LRMC-DEEPLABV3+: MULTICLASS LEAF DISEASE SEMANTIC SEGMENTATION BASED ON AN IMPROVED DEEPLABV3+ NETWORK

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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 **"LRMC-Deeplabv3+: Multiclass Leaf Disease Semantic Segmentation Based on an Improved Deeplabv3+ Network"**, submitted by **Tabassum Islam Mim** and **Nausin Shadia Onti** 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 **13-07-2024**.

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We hereby declare that this project has been done by us under the supervision of **Mayen Uddin Mojumdar, Sr. Lecturer, 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

The accurate and efficient segmentation of plant diseases is the key to sustaining plant growth quality and identifying disease severity. Unfortunately, many current plant disease segmentation techniques frequently fall short of precisely and quickly identifying diseased areas on plant leaves, more specifically when it comes to lightweight segmentation models with the goal of achieving high-level accuracy. The proposed model within this study will be using an improved version of DeepLabV3+ as the foundation for a deep-learning strategy that is intended to quickly and precisely segment common leaf diseases in six different species of plants. In order to modify and better the segmentation performance, the approach for this model combines the CBAM-FF (Convolutional Block Attention Module Feature Fusion) module which uses two analytical dimensions known as spatial attention and channel attention and they are needed to create a sequential attention structure that moves from channel to space. Moreover, the Lite R-ASPP (Lite Reduced Atrous Spatial Pyramid Pooling) attention module has been utilized to enhance the MobileNetV3_large backbone network's feature extraction performance for disease features. Furthermore, the impact of the optimizer, backbone network, and learning rate on the DeepLabV3+ network model's performance will be examined. The proposed model depicted an outstanding accuracy of 97.34% alongside an MIoU of 93.47%.

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LIST OF ACRONYMS

ML	Machine Learning
DL	Deep Learning
LR-ASPP	Lite Reduced Atrous Spatial Pyramid
CBAM-FF	Channel Attention and Feature Fusion

CHAPTER 1
Introduction

1.1 Overview

In recent years image segmentation has been playing a very important part of image analysis in the field of computer vision. Segmentation of any kind of image data is very important to understand and identify areas of interest [1]. Segmentation results can provide a deeper understanding of plant disease identification tasks. It can also be considered a very important parameter for measuring how much damage has occurred by leaf diseases and insects. Understanding the characteristics and structure of the affected area of leaves is key to better prevention of diseases [2].

Fig. 1.1 Example of leaf images

By utilizing the capabilities of an advanced deep learning framework architectures such as DeepLabV3+ have contributed to pushing the limits of what is possible in this field of computer vision. The addition of a MobileNetV3 backbone propels this technique ahead. Notably, the decoder module mentioned as CBAM-FF is included along with a streamlined version of the R-ASSP module [3].

When planting in real-world situations, gardeners and farmers can physically inspect the diseased patches on plant leaves to ascertain the type and severity of the disease. However, the process of identifying the kind and severity of the disease is time-consuming and challenging, requiring a large investment of both financial and human resources, and the outcomes are impacted by various factors. Automated and intelligent diagnosis of agricultural illnesses can be supported technically by the implementation of fast and accurate segmentation of disease degrees and fast and accurate identification of infected areas [4].

Disease indication or specific pesticide application should be done on the severity of the disease for better growth outcomes, saving costs on labor and precision medicine, and lessen pollution to the environment. Nonetheless, the primary factor influencing the diagnosis of disease severity is the precise division of the lesion area and the leaf area.

1.2 Background and Present State

The topical identification of diseases in agricultural sector is a fundamental aspect of the crop management and production of maximum yields. Manual inspection of large land spaces is not productive when it comes to resources and time. In this way, the development of the automated methods for leaf disease detection and classification can greatly help in the sustainable agriculture practices.

The technique mentioned in this study is based on imaging technology, particularly on the modified version of the DeepLabV3+ network which is being used for multiclass leaf disease semantic segmentation. The union of the LR-ASPP (Lite R-ASPP) and CBAM-FF (Channel Attention and Feature Fusion) components with MobileNetV3_large backbone allows the network to capture both global context and detailed information all over the body to achieve the best accuracy while segmenting the disease. LR-ASPP optimized the feature extraction by using Lite R-ASPP modules while CBAM-FF was used for effective feature fusion, which made the network to distinguish the subtle disease patterns and to accurately segment the diseased regions from the healthy ones.

The study contains very important lessons for agricultural research and virtues. Machines for recognizing leaf disease can have the ability of flagging up and dealing with the outbreaks in due time hence prevent losses due to diseases and enhance yield in general. Besides, the suggested methodology also leads to the development of deep learning methods for semantic segmentation tasks, thus demonstrating the effectiveness of the LR-ASPP and CBAM-FF modules in enhancing the performance of the DeepLabV3+ network. Generally, the results may lead to a better disease management approach, improving sustainable agricultural practice and global hunger issues.

1.3 Problem Statement

The research endeavors to address several pivotal problems within the domain of "LRMC-DeepLabV3+: Multiclass Leaf Disease Semantic Segmentation Based on an Improved Deeplabv3+ Network. "These inquiries can act as guidance, leading the research towards a full comprehension of the complexities in using advanced artificial intelligence methods for improved medical diagnoses, some of these research problems are as follows:

- If the modified DeepLabV3+ architecture that has a MobileNetV3_large backbone, Lite R-ASPP and CBAM-FF module decoder, perform well in terms of the disease segmentation accuracy when compared to the existing models.

This issue is intended to research the efficiency of the designed architecture in the classification of the plant diseases from the agricultural imagery. The acknowledgement of the performance of the method in comparison with the existing models and benchmarks enables the study to evaluate the progress that has been achieved by the proposed methodology.

- The computational power of the model proposed, and the comparison of the leading models against the model

The main thing to consider here is the computational resources required by the given model which is the basis for its application in real life, especially in the case of the mobile devices that are having the resource limitation. By the assessment of the computer's effectiveness and the comparison with the current ones, the study will be the source of the model's scalability and feasibility for the real world deployment.

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• The proposed model’s performance in the different environmental conditions and over the several crop diseases in real farming situations

This point is about the assessment of the model's fitness and stability in real-life agricultural scenarios. By the means of the different conditions of the environment and the crop diseases, the analysis will be able to find out the model adaptability and effectiveness in different agriculture situations.

• The types of deep learning strategies of the proposed model for plant disease segmentation and management that will need to be developed.

The main concern of this problem is to find out whether the proposed model is going to be a breakthrough in the field of deep learning that can be applied to plant disease segmentation and management. The analysis of its unique architectural features and the evaluation of its performance will be the base of the study which will give useful and new result to the agricultural image analysis and disease management.

• If the Lite R-ASPP and CBAM-FF modules in the modified DeepLabV3 architecture will be essential in the context of the model's ability to obtain both the global context and the fine-grained details in disease segmentation.

This scenario is concerned with the knowledge of the exact functions of the Lite R-ASPP and the CBAM-FF modules in the increase of the model's segmentation performance. By the deconstruction of the effects of the research on the world and the particulars of the disease segmentation, the research can reveal the processes that are responsible for the accuracy improvement of the disease segmentation.

- The main issues and the limitations that are encountered in the process of the development and the use of the proposed model in the agricultural fields

This issue seeks to highlight the difficulties and obstacles that will be faced when the model is implemented in the agricultural sphere. The study of the elements such as the data variation, the model interpretability and the hardware constraints can give an answer to the areas that need to be further improved and optimize

- The extent of the help the presented model offers in the detection and the control of the plant diseases, and how does it affect the crop yield and the agricultural sustainability

This research problem studies the actual consequences of the model in the identification and control of the diseases in the agricultural systems. The research that will deal with the deep learning technology in the first disease detection and its influence on the crop yield and sustainability indicators can show the real advantages of the technology adoption in the agriculture.

- The extent of the information that needs to be taken in the study that can be used elsewhere besides the plant disease segmentation

This issue is about how the findings and the methods of this study can be transferred to other fields or areas that are connected to the topic. Through the analysis of the similar parts of the proposed model architecture and the training strategies, one can see the potential for the cross-disciplinary collaboration and the knowledge exchange.

The research problems formed in this study altogether are directed to ascertain the effectiveness, practical applicability and the wider implications of the proposed model for the multiclass leaf disease semantic segmentation in agricultural imagery. First of all, the study aims to identify the performance of the modified DeepLabV3 architecture, which has the MobileNetV3 backbone, Lite R-ASPP, and CBAM-FF module decoder, in the context of the segmentation of plant diseases as compared to the current models. Moreover, the research goes further to explore the computational requirements of the model and its efficiency in various environmental conditions and crop diseases in real-life agricultural operations. Also, the study tries to explain the contributions of the suggested model to the progress of deep learning strategies for the plant disease segmentation and management and at the same time it will investigate the problems and the limitations that are brought by its development and deployment. Moreover, the study also addresses the question of the transferability of the knowledge acquired to other fields or applications other than plant disease segmentation and consequently, it shows the wider meaning and the usefulness of the proposed methodology.

1.4 Objectives

The objective behind this study comes from the critical role that accurate and timely plant disorder identification plays in agriculture. Plant diseases can have a significant effect on yield, which can change how much and how well food is produced. Effective disease control requires early and targeted segmentation, which could potentially prevent billions of dollars' worth of annual agricultural losses.

Nevertheless, conventional methods of disease segmentation, which frequently depend on experts' manual observation, are not scalable or appropriately timed to effectively handle these challenging circumstances. A potential path for automation and enhancement of the precision of plant disease diagnosis and segmentation is one of the main objectives. The stepped-forward interest mechanism of the CBAM-FF module, the improved spatial characteristic extraction functionality of light RASPP, and the efficiency and compactness of MobileNetV3 are all strengths that this method aims to capitalize on. It is anticipated that this combination will provide a version that is now superior in plant disease segmentation and also functions well on mobile devices and in-area diagnostic equipment, giving farmers and agricultural workers direct access to improved detection capabilities.

1.5 Scope and Limitations

Disease indication or specific pesticide application should be done on the severity of the disease for better growth outcomes, saving costs on labor and accurate medicine, and lessening pollution to the environment. Nonetheless, the primary factor influencing the diagnosis of disease severity is the precise division of the lesion area and the leaf area.

The main scopes for this paper are as follows:

- Broaden a modified DeepLabV3+ architecture that carries a MobileNetV3 backbone, Lite R-ASPP, and CBAM-FF module decoder, specifically modified for the segmentation of plant diseases in agricultural imagery.

- Examine the performance of the proposed version in phrases of accuracy, performance, and computational resource requirements, evaluating it towards existing models and benchmarks within the area of plant disease segmentation.

- Verify the practical applicability of the model in real-life agricultural settings and its overall performance in various environmental conditions and across specific crops.

- The modified DeeplabV3+ model has been proposed as a new architecture that is easy to implement and has shown success in accurate plant segmentation.

There are several limitations as well such as:

- As the model has been designed to be light weight but it may still struggle on extremely low-power devices like smart watches. It is an important balance between model complexity vs computationally efficiency.

- The model may perform well in one form of environmental condition, e.g., a room with good lighting, limited background clutter and no overlapping leaves so the systems see training examples similar to those where they would be deployed.

- The model need to be able to genralize over deferent crop and diseases. Specific crop conditions and disease types may necessitate additional fine-tuning/training.

• Implementation and Maintenance: Deployment in the real-world is subjected to usability, regular updates, and keeping relevant with time for your model to stay accurate at all times.

The insights that will be obtained from the development and evaluation of the improved model, will be of great assistance to the advancement of deep learning techniques for plant disease segmentation and management. Through the innovation of disease detection and classification techniques, the research is expected to boost crop health.

1.6 Report Organization

This research paper has been organized into several chapters. Every step to provide a systematic overview of the proposed LRCM-DeepLabV3+ model has been structured starting from Chapter 1, which briefly summarizes this thesis. The initial analysis is crucial in this first part and the motivation behind the proposed model has been discussed. Chapter 2, delves into the different research reviews surrounding plant disease detection and segmentation, with a particular focus on deep learning approaches. Lastly, in Chapter 3, the details of the framework of our improved Deeplabv3+ architecture has been explained.

Chapter 1: Introduction

The introductory chapter sets the stage for the research, providing a background on the significance of leaf disease detection, the application of the DeepLabV3+ network, and the need for automated and precise disease management solutions in agriculture. It outlines the research questions, objectives, and the overall framework of the study.

Chapter 2: Literature Review

This chapter offers a detailed exploration of relevant literature and prior research. It delves into the theoretical foundations, methodologies, and technological advancements related to semantic segmentation, deep learning, and agricultural disease detection. It establishes the context for the current study and highlights gaps in existing knowledge.

Chapter 3: Methodology/Requirement Analysis & Design Specification

The research methodology chapter outlines the approach taken to conduct the study. It provides insight into the research design, data collection methods, model architecture, and the rationale behind choosing specific methodologies. The chapter also discusses ethical considerations and any limitations that might impact the study.

Chapter 4: Implementation

This chapter presents the experimental results obtained from applying the improved DeepLabV3+ network in leaf disease detection. Detailed analyses of the performance of the semantic segmentation model are provided, along with visual representations and statistical measures to validate the outcomes.

Chapter 5: Result And Analysis

The results chapter explores the broader implications of the research findings on agricultural practices and crop management. It discusses how improved leaf disease detection methods can positively influence agricultural productivity, treatment outcomes, and the overall state of plant health. Consideration is given to potential advancements in technology and their implications for the farming community.

Chapter 6: Impact On Society, Environment and Sustainability

This chapter examines the societal and environmental impact of the research findings. It discusses how the automated detection of leaf diseases can lead to more sustainable agricultural practices, reduce the use of harmful pesticides, and improve the overall quality of crops. The potential benefits for farmers and the environment are considered.

Chapter 7: Conclusion And Future Work

This final chapter serves as a synthesis of the entire report. It summarizes the key findings, reiterates the conclusions drawn from the research, and offers recommendations for practical applications and further studies. The implications for future research are discussed, providing a roadmap for researchers interested in expanding upon the current study.

1.7 Summary

In summary, the model is created to introduce a novel approach that can analyze plant leaf disease, leveraging the capabilities of computer vision and deep learning, alongside the rationale the proposed model. The technology aims to address the challenges which are associated with accurate and efficient disease detection and offer a tool that is valuable and helpful for farmers and researchers in their efforts to safeguard crop health and enhance agricultural productivity.

CHAPTER 2

Literature Review

2.1 Overview

To ensure a thorough comprehension of the main ideas and techniques utilized in this study on "LRMC-DeepLabV3+: Multiclass Leaf Disease Semantic Segmentation Based On An Improved Deeplabv3+ Network" it is essential to lay down a groundwork by introducing basics and defining key terms. The proposed model integrates a modified DeepLabV3 architecture with a MobileNetV3 backbone, Lite R-ASPP, and CBAM-FF module decoder, as outlined in the code. As a result of these features, the model can have high ability to catch the global character of the viewed photos and the intricate patterns. Thus, the segmentation will be improved. Plant diseases lead to devastating yield losses and crippling economic burdens. Detecting these diseases early and with precision is crucial to implementing strategies for managing them and reducing the extent of these losses. However traditional methods of inspecting plants for diseases are often subjective, time-consuming, and impractical for agricultural areas. Fortunately, recent advancements in computer vision have provided many solutions. These approaches enable automated, accurate analysis and segmentation of plant leaf diseases opening the door to future disease control efforts that are more precise, effective, and less time-consuming.

2.2 Related Works

In recent years various kinds of Machine Learning (ML) and Deep Learning applications have been used for classifying plant diseases based on leaf images has gained significant traction. The goal of several research projects has been to improve these techniques' accuracy and predictive power. A different kind of classifiers have been used to classify leaf features and data can be removed using image-processing techniques. To preserve agricultural output and avoid potential harm to crop yields, early diagnosis of plant diseases is essential. The current state of ML and DL advances provides significant gains in the recognition and classification of plant disease symptoms.

Begum et al. [27] introduced GSAtt-CMNetV3, which was developed to employ the Osprey Optimization technique so that it can classify pepper leaf diseases. Significant improvements in the field of classification accuracy were gained by this approach.

Zhang et al. [28] developed a hybrid loss function combined with CBAM their purpose was to enhance the segmentation recognition of small disease spots on apple leaves so that it can achieve notable results.

Duhan et al. [29] for plant disease identification in challenging environments they invent explored attention mechanisms and in addition, they highlight the robustness of these mechanisms in adverse conditions.

Zu et al. [30] focused on using an advanced deep-learning model for identifying bacterial contamination in Lentinula Edodes logs, which further extends the application of DL techniques beyond plant leaves.

Yuan et al. [31] applied an improved DeepLab v3+ network for segmenting grape leaf black rot spots, exhibiting excellent disease segmentation accuracy.

Kumar et al. [32] for detecting leaf diseases they used ELM-SSA approach, for improved results they combined different algorithms.

Zhou et al. [33] introduced GS-DeepLabV3+, a network that combines enhanced shuffling attention and gated multidimensional feature extraction, producing superior segmentation performance.

Jamadar et al. [34] to estimate the severity of leaf diseases, which emphasizes the significance of precise segmentation in disease management.

Peng et al. [35] were able to segment litchi branches with a remarkable level of segmentation accuracy by using the DeepLabV3+ model.

Yang et al. [36] made methodological changes to the DeepLabV3+ model to increase segmentation performance.

Bhugra et al. [37] developed AnoLeaf, an unsupervised leaf disease segmentation algorithm inpainting generatively by and showed potential in disease diagnosis without significant labeled data.

Chilakalapudi et al. [38] optimized a deep learning network was for the multi-class classification of leaf diseases, demonstrating the effectiveness of DL models in managing a variety of disease kinds.

Liu et al. [39] employed a multi-task distillation learning technique to detect illnesses in tomato leaves, thereby enhancing the resilience of disease classification.
Hasan et al. [40] employed color segmentation and a modified DWT to detect apple leaf illnesses, and the results showed very accurate disease detection.
Bedi et al. [41] presented PDSE-Lite, a lightweight system for assessing the severity of plant diseases utilizing convolutional autoencoder and few-shot learning.
Yang et al. [42] when they applied the ECA-SegFormer model to the semantic segmentation of cucumber leaf disease spots excellent segmentation accuracy was achieved.
Wang et al. [43] demonstrated the value of DL in disease management by segmenting and classifying apple leaf disorders using a semantic segmentation network.
Li et al. [45] improved agricultural picture segmentation, demonstrating improvements in model adaptability and segmentation accuracy using the Agricultural Segment Anything Model adapter.

The improvements in DL and ML techniques for leaf disease segmentation are highlighted by these studies The improvements in DL and ML techniques for leaf disease segmentation are highlighted by these studies. By using this study, they improve the model for identifying accurate diseases from leaves by using this study they improve the model for identifying accurate diseases from leaves.

2.3 Comparison between existing works

A comparison of various methodologies and deep learning architectures for plant leaf disease segmentation and classification reveals a diverse landscape of approaches aimed at improving accuracy and efficiency in agricultural image analysis. Several studies leverage advanced deep learning models such as YOLOv8 combined with an enhanced DeepLabv3+ model, DenseASPP, and strip pooling strategies, resulting in precise segmentation of leaf images by effectively capturing delicate features and complex backgrounds. Similarly, the integration of techniques like CBAM-FF and SANet modules in DeepLabV3+ models enhance disease spot detection accuracy and efficiency, optimizing the grading of disease severity. These approaches exhibit an explicit tendency to use the cutting-edge deep learning models in order to generate that the best image segmentation results in different versions of leaf.

In addition, innovative deep learning approaches such as PSNet, STRNet, and DCNN-based methods demonstrate the indication of further improvement on disease detection and segmentation accuracy on the image data from agriculture domain. The models rely on the following techniques which include attention mechanisms, transformer encoders, and semantic transformer representation networks to get such outstanding performance when classifying and segmenting diseases in real-time while the image is being captured. Highlighting the combination of modern deep learning techniques, transfer learning, and attention mechanisms, those approaches prove their ability to do way beyond the scope of nowadays active areas. Finally, the comparison summarizes that the development and use of advanced deep learning techniques is necessary to overcome practical challenges of detecting and recognizing plant diseases, which are the key problems in image classification of agricultural crops.

The thorough examination of diverse research papers highlights the breadth and depth of innovative deep-learning approaches in plant disease segmentation and classification. Some of them has been discussed in the following table.

Table 2.1: Comparative analysis with previous work

SL NO.	**Author Name**	**Used Algorithm**	**Best Accuracy with Algorithm**
1.	T. Yang et al. [1]	YOLOv8 and Improved DeepLabv3+ .	Mean IoU = 90.8%
2.	P. Wu et al. [2]	Improved DeepLabV3+, CBAM-FF, SANet	MIoU = 90.23%, MPA = 94.75%

3.	Li, L. et al.[3]	DeepLabV3+, PSPNet, GCNet	mIoU=83.85% MPA=97.26%
4.	B. Lu et al.[4]	MixSeg, Convolutional Neural Network (CNN), Transformer, Multi-layer Perception (MLP)	98.22% IOU(Apple Leaf Disease)
5.	Simone Angarano et al.[5]	Ensemble Knowledge Distillation, Logit Standardization	Generalization across various domains
6.	Z. Yang et al [6]	Autoencoder, SVM	96.3% (Rice), 95.4% (Tomato)
7.	Liang-Chieh Chen, et al.l.[7]	DeepLabv3+, Atrous Separable Convolution	PASCAL VOC 2012: 89.0%, Cityscapes: 82.1%
8.	Jun Fu et al[8]	Improved DeepLabv3+ with MobileNetV2 and SE attention	mIoU = 86.32%, mPA = 88.97%
9.	Dongmei Liu et al. [9]	AlexNet, VGG-16, ResNet-50	Not clearly listed
10.	Vijai Singh et al. [10]	Genetic Algorithm, Image Segmentation	Not clearly listed
11.	Muhammad E. H. Chowdhury et al.[11]	EfficientNet-B7, U-net, Modified U-net	Accuracy: 99.95%, IoU: 98.5%
12	Xinran Li et al.[12]	Improved DeepLabV3+ with Xception and CBAM	MIoU = 90.37%

13	Howard et al.[13]	MobileNetV3, LR-ASPP	ImageNet: 75.2% top-1 accuracy
14	Shuaiping Guo et al.[14]	Deeplabv3+,Cascaded ASPP,CBAM	Not clearly listed
15	Cai, M. et al.[15]	MobileNetV2, DeeplabV3+, Attention Mechanisms, CBAM, SA	PA=94.5%, mRecall=85.4%, mIou=81.3%
16	Liang-Chieh Chen et al.[16]	Atrous Convolution, ASPP, DeepLabv3, Batch Normalization.	mIOU = 85.7%
17	Bhakti Baheti et al.[17]	Modified DeepLabV3+, Xception, MobileNetV2	mIoU = 68.41%
18	Shoaib M et al[18]	Inception Net, U-Net, Modified U-Net	InceptionNet1 = 99.95%
19	Luna-Benoso, B. et al[19]	SVM, K-NN, MLP	Not clearly described
20	Khalil Khan et al[20]	Optimized CNN, Semantic Leaf Segmentation	Accuracy = 97.6%
21	Wang J et al[21]	RAAWC-UNet: Residual Attention & Atrous Spatial Pyramid Pooling Improved UNet with Weight Compression Loss	Mean IoU = +1.91% (Leaf), +5.61% (Disease); Pixel Accuracy (Disease) = +4.65%
22	Yujie Yang et al[22]	SE-Swin Unet: Incorporates Swin Transformer modules and SENet modules.	Mean IoU = 84.61%, Accuracy = 92.98%, F1-Score = 89.91%

23	Zewen Xie et al[23]	ECD-DeepLabv3+: Includes MobileNetV2, Efficient Channel Attention, Dense ASPP, and Coordinate Attention modules	Mean IoU = 89.95%, Accuracy = 94.58%, F1-Score = 94.61%
24	Yubao Deng et al[24]	MC-UNet: Cross-layer Attention Fusion Mechanism combined with Multi-scale Convolution Module	Accuracy = 91.32%
25	Xin Jiang et al[25]	DeepLabV3+ with Squeeze-and-Excitation Block (SE-Block)	Not defined
26	Liu et al [26]	Morphological Skeleton refinement, F-3MS refinement	Not clearly defined
27	S. S. A. Begum et al[27]	GSAtt-CMNetV3, Osprey Optimization Algorithm (Os-OA)	97.87%
28	Zhang X., Li D., et al [28].	DFL-UNet+CBAM, U-Net, DeepLabV3+, PSPNet	DFL-UNet+CBAM - MIoU=91.07%
29	Sangeeta Duhan et al [29]	MobileNetV2, EfficientNetV2, ShuffleNetV2 with attention modules	Not clearly defined
30	Dawei Zu [30]	Ghost-YOLOv4, YOLOv4, Classic YOLOv4 Algorithm	Not clearly defined

2.4 Open Issues

There is an extensive body of literature on deep learning architectures and methodologies for plant leaf disease segmentation and classification, and the study of the effectiveness shows a mixed set of results, which have unique strengths and defects respectively. It is remarkable that advancements such as the integration of faster R-CNN and DeepLabV3+ for grape disease analysis, and the development of SDDNet for accurate and effective segmentation in addition to using LSTM for soybean leaf disease diagnosis, highlight how far we have come in terms of accuracy and efficiency, but caps remain. The limitation to this analysis is that it only covers a thorough comparative analysis too few of the existing state-of-the-art approaches, failure to review potential drawbacks in the methods studied by authors like Divyanth et al. and Ashwinkumar et al, and a general neglect of the possibility of model scalability and robustness in predicting diseases across diseases, crop types and crops type. In addition, there are some researches, such as those done by Abinaya et al. and Gokula Krishnan et al. in which they can detect a disease in high accuracy. However, the specificity of these approaches to certain crop types only, as well as the limitation to only certain plant diseases indicate areas that requires further studies. The literature in turn points out the imperative of developing multifaceted evaluation criteria, applicability that spans larger populations, and the examination of how these technologies link to the current agricultural framework.

2.5 Summary

The works of literature about plant leaf disease segmentation and classification present sophisticated deep learning methodologies that are widely being used for accurate as well as fast plant disease detection. Faster R-CNN, DeepLabV3+, SDDNet and LSTM are among the prominent methods that are employed for the purpose. While, that having said, it’s no doubt this issue leaves behind obstacles for equally comprehensive comparative analyses, discussing on the methodology pitfalls, scalability and consistence for diseases and crops as before. While the precision depends on the concrete case, conducting broader validation studies is essential, which shows the potentials for future research for efficient technology transfers into agriculture, so that the use of these technologies would be more effective in reality.

CHAPTER 3

Methodology/ Requirement Analysis & Design specification

3.1 Overview

The primary goal of this research is to investigate the DeepLabV3+ structure and the revisions that are done in order to improve the semantic segmentation performance. DeepLabV3+ is a great semantic segmentation model which is widely known for its ability to recognize the finest details and edges of the segmented images. The entire architecture is constituted by the encoder-decoder structure in which the central idea is the atrous separable convolution and the ASPP module that provides the multi-scale contextual information for the construction of the network. DeepLabV3+ is the successor of its previous generations and the decoder module that improves the segmentation effects and thus the segmentation results are more accurate especially along the edges of the objects. The amendments that came after DeepLabV3+ were intended to improve its segmentation, especially in the cases when it was vital to be highly accurate and at the same time, it had to be efficient in the computations. The new one is the Lite Reduced Atrous Spatial Pyramid Pooling (LR-ASPP) decoder, which is a technique that tries to get the spatial context information and at the same time is a way of saving the resources. Besides, the MobileNetV3-Large backbone architecture is the reason for the increase in the accuracy on ImageNet classification tasks and the decrease in the latency, which is very essential for the real-time applications. Lastly, the CBAM-FF that is the part of the decoder and has two sub-modules; Channel Attention and Spatial Attention is a structure that permits the discrimination of lesions from the background.

Hence, the study will be centered on the revamping of these changes, which will then in turn, help in the attainment of the best possible performance in the semantic segmentation. Therefore, the research also explores the application of the DeepLabV3+ model to the other areas and fields and the modification to the different features and the limitations of the other areas and fields. Moreover, the research is the outcome of a huge breakthrough in the semantic segmentation method development and can thus be applied to a number of computer vision tasks.

3.2 Proposed Methodology/System Design

About 3000 RGB images were gathered for each type of plant from diverse fields in Ashulia, Dhaka, Bangladesh manually. The image-collecting process was conducted between February and April, 2024 due to environmental factors like natural light which can impact the quality of the captured image dataset. These images consists of Bean, Rice, Cauliflower, Pumpkin, Eggplant, and Tomato leaves. Each classes have 500 images of various diseases mostly consisting of different stages of Blight. Fig. 3.2 displays representative images of the types of plants in the dataset.

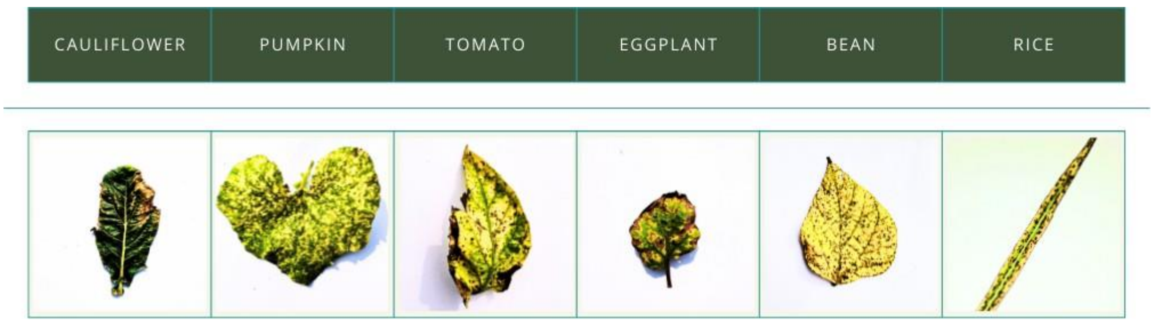

Fig. 3.2 Types of plants in the dataset

Later, all the images were resized into 526×526 pixels. The dataset was split into training and validation datasets with a ratio of 8:2 manually represented in fig.3.2.1.

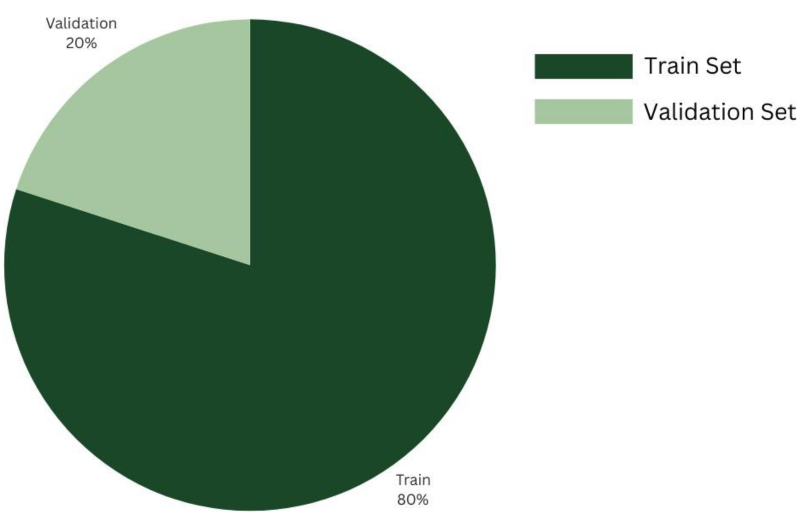

Fig. 3.2.1 Data Distribution

Annotated binary masks have been created using Intel's CVAT annotation tools and these annotations have been validated by five agriculture experts from Bangladesh Agriculture University (BAU).

Fig.3.2.2 show an example of some images in the dataset and their labeled version.

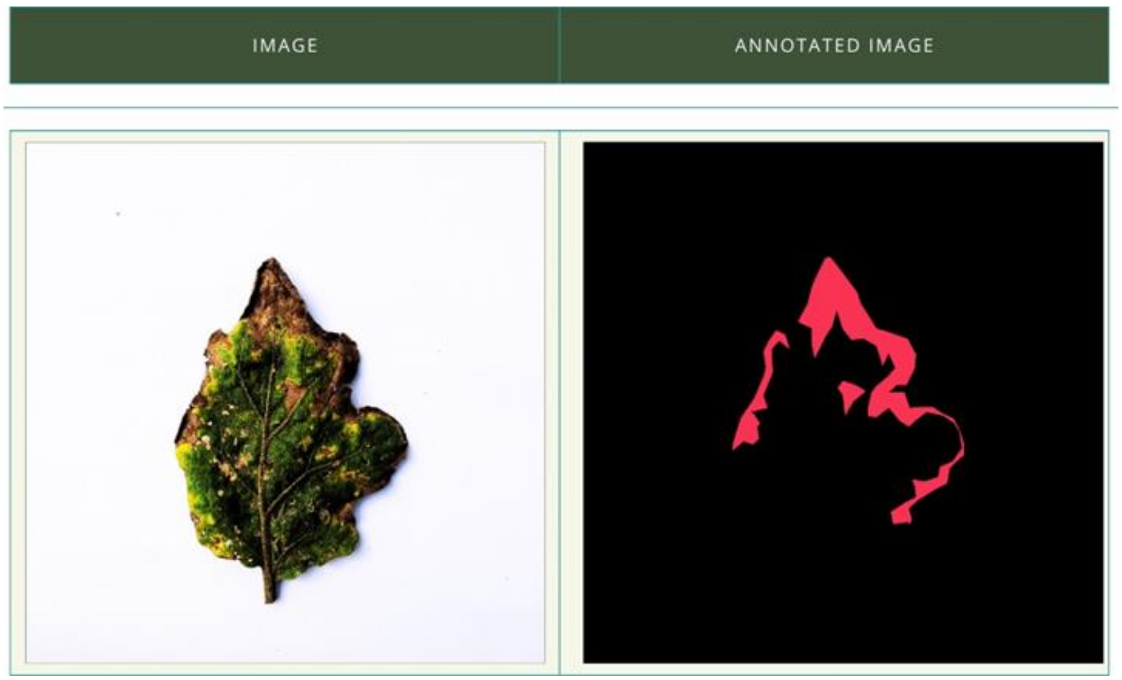

Fig. 3.2.2 Image and Ground truth mask

All the images collected in this paper have been annotated in accordance with their disease categories and have been saved in JPG format. validation. The data distribution of this study has been given.

Table 3.2: Data Distribution

Type	Original images	Augmented images	Test set	Train set
Cauliflower	500	1600	1280	320
Pumpkin	500	1600	1280	320
Tomato	500	1600	1280	320
Eggplant	500	1600	1280	320
Bean	500	1600	1280	320
Rice	500	1600	1280	320

Even with the immense capacity of neural networks3, insufficient images will cause overfitting, which will prevent the desired results from happening. Many researchers have conducted significant studies on this topic. To avoid over-fitting and to improve segmentation accuracy, data augmentation of the training and validation sets was done using the Albumentations library employing techniques which are: Resize, Horizontal Flip, Brightness, Contrast, Sun-flare, Fog, and Angle Rotation.

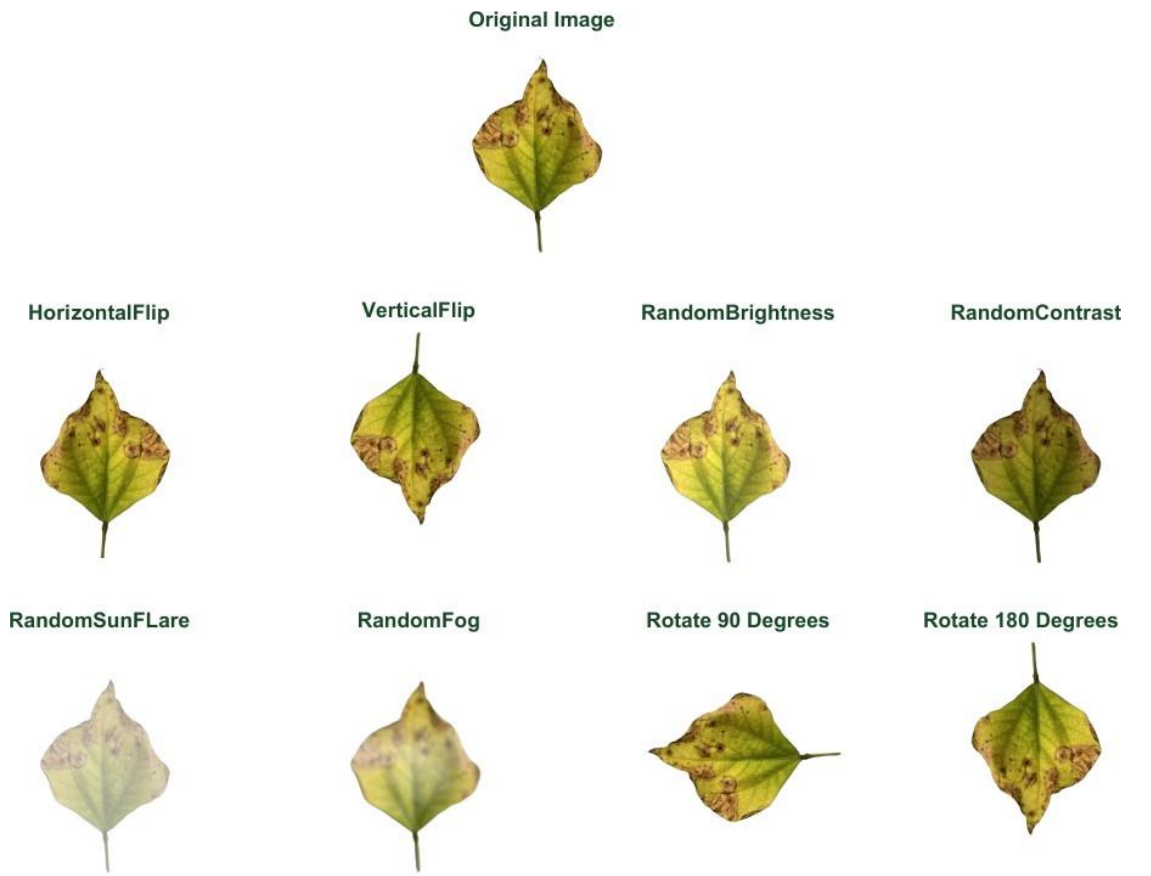

Fig. 3.2.3 Data Augmentation

This study introduces a complicated semantic segmentation framework based totally on Deeplabv3+ with a MobileNetV3 spine, similarly stronger through integrating a lightweight Atrous Spatial Pyramid Pooling (LR-ASPP) and a Convolutional Block Attention Module with Feed-Forward network (CBAM-FF) decoder.
The proposed model pursues to attain superior accuracy semantic segmentation with decreased computational overhead, making it suitable for real-time programs.

LR-ASPP: The LR-ASPP model's main objective is to do segmentation decoding tasks including semantic segmentation and it comes with characteristics such as being lightweight, allowing it to efficiently complete semantic segmentation tasks on platforms with limited resources like mobile devices, edge devices, or low-powered hardware. This is accomplished by combining model structures as well as optimizing computational resource usage.

The Atrous Spatial Pyramid Pooling module (ASPP), is an important part of the LR-ASPP module and enables the integration of features at various scales which utilizes atrous convolutions at multiple rates to capture every minute detail regarding contextual information. This module helps to capture both local and global contexts efficiently as it incorporates global-average pooling which improves the model's capacity to comprehend intricate scenes and objects for segmentation.

To be exact, the Lite R-ASPP module allows better semantic segmentation tasks on low-power devices as Atrous convolutions are applied to the last block of MobileNetV3+_large to extract denser features, which helps to enhance the segmentation performance.

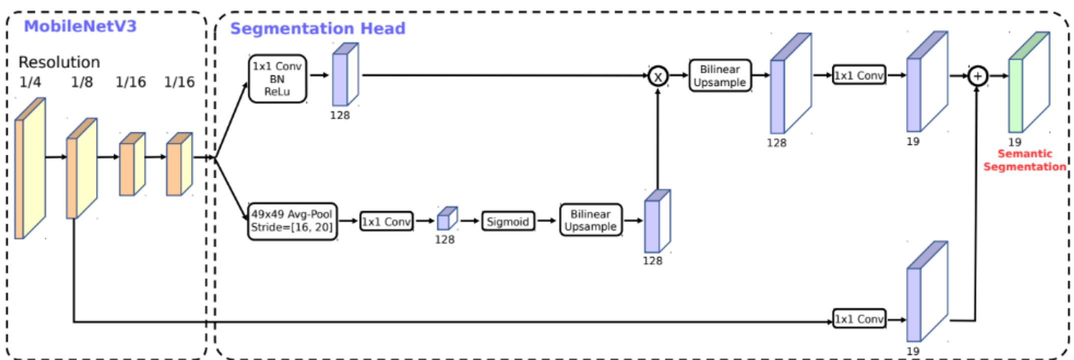

Figure 3.2.4: Building on MobileNetV3, with segmentation head, Lite R-ASPP

MobileNetV3_large: MobileNetV3 Large is the designed structure of the neural network which is the result of the application of neural network architecture to the development of mobile apps that require accuracy in the tasks, such as classification, detection, and segmentation. The base MobileNetV3 is built upon by MobileNetV3_Large which was aimed at models that require higher computation power. The main purpose of this model is not only to keep the structure of MobileNetV3 but also to add new features and performance. The framework of MobileNetV3 Large is composed of blocks utilizing new units containing h-swish and h-sigmoid activation functions plus linear bottlenecks.

These factors ensure that there is no wastage of resources, and the accuracy is also improved. The MobileNet_V3_Large is unique because the main feature extraction block in its structure has been replaced with an expansion module. This can be achieved via feature representation exploitation, what leads to overall better results of computer visual tasks. Instead of that, MobileNetV3_Large offers 27% speedup at a slight mAP loss. This shows that it can operate very quickly. The MobileNetV3 Large breaks the norm and can be used for modern design applications. It will perform the function of the adaptive solution when precision vision tasks should be accomplished but efficiency is also a factor. AI can be applied to different fields like real-time object detection and image classification in environments with limited resources.

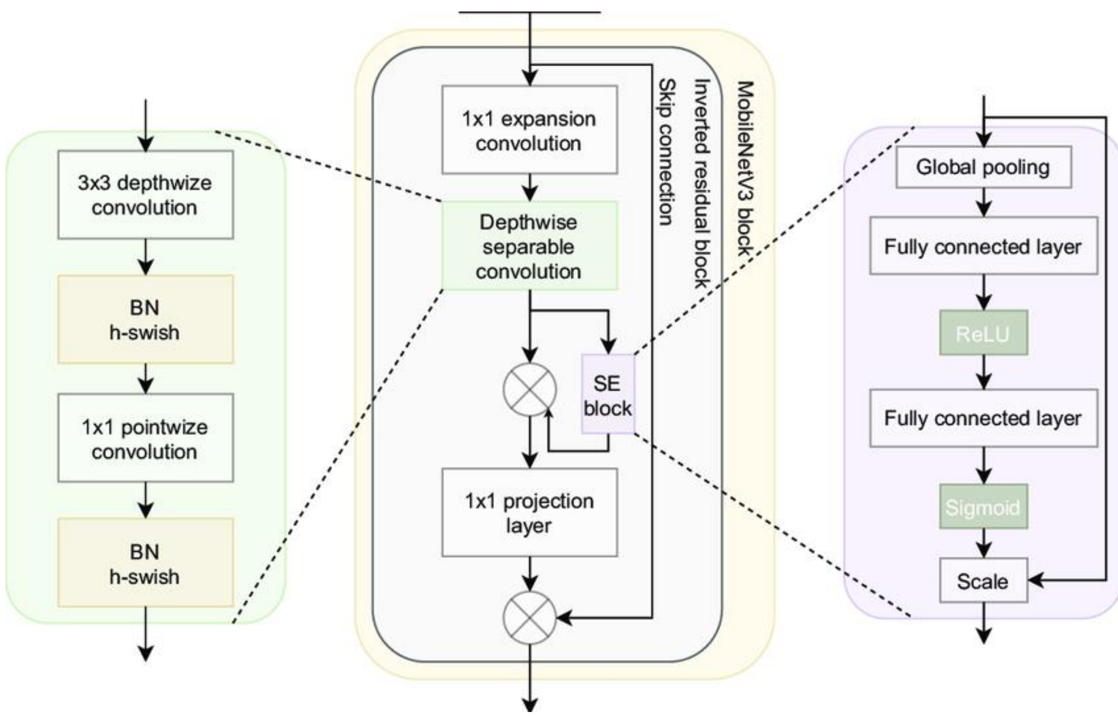

Figure 3.2.5: The structure of MobileNetV3 blocks and components

TABLE 3.2.2: Specification for MobileNetV3-Large

Input	**Operator**	**exp size**	***#out***	**SE**	**NL**
$224^2 \times 3$	conv2d	-	16	-	HS
$112^2 \times 16$	bneck, 3x3	16	16	-	RE
$112^2 \times 16$	bneck, 3x3	64	24	-	RE
$56^2 \times 24$	bneck, 3x3	72	24	-	RE
$56^2 \times 24$	bneck, 5x5	72	40	C	RE
$28^2 \times 40$	bneck, 5x5	120	40	C	RE
$28^2 \times 40$	bneck, 5x5	120	40	C	RE
$28^2 \times 40$	bneck, 3x3	240	80	-	HS
$14^2 \times 80$	bneck, 3x3	200	80	-	HS
$14^2 \times 80$	bneck, 3x3	184	80	-	HS
$14^2 \times 80$	bneck, 3x3	184	80	-	HS
$14^2 \times 80$	bneck, 3x3	480	112	C	HS
$14^2 \times 112$	bneck, 3x3	672	112	C	HS
$14^2 \times 112$	bneck, 5x5	672	160	C	HS
$7^2 \times 160$	bneck, 5x5	960	160	C	HS

CBAM-FF: The proposed model defines the architecture followed by performing deliberations and producing the final model after integrating the CBAM. CBAM begins by defining two scopes: the vertex and the spatial. Instead, it provides attention in two dimensions with the meaning that through space attention and channel attention are running as a step. SAM is the spatial attention module of the network that works upon concentrating on those pixels of the image which are unfavorable areas in cases of disease location detection and lessening the operations on unsignificant areas. The CAM is the instrument that handles the distribution relation among feature map channels. However, the advantage of such hybridization is that it will help the attention technique of the mechanism to use gain its effectiveness to a higher order higher degree.

CBAM bounds features through the attention on the channels and areas one needs that are of high priority, thus, attaching both deep and shallow features. The attention function within CBAM is an output of the successive combination of max and average pooling followed by the convolutional layers. The channel merging process describes these links and therefore the effort of the model is to concentrate on visualizing the main channels by rejecting the others. Nevertheless, spatial attention combines these two types as the layers go and have maximum and average pooled features for better results concerning spatial relationships. The algorithm is concentrating on the essential spatial objects, but at the same time, it is reducing the background noise and interference effects. Through doing this, the ground is paved for accurate measuring. FFNM takes advantage of the fusion module to combines the deep features with the shallow features through increasing the spatial size of the corresponding deep features and the squeeze and excitation of channel attentionally on the shallow features by taking into account of the CBAM mechanism. Lastly, the upsized deep features and the shallow features that channels have processed are combined and sent through convolutional layers. This synergistic union gives the deep-level semantic information context and the shallow-level considerable spatial context's features at the higher level, which helps to make the more robust feature representation that is suitable for the semantic segmentation tasks.

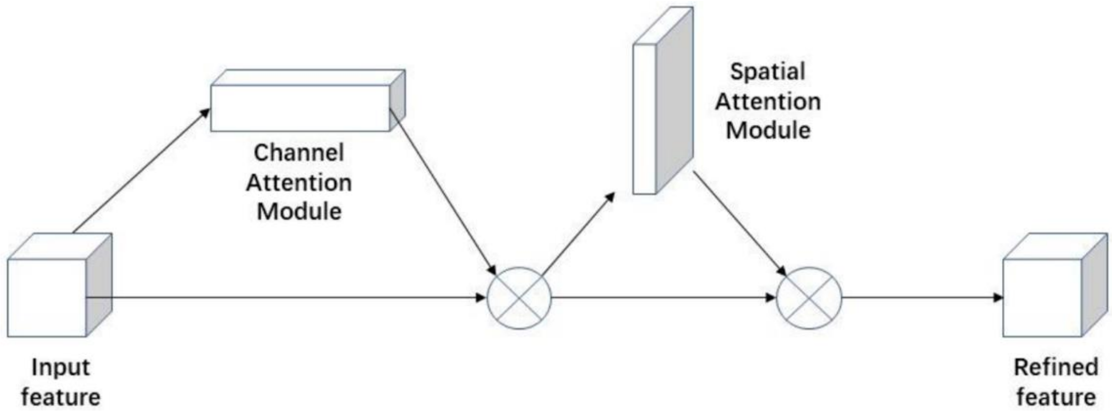

Figure 3.2.6: CBAM Structure Diagram.

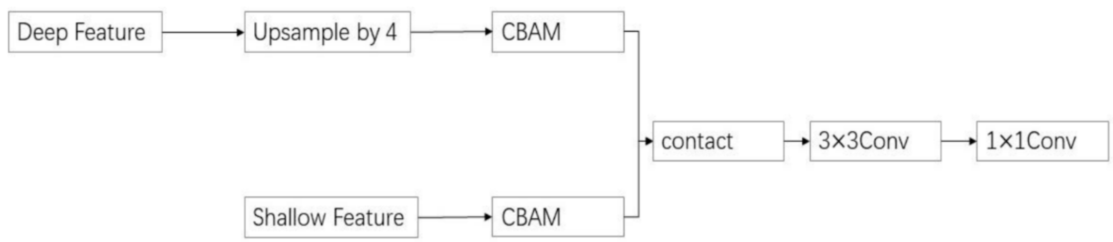

Figure 3.2.7: Feature Fusion Module

DeepLabV3+: This research has been done based on DeepLabv3+ model which is a deep learning network, and on the semantic segmentation which has been recognized as the one the most important tasks in the field of computer vision namely - the classing of every image pixel. At first, the backbone attribute is just performing a function of extracting features in the form of an feature exactractor in this role.

At the last step, mobile-V3 architecture is used, where the image is taken as the input. Characteristics like subjects' identity and location are so important because they give a clue on the semantic and are hence most important in semantic segmentation. The final part of the system is the convolutional layer, which attaches to a segmentation map. The given map can be split into a few part as it is divided into semantically which allows to put each of the pixel to a particular category. Another common element of DeepLabV3+ is the additional classifier that is often employed to boost the training stability. This value means that the system did not use this component. Hence, this part that is from the center of the backbone layer gives the forward thinking which assists with solving problems such as getting around the problem of vanishing gradient in the training. This style of image representation combines the detailed spatial information with the semantic data.

3.3 Hardware/ Software Requirement

In order to conduct experimentations, the following configurations were used:

TABLE 3.3: software requirement

Items	**Configurations**
Operating System	Windows 11
Processor	Ryzen 5 3600X
GPU	ZOTAC GTX1650 4GB
Environment	Anaconda version 23.7.4
Packages and Libraries	Python3.11.5, Albumentations 1.4.3, Jupyter 1.0.0, Pytorch 2.2.2 etc.

3.4 Project Management and Financial Analysis

- Develop an innovative web application for image segmentation and object detection in agriculture.
- Implement a user-friendly interface for farmers and consumers to access agricultural data and services.
- Integrate state-of-the-art deep learning models to enhance image recognition and analysis capabilities.
- Provide a platform for farmers to optimize crop management and make data-driven decisions.

- Ensure scalability and reliability of the web app for widespread adoption in agricultural communities.

Project Timeline:

A. Phase 1: Research and Planning (2-3 weeks)

B. Phase 2: Model Development and Testing (4-6 weeks)

C. Phase 3: Web App Design and Prototyping (1 week)

D. Phase 4: Front-End Development (1 week)

E. Phase 5: Back-End Development and Integration (3 weeks)

F. Phase 6: Testing and Optimization (1 week)

G. Phase 7: Deployment and Launch (1 week)

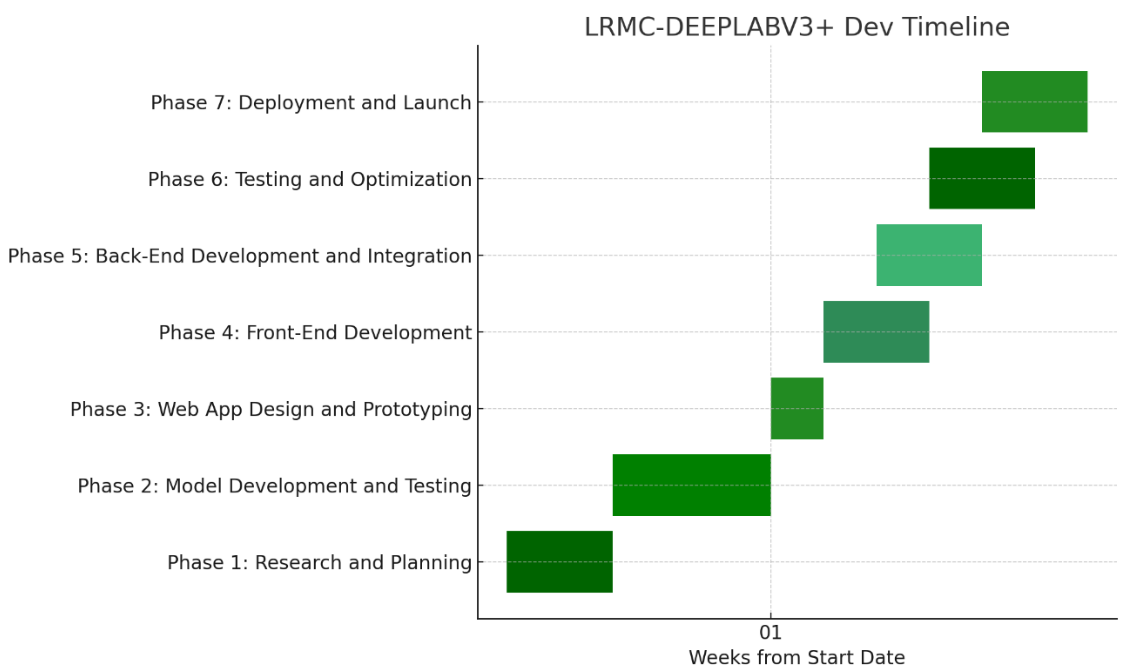

Figure 3.4.: Gnatt Chart representing project timeline

Resource Planning:

A. **Equipment and Tools:**

- High-performance Computers for Model Development
- Devices for Web App Testing (Computer)
- Collaboration Tools (Trello)
- Version Control System (Git)
- Development Tools (Jupiter Notebook, VSCode)

B. **Software and Technologies:**

- Deep Learning Frameworks (PyTorch, Keras, Tensorflow)
- Mobile App Development (Flutter, Dart)
- Server Hosting (Firebase)

C. Data and Content:

- Product Data: Manually collected image data from different farms with agreements with farmers.
- Annotated Data: Validated and monitored by agriculture experts.

D. Training and Skill Development:

- Ensure expertise in deep learning, mobile app development, and cloud computing within the development team.
- Provide training on specific tools and frameworks used in the project.
- Continuous learning and skill enhancement throughout the project.

Risk Management:

Here's a detailed SWOT analysis diagram including the Strengths, Weaknesses, Opportunities, and Threats of this project:

Figure 3.5.1: SWOT analysis

Communication Plan:

A. Change Control Meetings:

Purpose: Discuss and approve any changes to the project scope or requirements.

Participants: Supervisor and team members.

Frequency: Thrice a week.

Financial Analysis

Table 3.4: Estimated Cost for Machine Learning based Project

SN	Components	Estimated Cost (BDT)
01.	Data Collection and Processing	10,000 -15,000
02.	Miscellaneous	500 - 1000
03.	Contingency (10% of total)	1050 -1600
Total Estimated Cost		10,500 -16,000

3.5 Summary

LRMC-DeepLabV3+ is a function of a modified MobileNetV3 for an efficient segmentation, which is further embroidered with the lite Residual Aggregation with PSP-module (R-ASPP) and Changeable Bottleneck Attention Module with Focus Fusion (CBAM-FF) for high accuracy with capability of reducing the computational load and offers the highest accuracy It utilizes feature extraction, multi-scale context capture and the decoding that makes use of attention mechanism together with the different preprocessing and optimization techniques in a robust and optimized manner, which makes it reasonable that it provides the best possible image segmentation.

CHAPTER 4
Implementation

4.1 Overview

In this paper the research presents a method of semantic segmentation called LRMC-DeepLabV3+ which helps achieve high accuracy of segmentation and it's suitable for real-time applications due to the low amount of computations needed. The model is built on Deep Lab V3+ architecture and the weights pre-trained on the ImageNet dataset are used; the base network is MobileNetV3; an efficient Atrous Spatial Pyramid Pooling module, reduced ASPP, or lite R-ASPP is used; the decoder is CBAM-FF.

4.2 Train Model

This study introduces a complicated semantic segmentation framework based totally on Deeplabv3+ with a MobileNetV3 spine, similarly stronger through integrating a lightweight Atrous Spatial Pyramid Pooling (lite R-ASPP) and a Convolutional Block Attention Module with Feed-Forward network (CBAM-FF) decoder.

The proposed model pursues to attain superior accuracy semantic segmentation with decreased computational overhead, making it suitable for real-time programs.

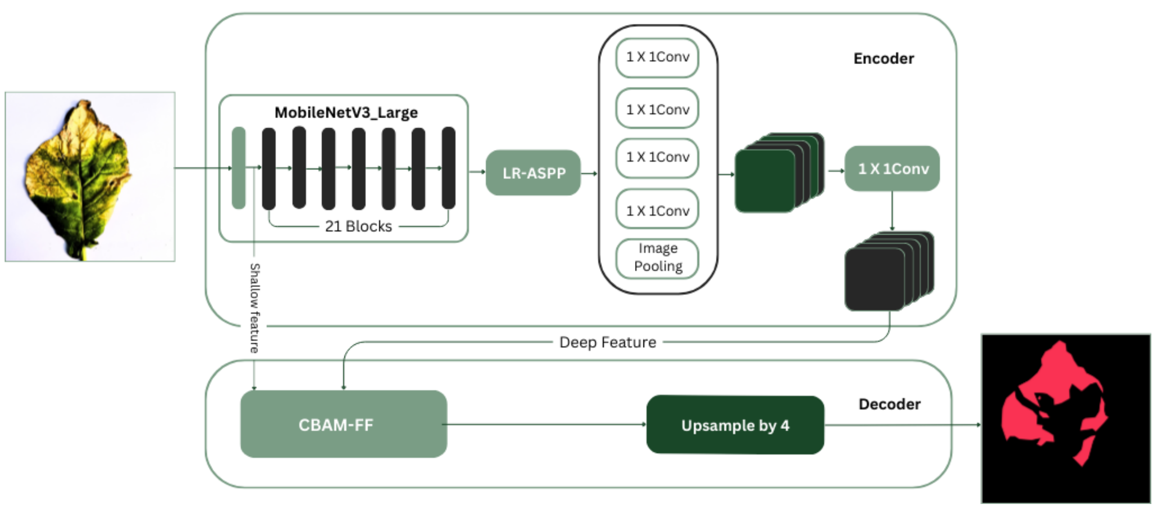

Figure 4.2: LRMC-DeepLabV3+ model architecture

The device will take RGB pictures of the monitored objects as input. Input pics undergo widespread pre-processing steps, such as resizing to a fixed size and normalization to suit the input requirements of the MobileNetV3 spine. The lightweight MobileNetV3 structure serves as the function extractor. Its efficiency and intensity-smart separable convolutions lessen the computational load whilst preserving the capacity to capture crucial functions for segmentation. A changed version of the Atrous Spatial Pyramid Pooling (lite R-ASPP) is applied for multi-scale feature extraction. This component is designed to be lightweight, decreasing the number of parameters and computational value as compared to the unique R-ASPP, whilst nonetheless taking pictures of context at numerous scales. The decoder consists of the Convolutional Block Attention Module (CBAM) for function refinement and a Feed-Forward community (FF) to correctly reconstruct the segmentation map from the encoded features. The CBAM enhances characteristic representations through channel and spatial interest mechanisms, enhancing the segmentation accuracy.

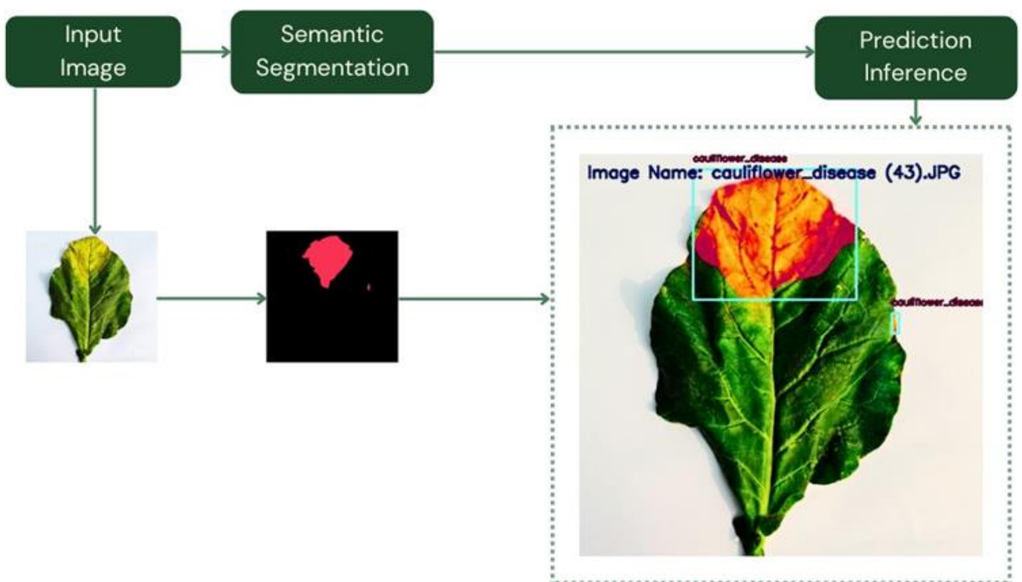

Figure 4.2.1: Experimentation Approach

The final output is a segmentation map that identifies distinct classes of interest, along with the circumstance of perishable items, based totally on the training dataset. The model will be optimized on the usage of an Adam optimizer. To enhance version robustness, facts augmentation techniques which include rotation, flipping, brightness and contrast adjustment are implemented for the pre-processing.

4.3 System Testing/ Model Evaluation

In the experimental study, four assessment metrics were employed: Mean Pixel Accuracy (MPA), Pixel Accuracy (PA), Intersection over Union (IoU) and Mean Intersection over Union (MIoU), Loss, Recall, Precision.

Pixel Accuracy (PA):

The overall effectiveness of a segmentation model is measured by calculating the ratio of correctly classified pixels to the total number of pixels, which is defined as PA. The formula representing PA is:

PA = Σ(i=0 to k) P^(ii) / Σ(i=0 to k) Σ(j=0 to k) P^(ij)

Mean Pixel Accuracy (MPA):

Individually computed PA for all classes is averaged out to calculate MPA. The formula is:

MPA = (1 / (k+1)) Σ(i=0 to k) P^(ii) / Σ(j=0 to k) P^(ij)

Intersection over Union (IoU):

The ratio of the intersection to the union of the predicted and ground truth segmentation results is defined as IoU, measured using the formula:

IoU = P^(ii) / (Σ(j=0 to k) P^(ij) + Σ(j=0 to k) P^(ji) - P^(ii))

Mean Intersection over Union (MIoU):

The average of the IoUs across all classes is evaluated using the formula, defined as MIoU:

MIoU = (1 / (k+1)) Σ(i=0 to k) P^(ii) / (Σ(j=0 to k) P^(ij) + Σ(j=0 to k) P^(ji) - P^(ii))

Loss:

In the loss function, the function quantifies the model's performance capability with respect to the real data. In this case, the Cross-Entropy Loss function is used, represented as:

$$\text{Loss} = -(1/n)\ \Sigma(i=1 \text{ to } n)\ \Sigma(c=1 \text{ to } C)\ y\_ic \log(\hat{}y\_ic)$$

Recall:

Recall is used to measure the proportion of true positives that were correctly identified by the model. The formula representing Recall is:

$$\text{Recall} = TP / (TP + FN)$$

Precision:

The proportion of positive identifications that are actually correct is measured by precision. The formula representing Precision is:

$$\text{Precision} = TP / (TP + FP).$$

4.4 Summary

The project on "Paddy Leaf Disease Detection using Deep Transfer Learning" utilizes advanced AI techniques to improve agricultural disease detection. It begins with collecting a diverse dataset of paddy leaf images, supplemented with data from Kaggle, followed by rigorous preprocessing and data augmentation to enhance model training. Models such as VGG-19, VGG-16, MobileNet-V2, DenseNet, ResNet-50, Xception, Inception-V3, and Customized Inception-V3 are fine-tuned for specific disease detection. The dataset is split into training, validation, and testing sets, ensuring robust model evaluation through metrics like accuracy, precision, recall, F1-score, and specificity. This comprehensive approach aims to develop a reliable and scalable disease detection system for practical agricultural applications.

CHAPTER 5

Result and Analysis

5.1 Overview

The experiment was a result of the training and evaluation of an semantic segmentation model for plant disease segmentation which had the modification of the DeepLabV3+ architecture. The hardware demands for a high-performance computing system that is supplied with a Graphics Processing Unit (GPU) to quicken the model training are high. Software requirements consist of the deep learning frameworks such as PyTorch which was the need for implementing the model and also the Python programming language for the coding of the experimental pipeline.

During the training phase, the model efficiency was rated with the help of indicators like the loss, pixel accuracy and the mean Intersection over Union (mIoU). The most suitable loss function for the task was Cross Entropy Loss which is the best one for the multi-class segmentation problems. The model was taught to minimize the loss while at the same time it was making the pixel accuracy and mIoU to the maximum level, which were the parameters used to measure the segmentation quality. The ethical aspects were the main reasons for the decision to collect the data in a way that it is ethical and the person who is collecting the data is following the law of the country that is giving permission to use such data. Moreover, the data collection was carefully done with the data provider's consent and the data provider's privacy.

The research was carried out in a way, which included the experiment set up, the dataset, the model architecture, the training parameters, and the evaluation metrics, and was thus reproducible and transparent. The codebase, datasets, and the experimental documentation were put on the internet so that it could be easily reproduced and for more research in the domain of agricultural disease segmentation and management.

5.2 Experimental/ Simulation Result

Within this research, the procedure of combining the disease area segmentation with was proposed to diagnose the disease grade of the plant leaves. The pipeline starts with the input image of the selected leaf followed by passing it through the MobileNetV3 - Large model with convolutional layers for feature extraction as the backbone of DeepLabV3+ architecture. After extraction, these features are further promoted with a Lightweight Atrous Spatial Pyramid Pooling (LR-ASPP) module, to effectively obtain multi-scale contextual features which are significant to the accurate segmentation task. At the same time, the shallow features go through a Convolutional Block Attention Module with Feature Fusion (CBAM-FF), which enhances the feature maps focusing on relevant features. After that, the deep features get followed by an up- sampling procedure that enlarges the specific features by a factor of four to maintain the spatial density. The feature maps are then passed on to a decoder that combines them to form a very accurate segmentation map that outlines the diseased areas on the leaf. It is then used for the classification feature to determine the specific disease in high precision.

Accuracy rate after 50 iterations for the training and validation parts for the model are represented in the graphs in fig. 5.2

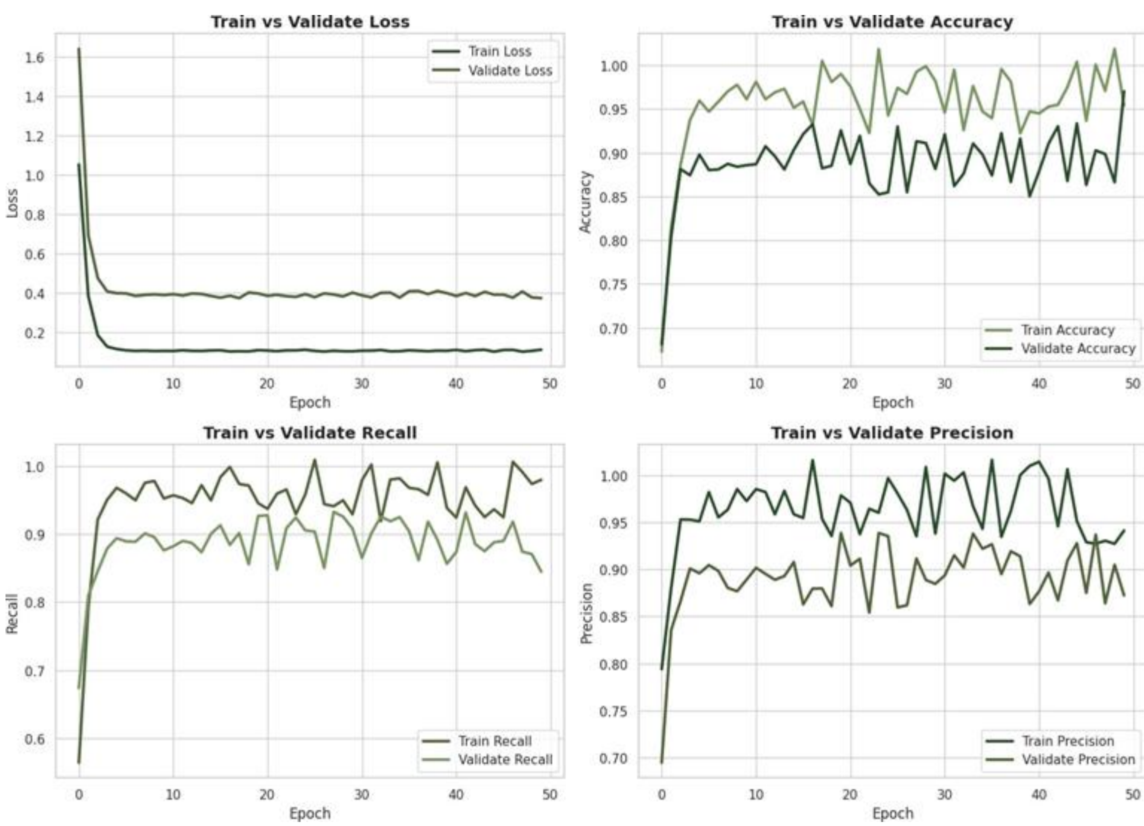

Fig. 5.2 Accuracy, Loss, Recall and Precision for Training and Validation

The values of all such measures that are associated with issues to do with precision, recall, as well as accuracy, are on the rise that signifies enhanced effectiveness of the model and exhibiting both a notable improvement in the major performance indicators and a significant convergence of the model.

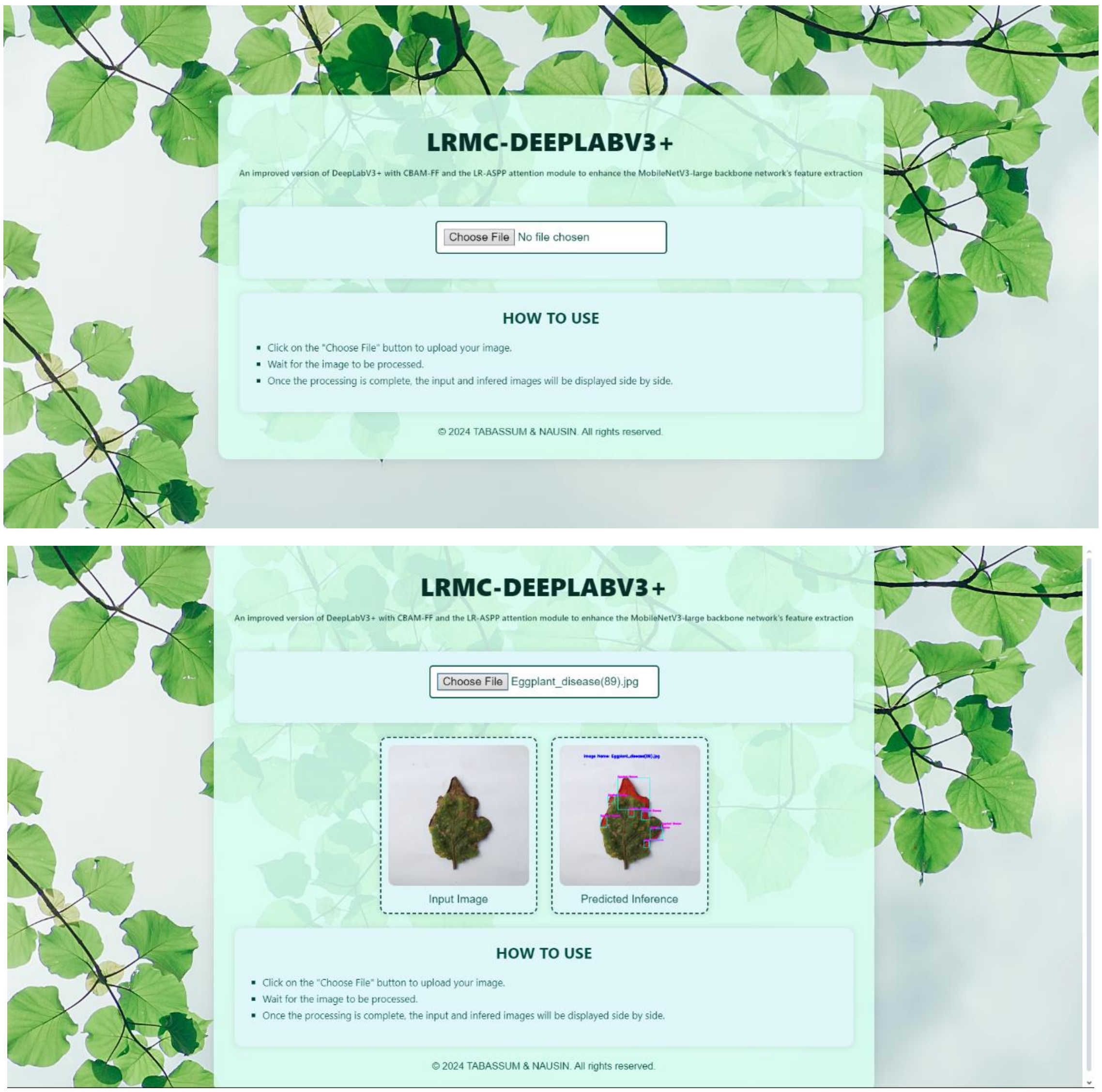

Fig. 5.2.1 Web application

5.3 Performance/ Comparative Analysis

To assess the improvements, a comparative study of segmentation accuracy for different plant disease types was carried out using the base model DeepLabV3+ and the upgraded model LRMC-DeeplabV3+. Pixel Accuracy (PA) and Intersection over Union (IoU) are the evaluation measures used.

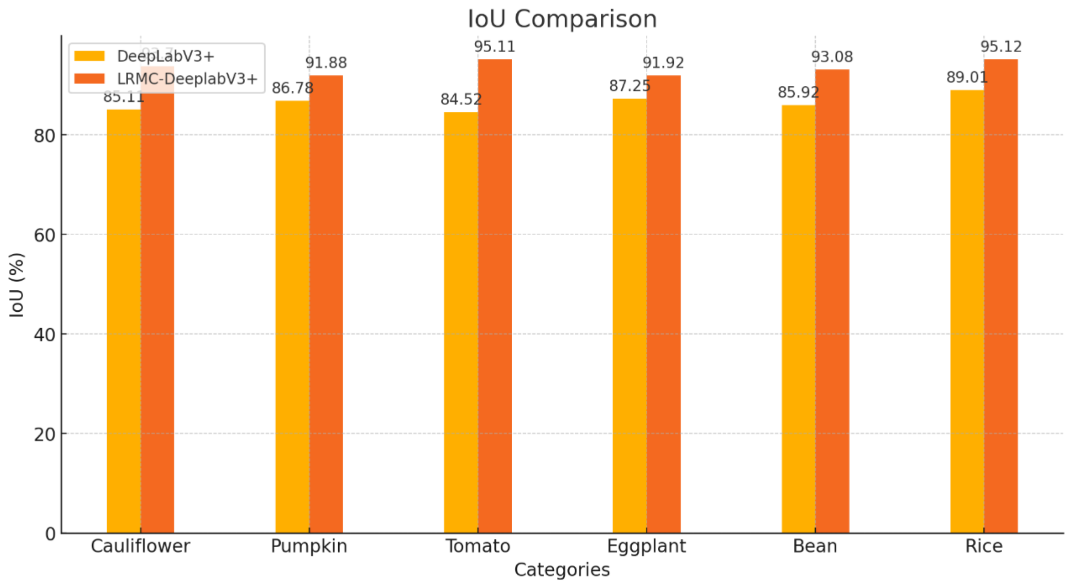

Fig. 5.3 IoU comparison

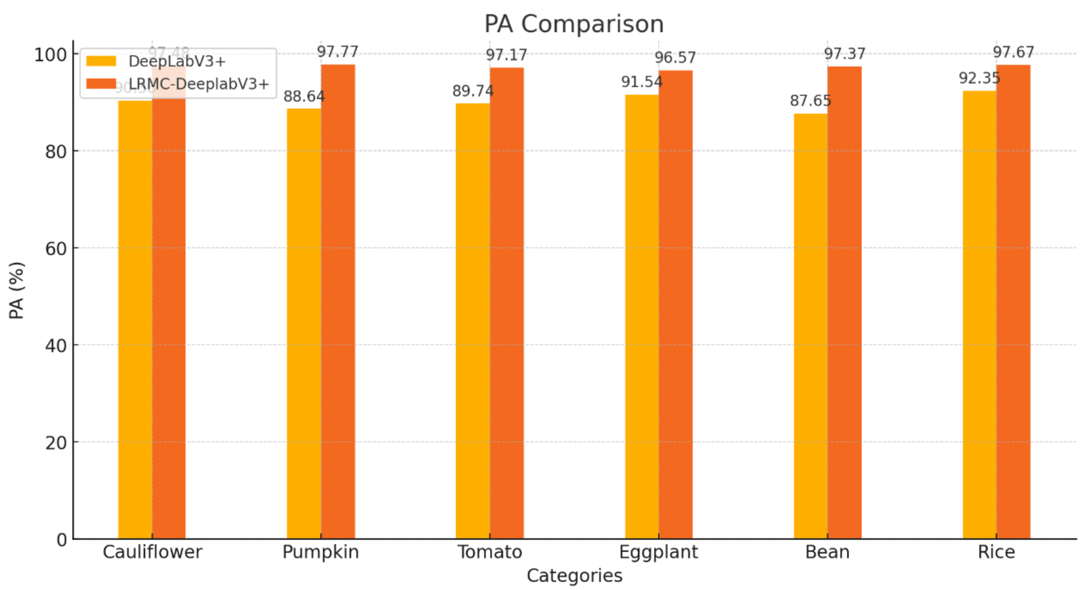

Fig. 5.3.1 PA comparison

LRMC-DeeplabV3+ obtains higher IoU scores such as 93.70% for cauliflower, 91.88% for pumpkin, 95.11% for tomato, 91.92% for eggplant, 93.08% for beans, and 95.12% for rice. In a similar vein, the Pixel Accuracy (PA) values significantly yield; 97.48%, 97.77%, 97.17%, and 96.57%, respectively. Comparably, the PA measure for DeepLabV3+ shows a notable improvement; for example, LRMC-DeeplabV3+ achieves 97.48% for Cauliflower and 96.50% for Pumpkin, compared to 90.36% and

88.64% for DeepLabV3+. Consequently, it is evident that the LRMC-DeeplabV3+ performs far better in terms of segmentation, offering better and more precise information for decision-making regarding plant diseases.

Table 5.3: Comparison of DeepLabV3+ and LRMC-DeepLabV3+

Metrics	**Model**	Cauliflower	Pumpkin	Tomato	Eggplant	B**ea**n	Rice
IoU/%	DeepLab V3+	85.11	86.78	84.52	87.25	85.92	89.01
	LRMC-DeeplabV3+	93.70	91.88	95.11	91.92	93.08	95.12
PA/%	DeepLab V3+	90.36	88.64	89.74	91.54	87.65	92.35
	LRMC-DeeplabV3+	97.48	97.77	97.17	96.57	97.37	97.67

The suggested model has been compared with related research that has been done previously in Table 5.3. The examined models are modifications of DeepLabV3+ associated with the various kinds of attention mechanisms and neural networks, together with CBAM, MobileNetV2, as well as PSPNet. Impressively, the LRMC-DeepLabV3+ model is seen to perform better, which proves that optimizations such as MobileNetV3, CBAM-FF, and Lite-RASPP improve the method's efficiency in terms of segmenting leaf diseases with high precision.

Table 5.3.1 Comparison with Pre-existing models

Previous work	Model	MPA	MIoU
P. Wu et al. [12]	Improved DeepLabV3+, CBAM-FF, SANet	94.75%	90.23%
Jun Fu et al. [32]	Improved DeepLabV3+, MobileNetV2, SE attention	88.97%	86.32%
Xiaoqian Zhang et al.[14]	DFL-UNet, CBAM	95.58%	91.07%
LRMC-DeeplabV3+	Improved DeepLabV3+, MobileNetV3,CBAM-FF, Lite-RASPP	97.34%	93.47%

5.4 Summary

In this chapter a modified semantic segmentation model, LRMC-DeeplabV3+ was discussed, aimed at accurately segmenting plant diseases using a combination of DeepLabV3+ architecture with enhancements including MobileNetV3-Large, LR-ASPP, and CBAM-FF modules. The model was trained using PyTorch on a GPU-accelerated high-performance computing system, optimizing for metrics like loss, pixel accuracy, and mean Intersection over Union (mIoU). Results demonstrated substantial improvements over base DeepLabV3+, achieving higher IoU and Pixel Accuracy (PA) scores across various crops (Cauliflower, Pumpkin, Tomato, Eggplant, Bean, Rice). Comparative analysis with previous models highlighted LRMC-DeeplabV3+'s superior performance, validating its efficacy in precise agricultural disease segmentation and management decision support.

CHAPTER 6

Impact on Society, Environment And Sustainability

6.1 Impact on Life

The study has impact on different aspects of life mainly revolves around increasing productivity and sustainability in the field of agriculture. It flags the onset of diseases in advance and intervention is made before it ravages crops – the consequence being higher yields and food security. Since the technology will be allowed through mobiles, many farmers, especially those in the rural areas, will be in a position to diagnose the plant diseases as they occur and thus, effectively determine the most appropriate next step to take or the most suitable resources to deploy. It helps in enhancing the farming practices as the democratization of high-tech agricultural tools results in better lives of farmers. The research also promotes innovation and collaboration among farmers in integrating age old practices in farming with the help of technology making a significant contribution to the enhancement of sustainable agriculture. Environmentally, early diseases detection reduces the application of pesticides which in turn reduces the effects on the soil, water, and overall impact on the ecosystem. It involves greater production in relation to the resources used in that it leads to environmentally friendly farming and combating of the gas that causes the greenhouse effect. In conclusion this research helps to increase the agriculture's robustness to environmental conditions hence encouraging sustainable farming and good relationship between agriculture and the environment for societies and planet benefit.

6.2 Impact on Society & Environment

The research has a wide-ranging impact on society, the most important of which is the achievement of significant advancements in the management of agricultural diseases and the optimization of crop yield. The developed semantic segmentation model that is specialized for plant disease detection, the research increases the chances of early disease detection hence, enabling timely intervention and mitigation strategies. This way of thinking starts with farmers which prevents the spread of diseases, decreases crop damage, and enhances the yield thereby food security and economic stability is achieved in agricultural communities.

Besides, the application of the model to mobile devices improves the accessibility and usability, and thus, the farmers are enabled to get the disease diagnoses on the move in the field. This accessibility lowers the dependency on specialized equipment and expert knowledge, thus, it makes the high-tech agriculture technologies available to everyone and at the same time, it gives the farmers in the remote areas the power to use them. Therefore, the farmers can take the right decisions about the disease management, the resource allocation, and the crop treatment, which will finally give them a better farming practice and also better livelihoods.

Besides, the research creates the incentive to innovate and cooperate among the farmers by applying the new deep learning techniques and the cross-disciplinary knowledge. Through the combination of agronomy, computer vision, and machine learning, this research connects the traditional agricultural practices with the modern technological solutions and thus, it is the basic unit of sustainable agricultural development. The scalability and adaptability of the model to different crops and environmental conditions are the factors that make the model's impact on society so big, thus the adoption and scalability of the model in different agricultural landscapes can be facilitated.

The main effect of this research is on the environment as it is mainly concentrated on the promotion of eco-friendly agriculture and the decrease of the environmental footprint of crop production. By the research scientists, they have the capacity to detect the plant diseases at the very beginning, then it will reduce the usage of the pesticides and, at the same time, the environment will be protected from the pollution and the ecosystem will not be degraded. By the process of generating this model, the treatments are only used where they are needed which therefore, the model reduces the whole amount of chemical inputs which as a result leads to the reduction of the harm that they cause to the soil health, water quality and biodiversity.

Besides, the research on the crop management practices is done to make it more efficient and now the resources are used more wisely and agriculture is conserved. The farmers can achieve more yields with fewer inputs hence they can use the land, water and energy resources more effectively than before, hence, the crop losses from disease outbreaks are minimized. The increased efficiency which comes from eliminating the old ways of work makes the farming system more eco-friendly, with less greenhouse gas emissions and the natural ecosystems are not under any pressure.

Apart from, the model on the mobile devices is made and so the agricultural technologies become more universal, hence the farmers can be empowered to make the data-driven decisions in real-time. The technology has become more accessible and in turn the farmers become more aware and understand of the environmental issues which in turn the farmers become more environmentally friendly and environmentally-conscious. The study proves that the mandatory usage of the precision agriculture techniques will make the farmers to use the practices that will lessen the environmental impact while at the same time increasing both the productivity and the profitability.

In the end, the research that employs the newest technologies for the detection of diseases and crop management contributes to the creation of resilience to the environmental stressors and at the same time the harmonious interaction of agriculture with the environment is raised. The research on the resource efficiency, conservation, and the environmental protection, which aims at a more sustainable and resilient agricultural sector, is the way to a more sustainable and resilient agricultural sector that will be able to thrive even in a changing climate and also, will protect the health and the integrity of the planet ecosystems.

6.3 Ethical Aspects

The research on "LRMC-DeepLabV3+: Multiclass Leaf Disease Semantic Segmentation Based On An Improved DeepLabV3+ Network" is underpinned by a commitment to ethical considerations throughout its methodology. Consent and privacy regulations must be adhered to above all else while gathering and utilizing data. Although plant disease imaging rarely contains personal information, researchers should still ensure that whatever data they get from farms or other agricultural organizations is legally obtained.

The issue of ownership of such data also becomes of paramount concern and must be employed strictly for the intended research objectives. Openness and replicability are key ethical considerations of this research. Documentation that explains the entire process from designing a methodology or an algorithm to dealing with data helps other researchers to repeat or verify the experiments, enhancing the reliability of results in the scientific community. It also entails opening up to the public and scientific community about the outcomes of clinical trials, including constructive results to help define new research areas and avoid irrelevance. Deploying models in real agricultural practices has to take into account the interests of farmers and farmworkers. It is quite important to make sure that the technology that will be adopted will be user-friendly to the end-users since most of them may not have in-depth technical knowledge. And assistance should be given to equip them to use these tools in the best way since they must enjoy equitably in the research. Further, it is a concern for researchers that their innovation may have socioeconomic consequences. Although automated plant disease detection provides high efficiency and crop losses minimization, its implementation might influence the employment rates, especially in rural areas where disease identification can be a major source of living. There should be efforts to address the side effects of the technology on the number of local jobs and on the diversification of people to new roles in case the technology is implemented. Fourthly, other factors in the external macro-environment have to be addressed. Though plant disease segmentation mainly aims at enhancing the quality of agriculture production the importance of a healthy and sustainable agricultural sector should not be forgotten. Future researchers should seek to find the role their research can play in promoting such environmentally-friendly practices as cutting on the use of chemicals by helping initiate disease attacks early and accurately.

6.4 Sustainability Plan

The research project “LRMC-DeepLabV3+: Multiclass Leaf Disease Semantic Segmentation Based On An Improved DeepLabV3+ Network” has a sustainability plan that aims to reduce its negative effects on the environment while maintaining its beneficial effects on society. The use and further sustainability of the plant disease segmentation and classification system depends on future development, data management, access, training, collaboration, ethics, resources, and further evaluation. Occasional revision with fresh information or continuous training with new datasets will help retain its usefulness, and strict data standards will maintain its reliability. Intuitive and modular systems will ease uptake while expandability and enterprise readiness can be backed by adequate documentation and product assistance. Partnerships with research institutes, governmental organizations, and local societies will also improve development and deployment. Ecological and ethical standards will be especially valued and encourage the development of sustainable agriculture. Getting the funding and resources is critical as well as a monitoring framework with a mechanism to measure performance and collect feedback on how the system is stacked up long-term and how it is benefiting farming practices.

6.5 Summary

The study "LRMC-DeepLabV3+: Multiclass Leaf Disease Semantic Segmentation Based on An Improved DeepLabV3+ Network" offers a thorough investigation of cutting-edge methods for agricultural diagnostics. The current study focuses on one of the core issues of plant leaf disease segmentation and classification – the improvement of the mentioned techniques in terms of accuracy and computational performance. The model at the core of this study is based on the previously proposed DeepLabV3+ framework and includes a number of modifications aimed at these objectives. Notably, it uses MobileNetV3 for the backbone; Lite Reduced Atrous Spatial Pyramid Pooling (LR-ASPP); and the Convolutional Block Attention Module with Feature Fusion(CBAM-FF). The combined use of these components is meant to offer enhanced segmentation with high accuracy without placing too much load on computation, a feature that makes the model viable for real-world applications through mobile and field-based diagnostic tools. This research is also a big step in the field of agricultural technology since they have developed an early disease identification in plants which has a very high level of accuracy and is efficient when it comes to computation. This work also has significant practical applications since it can increase the income of farmers and the competitiveness of agricultural specialists through the best ways to apply fungicides and increase the yield of the crop. This research strives to answer the question if the work on the development of advanced diagnostic tools contribute to ensuring the sustainability of the agricultural industry and enabling food safety or not. This model’s compatibility with low-resource devices also makes it a powerful tool for real-world applications as it proves that people no longer have to live in technologically isolated areas in order to enjoy the benefits of progressive solutions. The connection of this technological advancement and practical usefulness is a testimony to the significance and influence of this research in the area of plant disease detection.

CHAPTER 7
Conclusion and Future Research

7.1 Conclusions

In summary, the model is created to introduce a novel approach that can analyze plant leaf disease, leveraging the capabilities of computer vision and deep learning, alongside the rationale the proposed model. The technology aims to address the challenges which are associated with accurate and efficient disease detection and offer a tool that is valuable and helpful for farmers and researchers in their efforts to safeguard crop health and enhance agricultural productivity. LRMC-DeepLabV3+ is a function of a modified MobileNetV3 for an efficient segmentation, which is further embroidered with the lite R-ASPP and Changeable Bottleneck Attention Module with Focus Fusion (CBAM-FF) for high accuracy with capability of reducing the computational load and offers the highest accuracy It utilizes feature extraction, multi-scale context capture and the decoding that makes use of attention mechanism together with the different preprocessing and optimization techniques in a robust and optimized manner, which makes it reasonable that it provides the best possible image segmentation in lower powered devices.

7.2 Further Suggested works

Significant theoretical contribution to further research are manifold and possible areas for future study from this research are numerous and diverse. For example, further investigating how to improve the design and efficiency of the semantic segmentation model would produce better outcomes. Perhaps the further development of backbone networks, attention mechanisms or the variety of fusion strategies would contribute to the potential ability of the model to learn and express the response for complex features in different agricultural conditions as well. In addition, the inclusion of more samples of different crops, diseases, and environmental conditions would help the model learn better and be easily applicable. Conducting more large-scale investigations and trials in various areas and farming techniques may be useful for obtaining the information required to validate the model for application in commercial farming and for its further promotion in agricultural activities. Further, the considerations on how it will be impacting the socio–economic status of the Society in general and the moral concerns during the advent of the technology are important in filtering the technology for the whole Society. such an answer may be: Involvement of researchers from a variety of backgrounds, including those specializing in agriculture, information systems, ethics, and the development of policy, may help to promote greater complexity in the way that the challenges of contemporary agriculture are addressed. Thus, the influence of this work on society is not only related to the problem of technical progress and has shown the possibility of agrarian reform in the direction of sustainability and justice while mitigating the negative effects of existing conditions for infrastructure.

7.3 Limitations/ Conflict of Interests

As encouraging as the findings and contributions of this research are, it has several limitations that should be noted. Quality and diversity of the training data - The model accuracy highly depends on this aspect, as it is non-comprehensive and will not detect all possible plant diseases LRMC-DeepLabV3+ helps in reducing computational load but one may require more iterations to make fine-tuning possible on other hardware. The model only targets leaf disease detection, and it does not cover any other health problem your plants may encounter (e. g., root diseases or pest infestations). Commercial farming may require large-scale field trials conducted in variations of its target settings as well, with proper validation on the ground. It is these limitations and broader implications that must be addressed in order for the technology to yield its potential benefit upon application.

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Appendix A

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

Title:
LRMC-DEEPLABV3+: MULTICLASS LEAF DISEASE SEMANTIC SEGMENTATION BASED ON AN IMPROVED DEEPLABV3+ NETWORK

Student ID: 202-15-3848, 202-15-3827

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify **Leaf Disease Semantic Segmentation** 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, and CO3	We collect our required dataset manually and proposed a model which covers **K3 and K4.**	**Page no: 13-14**
				Our project requires the integration of different components **K5 and K6.**	**Page no: 12-13**
				We looked at models that already exist and have similar objectives **(K8).**	**Page no: 6-12**
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	We had to contact real agriculture experts; it was difficult to find them (**CEP, EP-2).**	**Page no: 13-16**

3.	**EP3: Depth of analysis required**	Yes	CO2	In order to overcome our research gap we had propose a custom model **(CEP, EP-3).**	**Page no: 12-13**
4.	**EP4: Familiarity of Issues**	Yes	CO3	For better understanding we had to study about agricultural gaps and plant diseases (**CEP, EP-4).**	**Page no: 9-10**
5.	**EP5: Extends of application codes**	Yes	CO3	To implement the proposed model, we had to learn advanced computer vision. (**CEP, EP-5).**	**Page no: 12**
5.	**EP6: Extends of stakeholders involved and**	Yes	CO3	The user base will vary from agriculture experts to regular farmers (**CEP, EP-6).**	**Page no: 2-3**
6.	**EP7: Interdependence**	Yes	CO3	Various interrelated subsystems compose the project we are working on. These includes tasks like collecting data, processing it building machine learning models and performing segmentation (**CEP, EP-7).**	**Page no: 13-14**

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	CO 11 N/A CO 11 CO 11 CO 11	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 leaf disease detection through deep learning models	**Page no: 26, Section: 3.3**
2	**EA2: Level of interaction**	No		N/A	**N/A**
3	**EA3: Innovation**	Yes		This project introduces a novel application of the improved DeepLabV3+ model in leaf disease segmentation, demonstrating innovative techniques in deep learning	**Page no: 24-26, Section: 3.2**

4	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by enhancing agricultural productivity through advanced leaf disease detection methods while also promoting environmental sustainability by enabling timely and precise interventions, reducing the need for excessive pesticide use	**Page no: 55-57, Section: 6.1-6.4**
5	**EA5: Familiarity**	Yes		This project builds on existing research by exploring a novel approach in leaf disease detection using deep learning techniques. Through foundational terminologies and an extensive comparative analysis, this study provides new insights into the effectiveness of advanced machine learning techniques in agricultural disease diagnosis	**Page no: 15-21, Section: 2.1-2.3**

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

SN	COs	Attainment	Justification	References
1	**CO4**	Yes	This project addresses **CO4** by integrating advanced image processing techniques and deep learning models, ensuring precise detection, classification, and segmentation of paddy leaf diseases, thereby optimizing agricultural productivity and disease management strategies.	**Page no:** [24-26, 35-36] **Section:** [3.2, 4.3]
2	**CO9**	Yes	The project demonstrates adherence to ethical principles by prioritizing data privacy, ensuring informed consent from farmers, and transparently documenting the research process.	**Page no:** [56] **Section:** [6.3]

			This ensures responsible knowledge dissemination and societal well-being through the ethical application of advanced agricultural technologies, which comply with **CO9**.	
3	**CO10**	No	N/A	N/A
4	**CO12**	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic agricultural technology landscape is reflected in its comprehensive data collection, rigorous model evaluation, meticulous methodology development, and thorough analysis of experimental results, showcasing a commitment to staying updated and refining techniques to address modern challenges in paddy leaf disease detection.	**Page no:** [32-36, 37-53, 56-57, 58-59] **Section:** [4.2, 4.3, 5.2, 6.4, 7.2]

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