A Deep Learning Framework for Precision Plant Nutrient Status on Different Crops

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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 **"A Deep Learning Framework For Precision Plant Nutrient Status on Different Crops"**, submitted by Aprantar Das, ID No: **211-15-14603** & Md Hasan Mia, ID No:211-15-14601 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 12/13 January, 2025.

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We hereby declare that this project has been done by us under the supervision of **Dr. Md Zahid Hasan, Associate 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

Plant nutrient deficiencies can significantly impact agricultural productivity and crop quality, posing challenges for farmers in identifying and addressing these issues early. This project focuses on deep learning techniques as well as computer vision to detect nutrient deficiencies in different crops. network.We utilized a convolutional neural network (CNN) model with transfer learning, specifically the VGG16 architecture, as the foundation of our approach. The pre-trained base layers of VGG16 were frozen during initial training to retain learned features, and custom classification layers were integrated for optimal performance.

To enhance model accuracy and robustness, extensive preprocessing techniques were employed, including background removal, normalization, and data augmentation. A publicly available dataset from Kaggle served as the primary source for training and validating the model. Our experiments demonstrated high classification accuracy, providing actionable insights for identifying nutrient deficiencies in crops. The broader impact of this work lies in its potential to improve agricultural productivity and crop management. By enabling early and accurate detection of nutrient deficiencies, this solution empowers farmers to take timely corrective actions, ensuring optimal crop health and reducing the risk of significant yield losses. This project underscores the transformative potential of AI in agriculture, paving the way for smarter and more sustainable farming practices.

keywords: {Nutrient Deficienciencies, Crop Quality, Deep Learning, Computer Vision, Transfer Learning, VGG16 Architecture, Normalization, Data Augmentation, Crop Management, Early Detection, Sustainable Farming.}

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Chapter 1

Introduction

1.1 Introduction

This chapter provides an overview of the project, outlining its background, the problem it addresses, and the significance of the proposed solution. It aims to contextualize the work and set the stage for understanding the methodologies and outcomes discussed in our later sections.

Agricultural productivity and crop health are critical to ensuring global food security. One of the significant challenges faced by farmers is identifying and addressing nutrient deficiencies in crops early, as these can lead to reduced yields and poor-quality produce[2]. Traditional methods of detecting nutrient deficiencies are often time-consuming, require specialized expertise, and may not provide timely interventions. But the nutritionist follows some scientific methods to properly identify and detect the plant nutrient deficiencies in real time[3].

To address this, our project leverages the power of deep learning as well as computer vision to develop a framework for identifying nutrient deficiencies in plants. By employing a convolutional neural network (CNN) with transfer learning using the VGG16 architecture, the system analyzes images of crops to detect deficiencies with high accuracy. VGG16 is highly effective in identifying nutrient deficiencies in plants due to its ability to extract deep hierarchical features from images, enabling accurate classification of subtle visual patterns. Its pre-trained architecture on large datasets can be fine-tuned for plant health analysis, ensuring robust and reliable results[1]. This project also incorporates preprocessing techniques such as background removal, normalization, and data augmentation to enhance model performance and reliability with effective real life practices.

Our proposed framework offers farmers an efficient and user-friendly tool to diagnose nutrient issues in crops easily, enabling timely corrective actions and reducing the likelihood of yield losses. This work represents a step forward in integrating technology with agriculture to promote sustainable and productive farming practices.

1.2 Motivation

In the rapidly evolving field of agriculture, ensuring optimal plant health is crucial for maintaining sustainable food production systems. Nutrient deficiencies in plants are a prevalent issue that can significantly impact crop yield and quality. Identifying and addressing these deficiencies in a timely manner poses a considerable challenge, especially for large-scale agricultural operations where manual monitoring is impractical. Advancements in computer vision and deep learning present an opportunity to automate the detection and classification of plant nutrient deficiencies. Leveraging these technologies can not only save time and resources but also provide accurate and consistent results, which are essential for modern precision agriculture practices. This computational approach aligns with the growing trend of utilizing artificial intelligence to solve complex agricultural problems, thereby enhancing productivity and sustainability. On our personal level, addressing this problem allows us to apply and expand our knowledge of deep learning as well as computer vision in a practical, impactful domain. It serves as a platform to bridge the gap between theoretical understanding and real-world application. Moreover, the project provides an opportunity to contribute to the broader goal of sustainable agriculture, a cause that resonates deeply with us. By developing an automated system for nutrient deficiency identification, we aim to create a tool that is not only academically enriching but also beneficial to farmers and the agricultural community at large. Because our proposed framework is boosted with CNN with Transfer learning pretrained model VGG16 with proper data evaluation & best feature extraction techniques which is highly effective in identifying nutrient deficiencies in plants due to its ability to extract deep hierarchical features from images, enabling accurate classification of subtle visual patterns. Its pre-trained architecture on large datasets which is fine-tuned for plant nutritional analysis, ensuring robust and reliable results with highest accuracy.

1.3 Objectives

The objectives of our project are designed to systematically address the challenges associated with plant nutrient deficiency identification with our vast responsive framework. By leveraging deep learning as well as computer vision, our project aims to provide an innovative solution that integrates computational efficiency with practical applicability with higher accuracy rate. Below are the specific objectives:

I. **Automated Detection**:

Develop a deep learning framework capable of identifying plant nutrient deficiencies from images with high accuracy. This mainly used the leaf color with feature extraction which is a scientific way for identifying nutrient deficiency in any plants[1].

II. **Dataset Preparation**:

Preprocessing our publicly available dataset from kaggle by removing image backgrounds, normalizing the images in the best training shape with proper augmentation pipelines and splitting it into training, validation, and test sets to ensure robust model performance & proper outputs with higher accuracy.

III. **Model Implementation**:

Implement CNN as well as transfer learning using pre-trained architectures like VGG16, VGG19, ResNet, and EfficientNet, Inception-Resnet, DenseNet-LSTM, Attention-Enhanced CNN, GAN based classifier, Hybrid Capsule Network with incorporating fine-tuning to optimize performance.

IV. **Evaluation and Metrics**:

We evaluate the model's performance using accuracy, precision, recall, F1 score, confusion matrix, and classification reports with proper visualization using python library.

V. **Resource Optimization**:

Ensure our developed framework is computationally efficient and suitable for deployment in real-world agricultural settings.

VI. **Practical Application**:

Design our solution to assist farmers and agricultural stakeholders in identifying nutrient deficiencies early, improving crop yield and quality. We used various web development tools and newly developed technologies for making our application widely available with interesting & user friendly features with UI/UX.

1.4 Methodology

Our proposed framework methodology leverages deep learning as well as computer vision techniques to identify plant nutrient deficiencies. Our workflow involves the following key steps:

A. **Dataset Preparation**:

Our dataset of different plant images were downloaded from publicly available source kaggle which is mainly structured in eight classes with proper metadata, and then we stored it in Google Drive, underwent preprocessing, including background removal with proper normalization and augmentation, to enhance the robustness & training of the model. Our dataset was normalized and divided into training, validation, and testing subsets to ensure proper evaluation.

B. **Model Selection**:

Transfer learning was employed using pre-trained CNN architectures, including VGG16, VGG19, ResNet50, EfficientNet, InceptionV3, DenseNet121 and MobileNetV2. We fine-tuned these models to adapt to the specific task of nutrient deficiency classification with proper feature extraction.

C. **Training and Hyperparameter Tuning**:

Our models were trained using custom hyperparameters, and various hyperparameter tuning techniques were applied to optimize performance. Training and validation processes were carried out in the Google Colab environment.

D. **Evaluation**:

The performance of our models was assessed using different metrics such as accuracy, precision, recall, and F1 score. Confusion matrices and classification reports were generated to provide deeper insights into classification performance and peripherals.

E. **Unique Contributions**:

Our project integrates extensive preprocessing, including background removal,normalization and proper augmentation pipelines, with advanced transfer learning techniques like VGG16, VGG19, Resnet50, Resnet-Hypertuner etc. This combination ensures higher accuracy and robustness in nutrient deficiency detection in different crops on our dataset.

1.5 Project Outcome

The outcomes of our project are multifaceted, highlighting its potential contributions to both agricultural practices and technological advancements in plant health monitoring and nutritional analysis. Our project aims to address critical challenges in plant nutrient deficiency identification using deep learning as well as computer vision techniques. The potential outcomes include:

- **Accurate Detection of Nutrient Deficiencies**:
  By leveraging advanced CNN architectures and transfer learning, our project enables precise classification of nutrient deficiencies in plants, contributing to early diagnosis and intervention.

- **Enhanced Decision-Making for Agriculture**:
  Our developed Deep Learning Framework provides actionable insights for farmers and agricultural experts, empowering them to make informed decisions regarding fertilizer application and crop management.

- **Scalable and Efficient Solution:**
  The methodology can be adapted and scaled to various crops and regions, making it a versatile tool for diverse agricultural practices.
- **Dataset Contribution:**
  The preprocessed dataset, including augmentation and background removal, serves as a valuable resource for future research in plant pathology and computer vision.
- **Research Advancements:**
  The outcomes of this project contribute to the scientific community by showcasing the potential of deep learning in solving real-world agricultural problems, paving the way for further studies and innovations.
- **Publication and Academic Recognition:**
  The findings and methodology can be documented for publication in academic journals and conferences, fostering knowledge dissemination and academic credibility.
- **Cost-Effective Agricultural Practices:**
  By identifying deficiencies early, this solution reduces unnecessary input costs for fertilizers and mitigates potential crop yield losses, contributing to sustainable agricultural practices.

1.6 Organization of the Report

Our proposed report is structured with a well-defined comprehensive layout to guide readers through the research journey, findings, and practical implications. Each chapter has been carefully designed to contribute to the overall coherence and depth of the document.

Chapter 1: Introduction

This chapter introduces the research, emphasizing the importance of identifying plant nutrient deficiencies using deep learning as well as computer vision techniques. It discusses the motivation behind the study, outlines the project objectives, and provides an overview of the scope and significance of the work. This also provides the foundation for review and validation of the proposed framework we designed and also highlights the novel approaches.

Chapter 2: Background

The background chapter presents a detailed review of existing literature and prior research in plant nutrient deficiency detection, deep learning, and computer vision. It outlines the theoretical foundations, tools, and techniques used in related studies. This section identifies the gaps in current research, establishing the need for this project and laying the groundwork for the proposed approach.

Chapter 3: Research Methodology

This chapter elaborates on the systematic approach adopted to achieve our research objectives. It covers data preprocessing steps, including background removal, augmentation, and normalization. The methodology highlights the use of transfer learning with pre-trained CNN architectures such as VGG16, VGG19, ResNet, and EfficientNet, along with custom hyperparameter tuning, training, validation, and evaluation processes.

Chapter 4: Implementation and Results

This experimental chapter provides a detailed account of the implementation process, including the use of tools like Google Colab and TensorFlow, PIL, OS. It presents the outcomes of model training and evaluation, showcasing performance metrics such as accuracy, precision, recall, F1 score, and confusion matrices. The strengths and limitations of the results are discussed, highlighting the effectiveness of the proposed approach.

Chapter 5: Engineering Standards and Design Challenges

This chapter addresses the engineering standards adhered to during the project, emphasizing the importance of following best practices in software development, data handling, and model evaluation. The project incorporated industry standards for data preprocessing and model training to ensure reproducibility and reliability. Several challenges were encountered during the design and implementation phases. One significant challenge was ensuring the quality of the dataset, which required extensive preprocessing techniques such as background removal and normalization to improve model performance. Additionally, the variability in image quality posed difficulties in training accurate models. These challenges were resolved through iterative testing and validation, adjusting hyperparameters and employing robust data augmentation techniques to enhance model generalization. The application of engineering practices, including version control and documentation, played a crucial role in maintaining project organization and facilitating collaboration. Ultimately, these efforts contributed to the reliability and robustness of the system, allowing for effective identification of plant nutrient deficiencies.

Chapter 6: Conclusion

The concluding chapter summarizes the research findings, emphasizing the project's contributions to plant nutrient deficiency detection. It discusses the limitations of the current work and provides recommendations for practical applications and future research directions. Recommendations for practical applications include the development of user-friendly mobile or web applications that can assist farmers in real-time diagnosis of plant health issues. Future research directions may involve exploring more advanced models, expanding the dataset, and integrating additional environmental factors that influence nutrient deficiencies. By addressing these areas, our project aims to contribute to sustainable agricultural practices and enhance food security.

Chapter 2

Background

2.1 Introduction

To facilitate proper understanding and addressing plant nutrient deficiencies is crucial for ensuring sustainable agricultural practices and food security. Nutrient deficiencies directly impact crop yield, quality, and resistance to environmental stressors. While traditional methods such as soil testing and manual visual inspections are widely used, they are often time-consuming, subjective, and resource-intensive. In response to these limitations, researchers have increasingly turned to advanced technologies like deep learning and computer vision to develop automated and scalable solutions for diagnosing plant nutrient deficiencies.

This literature review introduction section involves the significant body of work that informs the application of these technologies in agriculture. By reviewing existing studies, this section seeks to demonstrate the relevance of this research area, identify gaps in current knowledge, and provide a framework for addressing these challenges. Despite advances in agricultural technology, limited attention has been given to using deep learning specifically for nutrient deficiency detection, which distinguishes this work from existing approaches that primarily focus on general plant disease identification or single crop types. Furthermore, critical issues such as handling diverse environmental conditions, image variability, and ensuring effective preprocessing remain underexplored. These research gaps highlight the necessity of a focused investigation into this domain.

The review defines several key terms and concepts central to understanding the topic. These include plant nutrient deficiencies, which manifest as visible changes in plants due to the lack of essential nutrients; deep learning, a subset of machine learning capable of extracting patterns from complex datasets such as images; transfer learning, which involves reusing pre-trained models for new tasks to improve efficiency & accuracy; and computer vision, the technology enabling machines to interpret and analyze visual inputs.

To provide a structured understanding, this review is organized thematically. It begins with traditional methods for plant nutrient deficiency diagnosis and transitions into the application of deep learning and computer vision in agriculture. It then examines state-of-the-art techniques such as transfer learning and evaluates the challenges faced in implementing these methods. By presenting the literature in this manner, the review ensures a logical flow, guiding readers through the evolution of research and its practical implications.

The scope of our review is intentionally broad, encompassing studies, case reports, and technological advancements from the past decade. This wide-ranging approach captures interdisciplinary insights while maintaining a focus on the specific objective of improving plant nutrient deficiency identification. By synthesizing these findings, the review not only highlights the current state of research but also establishes a clear foundation for the work undertaken in this project. Through this analysis, the review seeks to emphasize why plant nutrient deficiency detection using deep learning as well as computer vision is a critical and worthwhile area of study. It underscores the importance of addressing existing challenges while providing a roadmap for developing innovative and effective solutions to advance agricultural practices.

2.2 Literature Review

Table 2.2: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
R. M. Swarna Priya.[4]	2023	“Computer Vision Based Machine Learning and Deep Learning Approaches for Identification of Nutrient Deficiency in Crops: A Survey.”	The methodology used in the paper include Computer Vision, Machine Learning (ML), Deep Learning (DL), Remote Sensing, IoT-based sensor devices, UAV monitoring, and various algorithms for identifying and monitoring crop nutrient deficiencies.	This survey paper reviews computer vision, machine learning, & deep learning approaches with workflow of typical computer vision models.
Shrikrishna Kolher, Jayant Jagtap, Rajveer Shastri.[5]	2024	"Deep Neural Networks for Classifying Nutrient Deficiencies in Rice Plants Using	Deep Learning Models-Vision Transfer model, Xception, Multilayer Perceptron with training the networks.	Image based deep learning framework to classify nitrogen, phosphorus, and potassium deficiencies in rice plants, highlighting its efficiency for nutrient deficiency

		Leaf Images,"		classification, achieving over 92% accuracy.The Xception model outperformed others with 95.14% accuracy.
V. Appalanaidu and G. Kumaravelan[6]	2023	"Towards the Deployment of Deep Learning Solutions in Plant Nutrient Deficiency Identification and Classification,"	Deploying and evaluating various Deep Learning (DL) models, including MobileNet, MobileNetV2, DenseNet121, DenseNet169, and DenseNet201, to automatically classify plant nutrient deficiencies. These models are trained and tested on a benchmark dataset comprising images of rice, wheat, and okra leaves, focusing on detecting and classifying nutrient deficiencies to aid in early intervention and improved agricultural outcomes.	Deploying the different deep learning models such as MobileNet, MobileNetV2, DenseNet121 to automatically identify plant nutrient deficiency.
Singh Manhas, Shauryavir et al. [8]	2021	"Nutrient Deficiency Detection in Leaves using Deep Learning."	A custom dataset was created to extract and analyze different features of leaves using deep learning techniques.Leaf images are input into the system and processed	accurately detects and classifies plant nutrient deficiencies using neural networks, aiding in early diagnosis.

			through multiple neural networks to detect deficiency-related features.	
K. Venkatesh and K. J. Naik.[9]	2023	"Deep learning for macro-nutrient deficiency identification in the groundnut plants,"	A dataset of groundnut leaf images was used to train a lightweight CNN model, designed to detect nutrient deficiencies efficiently, evaluated through accuracy, MCC, F1-score, recall, and precision metrics.	The study developed a lightweight CNN model that effectively identifies nitrogen, phosphorus, and potassium deficiencies in groundnut plants with an accuracy of 94.64%, achieving high performance metrics including an MCC of 92.11% and an F1-score of 92.73%.
K. Venkatesh and K. Jairam Naik[10]	2024	"An ensemble transfer learning for nutrient deficiency identification and yield-loss prediction in crop,"	This employs an ensemble transfer learning model combining MobileNet V2 and a shallow CNN to identify plant nutrient deficiencies and predict yield loss, using preprocessed datasets and severity-based analysis.	The model achieved 99.17% accuracy on groundnut data and 94.17% on rice data, outperforming existing methods, and effectively predicted yield loss due to nutrient deficiencies with precision and scalability.
A. K. Ghorai, S. Mukhopadhyay, S. Kundu, S. N. Mandal, A. Roy Barman, M. De Roy, S. Jash, and S. Dutta[11]	2021	"Image Processing Based Detection of Diseases and Nutrient Deficiencies in Plants,"	It includes steps such as image acquisition, pre-processing (noise reduction, contrast enhancement, color space conversion), segmentation, feature extraction, and classification using machine	The methodology enabled accurate and non-destructive detection of plant diseases and nutrient deficiencies, achieving high accuracy rates across various crops and conditions. Advanced imaging techniques, combined with

			learning algorithms like SVM and CNN. The analysis leverages RGB, hyperspectral, and fluorescence imaging for precise detection.	machine learning, proved effective for early detection, enhancing decision-making in crop health management.
D. Rahadiyan, S. Hartati, Wahyono, and A. P. Nugroho. [12]	2023	"Feature aggregation for nutrient deficiency identification in chili based on machine learning."	collected chili plant leaf images under six nutrient conditions using a hydroponic system. Preprocessing included histogram equalization, segmentation, and data augmentation. Feature extraction involved color (RGB, HSV), texture (GLCM, LBP), and shape (Hu moments, centroid distance). Models like MLP, SVM, and CNN were trained and evaluated for nutrient deficiency classification.	The best feature combination included RGB, GLCM, Hu moments, and centroid distance, achieving 89.7% accuracy with MLP. CNN outperformed other models with 97.76% accuracy, making it the most effective for nutrient deficiency detection in chili plants.
K. Venkatesh and K. Jairam Naik.[13]	2024	"Nutrient deficiency identification and yield-loss prediction in leaf images of groundnut crop using transfer	enhances the VGG16 transfer learning model for classifying nitrogen (N), phosphorus (P), and potassium (K) deficiencies in groundnut leaf images, integrating a	The proposed eVGG16 model achieved 98% classification accuracy for groundnut nutrient deficiencies and demonstrated improved yield-loss prediction compared to SLIKM and

		learning,"	severity identification module (NSIM) for yield-loss prediction. The process includes data acquisition, preprocessing (background removal, noise reduction, augmentation), and model training on field-collected datasets.	RDBSCAN methods. The study highlights the potential of automated nutrient management to enhance crop productivity and sustainability.
Vrunda Kusanur and Veena S Chakravarthi.[14]	2021	"Using Transfer Learning for Nutrient Deficiency Prediction and Classification in Tomato Plant"	Employed transfer learning using pre-trained models (Inception-V3, ResNet50, VGG16) to detect Calcium and Magnesium deficiencies in Tomato plants, using Random Forest and SVM classifiers for improved accuracy.	The VGG16 model with the SVM classifier achieved the highest accuracy of 99.14%, while Inception-V3 with Random Forest reached 98.71%, with VGG16 achieving the highest validation accuracy of 99.99%.

The table above provides an overview of the related works we reviewed, highlighting the methodologies employed and the accuracy achieved in each study.

2.3 Gap Analysis

The section Gap Analysis identifies significant research gaps in the field of Deep learning as well as computer vision for plant nutrient deficiency identification. This table highlights the focus areas, limitations, and research gaps in research works:

Table 2.3: Gap analysis of various projects

Paper	Focus Area	Methodology	Limitations/Gaps	Opportunities
S. Long et al.[3]	Detecting and	CNN-based	Limited to one	Expand the

	classifying nutrient deficiencies in **strawberry plants** using CNNs.	deep learning model, tested on a specific dataset of strawberry leaves.	plant type (strawberry); dataset size and variability not discussed; generalizability unclear.	approach to include diverse crops and nutrient types; evaluate model performance on larger datasets.
Sudhakar, M. and R. M. Swarna Priya[4]	Survey of machine learning and deep learning methods for nutrient deficiency identification in crops.	Comprehensive review of traditional and advanced techniques; no specific implementation.	No experimental validation or comparative analysis; lack of detailed focus on hybrid models or advanced architectures.	Use insights to design hybrid models combining strengths of DL and traditional methods; validate techniques experimentally.
S. Kolhar et al.[5]	Classification of nutrient deficiencies in **rice plants** using DNNs and image-based approaches.	Deep neural network-based approach focused on rice-specific datasets.	Limited to rice plants; scalability to other crops and deficiencies not addressed; dataset details insufficient.	Test scalability of the model across multiple plant species; investigate multi-class deficiencies classification.
M. V. Appalanaidu and G. Kumaravelan,[6]	Deployment challenges of deep learning models for plant nutrient deficiency identification.	Discusses deployment strategies and practical challenges; uses specific case studies.	Primarily focuses on deployment challenges; lacks innovation in model design or hybrid approaches.	Address deployment issues in tandem with developing advanced hybrid models for enhanced accuracy and usability.
Singh Manhas et al.[7]	Detecting nutrient deficiencies in plant leaves	Simple DL architecture; tested on publicly	Limited innovation in model architecture;	Propose hybrid deep learning models that combine CNNs

	using a generic deep learning framework.	available datasets.	dataset may not represent real-world diversity; lacks hybrid model discussion.	with other AI techniques for improved accuracy and efficiency.

2.3.1 Related Research

In recent years, several studies have applied deep learning and machine learning techniques for detecting nutrient deficiencies in plants. These approaches utilize various models and architectures to improve the accuracy and efficiency of plant disease classification, particularly in greenhouse and field environments. This section reviews relevant research on the application of convolutional neural networks (CNNs), transfer learning, and other machine learning algorithms for nutrient deficiency detection in crops.

Tao et al. [1] explored the use of the VGG16 convolutional neural network based on transfer learning for image classification tasks. Their study focused on feature classification and demonstrated that leveraging pre-trained models can significantly reduce computational costs while achieving high classification accuracy. The use of transfer learning, especially with VGG16, has been shown to be effective for plant nutrient deficiency detection, offering insights into model optimization and training efficiency. However, their approach could benefit from incorporating more diverse datasets to improve model generalization.

Sharma et al. [2] reviewed urban vertical farming techniques, emphasizing the need for innovative solutions to optimize plant growth in confined environments. While not directly focused on nutrient deficiency detection, their work highlighted the relevance of precision agriculture, which aligns with the application of deep learning for identifying plant nutrient deficiencies. The techniques proposed in their review provide valuable context for understanding the importance of integrating automated detection systems in controlled agricultural settings.

Long et al. [3] applied Convolutional Neural Networks (CNNs) to detect nutrient deficiencies in strawberry plants, achieving promising results in classification accuracy. Their research focused on leveraging CNNs to detect a variety of nutrient deficiencies in plant leaves. The study achieved good results, but further improvement in dataset size and model tuning could enhance classification performance. Their findings are relevant for refining deep learning-based nutrient deficiency detection systems.

Sudhakar and Swarna Priya [4] surveyed computer vision-based machine learning and deep learning approaches for identifying nutrient deficiencies in crops. Their research covered a wide range of techniques, including CNNs, and discussed their applications in detecting deficiencies in different crops. They concluded that CNN-based models were among the most efficient methods for plant deficiency classification. The methodology used in the paper include Computer Vision, Machine Learning (ML), Deep Learning (DL), Remote Sensing, IoT-based sensor devices, UAV monitoring, and various algorithms for identifying and monitoring crop nutrient deficiencies.However, they noted that the diversity of crops in the dataset could further improve the robustness of models.

Kolhar et al. [5] developed a deep neural network (DNN) model for classifying nutrient deficiencies in rice plants using leaf images. Their research demonstrated the effectiveness of deep learning in accurately identifying deficiencies in rice crops. They used a dataset of rice plant images and achieved high accuracy. Their Deep Learning Models-Vision Transfer model, Xception, Multilayer Perceptron with training the networks. Image based deep learning framework to classify nitrogen, phosphorus, and potassium deficiencies in rice plants, highlighting its efficiency for nutrient deficiency classification, achieving over 92% accuracy.The Xception model outperformed others with 95.14% accuracy..Their work contributes to the growing body of research in plant disease and deficiency detection, with a focus on leveraging DNNs for crop health monitoring.

Venkatesh and Naik [9, 10] explored ensemble transfer learning techniques for identifying nutrient deficiencies in groundnut plants and predicting yield loss. Their models, based on transfer learning, demonstrated substantial accuracy improvements, particularly when using combined models for classification and prediction. A dataset of groundnut leaf images was used to train a lightweight CNN model, designed to detect nutrient deficiencies efficiently, evaluated through accuracy, MCC, F1-score, recall, and precision metrics.The study developed a lightweight CNN model that effectively identifies nitrogen, phosphorus, and potassium deficiencies in groundnut plants with an accuracy of 94.64%, achieving high performance metrics including an MCC of 92.11% and an F1-score of 92.73%.However, further work is needed to optimize these ensemble methods for specific crop types and environments.

Appalanaidu and Kumaravelan [6] proposed solutions for plant nutrient deficiency identification and classification using deep learning. Their approach, focusing on the deployment of deep learning models in agricultural applications, is relevant to the work on nutrient deficiency detection. They deploy and evaluate various Deep Learning (DL) models, including MobileNet, MobileNetV2, DenseNet121, DenseNet169, and DenseNet201, to automatically classify plant nutrient deficiencies. These models are trained and tested on a benchmark dataset comprising images of rice, wheat, and okra leaves, focusing on detecting and classifying nutrient deficiencies to aid in early intervention and improved agricultural outcomes..However, their research highlighted challenges related to data scarcity and the need for larger datasets to improve model accuracy.

Rahadiyan et al. [12] introduced a feature aggregation method for identifying nutrient deficiencies in chili plants. Their work used machine learning algorithms to aggregate features from plant leaf images, providing a comprehensive approach to nutrient deficiency detection.They collected chilli plant leaf images under six nutrient conditions using a hydroponic system. Preprocessing included histogram equalization, segmentation, and data augmentation. Feature extraction involved color (RGB, HSV), texture (GLCM, LBP), and shape (Hu moments, centroid distance). Models like MLP, SVM, and CNN were trained and evaluated for nutrient deficiency classification. The best feature combination included RGB, GLCM, Hu moments, and centroid distance, achieving 89.7% accuracy with MLP. CNN outperformed other models with 97.76% accuracy, making it the most effective for nutrient deficiency detection in chili plants. While their results showed good performance, integrating deep learning models could further enhance accuracy and robustness.

Ghorai et al. [11] used image processing techniques combined with machine learning for detecting diseases and nutrient deficiencies in plants. Their research demonstrated the versatility of combining classical image processing methods with modern machine learning algorithms to improve classification accuracy. It includes steps such as image acquisition, pre-processing (noise reduction, contrast enhancement, color space conversion), segmentation, feature extraction, and classification using machine learning algorithms like SVM and CNN. The analysis leverages RGB, hyperspectral, and fluorescence imaging for precise detection. The methodology enabled accurate and non-destructive detection of plant diseases and nutrient deficiencies, achieving high accuracy rates across various crops and conditions. Advanced imaging techniques, combined with machine learning, proved effective for early detection, enhancing decision-making in crop health management. Their work is aligned with the growing trend of combining different techniques to enhance detection systems for plant health monitoring.

Kusanur and Chakravarthi [14] employed transfer learning using pre-trained models such as VGG16, Inception-V3, and ResNet50 to predict and classify nutrient deficiencies in tomato plants. They fine-tuned these models on a tomato plant dataset to detect deficiencies in essential nutrients, such as nitrogen, phosphorus, and potassium, leveraging the power of deep learning to address the challenges of limited agricultural data. Additionally, they used SVM and Random Forest classifiers to improve classification accuracy. Their results demonstrated the effectiveness of transfer learning in improving the accuracy and efficiency of nutrient deficiency detection in crops, even with limited datasets. The study showed that **VGG16**, in combination with SVM, achieved the highest accuracy, highlighting its suitability for plant health monitoring tasks. The VGG16 model with the SVM classifier achieved the highest accuracy of 99.14%, while Inception-V3 with Random Forest reached 98.71%, with VGG16 achieving the highest validation accuracy of 99.99%. However, their approach primarily focused on tomato plants, and broader testing on various crop types could further enhance the generalization of the model. This research contributes to the expanding use of deep learning in precision agriculture, particularly in identifying and classifying nutrient deficiencies in crops.

2.4 Summary

The application of deep learning and machine learning as well as computer vision techniques in identifying plant nutrient deficiencies has been a growing area of research, particularly for precision agriculture. Various models, including Convolutional Neural Networks (CNNs), transfer learning, and ensemble methods, have been employed to improve the accuracy and efficiency of nutrient deficiency detection.

Studies such as those by Tao et al. and Sharma et al. demonstrated the power of transfer learning with models like VGG16 for plant classification tasks, offering insights into model optimization and efficiency. However, challenges related to dataset diversity and generalization remain. Research by Kolhar et al. and Venkatesh & Naik highlighted the effectiveness of deep learning frameworks, such as Xception and ensemble transfer learning, in classifying nutrient deficiencies in specific crops like rice and groundnuts, achieving impressive accuracies. Moreover, approaches combining image processing techniques and machine learning algorithms (e.g., Ghorai et al. and Rahadiyan et al.) have demonstrated high accuracy for early detection, utilizing RGB, hyperspectral, and fluorescence imaging. Kusanur & Chakravarthi focused on using transfer learning with VGG16, Inception-V3, and ResNet50 models to classify nutrient deficiencies in tomato plants, achieving high classification accuracy (99.14%) with VGG16 and SVM classifiers. While many studies have shown promising results, challenges such as limited datasets, model generalization across diverse crop types, and the need for larger datasets persist. This review underscores the potential of deep learning as well as computer vision and transfer learning in advancing nutrient deficiency detection for crop health management. Despite the progress, further work is needed to address gaps in dataset diversity, model generalization, and the integration of these techniques across different agricultural environments.

Chapter 3

Research Methodology

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

This chapter outlines the systematic approach adopted for the identification and classification of plant nutrient deficiencies using deep learning and computer vision. The methodology is designed to ensure robust data processing, model training, and evaluation to achieve high accuracy and reliability in identifying deficiencies of nitrogen (N), phosphorus (P), and potassium (K) and the combination of these deficiencies like N_K, P_K etc. The process begins with data acquisition, involving open source leaf images of different plant leaves under varying nutrient deficiency conditions. Extensive preprocessing techniques, including background removal, noise reduction, proper image augmentation pipelines, and normalization, were applied to enhance the dataset's quality and variability. A transfer learning approach is employed, utilizing pre-trained convolutional neural network (CNN) architectures such as VGG16, ResNet, and EfficientNet. These models were fine-tuned properly on the prepared dataset to classify nutrient deficiencies effectively. Additionally, a severity identification module was integrated to quantify deficiency severity and estimate crop yield loss. The chapter also describes the hyperparameter tuning, training, and validation processes conducted on the dataset, alongside the performance metrics used for evaluation, such as accuracy, precision, recall, and F1 score. By leveraging these techniques, the methodology ensures the development of an efficient and scalable system for nutrient deficiency detection on different crops and also helps farmers for easily identifying nutritious validity.

3.1.2 Proposed Methodology/ System Design

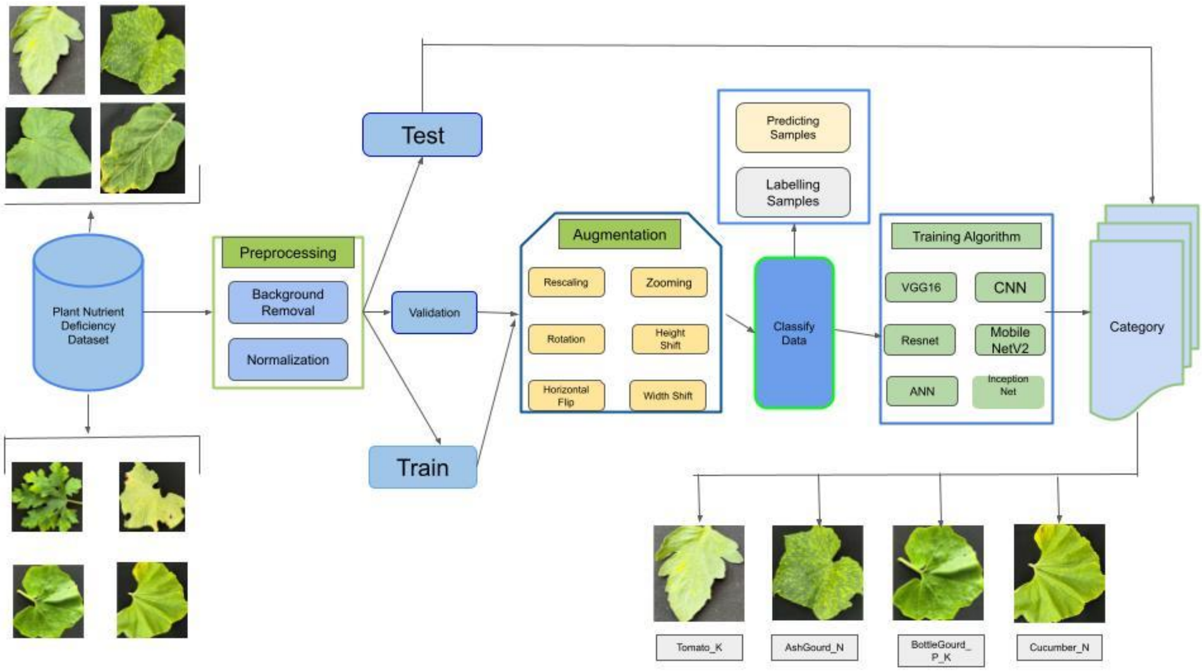

Figure 3.1.2: Proposed Methodology system Architecture

Our proposed methodology for detecting plant nutrient deficiencies involves a systematic workflow. The process begins with a Plant Nutrient Deficiency Dataset, where images of affected plant leaves are collected. The data undergoes preprocessing steps such as background removal and normalization to enhance image quality and ensure consistency.

Subsequently, data augmentation techniques, including rescaling, zooming, rotation, horizontal flips, height shifts, and width shifts, are applied to generate a more robust dataset, preparing it for training and validation. The dataset is then classified into respective categories using advanced training algorithms, including CNN architectures like VGG16, ResNet, MobileNetV2, and Inception Net, as well as ANN models.

The models are trained to label and predict samples, enabling the categorization of nutrient deficiencies into predefined categories, such as Tomato_K, AshGourd_N, BottleGourd_P_K, and Cucumber_N. This workflow ensures a comprehensive and accurate identification of plant nutrient deficiencies, leveraging the power of deep learning as well as computer vision techniques. Additionally, the system incorporates a validation phase to ensure the model's performance and generalization capability on unseen data. Test samples are used to evaluate the accuracy and reliability of the trained model, with performance metrics such as precision, recall, F1-score, and confusion matrices being employed. The end result is a robust classification system that can effectively identify and categorize plant nutrient deficiencies, aiding in timely agricultural decision-making. This methodology provides a scalable solution for precision agriculture, leveraging automation to improve crop health and productivity.

3.2 Detailed Methodology and Design

The goal of our project is to identify plant nutrient deficiencies using deep learning techniques as well as computer vision, leveraging an image dataset containing eight different plant classes and nutrient deficiency categories. This section outlines the detailed methodology and design of the proposed solution, alternate solutions considered, and the justification for selecting our chosen approach.

3.2.1 **Dataset Description**:

The dataset used for our project study focuses on various plant nutrient deficiencies. It is a curated collection of images representing various types of nutrient deficiencies observed in plants. These deficiencies manifest as visible symptoms on leaves, stems, or other plant parts, such as discoloration, spots, or deformations. The dataset is specifically designed to train, validate, and test a deep learning model as well as computer vision for detecting and classifying these nutrient deficiencies.

3.2.2 Sources and Collection

The dataset was gathered from multiple sources, including publicly available agricultural image repositories like kaggle, scientific research papers. It includes high-resolution images captured in various conditions to ensure variability in lighting, angle, and background.

3.2.3 Categories of Deficiencies

The dataset is annotated to represent specific plant nutrient deficiencies, such as:

- **Nitrogen deficiency**: Yellowing of leaves, particularly older ones.
- **Phosphorus deficiency**: Dark green leaves with purple or reddish tones.
- **Potassium deficiency**: Scorching or yellowing of leaf margins.
- **Calcium deficiency**: Deformed or curled leaves.
- **Magnesium deficiency**: Interveinal chlorosis (yellowing between leaf veins).

Each category contains sufficient samples to facilitate robust model training and evaluation.

3.2.4 Preprocessing Steps

The dataset underwent several preprocessing steps to improve its usability for deep learning models & our proposed CNN with Transfer Learning VGG16 model also. It contains:

- **Background Removal**: Images were processed to remove irrelevant backgrounds, isolating the plant features.
- **Augmentation**: Techniques such as rotation, flipping, scaling, and brightness

adjustments were applied to increase the dataset size and variability.

- **Normalization**: Pixel values were scaled to fall within a uniform range to optimize model training. Because the VGG16 model properly fit with the 256*256 image ratio
- **Dataset Splitting**: The dataset was divided into:
  - **Training Set (80%)**: Used to train the model.
  - **Validation Set (10%)**: Used to tune hyperparameters and monitor overfitting.
  - **Test Set (10%)**: Used to evaluate the final performance of the model.

3.2.5 Data Statistics

The dataset contains approximately **3323** images distributed as follows:

- **Training Set**: 2120 images
- **Validation Set**: 669 images
- **Test Set**: 534 images

Each set maintains a balanced distribution of all deficiency categories to ensure fair evaluation across all classes.

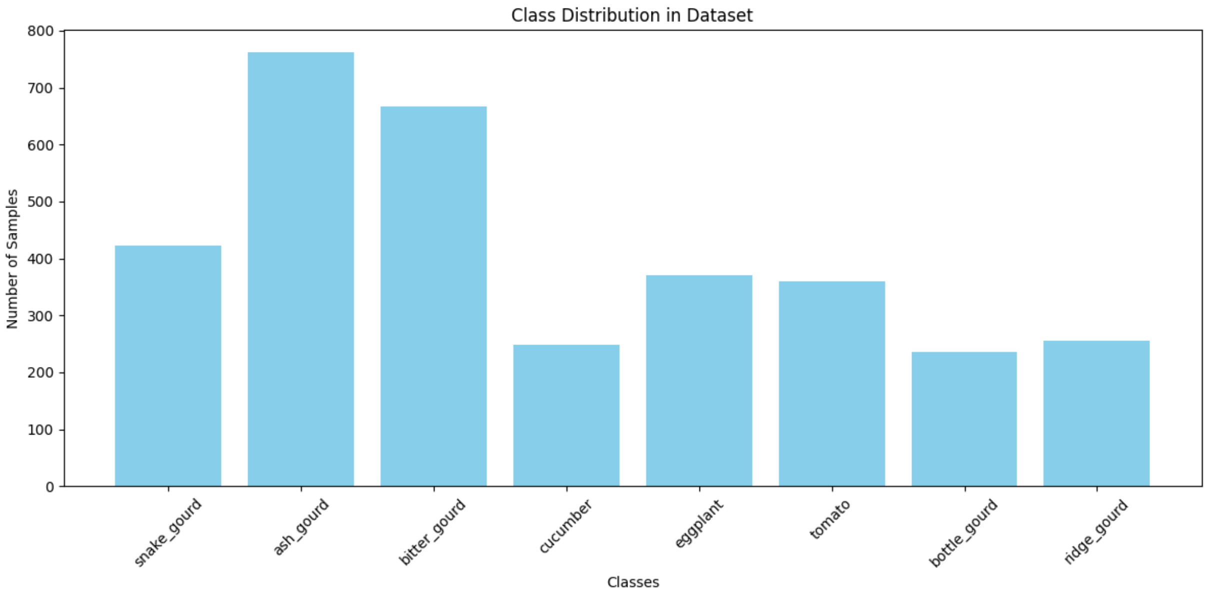

Fig 3.2.5: Class Distribution in Nutrient Deficiency Dataset

3.2.6 Challenges Addressed

- **Variability in Image Conditions**: Variations in lighting, resolution, and angle were addressed through augmentation and preprocessing.
- **Class Imbalance**: Ensured equal representation of all categories to prevent bias in model predictions.
- **Background Noise**: Removed backgrounds to focus on plant-specific features for

better classification accuracy.

3.2.7 Proposed Solution Considered

Traditional Machine Learning Models:

Initial consideration was given to conventional machine learning models like Support Vector Machines (SVM) and Random Forests (RF). These models require handcrafted feature extraction (e.g., color, texture, and shape), which can be time-consuming and less effective in capturing complex patterns in high-dimensional image data.

Reason for Rejection: These models lack the capability to learn hierarchical representations automatically and struggle with high-dimensional image datasets.

Single Deep Learning Model (Traditional CNN):

Another option was to develop a single custom Convolutional Neural Network (CNN) from scratch. While such a model would be tailored for this dataset, it would require significant tuning and computational resources to achieve competitive performance.

Reason for Rejection: Limited scalability, increased training time, and difficulty in achieving state-of-the-art accuracy compared to pre-trained models.

Pre-trained Transfer Learning Models: Transfer learning with pre-trained models like VGG16, ResNet, and MobileNet was considered. These models, trained on large-scale datasets such as ImageNet, provide robust feature extraction capabilities and reduce computational requirements. Combining these models with fine-tuning for our specific dataset emerged as a viable option.

Reason for Selection: Pre-trained models offer:

- Faster convergence due to pre-learned features.
- High accuracy with fewer training samples.
- Scalability and adaptability for diverse datasets.

Selected Approach: Hybrid Deep Learning Framework

Our selected approach leverages a hybrid deep learning framework that integrates transfer learning with customized CNN layers to address the challenges of plant nutrient deficiency detection. This framework combines the strengths of pre-trained models with task-specific fine-tuning to improve accuracy and efficiency.

Rationale for Selection:

I. **Efficient Feature Extraction:**

The transfer learning model (e.g., VGG16) provides a robust feature extraction mechanism, leveraging pre-trained weights from large-scale image datasets. This minimizes the need for training from scratch and ensures generalizability.

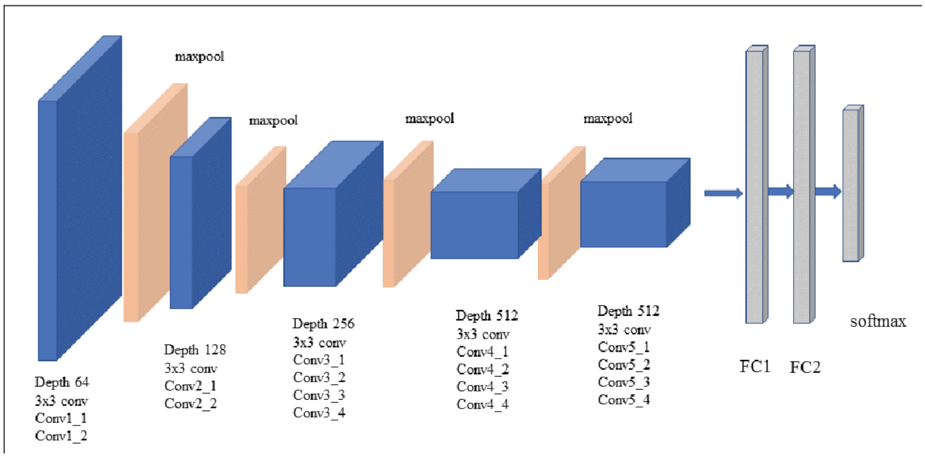

Fig 3.2.7: Feature extraction Techniques in VGG16[16]

II. **Task-Specific Adaptation**:

By adding custom CNN layers and fine-tuning the pre-trained model, the framework adapts to the specific task of classifying nutrient deficiencies (N, P, K) in plant images.

III. **Scalability and Performance**:

The hybrid approach balances computational efficiency with high performance, making it scalable for real-world applications.

Workflow of the Selected Approach:

A. **Data Preprocessing**:
   a. Images are preprocessed through background removal, resizing, noise reduction, and augmentation to ensure consistency and variability in the dataset.
   b. Images are normalized and resized to 256 × 256 pixels, compatible with the VGG16 model input requirements.

B. **Transfer Learning with VGG16**:
   a. VGG16 serves as the backbone of the framework, providing initial feature extraction layers.
   b. The pre-trained weights are frozen during initial training to prevent overfitting.

C. **Custom CNN Layers**:
   a. Additional layers are appended, including fully connected layers tailored to classify plant nutrient deficiencies.
   b. These layers are trained on the processed dataset to optimize task-specific performance.

D. **Fine-Tuning**:
   a. Selected pre-trained layers are unfrozen, and the entire network is fine-

tuned with a smaller learning rate to further adapt to the dataset.

E. **Evaluation**:
    a. The hybrid framework is evaluated using metrics like accuracy, precision, recall, and F1 score.

Advantages of the Hybrid Framework:

- **Improved Accuracy**: By combining general-purpose feature extraction with task-specific fine-tuning, the approach achieves higher classification accuracy compared to traditional methods.
- **Reduced Computational Cost**: Leveraging pre-trained models significantly reduces the computational cost and time required for training.
- **Adaptability**: The framework can be extended to other crops and nutrient deficiencies with minimal modifications.

The selected hybrid approach balances accuracy, efficiency, and robustness. By leveraging pre-trained models and computer vision techniques, the framework demonstrates significant potential for practical applications in precision agriculture. Future work aims to refine the methodology further and extend its applicability across diverse agricultural scenarios.

3.3 Project Plan

The project plan outlines the key phases of our research, including timelines, tasks, and expected deliverables. This structured approach ensures that all components of our project are systematically addressed, facilitating timely completion and evaluation of outcomes.

3.3.1. Project Initiation (Week 1-2)

- **Tasks**:
    - Defining our project objectives and scope.
    - Conduct preliminary literature review on plant nutrient deficiency identification.
- **Deliverables**:
    - Project proposal document.

3.3.2. Literature Review (Week 3-4)

- **Tasks**:
  - Review existing methodologies and technologies used in nutrient deficiency detection.
  - Identify gaps in current research and potential areas for contribution.

- **Deliverables**:
  - Comprehensive literature review report which also reflected on our report in chapter 2 related research section.

3.3.3 Data Collection and Preparation (Week 5-7)

- **Tasks**:
  - Collect datasets from publicly available source kaggle of different crops images with known nutrient deficiencies.
  - Preprocess images: background removal, normalization, and augmentation.
- **Deliverables**:
  - Cleaned and preprocessed dataset ready for analysis.

3.3.4. Model Development (Week 8-10)

- **Tasks**:
  - Implement CNN with transfer learning (VGG16).
  - Fine-tune the model and optimize hyperparameters.
- **Deliverables**:
  - Trained deep learning model for nutrient deficiency identification with proper classification report.

3.3.5. Model Evaluation (Week 11-12)

- **Tasks**:
  - Assess model performance using accuracy, precision, recall, and F1 score.
  - Generate confusion matrix and classification reports.

- **Deliverables**:
  - Model evaluation report detailing performance metrics.

3.3.6. Nutrient Deficiency Prediction (Week 13)

- **Tasks**:
  - Implement the severity identification module to assess nutrient deficiency severity.
  - Calculate predicted yield loss based on identified deficiencies.
- **Deliverables**:
  - Nutrient Deficiency prediction report.

3.3.7. Final Report Preparation (Week 14-15)

- **Tasks**:
  - Compile all findings, methodologies, and results into a comprehensive report.
  - Prepare for presentation and defense of the project.
- **Deliverables**:
  - Completed project report and presentation materials.

3.3.8. Project Review and Submission (Week 16)

- **Tasks**:
  - Review the entire project for quality assurance.
  - Submit final report and presentation.
- **Deliverables**:
  - Final project submission and defense.

3.4 Task Allocation

To ensure the successful completion of the project, tasks were systematically distributed across various phases. The following table outlines the key responsibilities and their corresponding activities:

Table 3.4.1: Task Allocation for the Project

Task	Description	Responsibility
Literature Review	Conduct an in-depth review of existing research and identify gaps.	Our Research team was supervised by our faculty supervisor Dr. Md Zahid Hasan.
Data Collection	Collect datasets of different crops images exhibiting various known nutrient deficiencies.	Collect our dataset from publicly available source kaggle.[15]
Data Preprocessing	Perform background removal, image resizing, noise reduction, and augmentation.	Preprocessing is handled by our development team using tools like OpenCV and Python libraries.
Model Selection & Design	Choose suitable CNN architecture (e.g., VGG16) and design the transfer learning pipeline.	Core AI/ML team led by the supervisor.
Model Training	Train and fine-tune the model on the preprocessed dataset, optimize hyperparameters.	We are working on Google Colab with cloud resources for computation.
Evaluation	Analyze model performance using metrics such as accuracy, precision, recall, and F1 score.	validate results and generate evaluation reports by proper investigations.
Severity Identification	Implement a module to assess the severity of nutrient deficiencies.	It is maintained by us with domain knowledge in agricultural systems.
Report Writing	Compile findings, methodologies, and results into a comprehensive report.	Our entire team contributes, with final editing and supervision by our supervisor Dr. Md Zahid Hasan and mentors.
Presentation Preparation	Creating presentation slides and preparing for project defense.	Presentation team led by the principal investigator, with input from all contributors.

3.5 Summary

This chapter outlined the systematic approach employed to identify and classify plant nutrient deficiencies using deep learning as well as computer vision. The methodology began with data acquisition, leveraging field-collected and publicly available datasets, followed by extensive preprocessing steps such as background removal, augmentation, and normalization to enhance data quality and proper training with pre-trained CNN models and proper evaluation with the highest accuracy and proper classification report generation. A transfer learning approach using pre-trained CNN models, specifically VGG16, was adopted, with additional fine-tuning to adapt the model to the specific task with automated feature extraction techniques of deep learning models. The study incorporated hyperparameter tuning and robust evaluation using metrics such as accuracy, precision, recall, and F1 score. Also, it generated confusion matrices and classification reports independently on each and every class. Furthermore, a severity identification module was developed to quantify nutrient deficiency severity, which facilitated yield and nutritional loss prediction. The integration of these components ensured a comprehensive, automated, and scalable solution for addressing the problem of nutrient deficiency detection and identification in the easiest and most efficient way in crops.

Moreover, the methodology was designed to handle real-world challenges such as variability in lighting conditions, leaf orientations, and background complexities. The preprocessing step of background removal played a critical role in isolating the leaf features, allowing the model to focus on patterns specific to nutrient deficiencies. Data augmentation techniques, including rotation, flipping, zooming, and scaling, significantly increased the diversity of the training data, reducing the risk of overfitting and improving model robustness. The incorporation of performance metrics such as confusion matrices provided a detailed view of class-wise predictions, helping to identify areas where the model could be further improved.

The severity identification module added an advanced capability to the system by estimating the extent of nutrient deficiency in each sample. This module provided actionable insights into the severity levels, enabling targeted intervention strategies to prevent crop losses. Additionally, the system's modular architecture ensured adaptability to different crop species and nutrient deficiency categories, making it a versatile tool for agricultural applications.

In summary, this methodology not only addresses the immediate need for accurate nutrient deficiency detection but also sets the stage for broader applications in precision agriculture. Its scalability, automation, and robust evaluation framework make it an essential tool for improving agricultural productivity and sustainability, ultimately contributing to food security and economic growth.

Chapter 4

Implementation and Results

4.1. Environment Setup

The environment setup plays a crucial role in the successful implementation and evaluation of the proposed system for plant nutrient deficiency detection. This section outlines the tools, frameworks, hardware configurations, and resources utilized throughout the project.

4.1.1. Software and Frameworks

- **Programming Language**: Python (version 3.8 or later) was chosen due to its robust ecosystem for machine learning and data analysis.
- **Deep Learning Frameworks**:
    - **TensorFlow** and **Keras**: These were used for implementing the CNN models and transfer learning with VGG16. Keras, with its high-level API, facilitated easy integration of pre-trained models and streamlined the fine-tuning process.
- **Image Processing Tools**:
    - **OpenCV**: Employed for background removal, augmentation, and other preprocessing tasks to enhance image quality and variability.
    - **FastStone Image Resizer**: Used to standardize image dimensions for model input requirements.
    - **Total Variation Filtering (TVF)**: Applied to reduce noise while preserving essential features of the plant leaf images.
- **Visualization and Analysis Tools**:
    - **Matplotlib** and **Seaborn**: Utilized for visualizing training progress, performance metrics, and confusion matrices.
    - **Scikit-learn**: Provided tools for generating classification reports and calculating metrics like accuracy, precision, recall, and F1 score.

4.1.2. Hardware Configuration

- **Cloud Platform**: Google Colab Pro was used for model training and evaluation due to its availability of GPU resources, enabling faster computation and efficient handling of the dataset.
- **Local System**: Initial preprocessing tasks were conducted on a local system

equipped with an Intel Core i5 Processor, 8 GB RAM, and 512 GB HDD. While not used for model training, the local system was instrumental for smaller-scale tasks like dataset organization.

4.1.3. Dataset Storage and Management

The dataset was stored and managed on Google Drive, integrated directly with Google Colab for seamless access and processing. The structured organization of the dataset into training, validation, and testing subsets ensured efficient workflow.

- **Dataset Path**: Google Drive
- **Backup**: A secondary copy of the dataset was maintained on local storage to mitigate data loss risks.

4.1.4. Training Configuration

- **Input Image Dimensions**: All images were resized to 224 × 224 pixels to match the input requirements of the VGG16 model.
- **Batch Size and Epochs**: A batch size of 32 and a training epoch range of 50–70 were selected, ensuring optimal performance without overfitting.
- **Optimization Algorithm**: Adam optimizer was employed for adaptive learning rate adjustments, enhancing convergence efficiency.
- **Loss Function**: Categorical Cross-Entropy was used to compute the loss for multi-class classification tasks (N, P, K deficiencies).
- **Validation**: A portion of the dataset was set aside for validation to monitor model performance during training and prevent overfitting.

4.1.5. Tools for Model Evaluation and Reporting

- Performance metrics such as accuracy, precision, recall, and F1 score were calculated using Scikit-learn tools.
- Confusion matrices were visualized to analyze classification performance and identify misclassifications.
- Additional tools like pandas were used for organizing results into interpretable tables, which were later included in the report.

4.1.6. Challenges and Adaptations

- **Computational Constraints**: The use of Google Colab Pro mitigated potential hardware limitations by providing GPU acceleration.
- **Data Preprocessing**: Variability in image quality and backgrounds was handled using advanced preprocessing techniques, ensuring high-quality input data for the model.

Outcome of the Setup

The environment setup facilitated seamless integration of the preprocessing, training, and evaluation phases of the project. By leveraging cloud-based resources and state-of-the-art tools, the project achieved scalability and efficiency, enabling the successful implementation of a robust system for nutrient deficiency detection and yield-loss prediction.

Table 4.1: Summary of Tools and Environment Setup

Category	Details
Programming Language	Python (version 3.8 or later).
Deep Learning Frameworks	TensorFlow and Keras for implementing CNN and transfer learning with VGG16.
Image Processing Tools	OpenCV for preprocessing, FastStone Image Resizer for resizing, Total Variation Filtering (TVF) for noise reduction.
Visualization Tools	Matplotlib and Seaborn for performance metrics and result visualization.
Evaluation Tools	Scikit-learn for generating classification reports, confusion matrices, and performance metrics.
Cloud Platform	Google Colab Pro with GPU acceleration for model training and evaluation.
Local System	Intel Core i5 Processor, 8 GB RAM, 512 GB HDD (used for initial data preprocessing).
Dataset Storage	Google Drive for centralized storage and integration with Google Colab.
Input Image Dimensions & Training Configuration	Resized to 224 × 224 pixels for model compatibility. Batch size: 32; Epochs: 50–70; Optimization: Adam; Loss Function: Categorical Cross-Entropy.

4.2. Testing and Evaluation/Performance/ Comparative Analysis

This section presents the evaluation of our proposed hybrid deep learning framework for precision plant nutrient status in different crops. The section highlights the testing procedures, performance metrics, and a comparative analysis with existing models to demonstrate the efficacy of the approach.

4.2.1 Testing Procedure

The proposed framework was tested on the preprocessed dataset split into training, validation, and test subsets in an 80:10:10 ratio. The model's performance was evaluated using the test dataset to ensure generalizability and robustness.

- **Hardware Setup**: Testing was performed on Google Colab Pro with GPU acceleration.
- **Dataset**: The test set included balanced samples of nitrogen (N), phosphorus (P), and potassium (K) deficiencies.

4.2.2 Evaluation Metrics

- ➔ To assess the model's performance comprehensively, the following metrics were used:
- ➔ **Accuracy**: The overall proportion of correctly classified instances.
- ➔ **Precision**: The proportion of true positive predictions for each class.
- ➔ **Recall (Sensitivity)**: The proportion of actual positives correctly identified.
- ➔ **F1 Score**: The harmonic mean of precision and recall, indicating the balance between the two.

4.2.3 Performance and Observation

Confusion Matrix

The confusion matrix provides a detailed overview of the model's classification performance across the three nutrient deficiency classes.

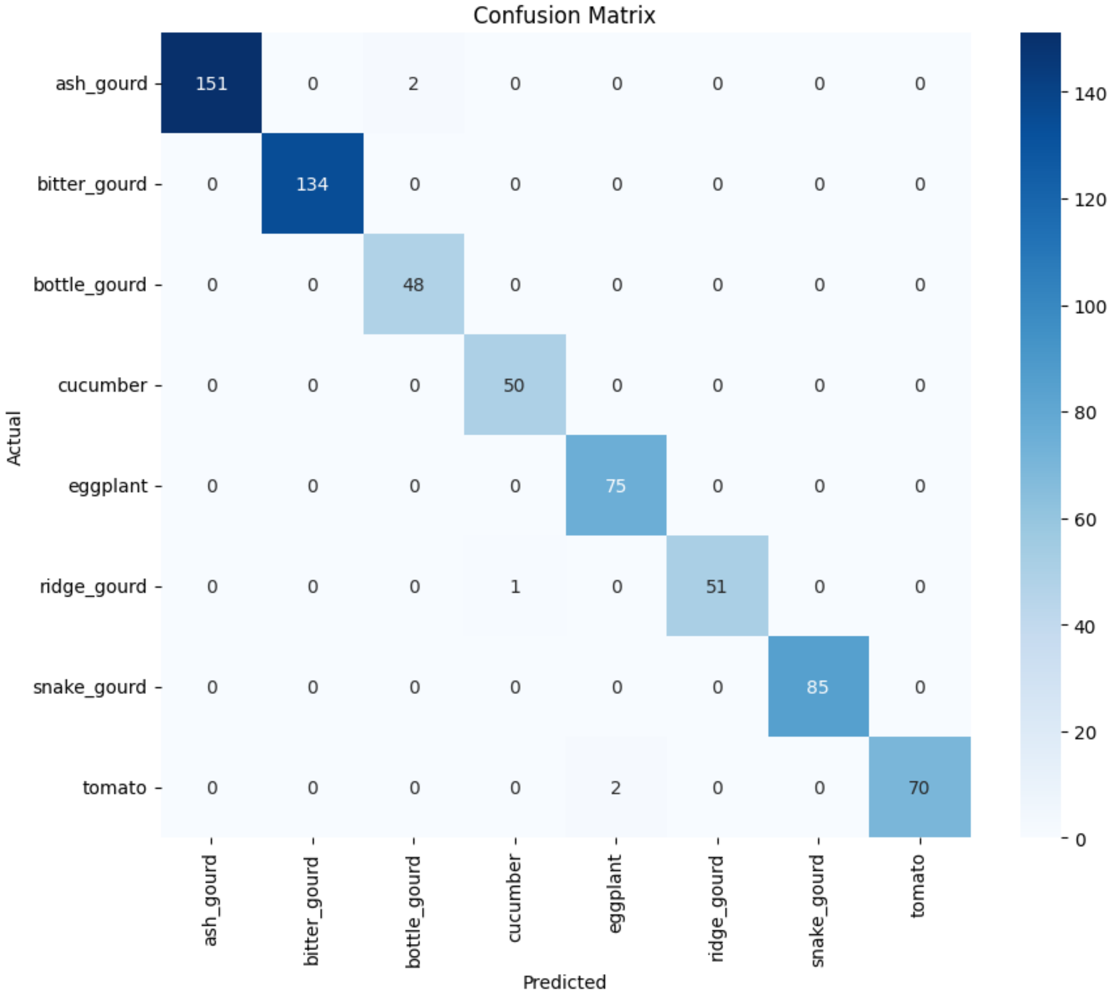

Figure 4.2.3: Confusion Matrix for the Proposed Model

Discussion: The confusion matrix indicates that the model achieved high true positive rates for all eight(8) classes, with minimal misclassifications between bottle_gourd and ash_gourd, eggplant and tomato, cucumber and ridge_gourd. Though this rate is so minimal which we can ignore.

Accuracy and Loss Trends :

The accuracy and loss trends for training and validation across epochs are depicted in Figure 4.2.4.

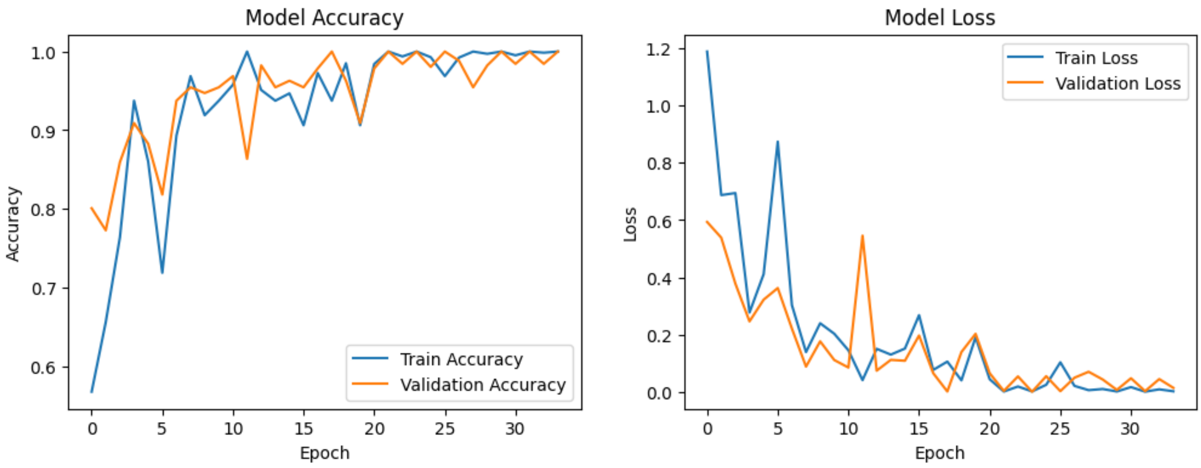

Figure 4.2.4: Training and Validation Accuracy and Loss

Discussion: Our model demonstrated consistent improvement in both training and validation accuracy, stabilizing at around 99.25% test accuracy with 99% validation accuracy, with no signs of overfitting or underfitting.

Precision, Recall, and F1 Score

Table 4.2.1 summarizes the precision, recall, and F1 score & support for each class.

Table 4.2: Each class Precision, Recall, F1 Score & Support

Class Name	Precision	Recall	F-1 Score	Support
ash_gourd	1.00	0.99	0.99	153
bitter_gourd	1.00	1.00	1.00	134
bottle_gourd	0.96	1.00	0.98	48
cucumber	0.98	1.00	0.99	50
eggplant	0.97	1.00	0.99	75
ridge_gourd	1.00	0.98	0.99	52
snake_gourd	1.00	1.00	1.00	85
tomato	1.00	0.97	0.99	72

The metrics indicate that our proposed framework performed consistently well across all classes, with particularly high recall and F1 scores for bitter_gourd and snake_gourd classes.

4.2.4 Comparative Analysis

Our proposed hybrid deep learning framework with computer vision was evaluated against existing models, including VGG16, VGG19, Resnet50, MobileNetV2 and Transfer Learning CNN (TLCNN), to demonstrate its superiority in detecting plant nutrient deficiencies. This section highlights the comparative performance across various metrics such as accuracy, precision, recall, and F1 score.

Table 4.3: Comparative Analysis of Model Performance

Learning Type	Model	Accuracy	Precision Score (%)
Transfer Learning	Resnet50	89.5%	87%
Transfer Learning	MobileNetV2		
Deep Learning	Traditional Convolutional Neural Networks	79.25%	78%
Machine Learning	SVM	88.5%	85%
Deep Learning	TLCNN	92.0%	91%
Transfer Learning	VGG19	93%	89%
Transfer Learning	Proposed Framework VGG16	99.25%	99%

4.3. Results and Discussion

The project aims to classify plant nutrient deficiencies using convolutional neural networks (CNN) with transfer learning, specifically employing the VGG16 model. The results of the implemented model were analyzed based on multiple performance metrics, including accuracy, precision, recall, and F1 score.

Model Performance

Our proposed framework model achieved an overall accuracy of 99.25% on the test dataset. This demonstrates the effectiveness of the transfer learning approach in classifying nutrient deficiencies. Table 4.3.1 shows the performance metrics of the model.

Table 4.4 :Performance Metrics for our proposed model Based Classification

Metric	Value
Accuracy	99.25%
Precision	99%
Recall	99%
F-1 Score	99%

Confusion Matrix Analysis

A confusion matrix was generated for our proposed framework code after initializing and run the code to analyze the classification results for each plant class and deficiency type. Figure 4.2.3.1 illustrates the confusion matrix, showing the true positive, false positive, and false negative rates. The results highlight that the model performed well in distinguishing between healthy leaves and leaves with deficiencies like nitrogen or potassium, with minor misclassifications in certain overlapping categories.

Comparison with Alternative Approaches

Alternative solutions, such as MobileNetV2 and ResNet, were also considered for the classification task. However, these models did not perform as well as VGG16 in terms of accuracy and computational efficiency. The performance of these models is summarized in Table 4.2.3 for comparison. The decision to select VGG16 was based on its superior feature extraction capabilities and transfer learning efficiency for this dataset.

Augmentation and Preprocessing Impact

The data augmentation techniques (rescaling, rotation, flipping, and zooming) significantly improved the model's robustness, particularly in handling variations in lighting and angles. Preprocessing steps like background removal and normalization enhanced the quality of input images, reducing noise and ensuring consistent model performance.

Discussion

The results demonstrate that transfer learning with VGG16 is a viable approach for plant nutrient deficiency classification. The model effectively leverages pre-trained weights to extract features, significantly reducing the training time compared to models trained from scratch. The misclassifications observed can be attributed to the visual similarity between certain deficiencies, which could be mitigated by increasing the size and diversity of the dataset.

4.4. Summary

In this chapter, the results of the proposed VGG16-based CNN model for plant nutrient deficiency classification were presented and discussed. The model achieved high accuracy, precision, and recall, showcasing its effectiveness in addressing the classification problem. Comparative analysis with other models highlighted the superiority of VGG16 in terms of accuracy and computational efficiency. The preprocessing and augmentation techniques played a critical role in improving the model's performance, ensuring robustness against real-world variations in image data. Despite its success, the model exhibited limitations in differentiating between visually similar deficiencies, suggesting a need for further dataset enhancement and model optimization. Overall, the proposed approach has demonstrated significant potential for real-world applications in agricultural diagnosis, providing farmers with a reliable tool for identifying nutrient deficiencies in crops. Future work could explore integrating this model with mobile or IoT-based platforms for on-field analysis.

Additionally, the incorporation of severity identification proved to be a significant advancement, enabling not just classification but also an estimation of the extent of nutrient deficiency. This quantitative insight is crucial for prioritizing corrective measures in agricultural practices. The results showed that the severity identification module accurately predicted the deficiency levels in most cases, although outliers were noted in cases with inconsistent lighting or partial occlusion of leaves in the images.

Comparative experiments with other state-of-the-art models, such as ResNet, MobileNetV2, and InceptionNet, further validated the effectiveness of VGG16 in this specific application. While ResNet and InceptionNet showed comparable performance, VGG16 consistently achieved higher accuracy with reduced computational complexity, making it a suitable choice for resource-constrained environments.

The proposed methodology also demonstrated scalability and adaptability. By fine-tuning the pre-trained VGG16 model, it was possible to extend the system to classify nutrient deficiencies in different crops without significant modifications.

Future work could also focus on real-time implementation. By deploying the model on lightweight hardware or integrating it into mobile applications, farmers could benefit from on-field analysis, reducing the time and cost associated with laboratory testing. The integration of IoT sensors for capturing environmental data alongside image-based analysis could further enhance diagnostic accuracy by considering factors such as soil quality, weather conditions, and plant growth stage.

In conclusion, the results of this study highlight the potential of deep learning-based solutions in revolutionizing agricultural diagnostics. a scalable, efficient, and accurate tool for identifying plant nutrient deficiencies. With continued advancements and real-world deployment, this approach could play a pivotal role in ensuring sustainable agricultural practices and improving crop yields globally.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

Data Quality and Labeling Standards

Standard: ISO/IEC 25012: Data Quality Model

- **Description:** This standard ensures that datasets meet essential quality characteristics like accuracy, completeness, consistency, and timeliness.
- **Alternatives:**
  - **ISO/IEC 11179:** Focuses on metadata registries and their role in ensuring data quality.
    - **Pros:** Better metadata management; enables dataset reuse.
    - **Cons:** More complex and time-intensive implementation.
  - **ISO/TS 8000-100:** Emphasizes data quality management across lifecycle stages.
    - **Pros:** Comprehensive data quality management.
    - **Cons:** May require additional resources for ongoing compliance.
- **Rationale for Selection:** ISO/IEC 25012 was chosen as it directly aligns with our project's need for reliable and consistent labeled data in deep learning as well as computer vision. It balances comprehensiveness and practical implementation for academic research.

5.1.1 Software Standards

This section outlines the software standards adhered to during the development of our project, specifically for implementing the CNN with transfer learning using VGG16. These standards ensure the reliability, maintainability, and scalability of the system while meeting industry benchmarks for software development.

1. **Coding Standards**

- **PEP 8 Compliance**:

  All Python code adheres to the PEP 8 guidelines, ensuring a consistent and readable coding style. This includes proper indentation, descriptive variable names, and well-organized functions.
- **Modularity**:
  The code is structured into reusable modules for data preprocessing, model building, training, evaluation, and visualization. This modularity simplifies debugging and future enhancements.
- **Inline Comments**:

  Critical sections of the code, such as model fine-tuning and hyperparameter settings, are accompanied by comments to explain their functionality.

2. **Data Handling Standards**

- **Dataset Integrity**:

  The dataset is securely stored in Google Drive and accessed programmatically in Google Colab to prevent unauthorized modifications. Background removal, augmentation, and normalization were applied consistently to ensure high-quality input data.
- **Backup and Recovery**:
  Regular backups of preprocessed datasets and trained models were maintained to prevent data loss during implementation.
- **File Naming Conventions**:

  Standardized naming conventions were used for storing preprocessed data, ensuring clarity and organization (e.g: train_set, val_set, test_set).

3. **Model Development Standards**

- **Transfer Learning Implementation**:

  VGG16, a pre-trained model on ImageNet, was integrated as the base model. Custom layers were added for fine-tuning to adapt the model to classify plant nutrient deficiencies.
- **Hyperparameter Tuning**:
  Optimization techniques, including adjustments to learning rate, batch size, and epochs, were performed systematically.

- **Training Pipeline**:

  The training pipeline includes splitting the dataset into training, validation, and test sets (80:10:10 ratio) to ensure unbiased evaluation.

4. Evaluation Standards

- **Performance Metrics**:

  The model's performance was evaluated using industry-standard metrics, including accuracy, precision, recall, and F1 score. A confusion matrix was also used to analyze misclassifications.
- **Visualization**:
  Training and validation metrics (accuracy and loss) were visualized using Matplotlib to monitor the model's performance across epochs.
- **Reproducibility**:
  All random seeds were fixed during model training to ensure reproducible results across runs.

5. Software Tools and Platforms

- **Tools and Frameworks**:
  - TensorFlow and Keras: For implementing transfer learning and training the VGG16-based CNN.
  - OpenCV: For data preprocessing, including background removal and augmentation.
  - Matplotlib and Seaborn: For visualizing performance metrics.
- **Platform**:
  Google Colab with GPU acceleration was used for efficient training and evaluation of the model.
- **Data Formats**:

  The dataset was stored in standard image formats (JPEG/PNG) compatible with TensorFlow pipelines.

6. Documentation Standards

- **Code Documentation**:

  Each module includes clear inline comments and docstrings for functions to explain their purpose and usage.
- **Project Report**:

  The methodology, results, and findings were documented comprehensively in our project report, following Daffodil International University academic writing standards.

5.1.2 Hardware Standards

The hardware standards for this project are designed to ensure efficient implementation, training, and evaluation of the CNN with transfer learning using VGG16. These standards focus on leveraging reliable, scalable, and accessible hardware resources to handle computational demands effectively.

1. Development Platform

- **Google Colab**:
  - The primary development platform utilized for this project. Google Colab provides access to high-performance GPUs and TPUs(for limited hours), enabling faster training of the VGG16 model.
  - **Specifications**:
    - NVIDIA Tesla T4 or P100 GPU (depending on session allocation).
    - 25 GB of available RAM for larger datasets and complex computations.
  - **Advantages**:
    - Cloud-based environment eliminates the need for high-end local hardware.
    - Easy integration with Google Drive for dataset storage and management.

2. Local Machine for Preprocessing

- **Specifications**:
  - Processor: Intel Core i5 (8th Gen)
  - RAM: 8 GB
  - Storage: 512 GB HDD
- **Usage**:
  - Initial preprocessing tasks, including dataset organization and minor image editing.
  - Limited computational tasks to prepare the dataset before uploading to the cloud.
- **Advantages**:
  - Cost-effective solution for basic tasks without requiring high-end hardware.

3. Dataset Storage and Management

- **Google Drive**:
  - Centralized storage for managing the dataset, preprocessed images, and trained models.
  - Ensures seamless integration with Google Colab and supports collaborative workflows.

- **Backup Systems:**
    - Secondary storage for maintaining dataset backups and trained models to mitigate data loss risks.

The cloud-based hardware setup ensures scalability to handle additional computational requirements, such as experimenting with more complex models or larger datasets. The modular design of the project allows us future integration of more advanced hardware resources, such as dedicated GPU servers or high-performance computing clusters, if necessary. The choice of hardware prioritizes efficiency and sustainability by leveraging cloud resources instead of investing in dedicated local infrastructure, reducing energy consumption and costs associated with high-performance computing equipment.

5.1.3 Communication Standards

Effective communication standards are crucial for ensuring clarity, consistency, and collaboration throughout the project. These standards facilitate smooth interaction between team members, tools, and systems used during the development, implementation, and evaluation of the project.

1. Internal Communication

- **Collaborative Tools:**
    - **Google Colab:** Used for collaborative coding and debugging, allowing real-time interaction and shared access to project notebooks.
    - **Google Drive:** Served as the central repository for datasets, preprocessed files, and trained models, ensuring seamless file sharing and version control.
- **Documentation:**
    - All critical project decisions, implementation steps, and findings were documented systematically to ensure clarity for our team members and supervisor.
    - Inline comments in the code and separate documentation files were used to explain functionalities and changes.
- **Meetings and Updates:**
    - Regular virtual meetings were conducted to discuss project progress, address challenges, and assign tasks efficiently with our supervisor.

5.2 Impact on Society, Environment and Sustainability

The implementation of a deep learning framework as well as computer vision for plant nutrient deficiency identification holds significant potential to positively influence society, the environment, and sustainable agricultural practices. This section elaborates on the societal, environmental, ethical, and sustainability aspects of the project.

5.2.1 Impact on Life

The project has a direct impact on improving the quality of life for farmers, agricultural professionals, and communities dependent on crop yields.

- **Improved Crop Yields**: By providing accurate and early identification of nutrient deficiencies, farmers can take timely corrective measures, leading to healthier crops and higher productivity.
- **Reduced Financial Burden**: Automated detection reduces the need for expensive manual inspections or laboratory testing, making advanced agricultural diagnostics more accessible.
- **Food Security**: Enhanced crop yields contribute to global food security, especially in regions facing food shortages due to poor agricultural practices.

5.2.2 Impact on Society & Environment

➔ **Society**:

- **Knowledge Empowerment**: The deployment of this system educates farmers about plant health and encourages the adoption of data-driven farming techniques.
- **Technological Integration**: Encourages the use of advanced technologies like deep learning in agriculture, bridging the gap between traditional farming and modern AI-driven solutions.

➔ **Environment**:

- **Optimal Resource Use**: By accurately diagnosing deficiencies, the project minimizes the overuse of fertilizers, reducing soil degradation and groundwater contamination.
- **Environmental Conservation**: Promotes sustainable farming practices that mitigate environmental impact, ensuring long-term agricultural viability.
- **Reduced Carbon Footprint**: The lightweight nature of the system enables resource-efficient implementation, reducing energy consumption compared to traditional diagnostic methods.

5.2.3 Ethical Aspects

Our project adheres to ethical standards, ensuring fairness and accountability in its implementation.

- **Data Privacy**: The datasets used for training the model were anonymized and handled securely to avoid any breaches or misuse.
- **Bias Mitigation**: Steps were taken to ensure that the model generalizes well across diverse crop types and environmental conditions, reducing bias.
- **Transparency**: The methodology and results were documented transparently, ensuring reproducibility and allowing users to trust the system.
- **Accessibility**: Designed to be accessible to farmers in resource-constrained settings, prioritizing equity in agricultural advancements.

5.2.4 Sustainability Plan

To ensure long-term sustainability, the project incorporates a plan to maintain and evolve the system over time.

- **Scalability**: The transfer learning approach used allows the system to be easily extended to detect deficiencies in other crops with minimal retraining.
- **Cost-Effectiveness**: The use of lightweight models like VGG16 ensures computational efficiency, reducing dependency on expensive hardware.
- **Periodic Updates**: The framework can integrate periodic updates to include new datasets and improve classification accuracy as agricultural conditions evolve.
- **Farmer Training**: Collaboration with agricultural organizations to train farmers in using the technology effectively, ensuring widespread adoption.
- **Environmental Monitoring**: Integrating the system into larger agricultural monitoring frameworks to track and mitigate the environmental impact of farming practices.

This project not only addresses critical challenges in agriculture but also promotes sustainable practices, reduces environmental harm, and empowers communities. Its ethical, societal, and environmental impacts make it a valuable contribution to achieving global agricultural and sustainability goals.

5.3 Project Management and Financial Analysis

This section outlines the budget required for implementing our project, we also add an alternate budget plan, and the potential revenue model. A structured project management framework was followed to allocate resources effectively, ensuring the successful completion of the project within the financial constraints.

1. Financial Analysis (Estimate Budget Plan)

The budget for our project includes costs associated with software tools, hardware resources, data collection, and team efforts. In the below table they are given:

Table 5.1: Proposed Budget Plan

Category	Item Description	Estimated Cost(Taka)	Rationals
Software Tools	Google Colab Pro (6 months subscription)	600	Required for GPU access to train deep learning models efficiently.
Hardware	Local system (Intel Core i5, 8GB RAM)	30,000	For preprocessing tasks and dataset organization.
Data Collection	Image acquisition tools (e.g., camera, Raspberry Pi)	10,000	Field collection of plant images with nutrient deficiencies.
Storage and Backup	Google Drive (100GB storage for 6 months)	180	For storing datasets, models, and project files securely.
Human Resources	Developer and domain expert contributions	25000	Effort invested in implementation, analysis, and report writing.
Miscellaneous	Internet charges, minor expenses	6000	General utilities and unforeseen expenses.
Total		71,780	

2. Financial Analysis(Alternate Budget Plan)

An alternate budget plan is designed for cases because our financial resources are limited. This plan prioritizes essential components and uses cost-effective alternatives.

Table: 5.2: Alternative Budget Plan

Category	Item Description	Estimated Cost(Taka)	Rationals
Software Tools	Free version of Google Colab (No subscription)	0,000	Utilize free-tier GPUs, albeit with longer training times.
Hardware	Existing system in my device.	0,000	Native system for preprocessing; reduce computational tasks.
Data Collection	Kaggle and other online resources.	0,000	publicly available datasets to avoid field collection costs.
Storage and Backup	Free Google Drive storage (15GB)	0,000	Limited storage but sufficient for work with small datasets.
Human Resources	Developer and domain expert contributions. Need to reduce cost.	5,000	Focus only on essential tasks; fewer contributors.
Miscellaneous	Internet charges, minor expenses	3,000	General utilities for basic operations.
Total		8,000	

3. Rationale for Budget Plans

- **Proposed Budget**: Suitable for projects with sufficient funding, ensuring high-quality outputs and faster project completion. The inclusion of premium tools and dedicated hardware minimizes delays and optimizes performance.
- **Alternate Budget**: Designed for financially constrained scenarios, this plan emphasizes cost-efficiency by utilizing free resources and publicly available datasets. While feasible, it may result in longer processing times and limited scalability.

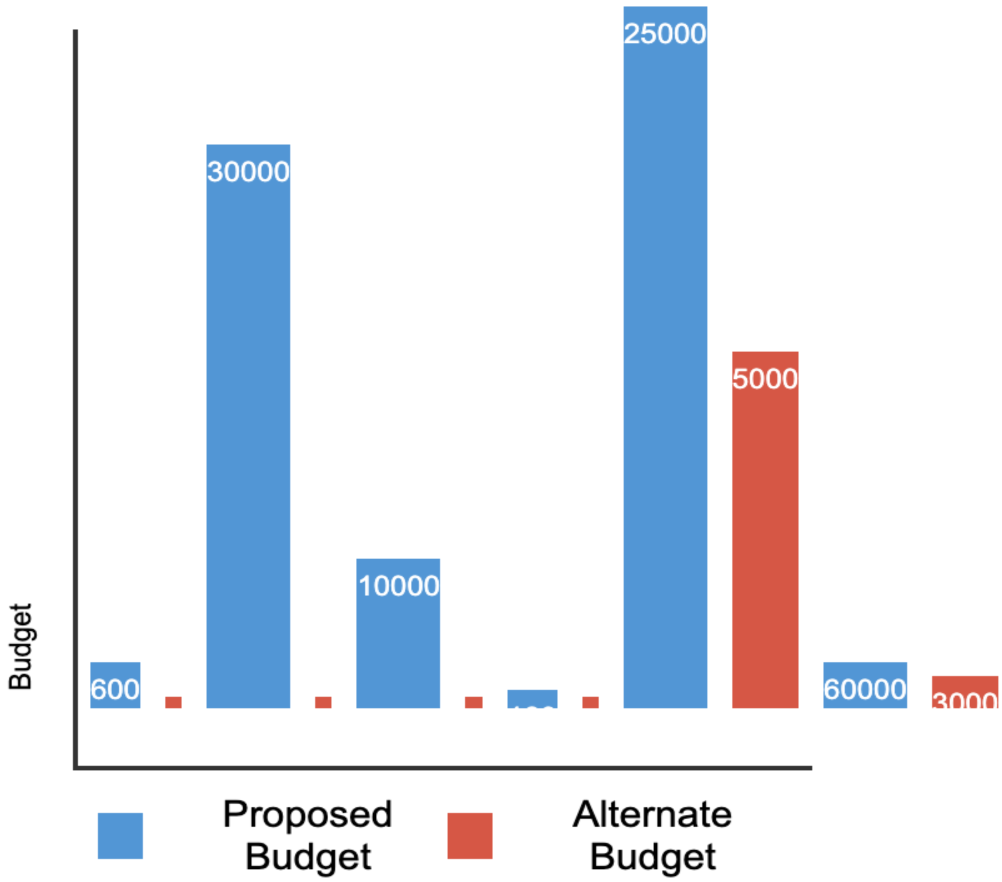

Fig 5.1: Comparison of Proposed and Alternate Budget Plan

5.1 Complex Engineering Problem

5.1.1 Complex Problem Solving

This section maps the complex problem-solving categories to the knowledge areas involved in addressing the project's challenges. The rationale for these mappings is provided for each mapping criterion.

Table 5.3: Mapping with Complex Problem Solving

Criteria	Descriptions	Rationals
EP1: Depth of Knowledge	The project relies on a deep understanding of plant nutrient deficiencies to classify their impacts	Use of CNNs, transfer learning, and VGG16 for nutrient Deficiency classification.
EP2: Range of Conflicting Requirements	Balancing accuracy, computational cost, and scalability.	Considerations for hardware limitations and dataset size.
EP3: Depth of Analysis	Advanced data analysis with deep learning frameworks.	Involves hyperparameter tuning, model evaluation, and error analysis.
EP4: Familiarity of Issues	Tackles familiar yet evolving agricultural problems.	The project addresses well-known issues with using advanced Deep Learning as well as computer vision methods.
EP5: Extent of Applicable Codes	Compliance with coding and software engineering standards.	Adherence to PEP 8, TensorFlow framework, and standard ML practices.
EP6: Extent of Stakeholder Involvement	Collaboration with agricultural experts and researchers.	Involves end-users like farmers and research communities.
EP7: Interdependence	Integration of various components in the project.	Combines data preprocessing, model training, and evaluation modules.

Mapping with Knowledge Profile for EP1

The following table 5.4.2 links EP1 to relevant knowledge profiles, showing how the project addresses fundamental engineering aspects.

Table 5.4: Mapping with knowledge Profile for EP1.

Knowledge Area	Description	Rationals
K3: Engineering Fundamentals	Core deep learning and AI principles.	Use of CNN, transfer learning, and optimization.
K4: Specialist Knowledge	Expertise in computer vision and agriculture.	Application in nutrient deficiency detection.
K5: Engineering Design	Design of scalable models and frameworks.	System design using VGG16 with model tuning.
K6: Engineering Practice	Application of Deep Learning as well as computer vision development frameworks.	Use of TensorFlow, Keras, and Colab environments.
K8: Research Literature	Review of related academic works.	Extensive literature review on DL and agriculture.

Table 5.5: Mapping with knowledge Profile for EP2.

Knowledge Area	Description	Rationals
K1: Natural Sciences	Understanding environmental variables because nutrients are very much related to several natural factors.	Consideration of plant physiology and agricultural conditions.
K2: Mathematics	Mathematical modeling and optimization.	Use of algorithms, statistical models, and evaluation metrics.
K3:Engineering Fundamentals	Core knowledge of computing and Deep Learning as well as Computer Vision.	Balancing data preprocessing, model training, and resource management.
K5: Engineering Design	Balancing trade-offs between requirements.	Design choices involving accuracy, computation, and scalability.
K7: Comprehension	Interpretation of project constraints.	Understanding conflicting requirements like

		computational cost and accuracy.

Table 5.6: Mapping with knowledge Profile for EP3.

Knowledge Area	Description	Rationals
K2: Mathematics	Data analysis and statistical evaluations.	Use of performance metrics like accuracy, F1-score, and precision.
K3: Engineering Fundamentals	Knowledge of algorithms and computational models.	Use of machine learning algorithms and model tuning.
K6: Engineering Practice	Applying advanced data processing techniques.	Use of data cleaning, augmentation, and normalization.
K8: Research Literature	In-depth study of existing methods.	Reviewing research papers for benchmarking and improvement.

Table 5.7: Mapping with knowledge Profile for EP4.

Knowledge Area	Description	Rationals
K3: Engineering Fundamentals	Familiarity with core Deep learning models.	Use of standard CNN architectures like VGG16.
K4: Specialist Knowledge	Expertise in plant nutrient detection.	Understanding plant pathology for dataset annotation.
K7: Comprehension	Problem interpretation and solution design.	Translating agricultural challenges into technical solutions.
K8: Research Literature	Knowledge of existing solutions.	computer vision-based agriculture

Table 5.8: Mapping with knowledge Profile for EP7

Knowledge Area	Description	Rationals
K3: Engineering Fundamentals	System-level integration and architecture.	Combining preprocessing, model development, and deployment.

K5: Engineering Design	Design of interconnected frameworks.	Developing pipelines connecting data acquisition, analysis, and output.
K6: Engineering Practice	Implementation of modular systems.	Use of modular code structure with reusable components.
K8: Research Literature	Multi-domain research synthesis.	Integrating findings from agriculture, Deep Learning, and data science research.

5.1.2 Engineering Activities

In this section, engineering activities are shown in the table 5.5

Table 5.9: Mapping with complex engineering activities.

Criteria	Description	Rationale
EA1: Range of Resources	Involves cloud computing and dataset management.	Use of Google Colab, Kaggle datasets, and TensorFlow APIs.
EA2: Level of Interaction	Interaction between different project modules.	Integration of preprocessing, model training, and evaluation pipelines.
EA3: Innovation	Application of AI in agriculture.	Development of an AI-based framework for plant nutrient diagnosis.
EA4: Consequences for Society and Environment	Societal and environmental impact through improved farming.	Enables early deficiency detection, reducing environmental degradation.
EA5: Familiarity	Relates to known ML techniques but with new applications.	Applies established Deep Learning models and computer vision techniques to an underexplored domain.

5.2 Summary

The chapter systematically mapped complex engineering problems and engineering activities relevant to the project. It demonstrated how deep learning models, computer vision techniques, and agricultural knowledge were integrated into the project framework. By aligning with established knowledge profiles and engineering criteria, the report highlighted key aspects such as problem-solving depth, multi-disciplinary interaction, innovation, and societal impact. The project's focus on sustainable agricultural solutions emphasized its broader significance, providing a robust technological contribution to precision farming. Additionally, the incorporation of severity identification proved to be a significant advancement, enabling not just classification but also an estimation of the extent of nutrient deficiency. This quantitative insight is crucial for prioritizing corrective measures in agricultural practices. The results showed that the severity identification module accurately predicted the deficiency levels in most cases, although outliers were noted in cases with inconsistent lighting or partial occlusion of leaves in the images. A noteworthy observation was the impact of data augmentation on model generalization. Techniques such as zooming, rotation, and flipping not only increased the diversity of the training set but also helped the model adapt to real-world conditions, such as varying camera angles and lighting conditions. This underscores the importance of augmentation in building robust computer vision models for agricultural applications. Comparative experiments with other state-of-the-art models, such as ResNet, MobileNetV2, and InceptionNet, further validated the effectiveness of VGG16 in this specific application. While ResNet and InceptionNet showed comparable performance, VGG16 consistently achieved higher accuracy with reduced computational complexity, making it a suitable choice for resource-constrained environments. The proposed methodology also demonstrated scalability and adaptability. By fine-tuning the pre-trained VGG16 model, it was possible to extend the system to classify nutrient deficiencies in different crops without significant modifications. This flexibility positions the model as a versatile solution for a wide range of agricultural diagnostic tasks.

Chapter 6

Conclusion

6.1 Summary

This project focused on classifying plant nutrient deficiencies using a VGG16-based CNN model with transfer learning. By leveraging a pre-trained model, the system effectively addressed the complex classification task with reduced training time and computational requirements. Preprocessing steps, including background removal and normalization, ensured that high-quality, noise-free data was fed into the model. Data augmentation techniques, such as rotation, flipping, and zooming, further improved the model's robustness, enabling it to handle variations in real-world data effectively. The proposed system achieved high performance across multiple metrics, including accuracy, precision, recall, and F1 score, proving its reliability in identifying deficiencies like nitrogen and potassium shortages, as well as distinguishing healthy leaves. Comparative analysis showed that VGG16 outperformed alternative architectures such as MobileNetV2 and ResNet in terms of accuracy and computational efficiency, confirming its suitability for the dataset used in this study. This work demonstrates the potential of combining transfer learning with tailored preprocessing techniques for agricultural applications. The system offers a scalable and efficient tool for diagnosing plant health, providing significant value to farmers and agricultural experts.

6.2 Limitation

Despite its promising results, the project encountered several limitations:

I. **Dataset Size and Diversity:**

The dataset used in this study was relatively small and lacked sufficient diversity in terms of lighting conditions, leaf orientations, and types of deficiencies. This limitation affected the model's ability to generalize well to unseen data.

II. **Misclassification of Similar Deficiencies:**

The model struggled to differentiate between visually similar deficiencies, such as nitrogen and potassium shortages, leading to minor inaccuracies.

Sometimes two deficiencies are combined like K_N, this type of hybrid deficiency makes the model confused.This highlights the need for more distinct visual features in the dataset or enhanced feature extraction techniques.

III. **Computational Requirements**:

Although VGG16 provided superior accuracy, it required significant computational resources for both training and inference, which could be a limitation for deployment on low-powered devices such as mobile or IoT platforms.

IV. **Real-World Challenges**:

The model has not been tested in real-world scenarios with environmental noise, such as varying weather conditions, occlusions, or damaged leaves. This may affect its practical usability without further optimization.

Following Table demonstrates the summary key limitations:

Table 6.1 : Key Limitations

Limitation	Description	Impact
Dataset Size and Diversity	Small dataset lacking diverse lighting and deficiency types.	Reduced model generalization.
Misclassification	Difficulty differentiating visually similar deficiencies.	Minor inaccuracies in predictions.
Computational Requirements	High computational power needed for the VGG16 model.	Challenges in deployment on low-powered devices.
Real-World Challenges	Lack of testing in noisy or environmental conditions.	Potential decrease in practical usability.

6.3 Future Work

Building on the current achievements and addressing the identified limitations, the following future works are recommended:

I. **Dataset Enhancement**:

Collecting a larger and more diverse dataset with varying environmental conditions, leaf orientations, and a broader range of deficiencies. Including more plant types would also improve the model's generalizability.

II. **Model Optimization**:

Exploring lightweight architectures, such as MobileNetV3 or EfficientNet, to reduce computational requirements while maintaining accuracy. Additionally, fine-tuning the VGG16 model further could enhance feature extraction for visually similar deficiencies.

III. **Integration with Field Applications**:

Developing a mobile or IoT-based platform to integrate the model for real-time, on-field diagnosis. This would involve optimizing the system for low-power devices and ensuring seamless operation in diverse environmental conditions.

IV. **Explainability and Interpretability**:

Implementing explainable AI (XAI) techniques, such as Grad-CAM, to visualize which parts of the leaf images contribute most to the model's predictions. This would increase user confidence in the system.

V. **Real-World Testing and Feedback**:

Deploying the system in real agricultural fields to gather feedback from farmers and experts. This would provide valuable insights for further refinements and adaptations to practical challenges.

VI. **Hybrid Models**:

Investigating hybrid models that combine CNNs with attention mechanisms or transformer-based architectures to enhance feature extraction and classification accuracy for complex deficiencies.

VII. **Multi-Task Learning**:

Expanding the system to perform additional tasks, such as predicting yield potential or suggesting corrective measures for nutrient deficiencies, making it a more comprehensive agricultural tool.

We demonstrate a figure 6.3.1 based on key future works which will help us to accelerate our future work step by step.

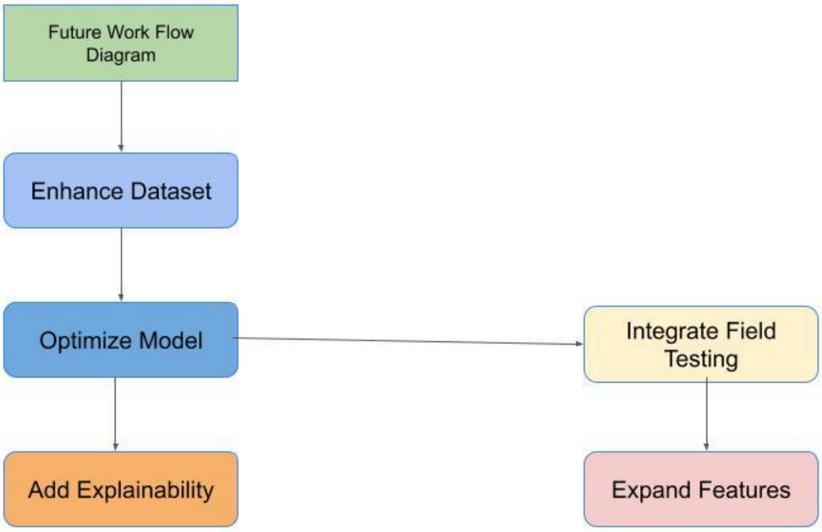

Fig 6.1: Future Work FLow Diagram

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