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# Implementation of Explainable AI in Deep Learning Methods for Multiclass Classification of Plant Diseases in Mango Leaves

Menaka Radhakrishnan*[1], Neerajaksha Monish [2], Parimi Siva Dev [2], Neha Kesavan[3], Nora Sara Thomas[2]

*[*1] Centre for Cyber Physical Systems, Vellore Institute of Technology, Chennai, India*
*[2]School of Electronics Engineering, Vellore Institute of Technology, Chennai, India*

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**Abstract**

Maintaining optimal yield plays a crucial role in the prosperity of agriculture and in turn the economy of the country. One way to optimize this yield is by early and accurate detection and diagnosis of crop diseases. Traditional methods that involve manual inspection or the like tend to be tedious and often inaccurate. Hence, the use of machine learning and convolutional neural networks have proven to be of great advantage in terms of accuracy, reliability, ease of implementation etc. This paper explores various deep learning models such as AlexNet, ResNet, Swin Transformer, Vgg-16, vit model for plant leaf disease detection and classification on a dataset of mango leaves and compares aspects such as accuracy and loss. Further the models have been combined using feature fusion, and their accuracies were compared. Finally, a combination of ResNet and AlexNet has been proposed with an impressive accuracy of 99.97%. Further, Grad-CAM (Gradient weighted Class Activation Mapping) has been implemented to highlight important regions in the leaf images which improves visualization. This can potentially provide an accurate identification and classification of plant diseases based on leaf images.

*Key Words*: plant disease, deep learning, CNN, Explainable AI, Grad-CAM, mango leaves, AlexNet, ResNet, model fusion

## 1 Introduction

Among the major occupational sectors around the world, agriculture has the highest level of involvement. Every year, this sector faces a substantial loss in production and profit due to a large number of diseases in crops and plants [1]. Plant disease identification is one of the most important aspects of maintaining an agriculturally developed nation. Early and efficient detection of plant diseases is essential for a healthy and productive agricultural sector and to prevent wasting money and other resources [2]. The prompt and accurate recognition of numerous crop leaf infections is a complicated job because of the presence of vast sample distortions like the prevalence of clutter, blur, texture, and luminance changes in samples. Moreover, the extreme resemblance between the normal and infected parts of visual samples also extends the difficulty of the

Correspondence to: menaka.r@vit.ac.in

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identification procedure [3]. Early classification and treatment of plant diseases are crucial for preventing crop losses and maintaining food security. Traditional methods for classifying diseases of plants involve manual inspection by experts. This situation can consume time and costs. Therefore, there is a need for automated and efficient methods for plant disease detection [4]. The major design of Deep Learning (DL) model helped in detecting plant disease and grants a dynamic tool with accurate results [5]. Use of artificial intelligence, computer vision in the field of agriculture has undergone a tremendous amount of transformation that has transformed many managerial functions into artificially intelligent systems to extract value from the growing amount of data coming from diverse sources [6]. Some commonly identified diseases in plant leaves are late blight, early blight, scab, rust, mildew, powdery mildew, grey leaf spot, bacterial spot, black measles, leaf curl virus and others [7].

Rice is an essential grain that has significantly contributed to global food security over the last half-century. Climate change, fast population expansion, rapid ecological degradation, pests, and rice diseases threaten global food security. These rice diseases reduce the annual rice production by around 37 % [8]. Wheat stands as a crucial staple crop globally. Nevertheless, various diseases pathogens, including fungi, bacteria, and viruses, pose a persistent threat to wheat harvests, contributing to diminished production and economic setbacks for farmers and the agricultural sector [9]. Of many crops, mango is a vital fruit here to meet the nutritional needs of inhabitants. However, various common diseases like Anthracnose, Die Back, Gall Midge, Bacterial Canker, Cutting Weevil, Powdery Mildew, and Sooty mold affect mango production severely and significantly impact the country's economy. Due to these diseases, farmers may face significant losses despite their efforts, which may go untreated due to a lack of knowledge or technical support. Many farmers in the Indian Subcontinent are not adequately trained to detect these diseases and primarily rely on their own visual experience, which may result in the production of low-quality mangoes despite significant investments. For proper disease treatment, timely and accurate detection is necessary [10].

# 2 Related Works

## 2.1 Machine learning methods

Local plant clinics and agricultural extension services have historically played a role in disease identification. Recently, the accessibility of online assets for disease detection has aided these initiatives by capitalising on the rise in Internet usage around the world. [11]Commonly used machine learning algorithms include Support Vector Machines, Random Forest, and Naive Bayes. These methods achieve disease detection and identification by constructing suitable feature vectors and selecting appropriate classifiers. However, compared to deep learning methods, these methods may demonstrate limitations when dealing with complex lesions and highly variable images.[12]A plethora of methods combining computer vision, image processing and machine learning have been proposed by researchers in this respect. Automated systems are proposed to detect diseases in plants such as Tomato, Mango, Papaya, Olive, Rice, Cassava, Palm and so on.[13]

Once the model is trained, it can be used to classify new diseased leaf images into different disease classes. Although machine learning models are reliable and easy to implement, the identification and extraction of suitable features for accurate disease detection is challenging, and it needs domain knowledge and expertise.[14]Leaf recognition systems have been developed using the fusion of Bag of Features (BOF) and Local Binary Pattern (LBP) texture features. These features serve as inputs for decision making. The classification was performed using a multiclass classifier based on a support vector machine (SVM).[15] The three primary aspects of leaf morphology, leaf contour, texture, and veins are the basis of the current methodologies. That restricts the certification's effectiveness and scope (Kalpana et al., 2020). Techniques for leaf image recognition have been studied extensively in identifying rice plant species. However, it's unclear if leaf type analysis gave enough details to distinguish the cultivars further.[16]

In the literature, a multiclass model is designed to address early disease detection and optimized both speed and accuracy in detecting apple diseases under complex orchard scenarios. The mean average precision (mAP) achieved was 91.2% with an F1 score of 95.9%, at a rate of 56.9 FPS (frames per second). Compared to existing models, the proposed model for multi-class plant disease detection showed significant improvement in mAP by 9%, 0.05% and F1 Score by 7.6%[17]. The SVM classifier is used to diagnose and manage cotton leaf diseases, as well as to monitor soil quality. It helps identify various diseases that can affect cotton leaves, including Bacterial Blight, Alternaria, Gray Mildew, Cereospra, and Fusarium wilt. An Android app provides the remedies for the detected disease. The app also demonstrates the soil parameter values inclusive of moisture, humidity, as well as temperature along with the water degree in a tank and allows farmers to control the motor and sprinkler to achieve a crop-suitable environment or spray pesticides. Sensors have been integrated for quality checking and the Raspberry Pi interface is used for the implementation and this gained an accuracy of 83.26% for disease detection.[18] Another extension of automatic plant disease detection would be to use it on an Edge Device like Raspberry PI or Jetson Nano to detect diseases on a field and report the GPS coordinates of the affected area of the field, thus an automated pesticide sprayer can be deployed in those areas. This will greatly improve and automate the plantations and cultivation process as we know it.[19]

### 2.2 Deep learning methods

Before deep learning-based severity estimation models, traditional image processing was used to identify pomegranate disease severity. Fuzzy logic was also used for corn disease severity estimation. Deep learning-based solutions are becoming accepted widely within the research community to learn important features for automatically estimating the disease severity.[20] Due to their potential in a variety of domains, deep learning techniques have lately made their way into numerous agricultural applications. Deep learning focuses on training artificial neural networks to learn and make predictions directly from data.[21]

DL algorithms provide good results on an image dataset. Mitali et al. implemented the CNN architecture by maintaining the minimum number of layers and trainable model parameters without compro-mising the model's performance. We have also performed fine-tuning to identify the best fit-arguments for the model. The best performing pa-rameters are then selected and considered for the experimentation. Mitali et al. also studied the pertinence of several DL algorithms for classifi-cation task [22]. The classification of leaf diseases is done with the support of the developed Multi-scale Feature Fusion-based Adaptive Deep Network (MFF-ADNet). In this developed MFF-ADNet, two processes are carried out such as feature extraction and classification. The collected images are given to the feature extraction phase, where the Visual Geometry Group (16) (VGG16), Variational Autoencoder (VAE), and Visual Transformer (ViT) network are used for extracting the features. The extracted features are fused and the resultant Multi-scale fused features are provided to the input of the classification process. Here, the Adaptive Convolutional Neural Network with Attention Mechanism (CNN-AM) is utilized for classifying the plant leaf diseases and the parameters are optimized using the Enhanced Gannet Optimization Algorithm (EGOA) approach [23]. Utkarsh et al. proposed a plant disease detection model based on transfer learning using the MobileNetV2 [24].

There is also a notable absence of comprehensive studies that review and compare these various approaches. Pabitra et al. aims to fill this gap by providing a comprehensive synthesis of UAV platforms, sensors, and analytical methods that have been employed for detecting and quantifying wheat diseases [25]. Deep learning model contributes better results than machine learning, as it has in-build capabilities to mine prime features from the unstructured data into feature vector. This intelligent system can frequently detect and classify specific patterns in input data.[26]

### 2.3 Research gaps and challenges

1. In the deep learning model, multi-scale feature fusion-based adaptive deep network, they are often considered black boxes, it becomes challenging to understand the features or characteristics they use for the classification of diseases. 2. While DL combined with CNN has become a popular way in diagonising plant leaf diesease, the future researches should try developing an application that can extend the existing solution to any of the plant dieases leaf species to have a significant impact on sustainable development by influencing agricultural production for succeeding generations [22]. 3. With MobileNetV2, in certain circumstances, the model might not be capable of reliably identify the crop-specific disease class. With the above proposed study, it started to predict false crop diseases somewhere [24]. 4. In deep spectral generative adversarial neural network, the scalability of the work is yet to be tested across other major crops. Hence, the addition of more crops and disease classes is the imminent challenge face for future endeavors [16].

### 2.4 Research contributions

To overcome these research gaps, several models were tested and trained on a selected dataset. We have also used the concept of explainable AI to improve the model performance by boosting the accuracy and reliability of the model used. 1. Different neural network architectures namely, AlexNet, ResNet, swin transformer, VIT transformer, VGG16 net were trained and tested including combinations of these models using feature fusion. The results from all the architectures were compared, with the Fusion ResNet and AlexNet model using Grad-CAM achieving the highest accuracy. 2. An explainable AI technique called Gradient-weighted Class Activation Mapping (GRAD-CAM)is deployed, which visualizes and explains the decisions made by the deep learning models and convolutional neural networks (CNNs).

## 3 Proposed Work

This research paper uses CNN framework and deep learning models approach to detect the diseases in a mango leaf. In this paper, we trained and tested the various pretrained deep learning models for plant disease detection and classification on a mango leaf. The dataset was collected from kaggle with a total of 4000 images comprising of 8 classes namely Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould and the healthy category. To detect the diseases in mango leaf, we are using combinations of the models present. We are combing them and trying to find the highest accuracy possible in these combinations. We will be focusing on using the models with the highest accuracy and combing it with GRAD-CAM (Explainable AI) which helps to visualize and explain the decisions made by the deep learning models. We are using already existing deep learning models like AlexNet, ResNet, Swin Transformer, Vgg-16, vit model for detection of diseases in the mango leaves. In Table 1, we stated the combination of models and their results in loss and accuracy.

### 3.1 ResNet

Residual network, or ResNet in short, is a deep convolutional neural network architecture introduced in 2015. It involves a concept called residual learning to help in training very deep networks. Instead of directly learning the underlying mapping, the network makes use of residual blocks to learn the difference between the output and inputs (also known as residual functions). This is an effective solution to the frequently encountered problem of vanishing and exploding gradients while training deep networks. The residual network is divided into three stages: Embedding, Mapping and Prediction. In the Embedding stage, the required features are extracted from input images using standard convolutional layers with a large kernel size (7 x 7), followed by a batch normalization layer and an ReLU activation function. A max-pooling layer follows, which further reduces

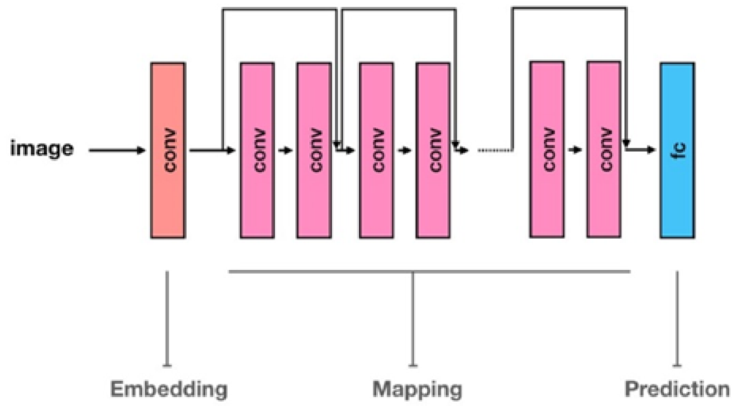



Figure 1: Architecture of ResNet

the spatial dimensions while retaining significant features. This stage helps to capture basic visual features such as edges and textures. The next stage is Mapping, which focuses on learning about the hierarchical and abstract feature representation through residual blocks. The residual block, which is the core of ResNet, consists of two convolutional layers (3 x 3 kernels). It can be expressed as:

$$Y = F(x, \{Wi\}) + x \quad (1)$$

Where x is the input to the residual block, F (x, {Wi}) is the residual function (usually consisting of two or three layers of convolutions), Wi the weights of the convolutional layer and y the output of the residual block. A defining feature of ResNet known as skip connection or shortcut, helps in ensuring better gradient flow, which solves the vanishing gradient problem and allows for deeper networks. In the Prediction stage, it uses global average pooling layer to reduce each feature map to a single value by averaging, which in turn drastically reduces the number of parameters compared to a fully connected layer. To reduce the spatial dimensions of the feature maps, the convolutional layers also perform down-sampling with a stride of 2. The final output is produced by a fully connected (FC) layer, into which the feature maps are fed after several residual blocks.

### 3.2 AlexNet

Another deep convolutional neural network architecture is AlexNet, introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. Its architecture consists of eight layers comprising five convolutional layers followed by three fully connected layers. It makes use of ReLU activation functions, overlapping max-pooling, and dropout to reduce overfitting. The input is an image of size 227 x 227 x 3 where 227 is the height and width of the image, and 3 represents the RGB color channels. The first convolutional layer uses 96 filters of size 11 x 11 with a stride of 4. The output size = ((227-11)/4 + 1) x ((227-11)/4 + 1) x 96 = 55 x 55 x 96. The second convolution layer uses 256 filters of size 5 x 5 with a stride of 1 and padding of 2. The output size = 27 x 27 x 256. The third convolution layer uses 384 filters of size 3 x 3 with a stride of 1 and padding of 1. The Output size = 13 x 13 x 384. Similarly, output size of fourth convolution layer = 13 x 13 x 384. And output size of the fifth convolution layer = 13 x 13 x 256.

It is these convolution layers that detect features in the input images, starting from the low-level features to more complex patterns. Each of these convolution layers is followed by ReLU activation and max pooling layers. These max pooling layers help reduce the computational complexity and control overfitting by reducing

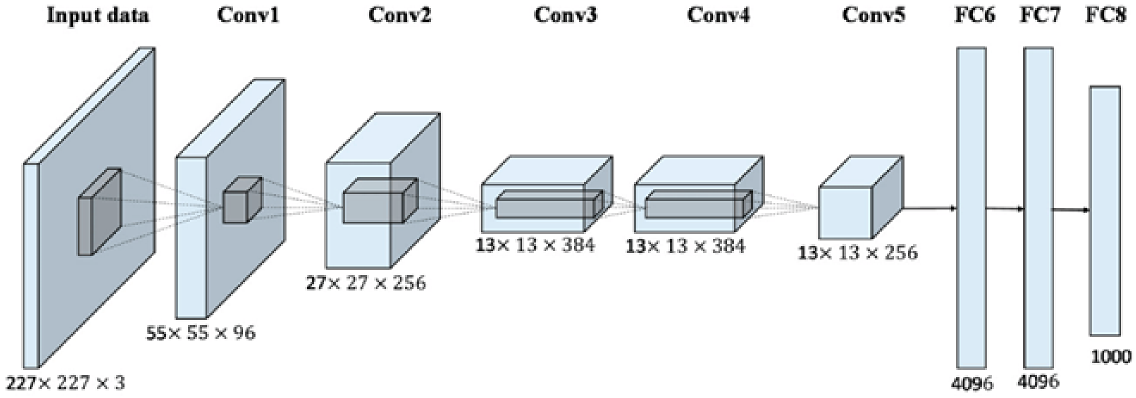



Figure 2: Architecture of AlexNet

the spatial dimensions of the feature maps while keeping the essential information. After the convolutional layers, the feature maps are flattened into a vector and passed through three fully connected layers. The first and second fully connected layers each have an output size of 4096 and are followed by ReLU activation and dropout regularization. ReLU introduces non-linearity, which helps the network learn more complex patterns. Dropout randomly sets a fraction of the neurons' outputs to zero and prevents overfitting. The third fully connected layer has an output size of 1000 and is followed by a softmax function. This function converts the output to a probability distribution.

### 3.3 Grad-CAM

Gradient-weighted Class Activation Mapping or Grad-CAM is a tool that provides visual explanations of the decision-making process of convolutional neural networks (CNN) by highlighting the regions of the input image that are important for classification. It does so by generating heatmaps in the important regions. An advantage of Grad-CAM is that it can be applied to any CNN model without having to change its architectural design. This is because Grad-CAM uses the gradients of a target class with respect to the final convolutional layer.

### 3.4 Proposed Model

Initially, the dataset is prepared for training to ensure that it is in a suitable format for the model to process. The first step is Dataset Extraction, where the dataset is extracted from a ZIP file and organized into directories representing different classes (e.g., various types of plant diseases). Once extracted, Data Transformation is applied to the images, which includes resizing them to a consistent size, and normalizing the pixel values using the mean and standard deviation values from the ImageNet dataset. These steps ensure that the data is standardized and ready for effective training of the neural network. The next step is to organize and feed the data into the model for training and evaluation. This includes using a Custom Dataset Class like PlantDisease-Dataset, which is specifically designed to handle the dataset's structure. This class reads image files from the dataset directories, applies necessary transformations, and labels each image based on its class. Once the data is prepared, a DataLoader is used to handle batching and shuffling of the data. Batching divides the dataset into smaller subsets, to make it more manageable during training, and shuffling ensures that the data is presented to the model in a random order, which prevents overfitting and improves generalization.

The next stage is feature extraction wherein useful information is extracted from the raw image data using pre-trained deep learning models. The proposed model uses two components, namely ResNet feature extractor and AlexNet feature extractor. It works by extracting high level features from the images, such as textures and shapes that help distinguish between the different classes. Both the AlexNet and ResNet models

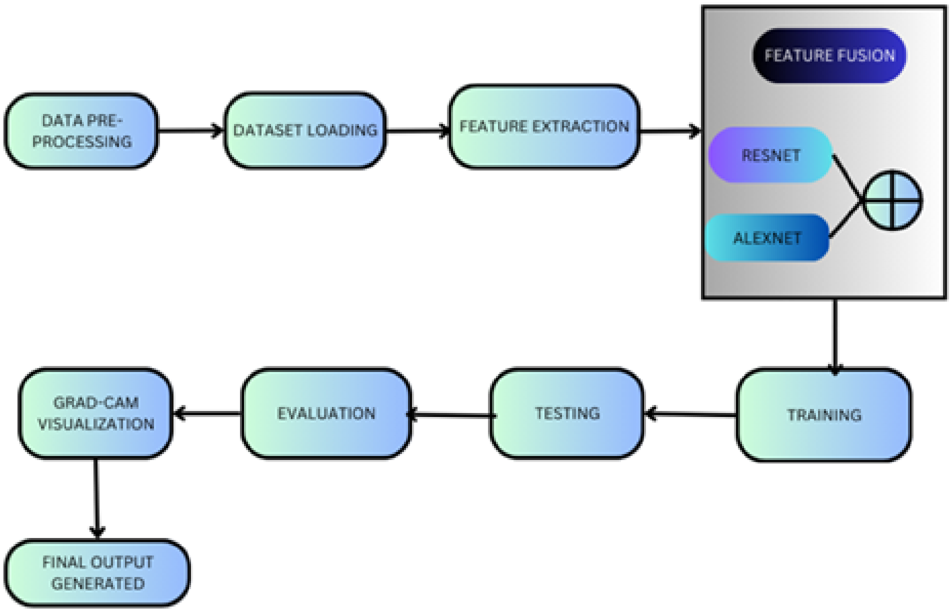



Figure 3: Block diagram of the proposed model

complement each other for maximum efficiency. The dimensionality reduction method is used to reduce the high-dimensional feature vectors obtained from ResNet50 and AlexNet and in turn make it easier to combine and use these features in the later stages. It essentially maps these feature vectors into a lower-dimensional space.

After that, feature fusion is performed, in which the extracted features from these models are combined to create a more powerful representation for classification. This involves creating a single larger feature vector, which preserves the strengths of both models. In this paper we combine ResNet and AlexNet using modal fusion technique which fuses the features extracted from the feature extraction process. The feature vectors of ResNet and AlexNet are concatenated to form a unified feature vector, which contains information from both the models. It is then further processed by passing through fully connected layers to reduce the dimensionality and map it appropriately. The next stage involves training the model wherein its parameters are updated in several iterations to increase the accuracy of its predictions. It is done in four steps: The forward pass that computes the output after passing the input images through the model. Loss calculation wherein the predicted outputs are compared with the actual classes to evaluate the model's performance. Backpropagation is used to compute the gradients of loss as compared to the model's parameters, and then update these parameters in such a manner that minimizes the loss. In each epoch of the training process, the loss and accuracy are tracked and plotted to visualize the model's learning progress and ensure decreasing loss and increasing accuracy.

The model is then tested by evaluating its performance on a separate validation dataset that it had not seen during training. This reveals the model's ability to make accurate predictions. Accuracy plays a crucial role in identifying the model's effectiveness. The model's performance is then assessed quantitatively using metrics such as accuracy, precision and recall. It is done by selecting a random image from the dataset and comparing it with the model's prediction for that image. This helps identify any potential weaknesses in the model. The next stage is grad-cam visualization which is a method that interprets and visualizes the decision-making process of these models by highlighting the most influential regions for a specific prediction. It works by capturing activations and gradients from the models during a forward and backward pass. Then class activation maps are generated and visualized by highlighting the regions in the image that have the most influence on the model's predictions. The final stage is output generation, wherein the model's results, such as predictions and performance metrics, are produced and presented in a format that is easily interpretable. This includes calculating the overall accuracy of the model and providing the confidence score, that shows how certain the model is about its prediction. These metrics are also displayed in visual form for easy interpretation of the model's effectiveness.

These models were trained and tested with mango leaf dataset. The source code was written using PyTorch deep learning programming framework and the runtime type used was T4GPU. First, we trained and tested the models and found their accuracy. Each model and combination gave a graph for training loss and training accuracy. We also used some images from the dataset to detect the disease present in it. Among all the models and combination, we did, the fused features of AlexNet and ResNet showed the highest accuracy. Then the fused features of AlexNet and ResNet were used along with GRAD-CAM to get the training loss, training accuracy, fusion model accuracy, predicted class and model confidence.

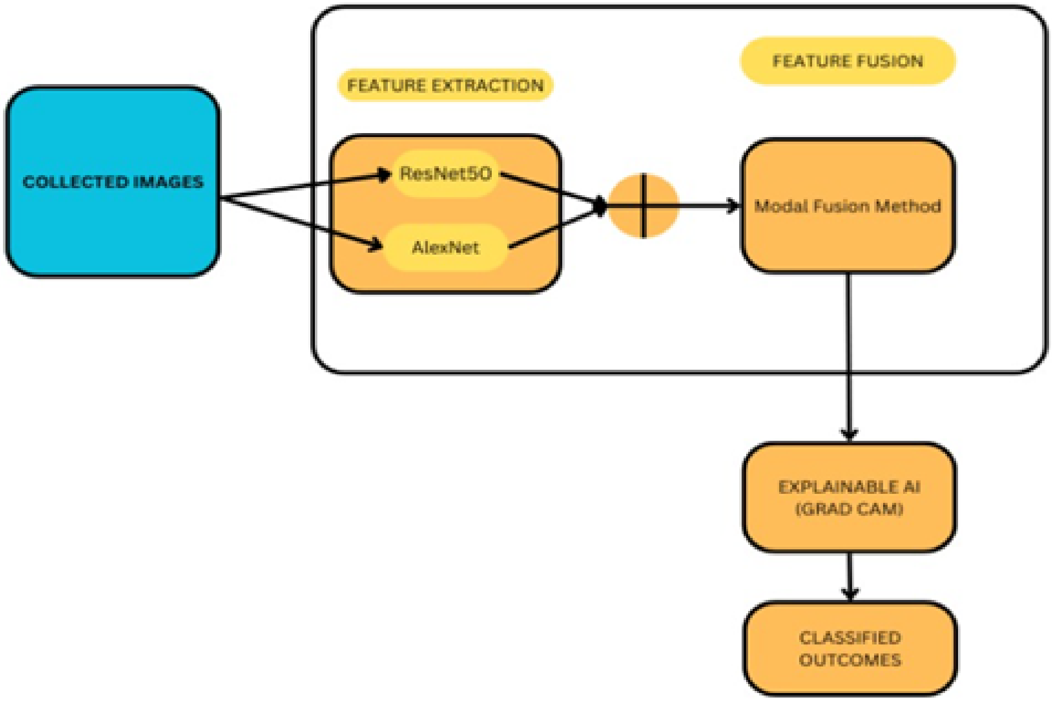



Figure 4: Block diagram showing the fusion mechanism

Modal fusion method is used to combine the features extracted by the AlexNet and ResNet neural networks and hence increase the accuracy of the classification system. Lower-level features such as edges, shapes and textures are extracted by AlexNet and are useful in understanding the basic patterns in the images. ResNet can extract higher level features and complex textures due to its deeper architecture and this is useful for obtaining better clarity of the images. Modal fusion makes use of the strengths of both these models by combining features extracted by both these models to enhance the extraction of data from the images. It works by concatenating the feature vectors from the models. The length of the combined feature vector will be the sum of lengths of each. Alternatively, if the feature vectors of both the models have the same length it could perform element-wise addition to form the new feature vector by adding the respective elements from each feature vector. Another approach would be to multiply each feature vector by a weight and learn these during the training process. Further, techniques like attention mechanisms or principal component analysis (PCA) can be used to extract the more important features from each model before combining them.

# 4 Results and Discussion

## 4.1 Dataset

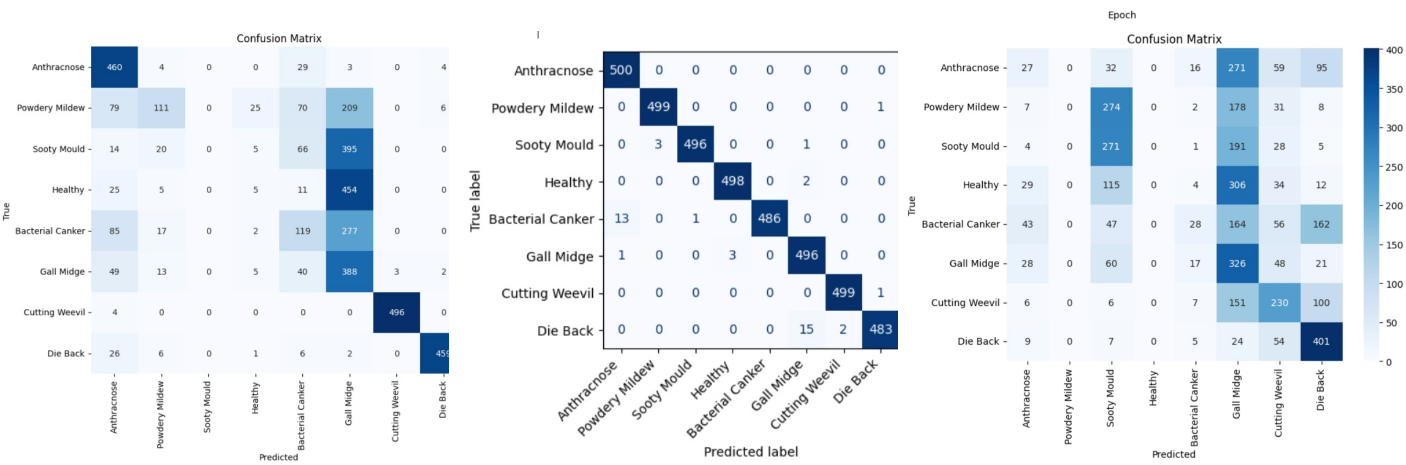
The dataset for mango leaf diseases was sourced from Kaggle and stored in a file, which was subsequently integrated into the model code and its combinations. The results are presented in Table 3 and Table 4. This data set comprises of 8 classes including one healthy class and seven disease classes. The images are resized to 224 x 224 pixel and are converted to Pytorch sensor. The image sensor is normalized based on the mean and standard deviation of the dataset making it more stable. The images are loaded onto data loader object which takes care of shuffling and parallel loading of images, making it more efficient. The hyperparameters for the code to get the resulted output is shown in Table 2.

## 4.2 Feature Extraction

The images are fed to the deep learning models AlexNet and ResNet which were already combined using feature fusion. The FusionModel class was created to extract the features of both AlexNet and ResNet. They are passed through fully connected layers in this class to get the final classification of the classes in the dataset.

## 4.3 Training and Testing

The models were trained and tested using the images from the dataset. During training, an accurate classification of the images was ensured on the basis of the calculated loss. The model evaluation function computes the accuracy and displays both the true and predicted class of the image. The confusion matrix and its values for the different models is given below:




(a) AlexNET (b) ResNET (c) Swin Transformer

Figure 5: Confusion Matrix

## 4.4 Explainable AI

An explainable AI called GRAD-CAM is used to visualize parts of images can help to categorize the image to its correct class. This is done by generating CAM, known as Class Activation Map, for specific layers of the model. These layers are overlaid on the original image to help the model to focus on the region where it can make its prediction accurately. The code shows outputs of GRAD-CAM for random images taken from the dataset. A tabulation of the loss and accuracy of different deep learning models before and after feature fusion is given in Table 1. A tabulation showing the hyperparameters used in the code to get the output is given in Table 2.

| MODEL | ACCURACY [in percentage] |
|---|---|
| AlexNet | 69.08 |
| ResNet | 91.33 |
| Swin Transformer | 96.55 |
| VGG-16 | 84.92 |
| Vit model | 98.50 |
| Fusion ResNet and VGG-16 | 97.17 |
| Fusion ResNet and AlexNet | 97.65 |
| Fusion ResNet and AlexNet with Grad-CAM | 99.97 |
| The fusion of ResNet and AlexNet with Grad-CAM shows the highest accuracy among all. | |

Table 1: A tabulation of the loss and accuracy of different deep learning models before and after feature fusion

| Sr. No | Hyperparameters | Values |
|---|---|---|
| 1 | Batch size | 32 |
| 2 | Learning rate (lr) | 0.001 |
| 3 | Number of epochs (numepochs) | 10 |
| 4 | Optimizer (lr) | 0.001 |
| 5 | mean | [0.485, 0.456, 0.406] |
| 6 | Standard deviation(std) | [0.229, 0.224, 0.225] |
| 7 | Image size | 224x224 |
| 8 | Model fusion layer sizes | 1024 dimensions reduced to 512 dimensions |
| 9 | Momentum (for SGD) | 0.9 |
| 10 | Dropout | 0.5 |
| 11 | Scheduler (stepsize, gamma) | (7, 0.1) |

Table 2: A tabulation showing the hyperparameters used in the code to get the output

We are adding GRAD-CAM(Explainable AI) to the features extracted from the feature fusion of ResNet and AlexNet. As discussed before, the GRAD-CAM s used to visualize parts of images which can help to categorize the image to its correct class. By combining the GRAD-CAM along with ResNet and AlexNet, we were able to get an overall evaluation accuracy and fusion model accuracy as 99.97 percent.

## 5 Conclusion

In this paper, we proposed a novel approach to plant disease classification by combining the strengths of ResNet and AlexNet CNN models along with Grad-CAM. The fusion of ResNet's deep feature extraction capabilities with AlexNet's streamlined architecture significantly improved classification performance. Through this feature fusion, the model achieved an impressive accuracy of 99.97 percent, demonstrating its effectiveness in

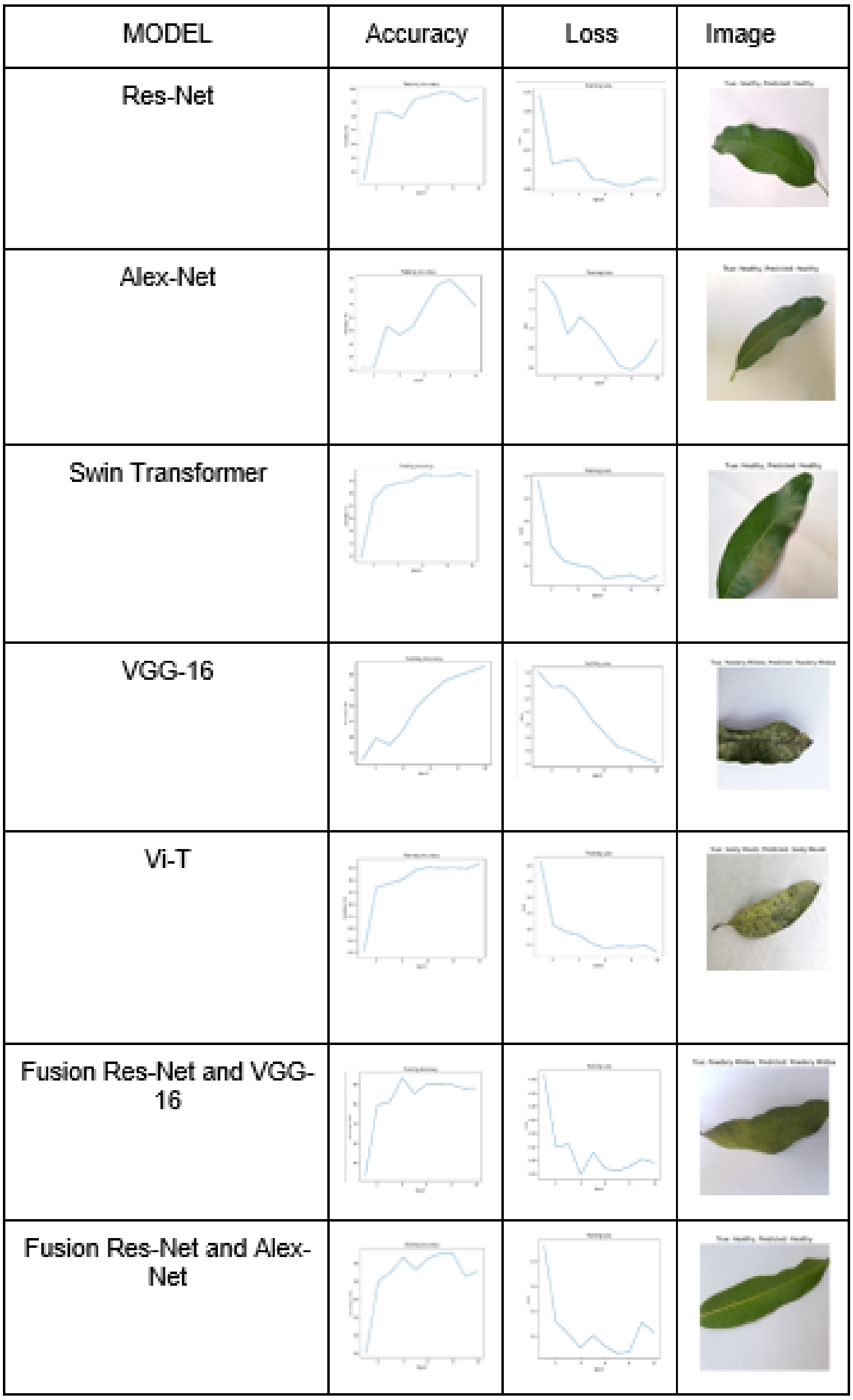



Figure 6: Training accuracy and training loss using various models and their fusion

accurately diagnosing plant diseases from leaf images. The use of Grad-CAM enabled us to get visual explanations by highlighting the most important regions in the image. This enhanced the model's interpretability, making it more trustworthy in the diagnosis of plant leaf diseases. These results also indicate that combining the features and strengths of multiple architectures can greatly improve overall performance and provide reliable classification and identification of plant leaf diseases.

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