

# AN AUTOMATED DEEP LEARNING MODEL TO CLASSIFY DISEASES IN ARECANUT PLANT

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## Abstract

Detecting diseases in plant at an early stage is important for ensuring healthy crops and reducing economic losses. Traditional methods are slow and require expertise. The recent technological developments bring in a lot of computational techniques that enables the detection of diseases at an early stage and more accurate. The proposed work has been implemented using deep learning algorithms. The work focuses on identifying the diseases in Arecanut leaf and analyzing the efficiency of the deep learning techniques in detecting the type of diseases. Different CNN algorithms like ReNet, MobiNet and VGG Net have been implemented and tested for their efficiency. The appropriate model is then optimized and deployed in an Android device so as to enable the farmer to use the application efficiently. The proposed work is implemented by collecting a dataset of arecanut diseased leaf images and dividing it for training, validation, and testing. The performance of the models are compared using the parameters (trainable and non-trainable) and the utilisation of the memory during runtime. The models are evaluated based on accuracy and precision. For the given dataset, ResNet performed with 79% accuracy, MobiNet with 86% and VGG with 92% accuracy. The performance efficiency of VGGNet is better than the other two architectures and deployed in Android device to help the stakeholders.

**Keywords:** Deep Learning; Arecanut Plant disease; Convolutional Neural Network; ResNet; MobiNet; VGG, Computation Power.

1. **Introduction** India is among the top three global producers of many crops, including wheat, rice, pulses, cotton, peanuts, fruits and vegetables.

India stands third among the producer's crops including rice, wheat, pulses, fruits, and vegetables across the globe. Numerous elements, including soil quality, climatic circumstances, disease, and others, have an impact on crop development. India is the major producer of arecanut which accounts for 50% of production and 43% area under arecanut in the world. As per the statistics from ICAR-Central Coastal Agricultural Research Institute, arecanut is cultivated on around 7.7 lakh hectares area with an annual production of 14 lakh tonnes and a yield level of 1.8 tonnes/ha (2021-22) in India. The following graph depicts the Area, production, and yield of arecanut in India.

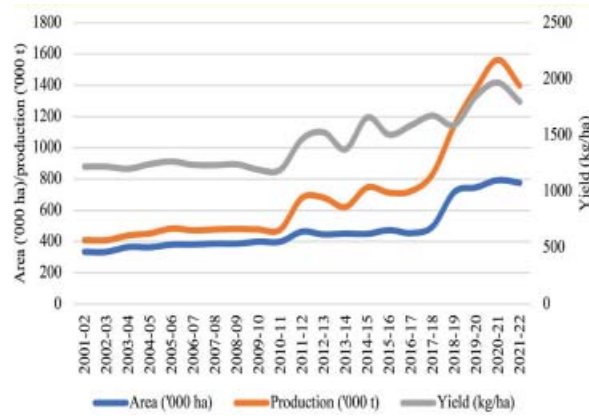


Figure 1.1 Area, production, and yield of arecanut in India (2001-02 to 2021-22)

Courtesy: ICAR-Central Coastal Agricultural Research Institute

It is inevitable to protect the agriculture of the nation for the wellbeing of the nation. Currently, plant diseases are only discovered through observation with the naked eye, and farmers must periodically examine each crop carefully to find any diseases. This is a very difficult task that takes a lot of time and manpower, and it also necessitates expensive equipment, well-equipped labs, and more manpower. Early disease detection and disease prevention are not currently possible. Consequently, a method for automatically detecting diseases is required to avoid the loss of vegetation.

Deep learning is a powerful subset of machine learning that allows computers to automate learning and understanding complex patterns in large datasets. Deep learning model's ability to handle high-dimensional data and automatically extract features has increased advancements in various domains. There are various types of DL models that have gained significant popularity and achieved state-of-the-art results in various domains, one of which is Convolutional Neural Network (CNN).

CNN has transformed the computer vision field by allowing computers to understand and interpret images. They are designed to learn and extract important features from images automatically, without the need for humans to explicitly telling them what to look for. CNNs have proven to be incredibly effective in tasks like recognizing objects in pictures, identifying faces, and detecting patterns in medical images.

The architecture of CNNs plays a critical role in their ability to extract hierarchical representations and achieve state-of-the-art performance in tasks like classification, object detection and image segmentation. This work discusses some of the key architectures commonly employed in CNN, each designed to address specific challenges in image analysis. These architectures include VGGNet, ResNet, and MobiNet. Additionally, the proposed work also provides a comparative study of computation power of CPU, memory consumption of the Deep learning models and deploying the model in an Android phone. This deployment would enable the farmers to use the application and get the benefit of the same.

This work concentrates on identifying Mahali Disease (Koleroga), Stem Bleeding and Yellow leaf spot diseases that affect areca trees. These conditions are brought on by constant rainfall and climatic changes, and they must be controlled in their early stages of infection to prevent loss to the trees.

## 2. Literature Survey

This section gives an overview of the survey of literature taken up on implementation of Deep learning techniques and evaluating its performance of the model. Additionally the survey also concentrates on the various performance issues and challenges that occurs during the deployment of the model and the different methods to overcome the challenges.

The multi-gradient-direction based deep learning model outperforms traditional methods, offering a valuable tool for timely disease diagnosis and improved productivity in arecanut cultivation [1]. Authors in [2] use convolutional neural networks (CNNs) for disease detection in arecanut plant species is suggested in the paper. The CNN model has a high level of illness detection accuracy, making it a useful tool for disease control in arecanut production.

S. B. Mallikarjuna et al. in [3] the research provides a CNN-based approach for accurately categorizing pictures of multi-type sick arecanuts. It offers the potential for efficient disease management in the production of arecanuts and contributes to the field of arecanut disease categorization. The potential for disease identification in arecanut plants is highlighted in the paper's discussion of the detection of arecanut illnesses utilizing image processing technologies. The study in [4] emphasizes the precision and efficiency of the suggested technique, which has a 92% accuracy rate for disease identification.

The classification of ill and healthy arecanut plants in [5] uses an SVM classifier, the study reports an accuracy rate of 87.6% in accurately differentiating between healthy and unhealthy areca nuts. With accuracy rates of 96.77% and 94%, respectively, Ritika Rattan et al. in the study [6] analyses automated disease classification in plants using CNN and VGG-16 algorithms, with implications for high crop production in agribusiness.

The study [7] describes an analytical method of identifying plant diseases in maize leaves using the EfficientNet architecture. The study focuses on using EfficientNet to accurately diagnose and detect disease in maize plants. The authors in [8] shows the potential for deep learning can be used widely in agriculture by using a VGG-16 model and deep learning algorithms to identify plant health with an accuracy of 95.2%.

R. R et al. in the work [9] uses a streamlined methodology and little processing power to address the issue of plant disease identification. An accuracy average of 94.8% was attained using a VGG16 training model and neural network approaches, proving the potentiality of the suggested system for accurate plant disease classification.

To help farmers identify plant illnesses by uploading leaf photographs, this project by Mr. Ashish Nage et al. in [10] suggests an Android application that makes use of image processing algorithms. The technology uses algorithms to determine the ailment kind and gives users results via the application.

To address the difficulties farmers confront, the study [11] examines plant diseases and cutting-edge detection technologies, with special emphasis on the demand for quick and dependable disease diagnosis procedures. The method by authors in [12] uses a sophisticated deep learning neural network to recognize plant diseases accurately and effectively based on changes to the outside of the leaves, providing a quick and easy classification strategy to find diseased plants and suggest remedies.

Authors present precise and general methods for forecasting plant illnesses and calculating crop production using deep learning techniques to assist farmers in underdeveloped nations in [13,14]. The proposed method, which uses conditional random fields, image processing, and convolutional neural networks, provides promising results when compared to current methods, helping the agriculture industry.

The goal of this study is to employ DL and machine learning to detect maize illnesses. Using AlexNet, a classification accuracy of 99.40% was attained, and performance indicators, such as the F1-score, were examined to gauge the model's robustness [15].

The paper [16] evaluated different methods for disease detection in processed arecanuts. While the LBP with histogram correlation achieved a success rate of 92.00%, texture features from Haar Wavelets, GLCM, and Gabor were also explored. A subset of features with high variance was selected, and the study focused on diseases occurring after processing.

K. Y. Huang et al. in the work [17] develop a machine vision system to classify and detect areca nuts on the basis of their quality grades. The system used image processing techniques, a deep learning algorithm, and a BPNN classifier. Defect regions were efficiently segmented, and various color and dimensional features were extracted. The system achieved efficient detection and classification of arecanuts in testing.

The study [18] generated maps to estimate the risk and probability of fruit rot(Mahali) disease in arecanut in Karnataka. These maps will assist in developing effective management strategies and control measures. Training programs are needed to increase understanding among farmers about FRD and its management.

Authors P. Balanagouda et al. in [19] focus on understanding the resistance mechanisms of wild Areca species and incorporating resistant genes into breeding programs that can reduce losses caused by Phytophthora diseases.

In study [20], R. O. Ogundokun et al. developed posture recognition models using machine learning, transfer learning and deep learning algorithms. Four models were tested on the MPII Human-Posture dataset, and the

best performance was achieved by AlexNet + HPO and VGG16 + HPO. Implementing the models with hyperparameter optimization has given good results than using image augmentation.

Muhammad Asif, et al. in [29] concentrates on the use of GPUs to improve the computation. It demonstrates that YOLOV5s is a good benchmark for object detection, classification, and traffic congestion using the Jetson Xavier GPU board. The highest success rate achieved is 98.89%. The study by Yingchun Wang, et al. in [30] explores two deployment approaches: local execution on mobile devices and distributed deployment using cloud and edge servers. Methods for reducing complexity, reusing intermediate results, and developing lighter frameworks for local execution.

Dong-Jin Shin, et al. in [31] concludes if using deep learning on mobile devices, it is efficient to use TF-Lite. If it is an embedded system with built-in Tensor Cores, it is most efficient to use TF-TRT and pure TRT. A study by Hengyi Li et al. on an architecture-level analysis on deep learning models for low-impact computations conducts a thorough study [32] on DNN inference workloads, providing insights into their characteristics on SIMD CPUs and suggesting research directions for future DNN accelerators.

In this work, the authors thoroughly review 88 publications from 2015 to the present to predict stock/Forex price movements using deep learning techniques. In the review, a few methods are discussed, including CNN, LSTM, DNN, RNN, Reinforcement learning, HAN, NLP, and Wavenet. The study looks at data sets, variables, models, and performance metrics. for each technique. It attracts attention to the absence of studies integrating different deep learning techniques, particularly with other deep learning approaches. The paper [33] by Hu et al. provides suggestions for the future research based on hybrid models that incorporate advanced algorithmic evolution and self-attention neural networks to advance the stock/Forex market forecasting.

Neil C. Thompson, Kristjan Greenewald, Keeheon Lee, Gabriel F. Manso [34] states that the increasing computational demands of DL models will soon restrict their performance improvements, potentially making it difficult to achieve important benchmark milestones. This limitation is attributed to the slowing progress in hardware performance. In conclusion, the article suggests that the field may shift towards less computationally intensive methods and explore more computationally efficient alternatives to deep learning.

The study [35] by Zhu L et al. suggested an Android app to identify butterfly categories using SVM, RF, 4-Conv CNN, and VGG19 (transfer learning) machine learning models. For best performance, parameters were adjusted. TensorFlow Lite was used to successfully deploy the app on Android while maintaining model correctness. It is necessary to further optimise model size. Overall, it is anticipated that the app will be helpful for both researchers and the business, encouraging deeper learning integration in mobile apps.

Yihui Ren, Shinjae Yoo, Adolfo Hoiis [36] evaluates the performance of different systems (DGX-2, AWS P3, IBM-P9, and RTX-2080 Ti server) for deep learning workloads in computer vision and NLP domains. Key findings include DGX-2's superiority in 16 GPU collective communication for training large models, similar performance among DGX-1, AWS P3, and DGX-2 when training on eight GPUs, RTX-2080 Ti server achieving about 61.46% throughput performance in comparison to leading-edge systems, minimal impact of cloud computing on performance for low communication-to-computation ratios, and scalability considerations up to the dimension of DGX-2 with potential for future work on scaling to production-size DL models.

The TPU platform is the focus of the paper's thorough benchmarking investigation of neural network training hardware and software. It pinpoints the TPU's architectural bottlenecks and makes recommendations for future advancements. The study [37] evaluates six real-world models against TPU, GPU, and CPU platforms using ParaDnn, a parameterized benchmark suite. The study by Yu Emma Wang et al. highlights the need for more development in this field and offers new viewpoints on specialised deep learning hardware and software.

Ji Wang, Bokai Cao, Philip S. Yu, Lichao Sun, Weidong Bao, Xiaomin Zhu [38] examines the challenges and potential of DL on mobile devices. The paper highlights the need to address efficiency, privacy, and security concerns for successful improvement of the domain.

Several studies [1-20] have demonstrated the productiveness of DL and machine learning techniques in accurately detecting and classifying diseases. These studies utilize various models such as CNNs, SVM, VGG-16, EfficientNet, and AlexNet, achieving high accuracy rates ranging from 87.6% to 99.40%. Practical applications include the development of Android applications for farmers to identify plant illnesses through leaf photographs and the generation of disease risk maps for effective management strategies. The choice of batch

size in training processes significantly affects the training ability of the process. Models having too many hidden layers tend to have longer training durations due to increased parameter learning. However, transfer learning can be leveraged to achieve more accuracy with fewer training epochs

From the study conducted [29-38] , the challenges and potential of DL models on mobile devices are explored, with a focus on addressing efficiency, privacy, and security concerns have been discussed. This suggests the need for developing approaches and frameworks that optimize model for mobile platforms while ensuring data protection and maintaining user privacy. The challenges and potential of DL models on mobile devices are explored, with a focus on addressing efficiency, privacy, and security concerns. This suggests the need for developing approaches and frameworks that optimize model for mobile platforms while ensuring data protection and maintaining user privacy.

GPUs play an important role in improving computational performance for DL tasks, particularly in tasks such as object detection, classification, and traffic congestion. When deploying DL models, considering the specific requirements and constraints of different deployment scenarios (such as local execution on mobile devices or distributed deployment using cloud and edge servers) is important for achieving optimal performance.

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The following challenges and issues will be addressed in the proposed system:

1. Identify the best CNN architecture to classify the plant disease by analysing the various CNN architecture like VGG, MobiNet and ReNet based on the performance and model accuracy
2. Deploy the model with best performance by testing the model efficiency based on computational power, time of inference and model size.

### 3. Proposed System

This section elaborates the proposed system in detail. The proposed system is carried over using four phases namely, Data Collection, Data Preprocessing, Model Training and Evaluation. The following figure 3.1 shows the block diagram of the implementation consisting of data collection, image preprocessing, model training, evaluation and deployment.

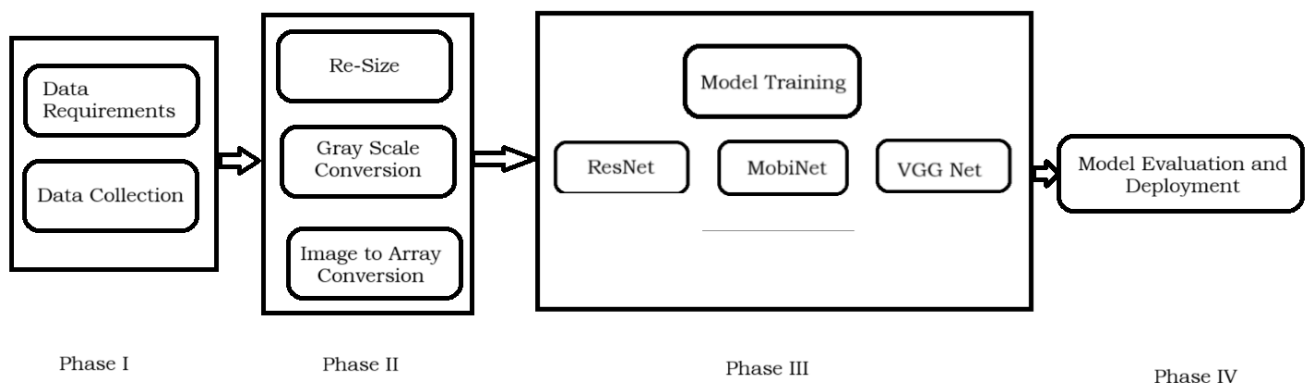


Figure: 3.1 Block Diagram of the Proposed System

#### 3.1 Data Collection

The arecanut plant pictures in the dataset include both healthy and sickly specimens. Images were captured using a mobile camera at 0.5 metres from the source. The photographs of diseased and healthy arecanut plants were gathered in the Sirsi region of Karnataka. These pictures were taken with the assistance of knowledgeable arecanut growers and researchers. The collection consists of 1200 images in total, including healthy and diseased arecanut trunk, nuts, and leaves. There are 500 images of healthy arecanuts and 700 images of arecanuts with diseases such as stem bleeding illness, Mahali/Koleroga, and yellow leaf spot disease. Before

training the model, the photos are reduced in size using open-cv to 256\*256 pixels. The images were labelled and segregated for training and testing.



Figure: 3.2 Sample dataset

### 3.2 Data Preprocessing

Pre-processing involves enhancing the quality of the images to remove noise and improve contrast. Preprocessing ensures image resizing, where all the images are resized to a consistent resolution that is suitable for input to the deep learning model. This ensures that all images have the same dimensions, maintaining uniformity during both the training and inference stages. The end of the phase is a set of preprocessed images, all resized to the appropriate form, ready to be fed into the deep learning model for effective training.

### 3.3 Model Training

A classification model was built using the training data from the dataset using Convolutional Neural Network (CNN). Different CNN architectures like ResNet, MobiNet and VGG Net were used to train the classification model.

#### a. Convolutional Neural Networks (CNN):

Deep learning algorithms known as convolutional neural networks (CNNs) are specialised for image processing. They are made up of layers that use convolution and pooling techniques to extract information. To reduce prediction mistakes, CNNs are trained with labelled data and have their weights adjusted. They are exceptional at operations like object detection, picture segmentation, and classification.

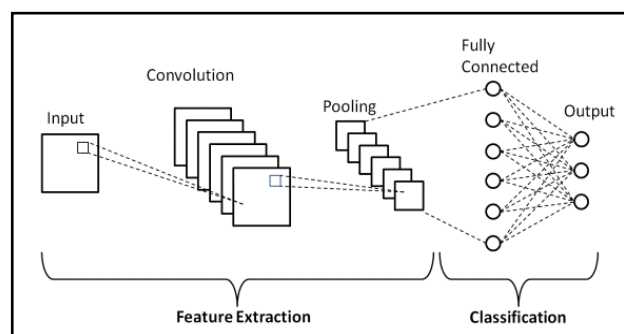


Figure: 3.3 CNN architecture [20]

Some of the most well-known CNN architectures include LeNet, AlexNet, ZFNet, VGGNet, GoogleNet, ResNet, DenseNet, MobiNet, and EfficientNet. Each architecture has unique characteristics and has performed exceptionally well in different types of computer vision tasks. LeNet and AlexNet were early pioneers, while

ResNet exploited residual connections to address the vanishing gradient problem and MobiNet was created with portable devices in mind. VGG is recognized for its simplicity.

**b. Residual Network (ResNet):**

This Network is ideal for deep neural networks. It utilizes skip connections, often referred to as residual connections, to get around the issue of vanishing gradients that arises as the network depth increases. ResNet-50, ResNet-101, and ResNet-152 are variations. Variants have different architectures. Each variant's name has a number that corresponds to the number of network layers. The following figure 3.2 depicts the ResNet Architecture with layers included in it, activation function used, numbers of layers and their arrangement order.

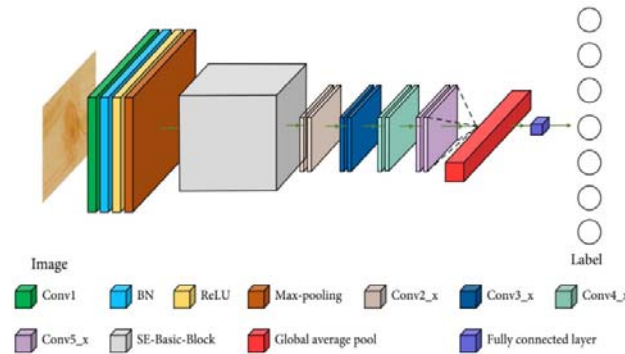


Figure: 3.4 ResNetarchitecture [26]

Convolutional layers, dropout layers, pooling layers, completely linked layers, and other layer types are included in these architectures. ResNet's fundamental building block is the residual block, which enables the introduction of skip connections during the training of very deep networks. For the proposed solution a classifier is set with a 2D max pooling with flatten layer setting of 128x512x1x1, a drop out ratio of 0.2 and Neural Layer with two classes specify Healthy or Diseased is set.

**c. MobiNet:**

MobileNet is a family of deep learning models optimized for efficient inference on mobile and embedded devices. It consists of three variants: MobileNetV1 with 23 layers, MobileNetV2 with 53 layers, and MobileNetV3 with two options, Large (213 layers) and Small (53 layers). These models reduce computational complexity and memory usage while maintaining competitive accuracy. They achieve this through techniques like depth-wise separable convolutions, inverted residual blocks, and SE modules.

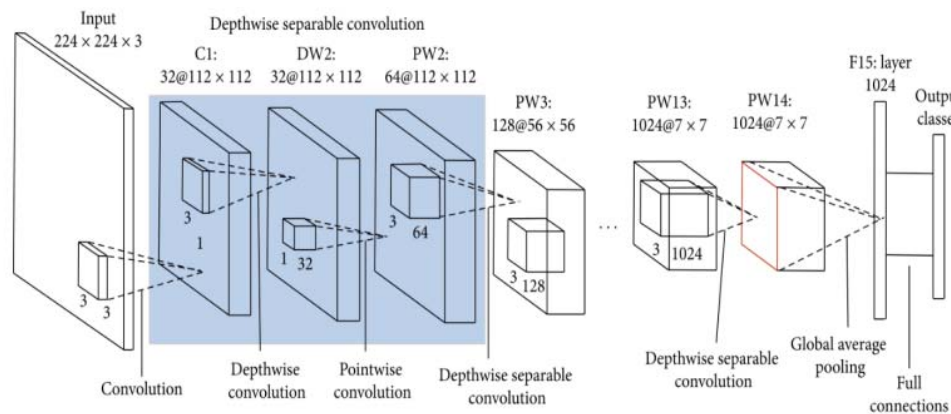


Figure: 3.5 MobiNet architecture [27]

MobileNetV3 introduces improvements like the hard swish activation function and h-swish non-linearity. These architectures enable real-time image recognition and object detection on devices with limited hardware capabilities.

**d. Visual Geometry Group (VGGNet):**

Compared to certain other architectures, it is deeper and has more parameters, which might make training and inference computationally expensive. VGG16 and VGG19 are the variants. The following figure 3.4 shows the VGG architecture with with layers included in it, activation function used, numbers of layers and their arrangement order.

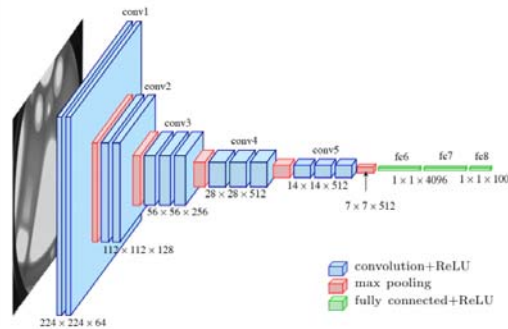


Figure: 3.6 VGGNet architecture [28]

It consists of fully linked layers that are followed by a sequence of convolutional layers. The extensive usage of 3x3 convolutional filters, which are repeatedly used throughout the network, is the distinguishing feature of VGG. Each variant's total number of layers, including convolutional and fully linked layers, is indicated by the number in the name.

The proposed work is carried over in an AMD Ryzen 5 5600H with Radeon Graphics system with 8.00 GB (5.86 GB usable) RAM and x64-based processor. Tensor flow lite is chosen to develop the model so that it can be deployed as a light weighted model in the Android device. The functioning of the model is evaluated based three metrics – accuracy, model size and time for an inference. Time is measure by taking start time before the inference and end time after the inference. The model’s size was evaluated by saving the model by .hdf5 format and checking the model size. The performance of the model is compared with the number of epochs and the accuracy of the model in classifying the disease.

**3.4 Model Evaluation and Deployment**

The dataset is split into training, validation, and test data. The model is building by using the training and validation set. The three different CNN architectures like ResNet, MobiNet and VGG Net are used to classify the diseased and healthy plant. The models are compared using the total params, Trainable params and non-trainable params. The following table 3.1 depicts the comparison using total params, trainable params and non-trainable params of all the three network architectures.

Table 3.1 Comparison of Architectural Parameters

	<b>Total Params</b>	<b>Trainable Params</b>	<b>Non-Trainable Params</b>
<b>ResNet</b>	25,636,712	25,583,592	53,120
<b>MobiNet</b>	4,253,864	4,231,976	21,888
<b>VGGNet</b>	138,357,544	138,357,544	0

Total params shows the points in the weight matrix and deviation matrix. Trainable parameters are those values that can be changed during the training and non-trainable parameters are those that cannot be changed during training phase. The lesser the non-trainable params, the accuracy of the model will improve.



The pre trained networks are run through 50 epochs and their accuracy is compared. The following figure 3.7 depicts the performance of the models based on their accuracy.

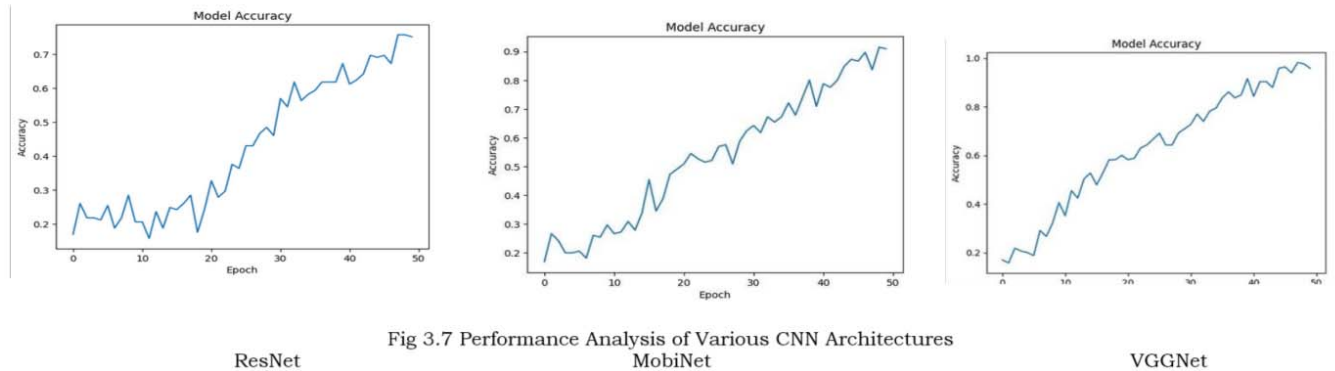


Fig 3.7 Performance Analysis of Various CNN Architectures

The accuracy of ResNet architecture is 79% , MobiNet is 86% and VGGNet is 96% against 50 epochs. Depending on the complications of the project and the available computing power, the size and number of blocks and the depth of each block may vary.

The memory utilization of the models have been analyzed and the following table 3.2 depicts the memory utilization of all the three types of architectures in detail.

Table 3.2 Memory Utilization of the Model

Architecture	Memory Usage in CPU	
	RAM Memory %	RAM Used (GB)
ResNet	33.6%	4.22574
MobiNet	31.8	3.98201
VGGNet	33.9	4.25515

The comparative analysis of all the three architectures confirms the efficiency of VGGNet in terms of accuracy and performance. Even though the storage of the model is little high when compared to MobiNet, VGGNet is preferred to be deployed for classification of the disease.

#### 4. Conclusion

In conclusion, this work demonstrates that deep learning models, specifically the ResNet, AlexNet, VGG, and MobileNet architectures, are effective in detecting and classifying plant leaf diseases. These models can perfectly identify different types of diseases based on their unique features. ResNet performs well with its deep architecture and unique connections, while MobileNet is particularly efficient in terms of computational requirements. Both architectures offer promising solutions for automated leaf disease detection in agriculture. But when compared with VGGNet, the accuracy and the computational power of VGGNet outperforms the other two.

The findings of this study contribute to the development of automated systems that can help farmers identify and manage plant diseases more effectively. By utilizing deep learning models, farmers can take timely actions to prevent crop damage and enhance overall productivity.

Further research can focus on exploring new architectures and techniques to improve the accuracy, precision, efficiency, and interpretability of leaf disease detection models. Additionally, investigating the applicability of these models across different plant species and disease types would be beneficial.

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