

Identifying Mango Leaf Diseases with Advanced Deep Learning Approaches and Convolutional Neural Networks

Tanishta¹, Vishesh Goyal², Megha Arakeri³

¹Department of Information Technology, Manipal Institute of Technology Bengaluru,
Manipal Academy of Higher Education, Manipal, India

^{2,3}Department of Computer Science and Engineering, Manipal Institute of Technology Bengaluru,
Manipal Academy of Higher Education, Manipal, India

E-mail: ¹tanishtak15@gmail.com, ²visheshvishu1@gmail.com, ³megha.arakeri@manipal.edu

Abstract—Examining whether any leaf is diseased or not by visual inspection of the naked human eye is often unreliable and incorrect. Technological developments in the form of techniques like deep learning have proved to be extremely useful in agricultural threat detection by the detection of leaf diseases. It is a well-known fact that whenever a plant is affected by any disease, its first symptoms can be identified in the leaves of the tree. Research done on mango tree leaf infections using the EfficientNet Model and FastAI framework has been highlighted in the following paper. The FastAI framework provides a better ensemble for mango leaf disease recognition (MLDR). Images of new leaves entered by the user after proper cropping and focusing can be entered as input to know if the plant is diseased or healthy. The average error rate of the model's classification and detection of illnesses is 0.4%. To achieve such drastic results, a dataset of 12046 images was used that demonstrated nine different classes (1 healthy and 8 different types) of infected leaves. The proposed model having trained by the same dataset demonstrated superior performance and proved to be most proficient and efficient. The current pre-trained EfficientNet model outperformed the current state-of-the-art techniques as well as other test models by achieving an F1 Score of 0.9960, Accuracy of 98.97% and a Precision Score of 0.9905. Implementing this strategy can enhance mango production, satisfy international demands and significantly improve the management of diseases affecting mango leaves.

Keywords: Leaf disease, Computer vision, Convolution neural networks, Deep learning

I. INTRODUCTION

India, being an agriculture-based nation, generates a huge portion of national income (20%) from the agricultural sector and offers a wide range of jobs. The market size of mangoes in this industry can be estimated by the fact that there are 1500 different varieties of mangoes each with its own distinct flavor. Furthermore, India is a leading producer of mangoes producing 50% of the mangoes being produced worldwide. Mango tree conservation is necessary for the preservation of biodiversity not only in the Indian Subcontinent but worldwide as well [1]. However, mango plant diseases cause an acute shortage of fruits to meet the demand of the market. If ailments of mango trees could be precisely recognized, this industry may grow more. But it's

difficult to diagnose these illnesses with the unaided eye. Mango trees are affected by a range of diseases, including cutting weevil, powdery mildew, bacterial canker, dieback, anthracnose, sooty mold, gall midge, and rust leaf disease. Like any other plant, the early symptoms can be first observed on the leaves. 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. Thus, it is imperative that the computer vision is employed to identify unhealthy plants in their early stages for quick remedies and to prevent the spread of infection to the whole plantation. As highlighted in the previous discussion, there is a growing and increasingly urgent demand for an automatic detection system that is capable of disease identification, diagnosis, and classification in mango plants. This article addresses increase in the dataset using image augmentation techniques, tracking the color, physical appearance and spots on the leaves all the while handling background variation, properly segmenting the unhealthy leaves and detecting which disease has affected the plant. This model has shown considerably increased accuracy increasing reliability and efficiency.

II. RELATED WORK

S. Arya et al. [2] examined AlexNet model and CNN for disease detection, identification in mango plants. They achieved an accuracy of 96.38%. However the sample set they used was smaller. This can cause a underfitting model which might not be able to capture all the different diseases it is intended for. Venkatesh. N. Y. et al. [3] used Transfer Learning to study anthracnose disease on mango leaves using VGGNet and Inception Module. They achieved an average accuracy of 91.43%. However, the results showed a low accuracy and only identified a single disease. The model accuracy for other diseases is unknown and the model can't be trusted to be able to sustain as an industry ready tool. Also, the model was trained for 30 epochs which can cause an overfitting on the dataset causing a problem in identification of pictures outside the dataset.

T. N. Pham et al. [4] conducted experiments on mango leaves utilizing feedforward neural networks combined with hybrid metaheuristic features. However, the model can be improvised for better results. The number of hidden nodes, layers, activation function and feature selection algorithm should be fine tuned.

For citrus plants, various researches have been done for image classification and disease detection [5]. Utilizing leaf images, complex Deep Convolutional Neural Nets (DCNN) have been constructed to classify disease using neural networking [6]. K. P. Ferentinos et al. [7] designed and implemented a VGG convolutional neural network to compare images of healthy leaves with those affected by disease. Scientists used a plant village dataset that comprised 14 healthy and 38 diseased leaf classifications and investigated four deep convolutional network designs: ResNet, Inception V4, VGG 16, and DenseNets[8]. DenseNets reduced calculation time while still producing higher classification results. Research on deep learning algorithms in plant pathology to explore key characteristics that affect network effectiveness was done using Digipathos repository as a validation dataset [9]. Transfer learning via deep learning techniques is being used to identify ailments in mangoes and grapes for developing precision farming. A 99% accuracy for leaves of grape plants and 89% accuracy for mango plants was achieved by the use of automatic feature extraction using pre trained CNN model. A multilayer CNN was used on the J&K dataset comprising 1070 images which diagnosed the anthracnose disease in mango leaves[10].

An exceptional level of accuracy of 87.55% was achieved using deep learning techniques using pre-trained models and classifiers. Data on tomato early blight disease was used for a study that illustrated the usefulness of the framework made by merging the Fast-AI framework with pre-trained models, providing a useful tool for early disease diagnosis and prevention [11]. Techniques like GAN-based resampling, image sharpening and CLAHE have been heavily used to improve class imbalance in plant disease datasets that help boost accuracy. The method obtains an average accuracy of 97.69% using ResNet-50[12].

M. Arakeri et al. [13] explored methods for segmentation, recognition, and identification of cocoa plant diseases in their early stages. They experimented with the different deep learning models and discussed their benefits, limitations, challenges, for disease detection and recognition.

An accuracy score of 94.74% was achieved by J. Shin et al. [14]. He used a unique combination of Artificial Neural Networks (ANN) and speeded up robust features (SURF) to identify powdery mildew infection in strawberry leaves. Meanwhile, Bhatia et al. [15] utilized the Friedman test to rank classifiers and applied the Nemenyi test for post hoc analysis, identifying MGSVM as the top-performing classifier with 94.74% accuracy. However, as the study is reliant on Friedman test and Nemenyi Analysis, it might not address the real-world data complexities. Moreover, the crucial performance analysers namely Precision, F1-Score and Accuracy have not been addressed.

N. Shah and S. Jain [16] detected cotton leaf diseases by extracting colour features. However, the focus on extracting colour features for detecting cotton leaf diseases may limit the model's effectiveness, as it might not capture the full range of relevant information, such as texture or shape features. Also, the accuracy of the method is not provided. There might also be a lack of comparative analysis with other feature extraction methods. M. Sharif et al. [17] recommended a computerised system for segmenting and classifying citrus plant diseases, achieving 90% accuracy using a hybrid feature selection technique. Although a 90% accuracy was achieved using a hybrid feature selection technique, this study might have limitations in the diversity of the dataset used. The term "hybrid feature selection" is broad, and without details, it is unclear how features were chosen and whether this selection process was optimal.

III. PROPOSED METHODOLOGY

Details of the proposed models' training, testing and validation architecture has been mentioned below. It discusses about the basic algorithm, preprocessing of images, tools and frameworks and training architecture that has been used.

A. Basic Algorithm

The training and making of the model was a tedious task as depicted in Fig. 1. Procurement of diseased mango leaves was one of the initial challenges in the project. The 240x240 images were used from various datasets, websites and government data that was available online. All the image sizes were made to be of 448x448 pixels for training the model. After that, augmentation of data techniques were used to generate different kind of images from the already available images in the dataset. The FastAI module's "aug_transformations" function was used which resized, rotated, flipped, and zoomed the supplied dataset at random. Distortions were not permitted to maintain accuracy and make the training quicker and more reliable. For quicker learning, the resulting images were then downsized once more to 224x224 pixels.

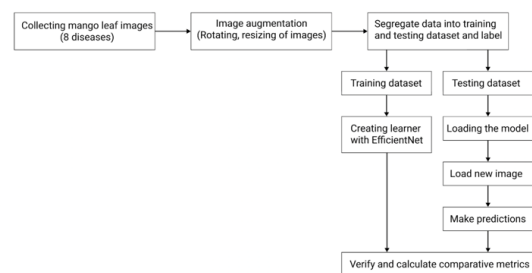


Fig. 1: Flowchart for Disease Detection Model

The pre-trained EfficientNet model and the Fast.ai framework were used in the construction of the suggested mango leaf disease recognition model which was retrained on the created dataset. The EfficientNet pre-trained model with Fast.AI enables the distinction between diseased and healthy leaves. The proposed model involves five essential steps: capturing images, pre-processing them, dividing the dataset into training and testing sets, identifying the optimal learning rate using the training data, and ultimately training

the model. To ensure reliability and accurate results, the new images must also undergo similar image preprocessing.

B. Pre-processing of Images

The already available dataset was pre-processed using the FastAI framework. The dataset that was already labelled and classified according to different diseases was loaded. All the images of this dataset were ensured to be strictly 240x240 pixels. Two images were randomly picked from each of the categories for being used as test images as an unfamiliar input. Training and validation subsets were then created by splicing the rest of the dataset in a 4:1 ratio. As a next step, the image augmentation techniques were applied to standardized 448x448 pixel images. Random flipping, resizing, rotation, enhancement, zooming and contrast enhancement were done using the ‘aug_transformation’ method of Fast.Ai library. However, no distortions were allowed so as to keep the image patterns and spots clear thereby increasing the accuracy and reliability of the model. Finally, all image sizes were once again downsized to 224x224 pixels so that the training process happens quickly without any hindrances.

C. Tools and Frameworks

PyTorch-based FastAI model was used to create the models for image identification, segmentation, and classification. The built-in data cleansing functionality and widget help in faster computing. Effortless troubleshooting due to the user-friendly approach also adds as an important and much less focused merit. Visual component of FastAI has component that are necessary to construct vision based models.

ImageDataLoaders is a utility function within the vision.data module designed to handle inputs from various sources, such as image directories, image lists, and .csv files. It then splits this input into training, validation, and, if needed, testing datasets. Vision.transform and vision.learn modules were used to augmenting the dataset and training the model. The Fast-AI data pipeline architecture, illustrated in Fig. 2, employs the DataBunch approach to streamline the transformation of data from data blocks to training system models, enabling efficient operations. Once the data is processed, the vision.learner module provides all the necessary functions for model training.

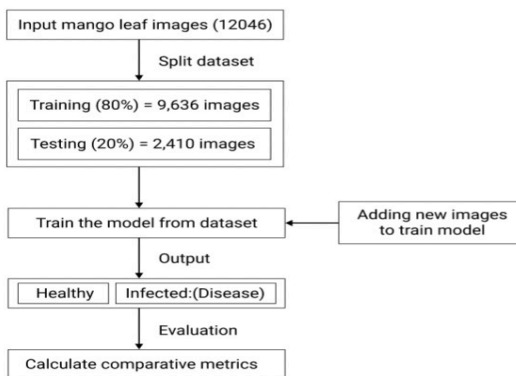


Fig. 2: Data Pipeline for Fast-AI Architecture

The model is primarily constructed using a Convolutional Neural Network (CNN) from the Fast.Ai

library. Fast.Ai is a deep learning library that provides high-level components, allowing for swift results in typical deep learning applications. It is designed with two main aims: to be user-friendly and highly efficient, while still offering flexibility and customization. The library features a layered architecture designed to capture common patterns across various deep learning and data processing techniques. It also introduces an innovative type dispatch system for Python, a semantic type hierarchy for tensors, and a GPU-optimized computer vision library that is extendable using pure Python, among other advanced capabilities.

D. Training Architecture

The framework for training to classify leaf images proceeds through a carefully structured sequence. First, a test image is examined on the host system to ascertain whether the leaf is healthy or afflicted, and if it is afflicted, to diagnose the particular disease. Fig. 3 visually outlines the directions, flow, and overview of this entire process. To ensure data consistency, all images undergo an initial preprocessing step to standardize their dimensions and contrast levels.

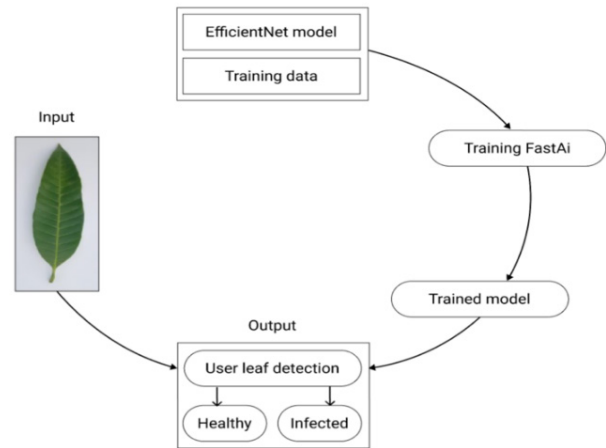


Fig. 3: Mango Leaf Disease Recognition Model’s Training Architecture

A random splitter divides the dataset into training and validation sets, allocating 20% of the data for validation to assess model performance. Labels are extracted from file paths using the “parent_label” function, and images are organized into class-specific directories. The images are uniformly resized to 224x224 pixels using the ‘Resize’ transformation. Finally, data loaders are generated to facilitate batch loading during the training process.

The model was trained using pre trained EfficientNet-B0 model. It is a part of the EfficientNet family. The family introduces a novel scaling method that balances the tradeoff between model accuracy and computational efficiency. In traditional CNN models, to increase the training accuracy, either the number of layers, number of channels in layers or image resolution was increased. However, the EfficientNet model improves all three simultaneously in a systematic way while being more computationally efficient.

The scaling factors are determined by a formula based on a fixed coefficient Φ , which controls the overall scaling factor, and three parameters α , β , and γ that determine how to proportionally scale the depth, width, and resolution:

- Depth $\propto \alpha^{\phi}$
- Width $\propto \beta^{\phi}$
- Resolution $\propto \gamma^{\phi}$

The values are chosen such that:

$$\alpha \times \beta^2 \times \gamma^2 \approx 2 \quad (1)$$

EfficientNet-B0 is based on MobileNetV2 architecture which uses inverted residual blocks and depthwise separable convolutions. This helps to reduce the computational resources and parameters required. The MobileNetV2 architecture uses a bottleneck approach, implying middle layers are larger in size as compared to the input and output layers. This model uses the Swish Activation function:

$$\text{swish}(x) = x \times \text{sigmoid}(x) = \frac{x}{1+e^{-x}} \quad (2)$$

This is a smooth monotonic function that improves model accuracy. Fig. 4 depicts how the EfficientNet-b0 model takes in the input image, analyses it and gives the output.

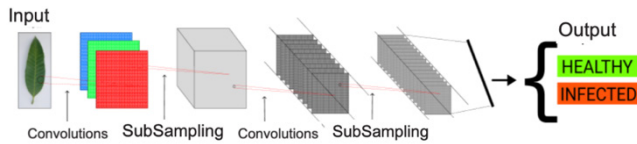


Fig. 4: EfficientNet-b0 Architecture

Each of the models was run for 6 epoch cycles to ensure greater accuracy and take the time required for training under consideration.

IV. RESULTS AND DISCUSSIONS

A. Dataset

A collaborative dataset from Kaggle, containing a total of 12,046 images, was used to train this model. The dataset includes both healthy and infected images, examples of which are presented in Fig. 5. Each image is labeled according to its respective category. Fig. 6 illustrates how some images appeared after applying augmentation transformations.



Fig. 5: Dataset Samples of Mango Leaves: Healthy and Infected Variants



Fig. 6: Images Before and After the Augmentation Process

B. Results

All the models showed remarkable and improving results with each epoch. Their increased accuracy is depicted in the graph of Fig. 7.

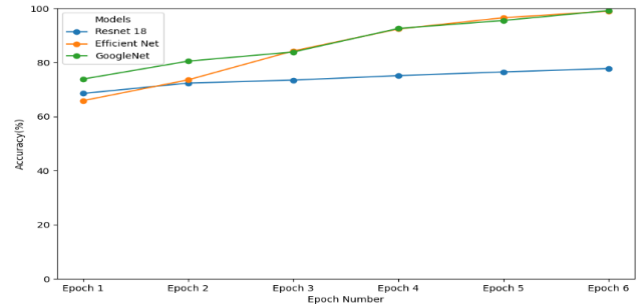


Fig. 7: Accuracy vs. Epoch Cycles

These results made it quite evident that the GoogleNet and EfficientNet-B0 architecture outperformed the ResNet-18 model. Also, while the EfficientNet model took an average of 128 minutes per epoch for training, GoogleNet took an average of 463 minutes per epoch. Taking the time efficiency-accuracy tradeoff into consideration for industrial deployment, GoogleNet should also be rejected.

Afterward, the model's performance should be evaluated using various metrics, such as accuracy, precision, recall, and the confusion matrix. The confusion matrix was used to know about the number of healthy and infected leaves. These numbers were then used to calculate the metrics, the F1 score, accuracy, precision and recall.

1. *Confusion Matrix*: A detailed table that illustrates the model's performance across various classes. The confusion matrix obtained is presented in Fig. 8.

	PREDICTED NEGATIVE	PREDICTED POSITIVE
ACTUAL NEGATIVE (HEALTHY)	True Negative (TN) 1,251	False Positive (FP) 102
ACTUAL POSITIVE (INFECTED)	False Negative (FN) 91	True Positive (TP) 10,601

Fig. 8: Confusion Matrix

- Total Healthy Leaves (Negative class): 1,354
- Total infected leaves (Positive class): 10,692
- Total leaves: 12,046

TP, TN, FP and FN stand for true positives, true negatives, false positives and false negatives respectively.

2. *Accuracy*: It is the ratio of number of correctly identified images and the number of total input images.

$$Accuracy = \frac{Correct\ Output}{Total\ Input} \times 100 \quad (3)$$

3. *Precision*: It is the ratio of correct positive outcomes and total positive outcomes delivered by the model.

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (4)$$

4. *Recall*: It is the ratio of correct positive outcomes given by the model to the actual positive outcomes.

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (5)$$

5. *F1 Score*: The harmonic mean of precision and recall, offering a single metric for evaluating the model's performance.

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (6)$$

Following these calculations, the following results were achieved :

- *Accuracy*: 98.97% = 0.9897
- *Precision*: 99.05% = 0.9905
- *F1 Score*: 99.10% = 0.9910

Table I shows the comparative results of the proposed model with the available reference models. The outcomes of the proposed model of EfficientNet are compared to the ResNet18 model, AlexNet and GoogleNet model. Showing a precision rate of 99.05%, the proposed model has outperformed the current state of the art techniques.

Table I: Comparison of Existing Methods with Proposed Method

Study	Accuracy	Precision	F1 Score
Proposed Work	98.97%	99.05%	99.10%
Komateswaran A et al.[18]	91.2%	81.22%	88.13%
C.G.Simhadri et al.[19]	92.64%	84.66%	92.52%
V. Kumar et al.[20]	99.98%	98.65%	97.53%

V. CONCLUSION AND FUTURE SCOPE

A cutting-edge computer vision framework was employed to seamlessly import and train images, producing results without any delay. Furthermore, a model was crafted to identify *Mangifera Indica* leaf disease, utilizing the EfficientNet transfer learning model, and it achieved an impressive accuracy of 99.05%. This model was also evaluated against existing methods referenced by researchers, using performance indicators such as accuracy, F1 score, and precision. Implementing this model effectively can greatly assist farmers and agricultural stakeholders in the early detection and management of diseases, thereby enhancing both the yield and quality of mangoes. Future efforts will aim to broaden the dataset, include more disease categories, and investigate the model's real-time application via mobile apps and edge devices for on-site disease identification.

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