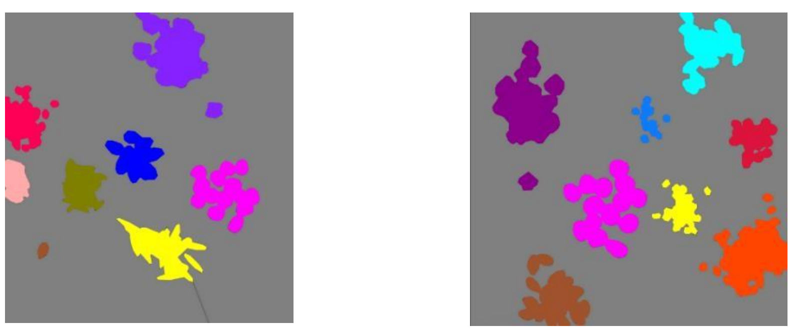

Figure 4.2.2: Annotated images.

Upon completing the preliminary phase of data processing, we partitioned the data in three distinct stages. During the training step, we extracted 70% of the data from the full dataset. In this phase we will develop a custom training YOLOv8 model to feed our data and make it ready for inference. Prior to announcing the epochs, we establish a directory in the cloud to house the analytical outcomes of the training phase. A total of 250 epochs were initially utilized to train the model. Each epoch required between 3 and 4 iterations per second to run.

YOLOv8, a successor to the widely-used You Only Look Once (YOLO) object identification framework, signifies a notable progression in actual time computer vision applications. YOLOv8 improves upon the advantages of its previous versions by utilizing a carefully designed architecture that incorporates state-of-the-art deep learning algorithms, resulting in increased speed and accuracy. There are three parts of YOLOv8 shows in Fig [4.2.3].

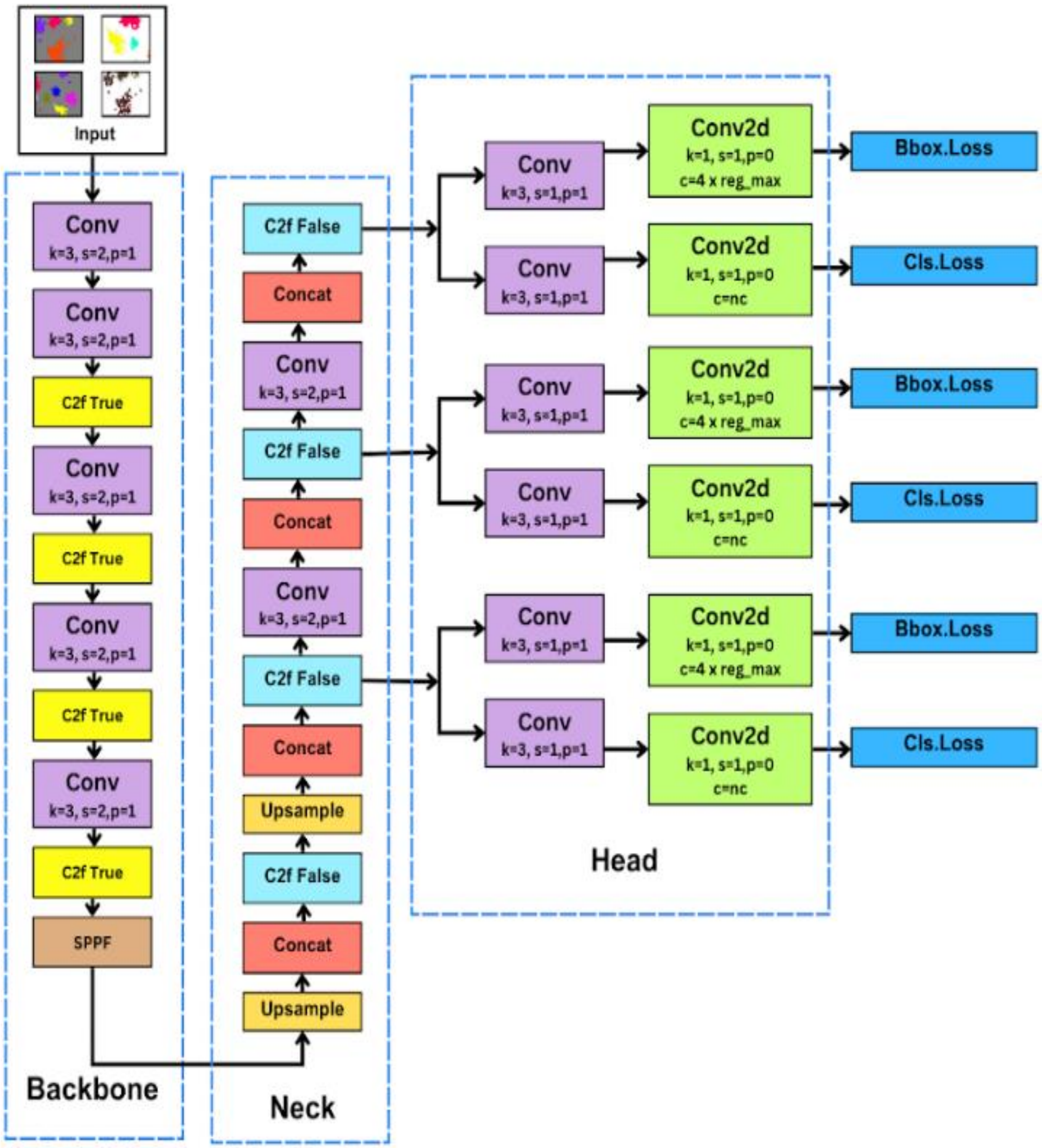

Figure 4.2.3: Fine-tuned Yolo-v8 architecture.

Backbone: The YOLOv8 backbone architecture is used to extract detailed characteristics that are crucial for accurately identifying and outlining seeds in agricultural images. By utilizing its origins within Darknet and CSPDarknet, the core system carefully examines input photos to extract hierarchical illustrations of seeds and their relation to their surroundings. The backbone utilizes a sequence of convolutional layers to gradually extract features that convey vital information like seed shapes, textures, and spatial connections. Down sampling layers systematically decrease spatial dimensions while enhancing feature channels, guaranteeing the inclusion of intricate information at different scales. This method is crucial for precisely dividing seeds of various sizes and densities inside the picture. Furthermore, the inclusion of skip connections inside the backbone allows for the smooth incorporation of input from various layers. This enables the model to accurately capture global as well as local properties that are important for seed segmentation. This architectural enhancement improves the model's capacity to accurately identify seeds even in difficult situations, such as instances that are overlapping or partially covered. Essentially, the YOLOv8 framework plays a fundamental role in seed segmentation by utilizing its complex structure to extract precise characteristics that are essential for accurately identifying and outlining seeds in agricultural images. The backbone of YOLOv8 utilizes convolutional layers, down sampling methods, and skip connections to generate accurate segmentation results.

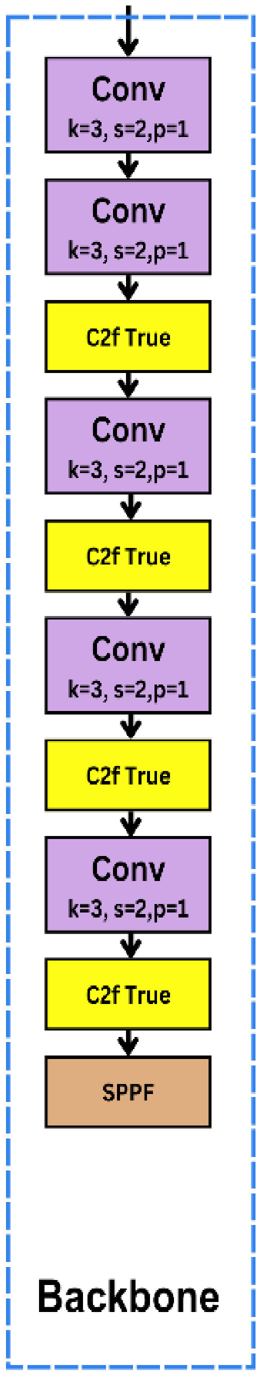

Figure 4.2.4: Backbone Architecture

Neck: The "neck" module plays a vital role as an intermediate among the backbone as well as the detecting head. The main purpose of the refinement process is to enhance the extracted features from the backbone in order to increase the accuracy of the model in recognizing and segmenting objects, such as seeds in agricultural photos. The neck module incorporates multi-scale characteristics derived from the backbone, merging intricate details with wider context to improve the model's comprehension of seed forms and spatial connections. The neck module allows the model to obtain a complete representation of seeds in the picture by combining information from multiple sizes. In addition, the neck module can use contextual information to enhance the accuracy of seed detection and segmentation outcomes. By integrating attributes from neighboring areas or utilizing worldwide context, the model acquires a more extensive comprehension of seed traits, enhancing the precision of identification in difficult situations.

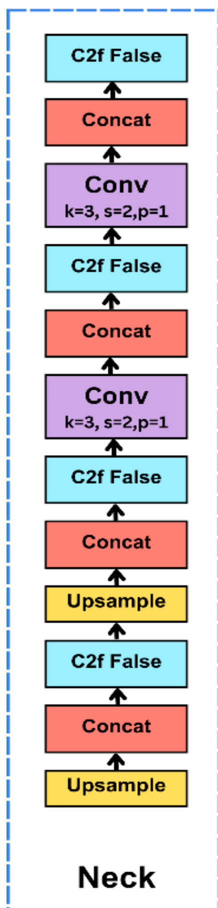

Figure 4.2.5: Backbone Architecture

Head: In addition, the neck module can use contextual information to enhance the accuracy of seed detection and segmentation outcomes. By integrating attributes from neighboring areas or utilizing worldwide context, the model acquires a more extensive comprehension of seed traits, enhancing the precision of identification in difficult situations. It utilizes the complex feature representations given by the neck to carry out the last steps of seed segmentation. The algorithm determines the precise positions of seeds and calculates the likelihood of each seed belonging to a certain class. This allows for precise and accurate identification and separation of seeds within the picture.

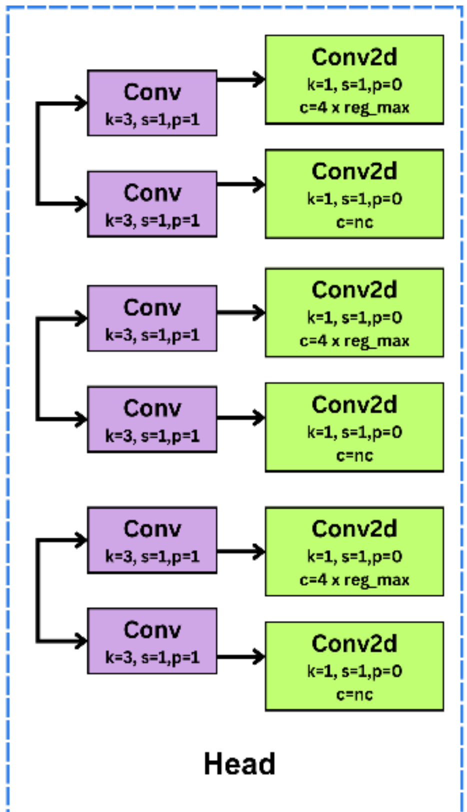

Figure 4.2.6: Backbone Architecture

YOLOv5**,** The YOLOv5 model's architecture showcases a complex configuration of layers specifically crafted to effectively extract and analyze information from input photos in real-time for object recognition. The model architecture is commonly partitioned into three primary components: the Backbone, the Neck, and the Head.

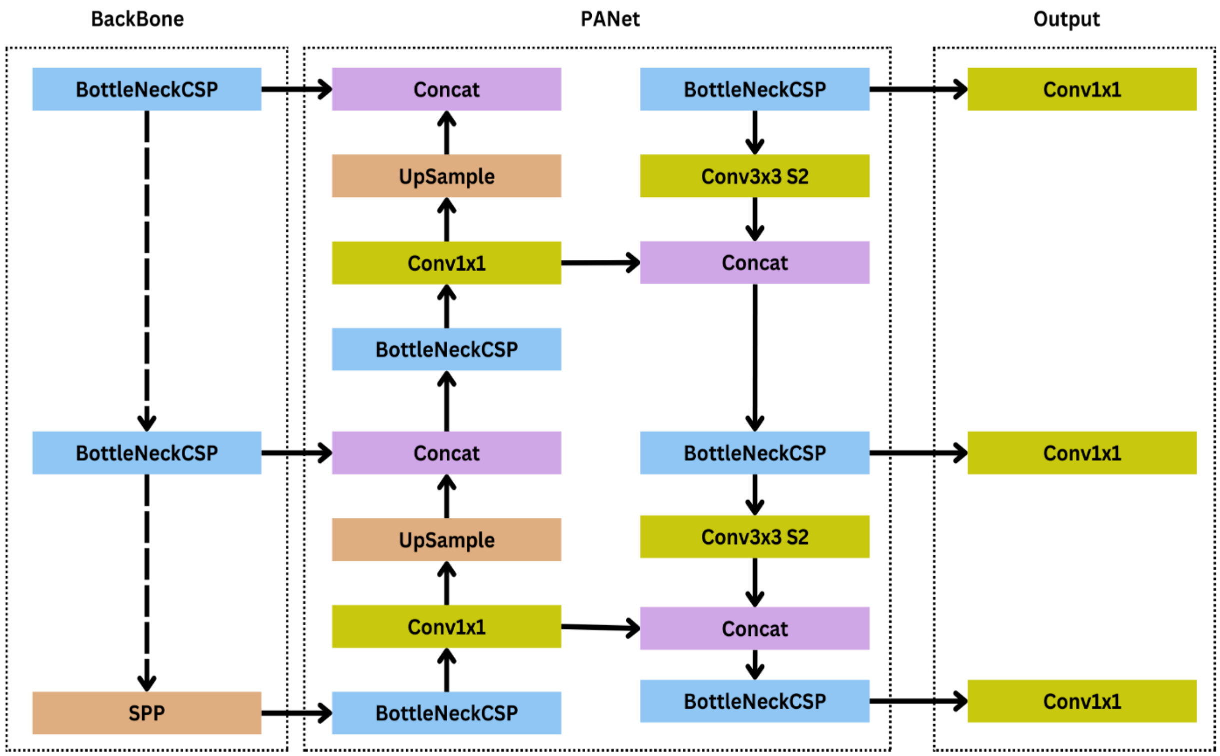

Figure 4.2.7: YOLOv5 architecture.

Backbone: The backbone architecture starts with the Focus layer, which partitions the input picture into four distinct portions, each corresponding to various components of the image. This process of dividing or segmenting helps in the formation or development of feature maps. Afterwards, the Conv 3x3 S1 layer, which is a convolutional layer with a 3x3 kernel and a stride of 1, continues to analyze these feature maps. Afterwards, the BottleNeckCSP layers are utilized. The layers in question utilize the Cross Stage Partial (CSP) architecture, which improves the flow of gradients and decreases computing complexity by dividing the feature maps into two sections, processing them separately, and then merging them together.

Neck: The neck of the YOLOv5 architecture consists of many essential layers that are designed to enhance and adjust the feature maps. The SPP (Spatial Pyramid Pooling) layer first performs pooling on feature maps to achieve fixed sizes, facilitating the identification of objects at different scales. Additional layers of BottleNeckCSP are used to further enhance the refining process. Up sampling layers are then employed to augment the spatial dimensions of feature maps, which are then combined using Concat layers to blend feature maps from various stages. The Conv1x1 layers, which have 1x1 kernels, are used to decrease the depth of the feature maps, making subsequent processing more efficient. The process of up sampling, concatenating, convoluting, and applying more BottleNeckCSP layers is repeated, using Conv 3x3 S2 layers to reduce the size of the feature maps as needed.

Head: The head is the last component of the YOLOv5 architecture and it comprises the Detect layer. The primary function of this layer is to generate the model's output, namely the bounding boxes and class probabilities for every identified item.

4.3 Model Evolution

System evaluation for a YOLOv8 segmentation model entails a comprehensive assessment to verify the model's proper functioning and efficient performance in diverse settings. Functional testing involves validating the right initialization of the model using various pre-trained weights, accurately executing segmentation on a range of test pictures, and appropriately handling diverse input sizes and formats. Performance testing aims to measure and enhance the speed and efficiency of the model. This includes analyzing the time it takes for the model to make predictions on various hardware devices like CPUs, GPUs, and TPUs. It also involves examining the throughput, which refers to the number of pictures analyzed per second, as well as tracking the memory consumption throughout the prediction process. This rigorous testing methodology guarantees that the model fulfills the necessary criteria for precision, efficiency, and dependability.

In order to evaluate and test our system, we obtained additional photos from the internet that were not part of our initial dataset, both images that include seeds and images that do not contain seeds. This heterogeneous dataset facilitates thorough validation and testing of the model. The visual representations of these pictures are displayed in Figure [4.3.1], Fig [4.3.2] and Figure [4.3.3]. This technique improves the durability of the review process by including a broader spectrum of picture changes and complexity.

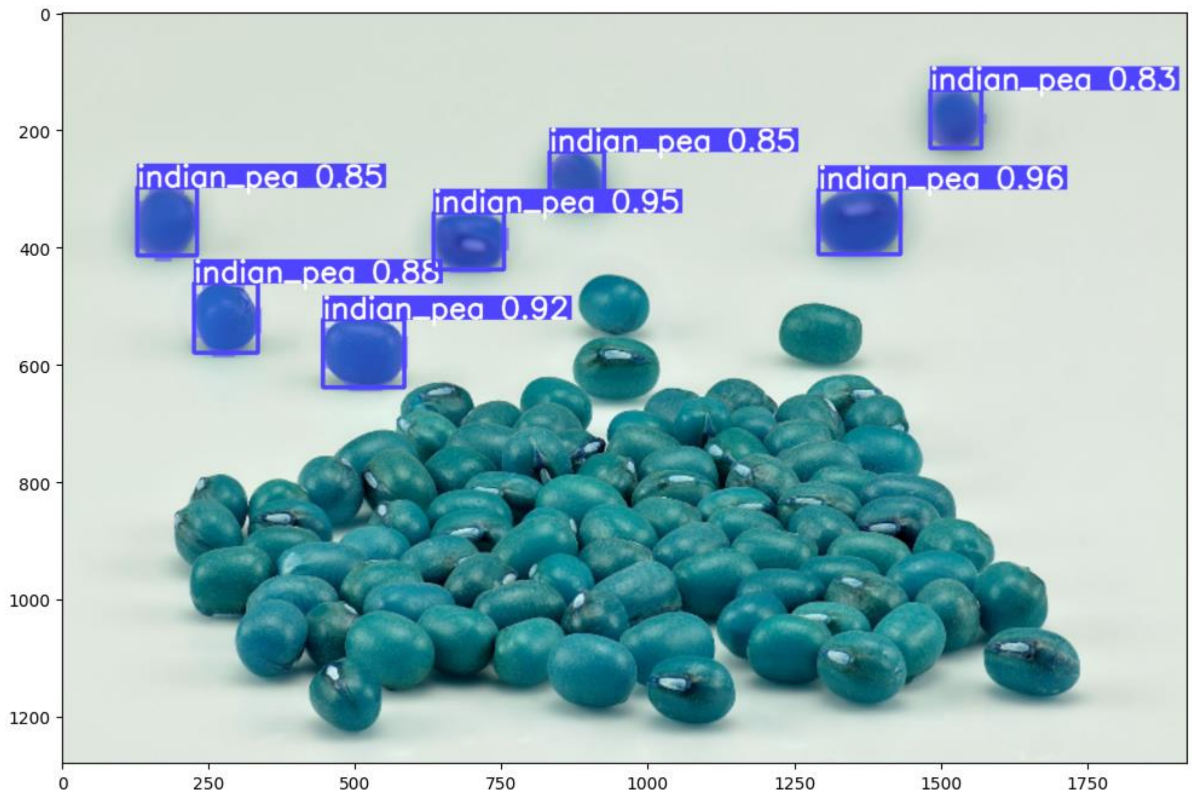

Figure 4.3.1: Testing images from internet source

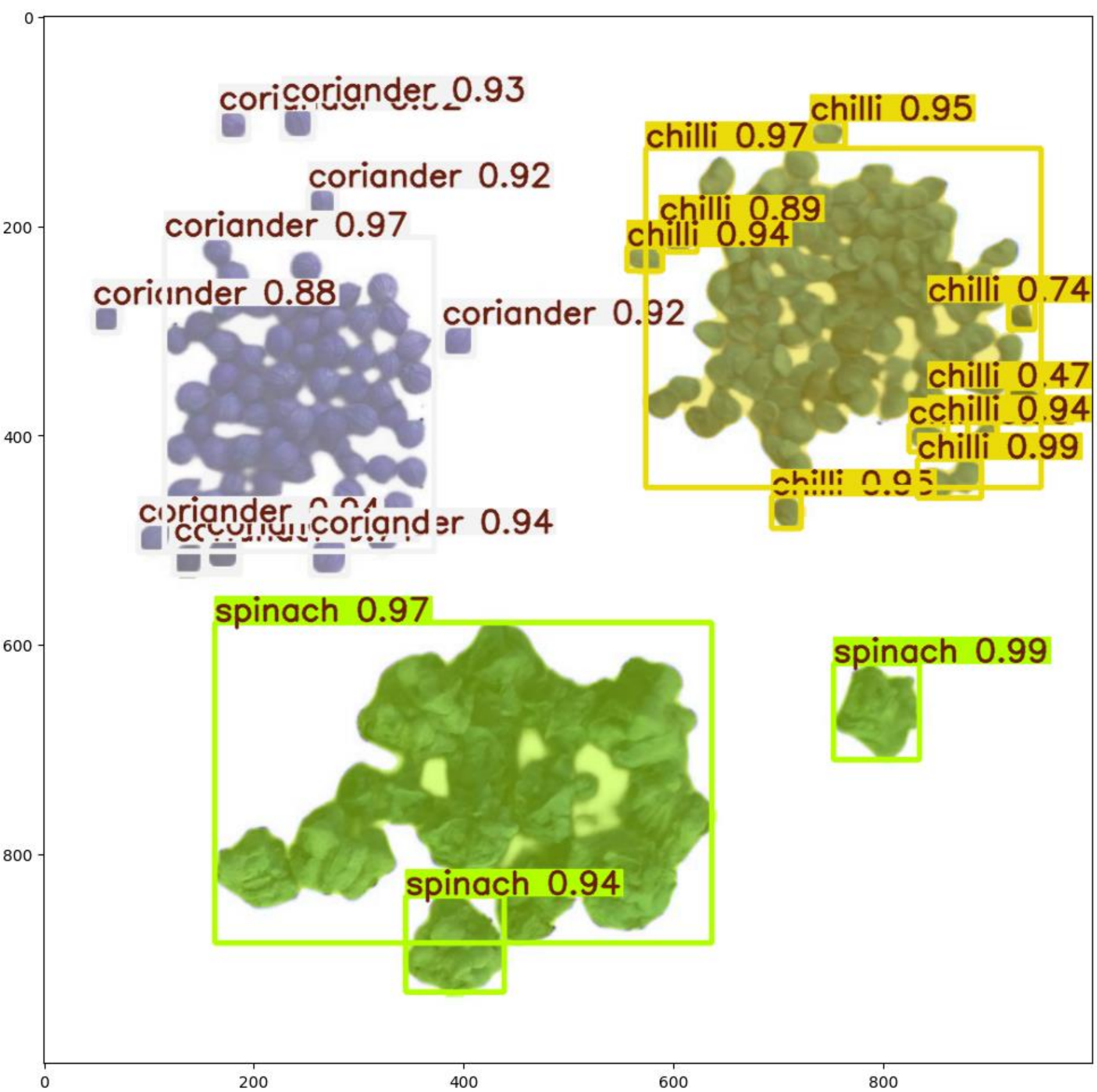

Figure 4.3.2: Our private test image

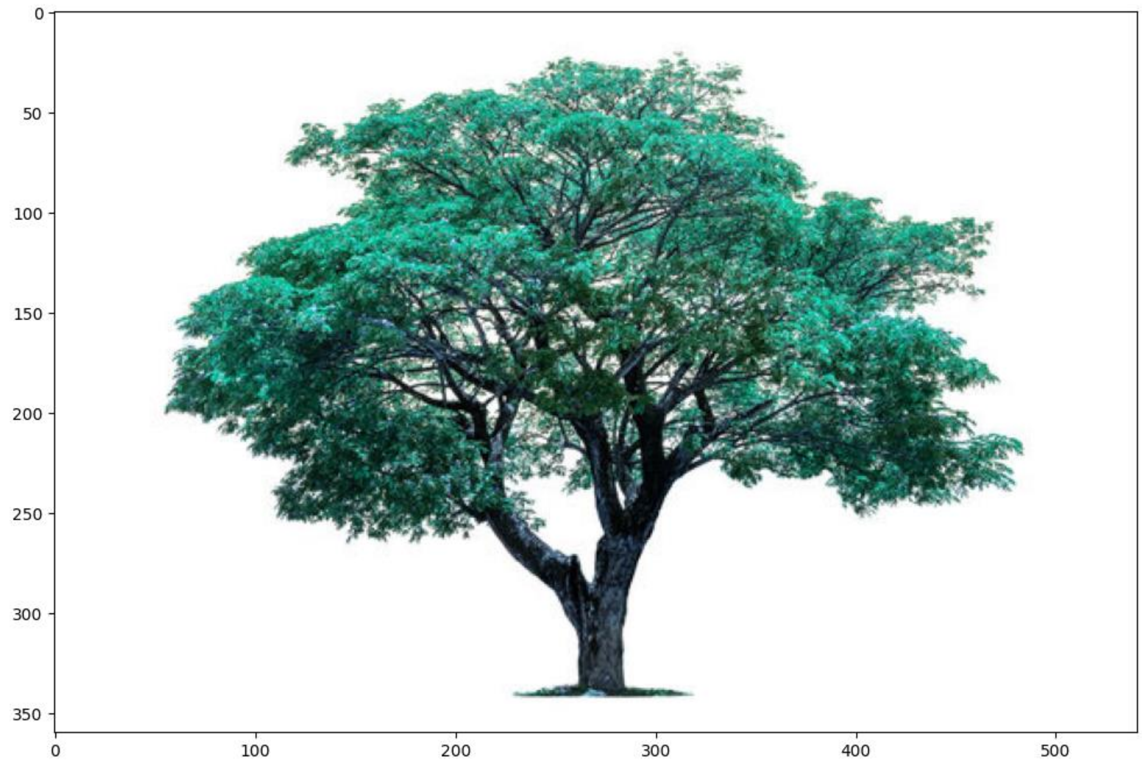

Figure 4.3.3: No detection for non-seed images

4.4 Summary

This study focuses on creating a strong system for revealing various types of seeds within a single image in computer vision. The goal is to present a segmentation model that solves the complex problem of identifying multiple seeds in a single image. The study divides subjects into functional and non-functional ones, focusing on accurately identifying several seed types in a single image, allocating work to each seed's relevant label, examining resilient performance across unbalanced datasets, focusing on effectiveness, adaptability, and explainability, improving processing in the efficiency section, scaling the model to manage extensive datasets and a wide range of seed types, and explaining the model's decision-making for openness and confidence. The YOLOv8 model, a successor to the You Only Look Once (YOLO) object identification framework, is used to extract detailed characteristics for accurately identifying and outlining seeds in agricultural images. The system evaluation involves a comprehensive assessment to verify the model's proper functioning and efficient performance in diverse settings.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The setup of the experiment for the study comprises a meticulously planned arrangement of computer software, data, and hardware resources to carry out thorough studies. This experimental setup entails a series of measures to guarantee an appropriate environment for training and evaluating the model. The Table [5.1.1], provides a comprehensive explanation of the full setup in order to arrive at a conclusion.

Table 5.1.1: Entire experimental setup.

Description	**Brief**
Software	Set up Python environment
Install dependencies	Libraries like NumPy, pandas
Prepare dataset	Making the dataset ready to use for training.
Install YOLOv8	Installed YOLOv8 framework from ultralytics.
Create configuration file	Creating configuration file for further use. Ex: data.yaml
Train the model	Split 70% data for training the model.
Evaluate the model	Taking the best or the last file from the training section to evaluate the model.
Inference on new images	Check new images if the model classification was correct or not.
Hyperparameter	By adjusting learning rates, batch sizes, etc.
Tuning	Replace initial 6x6 Conv with 3x3 Conv in backbone, delete 2 Convs from head, switch first 1x1 Conv in Bottleneck to 3x3 Conv, and use decoupled head while removing objectless branch.
Augmentation	Use data augmentation techniques.
Model Checkpoints	Save model checkpoints during training.

5.2 Experimental result

This chapter provides a detailed discussion of the outcomes achieved via the validation and testing of the model. We analyze the mean Average Precision measure (mAP), Precision, and Recall, and utilize several graphical representations, including confusion matrices, F1 Confidence curves, and validation batch data, to facilitate our discussion.

Fig [4.2.1] depicts the efficacy of a classifier in the job of distinguishing different kinds of seeds with a background class. The diagonal values demonstrate high classification accuracy for the majority of classes, achieving perfect scores for bitter gourd and cucumber, and almost perfect scores for other classes such as coriander, hyacinth bean, okra, pea, ridge gourd, rye, spinach, sugarcane, and vigna mungo.

However, some categories, like pumpkin and radish, exhibit notable misclassifications, notably in the confusion between pumpkin and radish, as well as ridge gourd. The backdrop class also encounters significant perplexity with some seed classes, particularly pumpkin and spinach. The most prominent misclassifications occur when distinguishing physically or contextually identical categories, like Indian pea as well as pea, or chile and coriander. To resolve these misunderstandings, it may be necessary to provide further training using larger datasets, employ more sophisticated methods for extracting features, and carefully analyze the preprocessing stages in order to improve the performance of the classifier. In general, although the classifier shows a high level of accuracy, there is room for focused enhancements to decrease the rates of misclassification in some areas.

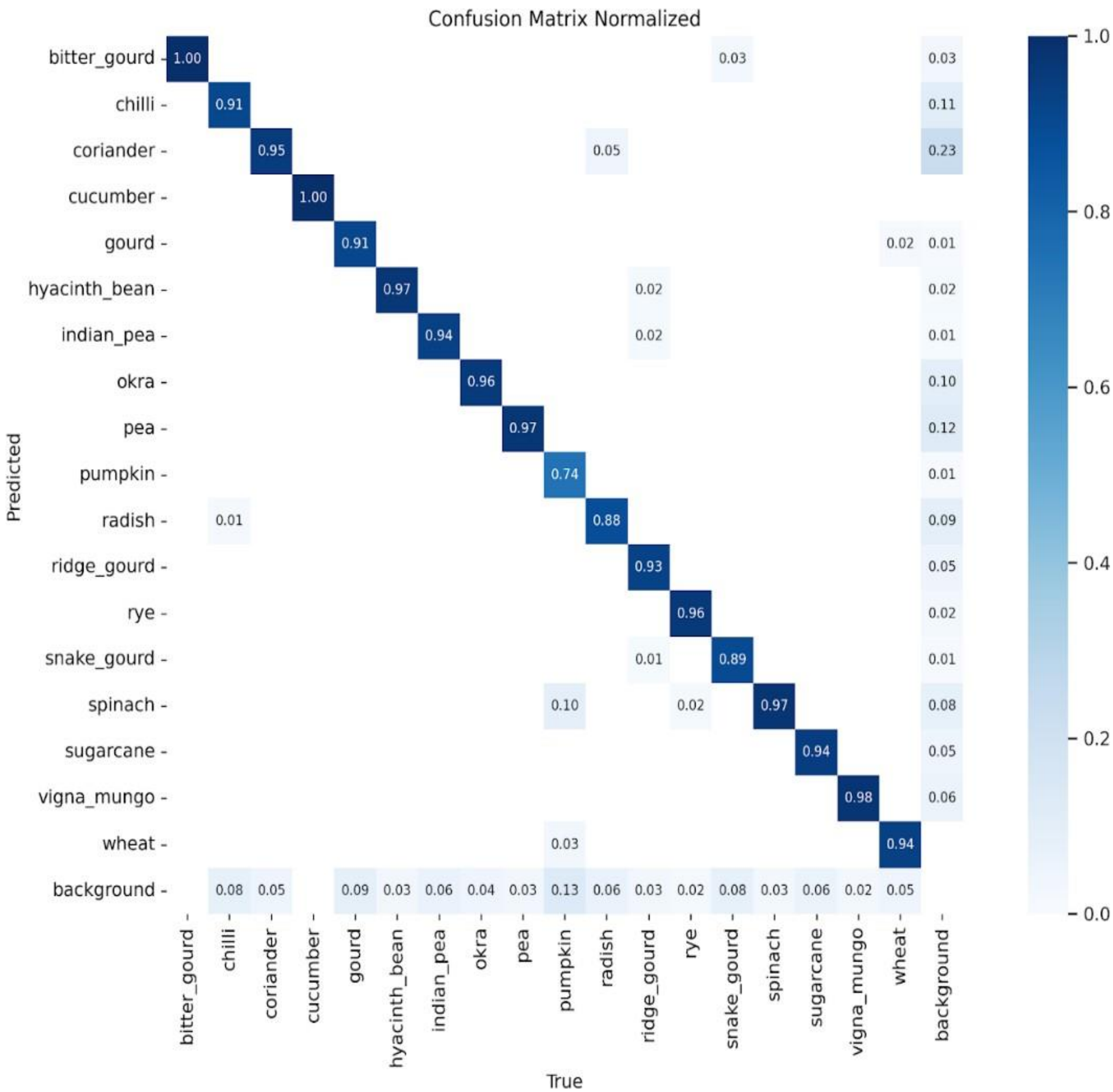

Figure 5.2.1: Confusion Matrix of 18 Class

Class	Images	Instances	BoxP	R	mAP50	mAP50-95	MaskP	R	mAP50	mAP50-95
all	206	2590	0.936	0.91	0.943	0.886	0.933	0.907	0.938	0.814
bitter_gourd	206	97	0.924	0.996	0.983	0.961	0.923	0.995	0.983	0.946
chilli	206	329	0.953	0.854	0.943	0.809	0.942	0.842	0.935	0.655
coriander	206	318	0.899	0.919	0.935	0.817	0.898	0.917	0.929	0.677
cucumber	206	35	0.959	1	0.978	0.978	0.96	1	0.978	0.972
gourd	206	34	0.908	0.867	0.91	0.877	0.908	0.867	0.91	0.822
hyacinth_bean	206	62	0.939	0.968	0.982	0.973	0.939	0.968	0.982	0.956
indian_pea	206	143	0.985	0.934	0.947	0.847	0.985	0.933	0.944	0.703
okra	206	186	0.906	0.935	0.967	0.921	0.896	0.925	0.951	0.831
pea	206	166	0.932	0.908	0.953	0.826	0.938	0.913	0.961	0.69
pumpkin	206	31	1	0.702	0.751	0.669	0.966	0.677	0.712	0.608
radish	206	283	0.89	0.859	0.897	0.817	0.886	0.855	0.891	0.705
ridge_gourd	206	127	0.905	0.83	0.938	0.899	0.905	0.829	0.934	0.862
rye	206	109	0.956	0.963	0.971	0.935	0.956	0.963	0.97	0.865
snake_gourd	206	38	0.945	0.902	0.968	0.951	0.945	0.902	0.968	0.93
spinach	206	192	0.916	0.961	0.974	0.931	0.916	0.96	0.969	0.904
sugarcane	206	330	0.949	0.909	0.941	0.839	0.943	0.902	0.935	0.716
vigna_mungo	206	46	0.896	0.913	0.959	0.936	0.896	0.913	0.959	0.868
wheat	206	64	0.995	0.969	0.976	0.967	0.995	0.969	0.967	0.936

Table 5.2.1: Result of 18 Different Class

The supplied figure displays a range of validation and training metrics for a model developed from deep learning over 100 epochs, including different forms of loss and performance indicators. The first row of figures illustrates the training losses, all of which exhibit a steady decline, suggesting enhanced model efficacy for identifying bounding boxes, segmentation, class predictions, as well as prioritizing challenging samples. The uppermost row also encompasses precision and recall metrics, both converging towards 0.9, which is and the mean average precision (mAP) metrics, which exhibit fast enhancement and convergence close to 0.9, signifying a high level of accuracy and resilience of the model across various IoU thresholds.

The validation losses displayed in the bottom row closely correspond to the patterns observed in the training loss, indicating a high level of model generalization. The validation measures exhibit
comparable patterns to the initial training metrics, with accuracy and recall reaching a plateau at about 0.9, but the mAP values demonstrate robust performance. Overall, the plots indicate successful acquisition and application of the model, with diminishing losses and enhancing, consistent assessment metrics, implying that the model has no signs of overfitting

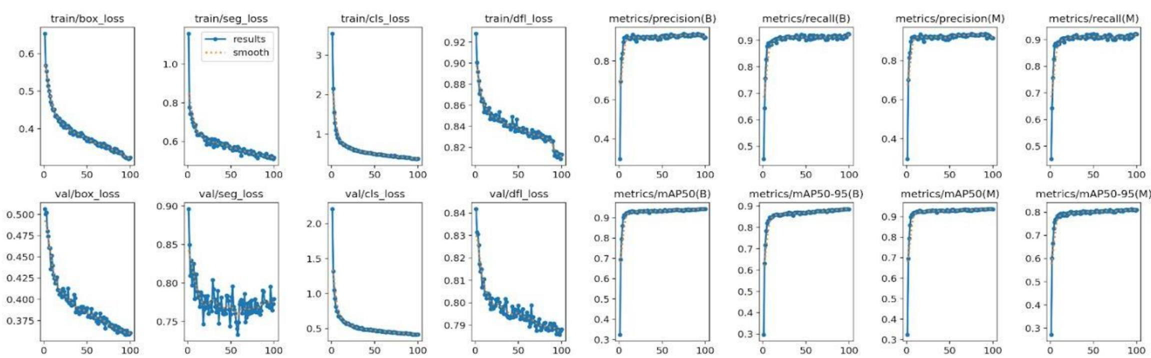

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Figure 5.2.2: Results of YOLOv8

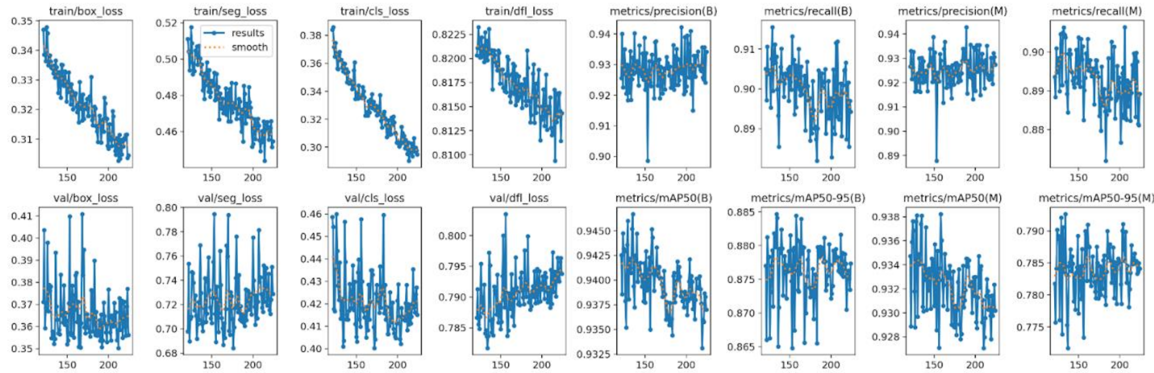

Figure 5.2.3 Results of YOLOv5

In Figure [5.2.3] The combined plots of training and validation loss show consistency or a decreasing loss value with time; hence, learning was successful. On the other hand, performance measures like mAP, recall, and precision portray prominent swings in graphs, indicating that it is tough to have very flat and stable performance across classes and evaluation metrics. These findings suggest that even if the model's loss metrics get better, further improvement and optimization are required for steady gain regarding detection precision and overall efficacy.

5.3 Comparative Analysis

At the starting stage of this study, we combined the multi-label separated model, specially designed and tuned for seed segmentation, with the YOLOv8 method. This approach now shows us some quiet improvements and surpasses the individual performance in the multi-labeled dataset. When the entire segmented seed data is trained, the most common issue with the final version is that the precision and recall rates are having the greatest difference. Furthermore, the approach's initial base case was evaluation only on the test of the private datasets which was 99% on some test classes, and the average of all the classes together was around 94.5%. Whereas the vanilla YOLOv5 conducted overall detection around 94.7%. The Tab [5.2.2] shows the comparison of both model performance and it's clear that the YOLOv8 performed better than vanilla YOLOv5.

Model	mAP (Mean Average Precision)	Precision	Recall
YOLOv8	94.5%	93.27%	92.2%
YOLOv5	94.7%	94.7%	89.9%

Table 5.3.1: Performance Results

YOLOv5 appears to have achieved a greater mean average precision (mAP) and precision rate, but its recall rate is lower. In our custom Trained YOLOv8 model, the rates of mean Average Precision (mAP), recall, and total precision were closely aligned.

5.4 Summary

A well-structured setup of the software, data, and hardware resources of a computer for training and testing a model; this could include setting up a Python environment, installation of availed dependencies, such as NumPy and pandas, preparation of the working dataset, setup of the YOLOv8 framework, configuration file, model training and evaluation, inference on new images, adjustment of hyperparameters, tuning, augmentation techniques, and saving model checkpoints at different training steps. The experimental results on most of the classes are very accurate, attaining perfect scores in the cases of bitter gourd and cucumber, and close to perfect in the other categories like coriander, hyacinth bean, okra, pea, ridge gourd, rye, spinach, sugarcane, and vigna mungo. These notable misclassifications in a few, like pumpkin and radish, can be sorted out only by further training on larger datasets, using more sophisticated methods for extracting features, and studying the preprocessing stages more carefully. Clearly, this model performance is going to be very accurate; there exists some scope for focused improvements in reducing the misclassification rates at places. The validation losses in the bottom row reveal very close correspondences to the pattern of training loss generalized.

It also, further, makes a comparison of the performance by the multi-label separated model with the YOLOv8 method, which indicated improvements in the multi-labeled dataset. However, with regard to precision and recall rates, the largest difference exists when the entire segmented seed data is trained.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The approach lets you use water, fertilizers, and pesticides only in places where it is necessary that increases the efficiency of the agricultural sector. Replacement of these manual processes with automated machines not only facilitates the reproduction of crops but also ensures that the area for agricultural purposes is not being expanded and consequently, the environment is less damaged in the process.

The inclusion of YOLOv8-equipped multi-labeled seed segmentation in the agricultural industry signals a big Bang in terms of social welfare through solution, growing in the market. With the aid of the best object detection algorithms like YOLOv8, the agricultural sector will utilize the evolution of precision, efficiency, and scalability in seed identification and crop monitoring processes like never before. Technological advancement presents a record-breaking potential for securing food supplies by

means of more precise and reliable crop yields, especially in the areas where food shortages or agricultural unpredictability are common. Also, YOLOv8 technology integration provides a direct route to agriculture, as it allows resource optimization and proposition of solutions with the least impact on the environment. Through the acquisition of YOLOv8, farmers are facilitated with state-of-the-art tools and data, through which they are able to make better decisions, manage crops more efficiently, and adapt to changes in the market and environment better.

Moreover, YOLOv8-powered multi-labeled seeds seeding is much more than just an innovative way to grow plants. The volume adoption of AI technology such asYOLOv8 in agriculture is not only agricultural information but is also of great social importance, fostering developments of technologies and economic prospects for other industries and society in general. In this manner, easily-accessible farms provide youth with a chance to learn, invent, and be creative, that means new jobs can be offered thanks to the farm that uses the IoT technology (where farming is being managed and monitored through sensors and the internet). The purveyor shares agricultural (how crops are produced, processed, and marketed) know-how and other tech/Service individual sections. Nevertheless, the application of YOLOv8 and other machine learning technologies such as convolutional neural networks (CNN) segments and hyperparameters optimization within the agricultural sector, through the parental seed market of Rhizobium bacteria royalty, will result in the production of new age agro-products that have the potential to be grown in even the toughest of climates. After Yanjun's tenure as a Ph.D. student at the University of Minnesota, he returned to China to apply his newly gained knowledge through a research lab

6.2 Impact on Society & Environment

The YOLOv8-powered multi-labeled seed segmentation has been integrated into agricultural practices and is a landmark scientific tool that has very big consequences for nature conservation. By using this type of technology, farmers now have total control of the resource distribution in the whole system that will constitute the very classic of forms of sustainable farming. With this process, the use of water, fertilizers, and pesticides can only be delivered when needed, thus reducing pollution and waste through the exact identification of seeds. The automation of these mechanical tasks besides making crops reproduce better also ensures that farmers do not have to extend their land and hence, earth is impacted less. However, the promises also hide the risks. The fact that I am scared of the potential impending genetic contamination, data privacy and the very real danger of overreliance on technology means that I must approach the issue with care. As a result, YOLOv8-based seed segmentation has brought in a period of environment-friendly agriculture. But its real potential can be achieved only by taking these complications into account in a responsible and thus preserving the harmony between technology and environmental health.

6.3 Ethical Aspects

The moral aspects of the integration of the YOLOv8-powered multi-labeled seeds segmentation into the agriculture field are of paramount importance. The main issue is the protection of data privacy and ownership, making sure that farmers maintain control over their information, among other issues. Widely available technology is a major factor causing an increase in the wealth inequality phenomenon. As a result of this, over-and-above deliberate actions have to be implemented to guarantee equal access to these advanced technologies. Transparency and accountability should be pursued during the development and introduction of products to bar misuse and maintain the trust of the public. Environmental justice principles must be the core of decision-making aiming to even an out, as the technology provided benefits are ensured to be shared across varied communities in a fair manner as both the heaviest impacts on disadvantaged groups are reduced and /or eliminated. Additionally, the concern should be extended to the human health and safety implications with the use of the mitigating methods that should be set up to counteract the risks associated with the so-called chemical precision boost. Meanwhile cultural and ethical dimensions dictate the need to give indigenous knowledge, and traditional farming practices their due which can be best done integrating them in with the use of technology and with sensitivity and in collaboration. It is in essence a concerted effort to stick with the basic idea of a holistic world/community by keeping everyone eco-wise/earth friendly, indeed, a green world. Every effort should be underpinned by a commitment to sustainability over a long period and should be done in an ethical way with special attention to the perceived possible frictions and the ways research and development will move together with the aforementioned themes to maintain a harmonic balance between technological progress, ethical principles, and the maintenance of agricultural integrity.

6.4 Sustainability Plan

Succeeding to incorporate YOLOv8 devices into the agriculture sector may be endangered if it is done without having a strong sustainability plan thus ensuring the long eco-social viability of projects like the YOLOv8 powered multi-labeled seeds segmentation service in agriculture. The first stage of the plan is a detailed landscape assessment to determine the potential impacts and guides sustainable agricultural practices. This is mainly focused on running the urban farming activities and exploring the easiest ways of effective participation. Our main strategies for these will be through youth seed program, community organizing, and co-generation of broches. The plan includes an environmental impact statement that is guaranteed to provide the necessary conclusions, thus, the bio-sustainable practices to be adopted will be successful.

6.5 Summary

The multi-labeled seed segmentation technology powered by YOLOv8 is making dramatic changes in the agriculture sector, yielding productive and cost-effective benefits while reducing the damage to the environment. It will enable farmers to take up activities in the application of the right input at the right time, leading to reduced pollution and waste from the activity. The technology similarly makes it easy to optimize resources with minimal solution offerings on the environmental effects. Farming decisions, crop management efficiency, and market changes adaptation will be better. It's not only about providing agricultural information; it is useful and conducive to social welfare. It brings new opportunities for learning, innovating, and being creative in their to make new jobs. By use of YOLOv8 and other machine learning technologies, like CNN segments and hyperparameters optimization, new age agro-products that can grow even in the toughest of climates will be produced. Therefore, the integration of YOLOv8-powered multi-labeled seed segmentation into agriculture has huge social and environmental overtones. Nevertheless, technological development should be counterpoised by ethic painfulness and a balance between technology and environmental health at the same time.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

The conclusion of this study is that it offers a comprehensive summary of the improvements that have been made in the process of developing a revolutionary seed segmentation approach by incorporating the YOLOv8 Model framework. Training and evaluation purposes were the motivations for the collection and preparation of the private datasets that were utilized as benchmarks. There has been a full range of analysis approaches that have been outlined, including qualitative and quantitative assessments, comparative evaluations, and error assessment. It has been observed that the preliminary beta phase has shown good results. It has been demonstrated that the YOLOv8 models have greater performance in comparison to their individual counterparts. These models have achieved a confidence level of 99% on some classes and an average of 93% across all classes.

By adhering to this study, individuals may proficiently categorize seeds of superior grade. Frequently, seed clusters consist of several superfluous items that may be distinguished from the primary seeds using multi-label categorization. This difference contributes to the promotion of agricultural product growth by guaranteeing the choice of superior grade seeds. As a result, this approach plays a role in enhancing agricultural production and guaranteeing higher crop yields.

7.2 Further Suggested Works

Further research on this topic may give a bigger impact on agriculture innovation and sustainability. YOLOv8 algorithm improvement for various environmental and crop conditions will be the researchers' concern. Time tracking is needed for monitoring the environmental impacts caused by YOLOv8-powered agriculture, which also uncovers the long-term ecologic blow. The awareness of the social and cultural reasons why people choose or not prefer certain technologies is essential for the purposes of sustainable technology. A study on the economic viability and scalability of the YOLOv8 agriculture product can afford decision-makers with the knowledge needed for correct planning and investment. Understanding the current policy framework can be helpful for the parties to see ways of integrating the YOLOv8 technologies into modern nations' regulatory systems, also, how to deal with the ethical issues. The cross-discipline team can bring new perspectives and proposes to devise solutions that would cover the problems that are associated with Agricultural Innovation. Doing comparative research using other techniques in the seed segmenting powered by YOLOv8 gives the idea of what the best the applications of YOLOv8 are. On the ending, the performance in the world level YOLOv8 powered farming will lead to their adoption in the different geographical areas and different socio-economic status. What is more, all these integrations of information will probably open up new horizons thereby yielding the most powerful technologies in the most efficient way.

7.3 Limitations

When exploring the novelties of the YOLOv8-powered multi-labeled seed segmentation technology in agriculture, it is crucial to acknowledge the various potential drawbacks and conflicting interests that are included in this field of research. In the first place, the stakeholders and the conventional agricultural practices may claim that the development and use of high-end technology can make them fight it as it may spoil the current processes if they are that obtrusive. Also, the discussion of data privacy and ownership arose due to the usage of sophisticated artificial intelligence algorithms for seed segmentation, particularly where private agricultural data is concerned. Moreover, smallholders are in danger of falling into the trap of being heavily dependent on technology because they have no exposure to them or the experience to cope with technological tools. This may grow the differences in agriculture productivity extensively. Furthermore, patent and commercialization AI-powered agricultural solutions conflict of interest, as such actions can send gain ahead of environmental sustainability. The military must resolve these difficulties first and then make their soldiers receive these devices as a first step, then in the next stage, in order to provide the appropriate and equal access to the YOLOv8-powered seed segmentation technology in agriculture, strict limitations.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: REVOLUTIONIZING AGRICULTURE: UNVEILING YOLOV-8-POWERED MULTI-LABLED SEEDS SEGMENTATION

Student ID: 202-15-3781, 202-15-3855

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a Multi-Labeled Seeds segmentation and classification" problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**

CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	EP1: Depth of Knowledge required	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This study necessitates a theoretical understanding of technology, machine learning and deep learning models, as well as their implications in agriculture which focusing on K1, K4, and K7	**Page no:** [1-3] **Section:** [1.2] **Page no:** [1] **Section:** [1.4] **Page no:** [3]
				The project utilizes engineering principles and design (K5) through the implementation of a systematic experimentation method. The project focuses on the use of the refined Yolov8 model to address engineering practice and technology in the K6 field.	**Page no:** [8-15] **Section:** [3.2] **Page no:** [9-12]

				This study aims to enhance the field of K8 (Previous State of Arts) by consolidating knowledge from recent studies and utilizing deep learning techniques to improve seeds segmentation. It demonstrates a thorough grasp of current methodology in this area.	**Page no:** [3-8] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses EP-2 by recognizing the conflicts of seeds segmentation and classification using Yolov8 framework. One of our biggest obstacles in this study is the small number of seeds image we collected for the study.	**Page no:** [24-28] **Section:** [5.2]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This study focuses on addressing EP-3 by conducting a detailed comparison of experimental results. It identifies Yolov8 as the preferred approach for improving the classification and segmentation of multi-labeled images in the context of seed analysis.	**Page no:** [24-28] **Section:** [5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	Research into various fields of agriculture is required for seeds and their classes, and we are not familiar with them. To overcome this obstacle we studied about the classes of seeds. Which indicates EP-4.	**Page no:** [8-15] **Section:** [3.2, 3.3]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The project's all-encompassing approach tackles This inquiry consists of many linked subsystems. Gathering data, categorizing the data, manipulating it, training models, examining the outcomes, and numerous other activities are all integral components of this process. EP-7 is guaranteed.	**Page no:** [8-15] **Section:** [3.2, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References

1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in pneumonia detection through transfer learning and deep CNNs.	**Page no:** [8-15] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		By following this study, society may effectively classify high-quality seeds. Often, seed clusters contain several unnecessary components that may be differentiated from the main seeds by multi-label classification. This distinction enhances the advancement of agricultural product expansion by ensuring the availability of high-quality seeds.	**Page no:** [28-30] **Section:** [5.1, 5.2, 5.3]
5.	**EA-5: Familiarity**	Yes		This project builds upon previous state of arts by investigating a new method for segmenting and classifying seeds using neural networks, CNNs, and Yolov8. The study includes preliminary terminology and a thorough comparison analysis, providing fresh perspectives in this subject.	**Page no:** [3-8] **Section:** [2.2, 2.3, 2.4]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project aims to tackle CO4 by including efficient project management including financial supervision. It involves careful planning, allocation of resources,	**Page no:** [8-15] **Section:**

			and calculation of budgets to maximize the use of resources throughout the whole study process.	[3.4]
2	CO9	Yes	The project showcases ethical conduct by giving priority to patient privacy, obtaining informed consent, and transparently documenting the research process. It ensures responsible dissemination of knowledge and promotes societal well-being through the ethical use of advanced agricultural sector that comply with CO9.	**Page no:** [28-30] **Section:** [6.2, 6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's commitment to continuous learning CO12 and adaptation within the ever-changing technological landscape is evident in its extensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis. This demonstrates a dedication to staying current and improving techniques to tackle contemporary challenges.	**Page no:** [8-15, 15-23] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2, 4.3]

APPENDIX B

LIST OF PUBLICATIONS

Publication Year	Paper Title	Conference/Journal Name
2023	A Machine Learning Approach for Estimating the Yield of Three Different Rice Types in Bangladesh	JESTECH
2023	Seeds Classification using Deep Neural Network: A Review	Springer Nature
2023	A Review on the Impacts of social media on the Mental Health	Springer Nature

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3	Emrah Dönmez, Serhat Kılıçarslan, Cemil Közkurt, Aykut Diker, Fahrettin Burak Demir, Abdullah Elen. "Identification of haploid and diploid maize seeds using hybrid transformer model", Multimedia Systems, 2023 Publication	1%
4	Florindo, Ricardo Jorge Pinto. "Medical Acts Ranking and Classification in Health Insurance: A Multilabel Approach to Increase Customer Satisfaction", Universidade NOVA de Lisboa (Portugal), 2024 Publication	<1%