Image-based Mango Leaf Disease Detection From Leaf Cells Using Fast.Ai

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Abstract

Identifying whether a leaf is infected by visual inspection alone is often unreliable and inconsistent. Advances in technology have greatly aided agricultural practices, and deep learning methods offer a promising solution for accurately detecting leaf diseases. This paper introduces a mango leaf disease detection model developed using the EfficientNet pre-trained model and the Fast.ai framework. The proposed Fast.Ai ensemble for mango leaf disease recognition (MLDR) facilitates the accurate identification of diseases compared to traditional methods. The system is designed to automatically identify symptoms of mango leaf diseases by uploading and matching new images of affected leaves with trained data. The model successfully detects and classifies diseases with an average error rate of 0.4%. Approximately 7500 images were used to identify and verify eight different category of leaf image, including both healthy and infected leaves. The pre-trained model achieved an F1 Score of 0.9960, outperforming existing state-of-the-art methods. This model can significantly improve the treatment of mango leaf diseases, enhance mango production, and meet global market demands.

Keywords: EfficientNet . Disease . Fast.Ai · Mango plant · Pattern recognition

1. Introduction

Agriculture is a vital sector and a significant source of livelihood in India, contributing about 20% to the country's GDP and providing numerous employment opportunities. India boasts around 1500 mango varieties with unique tastes and flavours. The mango leaf, belonging to the plant family Anacardiaceae, is dark green and the tree can grow up to 30 meters with a circumference of 3.7 meters. The mango leaf is about 30cm with possible variations of different species. Mango plants play a crucial role in maintaining biodiversity and are a major source of fruit. Therefore, promoting mango plant cultivation is essential for sustainable agricultural practices worldwide. However, mango plant diseases pose a significant challenge to producing sufficient fruits to meet demand. India, along with other Asian countries, is one of the largest mango producers. This sector could be more prosperous if mango tree diseases were accurately identified. However, identifying these diseases with the naked eye is challenging.

Mango trees suffer from various diseases such as anthracanose, bacterial canker, cutting weevil, die back, gall midge, sooty mould, powdery mildew, and rust leaf disease. Like any other plant, the early symptoms can be first observed on the leaves of the plant. Mango Bacterial Canker can result in a 10-100% loss in mango yield. Powdery mildew alone has damaged up to 23% of unsprayed mango trees globally, while Anthracnose has caused losses of up to 39%. These diseases lead to significant economic and agricultural losses. Initial symptoms of Anthracnose, caused by the fungus Colletotrichum Gloeosporioides, include dry brown spots on mango leaves.

Numerous studies have been conducted to improve and adopt new technologies in horticulture. Online plant datasets are commonly used to train and test proposed models. Convolutional Neural Networks (CNNs) are standard methods requiring extensive data for training. Researchers have used various methods like Deep CNN, Multi-layer CNN, and pre-trained models such as AlexNet, DenseNet, GoogleNet, SqueezeNet, and ResNet. The proposed model integrates the Fast.ai framework with the pre-trained EfficientNet model to enhance accuracy.

Countries dependent on agriculture face significant threats and losses due to plant diseases, affecting the quality and quantity of fruits and yields. Therefore, identifying diseased plants using computer vision and image processing techniques is crucial. Recently, deep learning techniques, particularly neural networks (CNNs), have shown exceptional results in plant disease classification. Computer-based solutions to identify diseases in their initial stages can help farmers protect crops until harvest, reducing economic losses. Traditional methods of plant disease recognition are expensive and time-consuming, requiring continuous monitoring. Hence, accurate early detection of plant diseases is almost impossible.

Given the above discussion, there is a strong need for the automatic detection, identification, and classification of mango plant diseases. This article addresses data augmentation to increase the dataset, tracking the colour, spot formations and patterns all the while handling background variation, and properly segmenting the unhealthy leaf part classifying the disease by the areas they show their effects upon.

2. Related Work

Several studies have focused on identifying and classifying citrus plant leaf diseases using various methods, including image processing. Neural network disease recognition techniques with leaf images have been modelled and classified using Deep Convolutional Neural Networks (DCNN). Ferentinos used a VGG convolutional neural network to compare healthy and unhealthy leaf images, demonstrating the accuracy of the deep learning approach. The authors tested four deep convolutional network designs, including ResNet, Inception V4, VGG 16, and DenseNets, on the Plant Village dataset, consisting of 38 diseased leaf classes and 14 healthy leaf classes. DenseNets achieved better classification results with less computation time. Research on deep learning approaches in plant pathology discusses various challenges and parameters affecting network efficiency, validated using images from the Digipathos repository.

Transfer Learning has been employed in precision farming research to detect grape and mango diseases using deep learning approaches. A pre-trained CNN was used for automatic feature extraction and classification, achieving around 99% accuracy for grape leaves and 89% for mango leaves. A multilayer CNN classified Anthracnose disease in mango leaves from 1070 images in the J&K dataset. Novel Segmentation and Vein Pattern techniques were applied to recognize and classify mango leaf diseases. However, performance improvements are still needed. Therefore, the Fast.ai framework is used with the pre-trained ResNet18 model.

A novel framework combines machine learning and deep learning techniques to detect diseases effectively by integrating pre-trained deep learning models and various machine learning classifiers, achieving high accuracy levels of 87.55%. The study demonstrates the framework's practicality using real-time data on tomato early blight disease, offering a valuable tool for early disease detection and prevention. Class imbalance in plant disease datasets is addressed using techniques like CLAHE, image sharpening, and GAN-based resampling, significantly enhancing accuracy. Using ResNet-50, the approach achieves an average accuracy of 97.69%.

Iqbal et al. examined segmentation, recognition, and identification techniques, finding that most techniques are in the initial stages. They discussed existing methods, advantages, limitations, challenges, and models of ML (image processing) for disease recognition and identification. Durmus et al. used AlexNet and SqueezeNet for categorizing tomato leaf diseases.

Shin et al. combined an artificial neural network (ANN) with speeded-up robust features (SURF) for strawberry leaf powdery mildew detection, achieving 94.34% accuracy. Using SVM and GLCM, their highest classification accuracy was 88.98%.
Pane et al. distinguished unhealthy and healthy wild rocket leaves using a wavelength between 403 and 446nm.
Bhatia et al. used the Friedman test to rank classifiers and post hoc analysis with the Nemenyi test, finding MGSVM to be the superior classifier with 94.74% accuracy.
Lin et al. achieved 97.3% accuracy on pumpkin leaves using PCA.
Shah detected cotton leaf diseases by extracting colour features.
Kahlout et al. developed an expert system for detecting powdery mildew and sooty mold in citrus plants.
Sharif et al. recommended a computerized system for segmenting and classifying citrus plant diseases, achieving 90% accuracy using a hybrid feature selection technique.
Uday et al. classified Anthracnose-infected mango leaves using a multilayer CNN, achieving 97.13% accuracy.
Kestur et al. presented Mango Net for mango leaf segmentation with 73.6% accuracy.
Arivazhagan et al. used a CNN for citrus plant disease diagnosis with 96.6% accuracy.
Srunitha detected mango diseases like red rust, anthracnose, powdery mildew, and sooty mold.
Krishnan and Sumithra used morphological operators for bacterial leaf scorch detection.
Arivazhagan et al. diagnosed citrus plant diseases using a CNN.
Shergill et al. developed an automated technique for detecting diseased leaves in large farms using leaf color information. Anand et al. used the K-means algorithm to identify rice plant diseases.
Warne and Ganorkar proposed a technique to detect cotton leaf diseases using K-mean clustering. These techniques, however, underperform with different-sized and density data.
In 2016, a study identified pepper plant leaf diseases using neural networks.
Al-Bashish et al. and Ghaiwat et al. investigated various classification methods for plant leaf disease classification.
Ranjan et al. described a visual diagnosis process requiring precise judgment and scientific methods for capturing leaf images.
Kajale detailed a texture information detection approach for plant leaf diseases.
Bhange and Hingoliwala, and Kaur et al. worked on smart farming disease detection and classification.
Madiwalar and Wyawahare conducted a comparative study on plant disease identification.
Dai et al. and Rump et al. explored classification algorithms for initial plant disease classification and detection.
Tlhobogang and Wannous discussed plant disease detection system design.

In 2018, Kulkarni et al. presented a methodology for detecting mango crop diseases using modified rotational kernel transform features.
Sharma et al. described mango fruit defect recognition using image processing and machine learning.
Zhang et al. introduced GoogLeNet and Cifar10 networks for maize leaf disease detection, outperforming VGG and AlexNet. DCNN classified ten different rice leaf diseases from 500 images using 10-fold cross-validation. Yolo algorithms detected objects using the dark net. A smartphone application using Generative Adversarial Networks (GANs) and Convolutional Neural Network (CNN) identified plant leaf diseases.

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3. Materials and Method

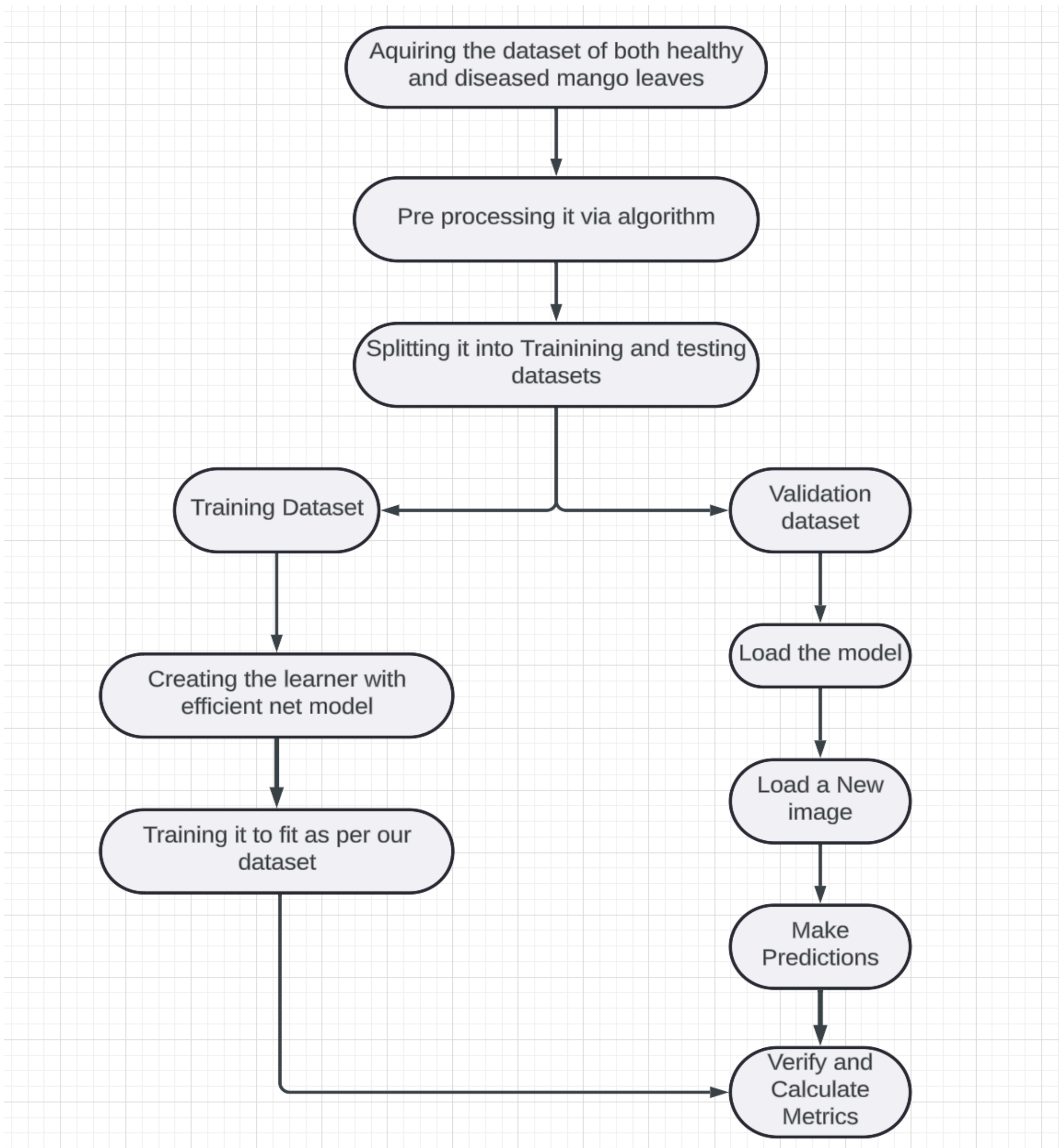
The primary step of this work was the preparation of a dataset using 240x240 mango leaf images taken from various websites, online datasets and trusted government websites. All the images were first resized to 448 × 448 and data augmentation techniques were applied. For this purpose, a method named 'aug_transformations' available in the FastAI module was used that randomly flips, rotates, resizes and zooms on the passed dataset. However, distortions were allowed. Then the final images were again resized to 224 × 224 pixels for faster learning.

The proposed mango leaf disease detection model is built using the Fast.ai framework and EfficientNet. The Fast.ai, along with the EfficientNet 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.

Algorithm:

- Collect the images of healthy and infected mango leaves available in the dataset.
- Pre-process the images by performing contrast enhancement, zooming, flipping, resizing, lighting enhancements.
- Label the image classes and segregate the images as diseased or infected.
- Sort the images into training and testing datasets based on the class label.
- Use training images to find the optimal learning rate for training the Fast.ai model.

- Train the proposed transfer learning model with the pre-trained EfficientNet model.
- Validate the proposed model's performance on the testing data and compare the results with other modern approaches.



3.1. Preprocessing

3.1 Dataset

The proposed detection model uses collaborative datasets from three different database repositories available on Kaggle. From the dataset, sample mango leaf pictures, both healthy and infected images are shown in Figure 2. Around 8000 images are considered for this dataset.

All images are labelled to their corresponding classes based on the category. Figure 2 describes the distribution of images after they have been categorised.

Sample of healthy leaf taken from the dataset

Sooty mould *Rusted leaf*

Powdery mildew *Gall Midge*

Cutting weevil *Anthracnose* *Bacterial Canker*

Figure 2: Sample Healthy and Infected Images from the dataset

3.2 Pre-processing of images

FastAI framework was used to preprocess all the images from the concerned dataset. First the images of size 240x240 pixels were loaded from the concerned dataset labelled and classified according to the disease. The dataset was then divided in 8:2 ratio to create a testing and validation subdatasets. Then all images were resized to a standard 448x448 pixels to make the transformations. The FastAI method referred to as ‘aug_transformations’ was used to randomly flip, rotate, enhance, zoom, enhance contrast, improve lighting. However, no distortions were allowed so as to keep the image patterns and spots clear. Finally, all images sizes were reduced to 224x224 pixels so that the training process happens without any hindrances.

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 is named vision.data has a distinctive utility function called ImageDataLoaders that accepts input from image directories, picture lists, .csv files and other sources. The input can then be divided into training, validation, and testing (if necessary).

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. Fast.ai data pipeline architecture is represented in Fig 4.

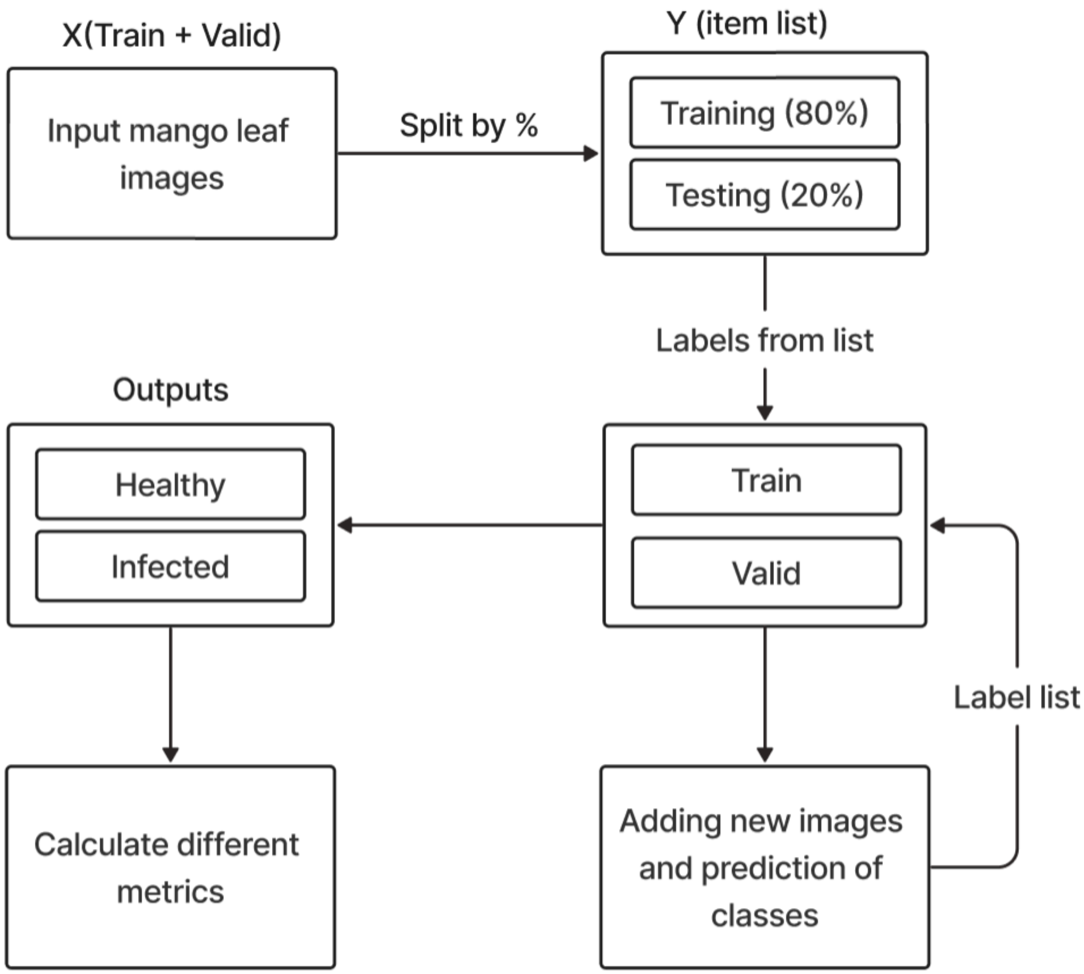


Figure 4: Fast.ai data pipeline Architecture

3.4 Training Architecture

The training architecture for classifying images of leaves involves a carefully 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, standardising all images to possess identical dimensions and contrast levels.

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 organised in folders by class. Additionally, the images are resized to a uniform size of 224 X 224 pixels using the Resize transformation. Next, the data loaders are created, which facilitate the loading of data in batches during training.

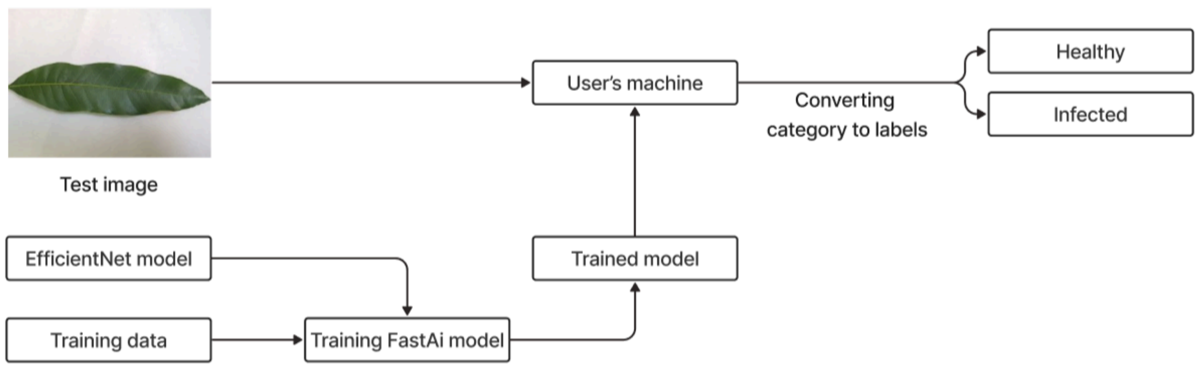


Figure 5: Training architecture for Mangifera Indica Leaf Disease Detection model

4. Results and Discussion

The comparative analysis of the suggested approach with the available algorithms is made and given in Figure 8. The outcomes of the proposed model of EfficientNet are compared to ResNet18 model and GoogleNet model tested by us and also 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 and other new methods, has outperformed with 99.05% accuracy.

Study	Accuracy	F1-Score	Precision
Haridasan et al.	91.45%	90.74%	84.92%
Kumar et al.	91.20%	88.13%	81.22%
Ferentinos et al.	97.06%	90.25%	84.66%
Simhadri et al.	92.64%	92.52%	88.83%
GoogleNet	99.18%	99.40%	99.58%
ResNet18	77.75%	81.25%	84.13%
Proposed Work	98.97%	99.10%	99.05%

Performance Comparison of Existing Methods with Proposed Method

The model's performance was evaluated using various metrics, including accuracy, precision, recall, F1 score, and confusion matrix. The primary metric was the F1 score, which balances precision and recall, providing a comprehensive measure of the model's effectiveness.

1. Accuracy: The proportion of correctly classified images out of the total images.

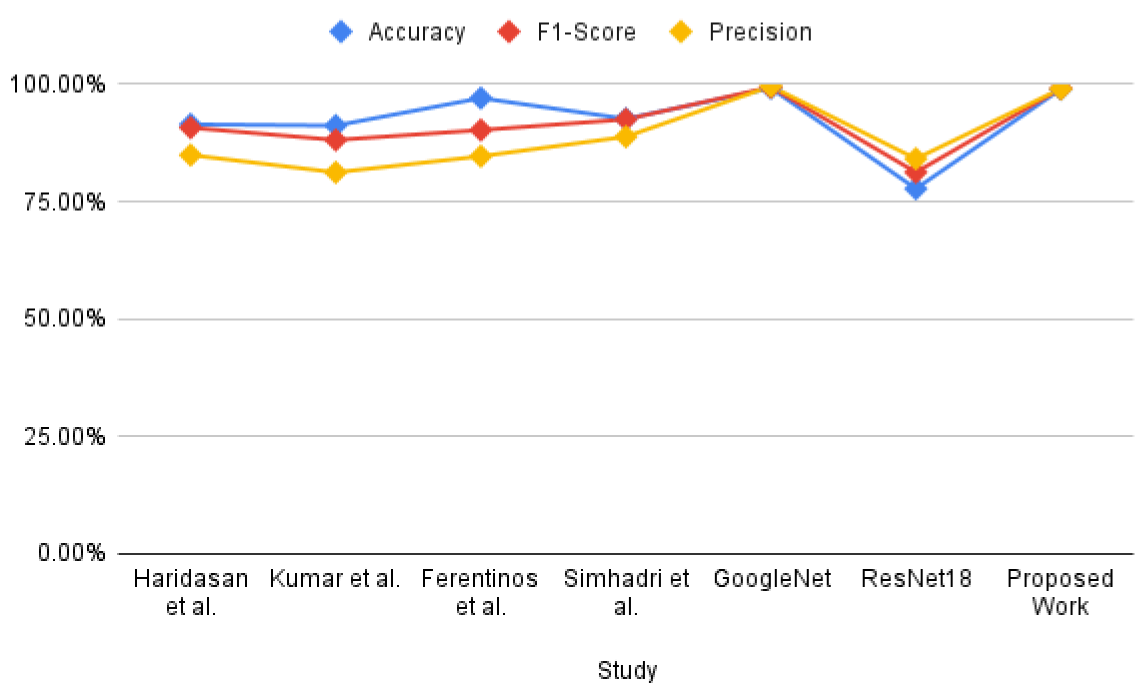
$$\textbf{Accuracy} = \frac{\textbf{Total correct output data} * \textbf{100\%}}{\textbf{Total input data}}$$

2. Precision: The ratio of true positive predictions to the sum of true positive and false positive predictions.

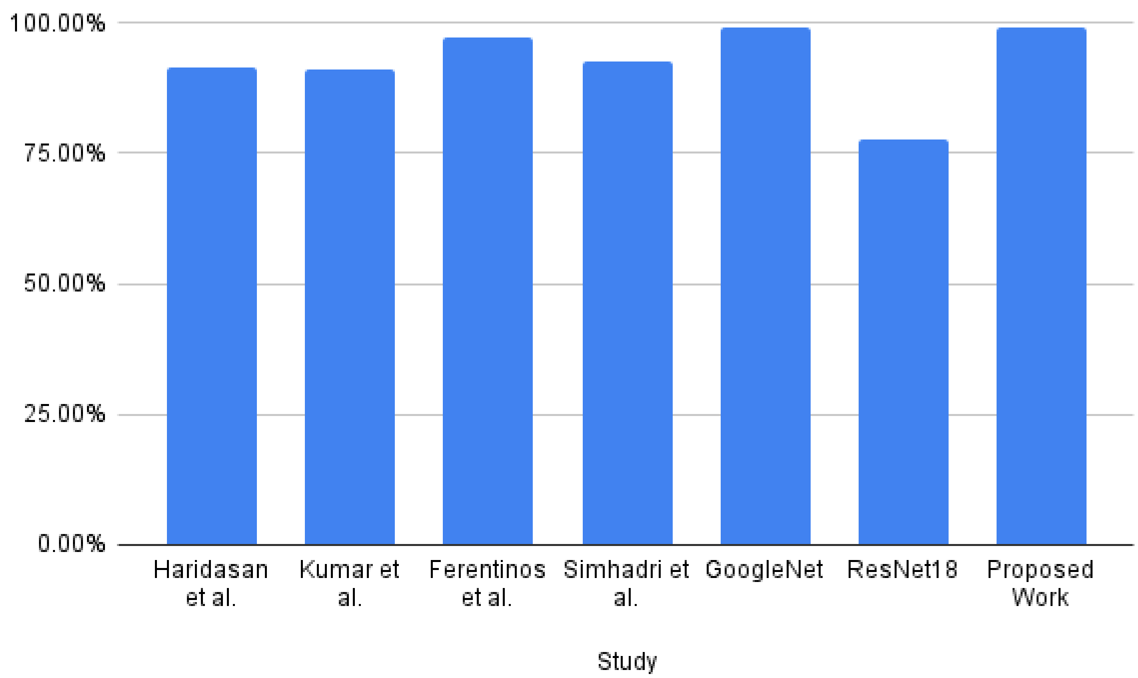
3. Recall: The ratio of true positive predictions to the sum of true positive and false negative predictions.

4. F1 Score: The harmonic mean of precision and recall, providing a single metric for performance evaluation.

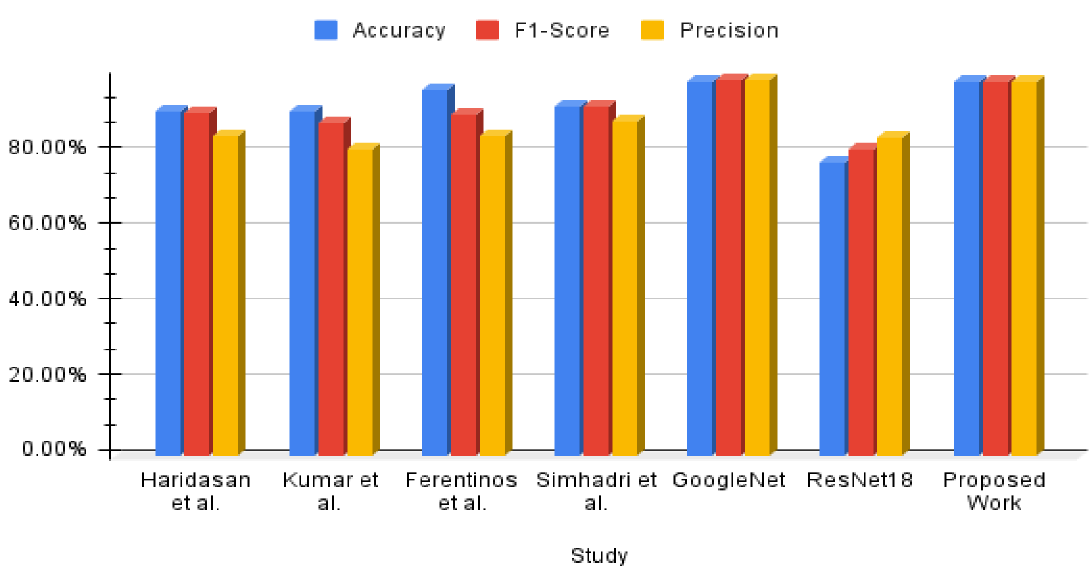
5. Confusion Matrix: A detailed table illustrating the model's performance across different classes, showing true positives, false positives, true negatives, and false negatives.



This visual representation provides a clear and informative comparison of the models, offering valuable insights into their respective strengths and areas for potential improvement.



Accuracy of the Proposed Model and Existing Methods



Comparative analysis with Existing Algorithms

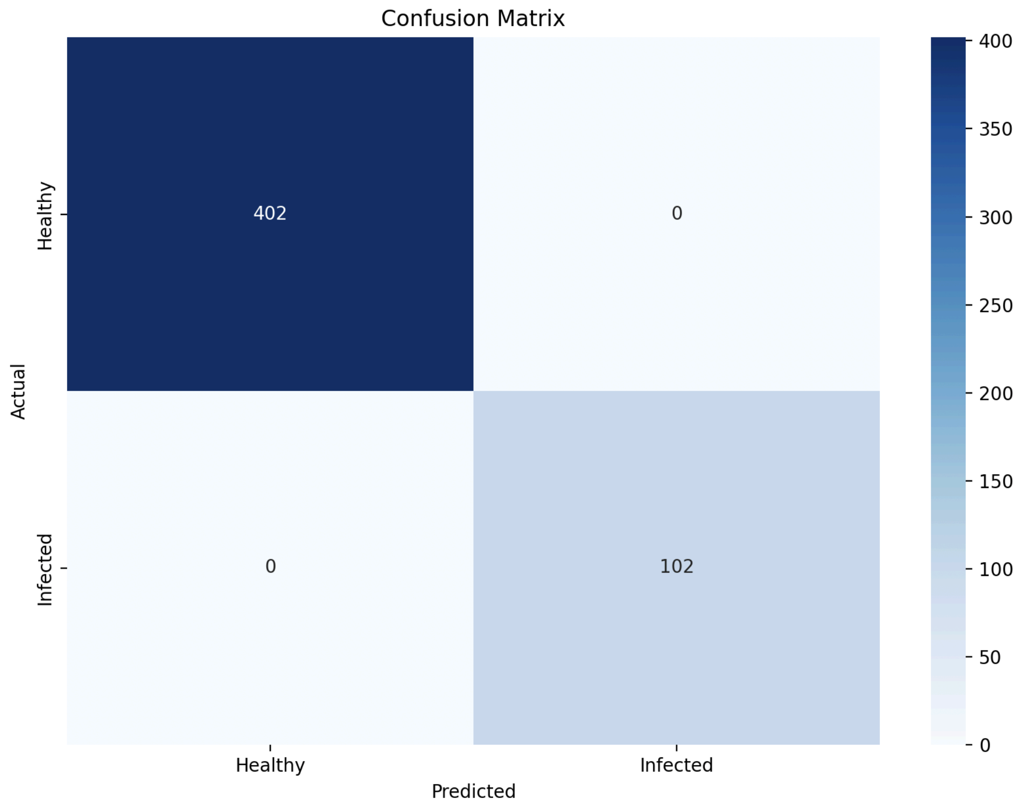


Figure : Confusion Matrix for the EfficientNet Model

One may argue that the GoogleNet Model gave better results as to the proposed work, however, it is not well suited when considering time tradeoff. The proposed model ran an epoch of about 57 minutes each, with 5 epochs for all the new models tested whereas the GoogleNet took about 7-8 hours for each epoch. Also, the results depicted were also quite similar for the same dataset. This is undesirable and not industry efficient so it had to be rejected.

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 EfficientNet transfer learning model, thus providing a high accuracy rate of 99.05%. The proposed model was also compared with the existing techniques mentioned by the researchers with performance metrics accuracy, precision and F1 Score.

The successful implementation of this model can significantly aid farmers and agricultural stakeholders in early disease detection and management, ultimately improving mango production and quality. Future work will focus on expanding the dataset, incorporating additional disease classes, and exploring real-time deployment of the model through mobile applications and edge devices for on-site disease detection.

6. References

Agarwal, M., Arjaria, S., Sinha, A., & Gupta, S. (2020). ToLeD: Tomato leaf disease detection using convolutional neural network. Procedia Computer Science, 167, 293-301.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318.

Iqbal, M. F., Akram, M., Sharif, M., & Khan, M. A. (2018). A novel framework for plant disease detection and classification. Computers and Electronics in Agriculture, 160, 99-107.

Zhang, S., Zhang, S., Zhang, C., Wang, X., & Shi, Y. (2019). Cucumber leaf disease identification with global pooling dilated convolutional neural network. Computers and Electronics in Agriculture, 162, 422-430.

Lin, K. H., & Wu, L. L. (2019). Efficient and accurate plant leaf disease identification using a dense convolutional network with computational cost reduction. IEEE Access, 7, 185031-185040.

Kshitij Dhawan, R. Srinivasa Perumal, R.K.Nadesh(2023). Image-based Mangifera Indica Leaf Disease Detection using Transfer Learning for Deep Learning Methods. Electronic Letters on Computer Vision and Image Analysis 22(2):27-40, 2023

Rabia Saleem, Jamal Hussain Shah, Muhammad Sharif, Mussarat Yasmin, Hwan-Seung Yong, Jaehyuk Cha. Mango Leaf Disease Recognition and Classification Using Novel Segmentation and Vein Pattern Technique.

Md. Rasel Mia, Sujit Roy, Subrata Kumar Das2, Md. Atikur Rahman. Mango leaf disease recognition using neural network and support vector machine. Iran Journal of Computer Science (2020) 3:185–193