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Hybrid Deep Learning and Explainable AI Frameworks for Predictive Analysis and Decision Support in Agriculture and Mental Healthcare

Thesis Submitted
in Partial Fulfilment of the Requirements for the
Degree of

MASTER OF TECHNOLOGY

in

BIOINFORMATICS

by

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(Roll no. 24/BIO/12)

Under the supervision of
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CANDIDATE'S DECLARATION

I Srimant Bhardwaj hereby certify that the work which is being presented in the thesis entitled “Hybrid Deep Learning and Explainable AI Frameworks for Predictive Analysis and Decision Support in Agriculture and Mental Healthcare” in partial fulfilment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Biotechnology, Delhi Technological University is an authentic record of my own work carried out during the period from January to May 2026 under the supervision of Dr. Navneeta Bharadvaja.

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SRIMANT BHARDWAJ
24/BIO/12

ABSTRACT

Agricultural sector remains a cornerstone for boosting economy of country, uplifting socio-economic development and leveraging livelihoods of underprivileged society. However, crop diseases remain a major threat to this sector. Past studies have highlighted about ML and DL model deployment and have even emphasized on complex architecture to bridge lab-to field gap, but, on specific crops or in assessing the performance drop. This study uses a hybrid architecture composed of an EfficientNet (variant B0) backbone as a feature extractor and a linear classification head across cross crop datasets, comprising lab-style images, and real field leaves images, encompassing 22,184 curated images. The essence of this research lies in implementing a unique approach. The deployed hybrid architecture achieved an average acc. of 99.8 % on controlled datasets and 97.35% on real field datasets. The novelty of this research lies in its implementation and practicality to achieve notable performance, by comparing performance across cross crop dataset of diverse crops. By utilizing EfficientNet-B0 backed by linear classification head, this study avoids architectural complications and achieves notable performance, emphasizing deployment on-device applications in agriculture.

Keywords: EfficientNet-B0, Hybrid Architecture, Transfer Learning, Lab-to-Field Gap, Precision Agriculture

CONTENTS

S. no	Title	P. N0.
1.	Candidate's Declaration	II
2.	Certificate	III
3.	Acknowledgement	IV
4.	Abstract	V
5.	Contents	VI
6.	Tables	VII
7.	Figures	IX
8.	List of Abbreviations	X

CHAPTER 1: INTRODUCTION.....12-18

1.1 AI	12-13
1.2 ML.....	13
1.3 DL	14
1.4 Background and socio-economic Importance.....	15
1.5 Transition of Plant disease detection methods	15-16
1.6 Motivation.....	16-17
1.7 Aim	17
1.8 Objectives	17-18
1.8.1 Train and test the Efficient Deep Learning Model	17
1.8.2 Bridge the Lab-to-Field Gap.....	17
1.8.3 Ensure Computational Efficiency for Precision Agriculture	18
1.9 Scope of the work	18

CHAPTER 2: LITERATURE REVIEW.....19-23

2.1 Progression of Diagnostic Techniques: From Manual Diagnosis to computational approaches.....	19
2.2 The Deep Learning Revolution in Plant Pathology	19-21
2.3 The Real-World Performance Challenge: Bridging the Lab-to-Field Gap	21
2.4 Emerging Efficient Architectures: Optimizing Accuracy and Efficiency.....	21-23
2.5 Critical-analysis-of-existing-studies	23

CHAPTER 3: METHODOLOGY 24-31

3.1 DATASET CURATION AND COMPOSITION	24-26
--	-------

3.2 DATA PREPROCESSING AND AUGMENTATION PIPELINE	26
3.2.1 Pre- processing (Image resizing and normalization)	26
3.2.2 Data augmentation	26-27
3.3 PROPOSED HYBRID EFFICIENTNET-B0 ARCHITECTURE	27
3.3.1 EfficientNet-B0.....	27-39
3.3.2 The Linear Classification Head.....	30-31
CHAPTER 4: RESULT	32-41
4.1 Performance analysis of applied EfficientNetB0 based model.....	32-33
4.2 Model Evaluation.....	33-34
4.3 comparative analysis.....	34-41
4.3.1 Dataset and experimental setup	35
4.3.2 Performance comparison across CNN models	35-40
4.3.3 Lab -to-Field Generalization.....	40-41
CHAPTER 5: DISCUSSION	42-44
5.1 Interpretation of Model Performance.....	42
5.2 Impact of Dataset Diversity	42-43
5.3 Computational Efficiency and Deployability	43
5.4 Limitations of the Study.....	44
CHAPTER 6: CONCLUSION & FUTURE PERSPECTIVE.....	45
REFERENCES.....	46
List of Publications	49-51
Plagiarism Certificate.....	52

LIST OF TABLES

TABLE NO.	TITLE OF TABLES	P. NO.
Table 1.	Solanaceae crops Datasets source and Description	16
Table 2.	Summary of related CNN architectures and their findings in plant disease detection	20
Table 3.	Composition and characteristics of the five-crop dataset	25
Table 4.	Represents the quantitative performance metrics of the utilized EfficientNet-B0-based hybrid architecture evaluated across five Solanaceae crops: Tomato, Potato, Bell Pepper, Brinjal, and Chilli	32
Table 5.	Represents the quantitative performance metrics across five Solanaceae crops: Tomato, Potato, Bell Pepper, Brinjal, and Chilli	35-36
Table 6.	Performance drop of benchmark models	37

LIST OF FIGURES

FIG. NO.	TITLE OF FIGURES	P. NO.
Figure 1.	The main types of ML.	14
Figure 2.	The relationship between A.I, M.L and DL	15
Figure 3.	(From L to R; T to B): The figure shows the sample images of five crops in order. Tomato, Potato, Bell Pepper, Brinjal and Chilli	24
Figure 4.	(From L to R; T to B): The figure shows the pre-processed and augmented images of five crops in order. Tomato, Potato, Bell Pepper, Brinjal and Chilli	27
Figure 5.	EfficientNetB0 architecture	20
Figure 6.	Schematic representation of the experimental pipeline from Data Acquisition to Lab-to-Field Analysis	30
Figure 7.	EfficientNet-B0 based disease classification pipeline	31
Figure 8.	Performance comparison of Hybrid architecture on both lab style crops images and real- field crops images	32
Figure 9.	Training and validation acc. and loss over epochs	33
Figure 10.	Confusion matrix for the hybrid model across all disease classes (combined test set).	34
Figure 11.	Performance comparison of benchmark models- ResNet50, DenseNet121 and EfficientNetB0 across 5 crops datasets.	36
Figure 12.	Confusion matrices of DenseNet121 architecture	37-38
Figure 13.	Confusion matrices of EfficientNetB0 architecture	38
Figure 14.	Confusion matrices of ResNet50 architecture	39
Figure 15.	Plot comparing the performance of three CNN models	40

LIST OF ABBREVIATIONS

A.I:	Artificial Intelligence
M.L:	Machine Learning
D.L:	Deep Learning
C.N.N:	Convolutional Neural Network
EfficientNet-B0:	Efficient Neural Network- Variant B0
MBConv:	Mobile Inverted Bottleneck Convolution
SE:	Squeeze-and-Excitation
ReLu:	Rectified Linear Unit
Swish:	Self-Gated Activation Function
FC:	Fully Connected (Layer)
BN:	Batch Normalization
GAP:	Global Average Pooling
ResNet50:	Residual Network with 50 Layers
DenseNet121:	Densely Connected Convolutional Network with 121 Layers
VGG16:	Visual Geometry Group Network with 16 Weight Layers
MobileNet:	Lightweight Mobile-Optimized Convolutional Neural Network
YOLO:	You Only Look Once (Real-Time Object Detection Framework)
ViT:	Vision Transformer
GoogLeNet:	Google Inception-Based Deep Neural Network Architecture
InceptionNet:	Inception-Based Deep Convolutional Neural Network
TL:	Transfer Learning
ILSVRC:	ImageNet Large Scale Visual Recognition Challenge
SMOTE:	Synthetic Minority Over-Sampling Technique
LR:	Learning Rate
Adam:	Adaptive Moment Estimation Optimizer
RGB:	Red, Green, Blue (Colour Channel Representation)
Acc:	Accuracy
ROC:	Receiver Operating Characteristic Curve
AUC:	Area Under the ROC Curve
CM:	Confusion Matrix
PA:	Precision Agriculture
IPM:	Integrated Pest Management
YLCV:	Yellow Leaf Curl Virus
TMV:	Tomato Mosaic Virus
IoT:	Internet of Things
GPU:	Graphics Processing Unit
FLOP:	Floating Point Operation
API:	Application Programming Interface
XAI:	Explainable Artificial Intelligence
UAVs	Unmanned Aerial Vehicles
SHAP:	SHapley Additive exPlanations
LIME:	Local Interpretable Model-Agnostic Explanations
NLP:	Natural Language Processing
SVM:	Support Vector Machine
TF-IDF:	Term Frequency- Inverse Document Frequency

DTU:
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CHAPTER- 1

INTRODUCTION

Agriculture facilitates the economy of a country, uplifts the G.D.P. Agricultural productivity is greatly hampered by Crop diseases, which significantly impact the cost of crop production, leading to substantial economic losses. For managing the yield loss, a timely and early disease detection is crucial. Traditionally, plant pathogenic identification relied on physical inspection by experts, a time-taking and labor-reliable process. The chances of accurate detection of diseases were very low, some of them were unnoticed by naked eyes. So, a need of scalable and efficient advances in technologies are important to uncover diseases in the earliest possible manner [26]. Recent advances are being used to solve past, delayed and time-consuming processes.

In modern times, M.L. and D.L. Models have surfaced out as a potential tool in the field of plant disease detection through leaf images, have brought about a transformative change. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown better results with high accuracy for image-based classification tasks [14] and they can learn features and patterns from image datasets easily. For instance, [14] achieved an accuracy of 100% and 98.58% with VGG16 and DenseNet121 respectively on tomato leaf images. Similarly, [20] achieved an accuracy of 99.34% across ten classes of tomato diseases by developing DTomatoDnet, a custom lightweight CNN. The initial research for identification and monitoring of pathogenic diseases, by leaves images have shown promises response through D.L., especially CNNs.

1.1 AI

Artificial Intelligence (A.I.), a branch of CS that mimics human cognitive to execute tasks like– Pattern recognition, learning, problem-resolution, and process automation. The prime goal of A.I. is to simulate human intelligence in machines so that they can act rationally and intelligently in practical scenarios.

AI systems are operated through predefined rules, logical reasoning and inference mechanism. They rely on using human knowledge and intelligence that are fed in the forms of rules or logic for making decisions. They are being extensively used in different sectors like- healthcare,

education, agriculture and many more. Overall, AI lay the foundation for intelligent systems and serves as the basis for more advance techniques such as ML and DL.

In this era, AI is significantly predominating itself and cutting the manual or human efforts, particularly in agricultural sectors, not limited to crop surveillance, irrigation management, disease identification, fertilization practices, task automation, image manipulation, data processing, yield forecasting, supply chain optimization, implementation of decision support system (DSS), weed control, and the enhancement of resource utilization [26].

1.2 ML

Machine Learning (M.L), a part of AI, help machines to develop predictive capabilities through data exposure, without explicitly programming. M.L algo., instead of relying on predefined rules, build a mathematical model that optimize their performance through training and data exposure. ML have eased the process of solving many biological problems and computational challenges, including- disease diagnosis and prediction, medical image analysis, protein str prediction, genomics and proteomics seq. analysis, and automated visual analysis. In agricultural sector, ML models have shown promising results, in identifying crop diseases through images datasets, enabling accurate detection of disease. [3], [11].

Types of ML methods

1. **Supervised Learning-** ML models are trained through labelled data, containing both input and output labels. Supervised learning models includes- SVM, RF, KNN, etc
2. **Unsupervised Learning-** ML models are optimized through unlabelled inputs and infers hidden patterns. Implemented for clustering similar data points and extracting hidden patterns, trends, or relationships within the dataset. Examples include – K means clustering, PCA
3. **Semi-supervised Learning-** This approach is used when there is limited labelled data and massive unlabelled data.
4. **Reinforcement Learning-** ML models are trained using trial and error or reward or punishment.

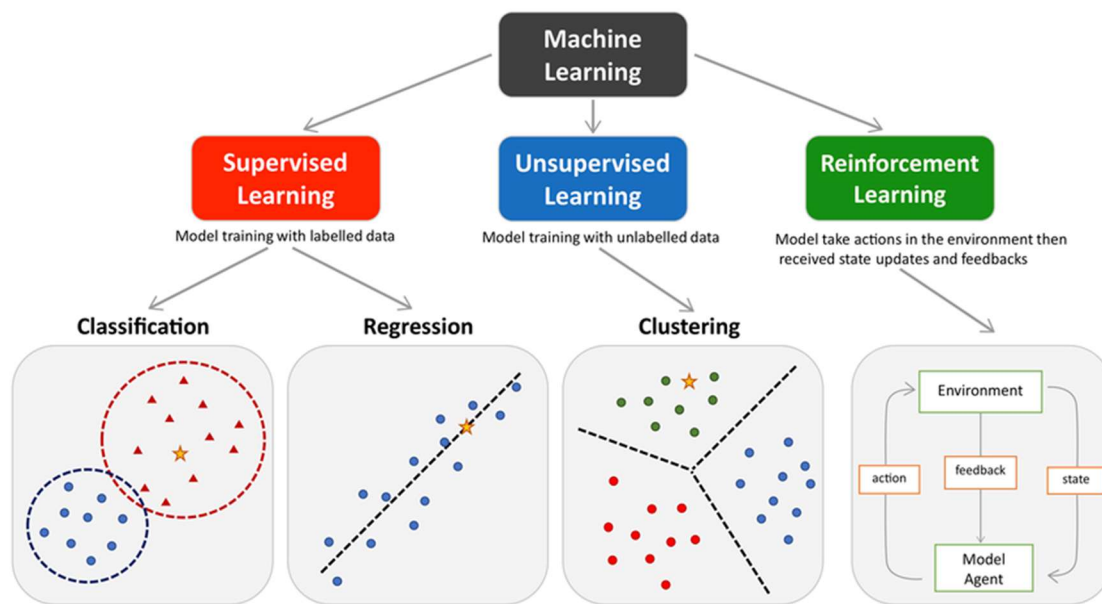


Fig 1: The main types of M.L.

Source- Peng, J., Jury, E. C., Dönnies, P., & Ciurtin, C. (2021). *Machine learning techniques for personalised medicine approaches in immune-mediated chronic inflammatory diseases: Applications and challenges*. *Frontiers in Pharmacology*, 12, 720694. <https://doi.org/10.3389/fphar.2021.720694>

1.3 DL

Deep Learning (D.L.), an advance subset of M.L., making the task easier for models to grasp complex illustrations explicitly from inputs using artificial neural network. DL models have enabled efficient utilization of unstructured data like images, speech, and text and are used heavily in areas like medical imaging, speech recognition, language processing and bioinformatics for tasks like disease localization and protein structure estimation. In agricultural sector, DL has paved the way for real- world applications on portable devices such as mobile phones or handheld systems [11], [27].

Though DL models require huge datasets and high computations, Transfer Learning (TL) have eased its use [4], [11]. This research utilizes hybrid architecture composed of an EfficientNet-B0 backbone as a feature extractor and a linear classification head for predicting diseases (Bacterial, Fungal and Viral) across five Solanaceae crops.

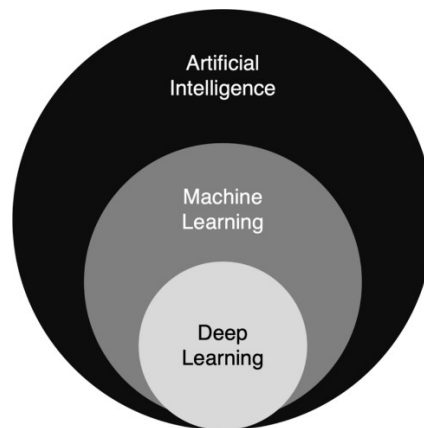


Fig 2: The relationship between A.I., M.L. and D.L.

Source- Lai, K. E., & Ko, M. W. (2023). *Can tele-neuro-ophthalmology be useful beyond the pandemic?* Current Neurology and Neuroscience Reports, 23, 15–23. <https://doi.org/10.1007/s11910-022-01248-w>

1.4 Background and Socio-economic Importance

The agricultural sector facilitates in uplifting the global economy. It provides employment to the underprivileged class of society, thus uplifting their livelihoods [11], [23]. Agricultural sector not only support local economy but at global level it enhances economic stability of a country. However, crop diseases hinder yield, leading to a substantial economic loss. They act as a threat to crop yield leading to inflation in the production cost and degradation in the quality produced. Early and accurate disease detection is important to control crop damage [3], [14]. Early detection helps minimize the loss caused by biotic factors such as fungi, bacteria, viruses, and insects [26].

1.5 Transition of Plant disease monitoring approach

Traditional plant disease monitoring approach relies on labour-intensive inspection, a time-consuming and unreliable approach. Many hidden patterns go unnoticed by the human eye [14], leading to delayed diagnosis and increased crop damage. To overcome these limitations, research shifted toward computational techniques. Early Machine Learning (ML) approaches relied on classifiers namely S.V.M, R.F, and G.B, but required manually extracted features—color, texture, and morphology—extracted using PCA, GLCM, and Haralick textures. For example, SVM achieved an accuracy of 98.4% on eggplant datasets but required extensive preprocessing [20], while Random Forest (RF) and Gradient Boosting performed well on chilli datasets with engineered features [12].

Plant diseases detection has seen a new height through the arrival of D.L. model, especially C.N.N has brought about a paradigm shift in detection task. Models such as VGG16, ResNet50, and DenseNet121 achieved high accuracy on controlled datasets [1], [2], [3], [5]. However, studies also report limitations related to computational cost, overfitting, and sensitivity to dataset variation [8].

The “lab-to-field” gap remains a major challenge, as highlighted by multiple studies where model’s performance drastically dropped on real-field data.[7], [1]. Studies have highlighted on advance algorithms in predicting diseases accurately and efficiently.

Here, in this research five solanaceae crops (Tomato, Potato, Pepper Bell, Brinjal (Eggplant) and Chilli were selected, sourced from Plant Village datasets, publicly available on Kaggle and Mendeley datasets. Table 1 provides the complete description of Five Solanaceae crops dataset source.

Table1: Solanaceae crops Datasets source and Description

S.NO	CROPS	SOURCE	DISEASE NAME	CAUSED BY
1.	TOMATO	PLANT VILLAGE DATASETS (KAGGLE)	T.B.S (2127) E.B. (1000) L.B. (1909) L.M. (952) S.L.S (1771) S.M (1676) T.S (1404) Y.L.C.V (3209) M.V (373) HEALTHY. (1591)	BACTERIAL FUNGAL FUNGAL FUNGAL FUNGAL PEST/MITES FUNGAL VIRAL VIRAL
2.	POTATO	PLANT VILLAGE DATASETS (KAGGLE)	E.B (1000) L.B (1000) HEALTHY. (152)	FUNGAL FUNGAL
3.	BELL PEPPER	PLANT VILLAGE DATASETS (KAGGLE)	B.S (997) HEALTHY (1478)	BACTERIAL
4.	BRINJAL	PLANT VILLAGE DATASETS (KAGGLE)	C.L.S (70) HEALTHY (63)	FUNGAL
5.	CHILLI	MENDELEY	B.S. (156) C.V. (423) C.L.S (180) W.S. (195) HEALTHY. (458)	BACTERIAL VIRAL FUNGAL FUNGAL

1.6 Motivation

Agriculture sector remains the cornerstone for supporting economy of a country and providing livelihood to the underprivilege class of society. Crop diseases have hampered its yield and

have resulted in severe economic losses. Thus, a need of accurate and easier disease prediction technique is required.

Early detection has focused on traditional manual inspection and has gradually shifted to ML algorithms. In recent times AI and advance DL algorithms have shown promise result in predicting diseases from real field images but these algorithms are computationally expensive. Existing studies have emphasized on lightweight architectures capable of generalizing better and running on portable devices. Models such as MobileNet, hybrid lightweight CNNs, and compact designs like DtomatoDNet and GoogLeNet-EL have been explored for efficiency [8], [13], [17], [21]. Among them, the EfficientNet family stands out for balancing accuracy and computational cost through compound scaling, with studies demonstrating its strong performance across crops [16].

Inspired by these insights, this research proposes a lightweight hybrid model using EfficientNet-B0 as the attribute encoder with a simple linear classifier. The model is evaluated on diverse lab and field images across multiple crops to address the lab-to-field gap and test cross-crop generalization.

1.7 Aim

To develop a reliable and energy-efficient lightweight hybrid model for detecting and classifying the diseases (Bacterial, Viral, Fungal) in Leaf images. This will help with early prediction of diseases and in checking the efficiency of model in real field environment and in cross-crop generalization.

1.8 Objectives.

The main objective of this research is to implement a hybrid light-weight architecture, EfficientNetB0 backed by Linear Classification Head to detect leaf diseases across five solanaceae crops images (lab style and real field), thus bridging lab-to-field gap.

- 1.8.1 **Train and test the Efficient Deep Learning Model:** To train and utilize an efficient hybrid model that detects diseases quickly and efficiently.
- 1.8.2 **Bridge the Lab-to-Field Gap:** EfficientNetB0 model across both datasets assess the model's efficiency on a diverse dataset, both controlled (lab-style) and real-world (field) images with complex backgrounds.

- 1.8.3 **Ensure Computational Efficiency for Precision Agriculture:** To implement a lightweight, computationally efficient model that can run easily on devices like smartphones or drones without needing heavy computing power.

1.9 Scope of the work

This work addresses on implementing a lightweight hybrid DL model, EfficientNetB0 across five solanaceae crops. The study emphasizes on model's generalization and efficiency to address lab-to-field gap. Additionally, a Json file containing remedies accordingly to the detected diseases in tabular format have been created as a supportive, application-level component. The scope is limited to image-based disease classification and in informational remedy mapping rather than in assessing the severity of diseases and in predicting yield.

CHAPTER-2

LITERATURE REVIEW

2.1 Progression of Diagnostic Techniques: From Manual Diagnosis to computational approaches

Traditional methods rely on manual inspection to find the causative agents, hidden patterns in leaves. It is a time-consuming process and an unreliable approach that requires significant domain expertise. Furthermore, these complex patterns are overlooked by our naked eyes.[14], resulting in delayed detection and enabling disease progression, leading to yield loss and making it an unrealistic approach for an early intervention.

To overcome these limitations, there is a shift from traditional approach to computational approaches. Researchers have revolutionized the plant disease detection methods. Early approach utilizes Machine Learning (ML) models for uncovering the hidden patterns(symptoms) from leaf images datasets. However, these methods need expert intervention as important features like- color, texture or shape from the data need to be extracted using feature extraction techniques like PCA, GLCM, Haralick textures, etc. before feeding it into the model. For example, [20]achieved an accuracy of 98.48% on eggplant dataset using Support vector Machine (SVM), but it required an extensive pre-processing steps and feature extraction techniques like- Principal Component Analysis (PCA) and Gray-Level Co-Occurrence Matrix (GLCM). Similarly, [12] applied Random Forest (RF) and Gradient Boosting models on real-field chilli images and achieved an accuracy approximately to 95%. However, the features were extracted through Haralick texture features and Hu moment to better understand and recognize the disease patterns.

2.2 The Deep Learning Shift in Plant Pathology

Plant diseases detection has seen a new height through the implementation of D.L. model, especially C.N.N.s has brought about a paradigm shift in detection task. Unlike, traditional ML algorithms, DL models do not need to depend on feature extraction techniques. CNNs automatically adapt itself in identifying and learning patterns from raw images datasets making the process faster, easier and more accurate rather than relying on manual feature extraction techniques. This adaptability of CNN has made it a suitable benchmark model in handling complex and variable visual symptoms associated with plants.

CNN architectures such as VGG16, ResNet50, and DenseNet121 validated the use of DL models for automated detection of plant diseases [3]. For example, [1] used VGG16 model on tomato leaf images and achieved 100% accuracy, while similar deep learning techniques have been effectively deployed for early detection of tomato diseases in real-world scenarios [15]. [5] used convnets (CNN) for predicting diseases in Potato, Pepper bell and Tomato leaves and achieved an accuracy of 98.3%, 98.5% and 94% respectively. Similarly, for potato leaf disease identification [2] used DenseNet121 and achieved 97.92% accuracy. Furthermore, specialized approaches have been developed for brinjal crops, leveraging modles like YOLOv8 for high-accuracy real-time detection [10] and integrating discrete Shearlet transforms with deep CNNs [18]. However, despite achieving better accuracy, study by [8] reveal the limitations by emphasizing on excessive computational demands and overfitting issues. The performance of these models is hampered by factors such as- network depth, complexity, the type of crop and the nature of datasets used for training and evaluation.

Table2: Summary of related CNN architectures and their findings in plant disease detection

Reference	Model Architecture	Target Crop(s)	Dataset Type	Key Findings & Performance
[4]	EfficientNet-B0(comparative)	Multi-crop (incl. Eggplant)	Mixed (Lab & Real-World)	Highlighted that EfficientNet-B0 matched the performance of DenseNet121
[11]	Hybrid: VGG16 + EfficientNet-B0 + Attention	chilli	Lab/Controlled	The hybrid architecture achieved 99% accuracy, significantly exceeding the independent performances of V.G.16 (96.8%) and EfficientNet-B0 (96.5%)
[19]	EfficientNet-B0 (comparative)	Chilli	Mixed (Lab & Private)	Evaluated alongside ResNet50 and MobileNet, confirming its place as a key architecture in modern transfer learning approaches
[7]	DenseNet, ResNet50, VGG16	Tomato	Controlled (lab) and real-world (field) conditions	Achieved 99% accuracy on controlled datasets but performance dropped significantly on real- field data
[16]	EfficientNet B3	Tomato	20,000 images	Achieved 94.91% accuracy and outperformed traditional models like ResNet50 and VGG16
[9]	Customized EfficientNetB4	chilli	Chilli leaf images (Heterogeneous)	The study noted that EfficientNet architectures balances accuracy and computational efficiency
[22]	Hybrid: Transfer Learning + XGBoost	Tomato, Potato, Pepper, etc	Multi-crop datasets	Hybrid approach significantly outperformed single models.

The above Table 2 compares various deep learning models across related crops of interest, used

for plant disease detection. It lists each model's target crops, dataset type, and the performance achieved in each study. The comparison highlights that hybrid or ensemble model achieved higher accuracy, stating that a hybrid of VGG16 and EfficientNet-B0 with an attention achieved an accuracy of 99% on chilli images datasets. Similarly, standalone EfficientNet-B0 model matched the performance of much larger model like DenseNet121 on multi-crop datasets, highlighting its efficiency. These studies suggest that efficiency of a model depends on dataset diversity and model architecture. These results indicate that model choice and dataset diversity critically affect accuracy. This summary table reinforces the inclusion of EfficientNet-B0 model as a versatile and lightweight backbone. Based on these insights, our study utilizes EfficientNet-B0 with a simple linear head to achieve notable performance, achieving higher accuracy with minimal complexity.

2.3 The Real-World Performance Challenge: Minimizing Lab-to- Real Field Gap

In Plant Pathology the practicability of D.L. model is hampered by the lab-to-real field discrepancy. Models that achieved high accuracies on uniform, lab- style images often fail to outperforms on complex backgrounds, variable lighting, real- field images as the models are not equipped to handle such variability.

This research gaps are clearly mentioned in the previous studies and this literature provides explicit evidence to this issue. For example, CNN model trained on both lab and real field images of tomato leaves, achieved an accuracy of 99% but its performance drastically dropped on real-field data [7]. Similarly, on testing DenseNet121 model across lab field and real field datasets, model scored 98.58 in offline testing, but upon deployment in a web application for farmer access, its accuracy dropped to 92% due to complex real-field datasets [1]. These resulting challenges associated with models trained on real- field images arise due to the unforeseen complex backgrounds, changing lighting conditions and different leaf angles. To mitigate these constraints, researchers have shown the urgency of a novel, robust and efficient model that can be capable of generalizing across diverse datasets, including real- field images.

2.4 Emerging Efficient Architectures: Optimizing Accuracy and Efficiency

Researchers have shifted their focus from achieving high accuracy on controlled datasets to developing models that can perform better on real- field data. Besides, achieving accuracy, emphasis is on making DL models computationally efficient and portable. Models implemented for real use must be able to run smoothly on modern technologies like – digital

devices, U.A.Vs, or sensor-based systems. This demand has encouraged the necessity for implementing lightweight and faster models like Mobile_Net and Efficient_Net. For example, testing of a hybrid transformer model on a Jetson Nano GPU showcases the growing trend toward real-time, portable plant disease detection [6].

This necessitates the advent of models like MobileNet, especially built for faster and lighter performance. Study by [8] for tomato disease detection highlighted MobileNet emerges as a stand out model among several deep learning model. Study have also reported MobileNet utilization in extracting features more quickly [13]. Custom lightweight models have also been designed by researchers for agriculture use. For example, introduction of DtomatoDNet, a compact 19-layer CNN model designed especially for efficiency [17] and the proposed GoogLeNet-EL model, that ensure about performance accuracy but reduces memory usage by about 87% [21].

Currently, EfficientNet family stands out as the best model in this domain. Their idea revolves around a method called compound scaling, that scales network's depth, breadth and input dimensions evenly to get a better accuracy without requiring heavy computation. Several well documented studies support this approach and have proven its effectiveness. For example, EfficientNetB3 model outperformed ResNet50 and VGG16 on a large tomato dataset [16], and a review on chilli images datasets concludes EfficientNet architecture- EfficientNetB4 achieves high computational efficiency and stable accuracy [9]. Furthermore, preliminary results analysis highlights EfficientNet-B0 as a standalone model that achieve similar results to that of much larger and complex DenseNet121 architecture and outperforms it, while being more computationally efficient [4].

This research introduces a hybrid architecture composed of an EfficientNet-B0 backbone as a feature extractor and a linear classification head. The reason behind selection of this proposed architecture revolves around addressing key challenges highlighted in the existing literature. EfficientNet-B0 selected as a base model since it provides high accuracy without requiring heavy computation. Being the smallest, fastest and computationally efficient variant among EfficientNet series, it is the suitable choice as a deployment model for real- world applicability on electronic gadgets like- mobile phones or handheld systems.

This proposed hybrid model architecture utilizes EfficientNet-B0 model as the backbone for feature extraction combining custom linear classification head. The backbone is already pre-trained on a very large datasets called ImageNet, learned to recognize image feature such as

shapes, colors and textures. So, through this transfer learning, the need for retraining all layers from scratch is avoided, thus enhancing computationally efficiency. The next part, linear head utilizes these high- level features for categorizing plant diseases.

The uniqueness of the model lies in its focus on ensuring practical efficiency by integrating feature extraction, deep learning model and utilizing linear head for classifying disease across cross -crop datasets, containing both controlled and real field images. This study despite having unavailability of lab style and real field style images of similar crop have focuses on assessing hybrid mode performance across diverse and distinct dataset types and varying crop conditions. Thus, this approach bridges the lab-to-field gap and establishes a performance enhancement on cross- crop datasets, by leveraging its simplicity and practicality, while avoiding architectural complications.

2.5 Critical analysis of existing studies

Recent studies have emphasized on developing specific ML and DL models. Models such as VGG16 and DenseNet121 have achieved optimal performance under laboratory conditions but exhibit substantial performance droppage upon deployment on real -field image datasets.

Furthermore, these complex and computationally expensive ensemble model and hybrid architecture makes the deployment unfeasible and ultimately restrict their scalability and limit their adoption on field based agricultural settings. These limitations highlight the need of the smallest, fastest and computationally efficient model.

CHAPTER-3

METHODOLOGY

3.1 DATASET CURATION AND COMPOSITION

The research utilizes images datasets curated from two openly available sources: the Plant-village (Kaggle) and the Mendeley. This study utilizes two openly available sources- Plant-village and Mendeley containing a total of 24,267 images. The plant village dataset comprises 16,012 leaf images of tomato, 2,152 of potato, 2,475 of bell pepper [23] and 2,216 of Brinjal [24]. These images includes both health and diseased samples for each crop. Out of the four crops in this plant village datasets, brinjal crop images appear as actual field image and the rest three crops appear as to be taken in lab conditions, having uniform backgrounds(black/white). Mendeley dataset comprises 1,412 actual field images of chilli, including both healthy and diseased samples [25].



Fig 3. (From L to R; T to B): The figure highlights the sample images of five crops in order. Tomato, Potato, Bell Pepper, Brinjal and Chilli

Figure 3 presents sample images from each crop's dataset, representing healthy and diseased symptoms in leaf images of each of the five crops the model must recognize. The samples clearly highlight the inter-crop variation: From lab settings (Tomato, Potato and Bell Pepper leaves) to actual field images (Brinjal and Chilli leaves) having complex backgrounds. The variation clearly emphasizes the model's challenge in identifying and distinguishing multiple diseases across species, under different conditions. By displaying both lab-style and complex field images together, Figure 3 reinforces the cross-crop objective. The variation in colour, texture and leaf patterns emphasize the importance of effective feature extraction by the model for achieving notable performance and generalizable model performance.

Further investigation of brinjal datasets revealed that the healthy and diseased leaf images folder contains pre augmented images (e.g.- Rotation, Scaling and Translation) so, these pre augmented images was removed and the left-over original images were utilized for this research. Initially there were total 2,216 images of eggplants and after removing those pre augmented images, the final curated set comprises of 70 healthy and 63 diseased, a total of 133 images. This approach reflects adherence to robust methodology and data accuracy. The dataset composition and characteristics is clearly mentioned in Table 3.

Table3: Composition and characteristics of the five-crop dataset

Crop	Source	Total Images	No. of Classes	Condition Type	Specific disease (Count)
Tomato	Plant Village	16,012	10	Lab	B.S (2127), E.B (1000), L.B (1909), L.M (952), S.L.S (1771), S.M (1676), T.S (1404), Y.L.C.V (3209), M.V (373), Normal (1591)
Potato	Plant Village	2,152	3	Lab	E.B (1000), L.B (1000), Normal (152)
Bell Pepper	Plant Village	2,475	2	Lab	B.S (997), Normal (1478)
Brinjal	Plant Village	133	2	Field	C.L.S (63), Normal (70)
Chilli	Mendeley	1,412	5	Field	B.S (156), C.V (423), C.L.S (180), W.S (195), Normal (458)

This above Table 3 summarizes the dataset composition for each crop, including the image source, total count, number of disease classes, and type of data (lab or field). Tomato leaf images, in controlled condition, sourced from Plant village, has the largest dataset comprising 16,012 images across 10 classes. In contrast, brinjal contributes 133 field images across 2 classes. Overall, the dataset combines 24,267 images across five species, including both Normal and infected leaves images. The inclusion of both controlled (Tomato, Potato, Bell Pepper) and actual field images (Brinjal and Chilli) data helps create a balanced and varied datasets, bridging lab to field gap in earlier research. By using images from different sources and disease types, Table 3 highlights that this diverse dataset makes the model capable of handling real- world conditions and different plant species.

3.2 DATA PREPROCESSING AND AUGMENTATION PIPELINE

For each of the five crops image datasets, the images were first divided into 3 distinct subsets- training-set, validation-set and testing-set in a ratio 70:15:15. To evaluate model performance in bridging lab-to-field gap, five solanaceae crops image datasets were grouped based on the imaging conditions, prior to training. Pre-processing was done for all sets and in contrast to it augmentation was only done for training-set in order to refine model stability, optimizing generalization & in curbing over-fitting risk. Performance metrics for test set were recorded individually per crop and further compiled and computed through arithmetic mean across each group, thus directly quantifying lab-to-field performance gap.

3.2.1 Pre- processing (Image resizing and normalization)

Every 22,184 images, irrespective of their original dimensions were rescale to dimension of 224×224 pixel to maintain uniformity and adhere to the EfficientNet-B0's input specifications. The pixel value of images was normalized to 0-1 from 0-255, aiding training stability and accelerating convergence.

3.2.2 Data-augmentation

Training set data's was augmented. Techniques were applied to synthetically expand volume of data's and in helping the architecture to learn complex patterns, variable lightning, thereby reducing the risk of overfitting.



Fig 4. (From L to R; T to B): The figure highlights the pre-processed and augmented images of five crops in order. Tomato, Potato, Bell Pepper, Brinjal and Chilli

Figure 4 illustrates sample images for all five crops after preprocessing steps (resizing). The transformations applied in the original images, artificially increasing the leaf images contributing to diversification in dataset. This augmentation enabled the model to identify diseases from different orientations and sizes.

3.3 PROPOSED HYBRID EFFICIENTNET-B0 ARCHITECTURE

This research introduces a hybrid architecture composed of an EfficientNet-B0 backbone as a feature extractor and a linear classification head. EfficientNet-B0 has the ability to recognize the complex patterns on leaves, and the linear classification head serve as a platform for final prediction, through its accurate classification of features. This synergistic architecture leverages the process, making the task computationally efficient while maintaining accuracy.

3.3.1 EfficientNet-B0

EfficientNet-B0, introduced by Google Research (2019) characterize a modern CNN architecture design that emphasize on maintaining balance between accuracy and computational efficiency. EfficientNet-B0 relies on computationally efficient MB-Conv

5

(Mobile-Inverted-Bottleneck-Convolution) blocks that utilizes depth wise separable-convolutions and S-E optimization for highlighting key features. It also employs Swish activation function, that has been proven to improve performance over ReLU in complex architectures. The innovation lies in its adaptability to pre-trained itself on large scale ImageNet datasets for recognizing image feature such as shapes, colors and textures. The pre-trained EfficientNet-B0 provides baseline for feature extraction, facilitating knowledge transfer to plant disease detection. During training, EfficientNet-B0 convolutional layers are frozen to preserve established feature mappings, thus resulting in reduced trainable parameters, enhancing training efficiency and reducing overfitting on smaller datasets.

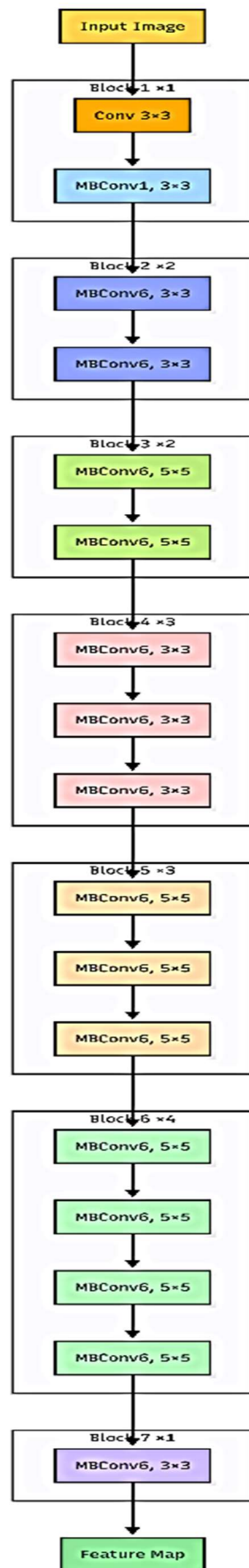


Fig 5.: EfficientNetB0 architecture

3.3.2 The Linear Classification Head

The high-dimensional representation extracted from the input image, through EfficientNet-B0 are passed to the linear classification head for final disease categorization. The linear classification head consist of a densely connected layer that transit the EfficientNet-B0 features into vector coordinating to the number of plant diseases classes, including the healthy, if applicable. This transition directs the learned feature embedding into the class score space, resulting in logits that corresponds to each disease class. These logits then finally generate a class probability distribution through the applied Softmax activation and the high yielding probability class acts as the model's prediction.

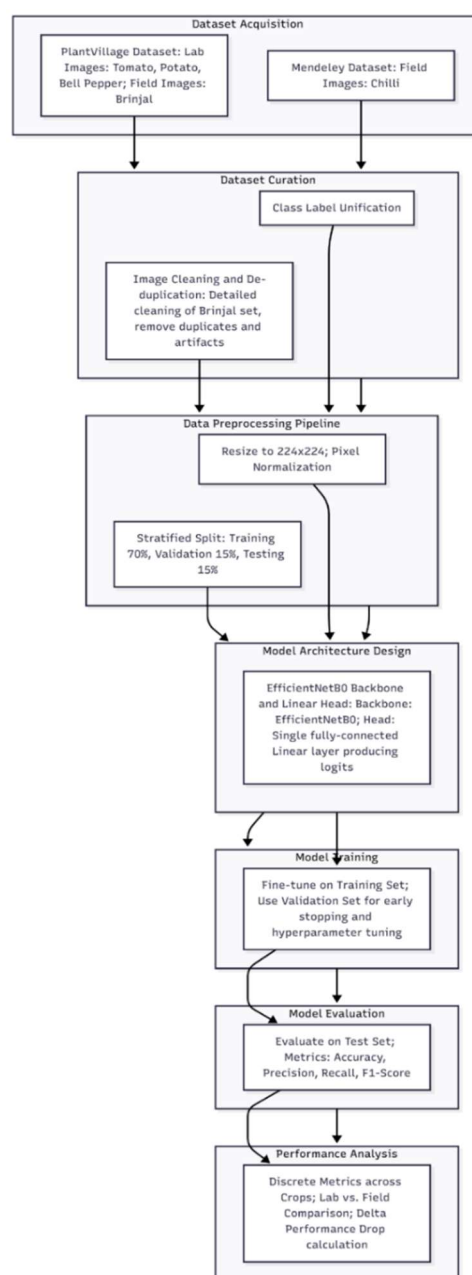


Fig 6: Schematic representation of the experimental pipeline from Data Acquisition to Lab-to-Field Analysis

Figure 6 illustrates the workflow of our study. It begins with data acquisition (Plant Village and Mendeley sources for all five crops) and moves through preprocessing (image resizing, normalization) and augmentation (as shown in Figure 4). The pre-trained EfficientNet-B0 layers extract features from each leaf image, and a custom linear classification head classifies them into disease categories. The result is then tested separately on lab and field datasets. The overall illustration addresses to bridge the lab to field gap as discussed in section 2.3. By including both controlled and field images at the training and evaluation stages, the pipeline aims to train a model to adapt in varied lighting, background and leaf orientation. Each block in the diagram highlights the cross-domain generalization, making the model to handle data from different sources, achieving cross- crop generalization and real – world performance.

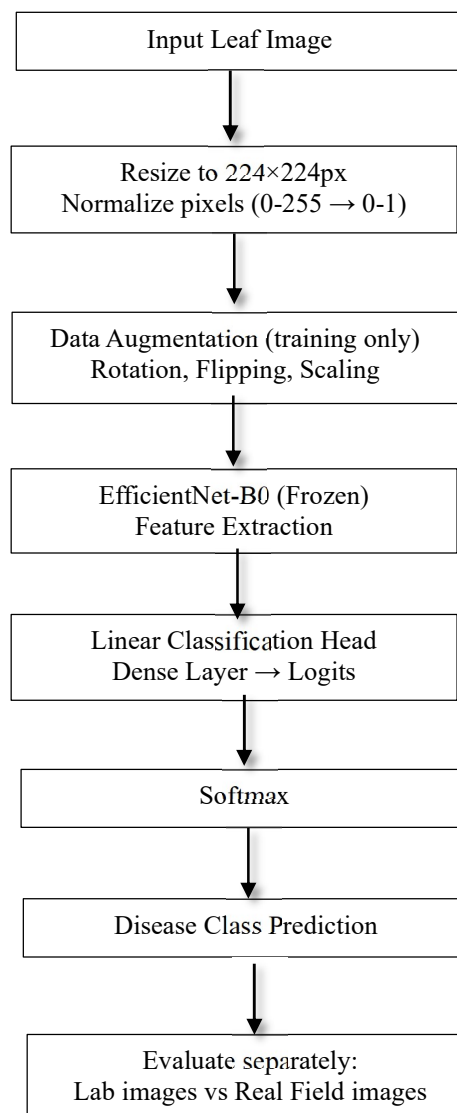


Figure7: EfficientNet-B0 based disease classification

CHAPTER- 4

RESULTS

4.1 Performance analysis of applied EfficientNetB0 based model

The applied hybrid architecture performance was evaluated across solanaceae crops (Tomato, Potato, Bell Pepper, Brinjal and Chilli) containing lab and real field images. Table 4 represent the quantitative performance metrics of the utilized EfficientNetB0 based hybrid architecture evaluated across five solanaceae crops.

Table 4: Represents the quantitative effectiveness metrics of the utilized EfficientNet-B0-based hybrid model evaluated across five Solanaceae crops: Tomato, Potato, Bell Pepper, Brinjal, and Chilli

Crop	Dataset Type	Acc. (%)	Pre.	Rec.	F1-Score
Tomato	Lab/Controlled	99.8%	99.9%	99.7%	99.8%
Potato	Lab/Controlled	100%	100%	100%	100%
Bell Pepper	Lab/Controlled	99.7%	100%	100%	99.7%
Eggplant	Real-Field	95.2%	95.8%	95.2%	95%
Chilli	Real-Field	99.5%	99.2%	99.3%	99.2%

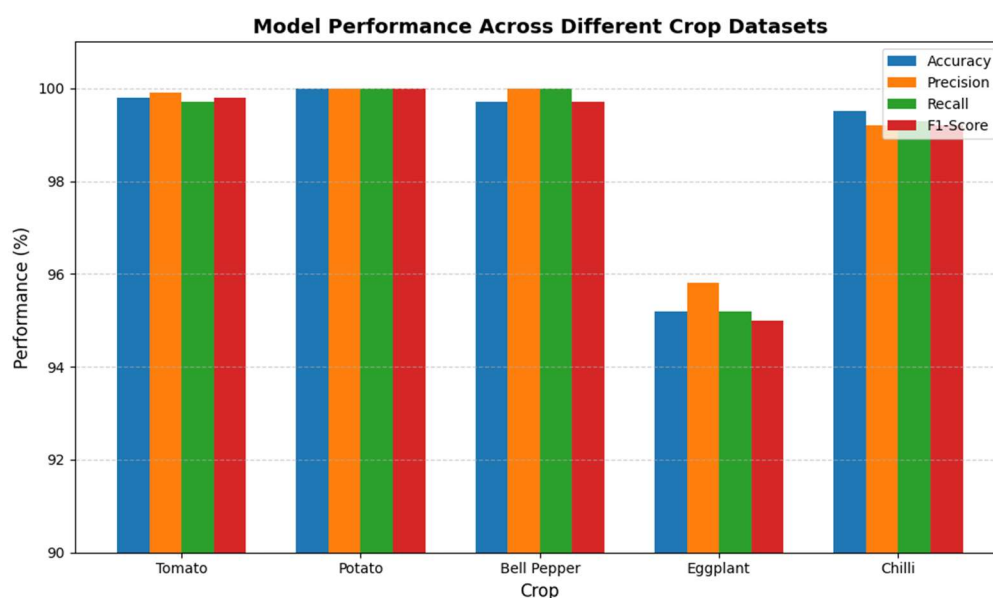


Figure 8: Performance comparison of Hybrid architecture on both lab style crops images and real- field crops images

Figure 8 presents the proposed architecture performance in quantitative metrics terms for each crop. The result shows variation in accuracy, on testing on varied dataset, attaining an accuracy and F1- score of $\sim 100\%$ on the lab-style datasets (Tomato, Potato, Bell Pepper) and a remarkable performance on real-field datasets, attaining an accuracy of 95.2% for Brinjal and 99.5% for Chilli. These values indicate that the model can handle complex natural images, having complexity in patterns. The balanced precision and recall values across both datasets suggest that the architecture precisely estimated healthy and diseased samples. The uniform consistency of result showcase that the architecture learned properly and free from overfitting. In contrast to previous studies that mentioned about performance droppage in accuracy, our proposed model maintains a stable performance from lab to field environments, maintaining computational efficiency. Overall, Figure 8 confirms that the EfficientNet-B0-based hybrid achieves robust cross-crop disease detection, meeting the study's objectives of high accuracy through a computationally efficient lightweight model on both controlled and real-world images.

4.2 Model Evaluation

The utilized architecture EfficientNetB0 gone for training up to 50 epochs, implemented through a batch_size of 8, a learning rate of 10^{-4} , and the Adam-Optimizer. Training & validation performance assessment was done using acc. and loss metrics as represented in Figure 9.

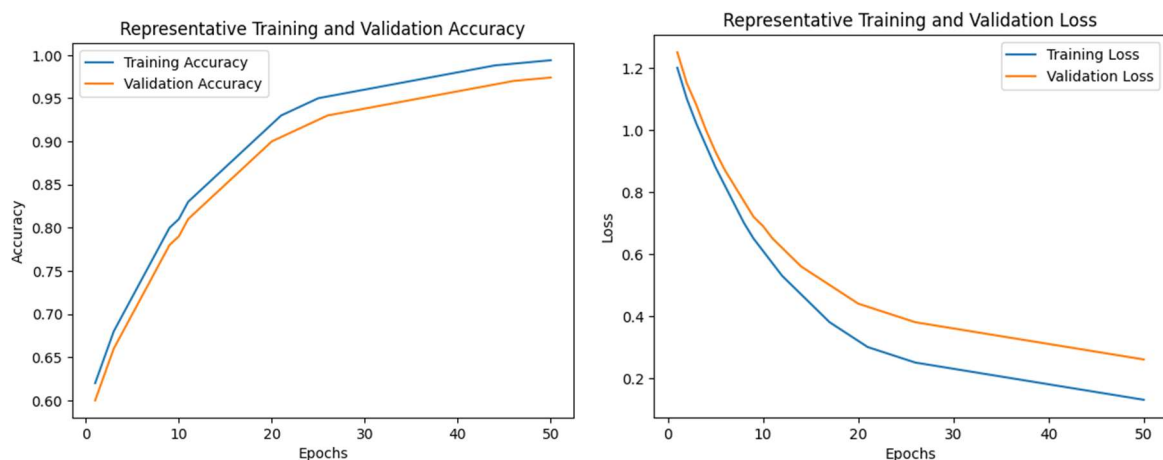


Figure 9: Training & validation acc. and loss over epochs

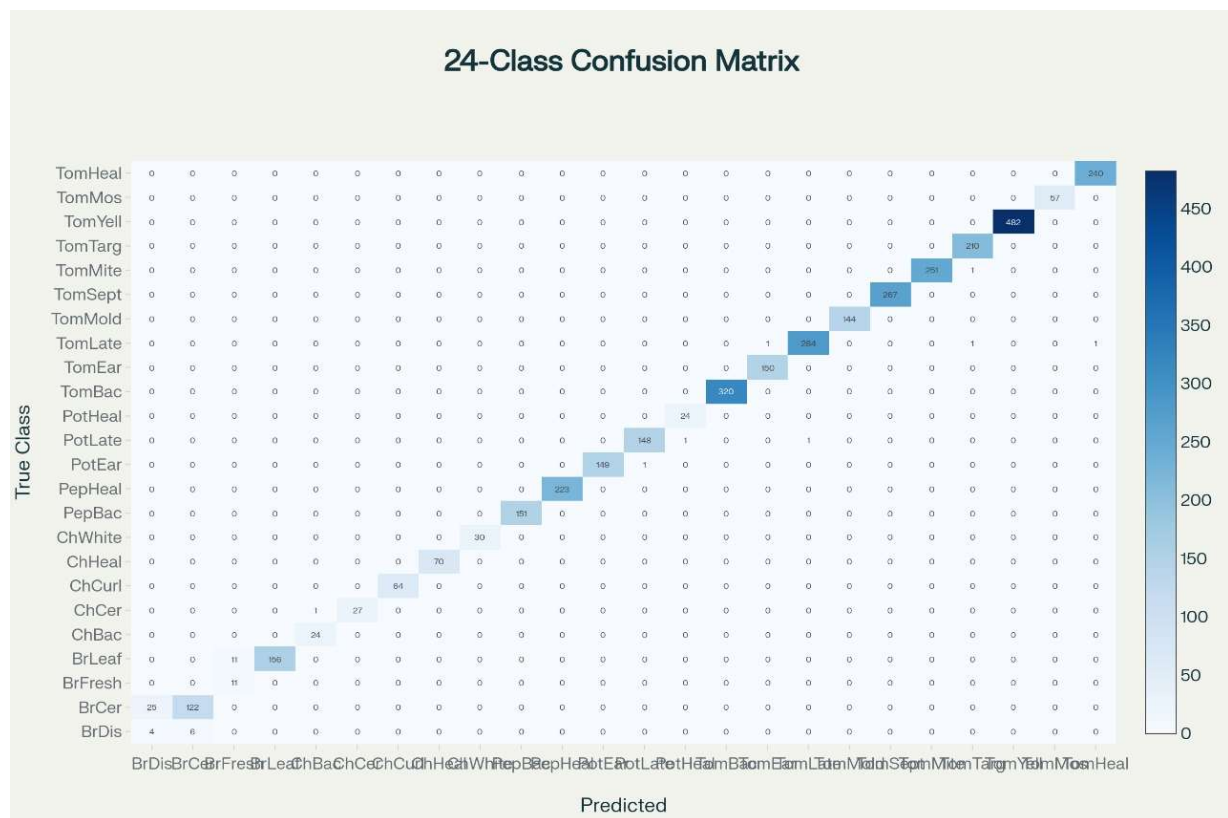


Fig 10: Confusion matrix of hybrid architecture across all disease classes (combined test set).

Figure 10 displays the hybrid model performance across varied classes through the confusion matrix. The dark diagonal lines represent that the test images were correctly classified into their actual healthy or diseases categories. The off-diagonal value highlights that the architecture rarely confuses between the similar pathological symptoms. This visualization supports that the architecture precisely evaluates each pathogenic type using high precision & recall value.

4.3 Comparative analysis

Further a comparative analysis was done using benchmark models- ResNet50 and DenseNet121. These benchmark models were evaluated on same publicly available datasets- Plant village and Mendeley, across 5 crops (Tomato, Potato, Bell Pepper, Brinjal and Chilli), containing lab style images of 3 crops (Tomato, Potato & Bell Pepper) and lab field images of 2 crops (Brinjal & Chilli). This independently carried out comparative analysis helps understand the model's architecture and their behaviour.

4.3.1 Dataset and experimental setup

For the comparative analysis, same plant diseases images datasets were utilized, containing both real- field and lab-field images, a total of 24,267 images. For each of the five crops image datasets, the images were first distinguished into 3 distinct subsets in a ratio 70:15:15. Pre-processing was done for all sets and in contrast to it augmentation was only done for training set in order to upgrade model's robustness, optimizing generalization and in curbing overfitting risk. For evaluating the model's functionality across each of the 5 crops dataset, quantitative metrics were used.

4.3.2 Performance comparison across CNN models

This performance comparison study provides how individual models generalize across varying conditions, as shown in Table 5.

Table 5: Represents the quantitative performance metrics—across five Solanaceae crops: Tomato, Potato, Bell Pepper, Brinjal, and Chilli

Dataset	Model's	Acc. (%)	Pre. (%)	Rec. (%)	F1-Score (%)
Tomato (Lab)	ResNet50	99.8%	99.7%	99.8%	99.7%
	DenseNet121	99.8%	99.8%	99.8%	99.8%
	EfficientNetB0	99.8%	99.9%	99.7%	99.8%
Potato (Lab)	ResNet50	99.9%	99.9%	100%	99.9%
	DenseNet121	99.9%	100%	100%	100%
	EfficientNetB0	100%	100%	100%	100%
Bell Pepper (Lab)	ResNet50	99.7%	100%	100%	99.7%
	DenseNet121	100%	100%	100%	100%
	EfficientNetB0	99.7%	100%	100%	99.7%
Brinjal (Field)	ResNet50	96.7%	100%	100%	94.7%
	DenseNet121	100%	100%	100%	100%
	EfficientNetB0	95.2%	95.8%	95.2%	95%
Chilli (Field)	ResNet50	99.5%	99.2%	99.5%	99.2%

	DenseNet121	99.1%	98.5%	98.6%	98.5%
	EfficientNetB0	99.5%	99.2%	99.3%	99.2%

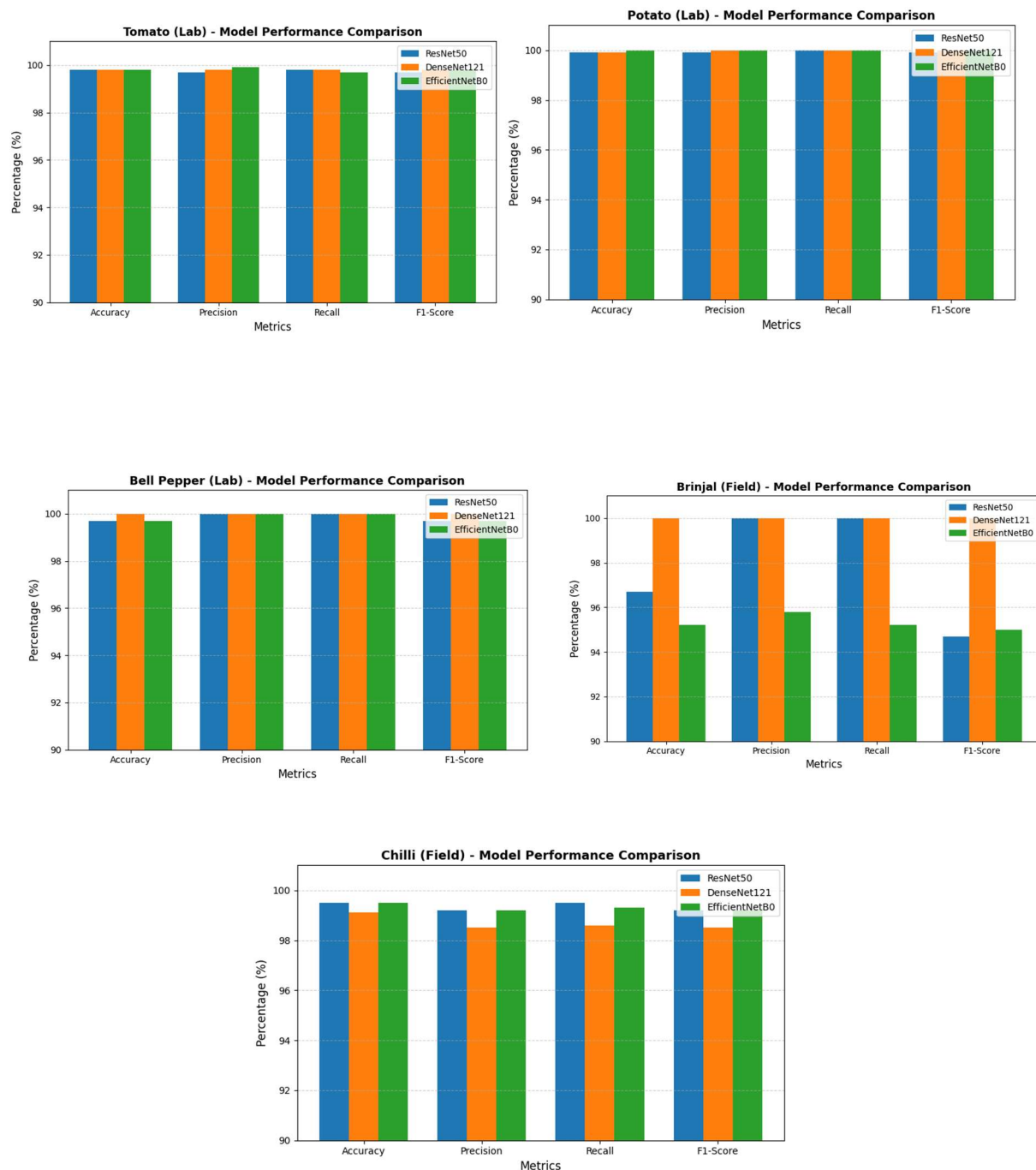
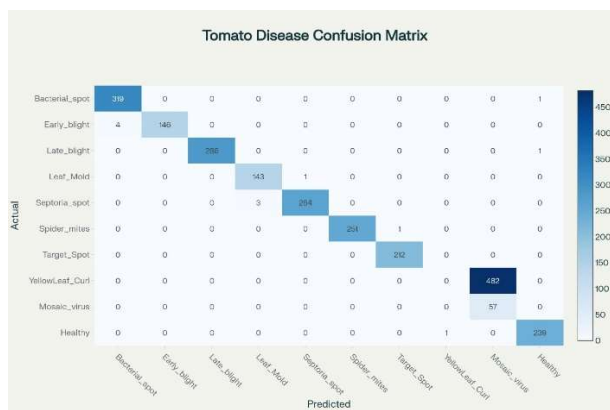


Figure 11: Performance comparison of benchmark models- ResNet50, DenseNet121 and EfficientNetB0 across 5 crops datasets.

Table 6: Performance drop of benchmark models

Model	Average Accuracy (Lab)	Average Accuracy (Field)	Performance Drop
ResNet50	99.8%	98.1%	1.7%
DenseNet121	99.5%	99.5%	0%
EfficientNetB0	99.8%	97.35%	2.45%



16



Fig 12: Confusion matrix for the DenseNet121 architecture

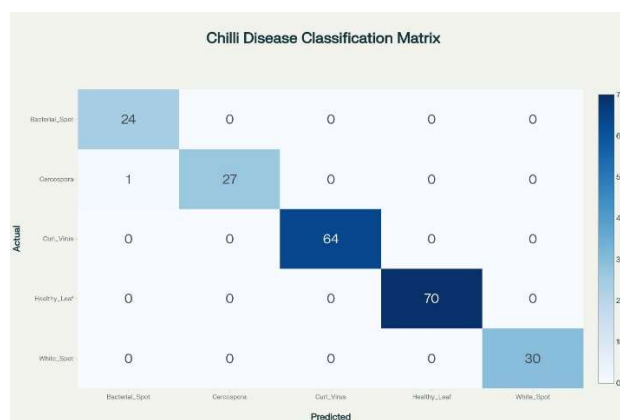
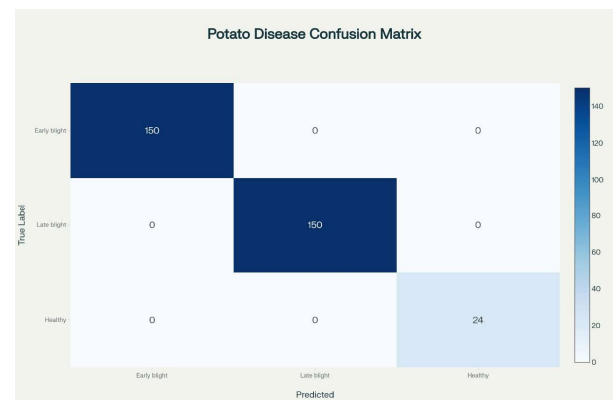
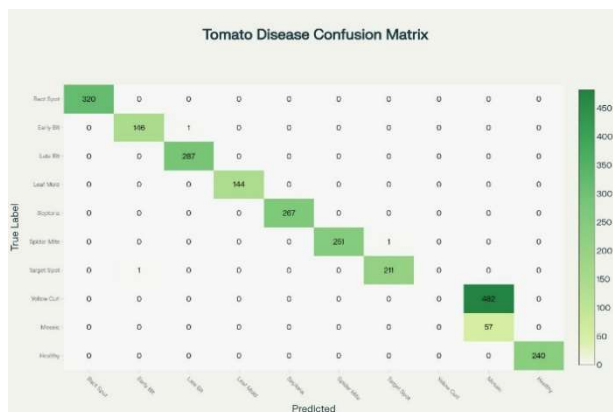


Fig 13: Confusion matrix for EfficientNetB0 architecture



Figure 14: Confusion matrix for ResNet50 architecture

The confusion matrices for all five crops (Figures 12–14) show overwhelmingly strong diagonals, indicating that most predictions were correct for each class. In other words, true positive rates exceed 98–99% across nearly all categories. Misclassifications are extremely rare and tend to occur between visually similar categories (for instance, between certain diseases or between disease and healthy labels). Notably, the lab datasets (tomato, potato, bell pepper) exhibit almost no off-diagonal entries (near-perfect classification). The field datasets (brinjal,

chilli) show just a few off-diagonal values: for example, ResNet-50 and EfficientNet-B0 sometimes confused healthy and diseased brinjal leaves, consistent with their slight accuracy drop. Overall, the matrices collectively confirm that all models achieve high per-class accuracy and that misclassification patterns are minimal and concentrated in the more challenging field scenarios.

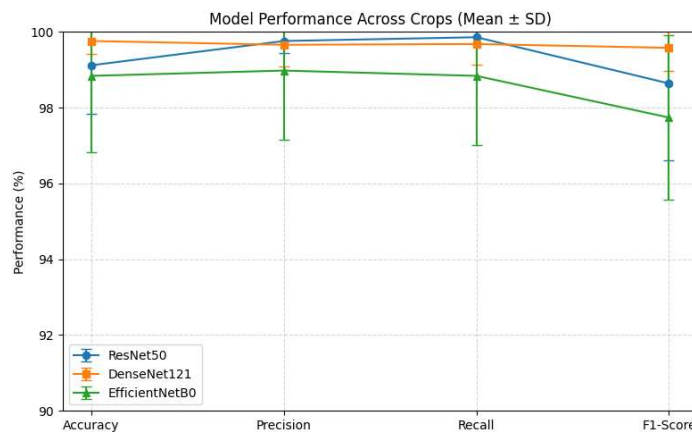


Figure 15: Plot comparing the performance of three CNN models. The lines represent the average scores across five crops, and the error bars show variation. DenseNet121 performs the best overall, with the highest and most consistent results, while EfficientNetB0 shows slightly lower and more variable performance.

4.3.3 Lab -to-Field Generalization

This work presented a comparative analysis between three highly efficient models namely, DenseNet121, EfficientNet-B0, ResNet50. The achieved result highlights the successful deployment and validation of these three models across five solanaceae crops datasets: Tomato leaves (10 classes), Potato leaves (3 classes), Bell Pepper (2 classes), Brinjal (2 classes) and Chilli (5 classes). All the three models performed equally well on all the five crops. ResNet50, DenseNet121 and EfficientNetB0 attained a mean acc. of 99.8%, 99.5% and 99.8% in same order on lab style images of Tomato, Potato and Bell Pepper crops. Performance dropped for two models – ResNet50 and EfficientNetB0, achieving an average accuracy of 98.1% and 97.35% respectively on real field crops images of Brinjal and Chilli. Although, DenseNet121 exhibit marginal performance droppage, but being a complex architecture, it requires high computational cost. DenseNet121 belong to the family of Densely Connected Convolutional Networks, emphasize on maximizing feature use. Rather than skipping connections, it links one layer to another layer within a dense block, ensuring smooth and efficient flow of information. In this manner feature map of a preceding layer is utilized as an input for current

layer and this current layer output act as an input for all subsequent layers. The dense connectivity pattern emerges out through concatenating the feature maps from previous layers, providing notable advantages such as helping in overcoming vanishing gradients, strengthening feature propagation and in reducing parameter count compared to architectures of similar depth. The network joins multiple dense blocks interconnected by transition layer-comprising batch standardization, 1×1 convolutions, and avg. pooling layer. The DenseNet121 represent the concept of 121- layer deep implementation. The same applied for ResNet50 model, architecture of ResNet50 initially comprises of convolution layer, and as it progresses it consist of four stages of these residual blocks, and finally at the end a densely connected layer for classification. In contrast, the EfficientNetB0 model, exhibits slightly higher performance margin; however, being a small, simple, computationally efficient architecture enables its efficient generalization for real-world conditions, making it deployable for practical use in precision agriculture. By integrating linear classification head with a pre-trained feature extractor, the framework achieves computationally efficient result, contributing to sustainable agricultural practices and in advancing global food security.

CHAPTER-5

DISCUSSION

5.1 Interpretation of Model Performance

The proposed hybrid model architecture displayed a remarkable performance across both datasets- laboratory controlled and real- field datasets. The architecture attaining an average acc. of 99.8% on lab- field images dataset's of Tomato, Potato and Bell Pepper indicates that it delivered exceptionally outstanding result under controlled environmental conditions. Similarly, a performance droppage of 2.45%, attaining an mean accuracy of 97.35% on real world conditions indicates that the model performed marginally lower due to complex natural images, having complexity in patterns. The balanced precision and recall values across both datasets suggest that the hybrid architecture accurately assessed both healthy & diseased samples. The uniform consistency of result highlights that the architecture learned concisely and free from overfitting. In contrast to previous studies that mentioned about performance droppage in accuracy, our proposed model maintains a stable performance from lab to field environments, maintaining computational efficiency.

EfficientNetB0 model, exhibits slightly higher performance margin; however, being a small, simple, computationally efficient architecture enables its efficient generalization for real-world conditions, making it deployable for practical use in precision agriculture. By integrating linear classification head with a pre-trained feature extractor, the framework achieves computationally efficient result, contributing to sustainable agricultural practices and in advancing global food security.

5.2 Impact of Dataset Diversity

The research utilizes images datasets curated from two freely available dataset sources: the Plant Village (Kaggle) and the Mendeley. The strength lies in utilizing complex datasets containing both laboratory- controlled datasets and real-field images datasets and implementing a light-weight, computationally efficient model to assess the performance across varied datasets, thus bridging lab-to field gap.

The inclusion of diverse datasets, containing varying diseases categories images of multiple Solanaceae crops have strengthened the cross- crop learning capability of model. The

preprocessing and augmentation further helped making the model training more robust. The model is not overfitted as the early stopping and preprocessing enabled a controlled training environment. The achieved results have emphasized that the model accurately predicted both healthy and diseased samples, across both datasets. The cross- crop generalization is importantly needed for practical deployment and for implementation of plant disease detection systems.

5.3 Computational Efficiency and Deployability

This research introduces a hybrid architecture composed of an EfficientNet-B0 backbone as a feature extractor and a linear classification head. EfficientNet-B0 has the ability to recognize the complex patterns on leaves, and the linear classification head serve as a platform for final prediction, through its accurate classification of features. This synergistic architecture leverages the process, making the task computationally efficient while maintaining accuracy.

ResNet50, DenseNet121 and EfficientNetB0 attained a mean acc. of 99.8%, 99.5% and 99.8% in the same order on lab style images of Tomato, Potato and Bell Pepper crops. Performance dropped for two models – ResNet50 and EfficientNetB0, achieving an average accuracy of 98.1% and 97.35% respectively on real field crops images of Brinjal and Chilli. Although, DenseNet121 exhibit marginal performance droppage, but being a complex architecture, it requires high computational cost. The same applied for ResNet50 model, architecture of ResNet50 initially comprises of convolution layer, and as it progresses it consist of four stages of these residual blocks, and finally at the end a densely connected layer for classification.

EfficientNetB0 model, exhibits slightly higher performance margin, 2.45% performance drop on field images. However, being a small, simple, computationally efficient architecture enables its efficient generalization for real-world conditions, making it deployable for practical use in precision agriculture, deployment on portable and edge-based computing devices such as smartphones, Unmanned Aerial Vehicles (UAVs), and IoT-assisted agricultural systems. By integrating linear classification head with a pre-trained feature extractor, the framework achieves computationally efficient result, contributing to sustainable agricultural practices and in advancing global food security. The hybrid architecture was tested for 50 epochs, implemented to reduce overfitting, implemented using a batch-size of 8, a learning-rate of 10^{-4} , and the Adam optimizer.

5.4 Limitations of the Study

This research utilized only five solanaceae crops leaf images datasets, the research can be further escalated by improvising more diverse crops and their images, improving the scalability and adaptability of the model.

Further task can be in estimating diseases severity, progression stage, or crop yield impact apart from disease prediction through computationally efficient detection framework. Moreover, EfficientNetB0 variations like EfficientNetB1 or EfficientNetB4 can be also implemented in identification of plant diseases.

CHAPTER-6

CONCLUSION & FUTURE PERSPECTIVE

The achieved result highlights the successful deployment and validation of hybrid deep learning framework based on EfficientNet-B0 across five solanaceae crops datasets: Tomato leaves (10 classes), Potato leaves (3 classes), Bell Pepper (2 classes), Brinjal (2 classes) and Chilli (5 classes). The hybrid architecture attained an impressive mean accuracy of 99.8% for lab style images of Tomato, Potato and Bell Pepper and an mean acc. of 97.3% for complex real field images of Brinjal and Chilli. The marginal drop performance across lab style crops images and real field images highlights that model can generalize efficiently on real-world conditions, making it deployable for practical use in precision agriculture. By integrating linear classification head with a pre-trained feature extractor, the framework achieves computationally efficient result, contributing to sustainable agricultural practices and in advancing global food security. This result suggests that even the smallest, light-weight model is capable of outperforming complex ensemble approaches. Based on these achievable outcome, future direction could aim at using more advance computationally efficient, simpler and faster models or in deploying hybrid models, integrating efficient architecture, such as Vision-Transformer (ViT), and harnessing Explainable A.I techniques (such as S.H.A.P and L.I.M.E) across more diverse and complex datasets of crops, thus enhancing interpretability and dependence of farmers on such model for an initial stage and accurate prediction of pathogenic diseases.

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<https://doi.org/10.3389/fpls.2016.01419>

LIST OF PUBLICATIONS

1. An EfficientNetB0-Based Hybrid Model for Leaf Disease Detection Across Five Solanaceae Crops. Accepted in 5th INTERNATIONAL CONFERENCE ON SMART SYSTEMS: INNOVATIONS IN COMPUTING (SSIC)- accepted for Publication in Proceedings (Springer Book Chapter), title of proceeding- Intelligent System and Data Analysis: SSIC 2025 Doctoral Symposium.





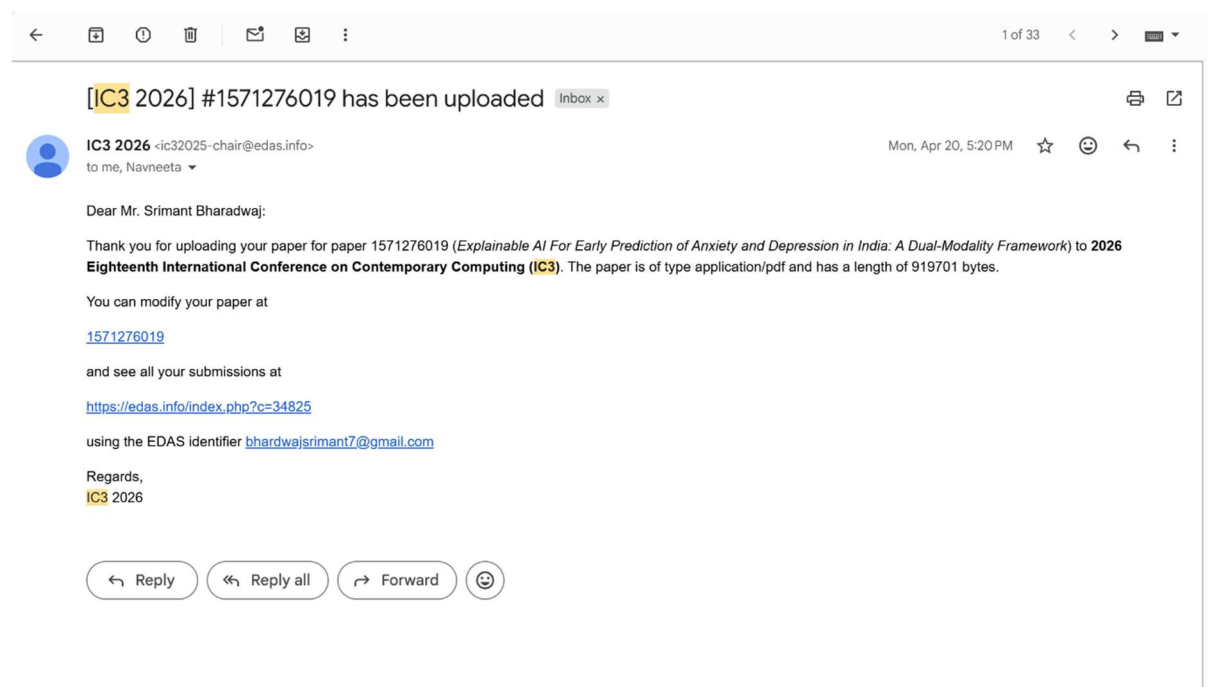
Explainable AI For Early Prediction of Anxiety and Depression in India: A Dual-Modality Framework

Abstract

Mental health disorders, specifically depression and anxiety, have become a serious global health crisis. In India, recent surveys highlight a prevalence rate of 13.7% for mental disorders. Despite heightened awareness, early detection remains elusive due to social stigma and the limited integration of socio-demographic, lifestyle, and behavioural factors into standard screening processes. Furthermore, despite the predictive capabilities of machine learning, the “black-box” nature of many models limits clinical trust. This paper proposes a dual-modality Explainable AI (XAI) framework for the early prediction of anxiety and depression. Phase 1 evaluates structured lifestyle and socio-demographic factors utilizing Extreme Gradient Boosting (XGBoost) balanced via the Synthetic Minority Over-sampling Technique (SMOTE), achieving an accuracy of 79.95%. Phase 2 employs a Natural Language Processing (NLP) pipeline leveraging Term Frequency-Inverse Document Frequency (TF-IDF) to analyze over 53,000 unstructured behavioural text statements and achieving a higher accuracy of 93.73%. By integrating SHapley Additive exPlanations (SHAP) for global feature importance and Local Interpretable Model-agnostic Explanations (LIME) for instance-level tabular and textual transparency, this framework achieves high predictive accuracy while ensuring model’s clinical interpretability and providing transparent, auditable, and clinically actionable insights.

Index Terms—Explainable AI, LIME, Mental Health, Mul-timodal ML, Natural Language Processing, SHAP, TF-IDF, XGBoost

Note: “Submitted to IEEE conference (under review).”



Link for the app- <https://mindbridgehealth-ai.netlify.app/> (inspired by the Conference Paper)



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