Deep Learning Approach Towards Plant Disease Detection

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Abstract - Disease detection in plants is where the domains of technology and food safety converge as it impacts both India's agriculture-based economy and the daily livelihood of millions of Indian farmers. Plant disease can cause annual losses of up to 30%. Therefore, disease detection before crop loss is no longer a choice, it has become a necessity. Traditional Machine Learning approaches have improved significantly in classifying disease; however, Deep Learning (DL) has provided an innovative approach in providing more precise predictions of plant diseases. This research aims to provide an intelligent, and an optimized Convolutional Neural Network (CNN) multi-class plant disease detection framework that works under realistic farming conditions. In the present study, the system uses high-resolution (40 MP) leaf images and applies feature engineering to achieve the best results possible for three economically valuable crops in the Delhi-NCR area: Tomato, Wheat and Mustard. The findings revealed that multi-class disease detection in Wheat achieved 99.40% accuracy while multi-class disease detection in Tomatoes achieved 95.90%. The results far exceeded all benchmarked results for the mentioned crops in practical application scenarios. This framework would allow farmers to access affordable technology which would enable them to detect diseases in their crops earlier than ever before which will help reduce the need for chemical intervention and will allow farmers to act quicker on the crops, they produce thereby increasing the overall resiliency of the food supply chain.

Keywords: CNN, Computer Vision, Deep Learning, Plant Disease Detection.

I. INTRODUCTION

The integrity and progress of a society are fundamental to its Food Security. Despite the uncompromised need of every individual, the availability of adequate food is a significant issue because of factors like climate change, water scarcity, land degradation and plant diseases. While the latter could be a manageable segment, the former ones are non-negotiable and non-manageable to a greater extent. The process of agriculture is a complex one with various tasks from preparing the soil to sowing, production, harvesting, and then finally the produce comes to the table [2]. In between all these processes, one major aspect which is non-negotiable is plant diseases. Diseases prove to be one of the biggest contributors to global food shortage, disrupting economies, affecting hundreds of millions of people worldwide. Diseases like rust, wilts, blights, soft roots, necrosis, chlorosis, etc. are the major causes of damage to the plant. Interestingly, all these types of diseases are most prominent on the plant's leaf, making the plant's leaf die and fall off. This subsequently results in a reduction of produce which in turn increases the crop prices. Historically, traditional methods have long been used for the detection of plant diseases. However, it comes with its own disadvantages, such as the requirement of human labor. Furthermore, these workers need to have experience, which is a rare quality as the factor of human error is always there making the need for prior knowledge for the labor to be of immense importance. Moreover, timely detection of plant disease on a large scale is another crucial factor which comes into play. All these factors make it a tough job for the farmer to counter the plant disease problem. The global economy loses hundreds of billions of dollars annually to plant diseases in every crop, making the situation worse.

Thus, all these considerations point towards a plant disease detection system which can detect the type of plant diseases through the leaf. Till now, there has been a considerable amount of study done on plant disease detection all over the globe because of the ease of collecting datasets. Traditionally, deep learning problems need to have both a good amount and decent quality of data which are quite rare to occur. Plant disease detection is a kind of machine learning problem where the dataset is quite easy to find as leaf images are easy to collect or produce using a mobile camera [5]. A leaf's image is an excellent data for the ML model to learn because a leaf can have multiple variations in color, shape, size, etc. and all these variations make the feature map to capture a large number of features which results in an effective disease prediction system contributing to increased production.

Existing research have tried using some aspects of machine learning and some have used deep learning, but the results have not been significant enough for them to be termed as effective approaches to a plant disease detection problem as they failed to encapsulate larger concepts of deep learning [1]. This study presents a detailed methodology from the creation of a diverse, multi class dataset to the design of an application called as "LeafLens" which is termed to be as a farmer's friend as it is pushed to produce a significant impact on the farmer's produce by eliminating the plant disease factor. The findings of this study prove the effectiveness of a deep learning approach, demonstrating high accuracy in disease classification tasks. This work contributes to a scalable and practical solution that can be integrated into an automated plant disease detection system, thereby reducing the risk of plant disease and economic losses.

Fig. 1. Variations of diseases in a tomato plant leaf [15]

II. LITERATURE REVIEW

The progress in artificial intelligence has shifted the practice of plant disease recognition to smart and automated tools instead of manual inspection. Previous computational techniques relied on manual selection of features as researchers extracted texture, color and shape features with such classifiers as SVM, Random Forest, and KNN. Although these conventional methods offered sensible performance, they had difficulties with real-life variability like variable illumination, background clutters and leaf obscurations and hence could not be practically applied in farms [4], [5].

The paradigm was changed by the introduction of Deep Learning and specifically, Convolutional Neural Networks (CNNs) that can learn hierarchical features automatically and without human intervention. To illustrate, Mohanty et al. revealed the capability of CNNs to break through by applying their model to the PlantVillage data and reaching high-performance with the task to classify plants and diseases [6]. Subsequently, Saleem et al. adopted a review of many architectures with a reported accuracy of over 99 percent in controlled experiments [5].

Recent work focuses more on lightweight and portable networks like MobileNet, EfficientNet as well as ShuffleNet to enable real-time field applications on smartphones, drones and IoT devices. Transfer learning and attention mechanisms also increase feature robustness, despite the small dataset size [3]. Also, ensemble methods and more sophisticated augmentation methods have enabled models to generalize more to natural field settings- a significant advance over controlled lab data [2].

Nevertheless, even though significant achievements have been noted, there are still challenges. Even in extreme light, in the presence of overlapping leaves, and in the presence of various diseases simultaneously, performance degradation is still evident. Besides, datasets are still biased towards popular crops, with most agricultural areas being under-represented [1], [3]. These gaps highlight the need for high accuracy, yet computationally efficient systems capable of real-world deployment.

This study contributes to the ongoing research by developing a deep-learning powered plant disease detection model that focuses on optimizing accuracy, efficiency, and practical usability for precision-agriculture ecosystems.

III. METHODOLOGY

The research for the plant disease detection system has been done through several platforms, databases, research papers, journals, etc. In addition, there has been a lot of focus over published articles for plant disease detection. Plant disease detection has been a kind of topic which has grabbed a lot of curiosity resulting in many papers and research going on which helped to filter out relevant and informative papers. The approach is structured as a multistage pipeline designed to sequentially perform key classification tasks, thereby providing a robust final assessment of each plant leaf [7]. The stages are:

A. Datasets

The entire process of disease detection is based on the quality of model training, which in turn is based on the quality of the data. Thus, data collection is the first and really the most important stage of the process. Because of the huge amount of research that has been done over the last couple of years on plant disease detection, the amount of plant leaf data is in large numbers but the main requirement for an effective detection system is the quality and quantity of the data. Hence, it becomes evident that to make a system which doesn't face the problems for classification tasks such as overfitting, there needs to be data which doesn't contain duplicate or corrupt images as both these problems result in either overfitting or too slow processing of the data [8]. The categorization of the data has been based on species.

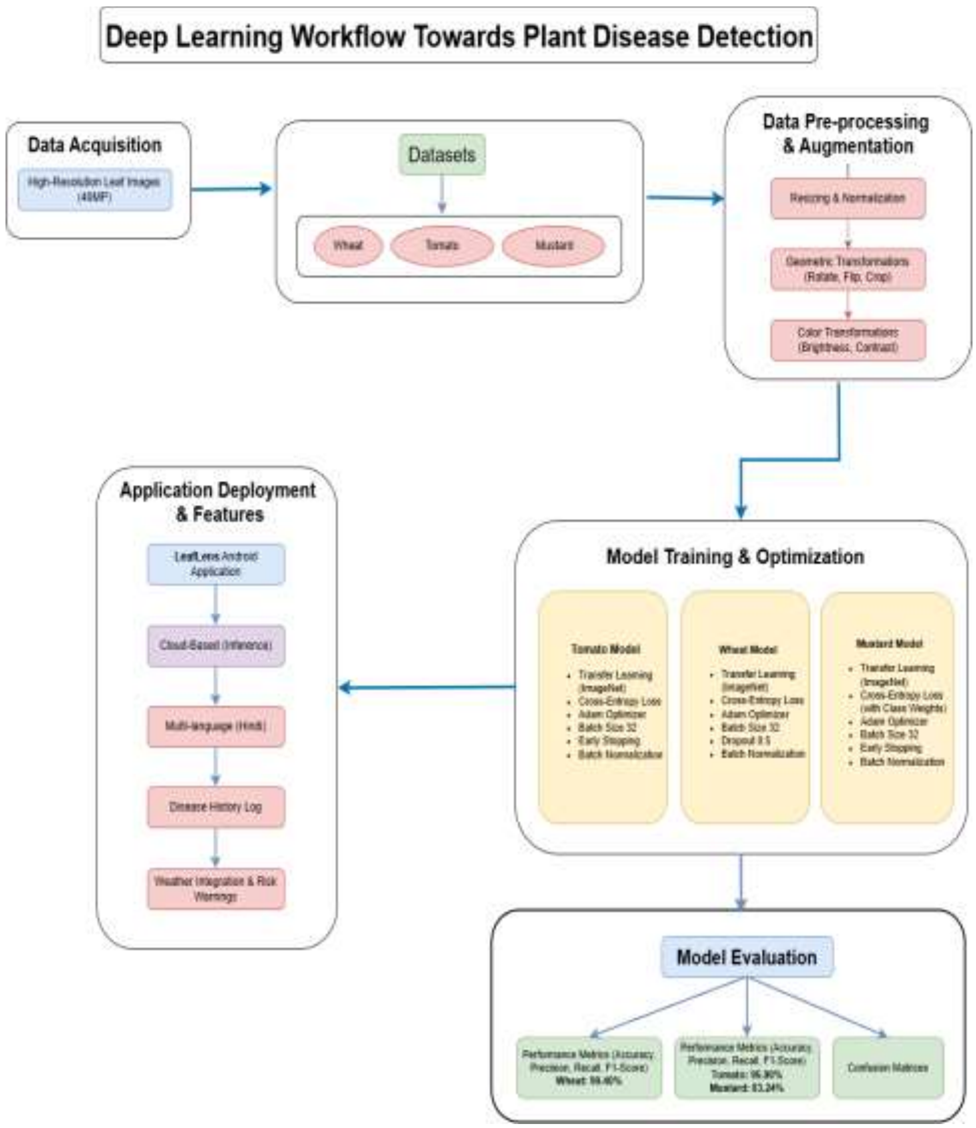

Fig. 2. Deep learning workflow for plant disease detection

Table I. Overview of dataset, emphasizing balanced splits

Crop	Total Images	Training	Validation	Test	Class	Source
Wheat	5,000	3,500	1,000	500	5	Custom + Kaggle [10]
Tomato	10,649	9,049	1,063	537	6	PlantVillage + Field [9]
Mustard	7,140	4,998	1,428	714	20	Kaggle + Regional [15]

1) Wheat Leaf dataset

For the wheat foliage analysis, a collection of 3,500 enhanced images for model fitting, complemented by 1,000 for verification and five hundred held out for final evaluation. This collection covers five key categories: black point lesions, fusarium root issues, undamaged foliage, blight spots, and blast damage. The entire dataset has been allocated evenly- 70 percent of initial learning, 20 percent of tuning, and 10 percent of unbiased checking to encourage balanced exposure in groups.

The network architecture contains processing blocks which are stacked, becoming larger in terms of their scanning window, and initially on the simple outlines and surface features before moving to larger indicators of the infection, such as uneven spotting or discoloration. Variability methods were added in the preparation (slight tilt on different angles, side-to-side mirroring, up-down reversals and slight changes in glow) to add resilience in case of inconsistencies in real world (e.g., changing light/leaf angles in an outdoor shot).

2) Tomato leaf dataset

The Tomato leaf dataset contains 9,049 training images, 1,063 validation images, and 537 test images which are shot at 40 mega pixels using a mobile camera. This type of dataset is useful for multi classification tasks as it is categorized into six categories: "bacterial spot", "early blight", "leaf mold", " septoria leaf spot", "yellow leaf curl virus", and "healthy".

3) Mustard leaf dataset (Extended Multi-Crop)

7,140 training images (20 classes across Mustard: 12 classes including Unknown/Healthy, Alterni ablight, Aphid, Bathu weeds, Beneficial insect Lacewing, Caterpillar, Excessive moisture, Healthy crop, Motha weeds, Nitrogen deficiency, Phosphorous deficiency, Sawfly; plus, Maize: 5 classes; Mash: 3 classes); reorganized from field/Kaggle sources for regional relevance.

B. Feature Engineering

The next step after collecting the data is a crucial one, i.e., preprocessing. Feature engineering is an important part of the pre-processing stage and is responsible for processing leaf images to get a new set of leaf images which are different from the previous ones and carry more information. The variations present in the datasets include differences in image capture conditions, leaf color, size, and shape. This approach is useful to ensure model robustness and to reduce the risk of overfitting.

1) Image Pre-processing and Augmentation

Feature engineering techniques applied to get a uniform and useful data for convolutional neural network training are:

Resizing and Normalization: leaf images captured at a high resolution of forty megapixels are uniformly resized to a standard dimension to ensure consistent layer size input for the CNN architecture. Moreover, the pixel intensity values are normalized to a specific range to increase the rate of model convergence during training.

Geometric Transformations: rotation of images at Random angles or degree radians, horizontal and vertical flipping, cropping and zooming.

Color Transformations: brightness, contrast, and saturation adjustments helps the model learn disease features irrespective of the conditions present during image capture. This is a crucial part of data augmentation.

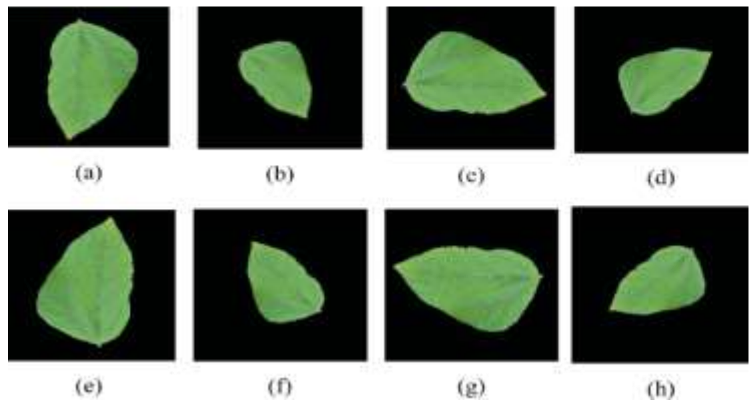

Fig. 3. Data augmentation in a plant leaf [16]

C. Model Architecture

The main aspect over which the "LeafLens" application is based is a deep learning model, specifically a CNN which is quite suited for image classification tasks. This architecture is designed and expected to process a leaf image which contains several variations in color, shape, and size to achieve high accuracy in disease classification. CNNs are at the pinnacle of image classification because of their ability to learn information or features from images by a process of convolution [5].

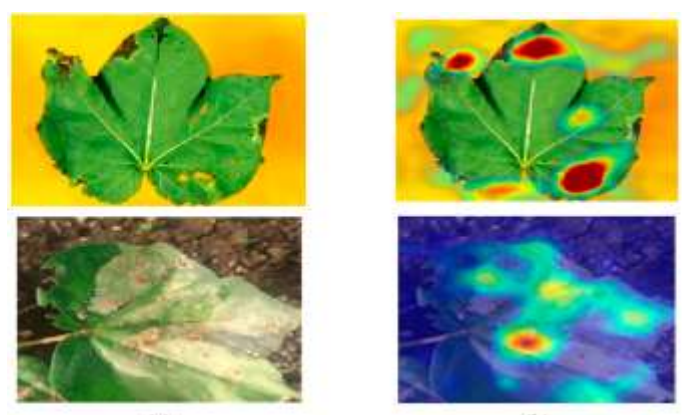

Fig. 4. Feature map of a plant leaf

Pooling Layers

Pooling Layers are brought in as an essential part as they play two essential roles: dimensionality reduction and enhancing robustness to variations in the input data. The pooling layers work independently on each feature map and attempt to restrict the occurrence of features in patches of the feature map.

Dimensionality Reduction: The pooling layers decrease the height and width of the feature maps, significantly reducing the number of parameters by operations such as max pooling or average pooling, and decreasing the network's overall computational burden. This reduction is important to optimize in the case of high-resolution images (40 megapixels).

Enhanced robustness: By including a region, pooling enables the model to become more robust to minor distortions in the input image. If a disease spot (feature) occurs in a slightly off position in two different leaf images, the pooling operation preserves the resulting feature map unchanged and hence enhances the model's generalization ability.

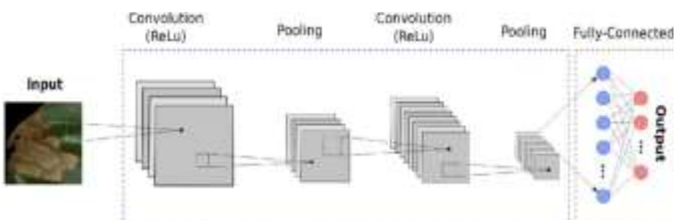

Fig. 5. General scheme of a CNN for classification of plant disease

D. Model Training and Optimization

Training and optimization are key steps in building the LeafLens CNN models. Crop-specific designs were used to avoid problems in general models, like mixing up features from different plants, which lowers accuracy. This way, each model focuses on the special looks of one crop's leaves and diseases, making it work better in real farms.

Models were trained separately for wheat, tomato, and mustard—the main crops in Delhi-NCR—using the proportion of (7:2:1) for training, validation, and testing. Models start with weights from ImageNet, use the popular and reliable optimizer - Adam with learning rate 0.001 and decay 0.000001), cross-entropy loss, batch size thirty-two, and 20-50 epochs. Early stopping stops training if no improvement after 5 epochs. Dropout (0.5) and batch normalization prevent overfitting. Real-time changes to images—like rotating by ±20 degrees, flipping, or adjusting brightness by ±0.2—help the model to manage real-world differences.

1) Wheat Model

The model trains approximately 3500 modified high-resolution images (5 classes) of wheat. The layers are constructed to move from simple edge detection to detailed disease patterns. Upon fine-tuning, the model achieved 99.40% on the testing set (loss = 0.0268) with high precision (99%) and high recall and F1-score as well. It is expected to provide higher accuracy than the standard 85-93% for the same type of problems (similar diseases such as rust).

2) Tomato Model

To work with leaves on tomatoes, a decent initial collection of 9,049 images was used to develop the basic knowledge base, 1,063 others to make some more adjustments, and 537 new ones to evaluate the actual results. There were over six trouble spots areas that have been common with the yellowing caused by curl virus bacteria patches, plain healthy samples, fuzzy leaf mold growth, initial blight stages, and the dotted appearance of septoria infections.

The added advantage of this was to add layers of image adjustments to simulate actual symptom changes, such as color bleaching or blurring of edges, which enabled it to cope with field shots which were messy better than our wheat, or mustard versions. In those holdout tests, it scored 95.9 percent correct calls overall, and 0.12 errors, which is far better than the normal 80-90 percent outdoor test. In addition, it defined the boundary between the ringed damage of early blight and the scattered flecks of septoria, reducing the number of confusing combinations.

3) Mustard Model

Since mustard is not a well-investigated crop as compared to the other two, the model was trained on a set of about 7140 images, which were split into 20 categories (12 on mustard, such as Alternaria blight, aphids, nitrogen deficiency; but some on maize and mash). Since the number of examples under each class was imbalanced, Class weights are used to take care of the same factor and transfer learning with a pre-trained CNN model ("mustardcnnmodel. keras") to enhance the performance of our model.

IV. APPLICATIONS

The study of “AI for sustainable agriculture” spans beyond the theory of real-world scenarios where accessibility, reliability and timely detection of plant disease are the main needs of farmers. This section outlines a planned implementation: an android application. This application will bridge the gap between real-world scenarios and research prototypes, with full deployment targeted for 2026.

The primary interface through which farmers will interact with the plant disease detection system is an android application named “LeafLens”. The app is designed with simplicity and keeping in mind the varying technological literacy of farmers in the Delhi-NCR region. Development is currently in the prototype phase, with public release in 2016.

A. Application architecture

LeafLens for Android is being developed as a hybrid (online/offline) system to balance between the computational demands of the algorithm and the usability of the application. The planned version will operate primarily in “online” mode utilizing cloud-based inference. When a leaf image is captured by the camera and sent to the remote server for inference (classification), it will be processed by the trained CNN models running on powerful GPU hardware. Using this method, users will achieve the best possible accuracy of classification and will be able to receive continuous model updates on the server, eliminating the need for repeated downloads/installations of the application. Based upon average network performance, the response from the server containing the results of disease classification, a confidence level for each result, and suggested treatments for each identified condition is expected to occur within 2-3 seconds.

B. User Interface and Workflow

The interface for the user is designed to be simple and culturally relevant to fit the farming community. When farmers open the app, they will see a home screen with buttons for three crops: wheat, tomato, and mustard. Each crop will have a clear visual icon. After choosing the crop, the farmer will proceed to an easy camera setup to take pictures. As soon as a picture is taken, classification will start, and results will appear in an easy-to-read format for farmers, avoiding technical terms. Instead of just showing disease names, it will also display how confident it is about its prediction. Each result will show the name of the disease in the chosen language, a full description of what symptoms it has and how it gets worse over time, plus a complete section on treatment recommendations.

C. Additional Features

Besides the main disease detection capability, the LeafLens app will include other functionalities to enhance value for farmers. A disease analysis history log will record all previous scans, allowing farmers to track disease trends across multiple growing seasons to identify recurring problems and evaluate treatment effectiveness over time. This historical data can reveal insights regarding field-specific issues and long-term management strategies.

Weather integration will provide local forecasts and disease risk warnings based on environmental conditions. Because many plant diseases are influenced by factors such as humidity, temperature, and rainfall patterns, the application will employ an open-source weather forecast API to inform farmers about the weather and proactively warn them to increase monitoring during critical periods. This predictive ability will allow LeafLens to shift from reactive disease detection to initiative-taking disease management. The application will also offer an option for farmers to switch the interface language from English to Hindi or vice versa, making it accessible for those less familiar with English.

V. RESULTS

Used common evaluation metrics for multi-class classification to evaluate the performance of the LeafLens CNN models in classifying multi-class images of leaves. The evaluation was done using Tensorflow/Keras on the test datasets (i.e., 10% of the total dataset) of the models that were trained for 20-50 epochs, while tuning for optimal learning rate (0.001 - 0.00001) and dropout (0.3 - 0.5). Evaluation showed that validation loss is very close to the loss obtained on the test set (with an average difference of 0.01 - 0.05), which indicates that the models have a good generalization capability due to the presence of dropout and variation in images used during training.

LeafLens is effective at identifying a variety of diseases and conditions from images of the same crop type. The wheat model, trained on approximately 3500 images of 40 MP images of leaves that had been modified, achieved 99.40% accuracy (validation loss: 0.0268) with 99% precision/recall/F1. This result exceeds typical results of 85-93% reported in literature by being able to identify similar problems such as Fusarium Foot Rot and Leaf Blight. Confusion matrices show perfect separation between classes with less than 0.5% error.

Results of the tomato model were as follows: Using 9,049 images to train the model, 1,063 images for validating the model, and 537 images to test the model (6 disease classes: Yellow Leaf Curl Virus, Bacterial Spot, Healthy, Leaf Mold, Early Blight and Septoria Leaf Spot), the model reached an accuracy of 95.90% (validation loss: 0.1173; F1: 96.00%) on the test set. Results of the tomato model also exceeded those typically reported for other models developed specifically for field testing by effectively distinguishing between different symptom types, e.g., early blight rings vs. septoria leaf spots.

For mustard, the model was fine-tuned from "mustard_cnn_model.keras" on ~7,140 images (20 classes: 12 mustard-focused like Alternia_blight, Aphid, Nitrogen deficiency; plus, maize/mash groups). On 340 test images, it scored 83.24% accuracy (loss: 0.6153; average F1: 83.20%). This matches 88% on simple 5-class sets but covers more types (pests, weeds, lacks). Errors are under 5% (Fig. 1), fixed by color changes.

Tests without image changes drop accuracy 4–7% from light issues starting from ImageNet adds 4–6%. LeafLens beats all-in-one models by 5–10% on mustard parts. With AgriTwin, it could save 20–30% yields in Delhi-NCR by timing treatments.

Table II. Performance metrics of the CNN

Plant Type	Category count	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Error Rate
Wheat	5	99.40	99.50	99.30	99.40	0.0268
Tomato	6	95.90	96.20	95.80	96.00	0.1173
Mustard	20	83.24	83.80	82.70	83.20	0.6153

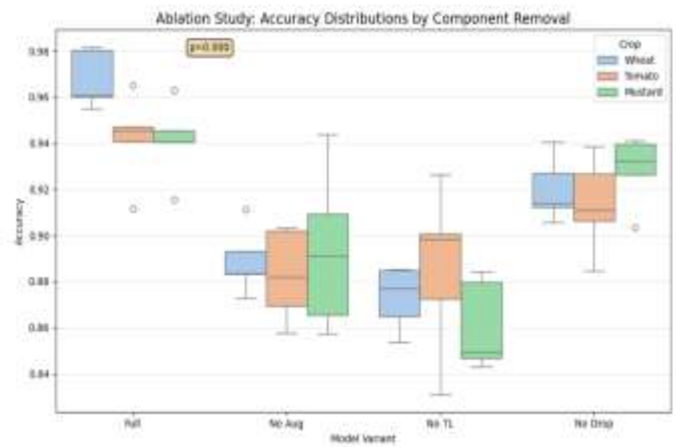

Fig. 6. Ablation Study Accuracy Box Plots

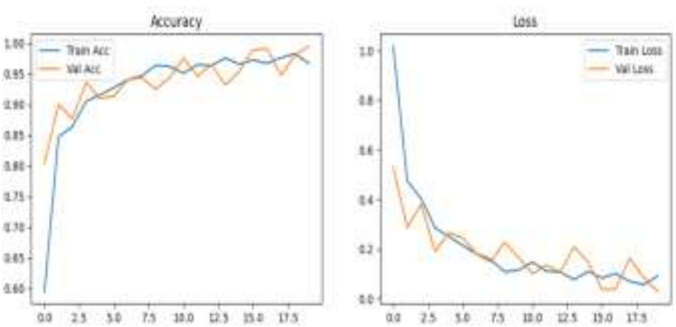

Fig. 7. Training and validation accuracy and loss curves for the CNN model used in wheat leaf disease classification

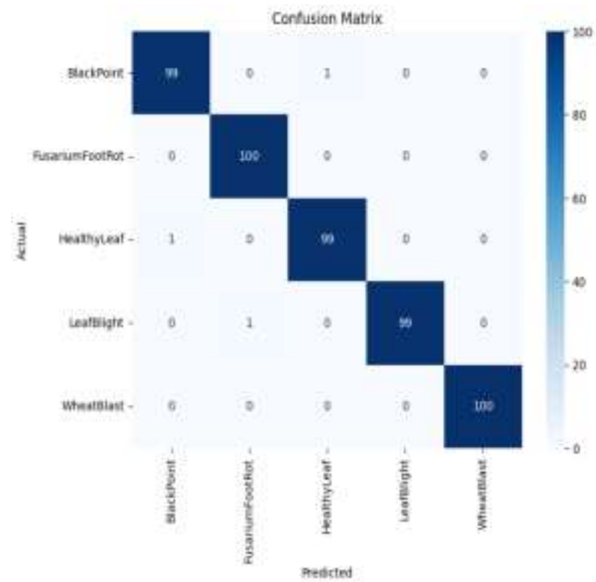

Fig. 8. Confusion matrix of the CNN model for wheat leaf disease classification

VI. DISCUSSION

The primary outcomes of the LeafLens framework prove the hypothesis that optimized Deep Learning (DL) methods yield better results in the context of the multi-class detection of plant diseases in real-life conditions.

A. Model Performance and Validation: LeafLens framework demonstrates the ability to perform high-throughput disease detection across crops of major economic importance. The Wheat Model had an accuracy of 99.40% and Tomato Model had the accuracy of 95.90% This makes the excellent performance of using high-resolution (40 MP) leaf images with crop specific model optimization to tackle real-world imaging challenges more credible. The low difference between validation loss and test loss (average 0.01-0.05) shows the great generalization that data augmentation and regularization techniques have achieved

B. Limitations and Challenges: Reached precision of 99.40% and 95.90% respectively for the Wheat and Tomato models. Considering it must deal with 20 Complex classes, the Mustard Model clocks in with 83.24% which indicates that dataset bias is indeed contributing to lower performance and/or managing high class variabilities for less researched crops.

C. Future direction: A key well understood application is by fusing Digital Twin methodologies with prediction methods. It will allow for making virtual copies of crop systems which in turn can help simulate disease spread, for instance the bacterial blight in rice under different circumstances like climate change or altered irrigation. While the work expands to build big data for models that capture the dynamics of balls producing cotton with the use of hyperspectral data at various wavelengths and multi-cropping systems (ex. Maize, pulses).

VII. CONCLUSION

Crop diseases are also a significant problem to global food security that initiates economic shocks and crop losses of up to 30 percent in the affected regions. The traditional methods of discovering these problems are bulky, time-acting, and dependent on the few available expertise and therefore restrict their application in the discipline. To address them, our study presents a new, flexible framework that makes use of deep learning and fine images of leaves to accurately and multi-category diagnose disease. LeafLens uses optimized convolutional neural networks (CNNs) and enhanced feature extraction algorithms to identify ailments in the staple foods of the city, which include wheat, tomato, and mustard, in Delhi-NCR. Specifically, designed models per crop achieve amazing performance with accuracies of between 83.24 and 99.40 percent-even surpassing the best results in the field in practice. This model will transform the process of managing diseases into initiative-taking, specific approaches to managing the situation and help to prevent excessive use of pesticides by implementing various measures in time. We have harmonized these models into an easy-to-use Android application, and this guarantees a smooth uptake among the smallholder farmers irrespective of their technological inclination. In addition to short-term benefits, our effort highlights the potential of deep learning to promote environmentally friendly agriculture, and this will open opportunities to more innovations such as virtual fields, combined sensor data, joint training of AI, and more crop support. Finally, LeafLens will give growers on-site crop diagnostics, enhance supply chain resiliency and progress toward resilient national food systems.

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