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COTTON LEAF DISEASE DETECTION USING DEEP LEARNING

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Abstract
Cotton is the most important crop for making textiles around the world. To protect the fiber, food, and environment, farmers need to use sustainable farming methods. Cotton crops are very important to farming economies, but sometimes diseases can hurt production. Among the major contributors to the global agricultural revolution, the cotton industry is one of the most influential. Timely and accurate detection of crop conditions is essential in this field, and deep learning has proven to be a powerful tool in addressing this challenge. This study provides a clear and efficient framework of Deep Learning with respect to automated detection of Multi-Class Cotton Leaf Disease Classification in response to a major challenge that determines the yield of crops, farmer productivity and the sustainability of agriculture as a whole. This thesis focuses on four advanced CNN architectures, including DenseNet201, ResNet50, InceptionV3, and MobileNetV3 to a comprehensive design of evaluation based on a systematic strategy, comprising data preprocessing, data augmentation, stratified splitting, model training, and multi-metric performance evaluation, using the SAR-CLD-2024 dataset. The DenseNet201 model was the best in the assessed models with the highest validation of 99.78% and exhibited good learning throughout training. However, MobileNetV3 showed the highest overall test results, with the test accuracy of 99.85% and equally high precision, recall, and F1-score (all equal to 99.86%), which is why it is the most trustworthy and can be easily deployed in the real-world environment. InceptionV3 and ResNet50 generated less competitive yet similar-in-quality results. The results indicate clearly that deep learning, particularly Convolutional neural networks (CNNs) models, can be used to give effective and precise answers to the problem of plant leaf disease classification. Despite being limited by computational resources and diversity of datasets, the study provides a strong basis on which it can improve in the future by investigating emerging architectures, increasing datasets in different regions, and creating mobile or edge-based diagnostic tools Altogether, this research presents a tested and proven system and emphasizes the high potential of AI in enhancing agricultural disease detection.

Keywords:
Cotton Leaf Disease, Convolutional Neural Networks (CNNs), Image Classification, Multi-Class Classifications, Deep Learning, SAR-CLD-2024 Dataset.

1- INTRODUCTION
Agriculture is the backbone of the economies of the world and is the source of livelihood for a large portion of the world's population[1]. It is a critical sector in the supply of food, raw materials and employment worldwide[2],[3]. In Pakistan, the agriculture sector has special importance and contributes about 19% to the total GDP, with great scope of growth in this sector. Within this agricultural landscape, the cotton plant is an important crop, which is valued not only for its economic return, but also for its industrial utility. Often called "white gold," it is the major source of natural fiber for the textile industry cotton seeds are the source of edible oil and animal food[4].
For Pakistan in particular, cotton has a very high economic significance, accounting for 55% of the total foreign exchange earnings and 10% of the GDP. Globally, Pakistan is the fifth largest producer of cotton after China, India, America and Indonesia. This vital crop is principally grown in the provinces of Sindh and Punjab which produce around 75% of the total cotton yield of Pakistan every year. Sowing normally takes place in March and April in Sindh and May to August in Punjab. The country is blessed with 59 different varieties of cotton each suitable to different environmental conditions and yield potentials. However, despite these favorable conditions, these valuable varieties are constantly challenged by various agricultural issues with disease attacks being a primary concern[5]. Preventing significant losses in crop thus requires

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careful management and timely spraying[6],[7].

The shortcomings of traditional agricultural management[8],[9] have given way to a worldwide movement towards smart farming[10], in which modern technology is exploited to improve productivity. Within the sphere of automatic detection[11], Computer Vision (CV)[12] and Artificial Intelligence (AI)[13] and more specifically Deep Learning (DL) have become powerful means. Computer vision helps machines to interpret digital images like human vision, detecting visual features such as color, texture, and shape for the purpose of distinguishing between healthy plants and diseased ones. Unlike the older image processing techniques involving manual extraction of features, there are deep learning techniques such as Convolutional Neural Networks (CNNs) that can learn complex patterns in the visual data automatically from scratch. Different architectures of CNN have been able to demonstrate excellent performance in training and testing images. This technological evolution provides a way to automate disease detection, which may detect delicate visual clues that a human observer may not.

Despite the improvements in agricultural technology, the cotton industry is facing a serious issue[14] that is the absence of a timely, accurate and broadly scalable technique for diagnosis of various leaf diseases in cotton. The fundamental problem is that current methods including both manual and automated are not yet satisfactory to avoid major yield losses. Cotton plant is susceptible to a number of pathogens like fungi, bacteria and viruses such as Cotton Leaf Curl Virus (CLCuV), Bacterial Blight and Leaf Reddening[15]. These diseases reduce plant health severely affecting photosynthesis and directly affecting the quality and yield of the fiber. Recent research reports the fact that diseases such as CLCuV alone have caused significant economic losses each year, usually greater than 20-30% of the crop in some areas of South Asia and Africa[16]. Farmers and agricultural experts have used visual checks in the past which are subjective and time-consuming and can lead to errors. Early symptoms of diseases often resemble nutrient deficiencies or environmental stress and are misdiagnosed in that regard. Furthermore, manual inspection of large fields is practically impossible to cover completely and disease occurrences may be able to spread undetected until they reach an irreversible stage

To guarantee a thorough and practical investigation, the main objective of this research is to explore how deep learning methods could be used to detect cotton leaf disease automatically. Specifically, the following three research objectives are concerned with this research:

1. To create a deep learning-based multi-class classification framework to detect and classify the different cotton leaf diseases using a real-time SAR-CLD-2024 dataset that contain both original and augmented data.
2. To compare the performance of several state of the art deep learning architectures, such as DenseNet201, ResNet50, InceptionV3 (GoogleNet), and MobileNetV3, on automated cotton leaf disease detection.
3. To evaluate the performance of each model using standard evaluation measures, including accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix to analyze the performance of the model in terms of class and overall performance.

2- LITERATURE REVIEW

Farming all over the world is in a constant struggle to produce more and utilize the available resources effectively. In this struggle, Deep Learning (DL), a highly developed arm of artificial intelligence has changed the way plant diseases are managed. Historically, detection of diseases was done by manual observation, laboratory tests or simple computer tool's methods that were slow, expensive, subjective and could not be used in large scale agriculture.

In order to address these challenges, Deep Learning models particularly Convolutional Neural Networks (CNNs) have been developed as powerful solutions. CNNs have the ability to figure out complex visual patterns in raw images and detect tiny signs of the diseases in plants, including changes in color, unusual textures, or the shape of the lesion, without being told how to

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do this. Such capability allows proper and effective diagnosis of diseases, which can be punctually responded in the current agriculture era.

One of the most important benefits of the DL-based systems is automation and speed. They are able to scan thousands of images in seconds; this allows them to monitor large areas that could not be done manually. This causes less reliance on human skills and creates a reliable and objective outcome. In addition, DL aids in timely diagnosis by identifying the small symptoms that manifest themselves before the damage is seen, preventing the local infections to go far and reduce the losses of crops.

To summarize, the Deep Learning implementation in the context of the plant leaf disease detection is a significant advancement that would substitute the older methods of handling them manually with automated, quick, and highly precise solutions. By enabling farmers to make crucial decisions that increase their productivity, sustainability, and food security in the entire world, DL can provide farmers with the most important information with the help of early detection, accurate classification, and flexibility in deployment. It is therefore the most appropriate and efficient method to use in research on cotton leaf disease detection.

Based on a review of deep learning in agriculture, this section provides a wide-ranging literature review of the latest deep learning methods to identify and multi-classify cotton leaf diseases. The analyzed literature shows that different neural network structures, attention models, and new preprocessing methods have greatly enhanced the accuracy of detection, strength, and feasibility of application in the real-life agricultural settings.

The article by Bishshash et al.[17] is a significant contribution, as it creates the SAR-CLD-2024 dataset that is also utilized in this work. They used the model InceptionV3 and the overall accuracy was 96.03%. They started out with 2,137 original field images of cotton leaves which were later increased to 7,000 images and seven disease classes, including bacterial blight, curl virus, herbicide growth damage, jassids, healthy leaves, reddening, and variegated leaves. The dataset was a good reference point in training deep learning models to improve early disease detection and minimize the efforts of manually inspecting them.

Togacar [18]also went further in this field and combined attention modules with deep learning model achieving an accuracy of 96.56%. Their Stochastic Gradient Descent (SGD) and ADAM optimization allowed the model to pay special attention to the important disease areas, and the classification accuracy of the healthy and infected cotton leaves increased.

A hybrid architecture developed by Reena et al. [19]was named Blend Unity Resqueeze with ResNet-50, and it achieved an accuracy of 92% with a Kaggle dataset. The model was able to extract stronger features, deal with the vanishing gradient problem, and multiclass classification.

Narwade et al. [20]employed the use of Mask R-CNN with a ResNet101 backbone and achieved 92% accuracy in detection and localization of cotton diseases. This method was very helpful in practical applications as compared to the traditional models because it not only classified diseases but also segmented and bounding boxes at the pixel level.

Ahmad et al. [21] examined Vision Transformer (ViT) to detect cotton leaf disease, with results of 96.72% binary classification and 93.39% multiclass classification. Their 3,475 leaf images dataset was properly preprocessed and expanded, and the findings revealed that ViT has a great potential to process complicated disease patterns and improve resilience.

Shao et al. made two new architectures. The original, CANnet [22], which was based on a CNN with inbuilt RFSC, PCA, and KANs modules, scored 96.3% on their own dataset and 98.6% on a public dataset. The second, which is based on ResNet34 including Bilinear Coordinate Attention Enhancement Module (BCAEM) [23]was able to reach an accuracy of 96.61% and efficiently extracts spatial information using fewer parameters. The two models were very effective in identifying diseases in complicated settings.

Azath et al. [24]suggested a CNN-based model that was trained with the help of OpenCV preprocessing and K-fold validation, achieving 96.4% accuracy in the diagnosis of cotton leaf

diseases and pest attacks. Their research revealed the possibilities of realistic real-time agricultural uses.
Khujamatov et al.[25] proposed CottoNet, which is a UAV-based detection system implemented with EfficientNetV2-S and a Dual-Attention Feature Pyramid Network (DA-FPN). Their model reached 89.7% mAP50, 88.2% F1-score and 91.5% early detection accuracy and is able to detect early disease symptoms using aerial RGB images at low-cost and at field-level, which is advantageous.
Kumar et al. [26] used VGG16 and combined it with classic feature extraction and selection feature Color Moments, Gabor Wavelet and Harris Corner, achieving an accuracy of 95.52%. Their strategy enhanced interpretability and computational efficiency, which enhanced feature representation.
Noon et al. [27]improved YOLOX to detect various diseases and severity levels with 73.13% mAP, which is an increase of 3.27% relative to the baseline. Their Spatial Pyramid Pooling (SPP)-block, which was modified, and a-IoU loss function enhanced the regression of bounding boxes and robustness of the model to the field conditions.
Caldeira et al. [28]used GoogleNet and ResNet50 on a big sample of 60,659 field images, getting 86.6% and 89.2% preciseness, separately. The models worked effectively in the uncontrolled natural environments and this proved the reliability of CNN-based detection techniques.
Sawant et al. [29]proposed an effective solution known as CottonCure which is an android-based CNN application used to detect cotton diseases automatically. The app was able to have 60-80% training accuracy and 58-75% validation accuracy and was a simple and inexpensive diagnostic instrument to the farmers in remote locations.
Balafas et al. [30]made a detailed computational analysis of deep learning models on the PlantDoc dataset. They found YOLOv5 to be the most successful at object detection (mAP.50= 0.560) and DenseNet121 to be the most successful at image classification (61.01% accuracy). This work was an excellent guide and future trends in enhancing computational efficiency and data heterogeneity.
A three-stage CNN-based system suggested by Ramacharan [31]had a 96.6% accuracy, which comprised disease identification, cotton development phase identification, and remedy recommendations. This combined methodology provided identification and actionable information.
With an integration of the previous studies as it is demonstrated in Table 1, this section provides a clear edge point to the current study and provides some of the major gaps to be filled in future to come up with more precise, efficient, and practical framework of deep learning to detect cotton leaf disease.

Table 1: Summary of the State-of-the-Art of Key Deep Learning Architectures for Cotton Leaf Disease Detection

Ref.	Study/ Year	Dataset Used	Key Algorithms/ models	Reported Accuracy / Metric	Purpose
[32]	Bishshash et al., 2024	SAR-CLD-2024	Inception V3 (CNN)	96.03% Overall Accuracy	To generate an inclusive cotton leaf disease dataset and use deep learning to detect and classify it correctly to aid precision agriculture.
[18]	Togacar, 2021	Kaggle	Deep Learning Model with	96.56% Overall Accuracy	To effectively identify cotton disease with the help of an artificial intelligence-based

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			Attention Modules, SGD, ADAM		system, namely, a deep learning model with attention modules.
[19]	Reena et al.,2025	Kaggle	Blend Unity Resqueeze with ResNet-50	92% Accuracy	To increase the classification of diseased and normal cotton plants by using deep learning method, which can help in preventing the loss of crops by agriculturists.
[20]	Narwade et al., 2024	Plant-Village	Mask R-CNN (with ResNet 101 backbone), Image Pre-Processing, Transfer Learning	92% Accuracy	To facilitate farmers in crop protection, fast, precise, and cost-effective cotton disease detection with the help of Mask R-CNN to enhance segmentation and classification.
[21]	Ahmad, 2024	Custom dataset	Vision Transformer (ViT), Shifted Window (Swin), CNN, ResNet50, DenseNet, CheXNet, U-Net	Binary: 96.72% accuracy, Multi-class: 93.39% accuracy, ResNet50: 95.72%: DenseNet 91.66%	To create and analyze deep learning and transformer-based methods of precise and automated recognition and classification of cotton leaf diseases.
[22]	Shao et al.,2024	Custom dataset + Public	CANnet (with) RFSC module, PCA module, improved KANs for classifier)	96.3% accuracy	To enhance detection of cotton disease in complicated background with a lightweight CANnet model and building of extensive datasets of images.
[23]	Shao et al.,2023	Custom dataset + Plant-Village	Bilinear Coordinate Attention Enhancement Mechanism (BCAEM) with ResNet34 backbone	96.61% Acc;21.55 × 10^6 parameters	To create a cotton leaf disease detection model that improves the accuracy and efficiency of disease detection in a complex environment by using disease areas and reducing unnecessary details.
[24]	Azath et al.,2021	Custom dataset	CNN (Keras, TensorFlow)	96.4% Accuracy	To create a deep learning model that will provide the efficient and accurate detection and diagnosis of the prevalent cotton leaf diseases and pests, to offer IT-based solutions to farmers.

[25]	Khujamatov et al.,2025	Custom UAV-based + SAR-CLD-2024	CottoNet (EfficientNet backbone, Dual-Attention Feature Pyramid Network (DA-FPN), Early Symptom Emphasis Module (ESEM))	mAP@50= 89.7%, F1score= 88.2%, Early Detection Accuracy (EDA)= 91.5%	To create a lightweight, high-performance, and field-deployable deep learning system to detect cotton disease at an early stage with the help of RGB image collected by UAVs, and to make it affordable to the smallholder farmers.
[26]	Kumar et al., 2024	Kaggle	VGG16 (CNN), Color Moments, Gabor Wavelet Transform, Harris Corner Method (for feature extraction)	95.52% Accuracy	To examine an approach to feature selection that can be used to detect cotton leaf disease with VGG16 deep learning models and enhance both model performance and interpretability.
[27]	Noon et al.,2022	Custom dataset	Improved YOLOX model, Modified Spatial Pyramid Pooling (SPP), a-IoU regression loss	73.13% mAP (3.27% better than original YOLOX)	To overcome the issues of identifying a variety of co-occurring diseases and their levels of progressive severity on individual cotton leaves on a single deep learning model of YOLOX that was improved.

3- RESEARCH METHODOLOGY

The proposed study will be conducted in the form of a deep learning pipeline, as suggested in cotton leaf disease detection and classification, as shown in Figure 1. It is a unified systematic multi-stage process through which all the proposed architectures namely as DenseNet201, ResNet50, InceptionV3 and MobileNetV3 will be trained and evaluated ensuring a fair and consistent basis for performance.

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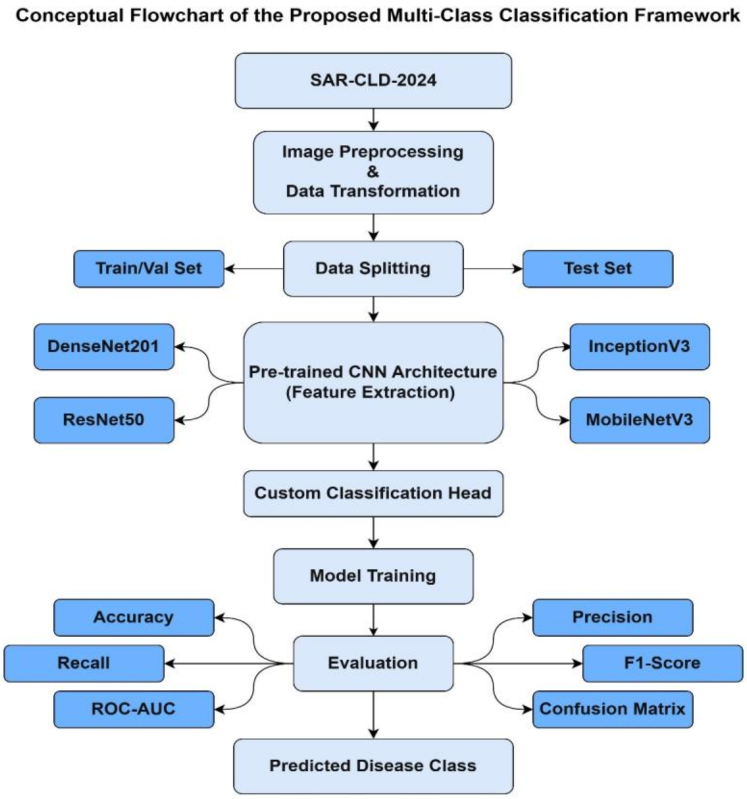
Figure 1: Conceptual Flowchart of the Proposed Multi-Class Cotton Leaf Classification Framework on SAR-CLD-2024



3.1 SAR-CLD-2024 Dataset Specifications:

This study is based on “SAR-CLD-2024: A Comprehensive Dataset to Cotton Leaf Disease Detection”, which is a publicly available dataset on the Mendeley platform .

Dataset Characteristics: The SAR-CLD-2024 dataset is divided into two major sections, i.e., the Original Dataset and the Augmented Dataset. Original Dataset consists of 2,137 real images of healthy and diseased cotton leaves that were measured in the field whereas the Augmented Dataset has 7,000 generated images to enhance diversity and the performance of the models. A total of 9,137 images were utilized as training and validation.

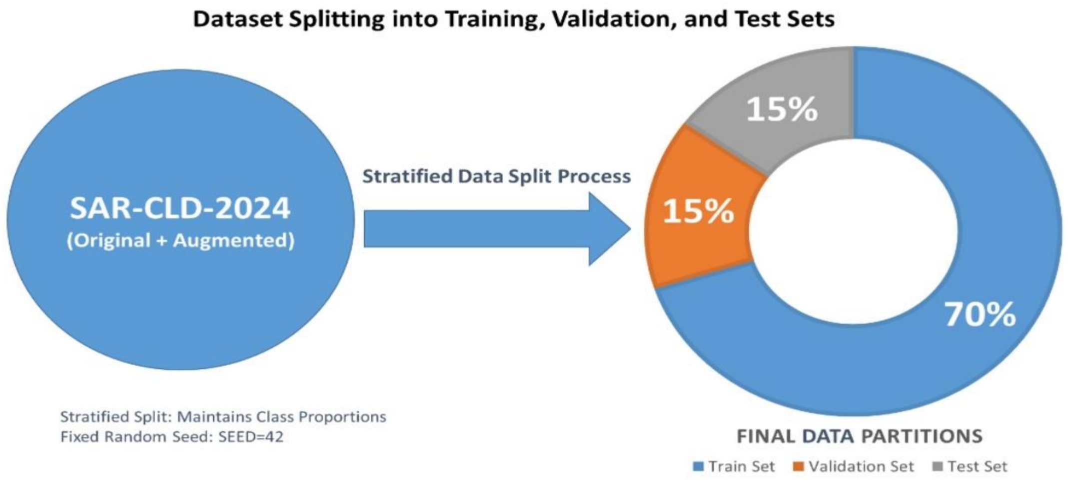
3.2 Image Preprocessing and Data Transformation:

In order to achieve the fair compatibility between the proposed architectures all image data were subjected to a series of basic preprocessing processes. The pixel resizing was standardized to their default sizes such as denseNet201, resnet50 and mobilenetV3 has 224x224 while the inceptionV3 has default size of 299x299. Such standardization is essential ac CNNs usually assume input to be of fixed size. Moreover, standard normalization as well as some required dynamic transformations which is usually training specific were applied, hence enhancing the robustness and generalization ability of the models

3.3 Data Splitting Strategy:

In order to provide strong and objective training, tuning, and evaluation of the deep learning models, the combined SAR-CLD-2024 dataset, which includes both original and augmented images, was logically separated into three separate, non-overlapping subsets, namely, training, validation, and test sets. This organized segment is essential to avoid overfitting and in making sure that the performance of the models can be regarded as their real capacity to deduce the available information. To maintain the same proportions of classes in every subset, a stratified shuffle split approach that was implemented with the Stratified Shuffle Split utility in scikit-learn was used as shown in Figure 2.

Figure 2: Strategy for Dataset Splitting into Training, Validation, and Test Sets on SAR-CLD-2024 dataset for Multi-Class Cotton Leaf Classification



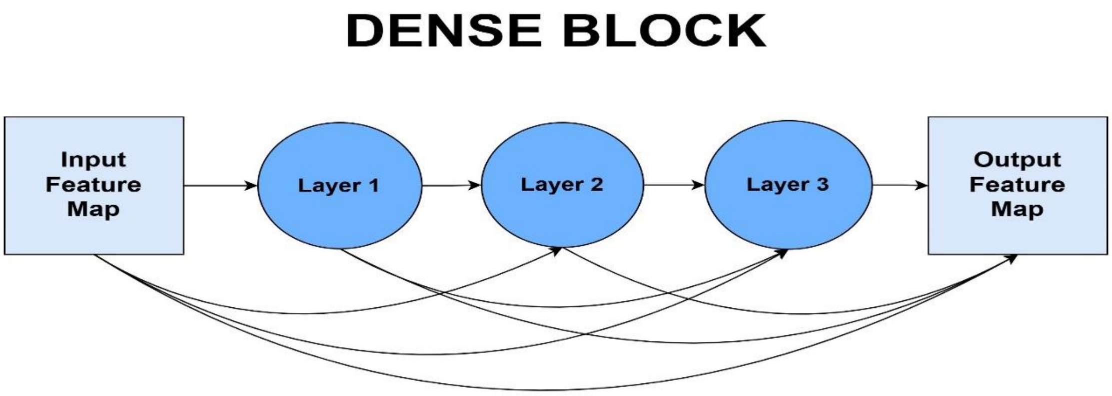
3.4 Proposed CNN Architectures for Feature Extraction:

This section describes the four improved CNN models that will be used in the detection of various cotton leaf diseases with multiple classes. The CNNs form an essential part of the contemporary image analysis, and it is characterized by the capability to learn hierarchical visual features, starting with simple edges up to complex patterns, directly by getting raw images. One of the central techniques of our work is transfer learning that makes use of models that have been pre-trained with large-scale datasets like ImageNet-1K. There are already models that already have a good visual perception of such features as textures, gradients, and shapes, which translate to a faster convergence and less overfitting upon our smaller, specialized dataset.

3.4.1 DenseNet201 Architecture:

DenseNet201 is very strategically selected to be incorporated into the proposed framework because of its excellent performance in terms of extracting complex visual features as well as its history of success in various image classification instances. The key distinctive feature of the model that makes it particularly useful is the dense connectivity pattern of each layer, wherein the layer is fed by all the previous ones in a block, allowing for the re-use of features and efficient information flow, as well as even alleviates the vanishing gradient issue. The structure enables the model to combine both low-level (e.g., edges, textures) and high-level (e.g., disease lesion patterns) features within it, which is highly efficient and expressive.

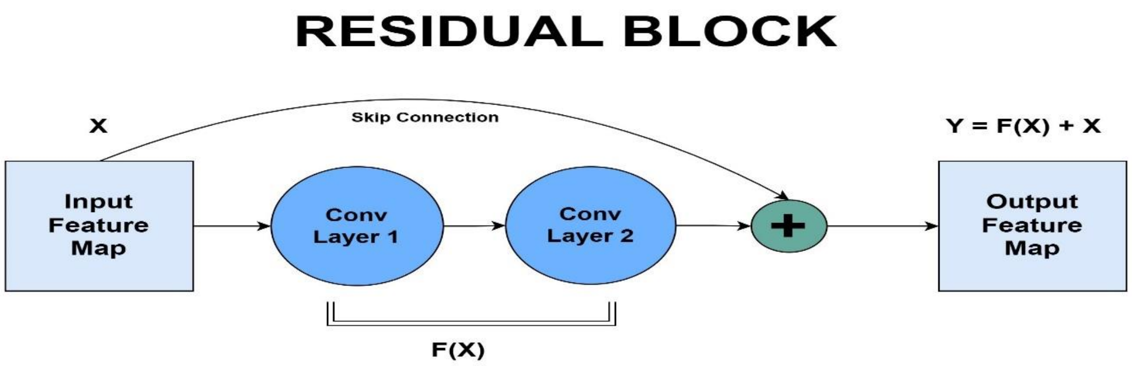
Figure 3: Conceptual Diagram of a Dense Block Illustrating Dense Connectivity



3.4.2 ResNet50 Architecture:

We have integrated ResNet50 in our framework with 50 layers of Residual Network as its use has been proved in complicated image identification. ResNet is famously known to have added the residual (or skip) connections, which is a novel innovation that solves the issue of degradation that is seen in very deep neural networks. ResNet instead trains the functions only as the residual, or the difference between the output and desired input of a layer, by summing the input of one layer with the output of a later layer. This cut trick system provides efficient gradient flow, reduces vanishing gradients, and is able to train much deeper architectures with no loss in performance.

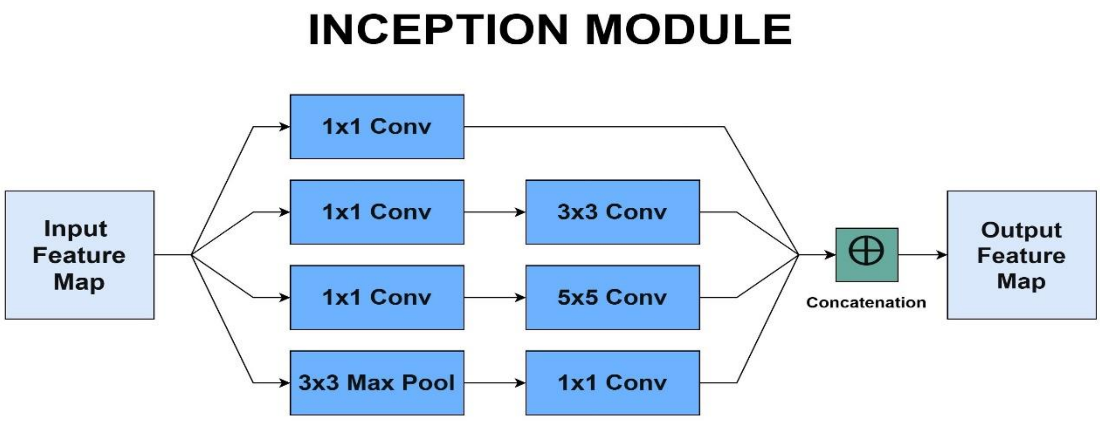
Figure 4: Conceptual Diagram of a Residual Block Illustrating Residual Connectivity



3.4.3 InceptionV3 (GoogleNet) Architecture:

InceptionV3 (GoogleNet) was chosen as a major element of our structure because, it has an exceptional ability to realize multi-scale visual features, and is extremely efficient in terms of computation. It has a unique design, and it does not follow the established structure of sequential CNNs, as it does parallel convolutional and pooling processes but with multiple filter sizes (e.g., 1x 1, 3x 3, 5x 5) in a single block. This parallelism allows the model to isolate and integrate features across various receptive field sizes in parallel with each other leading to a rich and discriminative representation of features.

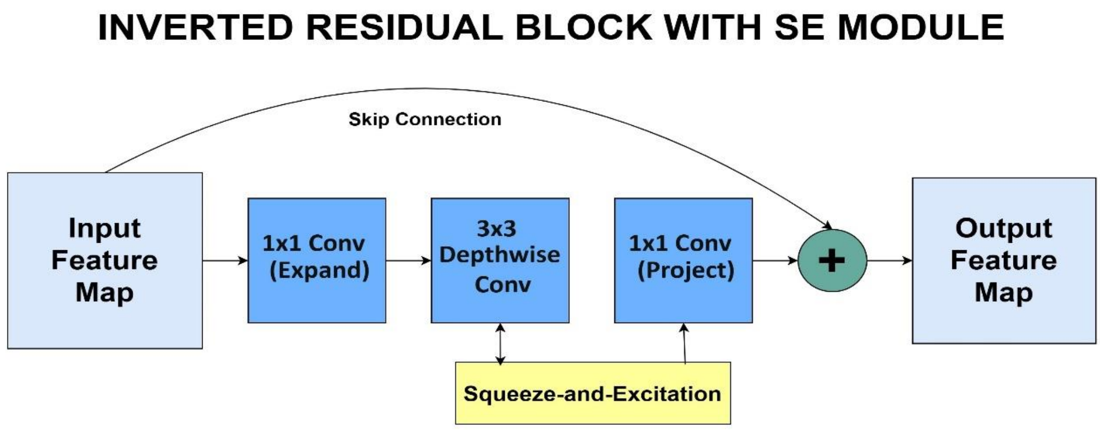
Figure 5: Conceptual Diagram of an Inception Module Illustrating Multiple-Scale Featuring



3.4.4 MobileNetV3 Architecture:

The potential to perform well under the limited hardware resources in a mobile or edge-based agricultural system, and its excellent trade-off between computational and classification performance led us to include MobileNetV3 in our framework. It is highly accurate with decreased trainable parameters and lower cost of computation when compared to the deeper CNNs. The efficiency of the model is also achieved through the fact that depthwise separable convolutions break down normal convolutions into two lightweight procedures; a depthwise convolution to filter in spatial dimensions by channel and a pointwise convolution to multiply channels. This greatly decreases learning but allows representational ability.

Figure 6: Conceptual Diagram of an inverted Residual Block with Squeeze and Excitation (SE) Module



Additionally, MobileNetV3 incorporates inverted residual along with Squeeze-and-Excitation (SE) modules, which increase the richness of the features as well as the ability to reweight channels in an adaptive fashion to focus on task-relevant information. The visual representation of the inverted residual structure in Figure 6 shows the central performance of MobileNetV3 based on SE-based dynamic channel recalibration.

These four CNN architectures are integrated to show a comprehensive way of getting successful features of SAR-CLD-2024 dataset. Each model was also optimized to the cotton leaf disease with the help of transfer learning and fine-tuning. Their unique features, such as the reuse of features in DenseNet, depth in ResNet, multi-scale learning in InceptionV3, and efficiency in MobileNetV3 can be used as valuable information on which model will be the most effective in this agricultural task.

3.5 Classification Head and Training Configuration

The purpose-built and simplified classification head was designed and appended to each of the pre-trained Convolutional Neural Network (CNN) backbones, namely as DenseNet201, ResNet50, InceptionV3, and MobileNetV3.

3.5.1 Classification Head:

The primary goal of this custom head was to provide the interface that converts the high-level abstract features that the CNN backbones extract into intelligible and understandable class prediction of cotton leaf diseases. This head was structurally a single layer, which transforms the extracted feature-vector in a linear way to produce the scores of the classes.

3.5.2 Loss Function:

A loss function is an evaluation of the difference between the actual outputs and the predictions of the model and is used to update the parameters to reduce this error, and in our case, the SAR-CLD-2024 dataset, where the true labels are expressed in the form of the index of a class.
Mathematically, Cross-Entropy Loss (L) for a single sample is calculated as follows:

$$L = -\sum_{i=1}^{C} y_i \, log(\hat{y}_i) \quad --- (Equation\ 1)$$

3.5.3 Optimizer Used:

AdamW optimizer, an improved version of its original Adam optimizer, is an extension of adaptive learning rates that have better weight regularization optimizer used to update model parameters iteratively in the course of training. There are two main hyperparameters that had been set:

- **Learning Rate (LR):** Set to $3e-4$ (0.0003), providing a balanced step size for fine tuning pre-trained models, allowing effective convergence without overshooting.

- **Weight Decay (WEIGHT_DECAY):** Set $1e-4$ (0.0001) to penalize excessively large weights and enhance model generalization. The $L2$ regularization term added to the total loss L_{total} is expressed as follows:

$$L_{regularization} = \frac{1}{2} \cdot WEIGHT\_DECAY \cdot \sum_{J} w_j^2 \quad --- (Equation\ 2)$$

Where w_j denotes each individual weight. This term discourages large weight magnitudes, promoting simpler, stronger feature learning for improved performance on unseen data.

3.5.4 Learning Rate Scheduler:

To maximize the learning process and stabilize convergence, CosineAnnealingLR scheduler was applied to change the learning rate dynamically in training. Unlike a fixed learning rate, which can either be unstable or slow to converge to a solution, this scheduler modifies the rate over time following a cosine decay pattern, enabling efficient exploration and fine tuning.
The leaning rate (η_t) at step t is defined as:

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})\left(1 + cos\left(\frac{T_{cur}}{T_{max}}\pi\right)\right) --- (Equation\ 3)$$

3.5.5 Training Parameters:
Each of the four deep learning models, DenseNet201, ResNet50, InceptionV3, and MobileNetV3 were trained under a highly structured standardized setup, to guarantee consistency of the experiment and to provide a fair comparison between the models.

- **Epochs:** Each model was trained to complete 20 epochs with each epoch comprising a forward and back pass on the entire training data. This value was selected by first experimenting and ensuring that there is enough convergence and that overfitting is reduced, which is measured by validation loss and accuracy.

- **Batch size:** 32 was used uniformly as the batch size. The value gives a good tradeoff between computation efficiency, gradient stability and memory usage- enabling good learning, and consistent convergence.

- **Computational Device:** All the experiments, such as training and inference, were performed only with the use of a CPU. This conscious decision is based on the opportunities and reproducibility of the offered solution, which proves that it is possible to achieve good results without the use of GPU acceleration.

- **Reproducibility:** To be able to be scientifically rigorous and repeatable, a fixed random seed (SEED = 42) was used in Python, NumPy and PyTorch. This managed all stochastic factors, including weight in it, data shuffling, and augmentation, where the same results are obtained when it is re-run and it helps in verifying the results.

3.6 Evaluation Measures
The metrics are a comprehensive measure of classification success other than accuracy and it makes sure that there is a fair and descriptive evaluation of the strengths and limitations of each model in the detection of cotton leaf diseases.

3.6.1 Accuracy: It is the proportion of the number of samples in a dataset that were predictable correctly (True Positives and True Negatives) to the number of samples in the dataset, which shows the overall accuracy of the model.
Mathematically, Accuracy (Acc) is calculates as:

$$Acc = \frac{TP_k + TN_k}{TP_k + TN_k + FP_k + FN_k} \quad --- (Equation\ 4)$$

3.6.2 Precision: It is the proportion of the positive samples which were correctly predicted (True Positives) to the total samples which were predicted to be positive (True Positives + False Positives).
For each specific class k , Precision (P_k) is calculated as:

$$P_k = \frac{TP_k}{TP_k + FP_k} \quad --- (Equation\ 5)$$

3.6.3 Recall: Recall (also known as Sensitivity or True Positive Rate) is used to measure the capability of a model to identify all the true positive samples. The proportion of the correct positive cases correctly predicted (True Positives) to the total of the actual positives (True Positives + False Negatives).

For each specific class k, Recall R_k is calculated as:

$$R_k = \frac{TP_k}{TP_k + FN_k} --- \text{(Equation 6)}$$

3.6.4 F1-Score: The F1-score is a harmonic mean of Precision and Recall and is a balanced measure of the false positives and false negatives. It is particularly applicable in unbalanced data sets, in which a model can be used to achieve high scores in determining all true positives with a low false alarms. The points are 0 to 1 and a 1 implies perfect performance.
For each specific class k, F1-Score ($F1_k$) is calculated as:

$$F1_k = 2 \times \frac{P_k \times R_k}{P_k + R_k} = \frac{2 \times TP_k}{2 \times TP_k + FP_k + FN_k} --- \text{(Equation 7)}$$

3.6.5 Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC): Receiver operating Characteristics (ROC) curve and Area under the Curve (AUC) gives a strong method of assessing the capacity of the model to discriminate between classes at different thresholds without the need to have a constant decision boundary.

- **ROC Curve:** In this curve, the True Positive Rate TPR versus the False Positive Rate FPR are plotted at varying thresholds and indicate the ability of the model to distinguish between the positive and negative samples. For each class k, FPR is calculated as:

$$FPR_k = \frac{FP_k}{FP_k + TN_k} --- \text{(Equation 8)}$$

Multi-class problems are solved by generating an ROC curve of each of the classes using a one-vs-rest strategy. An optimum classifier is in the upper-left of the plot (TPR = 1, FPR = 0), whereas random guesswork is close to the diagonal.

- **AUC- Area Under the Curve:** The AUC measures the ROC curve as one number which is the probability that the model ranks a random positive sample higher than a random negative sample.

3.6.6 Confusion Matrix: The Confusion Matrix is an important tool in determining the performance of a classification model, which provides a clear graphical representation of the correct and incorrect predictions per all classes. It presents a table where:

- The real (true) classes are represented by rows.
- Possible classes are represented as columns.
- The number of samples of true class i that were predicted as class j is represented by each cell $C(i, j)$.
- Elements in the diagonal ($C(i, i)$) denote true predictions - the True Positives of each of the classes.
- Misclassifications, i.e. cases when one sample of one class was incorrectly classified as an example of another, are represented by off-diagonal elements ($C(i, j), i \neq j$).

Using the confusion matrix, it is easy to identify the most common classes that are confused.
An example is that, when a large percentage of the samples of Bacterial Blight is predicted to be

Leaf Reddening, then it implies that these two features are similar. Accordingly, the confusion matrix is an effective diagnostic instrument in the determination of weaknesses in the model, the interpretation of error distributions, and the improvement of the classification results and outcomes on all varieties of cotton leaf disease.

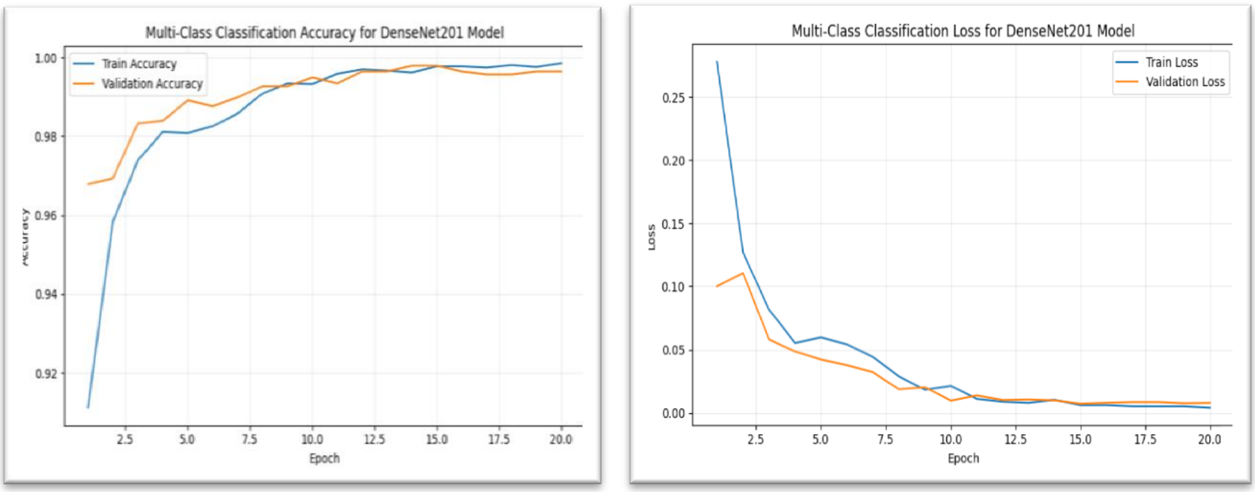
4- RESULTS AND DISCUSSIONS

This section gives a critical report on the performance of the proposed models for multi-class cotton leaf disease classification. The performance of each model is also assessed in terms of its training and validation curves, a detailed classification report, a confusion matrix, and ROC-AUC curves on the unknown test set. The results of each architecture are described in the following subsections separately along with their discussions.

4.1 DenseNet201 Performance:

The trends in the accuracy as well as loss observed throughout the training/validation of the DenseNet201 model are a clear indication of the effectiveness with which this model learnt within the 20 epochs. As illustrated in Figure 7, the close correspondence is a sign of effective learning and good generalization with no overfitting. Moreover, the maximum validation accuracy was 99.78%, which is reached approximately at the 14th epoch while the loss of validation over time entered a constant and low value, which is the lowest at 0.0071 at approximately the 15th epoch which can also confirming the reliability and consistency of the learning behavior of the model.

Figure 7: Training/Validation Accuracy and Loss Graphs for the DenseNet201 Model, trained for Multi-Class Classification of Cotton Leaf Disease using the SAR-CLD-2024 dataset



The testing of the DenseNet201 model on the test set provides a clear opinion of how the model will perform and be reliable in the end. The model had an Overall Test Accuracy of 99.71% that demonstrates a good ability of identifying various cotton leaf diseases accurately as shown in the Table 2.

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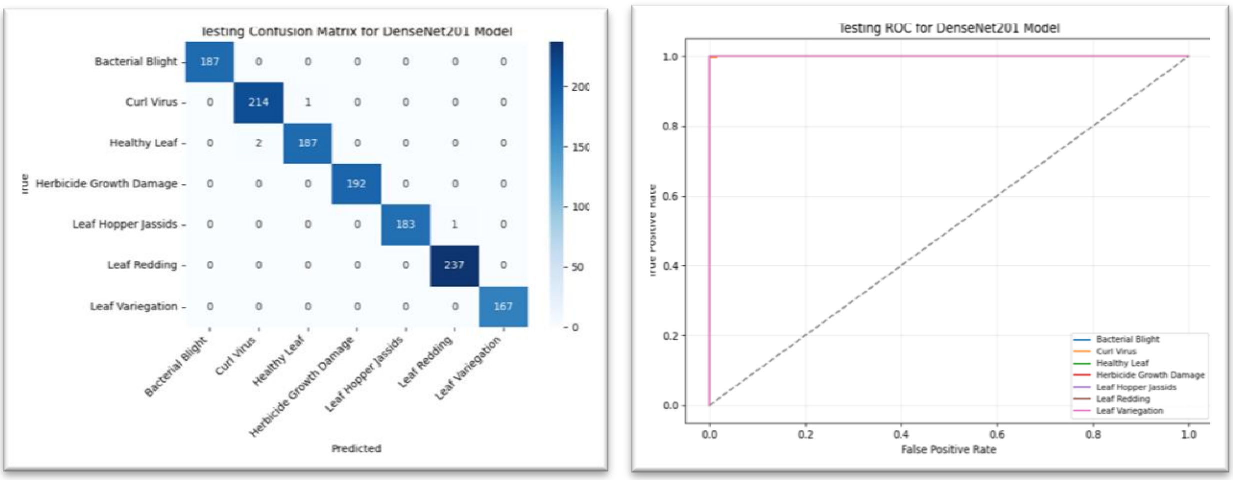
Table 2: Class-wise Precision, Recall, F1-Score, Support, and Overall Test Accuracy Report for DenseNet201 Model in Multi-Class Cotton Leaf Disease Classification

DenseNet201 Model					
Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support**	**Overall Test Accuracy**
Bacterial Blight	100	100	100	187	99.71%
Curl Virus	99.07	99.53	99.30	215	
Healthy Leaf	99.47	98.94	99.20	189	
Herbicide Growth Damage	100	100	100	192	
Leaf Hopper Jassids	100	99.46	99.73	184	
Leaf Redding	99.58	100	99.79	237	
Leaf Variegation	100	100	100	167	

Figure 8, the analysis of the matrix indicates that there is good performance of DenseNet201 by showing higher rate along the main diagonal which means the prediction is accurate while the misclassifications are depicted by the off-diagonal entries.

Figure 8: Confusion Matrix and ROC-AUC curve illustrating the testing performance of the DenseNet201 Model trained on the SAR-CLD-2024 dataset for Multi-Class Classification of Cotton Leaf Disease



Moreover, the macro-averaged ROC-AUC score of 0.99998 also confirms the high level of discriminative ability of the model of using all classes as equal DenseNet201. This very big AUC value indicates that the model is very good at distinguishing the different types of cotton leaf disease irrespective of the decision threshold. To conclude, the DenseNet201 model demonstrated good performance that was well-generalized in cotton leaf disease classification. The reliability is supported by clear training behavior, good metrics of classes, low misclassification, and a high macro ROC-AUC score. DenseNet201 is a suitable and precise

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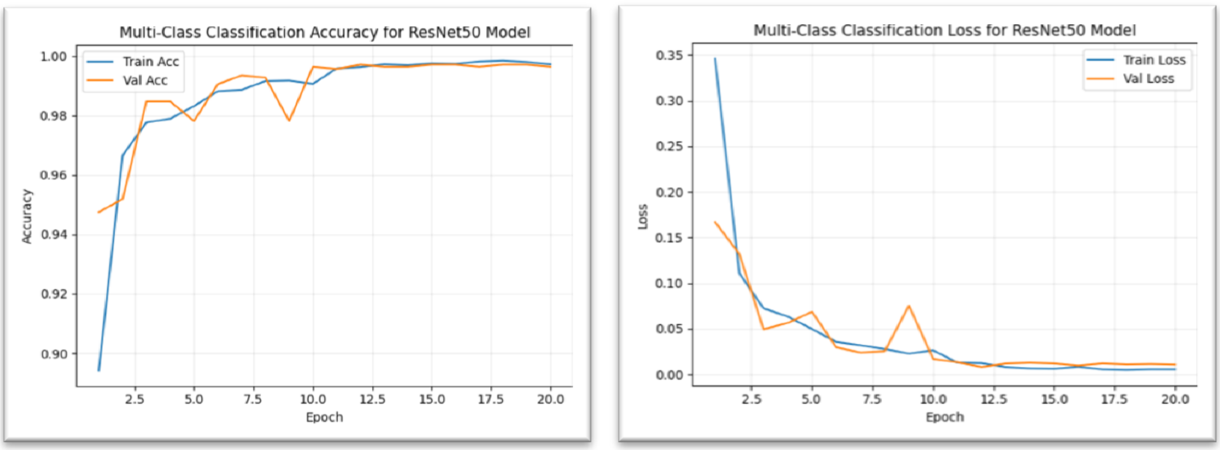
model on the dataset.

4.2 ResNet50 Performance:

The trends in the accuracy as well as loss observed throughout the training/validation of the ResNet50 model are a clear indication of the effectiveness with which this model learnt within the 20 epochs. As illustrated in Figure 9, the close correspondence is a sign of effective learning and good generalization with no overfitting. Moreover, the maximum validation accuracy was 99.71%, which is reached approximately at the 12th epoch while the loss of validation over time entered a constant and low value, which is the lowest at 0.0080 at approximately the 12th epoch which can also confirming its reliability and consistency.

Figure 9: Training/Validation Accuracy and Loss Graphs for the ResNet50 Model, trained for Multi-Class Classification of Cotton Leaf Disease using the SAR-CLD-2024 dataset



The testing of the ResNet50 model on the test set provides a clear opinion of how the model will perform and be reliable in the end. The model had an Overall Test Accuracy of 99.42% that demonstrates a good ability of identifying various cotton leaf diseases accurately as shown in the Table 3.

Table 3: Class-wise Precision, Recall, F1-Score, Support, and Overall Test Accuracy Report for ResNet50 Model in Multi-Class Cotton Leaf Disease Classification

ResNet50 Model					
Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support**	**Overall Test Accuracy**
Bacterial Blight	100	100	100	187	99.42%
Curl Virus	97.71	99.07	98.38	215	
Healthy Leaf	98.92	97.35	98.13	189	
Herbicide Growth Damage	100	100	100	192	
Leaf Hopper Jassids	99.46	100	99.73	184	

Leaf Redding	100	99.58	99.79	237	
Leaf Variegation	100	100	100	167	

Figure 10: Confusion Matrix and ROC-AUC curve illustrating the testing performance of the ResNet50 Model trained on the SAR-CLD-2024 dataset for Multi-Class Classification of Cotton Leaf Disease

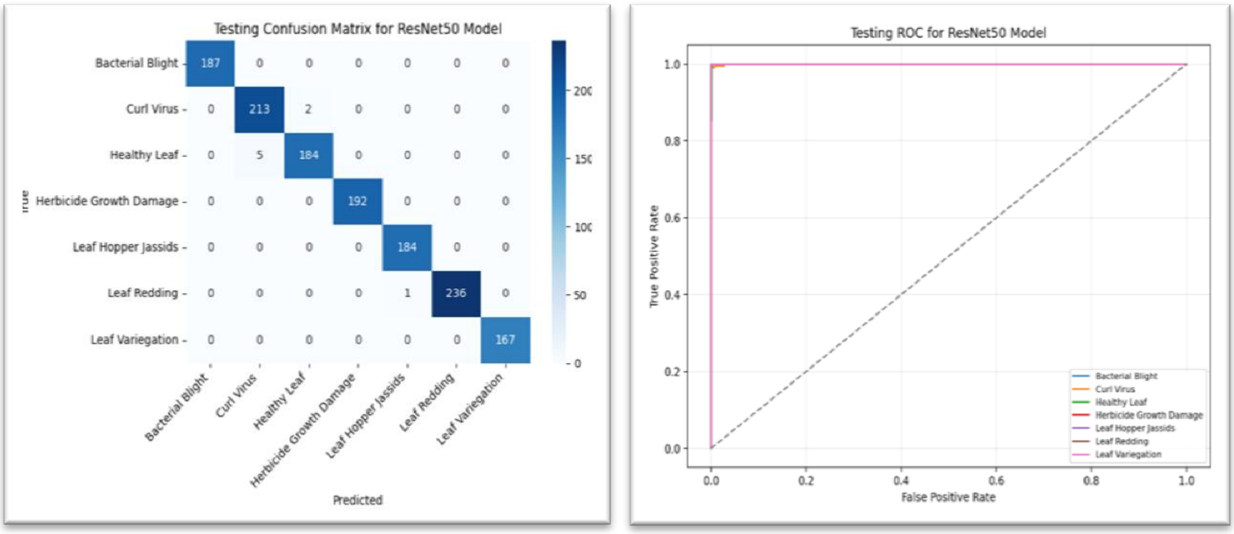


Figure 10, the analysis of the matrix indicates that there is good performance of ResNet50 by showing higher rate along the main diagonal which means the prediction is accurate while the misclassifications are depicted by the off-diagonal entries. Moreover, the macro-averaged ROC-AUC score of 0.9999 also confirms the high level of discriminative ability of the model of using all classes as equal ResNet50. This very big AUC value indicates that the model is very good at distinguishing the different types of cotton leaf disease irrespective of the decision threshold. In general, ResNet50 demonstrated the high and consistent performance in cotton leaf disease classification. It was an efficient learner with high generalization capability, high accuracy and good results in individual classes. The confusion matrix showed there was little misclassification but the high Macro- average ROC-AUC showed the high discriminative ability. These results prove ResNet50 to be a useful and reliable model on SAR-CLD-2024 dataset.

4.3 InceptionV3 Performance:

The trends in the accuracy as well as loss observed throughout the training/validation of the InceptionV3 model are a clear indication of the effectiveness with which this model learnt within the 20 epochs.

Figure 11: Training/Validation Accuracy and Loss Graphs for the InceptionV3 Model, trained for Multi-Class Classification of Cotton Leaf Disease using the SAR-CLD-2024

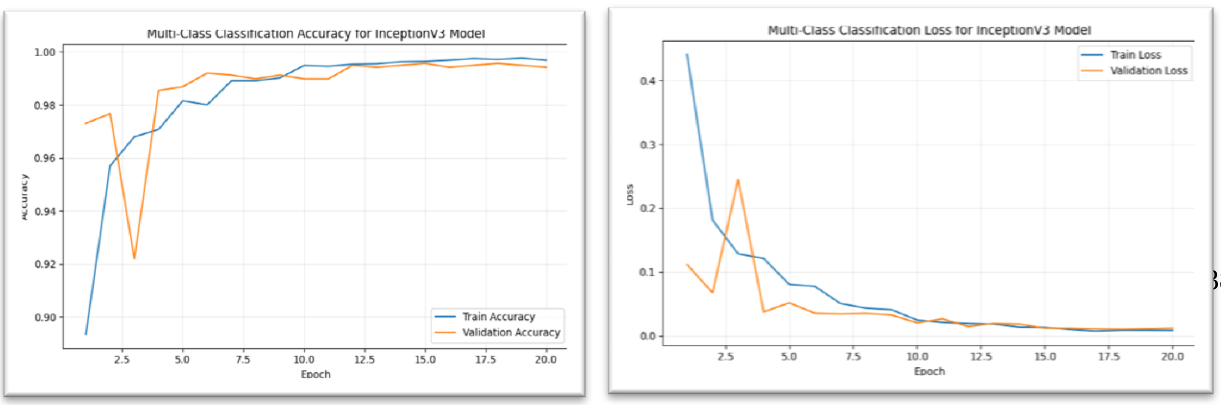


Table 4: Class-wise Precision, Recall, F1-Score, Support, and Overall Test Accuracy Report for InceptionV3 Model in Multi-Class Cotton Leaf Disease Classification

InceptionV3 Model					
Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support**	**Overall Test Accuracy**
Bacterial Blight	100	100	100	187	99.49%
Curl Virus	97.72	99.53	98.62	215	
Healthy Leaf	99.46	97.35	98.40	189	
Herbicide Growth Damage	100	100	100	192	
Leaf Hopper Jassids	99.46	100	99.73	184	
Leaf Redding	100	99.58	99.79	237	
Leaf Variegation	100	100	100	167	

As illustrated in Figure 11, the close correspondence is a sign of effective learning and good generalization with no overfitting. Moreover, the maximum validation accuracy was 99.56%, which is reached approximately at the 15th epoch while the loss of validation over time entered a constant and low value, which is the lowest at 0.0104 at approximately the 18th epoch which can also confirming the reliability and consistency of the learning behavior of the model.
The testing of the InceptionV3 model on the test set provides a clear opinion of how the model will perform and be reliable in the end. The model had an Overall Test Accuracy of 99.49% that demonstrates a good ability of identifying various cotton leaf diseases accurately as shown in the Table 4.

Figure 12: Confusion Matrix and ROC-AUC curve illustrating the testing performance of the InceptionV3 Model trained on the SAR-CLD-2024 dataset for Multi-Class Classification of Cotton Leaf Disease

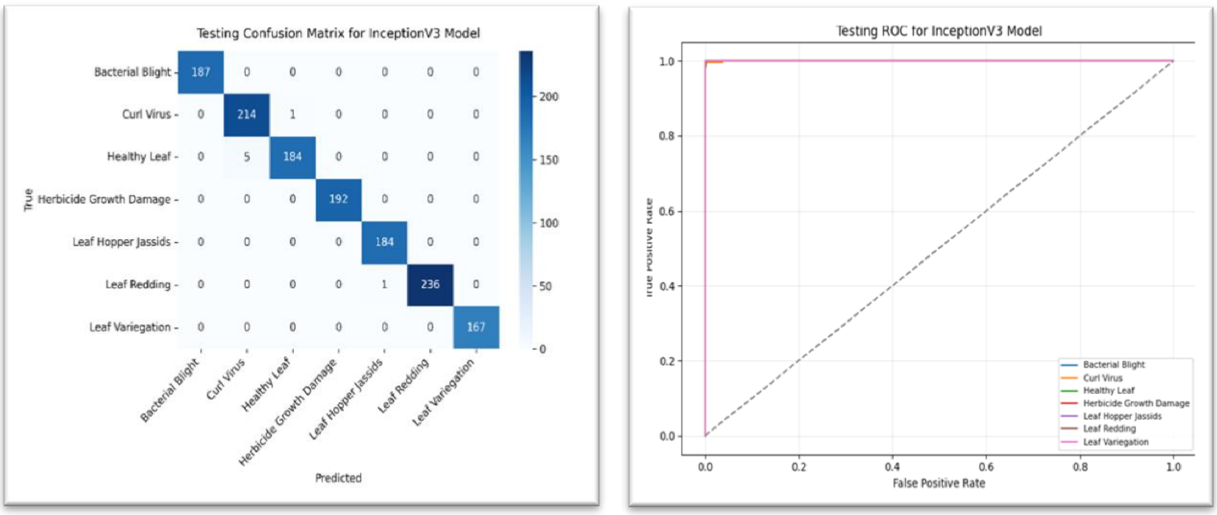
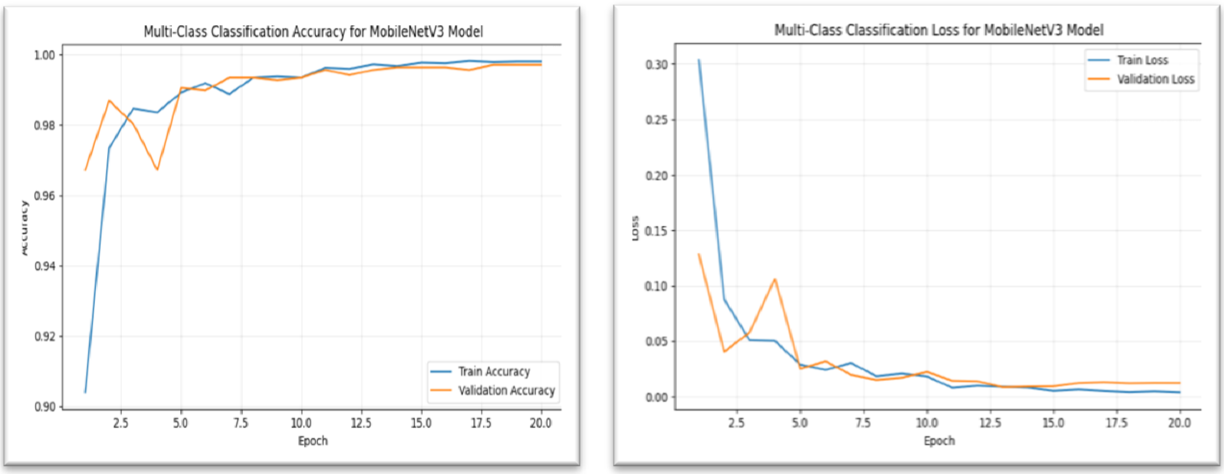


Figure 12, the analysis of the matrix indicates that there is good performance of InceptionV3 by showing higher rate along the main diagonal which means the prediction is accurate while the misclassifications are depicted by the off-diagonal entries. Moreover, the macro-averaged ROC-AUC score of 0.99995 also confirms the high level of discriminative ability of the model of using all classes as equal InceptionV3. This very big AUC value indicates that the model is very good at distinguishing the different types of cotton leaf disease irrespective of the decision threshold. To conclude, the InceptionV3 model has shown to be very reliable and consistent in terms of multi-class cotton leaf disease classification, based on its gradually increasing training and validation accuracy curves and lack of any considerable overfitting. Strong class-wise precision, recall and F1-scores were identified in the classification report whereas the confusion matrix visually confirmed the accuracy of prediction with a small error on the misclassification of similar disease types.

4.4 MobileNetV3 Performance:

The trends in the accuracy as well as loss observed throughout the training/validation of the MobileNetV3 model are a clear indication of the effectiveness with which this model learnt within the 20 epochs. As illustrated in Figure 13, the close correspondence is a sign of effective learning and good generalization with no overfitting. Moreover, the maximum validation accuracy was 99.71%, which is reached approximately at the 18th epoch while the loss of validation over time entered a constant and low value, which is the lowest at 0.0085 at approximately the 13th epoch which can also confirming the reliability and consistency of the learning behavior of the model.

Figure 13: Training/Validation Accuracy and Loss Graphs for the MobileNetV3 Model, trained for Multi-Class Classification of Cotton Leaf Disease using the SAR-CLD-2024 dataset



The testing of the MobileNetV3 model on the test set provides a clear opinion of how the model will perform and be reliable in the end. The model had an Overall Test Accuracy of 99.85% that demonstrates a good ability of identifying various cotton leaf diseases accurately as shown in the Table 5.

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Table 5: Class-wise Precision, Recall, F1-Score, Support, and Overall Test Accuracy Report for MobileNetV3 Model in Multi-Class Cotton Leaf Disease Classification

MobileNetV3 Model					
Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support**	**Overall Test Accuracy**
Bacterial Blight	100	100	100	187	
Curl Virus	99.53	99.53	99.53	215	
Healthy Leaf	99.47	99.47	99.47	189	
Herbicide Growth Damage	100	100	100	192	99.85%
Leaf Hopper Jassids	100	100	100	184	
Leaf Redding	100	100	100	237	
Leaf Variegation	100	100	100	167	

Figure 14: Confusion Matrix and ROC-AUC curve illustrating the testing performance of the MobileNetV3 Model trained on the SAR-CLD-2024 dataset for Multi-Class Classification of Cotton Leaf Disease

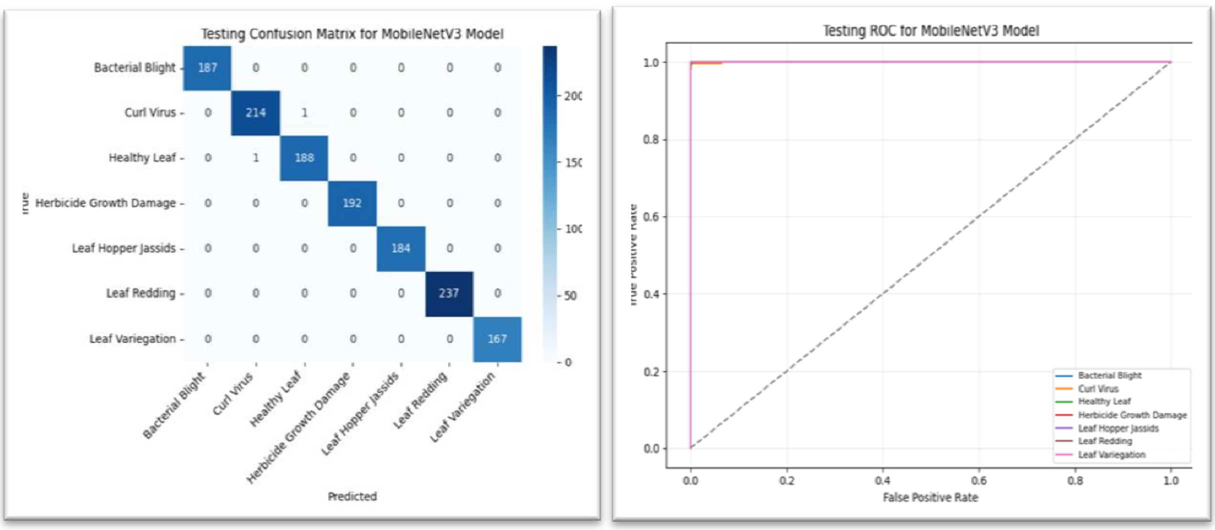


Figure 14, the analysis of the matrix indicates that there is good performance of MobileNetV3 by showing higher rate along the main diagonal which means the prediction is accurate while the misclassifications are depicted by the off-diagonal entries. Moreover, the macro-averaged ROC-AUC score of 0.99993 also confirms the high level of discriminative ability of the model of using all classes as equal MobileNetV3. This very big AUC value indicates that the model is very good at distinguishing the different types of cotton leaf disease irrespective of the decision threshold.

Overall, the MobileNetV3 model showed a high and effective performance in the process of multi-class cotton leaf disease classification, in spite of being a compact and efficiency-oriented model. It exhibited a smooth learning curve and good generalization with high accuracy without major overfitting as indicated by its training and validation curves.

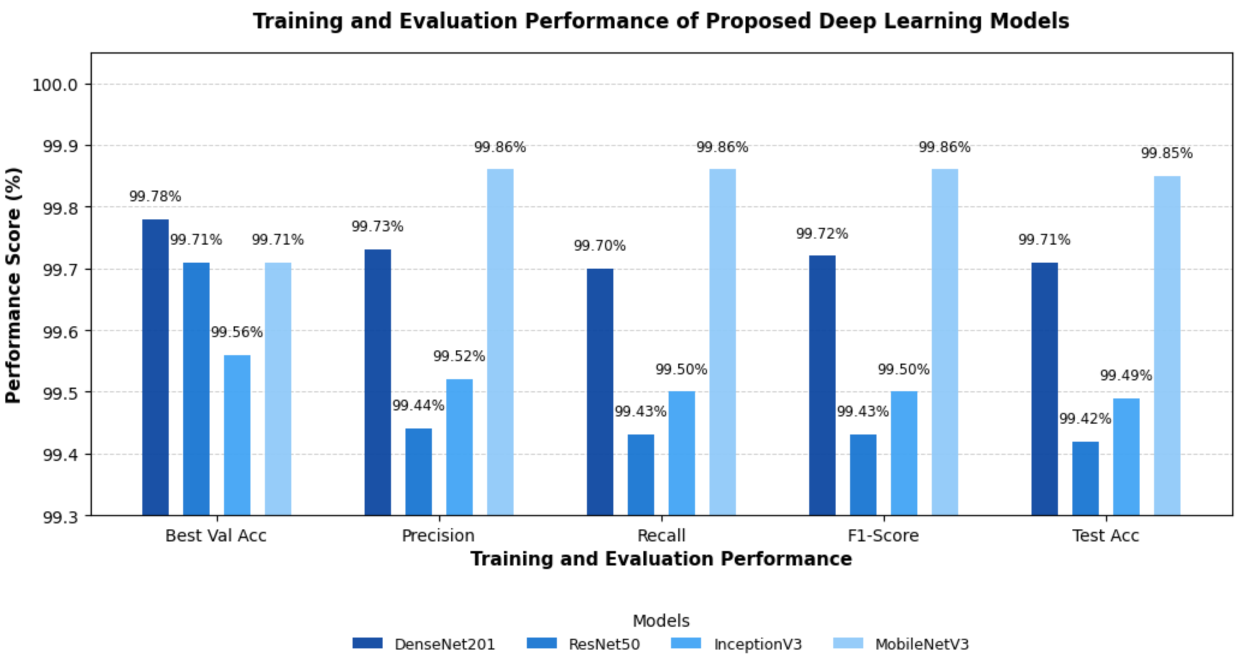
4.5 Comparative Analysis of Proposed Architectures:

This part is a comparative study of four deep learning architectures that were applied in this research work. The objective is to compare the model that had the most successful learning behavior, greatest generalization, and greatest predictive accuracy in the classification of multi-class cotton leaf disease with the use of SAR-CLD-2024 dataset. Table 6 along with the comparison Figure 15 gives a brief overview of the important performance measures of all the four models, including both validation and test phase performance.

Table 6: Comparative Summary of Validating and Testing Performance of Proposed Deep Learning Models for Multi-Class Classification of Cotton Leaf Disease on SAR-CLD-2024

Comparative Summary of Proposed Deep Learning Models							
Model	**Best Val Accuracy**	**Best Epoch**	**Precision**	**Recall**	**F1-Score**	**Test Accuracy**	**ROC-AUC**
DenseNet201	99.78%	14^{th}	99.73%	99.7%	99.72%	99.71%	0.99998
ResNet50	99.71%	12^{th}	99.44%	99.43%	99.43%	99.42%	0.9999
InceptionV3	99.56%	15^{th}	99.52%	99.5%	99.5%	99.49%	0.99995
MobileNetV3	99.71%	18^{th}	99.86%	99.86%	99.86%	99.85%	0.99993

Figure 15: Comprehensive Analysis of Proposed Deep Learning Models on Training and Evaluation Performance for Multi-Class Cotton Leaf Classification on SAR-CLD-2024



5- CONCLUSION:

In conclusion, this thesis has successfully created a solid and realistic deep learning framework to overcome the challenge of diagnosing cotton leaf diseases in practice. Motivated by the need to protect the global food security and farmer livelihoods, the study developed a Multi-Class Classification system that was designed, implemented and tested rigorously using the SAR CLD-2024 dataset and state of the art CNNs architectures. The research has shown consistently high performance and competitive results in the identification of various diseases categories.

These results are very compelling proof that Artificial Intelligence can perform well in real world agricultural diagnostics. Acknowledging some limitations, this work establishes a scientifically proven foundation for future developments in agricultural AI. It does not just provide a working solution but also forms a roadmap for further research to make it more efficient and accessible. Ultimately, this research shows the transformative potential of AI to revolutionize the agricultural industry as smarter cotton farming by providing more sustainable cotton farming around the world.

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