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Comparative Analysis of Different Deep Learning Methods to Detect Eight Major Mango-Leaf Diseases

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Abstract: Meeting nutritional demands and helping to alleviate the global food problem are both greatly impacted by fruit production. Tropical Indian weather is ripe for plant diseases, which significantly reduce crop yields and cost farmers a lot of money. To put it in perspective, a healthy harvest depends on prompt diagnosis of plant diseases. This study develops different methods like InceptionV3, ResNet50, VGG16, VGG19 and Proposed method based on convolutional neural networks (CNNs) to identify eight of the most prevalent mango leaf diseases by analysing leaf photos. An innovative collection of region-specific photos was used to train this model specifically for the pattern of mango leaf diseases (Anthracnose, Bacterial canker, Cutting weevil, Die Back, Gallmidge, Powdery meldow, Reddust, and Soothy mould) in India. It is capable of classifying almost all mango diseases that are widely accessible. The performance of developed models is evaluated with average accuracy & model loss and found to be 46.87% & 1.564%, 74.44% & 0.687%, 17.18% & 2.004%, 86.53% & 0.355%, and 90.74% & 0.14% respectively. In thirty iterations, the average accuracy of proposed model is found to be higher (90.74 %) and its model loss is found to be very low (0.14 %). Thus, the proposed model may aid in the early diagnosis of mango leaf diseases, which in turn can increase mango output and boost the national economy.

Keywords: *CNN, Mango leaf, Deep learning, InceptionV3, ResNet50, VGG16, VGG19*

1. Introduction

Rising populations and the effects of climate change have made food shortage a reality on a global scale. Over the next five years, the population is projected to rise by 22%, and the urgent need for food will impact the political, economic, and environmental systems. Over 193 million people have already been affected by severe food shortages in 2021, according to the FAO's annual report [1]. Despite the importance of grains and fruits to human nourishment, their cultivation is vulnerable to a wide range of bacterial and fungal illnesses. But ever since humans first started making intentional efforts to cultivate nutritious food, plant diseases have been seen as a major obstacle. Because of the damage they may do to food supplies, one of the best methods to combat this problem is to catch these infections early on. More than 166 million people call the tiny South Asian nation of Bangladesh home. The land area of this agricultural powerhouse is about 147,570 square kilometres [2] .

Mangoes are an important crop since they provide a fruit that people here can eat. However, the production of mangoes is greatly hindered and the economy of the nation is greatly affected by a number of common illnesses, such as Anthracnose, Die Back, Gall Midge, Bacterial Canker, Cutting Weevil, Powdery Mildew, and Sooty Mould. Preventing these diseases is a significant problem in mango agriculture. The fungal illness anthracnose, for example, tends to manifest more often in damp environments. Although stems and branches are less likely to be affected by bacterial canker, leaves are nonetheless susceptible. In India, the cutting weevil is a prevalent pest that devours young leaves. Mango hoppers and coccids are among the insects that may spread sooty mould. Discoloration of leaves is caused by dieback. whether you want to know whether your mango tree is sick, look at its leaves [3]. Figure 1 shows the architecture of the current study.

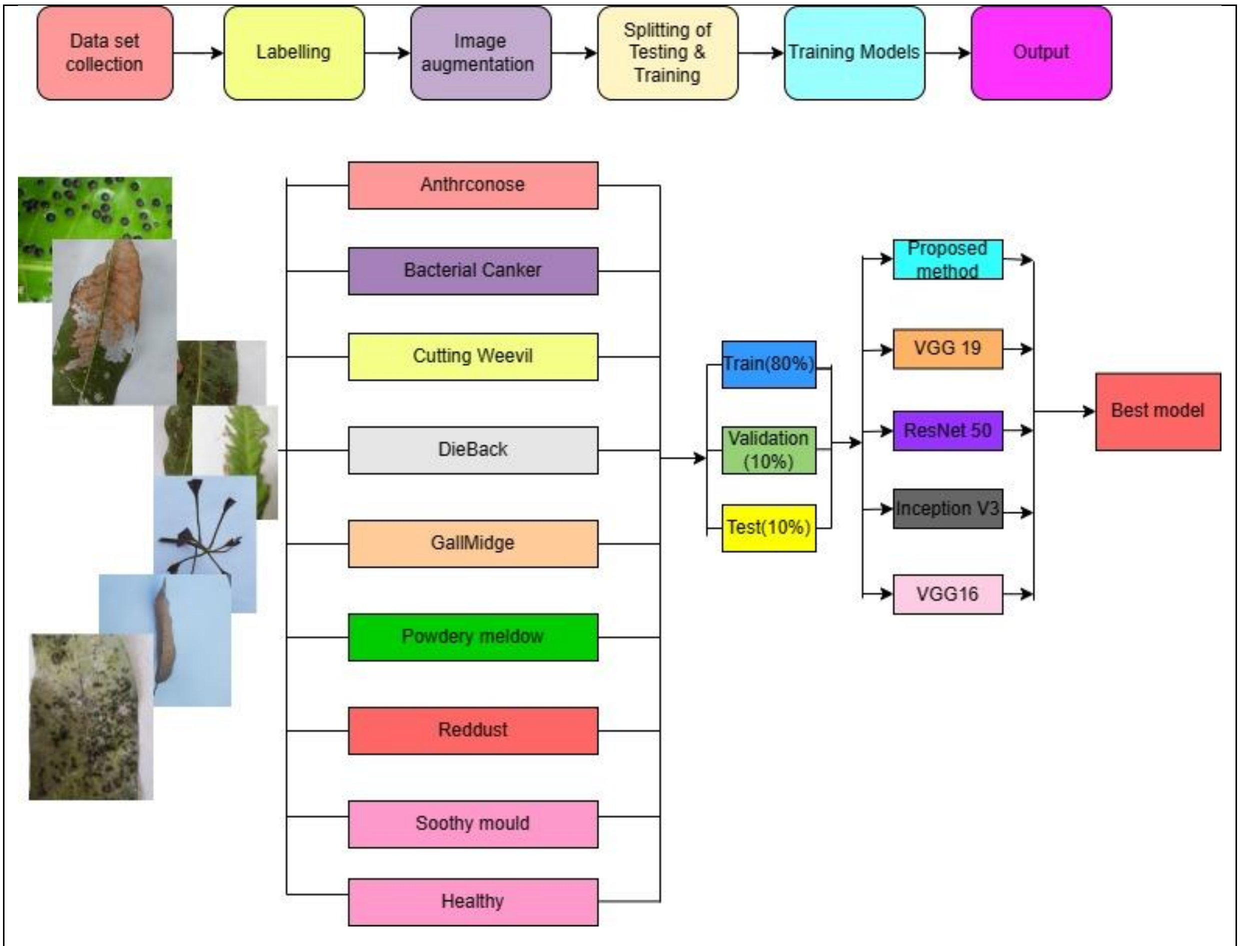

Fig1: Architecture of the study

Even with their best efforts, farmers may suffer heavy losses from these illnesses, and they may not know how to cure them or have access to the necessary professional assistance. Despite heavy expenditures, many Indian Subcontinental mango growers may end up with subpar fruit because they lack the proper training to identify these illnesses and instead depend on their own visual perception. Timely and precise diagnosis is critical for the correct treatment of diseases. This labor-intensive process used to be handled by trained agriculturalists. The hassle and expense meant that farmers often shied away from it. The disease status of leaves may be classified using artificial intelligence (AI) systems and methodologies. For instance, CNNs, or convolutional neural networks, are widely used in this domain. CNN's promising results and cheap computing cost make it one of the most popular deep learning algorithms for image-related tasks. There are fewer neurons needed, training takes less time, and the feedforward network is great at recognizing patterns in images. In order to train CNN to extract features and categorize picture datasets, specialized images may be used[4]. So, CNN is a good choice for mango leaf disease detection since it uses pictures to train its model. Image classification is carried out by the last layer, which employs an activation function, after the hidden layers have updated the weights. There is a vast array of agricultural uses for these robots and deep learning methods. Due to a lack of understanding or accurate diagnosis, plant disease detection is often disregarded. In order to provide very precise predictions, which can be impossible to see with the human eye, deep learning models can be trained on any kind of region-specific illness. Taking photographs and using the technology to immediately anticipate diseases is a breeze for farmers. While deep learning models may be built using any dataset of mango leaves, there are notable regional disparities in their applicability. With the right kind of study, this opens up a new window of opportunity for illness detection [5]. It is challenging to design models with bias-free parameters when working with unbalanced datasets, which is a prerequisite for creating such models. Testing state-of-the-art (SOTA) algorithms on relevant datasets is therefore an area where information is lacking. There has to be further investigation into the use of machine learning and deep neural networks to predict plant diseases, even if some studies have focused on fungal diseases like Anthracnose. There is a lack of machine learning and deep learning studies focusing on mango leaves in India because of the need for regional datasets, since disease patterns differ from one location to another. A number of mango tree leaves from various plantations were used to train the suggested model. This ensures that the dataset is of high quality, which means that the model may be used in places with comparable weather [6]. Disease identification in crop and fruit leaves is a complex topic, but this work provides a concise comparison of models based on machine learning and deep learning. Using a novel dataset of mango leaves that has not been used in any prior models, a deep learning-based architecture is constructed to be proposed. Using eight common diseases—Anthracnose, Powdery Mildew, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Sooty Mould—the proposed model can categorize mango leaf conditions. The author is informed that this work is the first of its type to use this dataset with all state-of-the-art (SOTA) methods, and that the dataset has been released by the same research group. For the purpose of validating its efficacy, the proposed performance is contrasted with other SOTA models. Researchers, farmers, and agriculturalists may all benefit from this study's evaluation of the model's ability to identify mango leaf diseases, which in turn can lead to healthier mango harvests. What follows is a synopsis of the manuscript's main contribution. A fresh collection of mango leaf photos gathered from plantations in Sasi Institute of Technology and Engineering, Tadepalligudem, India has been used for the study.

This new data set was used to create the CNN-based model that is being proposed. The model handles eight of the most common mango illnesses in India and the Indian subcontinent, dealing with multiclass categorization[7]. Evaluation metrics like as average accuracy and model loss reveal improved performance in the Proposed. Its computational complexity is lower than that of other SOTA models, such as VGG19 and VGG 16.

Many studies have used direct ways to identify illnesses in crops and leaves. Various non-invasive methods for plant disease detection have been studied and compared by Sankaran et al.[8] These methods include PCR-based molecular techniques, imaging and spectroscopic techniques (e.g., fluorescence spectroscopy and fluorescence imaging), and methods based on volatile organic compound profiling (e.g., electronic nose and GC-MS-based volatile metabolite analysis) for identifying plant diseases. In order to reduce crop damage, maximize output, and guarantee agricultural sustainability, Fang et al. [9] addressed the topic of plant disease diagnosis and preventive approaches. Thermography, hyperspectral techniques, and fluorescence imaging were among the indirect methods utilized in agriculture, in addition to direct methods including GC-MS, PCR, FCM, ELISA, IF, and FISH. Also included is a synopsis of biosensors that may be used to quickly identify plant illnesses; these biosensors are associated with bio-recognition components like enzymes, antibodies, DNA/RNA, and bacteriophages. Those methods are undeniably accurate and dependable, but they are also labor-intensive, time-consuming, and costly. Indirect approaches exist as well, such as the use of cutting-edge automated non-destructive technology for early, targeted illness detection in the field in real-time. One area where deep learning architectures have found use is in agricultural picture identification and categorization. Image capture, preprocessing, lesion segmentation, feature extraction, and classifier approaches are all covered in the work by Vishnoi et al. [10] that looks at automated plant disease identification. Similarly, Aftab et al. [11]

is concerned with using image processing techniques to detect plant diseases in their early stages. Using a Raspberry PI, you can connect a camera to a screen and upload the footage to the cloud. The method involves taking pictures of the leaves and analyzing them using tools including acquisition, pre-processing segmentation, and clustering. Faster RCNN and SSD Mobile net, two trained models, were shown to be sufficiently accurate in identifying almost all plant diseases. In large agricultural areas, this approach aims to reduce labor demand, expenditures, and productivity-boosting initiatives. A low-cost automated early disease detection system for avocado trees utilizing remote sensing was given in the study by Abdulridha et al. [12]. This method can distinguish between healthy and diseased plants, and it can even identify laurel wilt (Lw). They employed a Tetra camera and a modified Canon camera, in addition to two classification methods—K-nearest neighbors and neural network multilayer perceptron (MLP)—to build their system. A 99% success rate in detecting Lw was achieved using the MLP classification algorithm. Zang et al. [13] used a method to identify a bacterial illness in citrus tree leaves utilizing both global and region-based local characteristics in field-collected photos of the leaves. In addition, canker lesion identification is enhanced by a bi-level approach that employs the AdaBoost algorithm. In contrast to the 86.88% accuracy attained by human specialists, this study discovered that image processing could obtain an accuracy of 87.99%. By the way, convolutional neural network (CNN) models trained using deep learning techniques to identify plant illnesses in images of leaves have shown to be more effective in several investigations. One such study that used a convolutional neural network (CNN) model based on transfer learning to quickly and cheaply detect plant illnesses was Vishnoi et al. [10]. After sorting 87,867 photos into 38 categories, they were done. Many well-known transfer learning models have issues with optimization, deterioration, and disappearing gradients. These include AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, and VGG. After demonstrating an accuracy of around 99.90%, this research found that ResNet resulted in minimum losses and convergence time. A further research by Lu et al. [14] employed 500 natural photos of healthy and sick rice leaves to determine that DCNNs methods may be used for crop disease diagnosis as well. Using disease-specific labels, these photos demonstrated that CNN is capable of accurately classifying damaged leaves using image processing. In compared to existing models, their proposed method outperforms them in training, has a quicker propagation rate, and is more capable of recognition, with an accuracy of 95.48 percent. In a similar vein, Too et al. [15] laid forth the evidence that supports using deep learning for plant disease identification rather than ML or image processing. The researchers went a step further by studying DenseNets, ResNet, VGG net, Inception V4, and Inception V4. All of the deeper models worked well with the exception of VGG, which operates on shallow networks. They found that DenseNets had the greatest forecast for reaching state-of-the-art performance, thanks to its acceptable computation time and fewer parameters. On the other hand, there are a number of considerations that need to be made when using deep learning in plant pathology, according to Barbed et al. [16]. Among these concerns include insufficient data, problems with symptom representation, changes in covariates, picture backdrops, capturing settings, difficulties in symptom segmentation, and disorders sharing symptoms. Experimentation on 50,000 photos led to the identification of these parameters. Golhani et al. [17] conducted a similar research on illness identification, but instead of using a conventional vegetation index, they used a neural network in conjunction with a spectral disease index to identify anomalies in plants. In order to detect illnesses in maize leaves, Zhang et al. [18] suggested two better models: Cifar and GoogLeNet. The researchers divided their 500-image dataset into 9 groups, with 8 groups indicating unhealthy maize leaves and 1 group representing normal leaves. While traditional identification methods such as VGG and AlexNet structures need a large number of model parameters and a lengthy convergence time, their study shown that these models may reach the maximum efficiency and accuracy (98.8% and 98.9%, respectively). Researchers Durmus et al. [19] used deep learning frameworks SqueezeNet and AlexNet to identify illnesses affecting tomato leaves. The photos were culled from the Plant-Village collection, which had fourteen distinct crop types. They limited their effort to tomato leaves, which were categorized into 10 groups, and using AlexNet to get an accuracy of around 95%. Yet, SqueezeNet outperformed the other networks when considering model size and inference time. More than three thousand photos of 38 distinct wheat plant kinds in their natural habitat were also used by Johannes et al. [20] to detect three wheat illnesses that are unique to Europe. They suggested a two-step methodology that combines a traditional machine learning model with a statistical inference technique; the first stage handles picture normalization and preprocessing, while the second stage couples color and texture descriptors. But the color and texture descriptors restricted the model's expressiveness, so it couldn't become more general. For use in field collection circumstances, Picon et al. [21] refined the automatic multi-disease identification method first shown by Johannes et al. [20]. By verifying the same three illnesses on over 8,000 photos and testing in real-world situations, they were able to utilize DCNN to identify both early-stage diseases and simultaneous disorders. In order to diagnose cucumber infections from pictures of obvious symptoms on the leaves, Juncheng Ma et al. [22] suggested use a DCNN. The model was developed for symptom-wise classification, which allows for the detection of plant illnesses independently of each other, even when many diseases are present on a single leaf. A collection of images including cucumber disease signs, such as anthracnose, powdery mildew, downy mildew, and target leaf spot, was used to train the DCNN. When compared to more traditional models like Random Forest and Support Vector Machines, as well as AlexNet, the DCNN demonstrated a 93.4% identification accuracy rate, making it a viable method for disease detection in cucumbers grown in the field. Anthracnose has recently emerged as the most devastating fungal illness for a number of tropical fruits, mango included, according to disease detection methods used on mango leaves. In their study, Singh et al. [23] presented a multilayer convolutional neural network (MCNN) that used 2200 pictures of various mango leaf types. Using several picture datasets, our deep learning network can accurately diagnose diseased mango leaves. When contrasted with other cutting-edge methods, this model stands out due to its ability to adapt to specific tasks by analyzing data. The model's 97.13% accuracy is a result of its structure, which is based on the AlexNet architecture. Another study that utilized CNN for illness classification and identification was Rajbongshi et al. [24]. They used transfer learning methods such as DenseNet201, InceptionResNetV2, InceptionV3, ResNet50, ResNet152V2, and Xception. numerous leaf diseases, such as anthracnose, gall machi, powdery mildew, and red rust, were studied using a dataset consisting of 1500 photos of numerous mango species' damaged and healthy leaves. Acquiring images, segmenting them, and extracting features are the processes involved in illness detection. Further analysis of the performance matrices revealed that DenseNet201 achieves a maximum accuracy of 98%, placing it ahead of competing models. To identify and categorize illnesses affecting grape and mango leaves, Rao et al. [25] trained a deep convolutional neural network (CNN) using 8438 pictures illustrating both healthy and damaged leaves. Feature extraction and classification were carried out using a well-established CNN architecture known as AlexNet. The accuracy rate for grape leaves was 99% and for mangoes, 89%. For the same purpose, an app called "JIT CROPFIX" was developed specifically for Android smartphones. Problems with different lighting and occlusion, insufficient diversity in datasets, and the inability to identify minor defects are among limitations. The most prevalent four nutritional deficits in mango were found to be copper, iron, nitrogen, and potassium, according to a comparable research by Merchant et al. [26]. To locate the damaged leaf, we extracted the RGB values and texture indices using a well-known unsupervised ML model—the clustering approach. Depending on the amount of water present, digital image processing may tell you if mango leaves are healthy or not by how much they deviate from their normal green tint. Arya et al. [27] used two popular deep learning architectures, CNN and AlexNet, to assemble a dataset of around 35,223 photos in order to identify illnesses in mango and potato plants. Despite requiring more processing power to train, AlexNet achieved a higher accuracy rate of 98.33% compared to CNN. Unlike traditional methods, Mia et al.'s Neural Network Ensemble (NNE) for mango leaf disease detection (MLDR) [28] simplified and improved the accuracy of disease diagnosis. The research used NNE Support Vector Machines (SVMs) to detect four diseases affecting mango leaves: Dag disease, Golmachi disease, Moricha disease, and Shutimold. Their study found that this method was 80% accurate in identifying mango leaf illnesses. Using computer vision and deep learning, the authors presented a machine-learning approach for insect detection in expansive mango orchards. Taking into account the practical difficulties encountered by farmers in Indonesia, their method expanded the VGG-16 model using a fully linked network with two layers. With a total accuracy of 73% on validation data and 76% on testing data, the approach improved its accuracy by 13.43% when compared to testing data. Apples, maize, potatoes, grapes, sugarcane, and tomatoes were among the many plant kinds that Militante et al. [29] shown could be efficiently tested for several diseases. The system was trained using 35,000 photos of both healthy and sick leaves, and it obtained an accuracy of 96.5%, and in certain instances, 100%. Plant illnesses and healthy plants were identified with a 99.53% accuracy rate using a model created by Ferentinous et al. [30] using a convolutional neural network. The model was deployed to an open collection of 87,848 pictures. Using supervised learning and convolutional neural networks, Jain et al. [31] created a cloud-based solution to address crop health in distant parts of India.

They compared techniques to reduce the rate of misclassification and performed real-time categorization of photos of sick plants.

2. Dataset representation

This article makes use of a dataset whose picture data came from different parts of Andhra Pradesh, India. Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Red dust and Sooty Mould are eight of the mango illnesses included in this balanced dataset. Additionally, there are photos of healthy mango leaves, for a total of eight classes. The dataset is perfect for developing a deep-learning model to predict the prevalence of mango illnesses in India, which might differ by location. One hundred eighty-five pictures of individual mango leaves taken using cell phone cameras in four different plantations in India make up the dataset. Because photographs of sick leaves with a white backdrop could introduce bias and inaccuracy into the model training process, this dataset only contains images without a background. The final dataset included 4830 mango leaf examples from 8 categories, each with more than 500 photos. The images were further enhanced using magnification and rotation to make them larger and more scalable. This study aims to identify the eight kinds of mango leaves using the architectures utilized and presented. The eight types of leaves are grouped according to the diseases they symbolize. Anthracnose, a fungal illness caused by Colletotrichum gloeosporioides, is the first to be mentioned. Dark, sunken lesions on twigs and fruit, together with brown patches on leaves, are symptoms of this disease. A "shot hole" structure will appear on the leaves of plants that are affected, and it is particularly prevalent in moist and humid environments. The blossoms may be killed out in the latter stages of the illness. When the surrounding air is 95% humid and it's raining or misting, it's more common. Also, Xanthomonas campestris pv. Mangiferaeindicae bacterium may cause bacterial canker. Lesions that are submerged in water and found on the stem, branches, and leaves are signs of this illness. The mango leaves have small, irregular stellate lesions that start off bright yellow but eventually become yellow. On the underside of the leaves, you can observe brown areas and decaying cankerous patterns. Depending on how bad the illness is, the leaves could fall off, and the halos are bigger and more distorted on younger leaves than on older ones. You can get a comprehensive description of the mango leaves dataset in Table 2. In contrast, Fig. 2 shows the dataset in its entirety and gives the names of the classes that go along with each group. Sternochetus mangiferae, most often known as the Cutting Weevil, is a very damaging insect to mango plants. It causes wilting and eventual death in young trees by severing the bark of their shoots and branches. More harm comes from the weevil's egg-laying in the holes and the subsequent feeding of the larvae on the branches' sapwood. Cutting weevil damage manifests as withered shoots and leaves, accompanied by tiny, circular holes in the bark and frass around the holes. Mango dieback is caused by a variety of diseases, including fungus and bacteria. Mango trees are susceptible to dieback disease, which, if left untreated, may kill off all of the tree's branches, twigs, and leaves. Causes of dieback, such as Phytophthora spp., Fusarium spp., and Ceratocystis fimbriata, might differ according to environment and location. The illness may also be accelerated by environmental conditions such as soil that is too wet, excessive humidity, and extreme heat. The tree will eventually die from dieback, which manifests as wilting and browning of the leaves and branches. Yellowing and drying leaves, as well as darkened and sunken bark, are symptoms seen on affected branches. The fungus Oidium mangiferae causes powdery mildew, a devastating fungal disease that attacks mango trees' leaves, twigs, and fruits if not addressed. A powdery white fungal growth on twigs, fruit, and smaller, lower-quality fruit are symptoms. Curled and deformed leaves are another sign. Affected leaves may get yellow and drop off before their time as the illness advances. A black, sooty growth may form on fruit and leaves as a result of a fungal disease called sooty mould, which is caused by several species of the genus Capnodium. Consequently, the leaves begin to contort, and surface substances made of black pieces become sticky. Fungus usually affects blossoms, although it may also drop off early fruits. In orchards that are not well-managed, it is more common.

3. Modern algorithms

Using the suggested CNN-based model, this part will examine the design of five state-of-the-art algorithms: ResNet50, VGG16, Vgg19, InceptionV3 and Proposed methods developed to identify diseases in the mango leaves listed above.

When it comes to picture categorization, the Inception V3 is the deep learning model to turn to; it's built on CNNs. Introduced in 2014 as GoogLeNet, the original model Inception served as a foundation for subsequent iterations of the inception V3 model. It was created by a group at Google, as the name implies. The third version of the Inception model, which was out in 2015, is more accurate and has 42 layers instead of the previous versions' less. Let's have a look at the many enhancements that the Inception V3 model has. Among the most notable updates to the Inception V3 model include, Breaking Down into Independent Convolutions, Asymmetric Convolutions with Spatial Factorization, Auxiliary Classifiers: How They Can Help, A Superb Method for Minimizing Grid Size. With 42 layers altogether, the Inception V3 model is somewhat more complex than its predecessors, the V1 and V2 versions. However, this model's efficiency is really remarkable. We shall get to it later, but first, let's take a look at the Inception V3 model's components. You can see the basic structure of the Inception V3 model in the table below. Each module's output size serves as the input size for the subsequent module in this case.

The ResNet-50 architecture is a deep CNN that Kaiming brought to the table. The model is known as ResNet, an abbreviation for "Residual Networks. "One of the most well-known computer vision competitions, the yearly ImageNet Large Scale Visual Recognition Challenge, is where ResNet-50 really shines, because to its exceptional performance on picture classification tasks and other related tasks. The use of residual connections is the main innovation in the ResNet design. These connections aid in fixing the vanishing gradient issue, which is common in very deep neural networks. Shortcut connections, sometimes called skip connections or identity mappings, allow Residual Networks to omit one or more neural network layers. The network is able to learn residual functions—the difference between a layer's input and output—through these shortcuts. This allows ResNet models to train complex networks with hundreds of layers with no degradation in performance in either optimization or generalization. With its modular architecture and 50 layers, ResNet-50 streamlines the process of creating and training deep networks. Batch normalization, activation functions (often ReLU), residual blocks, and convolutional layers are all components of it. To reduce the input's spatial dimensions, ResNet-50 employs 3x3 convolutional kernels with changing filter sizes and pooling layers.

VGGNet design (VGG16) An upgrade over older Convolutional neural networks, AlexNet debuted in 2012. We may think of VGG as the next generation of AlexNet, but it was really developed by a separate group at Oxford University called the Visual Geometry Group, which is where the term "VGG" comes from. It takes a few cues from earlier versions, refines them, and applies deep Convolutional neural layers to make it more accurate. Most people agree that VGG16, an architecture of a Convolutional Neural Network (CNN), is the greatest computer vision model out there right now. Using a compact (3 × 3) convolution filter architecture, the inventors of this model enhanced the depth by analyzing the networks, surpassing state-of-the-art settings. The number 16 in VGG16 indicates that the network has sixteen weighted layers. There are 138 million parameters in this massive network. One variant of VGG Net is VGG-16. A RGB picture with a fixed size of 244 by 244 pixels is fed into VGG-16. A pre-processing step involves subtracting the average RGB value from each pixel in a photograph. After the pre-processing is finished, the images are sent through a series of convolutional layers that include small receptive-field filters with a size of 33. A few configurations have the filter size set to (11) which means that the input channels have been processed linearly (then non-linearly). The stride of the convolution process is initially set to 1. When it comes to spatial pooling, five max-pooling layers are used. These layers follow a series of convolutional layers. For max-pooling, we use a stride size of and a window size of (2, 2). The standard configuration for fully-connected layers is as follows: two 4096-channel layers, a third with 1000 channels (one for each class) to perform 1000-way ILSVRC classification, and a final softmax layer. Each hidden layer of the VGG network is activated using the ReLu activation function.

An updated version of the VGG model, VGG19 has 19 layers total: 16 convolution layers, 3 fully linked layers, 5 MaxPool layers, and 1 SoftMax layer. There are 19.6 billion FLOPs in VGG19. Basically, VGG is a deep convolutional neural network (CNN) that can identify pictures. Although the ILSVRC was the primary motivation for developing the VGG net, it has found several additional applications. Used as-is or with little tweaks for other comparable tasks; authors made models publicly accessible; used as-is or with minor tweaks for many additional datasets.Facial recognition tasks are also under the purview of transfer learning. Other frameworks, like keras, make weights readily accessible, allowing users to manipulate and utilize them as they like.

However, unlike AlexNet, every convolutional block has two layers: one for convolution (CONV) and one for max pooling (Max Pool). To make predictions, it also has a softmax layer, two FC layers, and one more layer. To lessen the likelihood of overfitting, many regularizations are used, such as batch normalization and dropout layers. Here, the suggested architecture is described in Table 5, and a picture of it may be seen in Fig. 5. 4. Techniques for training and testing as well as hyperparameters Since there were no independent testing cases, the cross-validation approach was used to verify each cross. The method employs a total of five rounds of random seeding. Eighty percent of the data instances for each fold were from the training dataset, ten percent were from the validation dataset, and ten percent were from the testing dataset. The performance was validated after each epoch using the validation dataset. Using the optimal state or weights seen across the validation dataset, the testing dataset was examined after training had finished. As a relatively important amount to record unexpected abrupt changes in the loss, 60 lies between [1100], the typical practice, and the patience value. The early stopping callback caused all the architectures' training to terminate before to the maximum Epoch 300 in most instances, even though the maximum was set.

4. Result and analysis

Model accuracy: The graph presents a comparative assessment of five distinct models utilized for detecting mango leaf diseases: VGG16 (Visual Geometry Group 16), VGG19 (Visual Geometry Group 19), InceptionV3, ResNet50, and an innovative proposed method. The x-axis represents the training iterations, encompassing 30 epochs, while the y-axis demonstrates the accuracy achieved by each algorithm.

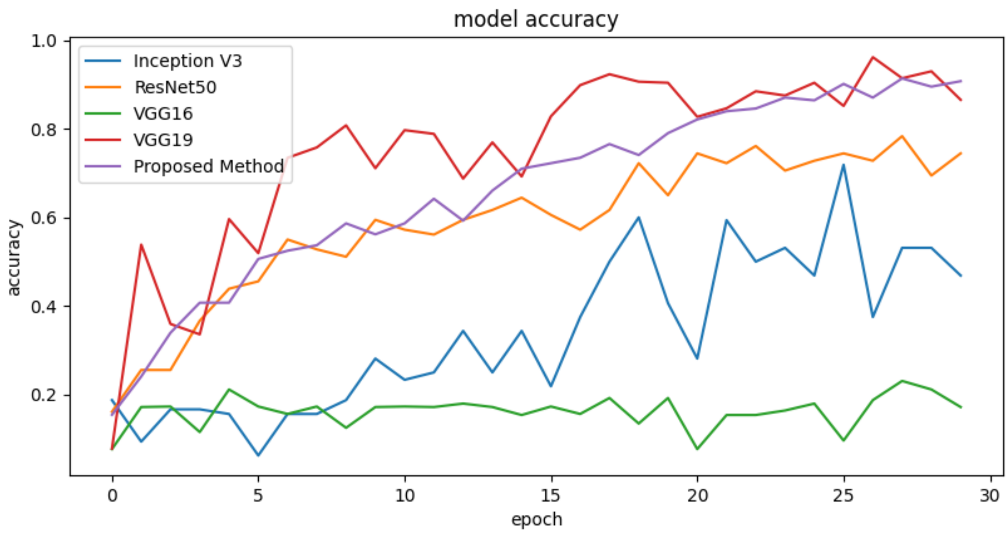

Fig 2: Model accuracy of identifying deceased leave

Over the course of 30 epochs, the graph visually represents the accuracy achieved by each model in the identification and classification of mango leaf diseases. This comparison enables a comprehensive evaluation of the performance trends and relative efficacy of these models during the training process[32]. Notably, the graph highlights that the proposed method exhibits significantly higher accuracy compared to the other models, indicating its superior performance in accurately identifying and classifying mango leaf diseases.

Model loss: The graph depicts a comparative evaluation of five distinct models employed for mango leaf disease detection: VGG16 (Visual Geometry Group 16), VGG19 (Visual Geometry Group 19), InceptionV3, ResNet50, and an innovative proposed method. The x-axis represents the training iterations across 30 epochs, while the y-axis showcases the loss metric for each algorithm [33].

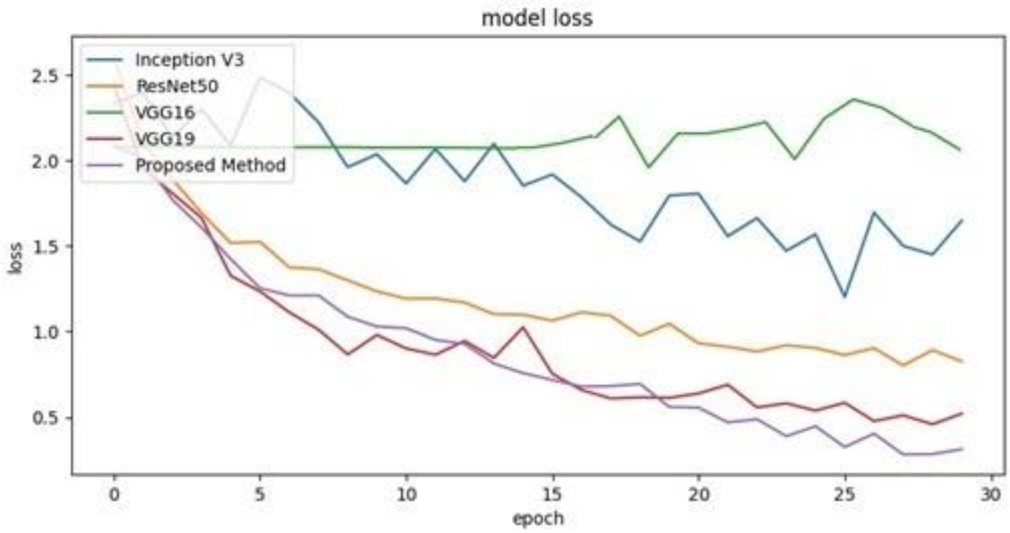

Fig 3: Model accuracy of identifying deceased leaf

Throughout the 30 epochs, the graph visually displays the loss incurred by each model during the identification and classification of mango leaf diseases. This comparative analysis allows for a comprehensive assessment of the performance trends and relative effectiveness of these models during the training process. Notably, the graph underscores that the proposed method demonstrates significantly lower loss compared to the other models, signifying its superior performance in accurately detecting and classifying mango leaf diseases.

Accuracy Comparison:

The bar chart displays the training accuracy of five distinct models—VGG16, VGG19, InceptionV3, ResNet50, and a proposed method—represented along the X-axis. The Y-axis measures the accuracy achieved during training.

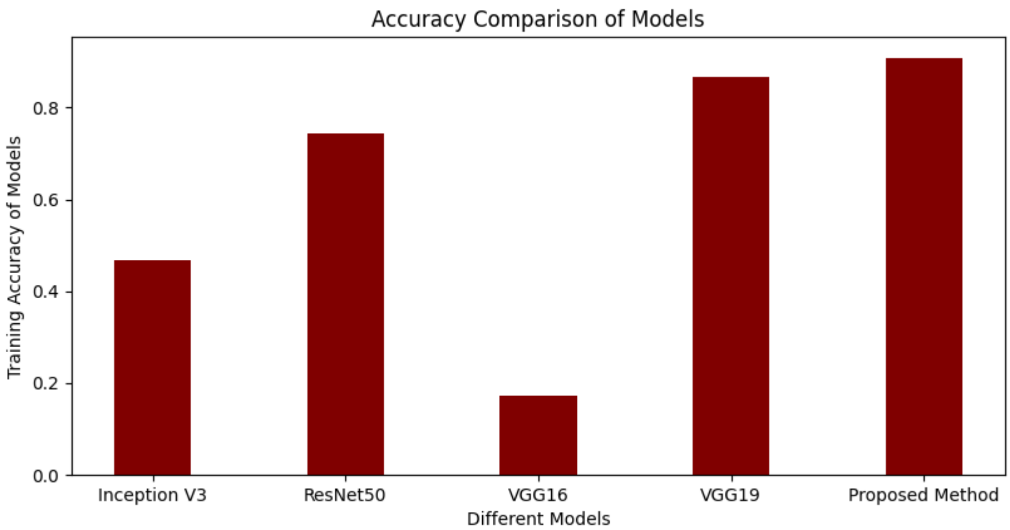

Fig 4: Accuracy comparison of models in identifying deceased leaf

Among these models, the proposed method notably demonstrates higher accuracy compared to VGG16, VGG19, InceptionV3, and ResNet50. The chart visually showcases the varying training accuracies of these models, emphasizing the superior performance of the proposed method in accurately learning and predicting outcomes during the training process.

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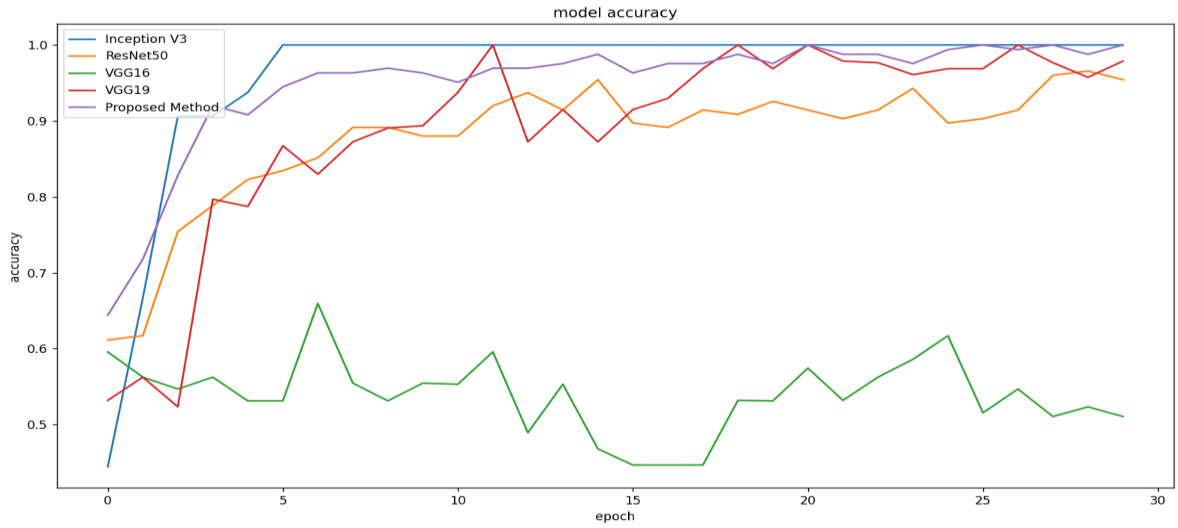

Fig 5: Model accuracy of identifying name of the decease

Over the course of 30 epochs, the graph visually represents the accuracy achieved by each model in the identification and classification of healthy mango leaf and diseased mango leaf . This comparison enables a comprehensive evaluation of the performance trends and relative efficacy of these models during the training process. Notably, the graph highlights that the proposed method exhibits significantly higher accuracy compared to the other models, indicating its superior performance in accurately identification and classification of healthy mango leaf and diseased mango leaf

Model loss: The graph depicts a comparative evaluation of five distinct models employed for mango leaf disease detection: VGG16 (Visual Geometry Group 16), VGG19 (Visual Geometry Group 19), InceptionV3, ResNet50, and an innovative proposed method. The x-axis represents the training iterations across 30 epochs, while the y-axis showcases the loss metric for each algorithm.

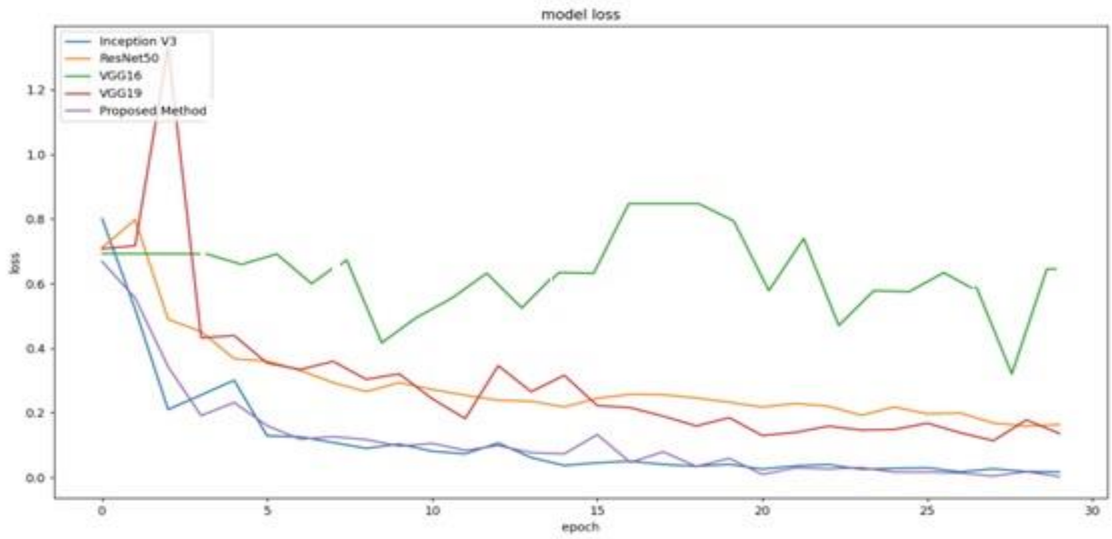

Fig 6: Model loss of identifying name of the decease

Throughout the 30 epochs, the graph visually displays the loss incurred by each model during the identification and classification of healthy mango leaf and diseased mango leaf. This comparative analysis allows for a comprehensive assessment of the performance trends and relative effectiveness of these models during the training process. Notably, the graph underscores that the proposed method demonstrates significantly lower loss compared to the other models, signifying its superior performance in accurately identification and classification of healthy mango leaf and diseased mango leaf.

Accuracy comparison

The bar chart displays the training accuracy of five distinct models—VGG16, VGG19, InceptionV3, ResNet50, and a proposed method—represented along the X-axis. The Y-axis measures the accuracy achieved during training.

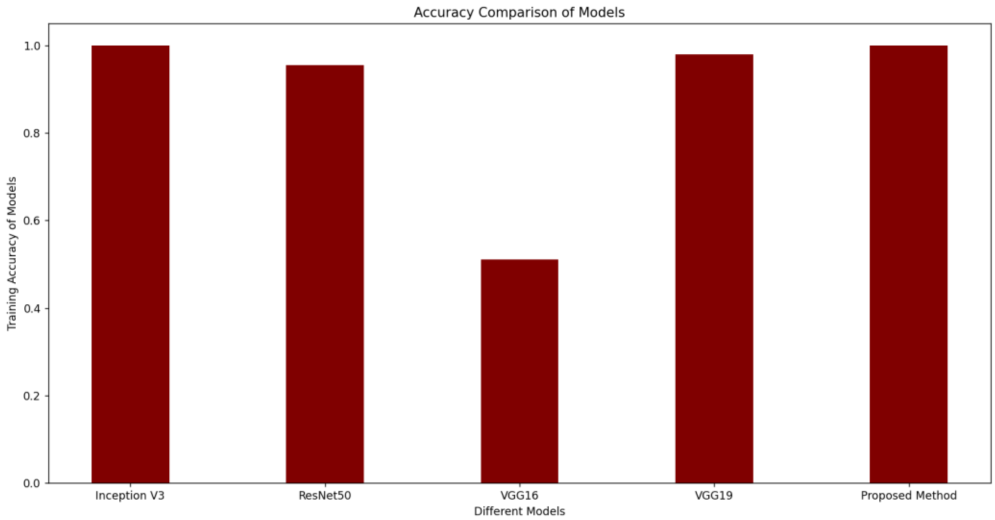

Fig 7: Accuracy comparison of models in identifying name of the decease

Among these models, the proposed method notably demonstrates higher accuracy compared to VGG16, VGG19, InceptionV3, and ResNet50. The chart visually showcases the varying training accuracies of these models, emphasizing the superior performance of the proposed method in accurately learning and predicting outcomes during the training process.

Table 1 : Model comparison

Name of the method	**Objective 1**		**Objective 2**	
Proposed CNN method	90.74	0.14	93.86	0.083
VGG19	86.53	0.355	81.25	0.372
ResNet50	74.44	0.687	78.85	0.4002
InceptionV3	46.87	1.564	70.37	0.498
VGG16	17.18	2.004	53.12	0.646

5. Conclusions

Developing nations like India are far behind the current norms when it comes to agricultural automation, which is an absolute requirement. Artificial intelligence (AI) has recently become an important tool for plant disease detection since it provides a unified system that can function in practical settings and aids those who are not specialists in the field (such as non-pathologists, non-expert botanists, etc.). The goal of this study's model design is to create a convolutional neural network (CNN) model that can detect eight distinct mango leaf diseases (Anthracnose, Bacterial canker, Cutting weevil, Die Back, Gallmidge, Powdery meldow, Reddust, and Soothy mould) , most common in India. We manually sorted 4,000 photos of diseased leaves from India into 7 classes: sick, healthy, and neutral. In order to facilitate feature mapping and prepare them for input into five state-of-the-art convolutional neural network (CNN) models—namely, InceptionV3, VGG16, VGG19, ResNet50, and the proposed CNN model—the pictures were 3-channel colored and 227x227x3. Using average accuracy and model loss, we discovered that the created models performed as follows: 46.87% with 1.564% accuracy, 74.44% with 0.687% accuracy, 17.18% with 2.004% accuracy, 86.53% with 0.355% accuracy, and 90.74% with 0.14% accuracy, respectively. The suggested model achieves a better average accuracy (90.74%) and a very low model loss (0.14%) after thirty iterations. The suggested model reduces computing complexity while maintaining accuracy, as shown by its extremely low loss of 0.14% and average accuracy of 90.74%. Using 5-fold cross-validation, we confirmed that the model worked as expected on new data. When comparing different deep learning architectures, this model is used as a reference point.

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