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Image-based Mangifera Indica Leaf Disease Detection using Transfer Learning for Deep Learning Methods

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Abstract

Mangifera Indica, ordinarily known as mango, comes from a large tree. The leaf of the mango tree has human health benefits; the mango leaf extract is used for curing various diseases, including patients with cancer and diabetes. It also has an anti-oxidant and anti-microbial biological activity. Leaf disease, including fungal disease, is a severe security threat to nourishment and food paramours. Sometimes, it leads to decreased productivity and a huge loss for the farmers. Observing and determining whether a leaf is infected through the naked eye is unreliable and inconsistent. Technology advancement has helped agriculture people in several ways, and deep learning methods are a promising approach to spotting leaf diseases with the best accuracy. A mango leaf disease detection model is developed with the pre-trained model of ResNet18, which is used in transfer learning along with the Fast.ai framework. Around 2000 images were used, including images of healthy and infected leaves. The trained model achieved an accuracy of 99.88% and performed well compared to the existing state-of-the-art methods.

Key Words: Mango Leaf Disease, Image Classification, ResNet, Transfer Learning, Fast.ai.

1 Introduction

Agriculture is an important sector and source of living hoods in India. It also generates many employments in the country and contributes around 20% of its share in the country's GDP. More than 50% of the workforce is employed in agriculture. The topographies, soil of India, and weather are diverse. Therefore, an extensive range of crops is cultivated in India. India has about 1500 mango varieties and unique tastes & flavors. Andhra Pradesh state is the major contributor and is located in the mango name Banaganapalli. The mango leaf is a class of flowering plants and belongs to the plant family Anacardiaceae. Mangifera Indica leaf is dark green and grows up to 30 meters with a circumference of 3.7 m. Even though there are many advantages to growing a mango tree and extracting the benefits from the fruit, leaf, and wood, there are still disadvantages if the trees are not maintained properly. Unfortunately, if there is an outbreak of disease, they are at risk, including the welfare and livelihood of farmers, food supply, and nutrition security of the nation [6].

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The different fungal leaf diseases include Anthracnose, Dieback, Bacterial canker, Algal leaf spot, Green algae, etc. Treating fungal diseases is done using a fungicide. All susceptible parts of the tree should be thoroughly coated with the fungicide before infection occurs. Dry brown spots on the leaves of a mango tree are an initial pointer of the disease anthracnose. It is caused by a fungus identified as Colletotrichum gleosporioides. Plant Pathologists and farmers have traditionally used their eyes to detect diseases and make decisions based on their experiences. It is only sometimes accurate and is often skewed because many diseases appear to be the same at the early stages [20].

Moreover, their experiences should be passed on from generation to generation. As a result of this approach, pesticides were used excessively, increasing production costs and reducing the interest of farmers and buyers because of pesticides used. Sometimes, the rural agri-business is lost, leading to the wastage of fruits. Considering these reasons, these problems can be technically addressed using a reliable database and disease detectors and are needed to assist farmers, especially those young and employed in agriculture in all kinds of farming [7]. Recent advances in computer vision enable this, using the latest deep-learning approaches. It is also imperative that an early disease detection system should be implemented to protect leaves, fruits, and wood.

Numerous studies have been conducted on this topic in the past by several researchers to improve and also to adopt new technologies in horticulture. Various plant datasets are available online and widely used to train and test the proposed models. Convolutional Neural Network (CNN) is a standard method practiced by most researchers that need a lot of data to be trained. Deep CNN, Multi-layer CNN, and pre-trained models like AlexNet, DenseNet, GoogleNet, SqueezeNet, and ResNet are some of the available methods used by many researchers [5]. The Fast.ai framework is integrated with the pre-trained Resnet18 model in the proposed model. The framework presented here is intended to increase the accuracy of the model. The remaining sections are as follows: Section II summarises the literature review; Section III explains the technique and how the proposed model work; Section IV displays the experimental results; it analyses the obtained result; and finally, Section V concludes the effort made to showcase the best result.

2 Related Work

Numerous studies have identified and classified citrus plant leaf diseases in different environments [1]. The authors used various aspects of disease identification methods, including image processing, and explored the best possibilities. Neural network disease recognition and characterization techniques with leaf images are modeled and classified [2]. In the research of identifying the four cucumber illnesses are recognized from the leaves. All real-time images are categorized using the Deep Convolutional Neural Network (DCNN)[3]. For the recognition and characterization of plant leaves, ferentinos presented a VGG convolutional neural network [4], and the authors compared the healthy and unhealthy pictures. The outcome demonstrated the correctness of the deep learning approach, which was validated on a large dataset. Tested with four distinct deep convolutional network designs for disease classification from images, including ResNet, Inception V4, VGG 16, and Dense Nets [5]. The images are from the plant village dataset, consisting of 38 diseased leaf classes & 14 healthy leaf classes.The DenseNets network achieves better classification results and takes less time to compute. Research using deep learning approaches in plant pathology discusses several difficulties and parameters influencing the network's efficiency. Finally, the findings are validated with the convolutional neural network's performance with the help of images from the Digipathos repository [6].

Various research aspect of deep learning in agriculture was introduced by Kamilaris et al., and it covers computer vision theories, related challenges, applications, and assessment-related metrics [7]. When dealing with deep learning ideas, the amount and diversity of the images in the database are significant considerations [8]. As a result, Barbedo et al. have raised several concerns and obstacles in categorizing plant diseases. The author tested twelve different plants, each with its characteristics and illnesses. An enhanced Local binary pattern is used to recognize images, and the method divides the pictures into sub-regions [9]. Computer vision principles and methodologies are also used for plant leaf identification and categorization. The benefits and drawbacks of the various studies were explored separately [10]. Picon et al. employed DCNN to categorize three fungal infections affecting wheat plants. The image data set in the proposed approach were acquired over three years in a real-time context from two locations [11].

Zhang et al. introduced GoogLeNet and Cifar10 networks for disease detection from maize leaf pictures. In classifying nine varieties of maize leaves, the suggested models outperform other networks, such as VGG and AlexNet [12]. DCNN is used to classify ten different forms of rice leave disease from roughly 500 images with healthy and infected images [13]. To improve classification accuracy, the authors used a 10-fold cross-validation technique. Yolo algorithms were used to detect objects with the help of the dark net [14].A smartphone application that used Generative Adversarial Networks (GANs) and CNN to identify illnesses from plant leaf images was introduced [15]. Durmus et al. employed the AlexNet and then SqueezeNet deep learning networks for categorizing plant leaf diseases and the images related to the tomato leaf [16].

Transfer Learning is engaged in detecting grapes and mangoes as part of the research in precision farming using deep learning approaches. A pre-trained CNN is used to model the automatic feature extraction and classification. Matlab is used to deploy, and the obtained accuracy is around 99% for grapes leaves and 89% for mango leaves. The same was made as an application for farmers' use and accessible on smartphones [17]. Metaheuristic enabled approach is followed for identifying botanical leaf diseases using CNN, and several optimization algorithms are used to improve the accuracy[18]. Classification of anthracnose disease in mango leaf is classified with the multilayer CNN from 1070 images from the region J&K dataset [19]. Novel Segmentation and Vein Pattern techniques are applied to recognize and classify mango leaf diseases [20]. However, several authors have investigated closely identifying the mango leaf disease; the performance still needs improvement. Therefore, the Fast.ai framework is used with the pre-trained model of Resnet18.

An innovative approach using deep learning for automated detection and classification of diseases in paddy plants using integrated computer vision techniques was introduced and the system accurately identifies common diseases in Indian rice fields. The proposed method achieves high validation accuracy and also in enhancing crop protection and agricultural productivity. The novelty in the combination of a SVM classifier and CNN networks for disease recognition and classification, results in an accuracy of 0.9145 [21]. Efficiently identifying the diseases in rice plants is important for global food security. Transfer learning with pre-trained CNN models is used to automatically detect rice leaf diseases. InceptionV3 model's exceptional accuracy of 92.64% is outperforming when compared with the other computational techniques in plant disease management [22].

A novel framework that combines the strengths of both machine learning and deep learning techniques to detect diseases effectively is by integrating pre-trained deep learning models and various machine learning classifiers, the approach achieves high accuracy levels of 87.55%. The study demonstrates the practicality of the framework using real-time data on tomato early blight disease. The proposed method offers a valuable tool for farmers to detect and treat diseases early, preventing crop deterioration and economic losses [23]. Class imbalance in plant disease datasets is highlighted. Techniques like CLAHE, image sharpening and GAN-based resampling notably enhanced accuracy. Using ResNet-50, the approach achieves an impressive average accuracy of 97.69%. The study provides a practical workflow for disease detection systems, adaptable to specific needs, contributing to more effective plant disease management and food security [24].

Hybrid Random Forest Multiclass SVM (HRF - MCSVM) enhances computation accuracy through pre - processing and spatial fuzzy C-Means segmentation. The study uses a comprehensive dataset of 54,303 leaf images, both healthy and diseased. Performance metrics like accuracy, F-measure, specificity, sensitivity, and recall value are employed to evaluate the system's effectiveness. The HRF-MCSVM method is compared with existing techniques, showcasing its efficiency in plant disease detection [25].Disease attacks lead to significant agricultural losses worldwide. The imaging technology and cloud-based data analysis is used for accurate and rapid disease identification. The system not only diagnoses diseases but also includes preventive measures. It offers a practical and efficient solution to enhance productivity in both agriculture and irrigation [26].

3 Materials and Methods

The proposed mango leaf disease detection model is built using the Fast.ai framework and Resnet18. The Fast.ai, along with the Resnet18 pre-trained model, allows for classifying infected and healthy leaves. Image acquisition, Image pre-processing, segregation of dataset into training and testing dataset, then finding the optimal learning rate for the model based on the training data and training the model are the key five steps followed in the proposed model, and the same is depicted in the below flowchart represented in Figure 1.

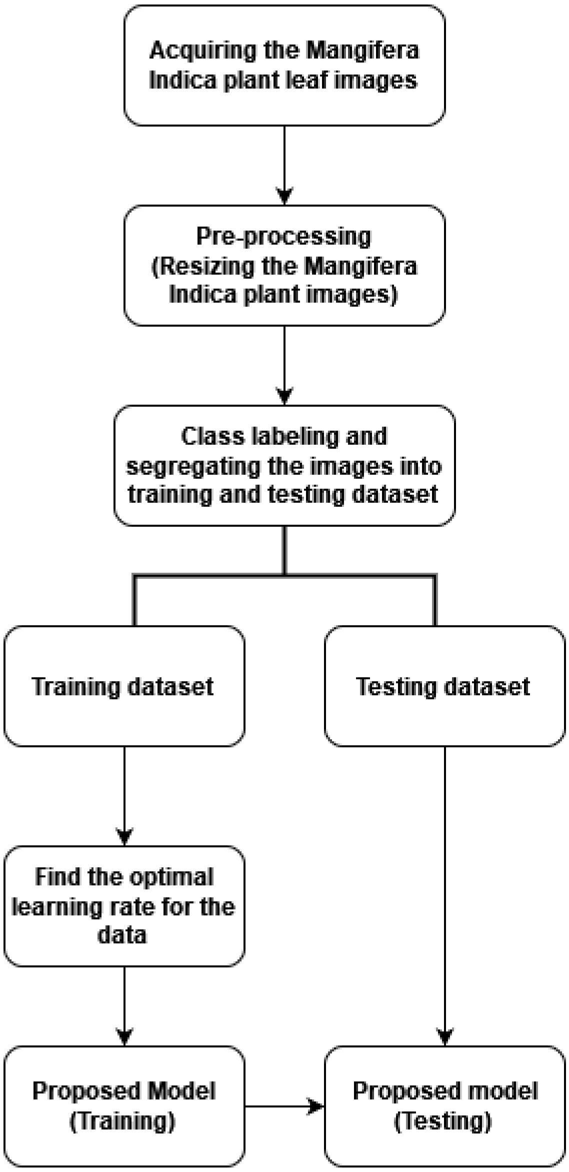

Figure 1: Proposed Mangifera Indica Leaf Disease Detection model

Algorithm

1. Collect the images of healthy and infected mango leaves available in the dataset.
2. Pre-process the images by performing contrast enhancement using the histogram equalization method

and resizing using the central square crop method.

3. Label the image classes and segregate the images as diseased or infected.
4. Sort the images into training and testing datasets based on the class label.
5. Use training images to find the optimal learning rate for training the Fast.ai model.
6. Train the proposed transfer learning model with the pre-trained Resnet18 model.
7. Validate the proposed model's performance on the testing data and compare the results with other modern approaches.

3.1 Dataset

The proposed detection model uses datasets from two different database repositories, namely, a database of leaf images: from mendeley data available in Kaggle and mango plant leaf images from the plant village dataset. Both of the datasets contain mango leaves. From the dataset, sample mango leaf pictures, both healthy and infected images are shown in figure 2. Around 2000 images are considered.

Figure 2: Sample Healthy and Infected Images from the dataset

All images are labeled to their corresponding classes based on the category. Figure 3 describes the distribution of images after they have been categorized.

3.2 Pre-processing of images

The training and testing images were initially pre-processed for contrast enhancement and resizing to a 128*128 dimension. For the complete set of databases, two main techniques, histogram equalization used for contrast enhancement and central square crop, are used for resizing the images. Using the histogram of an image and the histogram equalization method given by eq. (1) The pictures' contrast is enhanced by allocating a

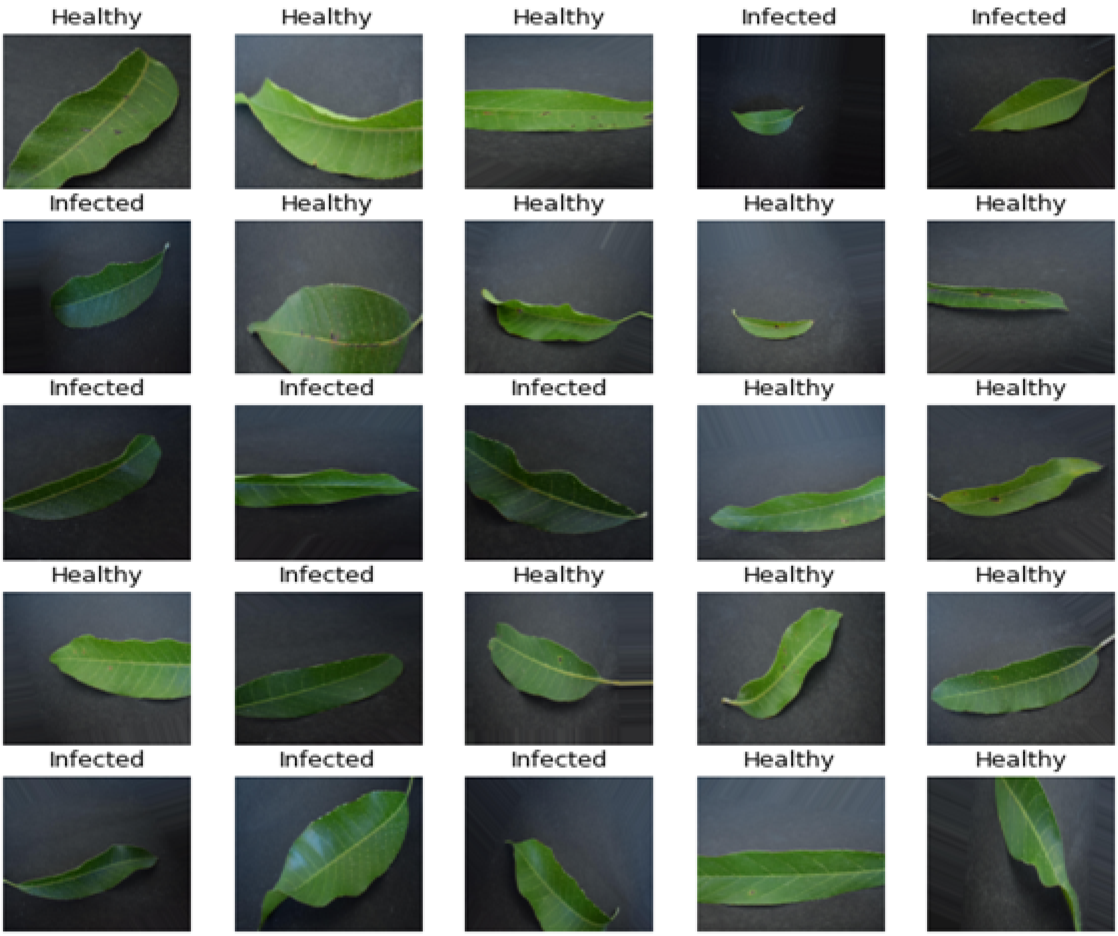

Figure 3: Categorization of Images of different mango leaves

homogeneous intensity value to every pixel. The pictures are then resized employing the central square crop technique described by eq (2).

$$H(P_{(x,y)}) = round\frac{(f_{cdf}(P_{(x,y)}) - f_{cdf_{min}}}{(RC) - f_{cdf}} \times L - 1 \tag{1}$$

where fcdf is the cumulative frequency of the grey level, f(cdfmin) is the minimum value of the cumulative distribution function, fcdf (p((x,y))) is the intensity of the current pixel, R and C are the product of the number of pixels in rows and columns, and L is the amount of intensities.

$$LeafImageResizing(img, new\_h, new\_w) \tag{2}$$

3.3 Tools and Framework

The Fast.ai framework is used to create the models. The framework is based on PyTorch-based architecture, which is used for object identification, picture segmentation, and image classification. It supports faster computing with the help of its built-in data cleansing functionality and widgets. Another of its primary merits is its user-friendly approach, which makes troubleshooting much more effortless. Fast.ai has a visual component that includes all the operations needed to construct a database and train vision-based models. The module named vision. data has a distinctive utility function called ImageDataLoaders that accepts input from.csv files, image directories, picture lists, and other sources. The input can then be divided into training, validation, and testing (if necessary). Another function provided by vision.data is DataBunch, which organizes the data for training into groups. These batches are sent to the training model in the order they were received.

Further sub-modules, such as vision.transform, and vision.learn, provide methods for transforming/augmenting and training data accordingly. The DataBunch approach facilitates the transformation from data blocks to training system models by allowing quick operations. After receiving data, 'vision.learner' provides all the functions needed to train the model. As previously stated, the backbone architecture for transfer learning in this research is Resnet-18. The model layers are trained repeatedly, utilizing various epochs and suitable model parameters on top of Resnet-18's convolutional foundation layers. The 'lr find' approach determines the appropriate learning rate. Two methods provided by Fast.ai for efficiently monitoring validation and training losses with the set learning rate are Callbacks and EarlyStopping. For a given number of training iterations, learning rates fluctuate evenly. The 'fit one cycle' strategy is used for this. Stochastic Gradient Descent is used to train and fine-tune the layers precisely. Fast.ai also has a feature that allows you to freeze and unfreeze layers and keep gradient descent under grasp. A lot of hyperparameter tuning is performed during model training to find the best classification accuracy. Fast.ai data pipeline architecture is represented in Fig 4.

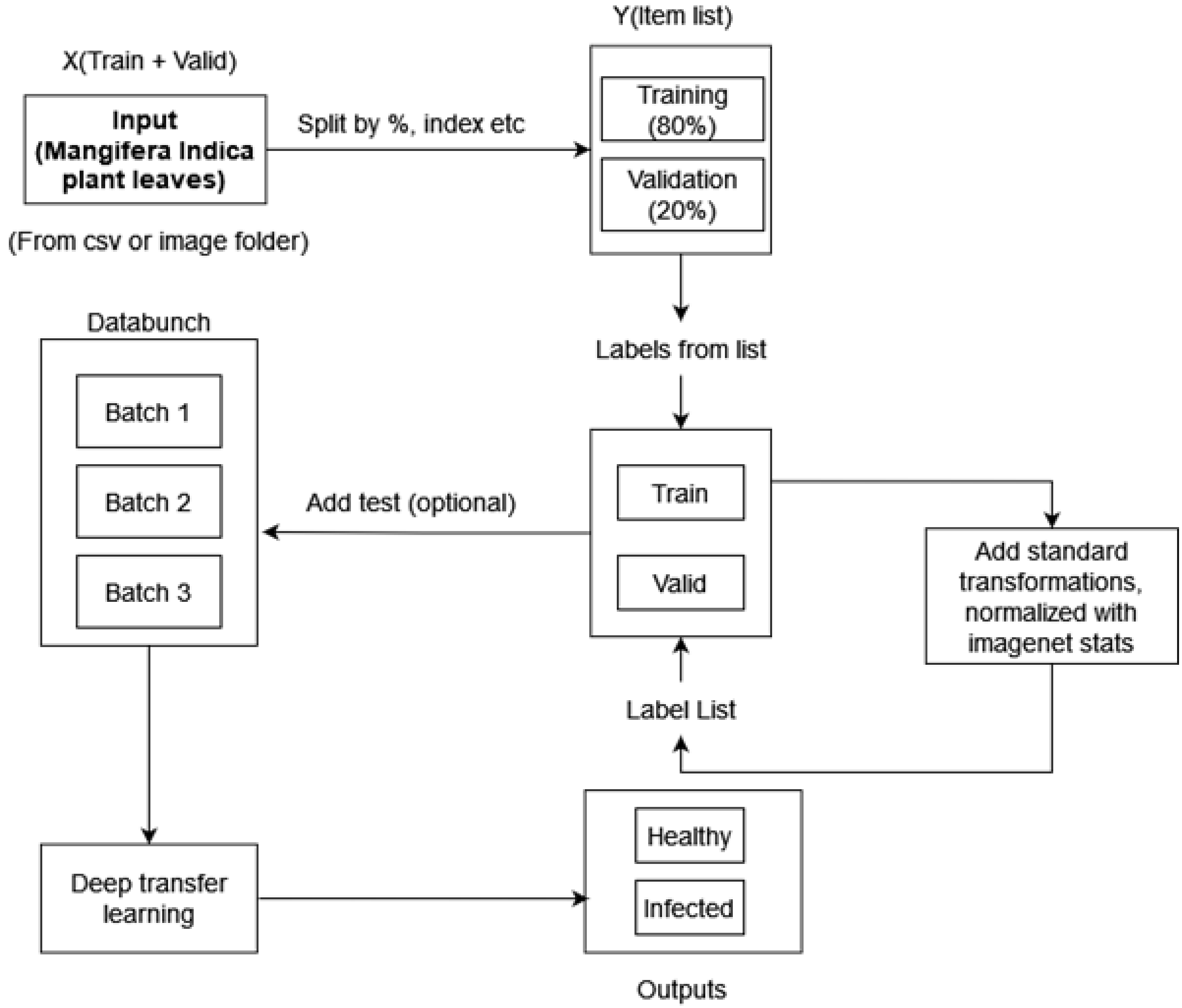

Figure 4: Fast.ai data pipeline Architecture

FastAi combined with resnet-18 to predict plant diseases specifically in mango plant leaves. The proposed model solves the prevailing problem in existing models of overfitting and class imbalance which arises due the small size of the dataset. Dynamic Quantization is performed on the Resnet-18 model which significantly reduced the processing time of the model when compared with the existing models.

3.4 Training Architecture

The training architecture for classifying images of leaves involves a careful orchestrated process. A test image is taken as input, which is then processed on the user's machine to determine if it depicts a healthy or infected leaf. The entire flow of this training model is visually depicted in Figure 5, providing a clear overview of the process. To ensure uniformity in data, a pre-processing step is initially undertaken, standardizing all images to possess identical dimensions and contrast levels. It begins with the setup of a data pipeline using a DataBlock, a component that defines how the data will be processed and prepared for training. This pipeline involves two main data blocks: ImageBlock for handling images and CategoryBlock for dealing with categorical labels.

A random splitter is used to divide the dataset into training and validation sets, allocating 20% of the data for validation to assess the model's performance. Labels are extracted from the file paths using a function named parent_label, likely indicating that the images are organized in folders by class. Additionally, the images are resized to a uniform size of 128 X 128 pixels using the Resize transformation. Next, the data loaders are created, which facilitate the loading of data in batches during training. The chosen batch size is 64, and data loading is conducted in the main process without any additional worker processes.

The determination of an optimal learning rate is a pivotal step in training the Fast.ai model. The learning rate is composed of two crucial components: lr_steep, representing the slope of the curve obtained during training, and lr_min, indicating the minimum point on the curve. Lr_steep that came out to be around 0.00019 is selected as the learning rate that will be employed to train the Fast.ai model. Leveraging a transfer learning approach, the model capitalizes on a pre-trained ResNet-18 architecture, known for its effectiveness in image classification tasks. The training cycle iterates through four epochs to refine the model's performance. Following this training phase, the model undergoes testing on a separate dataset. This test dataset, distinct from the training data, classifies input images as either healthy or infected leaves based on the knowledge acquired during training.

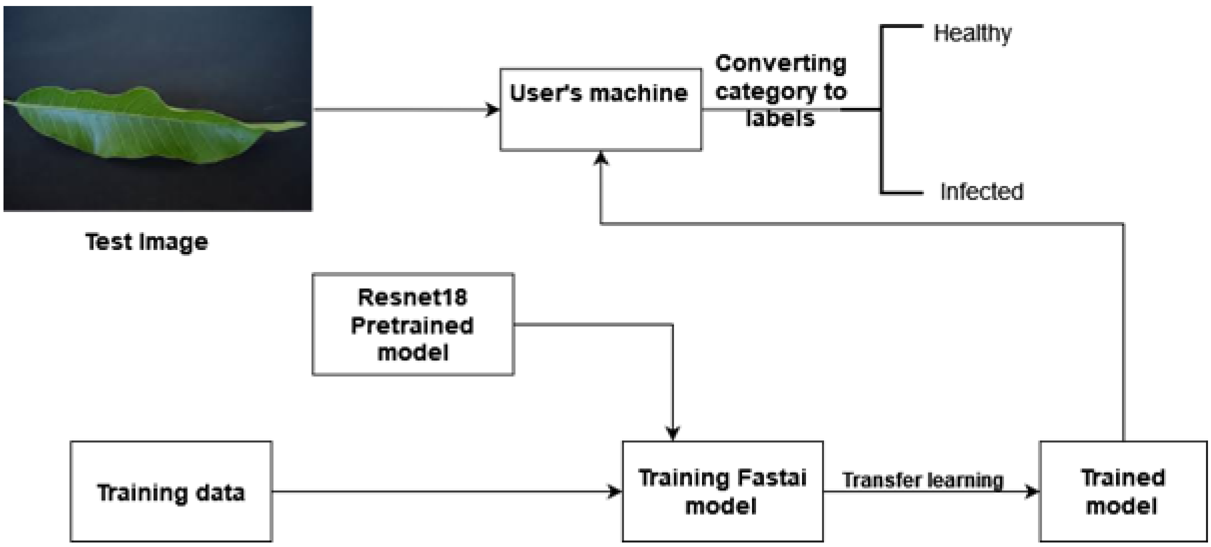

Figure 5: Training architecture for Mangifera Indica Leaf Disease Detection model

4 Results and Discussion

As stated earlier in the proposed tools and framework, Fast.ai and a resnet18 pre-trained model for transfer learning were used to create the proposed model, which consisted of the training and testing process. The proposed method was validated on two images; a database of leaf images: from mendeley data available in Kaggle and mango plant leaf images from the plant village dataset. 80% of training images and 20% of testing were split across the training and testing databases. The images are normalized using histogram enhancement and rescaling before the training procedure. The optimal learning rate is found to train the Fast.ai model. The learning rate value is 0.00019. The training process was implemented using Google Colab's K80 GPU. Testing was carried out in the system having Intel core I5 processor 12th generation, Windows 10 OS, 12 GB RAM, AMD Radeon RX 6400 ITX Graphics Card with 4GB GDDR6 Memory, 1TB SSD, and 1TB HDD. The trained model gave a classification accuracy of 99.88% on the test data using the Resnet18 backbone architecture and Fast.ai framework. The confusion matrix of the created model is represented in Figure 6.

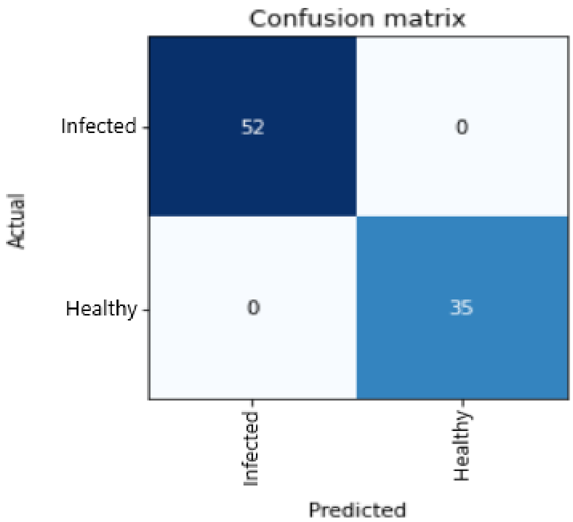

Figure 6: Confusion Matrix

The confusion matrix clearly shows zero false positives and false negatives, indicating that the model can predict both classes with a precision of 100%. The below-mentioned performance metrics were evaluated against the test dataset and given in Table 1 and 2.

Table 1: Performance Metrics

Metrics	**Relation**	**Value Obtained**
Recall	True positive / (True positive + False negative)	1.0
Precision	True positive / (True positive + False positive)	1.0
F1 score	2*(Precision*Recall) / (Precision Recall)	1.0

The comparative analysis of the suggested approach with the available algorithms is made and given in Figure 8. The outcomes are compared with other cutting-edge techniques such as Radial basis function neural network (RBFNN), Support Vector Machine (SVM), Particle Swarm Optimization (PSO), and Multi-column Convolutional Neural Network (MCNN). The obtained accuracy of the proposed model, when compared with the existing methods, has outperformed with 99.88% accuracy.

Figure 9 provides a visual comparison of several machine learning models such as PSO, SV, RBFNN, and MCNN. Three critical performance metrics like precision, recall, and F1-scoreare assessed for each model. Precision, which gauges the accuracy of positive predictions, shows the proposed model achieving the highest precision. Recall, representing the models ability to correctly identify positive instances (healthy leaves). Meanwhile, the F1-score, a balanced measure of both precision and recall, highlights the performance of proposed Model. This visual representation provides a clear and informative comparison of the models, offeringv

Table 2: Performance Comparison of Existing Methods with Proposed Method

Study	Accuracy	F1-score	Recall	Precision
Haridasan et al.[21]	91.45%	90.74%	97.41%	84.92%
Simhadri et al.[22]	92.64%	92.52%	96.52%	88.83%
Chug et al.[23]	87.55%	55.52%	80.61%	42.35%
Ojo et al.[24]	97.69%	92.83%	97.81%	88.33%
Sahu et al.[25]	90.68%	83.1%	95.32%	73.65%
Kumar et al.[26]	91.2%	88.13%	96.32%	81.22%
Durmus et al.[16]	94.3%	89.08%	92.04%	86.3%
Ferentinos et al.[4]	97.06%	90.25%	96.62%	84.66%
Proposed Work	99.88%	100%	100%	100%

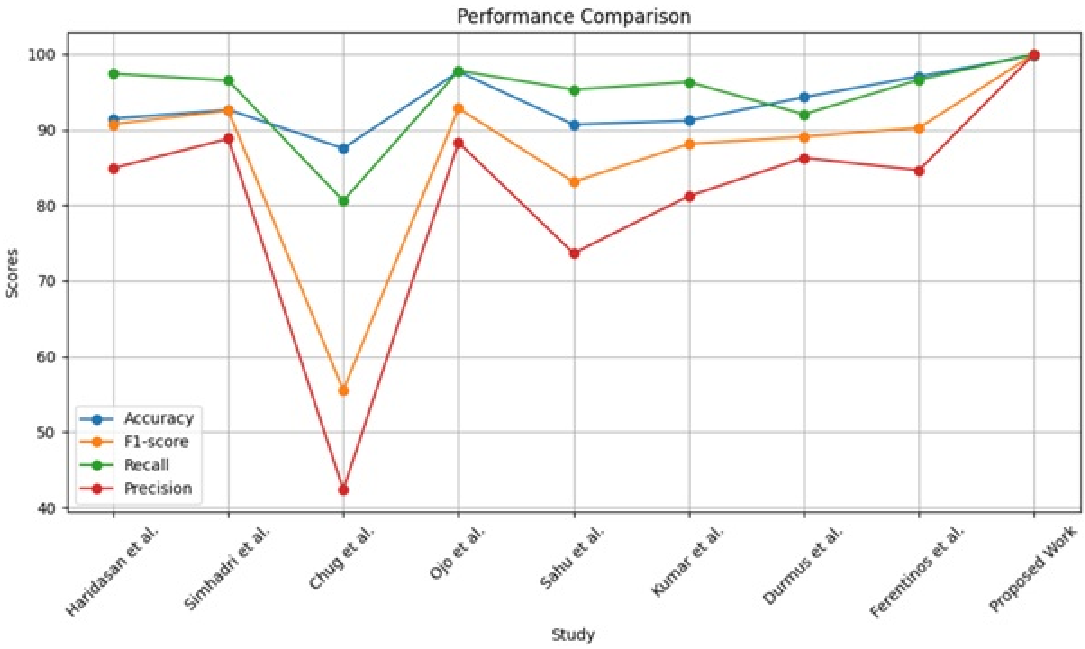

Figure 7: Performance comparison of Existing works with proposed work

aluable insights into their respective strengths and areas for potential improvement.

The training and validation losses begin at a high point and decrease to virtually comparable values as the epochs progress, indicating little over-fitting in the final model considering the allocation of categories in the training data. It is evident from the graph that pre-processing of the images helped in reducing the validation and training losses. Training and validation accuracy after 25 epochs are given in Figure 10 and Training and validation losses after 25 epochs are given in Figure 11.

To measure the model's processing efficiency, its inference time is assessed, which denotes the duration taken by a trained machine learning model to process a single input and yield an output. To enhance this process, the model employed dynamic quantization (DQ) on the pre-trained ResNet-18. This technique involves converting specific layers, such as linear layers, to utilize integer-based computations, potentially accelerating the inference process. The observations revealed that without quantization, the model exhibited an average inference time of 10.6 ms $\pm$ 3.82 ms per loop. With dynamic quantization, this time was reduced to 9.61 ms $\pm$ 1.11 ms per loop, demonstrating an improvement in prediction speed.

The application of transfer learning in mango leaf disease classifications are promising but has certain limitations. One key challenge lies in the model's ability to generalize across different plant species. Proposed

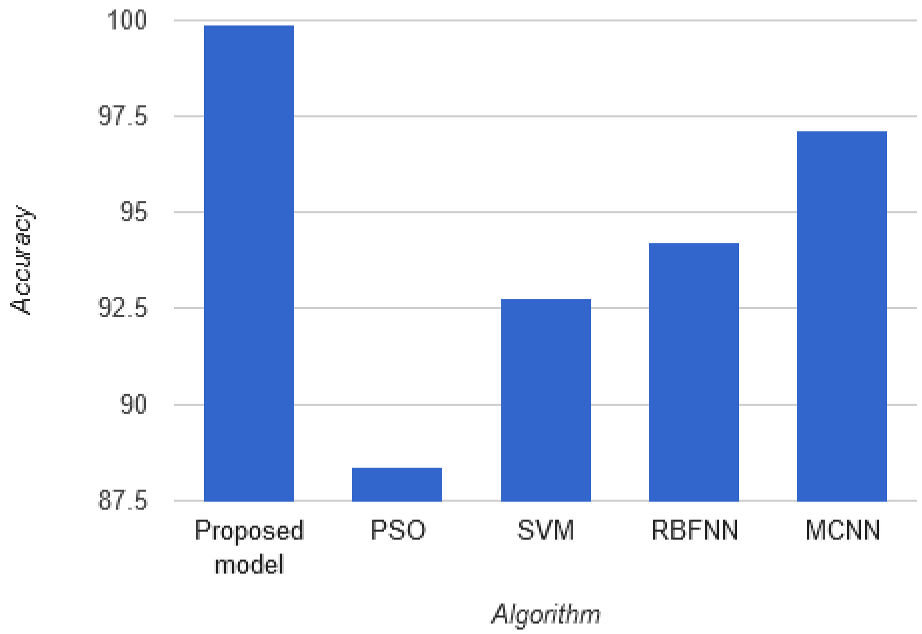

Figure 8: Accuracy of the Proposed Model and Existing Methods

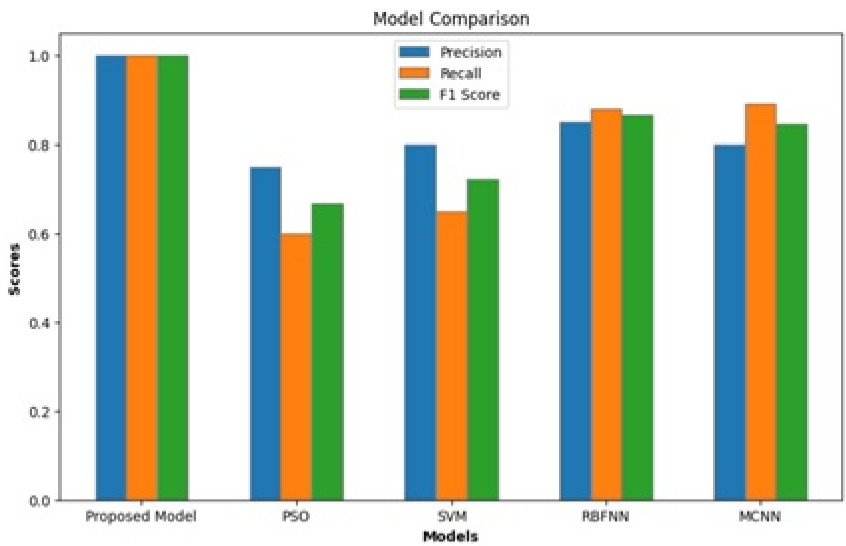

Figure 9: Comparative analysis with Existing Algorithms

model trained on mango leaf data may not exhibit optimal performance when presented with images from other plant species, potentially resulting in misclassification and reducing the model's reliability. Additionally, the model's capacity to generalize to dissimilar types of leaf images not present in the training set poses a potential constraint. Furthermore, a noteworthy limitation arises from the possible misclassification of nutritional deficiencies as diseases. For instance, diseases often manifest as dark circles or lesions on leaves, whereas nutritional deficiencies tend to induce yellowing or hindered growth.

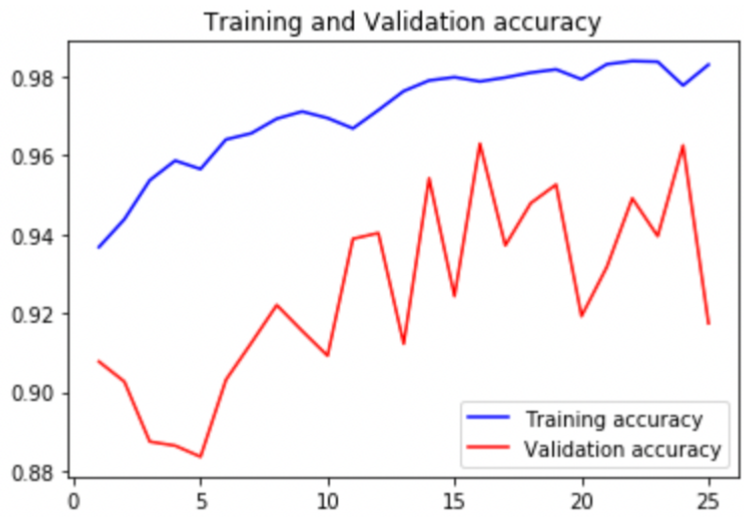

Figure 10: Training and Validation accuracy after 25 epochs

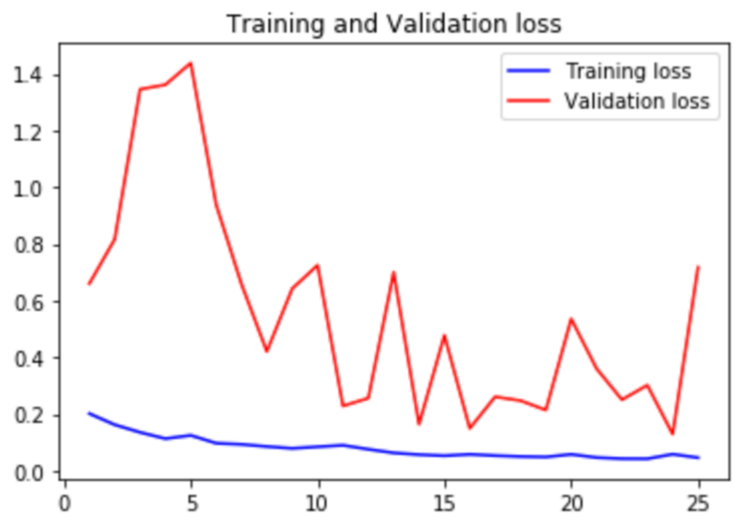

Figure 11: Training and Validation losses after 25 epochs

5 Conclusion and Future Scope

A cutting-edge computer vision framework was used to import and train Images quickly and deliver the results without any latency. Further, a model was proposed to detect the Mangifera Indica Leaf Disease and implemented using the Resnet18 transfer learning model, thus providing a high accuracy rate of 99.88%. The proposed model was also compared with the existing techniques mentioned by the researchers with performance metrices accuracy, precision, recall and f1 score. The proposed model output is promising and better than the existing methods. In the agriculture field implementation, the leaf image categorization can be done using the web or mobile application in the edge node. Estimating the severity of the disease and alerting the farmers will definitely give the high yield, through this proposed model, it is concluded that the agriculturalist can use this type of model and guide the farmers for high production and enhance the plants fertility and durability.

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