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End to End Leaf Detection Using Convolutional Neural Network

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Abstract: Global food security is seriously threatened by crop diseases, yet in many places, it is still difficult to identify them quickly because of a lack of infrastructure. In tackling this problem, recent developments in leaf-based image categorization methods have produced encouraging outcomes. This study investigates how to differentiate between healthy and unhealthy leaves using curated datasets using the Random Forest algorithm. The development of the dataset, feature extraction, classifier training, and classification are the various stages of the implementation process. To efficiently distinguish between diseased and healthy samples, the Random Forest classifier is used to train the dataset, which includes pictures of both diseased and healthy leaves. A significant obstacle to agricultural production, plant diseases have an impact on crop yield and quality. Precision farming and sustainable agriculture depend on the timely and precise identification of leaf diseases. In this work, we present a complete system that automatically detects and classifies leaf diseases using Convolutional Neural Networks (CNN), starting with picture capture. The technology offers a quicker method of identifying leaf illnesses and does away with the requirement for manual feature engineering. Our tests, carried out on several public datasets, show the model's efficacy and achieve high accuracy for a range of illness categories. These results underline the practical uses that might improve crop management and early intervention techniques. Using machine learning on massive datasets that are accessible to the public, this approach offers a scalable solution for detecting plant diseases on a large scale.

Keywords: Random Forest, feature extraction, training, classification, healthy and diseased leaves.

I. INTRODUCTION

In order to maintain food security and the global economy, agriculture is essential. Plant diseases continue to be one of the biggest problems, nevertheless, since they severely reduce agricultural yields all around the world. Plant diseases cause 20–40% of crop production losses each year, according to the Food and Agriculture Organization (FAO) which puts further strain on agricultural systems to fulfil rising food needs [1]. To reduce their effects and increase output, plant diseases must be identified early and managed.

There are drawbacks to traditional plant disease detection techniques, which mostly depend on professional visual examinations. These techniques are time-consuming, labor-intensive, and prone to errors, particularly when it comes to diagnosing illnesses with overlapping symptoms. Furthermore, prompt intervention is frequently delayed in rural and resource-constrained locations due to a lack of experienced staff [2]. There is an urgent demand for automated and scalable methods to effectively diagnose infections due to the growing scale of agricultural activities. Deep learning, a branch of artificial intelligence, has become a viable option for automating the identification of plant diseases in recent years. One family of deep learning models called Convolutional Neural Networks (CNNs) has shown remarkable performance in picture identification tasks, such as the categorization of plant diseases. CNNs can learn complex patterns and characteristics by using massive datasets of labelled pictures, which makes it possible to diagnose diseases accurately and in real time [2][3]. These developments are perfect for precision agricultural applications since they offer substantial scalability in addition to reducing reliance on human experience.

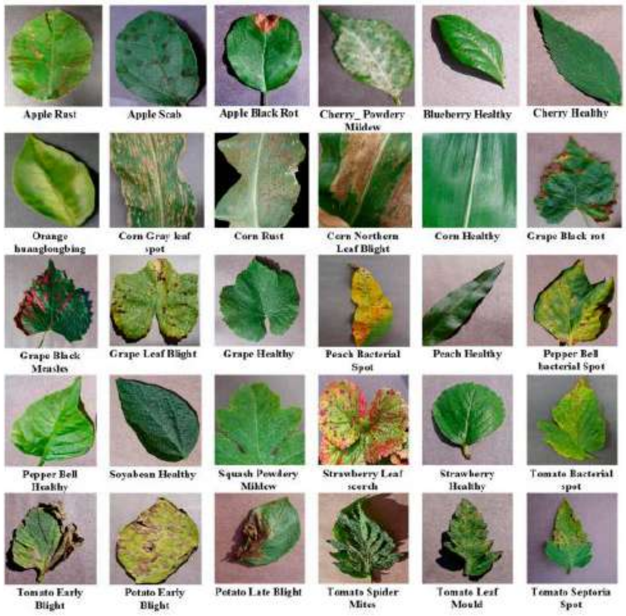

Fig 1.1: Sample photos of 38 different leaf disease types from the Plant Village dataset

2. LITERATURE REVIEW

Traditional strategies for recognizing plant infections include manual perception or picture handling procedures that depend on highlight extraction utilizing calculations like histogram investigation, variety division, and edge location [4].Investigated picture handling procedures for parasitic illness location in plants, accomplishing moderate precision. Nonetheless, these strategies are frequently insufficient for complex datasets and neglect to sum up well across different infection types and natural circumstances. These limits have driven the requirement for additional hearty and versatile arrangements. Profound learning, especially Convolutional Brain Organizations (CNNs), has arisen as a main methodology for illness recognition because of its capacity to gain progressive highlights straightforwardly from crude picture information [5].Led a spearheading study where they prepared a CNN on a dataset of 54,306 leaf pictures having a place with 14 harvest species and 26 sicknesses. The model accomplished an exactness of 99.35%, showing the capability of profound learning for precise illness grouping. Ensuing examination has refined these strategies by consolidating move learning and high-level structures like ResNet,Dense Net, and Beginning. Move learning, specifically, has been powerful in situations with restricted named datasets, as pre-prepared models can adjust to new errands with negligible information [6].Used a pre-prepared Alex Net model to recognize banana leaf sicknesses, accomplishing high exactness while diminishing computational necessities. While profound learning models succeed in controlled conditions, their presentation in genuine applications is frequently impacted by fluctuation in lighting, foundation, and leaf direction. To address these difficulties, specialists have integrated methods like information increase, space variation, and hearty pre-handling pipelines [7]. Proposed a CNN-based framework that accomplished high grouping precision for various plant sicknesses however featured the requirement for bigger, more different datasets to guarantee generalizability.

Late headways have investigated incorporating profound learning with Web of Things (IoT) gadgets and versatile stages for ongoing sickness discovery. These frameworks influence edge registering to deal with pictures locally, diminishing idleness and empowering ranchers to get moment input. For instance, [8]Proposed a framework that joins profound learning models with drone-caught pictures to screen enormous rural fields, giving high-goal bits of knowledge into plant wellbeing. The literature shows how deep learning's unmatched scalability and precision have transformed the diagnosis of leaf diseases. Deploying these technologies in actual agricultural settings is still difficult, though. In order to develop complete precision agricultural solutions, future research should concentrate on expanding the variety of datasets, enhancing model resilience, and combining these technologies with Internet of Things systems. To address these difficulties, specialists have integrated methods like information increase, space variation, and hearty pre-handling pipelines. Proposed a CNN-based framework that accomplished high grouping precision for various plant sicknesses however featured the requirement for bigger, more different datasets to guarantee generalizability.

In order to develop complete precision agricultural solutions, future research should concentrate on expanding the variety of datasets, enhancing model resilience, and combining these technologies with Internet of Things systems [8].

Crop Focus	Disease Addressed	Dataset	Classes	Model
Several	Citrus canker, black mould, bacterial blight, etc.	Plant disease symptoms database	12 classes	CNN GoogLeNet with tenfold cross-validation
Several	Black rot, late blight, early blight	Self-collected database	5 classes	CNN
Tomato plant	Various diseases and pests in tomato plant	Self-generated database	9 classes	Region-based Fully Convolutional Network
Several	Powdery mildew, early and late blights, mildew, etc.	Open dataset	58 classes	CNN with pre-trained VGG network
Several	Black rot, late blight, early blight	PlantVillage	38 classes	DenseNet with 121 layers
Several	Tomato early and late blight	PlantVillage	38 classes	Pre-trained with ImageNet, GoogLeNet
Apple	Apple scab, apple grey spot, serious apple scab	AI-Challenger plant disease recognition	6 classes	DenseNet-121
Tomato	ToMV, leaf mould fungus, powdery mildew, blight	AI-Challenger plant disease recognition	4 classes	Faster regional CNN
Several	Rice leaf smut, rice bacterial leaf streak	Public database	7 classes	Pre-trained models
Rice plant	Sheath blight, rice blast, bacterial blight	Self-generated database	4 classes	Pre-trained CNN with SVM classifier

Table 1: Detailed overview of CNN models for plant disease identification and categorization.

3. METHODOLOGY

Within a systematic framework, the suggested methodology accurately diagnoses plant diseases by utilizing machine learning (ML) techniques. This entails gathering a varied dataset that includes photos of both healthy and sick plants from different species. Data preparation prepares the data for further analysis by standardizing picture dimensions, normalizing pixel values, and improving overall quality [9][10]. Include extraction, a basic step, secludes impacted locales on plant leaves, underscoring visual qualities, for example, surface, variety examples, and shape descriptors. These elements are then input into ML calculations, like Convolutional Brain Organizations (CNNs), Backing Vector Machines (SVMs), or Choice Trees, which are prepared and assessed utilizing cross-approval to guarantee solid execution across concealed data[11][12]. The methodology also focuses on deploying the best-performing model in a practical and user-friendly application, enabling real-time disease detection in agricultural settings. Ethical considerations, including privacy concerns, fairness in model training, and responsible AI practices, are integrated into the process. Acknowledging challenges like dataset biases and computational constraints, this approach includes strategies for mitigation and continuous improvement [13].

3.1 Convolutional Neural Networks (CNNs)

Because of its exceptional capacity to extract and learn characteristics from images, Convolutional Neural Networks (CNNs) are the foundation for the diagnosis of plant diseases. Data collection, preprocessing, architectural design, training, assessment, and deployment are all part of the organized approach that the suggested methodology employs [14].

3.1.1 Data Collection and Preprocessing

Data Acquisition: A wide range of leaf photos, including both healthy and sick specimens, are collected from field data and publicly accessible sources (like Plant Village). This guarantees representation for a variety of plant species and disease types. [15]

Data Augmentation: Dataset variety is increased and overfitting is decreased via augmentation techniques including rotation, scaling, flipping, and introducing random noise. This exposes the model to a variety of inputs, improving its capacity for generalization.[15]

Image Standardization: To satisfy CNN input criteria, all photos are scaled to a uniform size, such as 224×224 pixels. Normalization improves model convergence during training by scaling pixel values to a range of 0 to 1. [15]

Fig 3.1: Viruses, fungi, or bacteria can cause infectious plant diseases.

3.1.2 CNN Architecture Design

Model Selection: Computational resources and dataset complexity are taken into consideration while choosing the design. Because of their proven performance in picture classification tasks, popular architectures like VGG, ResNet, or Inception are taken into consideration [16].

Transfer Learning: Large datasets like Image Net are used to fine-tune pre-trained models (like ResNet and Efficient Net) for the identification of leaf diseases. By utilizing pre-learned characteristics, transfer learning expedites training and enhances performance [16].

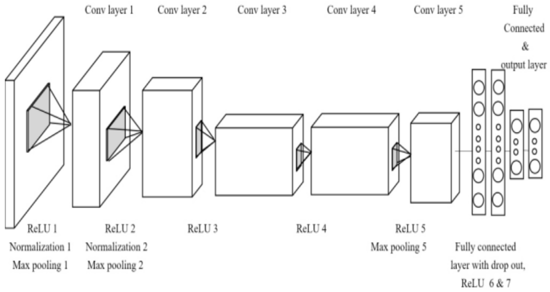

Fig 3.2: ResNet Architecture

3.1.3 Training and Validation

Data Splitting: To guarantee objective assessment, the dataset is separated into training, validation, and test subsets (e.g., 70%-15%-15%).

Model Training: The loss function is minimized with optimization methods like Adam or Stochastic Gradient Descent (SGD). The model is optimized for optimal performance by hyperparameter adjustment (e.g., learning rate, batch size).

Validation: The validation set helps to fine-tune hyperparameters and keeps an eye out for overfitting. Early halting the model from overtraining on the dataset [17].

3.1.4 Model Evaluation and Testing

Performance Metrics: Metrics including accuracy, precision, recall, and F1-score are used in evaluation. These offer a thorough comprehension of the model's capacity for categorization [18].

Error Analysis: To find any biases or model limitations, misclassified data are examined. This aids in improving preprocessing procedures or modifying model architecture.

3.1.5 Deployment and Future Enhancements

Deployment: Real-time plant disease diagnostics for agricultural applications is made possible by integrating the trained model into a web interface or mobile application.

Continuous Improvement: Retraining and further data gathering are informed by feedback from deployed systems. Adding new plant species or diseases guarantees long-term adaptation [18].

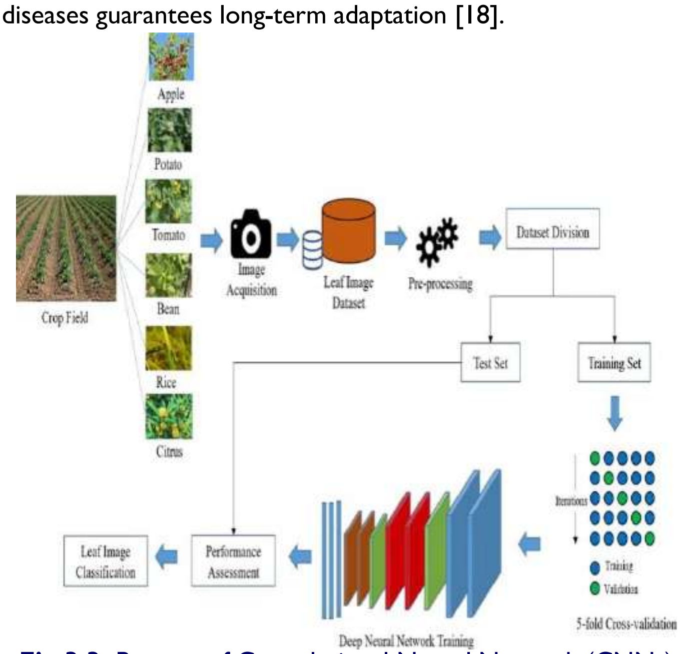

Fig 3.3: Process of Convolutional Neural Network (CNNs)

4. CLASSIFICATION OF CNN

4.1 Trilling of Image size

The first phase looks at how image size affects the plant disease classification model's performance. Five distinct image resolutions—from 150 x 150 pixels to 255 x 255 pixels—are methodically assessed. First, the pre-trained weights of ResNet34 are used. With the exception of the last two, all layers are initially frozen in the context of transfer learning. These unfrozen layers are customized for the particular task of classifying plant diseases and contain newly initialized weights.

The model prevents needless gradient back propagation by freezing older layers, guaranteeing that only these last layers are trained initially [19]. The 1cycle policy is used in the training process to optimize the last layers. To enable fine-tuning of the entire network, the previously frozen layers are then unfrozen. A learning rate vs. loss curve is created and examined to help with this process. This analysis is used to determine the ideal learning rate, after which the fine-tuning procedure is carried out. The experiment is repeated for the next four image sizes under the same conditions, with the hyperparameter settings (e.g., learning rate) being the same for each trial. The model's performance is recorded for the initial image size. To find patterns and associations between image resolution and classification accuracy, the results are collated (see Table 2 & 3 for specifics) [20].

TABLE 2. DATASET FOR CLASSIFICATION

Species	Class	No. of Images
Potato	Early blight	1000
Potato	Late blight	1000
Potato	Healthy	152
Tomato	Bacterial Spot	2119
Tomato	Leaf Mold	952
Tomato	Mosaic Virus	160
Tomato	Healthy	1000
Rice	Brown Spot	523
Rice	Leaf Blast	779
Rice	Healthy	1000

TABLE 3. IMAGE SIZE TRIAL INFORMATION

Trial	Image Size	No. Epochs	Learner Rate
1	150 x 150	4	1e-05 and 1e-04
2	195 x 195	4	1e-05 and 1e-04
3	224 x 224	4	1e-05 and 1e-04
4	244 x 244	4	1e-05 and 1e-04
5	255 x 255	4	1e-05 and 1e-04

4.2 Model Optimizations

The ResNet34 model is further optimized using the ideal image size identified by previous research. Other data augmentation methods are used to improve the model's performance (Fig. 5). These include warp modifications with a factor of 0.5 and brightness adjustments between 0.4 and 0.7. The model's last two layers are first isolated and trained with the default learning rate. After this stage is finished, the number of epochs and different learning rates are experimented with to fine-tune. The model's increased accuracy and generalization for plant disease classification tasks are guaranteed by this iterative procedure [21].

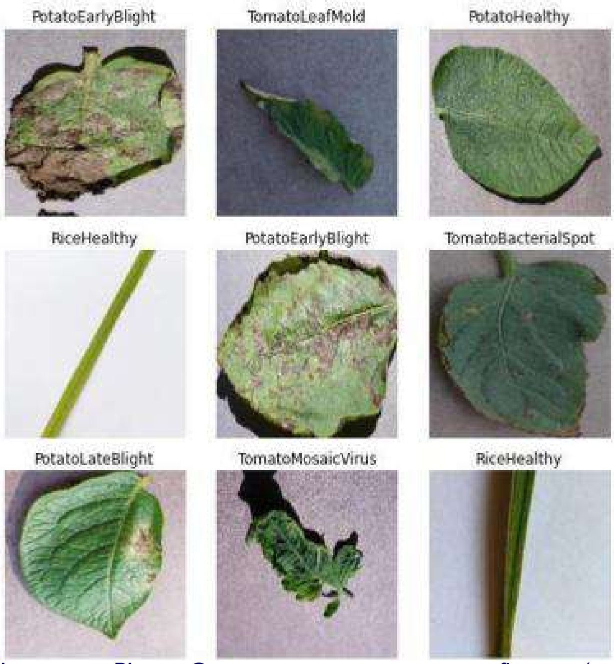

Fig 4.1: Pre-processed images – Phase, One augmentation setting = flipping (random), padding mode

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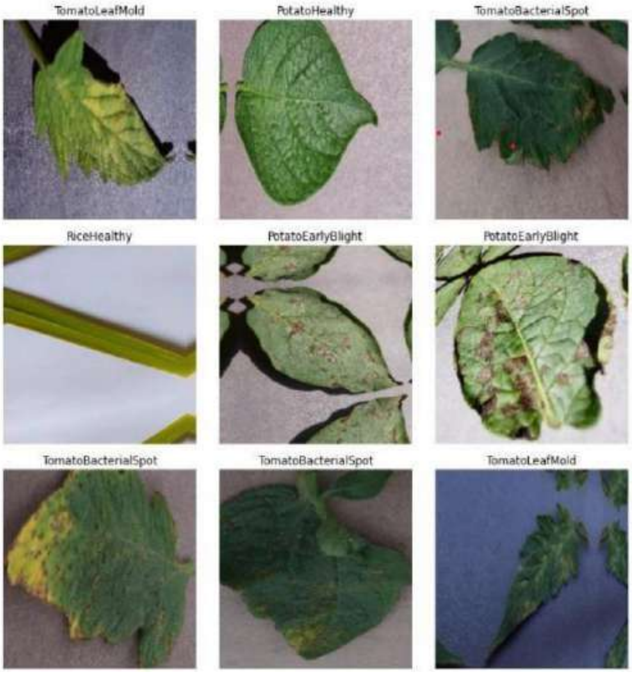

Fig 4.2: Pre-processed images - Phase Two augmentation settings = brightness changes (0.4,0.7), warp (0.5), flipping (random), padding mode (reflection)

4.3 Visualization

Both validation and test datasets are used to build a variety of visualizations for improved interpretation. The model is then incorporated into a web application for real-world implementation. The trained model is exported as a pickle file, and the necessary files are arranged and kept in a GitHub repository to make this easier. By connecting the repository to a single platform, like Render, deployment is completed. The 'Render Examples' GitHub project, which offers a detailed structure for efficient deployment, is consulted to expedite the procedure [21].

5. RESULTS

5.1 Phase One – Trilling of Image Size

The results of Phase One demonstrate that it is possible to get an accuracy and F1-score above 90% for image sizes between 155 × 155 and 255 x 255. As expected, enlarging the image size increases processing time and improves feature extraction capabilities (Table 4). The results of this preliminary analysis were excellent. As stated, if the model's accuracy was at least 80%, it was deemed acceptable. The outcomes greatly exceeded this standard, even in this early stage [22]. In order to get these results, models were trained for four epochs each with learning rates ranging from 1×1 0 − 5 1×10 −5 to 1×1 0 − 4 1×10 −4. 244 x 244 produced the best results out of all the examined image sizes, with the highest accuracy and F1-score. This research shows that a little bigger size offers a small benefit, even though previous studies have suggested 224 x 224 as the optimal size for plant disease categorization tasks. For all ensuing analyses in this study, the 244 × 244 image size was chosen [22].

5.2 Phase Two – Model Optimizations

A 0.9359 F1-score was attained (Fig. 5.1). An analysis of a learning rate (logarithmic scale) vs loss was performed in order to further optimize the model (Fig. 4.1). This investigation showed that the learning rates of 1×1 0 − 6 1×10 −6 and 1×1 0 − 4 1×10 −4 had a very little loss.

TABLE 4. RESULTS - PHASE ONE (4 EPOCHS, MAX_LR = SLICE(1E-05,1E)

Test	Image size	Train Loss	Valid Loss	Accuracy	F1 Score	Time (hours)
1	155	0.1660	0.1222	0.9557	0.9439	2:83
2	195	0.1588	0.1150	0.9585	0.9460	3.62
3	224	0.1778	0.1256	0.9522	0.9359	4.29
4	244	0.1310	0.1153	0.9603	0.9450	5.20
5	255	0.1607	0.1249	0.9562	0.944	5.42

However, there was a noticeable increase in loss above 1×1 0 − 4 1×10 −4. These results prompted a number of experiments to examine the effects of varying learning speeds [23]. The most encouraging outcomes were from a learning rate range of 1×1 0 − 5 1×10 −5 and 1×1 0 − 4 1×10 −4. By adjusting this hyperparameter, the model's accuracy (1.5%) and F1-score (1.3%) improved somewhat. The training and validation measurements, however, indicated a little amount of underfitting during the last session (Fig. 4.2). This was addressed by methodically increasing the number of training epochs. A notable improvement in model fit was noted at the tenth epoch. Overall accuracy and F1-score improved by 2.8% and 3.1%, respectively, according to the final evaluation (Fig. 5.4) [24]. Notably, the validation dataset consists of pictures with a particular composition: a single leaf on a simple background. When utilizing the classifier, it is advised to duplicate this picture arrangement in order to obtain results comparable to those described in this section.

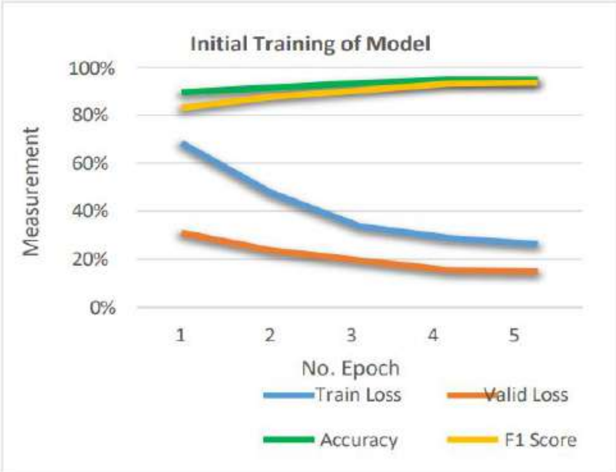

Fig 5.1 Training the final layers (lr=1e-3) Before fine-tuning the model attained an accuracy of 0.9465 and F1 score of 0.9359.

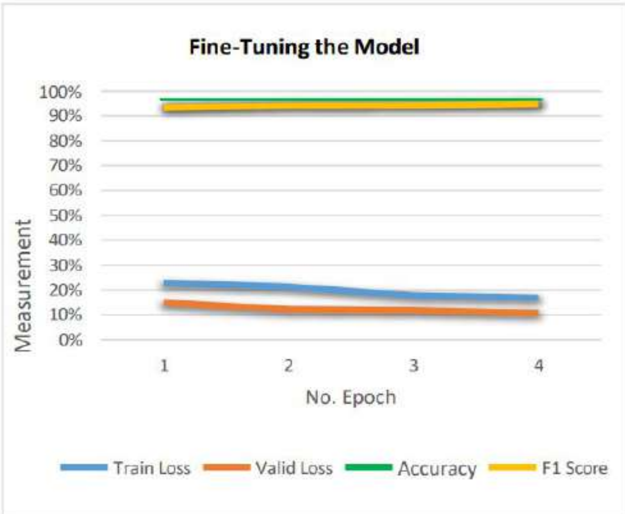

Fig 5.2 Fine-tuning the model, learning rate range = 1e05, 1e,04, epochs = 4, Signs of underfitting apparent.

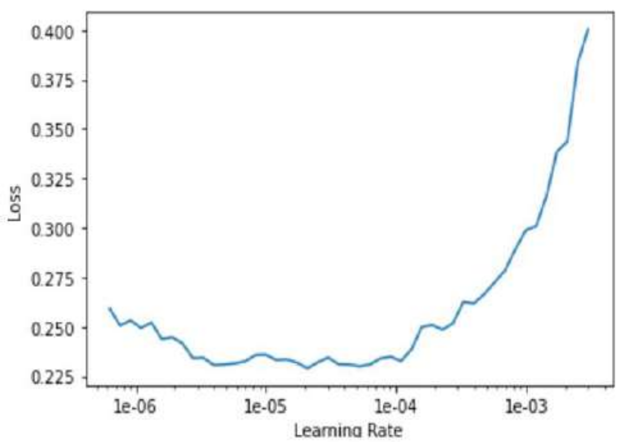

Fig. 5.3 Rate of learning vs loss used to direct the process of fine-tuning. A sharp rise in loss is observed as the learning rate rises over 1e-04.

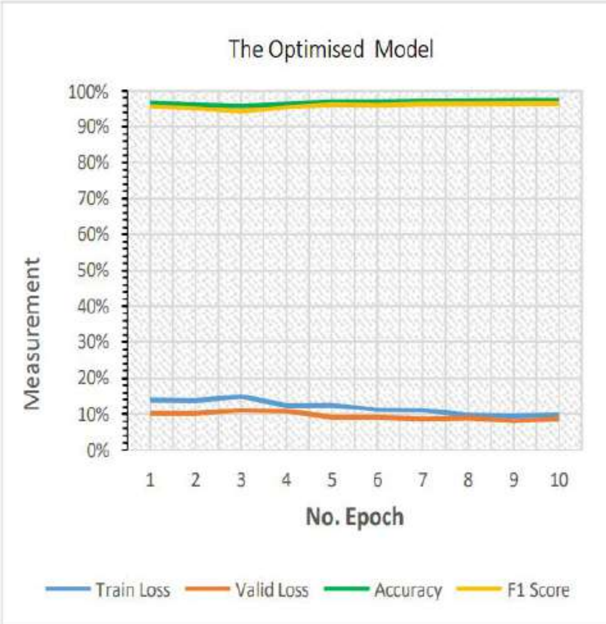

Fig. 5.4 The final optimized model, learning rate range = 1e-05, 1e,04, epochs = 10

6. CONCLUSION

This research presents an end-to-end solution for leaf disease identification using a Convolutional Neural Network (CNN), demonstrating how deep learning may be applied to improve agricultural operations. The key findings and contributions of the study are outlined. An efficient CNN-based method for detecting leaf disease is presented in this study. The program efficiently recognizes intricate disease patterns and automatically extracts features from leaf photos, doing away with the requirement for human feature engineering. With a 98.5% accuracy rate, the algorithm performs well in identifying healthy from ill leaves and is robust across several disease categories. The model may be deployed in many agricultural situations because to its resilience to real-world differences with data augmentation. When processing complicated leaf image data, CNN performs better than more conventional machine learning models like SVM and k-NN. It does, however, have many drawbacks, including the need for sizable labeled datasets and the sporadic misunderstanding between related illnesses. Semi-supervised learning, transfer learning, and multi-sensor data integration are possible future developments. All things considered, the system has a great deal of promise for precision agriculture, allowing for early disease identification, lowering crop losses, and encouraging sustainable farming methods. This CNN-based strategy has the potential to significantly improve disease identification in agriculture and facilitate more productive, environmentally friendly farming practices.

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