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Cotton Leaf Disease Detection: An Integration of CBAM with Deep Learning Approaches

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ABSTRACT

Cotton is a major contributor to Bangladesh's economy, serving as one of the primary cash crops. However, cotton production faces substantial challenges due to various diseases affecting the leaves, collectively referred to as Cotton Leaf Disease. Bacterial blight, leaf curl virus, fungal infections, and pest attacks negatively impact crop yield and quality, leading to economic losses. Conventional manual inspection techniques are inefficient, labor intensive, and prone to inaccuracies, which hinder timely disease identification and intervention. This study presents a deep learning system incorporating the Convolutional Block Attention Module (CBAM) for the automatic detection of cotton leaf diseases. A public dataset was utilized, consisting of 2,137 images in the original set and 7,000 images in the augmented set, categorized into seven classes: Bacterial Blight, Curl Virus, Herbicide Growth Damage, Leaf Hopper Jassids, Leaf Reddening, Leaf Variegation, and Healthy Leaf. Multiple deep learning models, including EfficientNetB1, DenseNet121, DenseNet169, MobileNet, Xception, and InceptionV3, were trained following the application of critical preprocessing techniques such as image resizing, noise reduction, and image normalization to improve image quality. The integration of CBAM into the models enhanced the emphasis on relevant image features, thereby improving detection performance. Among the models evaluated, DenseNet169 achieved an accuracy of 96.26% on the original dataset, whereas EfficientNetB1 with CBAM attained the highest accuracy of 99.21% on the augmented dataset.

Keywords

Cotton Leaf, Deep Learning, CBAM, EfficientNetB1, SAR-CLD

1. INTRODUCTION

The global significance of cotton as a cash crop has a substantial positive impact on Bangladesh's economy, supporting both rural Work and the national textile industry [1]. Cotton Leaf Disease refers to a cluster of leaf-affecting diseases that can severely hinder cotton crop production. If not effectively managed, these diseases can lead to notable economic losses, posing risks to employment in both the agricultural and textile sectors [2].

In Bangladesh, cotton plays a crucial role in the textile industry, making optimal disease management key for enduring sector growth. High-tech, including remote sensing, image processing, and machine learning, enable early disease detection and relief by identifying symptoms such as leaf discoloration, wilting, and spotting. Precision agriculture practices refine the use of fertilizers, pesticides, and water, leading to cost reduction and improved crop health. Collaboration among agricultural experts, policymakers, and researchers is vital for developing integrated management strategies that safeguard cotton production and strengthen the stability of Bangladesh's agricultural and textile sectors [3].

To address these challenges, this study employs multiple deep learning models, including EfficientNetB1, DenseNet121, DenseNet169, MobileNet, Xception, and InceptionV3, for the autonomous detection of cotton leaf diseases. Essential preprocessing steps were applied to enhance image quality and model performance, including image resizing, noise reduction, and normalization. The Convolutional Block Attention Module (CBAM) was integrated into the model architecture, enabling the models to focus on critical visual features and enhance detection accuracy. The findings demonstrate that CBAM and other advanced attention mechanisms play a significant role in improving the efficiency and accuracy of cotton leaf disease detection.

2. RESEARCH FOUNDATIONS

Cotton is a vital agricultural commodity for Bangladesh's textile sector, contributing approximately 11% to the nation's GDP and accounting for over 80% of total export revenues. The country imports around 8.5 million bales of cotton annually, while domestic cultivation remains limited to regions such as Jessore and Rangpur. Ensuring the quality and yield of locally produced cotton is essential for reducing dependence on imports.

Cotton leaf diseases pose a significant threat, with potential yield reductions of up to 40% in affected areas, leading to financial losses amounting to millions of dollars annually. Conventional methods, such as manual assessments by agricultural specialists, are inefficient and labor-intensive, making scalability challenging for the 15,000 hectares of cotton cultivation in Bangladesh. Modern methodologies, incorporating image processing and machine learning, are increasingly used for disease detection. The integration of drone technology and mobile diagnostic tools enables real-time monitoring, potentially reducing yield losses by 20–30% and improving cotton supply chain management. These advancements are critical for safeguarding Bangladesh's textile sector, which employs over 4 million individuals and plays a significant role in the country's economic development.

2.1 Key Contributions

The key contribution of this research is the integration of the Convolutional Block Attention Module (CBAM), which enhances the models' ability to focus on critical image features, thereby improving detection accuracy. Preprocessing techniques, including image resizing and noise reduction, were applied to optimize input data, leading to enhanced model performance. Additionally, deep learning models were utilized for disease detection, achieving an accuracy of 96.26% on the original dataset and 99.21% on the augmented dataset.

3. REVIEW OF RELATED STUDIES

This section discusses previous research on cotton leaf disease detection.

Bishshash et al. [1] developed the SAR-CLD-2024 dataset, containing 2,137 original and 7,000 augmented images of cotton leaf diseases, classified into eight categories, including bacterial blight, curl virus, and healthy leaves. They trained an Inception V3 model on this dataset, achieving an accuracy of 96.03%, contributing to precision agriculture by automating disease detection and promoting sustainable cotton farming solutions.

Herok and Ahmed [2] employed transfer learning to detect cotton leaf diseases using a dataset of 6,158 samples across seven disease classes and one healthy class. Among the pretrained models evaluated, VGG16 achieved the highest accuracy of 95.02%, demonstrating the effectiveness of deep feature extraction for classification tasks.

Ahmad et al. [3] utilized 3,475 images to classify cotton leaf diseases using Vision Transformers (ViT) and other deep learning models. Their ViT-based system automated disease diagnosis with a binary classification accuracy of 96.72% and a multiclass classification accuracy of 93.39%, showcasing the potential of transformer-based architectures in plant disease detection.

Kumar et al. [4] developed a CNN-based model using TensorFlow's Keras API, achieving 90% accuracy in detecting cotton leaf diseases. The model was later converted to CoreML for iOS application integration, enabling offline disease identification and providing farmers with real-time recommendations for disease management.

Udawant and Srinath [5] implemented Mask R-CNN with transfer learning to detect cotton leaf diseases in real-world settings, achieving 94% accuracy. Their study emphasized the importance of instance segmentation techniques for precisely localizing disease-affected regions, outperforming methods limited to controlled environments.

Kumar et al. [6] proposed using VGG16 for feature selection in cotton leaf disease detection. Their dataset contained 2,238 images in six categories. Feature selection significantly improved the model's ability to detect early-stage diseases, achieving 95.52% accuracy. This approach reinforced the effectiveness of feature engineering in deep learning-based plant disease diagnosis.

Caldeira et al. [7] employed GoogleNet and ResNet50 CNNs to detect cotton leaf damage, achieving 89.2% precision. Their study highlighted CNN-based feature extraction and unsupervised classification for lesion detection, demonstrating the feasibility of deep learning in real-time agricultural applications.

Kotian et al. [8] developed a ResNet50-based system for detecting bacterial blight and curl virus in cotton leaves. The dataset, comprising 2,000 images, achieved 95% accuracy with ResNet50, demonstrating the effectiveness of transfer learning combined with traditional classifiers for disease management.

4. METHODOLOGICAL FRAMEWORK

This research utilizes a public dataset of cotton leaf images, apply- ing preprocessing techniques such as image resizing, noise reduc- tion, and normalization to enhance data quality. After preprocess- ing, the dataset is divided into training and testing sets to ensure a balanced evaluation. Deep learning models

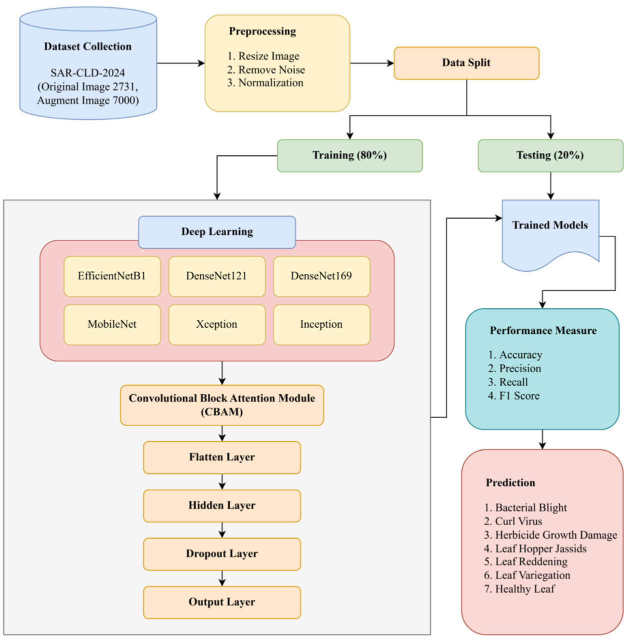

Fig. 1: Proposed Methodology

incorporating the Convolutional Block Attention Module (CBAM) are utilized to enhance feature extraction by prioritizing the most

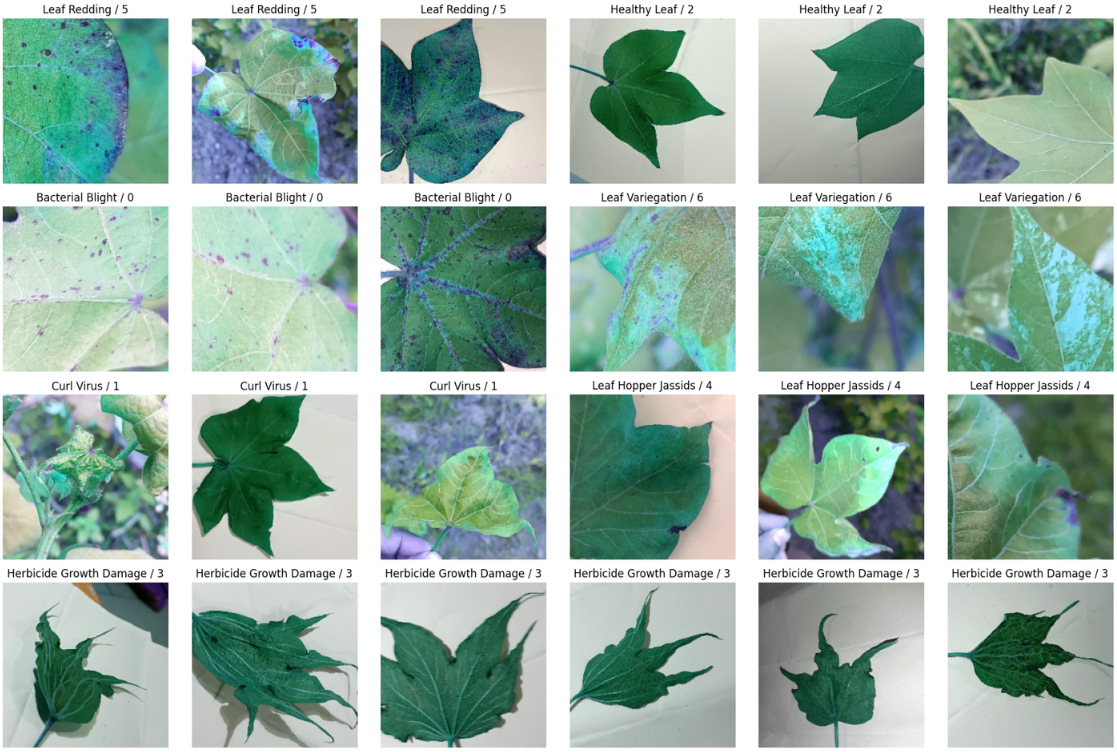

Fig. 2: Data Sample

critical regions in images. This technique improves the model's capability to differentiate between healthy and diseased leaves. Model performance is evaluated using accuracy, precision, recall, and F1-score, with comparative analysis against baseline models highlighting the effectiveness of CBAM in disease classification.
Figure 1 illustrates the overall methodology of the research, highlighting the key stages from data acquisition to final classification.
The figure 2 shows the data samples of the dataset.

4.1 Dataset Collection

The SAR-CLD-2024 dataset was utilized to advance research in cotton leaf disease detection [1]. Data collection was conducted through field surveys at the National Cotton Research Institute in Gazipur, Dhaka, Bangladesh, between October and January. A total of 2,137 original images were captured, representing seven categories: bacterial blight, curl virus, herbicide growth damage, leaf hopper jassids, leaf reddening, leaf variegation, and healthy leaves.
To enhance the dataset and improve its applicability, 7,000 augmented images were generated. This dataset serves as a valuable resource for researchers developing machine learning models for accurate and automated disease classification in agriculture. Dataset Source: https://data.mendeley.com/datasets/b3jy2p6k8w/2.
The following figure 3 shows the data size of each class for both original and augmented datasets:

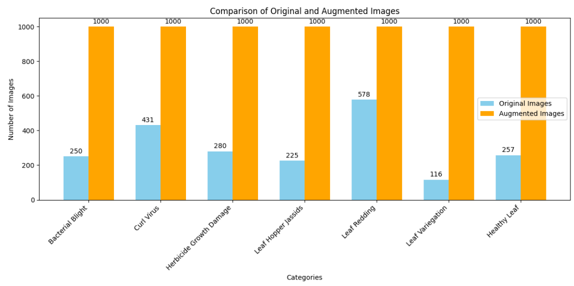

Fig. 3: Data size of each class

4.2 Data Preprocessing

Data preprocessing is a crucial step, particularly for image datasets, as it prepares raw images for analysis [9]. This study emphasizes resizing images to maintain consistent dimensions, removing noise to enhance image clarity, and normalizing pixel values to standardize the data range. These preprocessing techniques enhance model efficiency and accuracy by minimizing inconsistencies and irrelevant variations, ensuring improved feature extraction and classification.

4.2.1 ***Image Resize.*** As part of the initial step, the OpenCV tool was utilized to standardize the dimensions of all images in the dataset to 81x81 pixels. Standardizing image sizes facilitates efficient processing and analysis, ensuring consistency across the dataset [10].

4.2.2 ***Reduce Noise***. To remove noise and enhance image quality, Gaussian blur was applied. The OpenCV function cv2.GaussianBlur was utilized with a 5x5 kernel size [11]. This preprocessing step ensures clearer and cleaner images, improving the model's performance.

4.2.3 ***Normalization***. After noise removal, normalization was applied to scale pixel values within the range of 0 to 1. This was achieved by dividing each pixel value by 255.0, the maximum possible pixel intensity. Normalization enhances data consistency, facilitating efficient model processing while preventing large values from dominating. This step improves training effectiveness by ensuring faster and more stable learning [12].

4.3 Learning Models

This research utilized six different pre-trained models for experimentation: EfficientNetB1, DenseNet121, DenseNet169, MobileNet, Xception, and Inception. Additionally, the Convolutional Block Attention Module (CBAM) was incorporated to enhance the performance of each pre-trained model. Further details regarding these models and the attention mechanism are provided in the following sections.

4.3.1 ***EfficientNet B1***. EfficientNetB1 is a convolutional neural network (CNN) architecture designed to achieve high accuracy while minimizing computational resource usage. This is accomplished through a compound scaling method that uniformly adjusts depth, width, and resolution [13]. Its core building blocks, MBConv, utilize depthwise separable convolutions and squeeze-and-excitation techniques to enhance feature representation efficiently. Figure 4 illustrates the architecture of the EfficientNetB1 model.

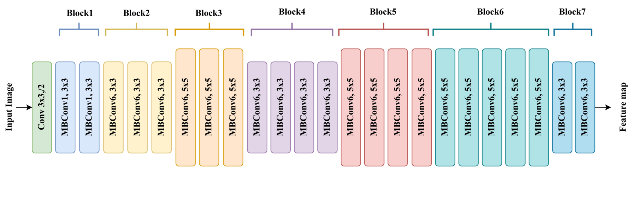

Fig. 4: Architecture of EfficientNetB1

4.3.2 ***Convolutional Block Attention Module***. The Convolutional Block Attention Module (CBAM) is an attention mechanism designed to enhance the effectiveness of convolutional neural networks (CNNs) by emphasizing relevant features while suppressing less important ones. It sequentially applies two attention mechanisms: channel attention and spatial attention. The channel attention module identifies significant channels by analyzing inter-channel dependencies, whereas the spatial attention module highlights essential spatial regions by capturing inter-spatial relationships [14][15]. By integrating these attention mechanisms, CBAM refines feature maps, leading to improved accuracy in tasks such as image classification and object recognition. Figure 5 illustrates the CBAM mechanism.

4.3.3 ***DenseNet121***. DenseNet121 is a convolutional neural network (CNN) consisting of 121 layers, specifically designed to improve image classification tasks [16]. Its distinctive architecture connects each layer to all subsequent layers, ensuring efficient information flow and feature reuse. This design helps mitigate the vanishing gradient problem by allowing features to be reused,

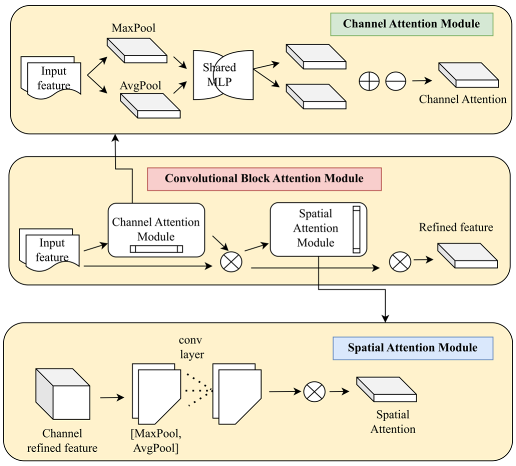

Fig. 5: Mechanisms of CBAM

thereby reducing the number of parameters. As a result, the model is both efficient and less prone to overfitting [17].

4.3.4 ***DenseNet169***. DenseNet169 is an enhanced version of DenseNet121, featuring 169 layers designed for improved image classification tasks. It retains the architecture that connects all layers, ensuring efficient feature reuse [18], while addressing the vanishing gradient problem by reducing the number of parameters. With additional dense blocks, DenseNet169 is capable of handling more complex tasks, delivering higher accuracy compared to its predecessor [19].

4.3.5 ***Mobilenet***. MobileNet is a lightweight CNN by Google with 28 layers [20], designed for mobile and embedded devices. It uses depthwise separable convolutions and bottleneck layers for efficient feature extraction, significantly reducing parameters and computational cost [21].

4.3.6 ***Xception***. Xception is an advanced CNN model developed by Google, built upon the Inception architecture. It replaces traditional Inception modules with depthwise separable convolutions, improving efficiency and performance [22]. This approach reduces computational complexity and the number of parameters while enhancing feature learning [23].

4.3.7 ***Inception V3***. The Inception-V3 model is a deep image classification model known for its use of factorized convolutions and batch normalization, allowing it to extract more features while reducing computational complexity [24]. It employs global average pooling to replace traditional fully connected layers, improving efficiency and reducing overfitting. While it performs well in image recognition and transfer learning, it requires significant computational resources and has a large model size, making it less suitable for resource-constrained environments [25].

4.4 Data Split

The dataset was divided into an 80:20 ratio to ensure effective model learning, with 80% of the data being used for training and 20% for testing. Table 1 compares the original dataset with the augmented dataset, illustrating the distribution of training and testing data both before and after augmentation.

Table 1. : Distribution of Train and Test Data in Original and Augmented Datasets

Dataset	Train Data	Test Data
Original Dataset	1709	428
Augmented Dataset	5600	1400

5. RESULTS AND ANALYSIS

This section presents the findings from various deep learning models, including accuracy, precision, recall, F1-score, confusion matrix (CM), classification report (CR), learning rate (LR) curve, and receiver operating characteristic (ROC) curve.

5.1 Performance Measures

The table 2 compares accuracy, precision, recall, and F1 score of deep learning models EfficientNetB1, DenseNet121, DenseNet169, MobileNet, Xception, and Inception. With an F1 score of 0.9579, accuracy of 0.9605, and recall of 0.9555, DenseNet169 performs best. With 0.9545 F1, EfficientNet B1 follows closely. MobileNet demonstrates modest performance compared to other models with an accuracy of 0.8831 and an F1 score of 0.8949.

Table 2. : Performance table of various deep learning for original dataset

Model	Accuracy	Precision	Recall	F1 Score
EfficientNetB1	0.9509	0.9480	0.9640	0.9545
DenseNet121	0.9322	0.9274	0.9397	0.9333
DenseNet169	**0.9556**	**0.9605**	**0.9555**	**0.9579**
MobileNet	0.8831	0.8852	0.9109	0.8949
Xception	0.9369	0.9408	0.9384	0.9391
InceptionV3	0.9299	0.9340	0.9343	0.9331

The table 3 compares accuracy, precision, recall, and F1 score of EfficientNetB1, DenseNet121, DenseNet169, MobileNet, Xception, and Inception deep learning models for augment dataset. Xception has the highest F1 score of 0.9854, followed by DenseNet121 with 0.9842. Inception and DenseNet169 both perform well with F1 scores of 0.9831 and 0.9819. MobileNet consistently scores 0.9716, whereas EfficientNetB1 scores 0.9803. Xception and DenseNet121 performed well in the task.

Table 3. : Performance table of various deep learning for augment dataset

Model	Accuracy	Precision	Recall	F1 Score
EfficientNetB1	0.9807	0.9803	0.9806	0.9803
DenseNet121	0.9842	0.9845	0.9840	0.9842
DenseNet169	0.9821	0.9820	0.9819	0.9819
MobileNet	0.9721	0.9721	0.9714	0.9716
Xception	**0.9857**	**0.9857**	**0.9853**	**0.9854**
InceptionV3	0.9835	0.9836	0.9828	0.9831

The table 4 highlights the performance of our implemented models across accuracy, precision, recall, and F1 score. DenseNet169 achieves the best results with an F1 score of 0.9652, followed by DenseNet121 with 0.9611. Inception and Xception also perform well, with F1 scores of 0.9423 and 0.9384, respectively. MobileNet shows competitive performance with an F1 score of 0.9337, while EfficientNetB1 delivers steady results with an F1 score of 0.9090.

Table 4. : Performance table of various deep learning for original dataset using CBAM

Model	Accuracy	Precision	Recall	F1 Score
EfficientNetB1	0.9065	0.9103	0.9110	0.9090
DenseNet121	0.9602	0.9631	0.9610	0.9611
DenseNet169	**0.9626**	**0.9666**	**0.9642**	**0.9652**
MobileNet	0.9275	0.9321	0.9369	0.9337
Xception	0.9369	0.9316	0.9483	0.9384
InceptionV3	0.9392	0.9428	0.9442	0.9423

The table 5 compares deep learning models. The highest F1 score is 0.9919 for EfficientNetB1, followed by 0.9890 for DenseNet169. With 0.9840 F1, DenseNet121 performs well. F1 ratings of 0.9832 and 0.9780 for Xception and Inception are similarly good. An F1 score of 0.9790 shows MobileNet's consistency. Both EfficientNetB1 and DenseNet169 performed well.

Table 5. : Performance table of various deep learning for augment dataset using CBAM

Model	Accuracy	Precision	Recall	F1 Score
EfficientNetB1	**0.9921**	**0.9922**	**0.9918**	**0.9919**
DenseNet121	0.9842	0.9842	0.9839	0.9840
DenseNet169	0.9892	0.9890	0.9892	0.9890
MobileNet	0.9792	0.9794	0.9789	0.9790
Xception	0.9835	0.9838	0.9828	0.9832
InceptionV3	0.9785	0.9785	0.9776	0.9780

In this research, EfficientNetB1 constantly succeeds. In subsequent comparisons, it improved from good first findings. Its F1 score of 0.9919 beat DenseNet169 and DenseNet121 in the final examination. Its great performance across various measures makes EfficientNetB1 the top model in this investigation.

5.2 Prediction Outcomes of the Model

The image 6 showcases examples of the model's predictions for various cotton leaf conditions, comparing the actual and predicted labels. Most predictions align correctly, such as Leaf Redding, Curl Virus, and Leaf Hopper Jassids. However, some misclassifications are evident, such as a Curl Virus leaf being predicted as Herbicide Growth Damage and a Leaf Hopper Jassids leaf misclassified as Healthy Leaf. These examples highlight the model's overall strong performance but also demonstrate areas where classification errors occur, providing insights for further refinement.

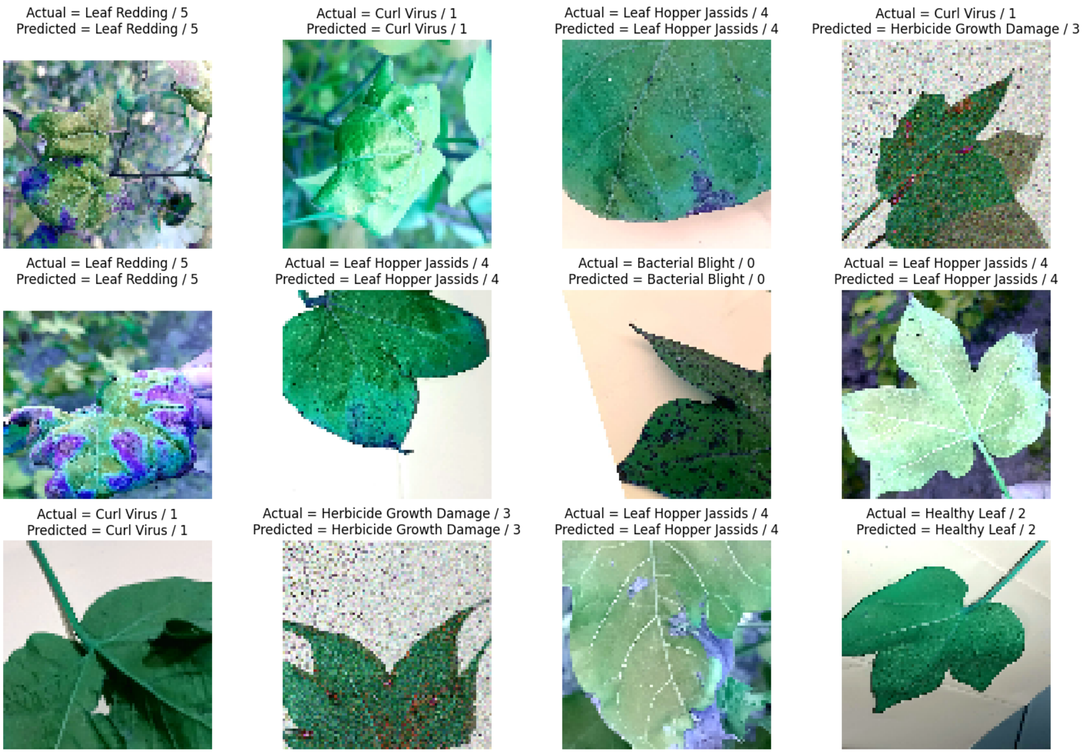

Fig. 6: Prediction of Best Model

5.3 Comparison with the State of the Art

In this research, various models were implemented to determine the most effective approach for the task. Among these models, EfficientNetB1 demonstrated superior performance, achieving the highest accuracy of 99.21%, highlighting its exceptional robustness. To further validate the approach, the InceptionV3 model, based on the foundational work by P. Bishshash [1], was also implemented, achieving an accuracy of 97.85%. This comparative analysis underscores that the proposed EfficientNetB1-based model significantly outperforms InceptionV3, reinforcing the effectiveness of the approach in achieving state-of-the-art results. The comparison with previous work is summarized in Table 6.

Table 6. : Comparative analysis with previous work

Model	Methods	Accuracy
InceptionV3	P. Bishshash [1]	96.03%
	Proposed Method	97.85%

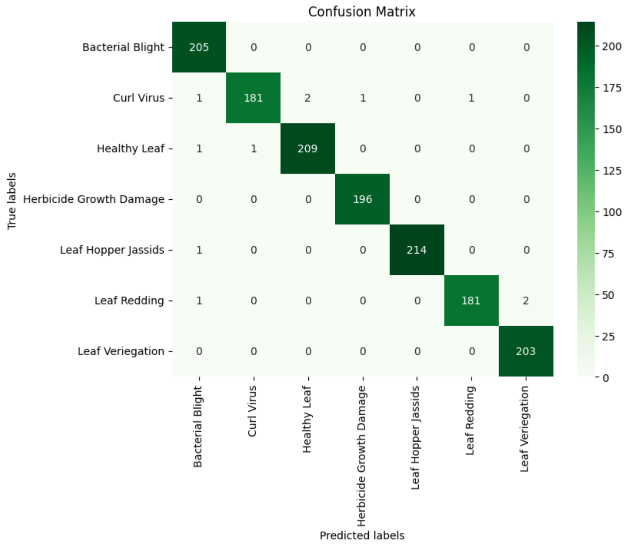

Fig. 7: Confusion Matrix of Best Model

5.4 Confusion Matrix

The confusion matrix shows (see figure 7) the model's performance across seven cotton leaf conditions: Bacterial Blight, Curl Virus, Healthy Leaf, Herbicide Growth Damage, Leaf Hopper Jassids, Leaf Redding, and Leaf Veriegation. Most predictions align with the diagonal, indicating accurate classification, with the highest correct predictions for Leaf Hopper Jassids (214) and Leaf Veriegation (203). Misclassifications are minimal, such as one Healthy Leaf labeled as Curl Virus and two errors in Leaf Redding, reflecting strong overall accuracy.

5.5 Classification Report

The classification report for the EfficientNetB1 with CBAM model (see table 7) indicates outstanding performance, with precision, recall, and F1-scores nearing 1.00 for all classes. The overall accuracy of 99% demonstrates the model's exceptional ability to classify plant conditions accurately. Perfect scores were recorded in classes such as Herbicide Growth Damage, Leaf Hopper Jassids, and Leaf Variegation. Other classes also demonstrated strong performance, with slight variations; for instance, the Curl Virus class attained a recall of 0.97. The macro and weighted averages of 0.99 indicate the model's balanced and robust performance across all categories.

Table 7. : Performance table of various deep learning for augment dataset using CBAM

Classification Report for EfficientNetB1 with CBAM				
	precision	**recall**	**f1-score**	**support**
Bacterial Blight	0.98	1.00	0.99	205
Curl Virus	0.99	0.97	0.98	186
Healthy Leaf	0.99	0.99	0.99	211
Herbicide Growth Damage	0.99	1.00	1.00	196
Leaf Hopper Jassids	1.00	1.00	1.00	215
Leaf Redding	0.99	0.98	0.99	184
Leaf Veriegation	0.99	1.00	1.00	203
accuracy			0.99	1400
macro avg	0.99	0.99	0.99	1400
weighted avg	0.99	0.99	0.99	1400

5.6 Learning Curve

The learning curves 8 show that the model performs well on both the original and augmented datasets. For the original dataset, training and validation accuracies rapidly increase, with minimal overfitting, as reflected by the low and stable loss. Similarly, for the augmented dataset, the model achieves high accuracy and low loss, with smoother and more stable validation curves, indicating improved robustness and generalization through data augmentation. Both datasets demonstrate effective learning and convergence.

5.7 ROC Curve

The Receiver Operating Characteristic (ROC) curve evaluates the model's ability to classify seven cotton leaf conditions.
The curve 9 for each class is plotted, with the Area Under the Curve (AUC) indicating the model's performance. The AUC is perfect (1.00) for Bacterial Blight, Herbicide Growth Damage, Leaf Hopper Jassids, and Leaf Veriegation, showing exceptional classification. Healthy Leaf and Leaf Redding achieve a near-perfect AUC of 0.99, while Curl Virus slightly trails with an AUC of 0.98. The high AUC values across all classes highlight the model's strong overall predictive capability.

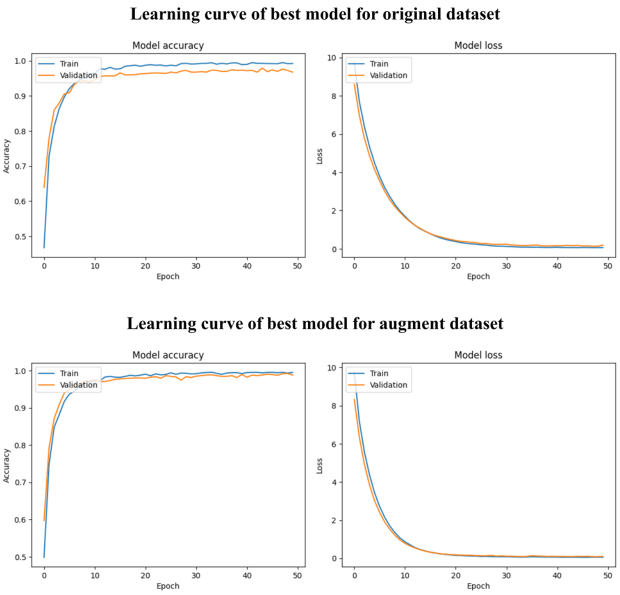

Fig. 8: Learning curve of best model for both datasets

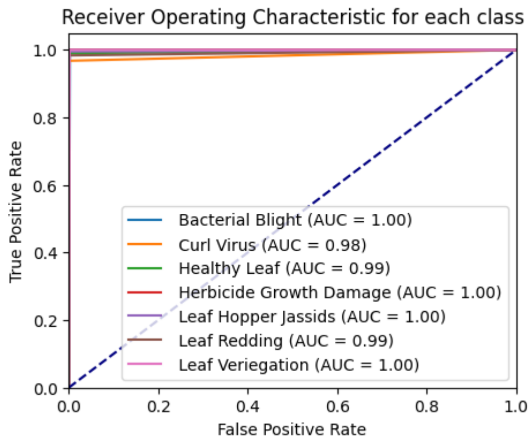

Fig. 9: ROC Curve of Best Model

6. CONCLUSION AND FUTURE WORK

In conclusion, the research effectively identifies cotton leaf diseases using deep learning, significantly enhancing the efficiency and precision of human assessment. The integration of the Convolutional Block Attention Module (CBAM) with preprocessing techniques, such as image scaling and noise reduction, resulted in improved detection accuracy on both the original and augmented datasets. This approach not only facilitates disease detection automation but also aids farmers in reducing crop loss. The system demonstrated robust performance under various conditions, showcasing its versatility for different crops and its potential in agricultural disease management.
Looking forward, hybrid model designs will be explored to further enhance detection accuracy. The system will be expanded to accommodate a broader range of environmental conditions and cotton leaf diseases, incorporating additional datasets for

wider application. Real-time monitoring technologies, including mobile applications, will be developed to provide immediate disease identification and prevention strategies for farmers. To augment model robustness, Hopfield Neural Networks will be examined, especially to handle novel disease strains. Additionally, incorporating IoT sensors and multispectral imagery is expected to improve early illness detection and prevention, reinforcing the system's effectiveness and scalability in reducing agricultural losses globally.

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