RESEARCH PAPER

Mulberry leaf classification based on a hybrid deep learning approach - DCGAN synthesis and EfficientNetB0

Hemanth Chandra N[1], Vidyashree[2] and Dr Thriveni J[3]

[1] Research Scholar, Department of CSE, UVCE K R Circle, Bangalore, India- 560001

[2] Student, Department of CSE, UVCE K R Circle, Bangalore, India- 560001

[3] Professor, Department of CSE, UVCE K R Circle, Bangalore, India- 560001

[1] Assistant Professor, Department of ISE, Global Academy of Technology, Bangalore, India - 560098

Abstract

Sericulture is an important part of agriculture. The productivity, both in terms of quality and quantity of silk in sericulture, relies on the cultivation of Mulberry leaves, as silkworms' main source of food is mulberry leaves. Silk worms fed on healthy leaves produce high-quality silk. Productivity and nutrient value of Mulberry leaves often suffer from diseases that appear seasonally or regularly, like leaf rust, leaf spot, mildew, etc. These diseases spread rapidly, reducing the nutrient value of leaves, which leads to a reduction in silk production. Manual detection of diseased leaves is time-consuming and often inaccurate; therefore, using deep learning technology for disease identification and leaf classification is more effective and faster. Hence, in this paper we suggest that CNN-based EfficientNetB0 model used for classification; EfficientNetB0 is baseline models of the EfficientNet family that achieve high accuracy with fewer parameters and lower computational cost compared to traditional CNNs, It can work on a wide range of datasets, but it's good to have at least a few thousand images per class to avoid overfitting for good performance. Hence, in this research, we use Generative Adversarial Networks (GANs) for high-fidelity synthetic image generation that helps to expand the original dataset. The original dataset, which contains 1091 real images belonging to 3 different classes, was enlarged using Deep Convolutional GAN (DCGAN) to over 2000 images in each class, resulting in a balanced dataset of 6000 images. The dataset split ratio followed is 70:15:15 (training: validation: test). Lightweight tensor flow-based model EfficientNetB0 was fine-tuned and trained on the enhanced dataset and achieved an accuracy of 99%. Results demonstrate the effectiveness of the EfficientNetB0 with a limited size of dataset.

Key Words: CNN network, Compounded scaling, DCGAN, Deep learning, EfficientNetB0, Mulberry leaf, Sericulture.

How to cite this article: Hemanth Chandra N, Vidyashree, Thriveni J. Mulberry leaf classification based on a hybrid deep learning approach - DCGAN synthesis and EfficientNetB0. Int J Drug Deliv Technol. 2026;16(50s): 748-761.

DOI: 10.25258/ijddt.16.50s.76

1 INTRODUCTION

Mulberry leaves serve multiple vital uses and have a lot of commercial applications. They are the main source of food for silkworms in sericulture. Silkworms have a lifecycle of 8 days, day 5 is the stage of silkworm life during which formation of silk happens rapidly, yield of silk is high and of good quality if they are fed on good quality, disease free mulberry leaves during their short lifespan [1]. Mulberry leaves can be used as food source for livestock, they can be used as fish feed for healthy fish, cows and goats fed on mulberry leaves will increase milk production, fat and protein content in flesh(meat/beef) is also high [2]. Human consumption of mulberry leaves has many benefits, Composition of mulberry leaves is rich in vitamins mainly B and C that helps to boost digestion and fight infections [3]. Mulberry leaves composition also contains fiber, calcium, magnesium, and iron etc., to extract benefits of all these components herbal tea is prepared, mulberry herbal tea is gaining popularity due to its high nutritional content and flavor, consumption of this mulberry herbal tea will help to develop strong immune system [4].Mulberry herbal tea is available in many of Asian countries like china, Thailand, japan [5]. Phyto-chemicals found in Mulberry leaves are helpful in modulating cardio metabolic risks. Various nutrients and functional phytochemicals were found in mulberry leaves [6]. Mulberry leaves can be used for prevention or treatment of type 2 diabetes and hyperuricemia [7]. Fruits grown on mulberry trees are called mulberries, two famous types of mulberries are Black Mulberry and Red Mulberry Fruits. Mulberries are popular among human consumption fruits in china and are also known as "king of fruits" in china due to their sweetness and juicy nature [8]. Consumption of mulberries regularly have various benefits like helps for nourishment of kidney and liver, improves vision clarity and helpful in blood enrichment [8]. Mulberry fruits can also be used for weight loss and cure issues like constipation, heart related diseases, burning sensation and to reverse aging effects [9]. Mulberries are consumed fresh, dry, or processed into jam, wines, teas, jellies, etc.

However, benefits extracted from mulberry leaves will be compromised if the leaves are not healthy and prone to diseases like leaf rust and leaf spot which in turn impact on plant growth and fruit production. These diseases also impact on quality and quantity of leaves produced, which directly impacts silk production. Hence, there is a need to accurately identify and classify the leaves, as early identification can help us to prevent the spread of diseases, take corrective measures, and

*Author for Correspondence: Hemanth Chandra N

mitigate the loss. Manual detection is time-consuming, requires a lot of labor effort, and is prone to human errors alternative to human detection, automated computer vision-based models would be beneficial in reducing time and manual labor efforts. In recent days, Deep Learning (DL) based algorithms are widely used for image processing tasks like classification and are very effective in performing the assigned tasks as these algorithms learn about relevant features from raw images automatically. A branch/subset of DL models designed to be specialized in image processing, segmentation, detection and classification task are Convolutional Neural Networks (CNNs) and are widely used [10]. CNN architecture is inspired by the connectivity pattern of the human brain, based on the concept of the working of the visual cortex, a part of the brain responsible for processing visual information. Each convolutional layer is designed to recognize spatial hierarchies and local patterns within images, which helps the model capture both local and global image features, making it highly efficient.

CNN based DL algorithms are most popular in agricultural domain for various plant leaf disease detection like wheat [11], Rice plant [12], Tomato [13], Apple [14], coffee maturity [15] etc. Our study focuses on mulberry leaves, previously various authors have proposed various algorithms for classification/detection of mulberry leaves [16]- [18]. Small imbalanced datasets used in DL/CNN algorithms will lead to issues such as overfitting, biased prediction, poor generalization, and noisy validation scores, hence there is need for large dataset as accuracy of these algorithms depends on availability of large, balanced, and diverse datasets. Collecting large datasets may be impractical due to regional dependency, seasonal constraints, and labor costs etc. Hence we need to focus on alternative methods for enlarging and balancing dataset like argumentation and GAN networks. In our work proposed in this paper to deal with small, imbalanced mulberry leaf dataset we use Deep Convolutional Generative Adversarial Network (DCGAN) an advancement of GAN, it generates realistic images using deep convolutional layers. Two building blocks of DCGAN architecture are a generator and a discriminator, which work opposite to each other during the training process. The generator task is to learn about the latent space in the in- put image and generate a fake image that resembles the real data, it uses a series of convolutional layers stacked one above the other used to up-sample the low-dimensional noise vector into a full-size image. The discriminator's job is to distinguish real dataset images from fake images produced by the generator, it uses standard convolutional layers to down-sample the input image and make a decision about whether the image is real or fake. During training, the generator aims to improve by trying to fool the discriminator, while the discriminator improves by becoming better at detecting fake images produced. This adversarial process helps both the generator and discriminator networks to evolve in each epoch, resulting in the generator producing images that are classified as real images by the discriminator and resemble real images. DCGAN is used to generate images similar to that of real mulberry leaf images, generated images combined with real images to enlarge and balance the datasets, combined dataset contains diverse images that help for obtaining high accuracy with more generalized model [19]-[27].

Model selected for training in our proposed work is EfficientNet, It further enhances the CNN architecture by introducing a compound scaling method that helps the network to uniformly scale in depth, width, and resolution [28]. CNN-based EfficientNet models require fewer parameters and computational resources in comparison with traditional architectures like ResNet or Inception, which in turn makes it possible for EfficientNet models to achieve state-of-the-art accuracy while being fast and re- source efficient but the Effectiveness and success of CNN-based EfficientNet models depend on the availability of large, balanced, and diverse datasets.

In this paper, we suggest a hybrid approach for mulberry leaf detection and classification that combines DCGAN and EfficientNetB0 architecture.

The work proposed in this paper includes the following aspects:

i. The method proposed uses DCGAN with Convolutional and Transposed Convolutional Layers for the synthesis of high-quality, realistic images, which helps to augment the training dataset, improving the performance and generalization of downstream image classifiers.

ii. CNN-based EfficientNet family's baseline model, EfficientNetB0, was trained to perform im- age classification

iii. The effectiveness of the proposed model's accuracy was evaluated to show an increase in accuracy with limited parameters.

iv. Comparisons were made between the proposed model and some other state-of-the-art models on the same datasets.

2 LITERATURE REVIEW

Different deep learning algorithms have been used for disease detection in plants, the review conducted mainly focuses on how the use of CNN-based deep learning algorithms increases the accuracy and speed of disease detection. The study focuses on developing models to perform accurately with limited, imbalanced datasets using DCGAN.

Sokhibova, N.S *et al.* [1] explore the benefits of feeding silkworms with healthy and nutritious mulberry leaves, which aids in the development of the silk gland, making them healthy enough to produce high-quality cocoons. According to the study, silkworms have a lifespan of just 8 days, during which nutrition is critical for high silk yield. Silk productivity in terms of both quantity and quality was found to be higher in silkworms fed on mulberry leaves, resulting in significant economic benefits for farmers.

Mwai *et al.* [2] reviews the potential benefits and nutritional value of mulberry leaves as food to feed livestock (cattle, goat, ships and rabbits) in Kenya. Mulberry leaves are basically grown for silkworm and are rich in proteins, vitamins and minerals making them suitable for animal feed. As per the study feeding livestock on mulberry leaves improved digestion with impressive growth in milk and meet produced which was beneficial to farmers by increasing income.

Afzal *et al.* [3] presents comprehensive review on the nutritional benefits of mulberry leaves that help to promote health while preventing disease on the basis of evidences collected from both traditional and modern methods. As per the study mulberry leaves contain Vitamin (A, B, C, and K), Minerals (Calcium, iron, magnesium) and Macronutrients (protein, fiber) all these healthy composition helps to reduce cholesterol and stabilizing blood glucose levels.

Nyehangane *et al.* [4] paper explores different preparation methods and health benefits of herbal tea pre- pared from mulberry leaves. Mulberry tea can be prepared using dry or fresh leaves. Mulberry tea is rich in nutritional composition with components such as polyphenols, 1-deoxynojirimycin, flavonoids, calcium, iron, and magnesium that are useful in promoting health. Mulberry tea has good flavor and caffeine-free making it a healthy beverage that promotes health alternative to unhealthy caffeinated beverages.

Yanfang Yu *et al.* [5] conducted a study on nutritional composition of 19 variety of mulberry leaves found in china. Main aim of study was to review about nutritional quality of mulberry leaves that make mulberry leaves one of the food ingredient promoting good health. Authors concluded mulberry leaves are composed of significant compounds which increase the nutritional value of diet, helpful for regulating blood glucose.

Thanchanit Thaipitakwong *et al.* [6] conducted a review on chemical compositions and biological properties of mulberry leaves that can be helpful in minimizing cardio metabolic risks. Authors identified bioactive compounds such as 1-deoxynojirimycin (DNJ), phenolic, and flavonoids from various preclinical and clinical studies. These compounds are helpful for managing disorders related to metabolism like type 2 diabetes and cardiovascular diseases.

Hunyadi *et al.* [7] conducted a study to investigate on mulberry leaf extracts metabolic benefits that are helpful for managing diseases like diabetes (type-2) and hyperuricemia. Study was made by conducting experiments in both in vitro and in vivo environments. As per their study mulberry leaf extracts have useful compounds like DNJ (1-deoxynojirimycin) useful to slow down absorption of sugar, Chlorogenic acid and rutin helps to reduce inflammation and improvement of improve blood health, other flavonoids and antioxidants are helpful to protect body organs and cells.

Zeqi Hu *et al.* [8] conducted a systematic review with bibliometric analysis on the nutritional, pharmacological, and industrial potential of mulberries. Mulberries are rich in proteins, vitamins (A, C, E, B complex), minerals (e.g. iron, zinc), and alkaloids (notably 1 deoxynojirimycin, DNJ) due to its rich nutritional composition and flavor mulberries are used as juices, jams, wines, syrups, functional drinks, and dried snacks that help to improve nutrient digestibility, immunity, growth parameters, and antioxidant status.

R. Venkatesh Kumar and Seema Chauhan [9] conducted research to study the medicinal values of mul- berry species. Mulberry leaf extracts are rich in Deoxynojirimycin (DNJ), which is known to help reduce blood sugar levels. Other compounds such as flavonoids and stilbene glucosides present in the extracts are beneficial in minimizing cardiovascular and neurological risks, while also enhancing metabolic functions and providing anti-aging effects. Mulberry leaves can be consumed in various forms such as juice, syrup, wine, and leaf tea.

Younesi et al. [10] explained convolution methods used in deep learning and presented a review of their workings, applications, challenges, and future improvements. According to their study, there are five main types of convolution techniques: Basic Convolution, Dilated Convolution, Grouped and Depthwise Convolutions, Transposed Convolution, and Attention-based Convolution. These methods are applied in real-world tasks such as image classification, object detection, speech and audio recognition, medical image analysis, autonomous vehicles, and security systems. However, a major limitation of convolutional methods is their high computational cost and the requirement for large datasets.

Md Helal Hossen *et al.* [11] proposed a CNN based algorithm to detect and classify diseases in wheat plants using images of their leaves. Authors developed a 2D convolutional model trained on 4800 images to classify wheat into 11 classes of diseased leaves and 1 class of healthy leaves, Data augmentation like flipping and rotation was performed on images of dataset to make model robust, the model used pre-trained features achieved an accuracy of 98.84% in correctly identifying and classifying wheat diseases.

Ghazanfar Latif *et al.* [12] conducted a research using a deep learning technique called CNN for detecting diseases in rice plants, improved VGG19 model using transfer learning and image augmentation was trained on images of healthy leaves and five common rice diseases- Brown Spot, Narrow Brown Spot, Leaf Blast, Leaf Scald, and Bacterial Leaf Blight. Pre-trained model was able to accurately identify diseases and differentiate healthy leaves from diseased ones with a high accuracy of 96.08%. This model is helpful for farmers in early and accurate detection of diseases thereby reducing crop loss and increasing production.

Ouamane, A *et al.* [13] built a system using advanced AI techniques to detect diseases in tomato leaves using advanced AI techniques. Authors combined from multiple pre trained CNN models(e.g. Dark- net53, DenseNet201, ResNet50, EfficientNetB0) into a multidimensional (tensor) representation, then apply a two-step learning process called HOWSVD TEDA (Higher Order Whitened SVD followed by Tensor Exponential Discriminant Analysis) to improve disease classification. PlantVillage (tomato leaf diseases) and Taiwan tomato disease dataset were used for training the model, model achieved an accuracy of 98.36% (PlantVillage) and 89.39% (Taiwan dataset).

Ibrahim *et al.* [14] custom-designed CNN based lightweight model named AppleCNN to classify apple leaf images into healthy or diseased (Apple Scab, Black Rot, and Cedar Apple Rust) and help farmers for early detection. AppleCNN trained using supervised learning with labeled preprocessed (resized, normalized, and augmented) image data and achieved an accuracy of 99.3% on the test dataset.

Tamayo Monsalve *et al.* [15] developed a model to determine five stages (dry, mature, semi-mature, overripe, and immature) of riping of coffee cherries are using CNN architectures (e.g., VGG16, ResNet, etc.), models were pre-trained on balanced training datasets of fruits obtained after data augmentation. Model achieved an accuracy of 98% being fast, accurate, and useful for real-world coffee sorting and grading. Abdus Salam *et al.* [16] proposed a lightweight CNN-based MobileNetV3-Small model, which was trained and integrated with an Android application for real-time mulberry leaf disease detection. The authors collected approximately 1091 images and labeled them into three classes: healthy disease free, leaf rust, and leaf spot. These images were expanded to 6000 using data augmentation techniques to improve model generalization. The pre-trained model achieved an average accuracy of 96.4%, a precision of 97.0%, and an F1-score of 96.4% across five-fold cross-validation. As MobileNetV3-Small is small in size (less than 100 MB), it is ideal for deployment in mobile environments. To provide visual insight into the regions contributing to classification, Gradient-weighted Class Activation Mapping (Grad-CAM) was utilized.

Nahiduzzaman, M *et al.* [17] Proposed an effective and explainable deep learning lightweight convolutional neural network called PDS-CNN (Parallel Depthwise Separable Convolutional Neural Network). Proposed model has 0.53 million parameters and a size of 6.3 MB making it lightweight and ideal for mobile devices. To Visualize parts of the leaf images influencing the model's predictions SHAP (SHapley Additive exPlanations) was applied, model achieved an accuracy of 95.05% three-class classification (healthy, rust, spot) and accuracy of 96.06% on binary classification (healthy vs. diseased).

Duragkar *et al.* [18] Addresses the critical problem of disease detection in mulberry leaves as either infected or healthy using Capsule Neural Network (CapsNet) in combination with a VGG16 transfer learning model. Dataset containing annoted images of healthy and infected leaves for model training was collected from Multi-agent Intelligent Simulation Laboratory (MISL), for better model generalization images were augmented. The best results were obtained in Experiment of 10 epochs, achieving 82.04% accuracy.

Bin Liu *et al.* [19] proposed a GAN-based method for data augmentation to improve the accuracy for disease identification in grape leaves. GAN was trained to generate disease leaf images similar to those of real images to address issues of imbalanced datasets. GAN-augmented data helped to generalize convolutional neural network (CNNs) models, and there was a significant improvement in model performance.

Zhao Zhang *et al.* [20] Performed image augmentation using a Dual GAN. They conducted a study on a high-quality rice leaf disease. Dual GAN is a combination of two GANs to generate highly diverse and more realistic images. Generated images were used to enrich the limited dataset and further enhance the model training. There was an improvement in the model's accuracy in rice disease classification tasks.

Zahid Ur Rahman *et al.* [21] Used different GAN architectures for image augmentation of crop images to diversify the dataset, which in turn helps to improve the model performance in crop disease detection. The Authors compared and analyzed the effectiveness of various GAN architectures.

S. N. Bushra *et al.* [22] Conducted a comprehensive survey for COVID-19 diagnosis using chest X-ray and CT-scan images with help of Deep Convolutional Generative Adversarial Networks (DCGANs) by addressing problems related to limited dataset in medical field. DCGANs used for generation of synthetic data to improve model diagnostic performance. Authors tested model performance by combining 10% real data with 90% of generated data, this small and large combination of real and generated data resulted in high accurate results.

Liu, B *et al.* [23] Presented an enhanced version of Deep Convolutional Generative Adversarial Network (DCGAN) model designed to generate good quality images with high diversity. (DCGAN) was enhanced by designing the network structure to prevent gradient vanishing and using activation functions like LeakyReLU in the discriminator, ReLU in the generator. The improved DCGAN produced images with 2.02× better quality and 1.55× better diversity than standard GANs and outperformed the traditional GANs in both image clarity and variety.

Shibo. Lu *et al.* [24] Proposed a novel technique for detecting dangerous DC series arc faults in photovoltaic (PV) systems using a deep learning-based approach named as DA-DCGAN, which combines domain adaptation with Deep Convolutional Generative Adversarial Networks (DCGANs) to address the challenge of limited arc fault data in real-world PV installations. Authors trained DCGAN fault data from source domain and used to generate synthetic arc fault signatures in target domain, where real arc fault data is unavailable. This allows the model to detect faults accurately in new PV systems without needing labeled arc fault data for each system. Results show DA-DCGAN is an effective, transferable, and real-time solution for improving the safety of PV systems through reliable arc fault diagnosis.

Qiufeng wu *et al.* [25] explore how Deep Convolutional Generative Adversarial Networks (DCGANs) generate realistic tomato leaf images across multiple disease categories to improve the identification of tomato leaf diseases effectively increasing its size and diversity. Authors trained and tested GoogLeNet classifier for disease recognition using the PlantVillage dataset. Experimental results show that the inclusion of DCGAN-generated images leads to a notable improvement in classification accuracy, reaching up to 94.33

Devi, Y. S., and Kumar, S. P. [26] introduce DR-DCGAN, a Deep Convolutional Generative Adversarial Network designed for synthetic image generation in the context of diabetic retinopathy (DR) a critical complication of diabetes that affects the eyes. Limited availability of annotated DR images are available, DCGANs generate high-quality synthetic fundus images that can augment medical datasets. This helps improve the performance of deep learning models used for DR detection and classification. The proposed model was evaluated using standard datasets and was shown to improve the diversity and volume of training data, thereby addressing class imbalance issues and boosting model robustness.

Devakumar S, *et al.* [27] explores the use of DCGANs to convert forensic sketches into photorealistic facial images. This method aims to bridge the gap between manually drawn sketches—commonly used in criminal investigations and real facial photographs, which can significantly enhance the accuracy of suspect identification. The authors used paired datasets of sketches and corresponding real face im- ages for model training. The generator learns to synthesize realistic images from sketch inputs, while the discriminator evaluates how realistic the generated images are. Their results show that the DCGAN model can effectively generate visually convincing facial images from input sketches, offering potential applications in law enforcement and forensic science.

Tan, M., and Le, Q [28] introduce a new deep learning model for introduces a new model for compound scaling that scales easily in depth, width, or input resolution using compounding coefficient, which helps to get better accuracy and efficiency compared to scaling any one dimension alone. They use neural architecture search to design a small but highly efficient baseline model called EfficientNet-B0. From this base, they derive a series of models (EfficientNet-B1 to B7) by uniformly scaling up the architecture using the compound coefficient.

3 METHODOLOGY

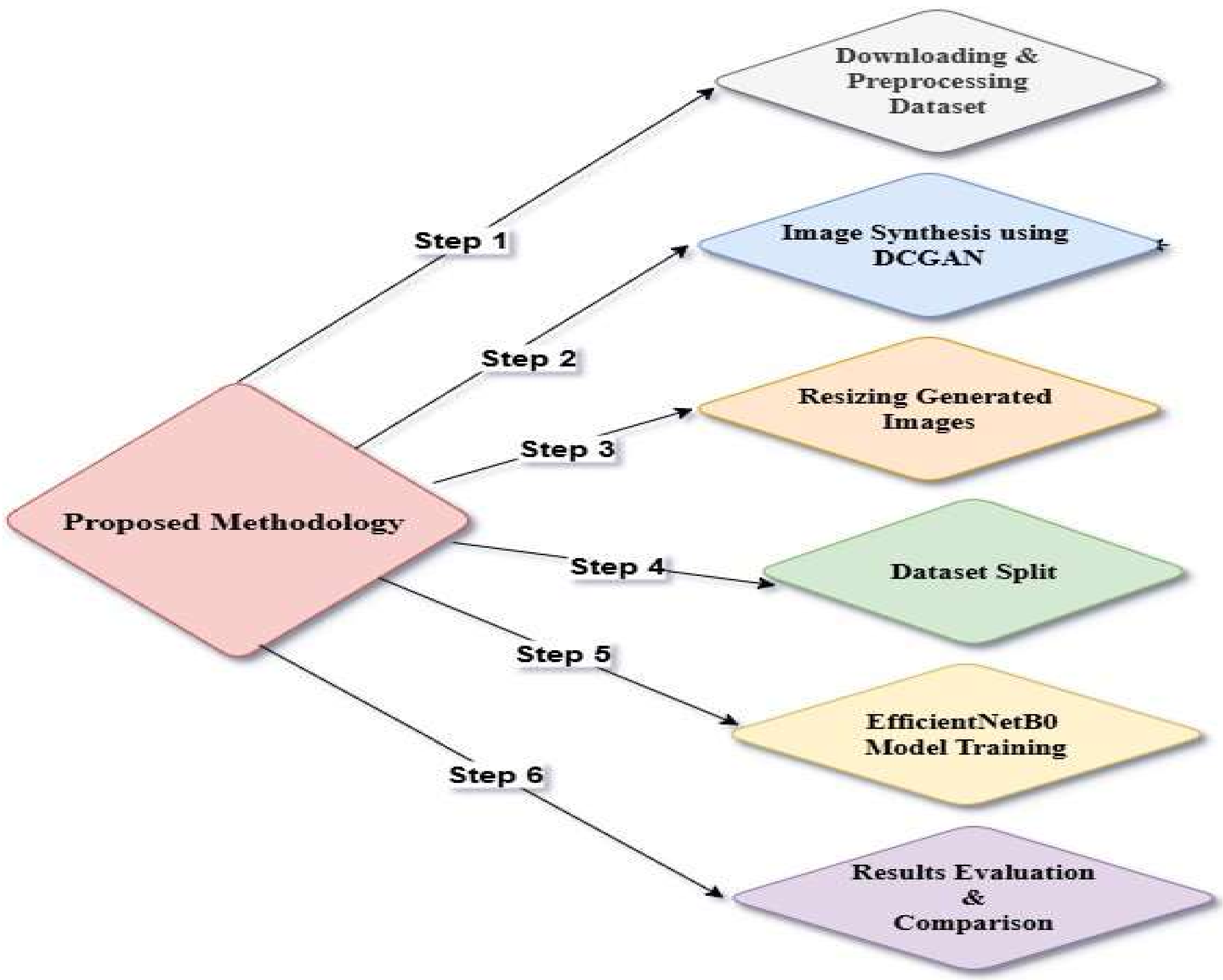

Figure 1 : Steps followed in the proposed methodology.

The methodology adopted is divided into different phases: Downloading and preprocessing the dataset, Image Synthesis using DCGAN, Resizing Generated Images, Dataset split, Model Selection-EfficientNetB0, and Training. Figure 1 demonstrates the steps followed in the proposed methodology.

3A DOWNLOADING AND PREPROCESSING THE DATASET

Initially, a dataset of 1091 high-resolution (4000×6000) mulberry leaf images was downloaded from the Kaggle website, which was made available by the authors of the paper [16], [17]. It contained images collected from multiple mulberry gardens in Rajshahi, Bangladesh. These images were categorized into three classes: disease-free (440 images), leaf rust (489 images), and leaf spot (162 images). Figure 2 showcases original mulberry leaf images. Each image was resized to 224×224 pixels to maintain consistency and compatibility with deep learning model input specifications. However, the dataset was small and imbalanced. CNN-based models used for classification require balanced and large datasets for better efficiency.

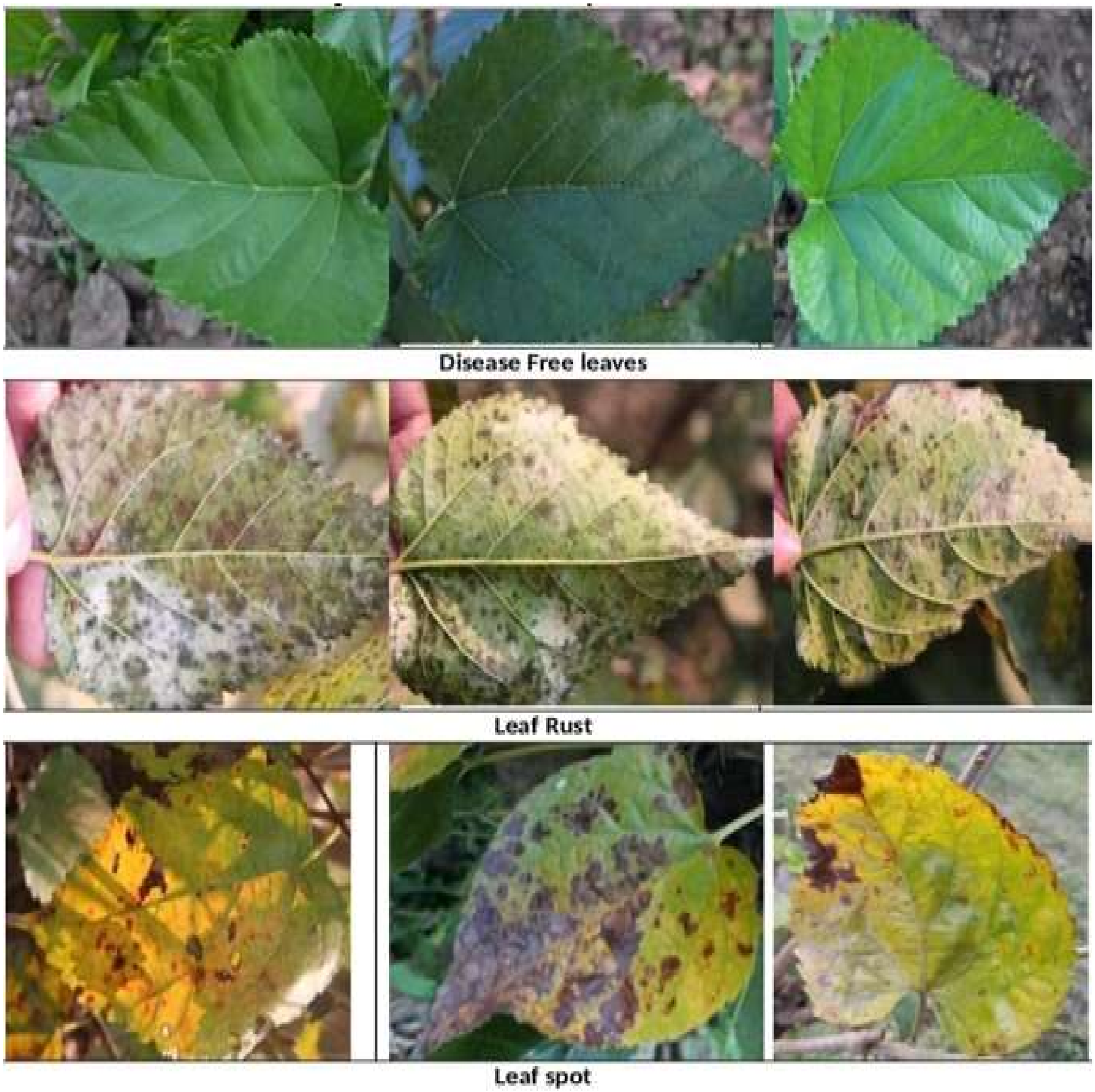

Figure 2: Original mulberry leaf images

3b IMAGE SYNTHESIS USING GAN

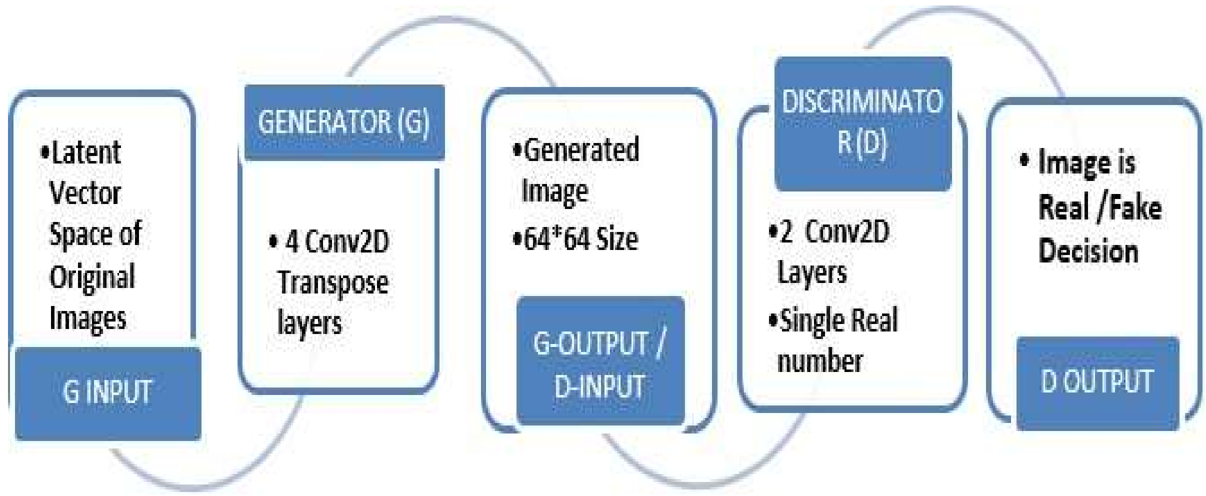

Figure 3: Steps followed in the proposed methodology.

To enhance and balance the datasets, Deep Convolutional Generative Adversarial Networks (DCGANs) were employed for synthetic image generation. DCGAN is an advancement of GAN, it generates realistic images using deep convolutional layers. Since there are three classes in the original downloaded dataset, separate DCGANs specifically, one for each class were trained to learn the underlying distribution and generate new, diverse images. As we want to develop a simple GAN for quick prototyping, perform faster training with low memory usage, and be less GPU intensive, we will develop DCGAN to generate 64*64 images. Generated images will be upscaled to 224*224 quality to feed the Efficient- NetB0 model for training. Figure 3 demonstrates block diagram of DCGAN and Figure 4 demonstrates the architecture of DCGAN used in proposed model to generate leaf images. Table 1 describe DCGAN model specifications. Table 2 describes purpose served by 4 Conv2D transpose layers of generator. Table 3 describes purpose served by 2 Conv2D layers of Discriminator.

Aspect	Generator	Discriminator
Function	Upsampling: starts from latent noise, grows into an image	Downsampling: Takes an image, downsamples and classifies
Output	Synthetic image	Real/fake score
Layer type	Transposed convolution	Convolution
No of Conv. Layers	4	2
Kernel size	5×5	5×5

Table 1: DCGAN model specifications

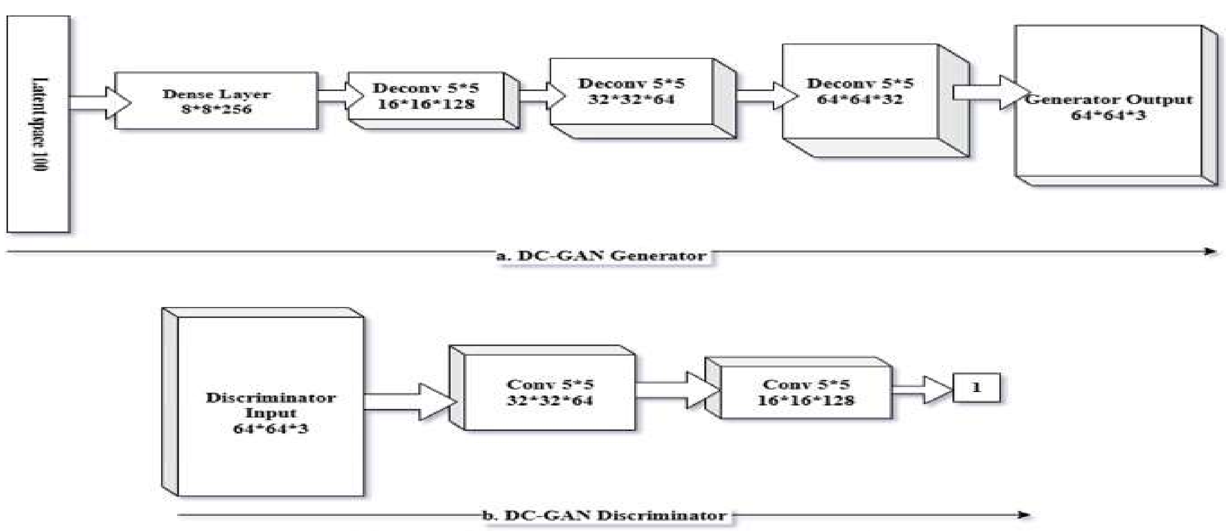

Figure 4: DCGAN Architecture

Layer	Output Shape	Filters	Purpose
Conv2DTranspose	(16, 16, 128)	128	Upsample & refine features
Conv2DTranspose	(32, 32, 64)	64	Further upsample
Conv2DTranspose	(64, 64, 32)	32	Final upsample step
Conv2DTranspose	(64, 64, 3)	3	Produce RGB image in [-1, 1]

Table 2: Purpose served by 4 Conv2D transpose layers of generator

Layer	Output Shape	Filters	Purpose
Conv2D	(32, 32, 64)	64	Detect low-level patterns (edges, textures)
Conv2D	(16, 16, 128)	128	Capture higher-level features

Table 3: Purpose served by 2 Conv2D layers of Discriminator

Different DCGAN are used one for each class of leaves to generate leaves of respective class with a bath size of 32 for 12000 epochs The Training process of 3 different GAN's generated high-quality synthetic images that were visually indistinguishable from the original ones. In total, more than 5000 synthetic images were generated, when these generated images combined with original images achieving a balanced dataset of 2000 images in 3 different classes that contributed to improved model generalization. Figure 5 showcases the generated mulberry images.

Figure 5: Generated mulberry images

3C. RESIZING GENERATED IMAGES

In our proposed model, we are generating 64*64 images as a few pixels will lead to fewer computations in both the generator and discriminator, with less time needed for each iteration, and can be trained on moderate GPU or CPU without running out of memory. 64*64 images then resized into 224*224 images as needed for the EfficientNetB0 model training, Since the model selected is EfficientNet-B0, which was designed and pre-trained on ImageNet, and it expects 224×224 input images, the architecture (convolution layers, down-sampling rates, and positional patterns) is optimized for this size. Hence, generated images were resized to 224*224. Training of selected model with resized

images has various benefits like, it's easier to stabilize, less prone to collapse, and best suited for research carried out on laptops or low-resource devices with small datasets.
Generated resized images were added to the original dataset, and the combined dataset (GAN +Original) was split into 70% training, 15% validation, and 15% test datasets. Table 4 provides a detailed description of the dataset used for model training

Type	Original Images	DCGAN Images	Final Count	Training Dataset	Validation Dataset	Test Dataset
Disease Free Leaf	440	1560	2000	1400	300	300
Leaf Rust	489	1511	2000	1400	300	300
Leaf Spot	162	1838	2000	1400	300	300
Total	1091	4887	6000	4200	900	900

Table 4: Dataset Description

3D. MODEL SELECTION

Google researchers developed a family of pretrained convolutional neural network (CNN) based models for efficient depth, width, and resolution-wise scaling called the EfficientNet family. Efficient Net introduces compound scaling, a balanced way to scale all three dimensions [28]. EfficientNetB0 is the smallest model in the series, it offers a good balance between accuracy and computational cost, hence EfficientNetB0 is selected as the classification backbone due to its compound scaling ability and lightweight architecture. It's a popular choice, especially when computational resources are limited. Description of EfficientNetB0 model specification proposed in this work in provided in Table 5. Since EfficientNetB0, is pretrained on ImageNet, but we are using for a different classification problem, we need to remove the top classification layer to leverage its robust feature extraction capabilities. Figure 6 demonstrates Architecture used for training EfficientNetB0 model on combined (generated + real) balanced mulberry leaf dataset.

Feature	EfficientNetB0
Input Image Size	224×224
Top-1 Accuracy (ImageNet)	~77.1%
Top-5 Accuracy	~93.3%
Parameters	~5.3 million
FLOPs	~0.39 billion
Depth (Network Layers)	Base depth
Width (Channels)	Base width
Scaling Coefficient (ϕ)	0
Training Time	Shorter
Use Case	Lightweight applications

Table 5: Proposed model EfficientNetB0 model specifications.

3E. Model Training

Three convolutional layers with 256, 128, and 64 filters are added in our proposed model. The kernel size used is 3×3, and the activation function is ReLU. To stabilize and regularize the training process, batch normalization is performed along with dropout layers after each CNN layer. A Flatten layer is added after the stack of CNN layers to convert the multidimensional data into a 1D vector, followed by two Dense layers, First Dense Layer (128 units, activation = relu): A decision-making layer that interprets extracted features. This is followed by batch normalization and a dropout rate of 0.3. Second Dense Layer (number of classes, activation = softmax): The final classification layer that outputs class probabilities.
Since this is a multi-class classification task, the model is compiled using the Adam optimizer and categorical cross-entropy loss. The model is trained for 60 epochs with a batch size of 32. Data augmentation techniques such as rotation, shift, zoom, and flip are applied to the training set to enhance generalization. Validation is performed using unaugmented images to monitor actual model performance. Early stopping (patience = 15) and learning rate reduction (patience = 3, factor = 0.2) callbacks are used to prevent overfitting and dynamically adjust the learning rate. A detailed description of the specifications used in model training is provided in Table 6

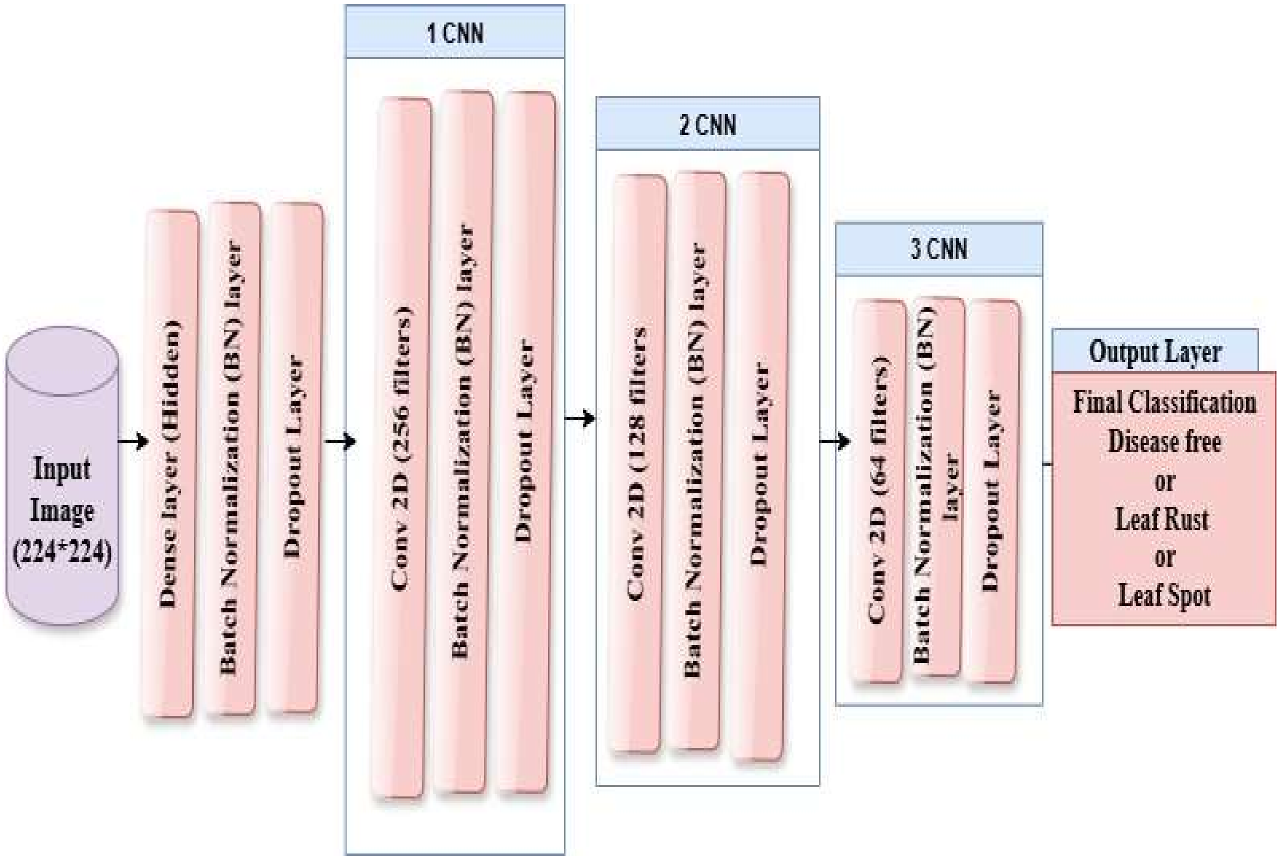

Figure 6: Architecture used for training EfficientNetB0 model.

4 RESULTS AND DISCUSSION

After training, the model's performance is evaluated using accuracy/loss plots, a confusion matrix, a classification report, and ROC curves for each class. This comprehensive evaluation provides insights into both the overall and per-class classification behavior, making the model suitable for practical deployment in multiclass image classification tasks. Formulas used to measure the performance of the proposed model are given below,

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Component	Specification
Base Model	EfficientNetB0
Input Shape	(224, 224, 3)
Image Augmentation	Rotation, shift, shear, zoom, flip
include top	False (original Flatten, Dense, Softmax layers removed)
No. of Convolutional layers (CNN)	3 (Conv2D layers with 256, 128, 64 filters of 3 × 3)
No. of Dense layers	2
No. of Batch Normalization layers	4 (3 CNN + 1 Dense)
No. of Dropout layers	4 (3 CNN + 1 Dense)
No. of Flatten layers	1

Total No. of Custom Layers	13
Dropout Rate	0.2 for CNN, 0.3 for Dense
Activation Function	ReLU, Softmax
Optimizer	Adam
Loss	categorical crossentropy
Epochs & Batch Size	60 epochs, batch size 32
Early Stopping	patience = 15
Learning Rate Scheduler	patience = 3, factor = 0.2
Data Split (Train/Val/Test)	70%, 15%, 15%

Table 6: Description of specification used in model training.

Type	Precision	Recall	F1-Score	Support
Disease Free Leaf	0.99	1.00	0.99	300
Leaf Rust	1.00	0.99	0.99	300
Leaf Spot	0.99	0.99	0.99	300
Accuracy	0.99	0.99	0.99	900
Macro Avg	0.99	0.99	0.99	900
Weighted Avg	0.99	0.99	0.99	900

Table 7: Summary of classification model Performance.

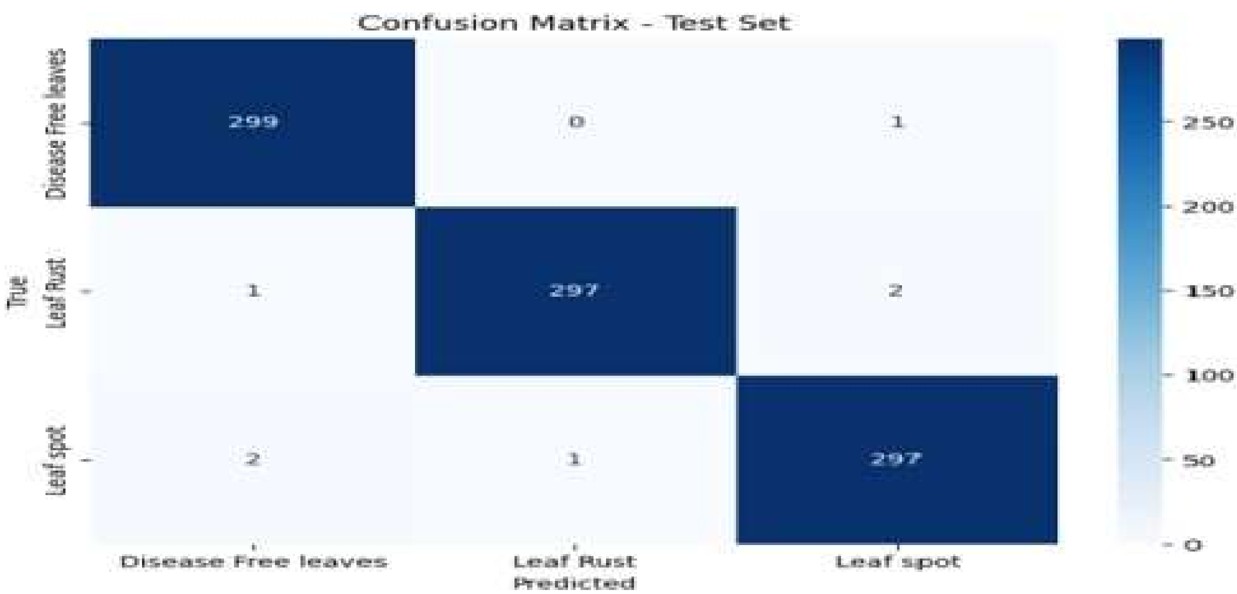

Figure 7: Confusion matrix of proposed classification model

Table 7 shows the summary of the multi-class classification model involving three classes of leaves: Disease- Free Leaf, Leaf Rust, and Leaf Spot. It provides four main metrics for each class: Precision, Recall, F1-score, and Support. From the above numbers, we can say the model is highly accurate. The model demonstrated an accuracy of 99% across all prediction classes. Hence, we can say the proposed model is performing exceptionally well with very high precision, recall, and F1-score for all classes. The classification is balanced, and the model generalizes well across the three classes of leaves.

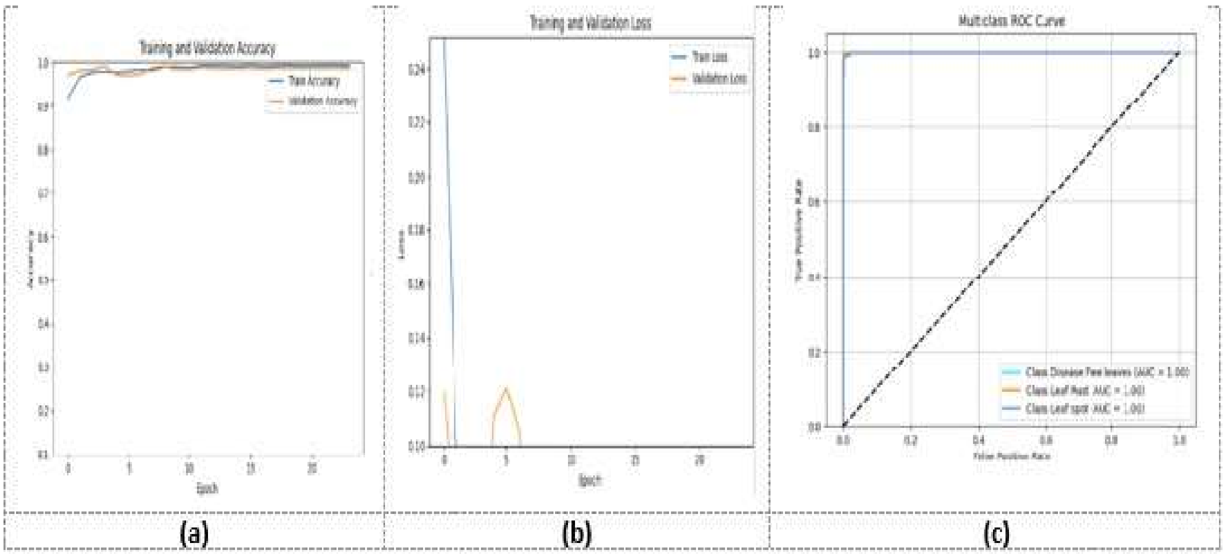

Figure 8: (a) Models Training and Validation Accuracy plot (b) Models Training and Validation loss plot (c)Models ROC curve.

Figure 7 illustrates the confusion matrix for the proposed model. It can be observed that model performs well, but their exist Slight confusion between Leaf Rust Leaf Spot and Leaf Spot Disease-Free, which is normal in fine-grained visual classification tasks.

Figure 8(a) shows the plots of Training and Validation Accuracy of your mulberry leaf disease classification model over training epochs, model quickly reaches above 95% accuracy on both training and validation sets within the first few epochs and there's no significant gap between training and validation curves, which means the model is not overfitting it performs equally well on both training and unseen data.

Figure 8(b) shows the plots of Training and Validation loss, it is observed that drops steeply within the first few epochs, indicating the model quickly learned from the training data, Validation loss is also very low both losses are consistently low and close, which suggests the model is well-generalized. The final loss values are extremely low, confirming high accuracy and minimal error.

Figure 8(c) shows the plot of ROC (Receiver Operating Characteristic) curve, it can be observed that all three classes have an AUC (Area Under Curve) of 1.00, which means the model perfectly distinguishes each class from the others. AUC = 1.00 is ideal and rarely achieved unless the dataset is clean, well- preprocessed, and the model is very well-tuned.

Proposed model EfficientNetB0 performance is compared with MobileNetV3Small and NASNetMobile. MobileNetV3Small is specially designed for lightweight low resource environments with 2.5 million parameters and approx. 66M FLoating point Operations (FLOPs), MobileNetV3Small proven to achieve better accuracy [16] on tasks like classification, object detection, and segmentation. We trained Mo- bileNetV3Small on combined dataset with parameters specified in Table 6, we achieved an accuracy of 99% which is equal to that of selected model EfficientNetB0, but MobileNetV3Small has scaling limitation as adding up more layers will affect the model optimization and accuracy. NASNetMobile Reinforcement learning based Neural Architecture Search (NAS) mobile-focused model, NASNetMobile trained on combined dataset with parameters specified in Table 6, we achieved an accuracy of 97% which is less than selected model EfficientNetB0 accuracy, Table 8 shows the summary of Mo- bileNetV3Small and NASNetMobile classification models involving three classes of leaves: Disease- Free Leaf, Leaf Rust, and Leaf Spot. Hence our selected model EfficientNetB0 is best, performance wise and can scale efficiently in Depth (number of layers), Width (number of channels per layer), and Resolution (input image size) called as compound scaling method.

MobileNetV3Small					NASNetMobile			
Type	**Precision**	**Recall**	**F1-Score**	**Support**	**Precision**	**Recall**	**F1-Score**	**Support**
Disease Free	0.99	1.00	0.99	300	0.96	0.97	0.97	300
Leaf Rust	1.00	0.99	0.99	300	0.97	0.98	0.97	300
Leaf Spot	0.99	0.99	0.99	300	0.98	0.96	0.97	300
Accuracy	0.99	0.99	0.99	900	0.97	0.97	0.97	900
Macro Avg	0.99	0.99	0.99	900	0.97	0.97	0.97	900
Weighted Avg	0.99	0.99	0.99	900	0.97	0.97	0.97	900

Table 8: Summary of MobileNetV3Small and NASNetMobile model Performance.

5 CONCLUSIONS

In this paper, to address the issue of small imbalanced datasets, we generated images that approximate real images of resolution 64*64 using DCGAN we combined the generated images with real images of the original dataset to enlarge and balance the dataset of mulberry leaves, combined dataset has 2000 images in, each of three categories: healthy disease free, leaf rust, and leaf spot. We aim to design efficient, lightweight models suitable for mobile and embedded systems. Hence, the EfficientNet family baseline model, EfficientNetB0, was trained on the combined dataset and obtained an accuracy of 99%. The EfficientNet model was selected due to its compounded scaling ability, which helps to scale up in a balanced way without affecting the model's efficiency. The accuracy of EfficientNetB0 was higher than other popular CNN models like NASNetMobile (0.97) and MobileNetV3Small (0.99). In future work, we would plan to generate high-resolution, more realistic images using advanced GAN architectures like StyleGAN2 and Progressive GAN. Our classification model is trained on only 3 categories. In the future, we aim to expand the dataset to incorporate additional disease classes like Powdery Mildew, anthracnose, etc. These enhancements will help to further develop the more accurate, robust, and generalized model.

6 ACKNOWLEDGMENT

I express my sincere gratitude to the authors of [1] and [2] for providing access to the mulberry leaf image dataset used in this study. This research is based on and cites the foundational works of [1] and [2]. I gratefully acknowledge the use of AI-powered tools such as OpenAI's ChatGPT, which provided valuable assistance in drafting and refining the technical documentation and literature throughout the research process. I express thanks to my guide, Dr. Triveni J, for her valuable guidance and continuous support throughout this research

References

[1] Sokhibova, N. S., Nazirova, M. I. K., & Botirovna, S. M. (2020). Influence of rearing silkworms with high productive mulberry leaves on the biological indicators of silk gland and raw silk effectiveness. *Life Sciences and Agriculture*, (2), 87–90.

[2] Mwai, L. M., King'ori, A. M., & Ambula, M. K. (2021). Mulberry leaves as a feed source for livestock in Kenya: A review. *Tropical and Subtropical Agroecosystems*, **24**, Article #63. Published online 31 December 2021.

[3] Afzal, F., Khalid, W., Asif, M. N., Jabeen, A., Jha, R. P., Khalid, M. Z., Fizza, C., Aziz, A., Akram, R., Bashir, A., Younas, S., Nayyer, F., Yasin, R., & Ahmad, M. Z. (2021). Role of mulberry leaves in human nutrition: A review. *Acta Scientific Nutritional Health*, **5**(3), 43–50.

[4] Nyehangane, A., Lukoye, D. K., Masiga, S. N., & Masiga, C. W. (2025). Preparation and health benefits of herbal tea from mulberry leaves. *Journal of Medicinal Plants Studies*, 13(1), 116–121.

[5] Yu, Y., Li, H., Zhang, B., Wang, J., Shi, X., Huang, J., Yang, J., Zhang, Y., & Deng, Z. (2018). Nutritional and functional components of mulberry leaves from different varieties: Evaluation of their potential as food materials. *International Journal of Food Properties*, 21(1), 1495–1507.

[6] Thaipitakwong, T., Numhom, S., & Aramwit, P. (2018). Mulberry leaves and their potential effects against cardiometabolic risks: a review of chemical compositions, biological properties and clinical efficacy. *Pharmaceutical Biology*, 56(1), 109–118.

[7] A. Hunyadi et al., "Metabolic Effects of Mulberry Leaves: Exploring Potential Benefits in Type 2 Diabetes and Hyperuricemia," *Evidence-Based Complementary and Alternative Medicine*, vol. 2013, Article ID 948627, 10 pages.

[8] Z. Hu, Su, Y., Jia, J., Bian, X., Gu, Y., Lv, G., Chen, S., & Jiang, N. (2025). Mulberry– Nutritional Value, Health Benefits, and its Applications in Food, Biomaterials, and Medicine: A Systematic Review with Bibliometric Analysis. *Natural Product Communications*.

[9] Venkatesh Kumar, R., & Chauhan, S. (2008). Mulberry: Life Enhancer. *Journal of Medicinal Plants Research*, 2(10), 271–278.

[10] Younesi, A., Ansari, M., Fazli, M. A., Ejlali, A., Shafique, M., & Henkel, J. (2024). A Comprehensive Survey of Convolutions in Deep Learning: Applications, Challenges, and Future Trends. *IEEE Access*, CoRR abs/2402.15490.

[11] Hossen, M. H., Mohibullah, M., Muzammel, C. S., Ahmed, T., Acharjee, S., & Panna, M. B. (n.d.). Wheat Diseases Detection and Classification using Convolutional Neural Network (CNN). *Comilla University, Noakhali Science & Technology*

University, and Jahangirnagar University, Bangladesh.

[12] Latif Ghazanfar, Abdelhamid, S. E., Mallouhy, R. E., Alghazo, J., & Kazimi, Z. A. (2022). Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model. *Plants*, 11(17), Article 2230.

[13] Ouamane, A., Chouchane, A., Himeur, Y., Debilou, A., Amira, A., Mansoor, W., Atalla, S., & Al-Ahmad, H. (2024). Knowledge Pre-Trained CNN-Based Tensor Subspace Learning for Tomato Leaf Diseases Detection. *IEEE Access*, 12, 11229–11246.

[14] ˙I. Ç etiner, ”AppleCNN: A new CNN-based deep learning model for classification of apple leaf diseases,” *Gümüşhane University Journal of Science and Technology (GUJS)*, vol. 15, no. 1, pp. 51–63, 2025.

[15] Tamayo Monsalve, M. A., Mercado Ruiz, E., Villa Pulgar´ın, J. P., Bravo Ort´ız, M. A., Arteaga Arteaga, H. B., Mora Rubio, A., Alzate Grisales, J. A., Arias Garzón, D., Romero Cano, V., Orozco Arias, S., Osorio, G., & Tabares Soto, R. (2022). Coffee Maturity Classification Using Convolutional Neural Networks and Transfer Learning. *IEEE Access*, 10, 42971–42982.

[16] Abdus Salam, M., Naznine, N., Jahan, E., Nahid, M., Nahiduzzaman, M., & Chowdhury, M. E.
H. (2024). Mulberry Leaf Disease Detection Using CNN-Based Smart Android Application. *IEEE Access*, vol. 12, pp. 83575–83588. doi: 10.1109/ACCESS.2024.3407153.

[17] Nahiduzzaman, M., Chowdhury, M. E. H., Salam, A., Nahid, E., Ahmed, F., Al-Emadi, N., Ayari,
M. A., Khandakar, A., & Haider, J. (2023). Explainable deep learning model for automatic mulberry leaf disease classification. *Frontiers in Plant Science*, 14, 1175515.

[18] Duragkar, H. A. (2023). Identifying diseases in mulberry leaves that affects silk production: A deep learning approach (Master's thesis, *National College of Ireland*).

[19] Bin Liu, C. Tan, S. Li, J. He, and H. Wang, ”A data augmentation method based on generative adversarial networks for grape leaf disease identification,” *IEEE Access*, vol. 8, June 2020.

[20] Z. Zhang, Q. Gao, L. Liu, and Y. He, ”A high-quality rice leaf disease image data augmentation method based on a dual GAN,” *IEEE Access*, vol. 11, Mar 2023.

[21] Z. U. Rahman, H. Ibrahim, I. S. Zainal Abidin, M. S. Mohd Asaari, and M. K. Ishak, ”Generative adversarial networks (GANs) for image augmentation in farming: A review,” *IEEE Access*, vol. 12, Nov. 2024.

[22] N. Bushra and G. Shobana, ”A Survey on Deep Convolutional Generative Adversarial Neural Network (DCGAN) for Detection of Covid-19 using Chest X-ray/CT-Scan,” in *Proc. of the Third International Conference on Intelligent Sustainable Systems (ICISS 2020)*, IEEE, pp. 702–708, 2020.

[23] Liu, B., Lv, J., Fan, X., Luo, J., & Zou, T. (2022). Application of an improved DCGAN for image generation. *Mobile Information Systems*, 2022, Article ID 9005552.

[24] S. Lu, T. Sirojan, B. T. Phung, D. Zhang, and E. Ambikairajah, "DA DCGAN: An Effective Methodology for DC Series Arc Fault Diagnosis in Photovoltaic Systems," *IEEE Access*, vol. 7,
pp. 45831–45840, Apr. 2019.

[25] Q. Wu, Chen, and J. Meng, "DCGAN Based Data Augmentation for Tomato Leaf Disease Identification," *IEEE Access*, vol. 8, pp. 98716–98728, 2020.

[26] Y. S. Devi, and S. P. Kumar, "DR-DCGAN: A Deep Convolutional Generative Adversarial Network (DC-GAN) for Diabetic Retinopathy Image Synthesis," *Department of Computer Science and Engineering, GITAM Deemed to be University, Hyderabad, Telangana, India*, (n.d.).

[27] S. Devakumar and G. Sarath, "Forensic sketch to real image using DCGAN," *Procedia Computer Science*, vol. 218, pp. 1612–1620, 2023.

[28] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in *Proceedings of the 36th International Conference on Machine Learning (ICML)*, PMLR 97:6105–6114, 2019.