

A HYBRID DEEP LEARNING WEB PLATFORM FOR COTTON CROP MONITORING AND DISEASE MANAGEMENT

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Abstract

Cotton crop productivity is significantly affected by leaf diseases, which can reduce both crop quality and agricultural yield. Early and accurate disease detection is essential for effective crop monitoring and management in smart agriculture. This research presents a hybrid deep learning web platform to monitor cotton crop and disease management. The proposed system is developed to classify cotton leaf images into three categories: Bacterial Blight, Cotton Curl Leaf Disease, and Healthy Leaf. The developed platform integrates deep learning and machine learning techniques within a web-based environment to provide automated disease diagnosis and management support for farmers and agricultural experts. Several state-of-the-art models, including MobileNetV2, EfficientNetB3, EfficientNetV2S, Random Forest Classifier, and proposed hybrid architectures, were evaluated for disease classification performance. Experimental results show that the proposed HybridEfficientRForest model achieved the highest performance with 98% accuracy. Similarly, the proposed HybridEfficientMobiNet model achieved 92% classification accuracy with strong overall performance. In comparison, standalone models produced comparatively lower results. The proposed web platform underscores the significance of hybrid deep learning approaches in precision agriculture by providing a user-friendly, scalable, and intelligent platform for real-time monitoring and management of cotton crop diseases.

Introduction

Agriculture plays a vital role in global food security and economic development, where cotton is considered one of the most important cash crops due to its extensive use in the textile industry. However, cotton production is frequently threatened by various leaf diseases that are Bacterial Blight and Cotton Curl Leaf Disease, which can severely reduce yield and fiber quality if not detected at an early stage [1]. Traditional disease identification procedures rely heavily on manual inspection by agricultural experts, which is time-consuming, subjective, and often inefficient for large-scale farming. With the rapid advancement of Artificial Intelligence (AI) and Deep Learning (DL), automated plant disease detection systems have gained significant attention in precision agriculture. Deep learning models, have demonstrated strong capabilities in image-based recognition tasks, enabling accurate and early detection of plant diseases from leaf images. In recent years, hybrid models combining deep learning and machine learning techniques have further improved classification performance by leveraging the strengths of multiple algorithms. In this study, we propose a Hybrid Deep Learning Web Platform for Cotton Crop Monitoring and Disease Management, designed to assist farmers and agricultural stakeholders in real-time disease diagnosis. The system classifies cotton leaf images into three categories: Bacterial Blight, Cotton Curl Leaf Disease, and Healthy Leaf. The platform integrates multiple models, including MobileNetV2, EfficientNet variants, Random Forest Classifier, and two proposed hybrid architectures, namely HybridEfficientMobiNet and HybridEfficientRForest, to enhance prediction accuracy and robustness. To ensure easy accessibility and user-friendly interaction for end-users, the proposed system is designed as a web-based application, which does not require any technical skills to use. Experimental evaluation demonstrates that the hybrid approach significantly outperforms standalone models, achieving higher accuracy and reliability in disease classification. The best-performing model, HybridEfficientRForest, achieves superior results, highlighting the effectiveness of combining deep feature extraction with traditional machine learning classifiers.

The major contributions of this research are summarized as follows:

1. Developed AI based solution for recognition of cotton crop diseases.
2. Comparison of multiple deep learning and hybrid models, find the best model to implement in web-based platform.
3. Evaluation the performance of models with standard metrics for validation and reliability.
4. Development of a web-based AI platform for cotton crop disease monitoring and management.

1. Literature Review

Recent advancements in cotton crop disease detection have increasingly focused on deep learning, machine learning, and hybrid intelligent systems. Early work by [2] utilized TensorFlow-based CNN models on publicly available cotton leaf datasets, achieving 94-97% accuracy in recognizing diseases such as bacterial blight, and leaf curl, demonstrating the significant effectiveness of deep learning for image-based diagnosis. Similarly, [3] and [4] applied traditional machine learning classifiers such as SVM, KNN, and Random Forest with handcrafted features, achieving moderate accuracies of 90-95%, highlighting the limitations of feature engineering-based approaches compared to deep learning. Several studies have extended disease analysis to environmental and predictive modeling. [5] and [6] incorporated ecological and climatic variables such as temperature, humidity, and rainfall to predict Cotton Leaf Curl Virus (CLCuD) outbreaks using models like Random Forest and SVM, achieving 92-96% accuracy. These approaches demonstrate the importance of integrating environmental data for early disease prediction and crop management. However, they remain limited in visual disease interpretation and real-time field application. More recent research has shifted toward hybrid and optimized deep learning frameworks. [7] proposed a

ResNet-BERT-PSO hybrid model achieving 98–99% accuracy, while [8] integrated EfficientNetB3 and InceptionResNetV2 with genetic algorithm optimization and explainable AI, reporting 98%+ performance along with interpretability using LIME and SHAP. Similarly, [9] and [10] employed CNN-based architectures with transfer learning and achieved up to 98.7% accuracy, demonstrating strong robustness in multi-class cotton disease classification. Additionally, [11] introduced a lightweight MobileViT-based RF-Cott-Net achieving 98.4% accuracy with improved computational efficiency, making it suitable for real-time applications. Traditional image processing approaches, such as [12], still rely on preprocessing, segmentation, and handcrafted features, achieving only 85–90% accuracy, indicating their limited scalability in complex field environments. [13] proposed a CNN model enhanced with Multi-Head Attention (MHA) using RGB cotton leaf images, achieving 97–98% accuracy and demonstrating improved localization of disease-relevant regions compared to traditional CNNs. Similarly, [7] developed a hybrid framework combining a BERT-inspired vision encoder, ResNet, and Particle Swarm Optimization (PSO) on the PlantVillage dataset, achieving 98.5% accuracy and outperforming standard CNN models. [14] introduced an attention-enhanced ensemble of lightweight CNNs with Multi-Head Self-Attention (MHSA) and explainable AI (Grad-CAM), achieving 98.33% and 99.43% accuracy on two datasets, showing strong generalization and interpretability. Likewise, [15] evaluated multiple transfer learning models including EfficientNet, VGG16, and ResNet50 on a cotton leaf dataset, where EfficientNet achieved the best accuracy of 97.9%, confirming the effectiveness of deep transfer learning. Overall, existing literature confirms that deep learning and hybrid metaheuristic-optimized models significantly outperform classical machine learning techniques in cotton disease detection. Despite significant

progress, several gaps still exist in the literature. First, most existing studies focus on standalone classification models rather than integrated web-based systems for real-time monitoring and decision support. Second, although high accuracies (98%+) are reported, many models lack deployment-oriented design, limiting their usability for farmers and agricultural stakeholders. Third, few approaches combine disease detection, prediction, and management recommendations within a unified platform. Additionally, most studies rely on static datasets and do not effectively address real-time field variability, scalability, and cloud-based accessibility. Finally, there is limited work on hybrid deep learning web platforms that integrate optimized CNN models with user-friendly interfaces for cotton crop monitoring and disease management. Therefore, this study proposes a Hybrid Deep Learning Web Platform for Cotton Crop Monitoring and Disease Management to bridge these gaps by integrating accurate disease classification, optimized deep learning models, and an accessible web-based decision-support system.

2. Material and Methods

2.1 Proposed Methodology

The method of research to be adopted are the different steps of the proposed work such as Image acquisition, Image preprocessing, Dataset preparation, Model training, Model evaluation and disease prediction. The whole system of proposed system is described in Figure 1. At the farm level, the farmers are first recognizing the pictures of cotton leaves using their mobile phones in the agricultural fields. The images are taken under different conditions, leading to diversity of data points in the data set and better model generalisation. Images captured are then stored in secure image repository database for additional processing and handling. The cotton leaf images are collected and pre-processed by several image enhancement methods, to improve the image quality and model performance. It

involves various pre-processing steps such as data augmentation, noise reduction, re-size and normalization of image. Both resizing and normalization of pixel intensity values will lead to images of uniform size and uniform pixel intensity, which will benefit deep learning

models. To prevent overfitting and to give variations of data sets, data augmentation methods are applied i.e. rotation, zooming, and flipping. The unwanted distortions in field images are also reduced by noise reduction.

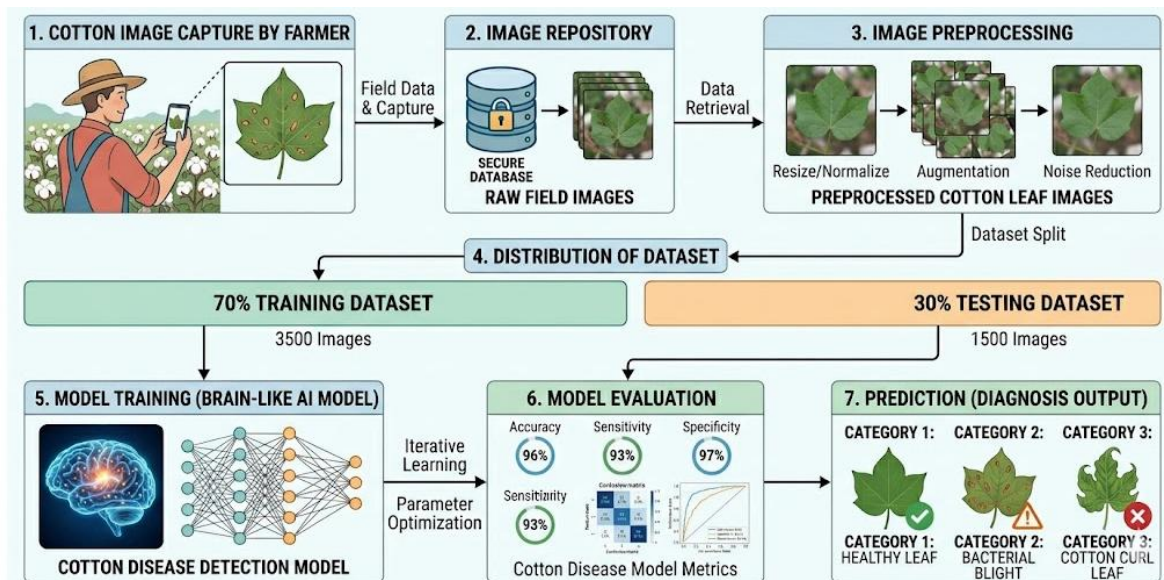


Figure 1: The proposed methodology for hybrid deep learning web platform

After preprocessing, the data set is partitioned into two parts: training set and test set, with a ratio of 7:3. The model is trained with about 70% of the images and tested and evaluated with 30% of the images. This split approach provides for the models to be reliably validated. In the training phase, several models of deep learning as well as machine learning related to the classification of cotton diseases are implemented. The prepared dataset of cotton leaves is used to train several architectures including MobileNetV2, EfficientNetB3, EfficientNetV2S, Random Forest Classifier and the proposed hybrid architectures: HybridEfficientMobiNet and HybridEfficientRForest. The hybrid models employ the feature extraction ability of deep learning networks along with the classification ability of machine learning methods in order to increase the diagnostic accuracy. For model evaluation, various performance measures are used such as accuracy; precision; recall, F1 score, sensitivity and specificity for evaluating the

effectiveness of classification. In the process of evaluation comparing the proposed model with the existing model to determine the best performance of the model in terms of cotton diagnosis. Lastly, trained system provides prediction outcomes in one of the three classes: Healthy Leaf, Bacterial Blight, Cotton Curl Leaf Disease based on the cotton leaf image. The prediction results are presented on web-based platform allowing farmers and agriculturalists to diagnose and manage diseases in real-time. The technique proposed is an intelligent, scalable and efficient system for automation of cotton crop monitoring and precision agriculture.

2.2 Data Collection

This study uses an open access dataset of Cotton Leaf Disease data from Mendeley Data. This will help develop deep learning computer aided diagnosis (CAD) system for classification and monitoring cotton crop disease. A real agriculture environment was captured, and images were classified to adequate classes for

supervised learning techniques in this research. This database consists of images of different stages of Cotton Leaf Bacterial Blight (CLBB), Cotton Curl Leaf Disease (CCLD) and Healthy Leaf as depicted in Figure 2. The images are then labeled according to the type of disease and the deep learning models are trained with labels, where the classification of the disease is done

automatically as illustrated in Figure 1. The images were taken under different environmental conditions such as intensity of light, background, orientation of leaves, quality of the images and it reflects actual on-farm cotton disease recognition challenges. These changes boost the strength of the proposed deep learning models and their generalisation capability.

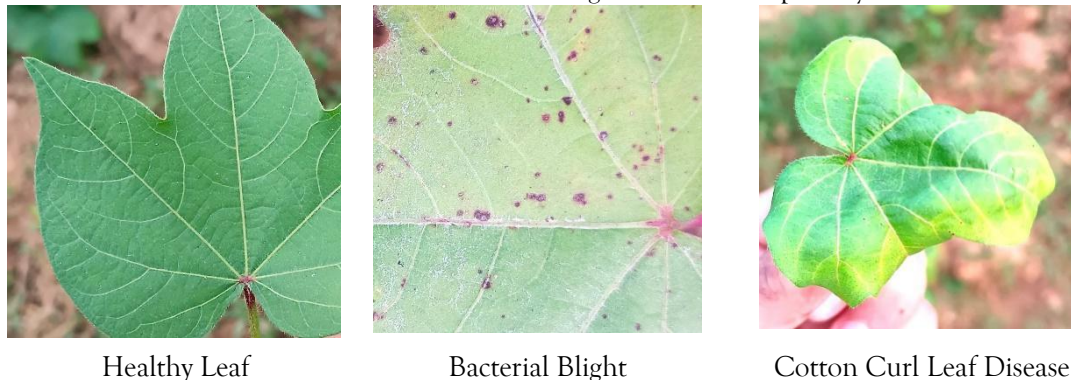


Figure 2: Cotton Crop Diseases 3 Classes

The data set is a valuable information source for training and testing AI model to identify and classify cotton leaf diseases. In this research, the balanced data set is created, which includes 3

classes and 3000 images of cotton leaves. To ensure a balance in all classes there were 1000 images per class as shown in Figure 3.

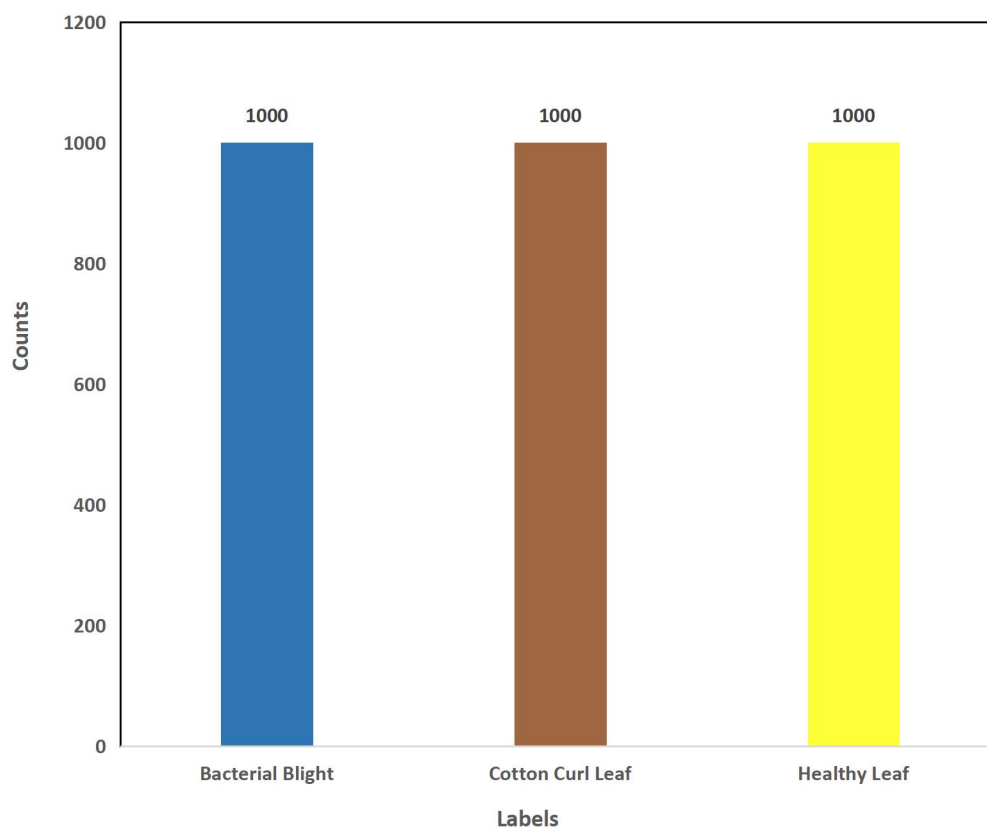


Figure 3: Dataset class distribution

2.3 Data Preprocessing

To improve the classification accuracy of cotton diseases using deep learning, the complete cotton leaf image preprocessing pipeline was proposed. All cotton leaf images were resized to a common size of 224×224 pixels, to ensure uniformity and compatibility of the different pre-trained CNN models such as MobileNetV2 and EfficientNet variants. By doing so, the data size would be uniform, and the computation required in training the model would be reduced. After sizing, it was scaled to be intensity normalized. This normalisation process was helpful for achieving numerical stability, a quick convergence of the model and a similar learning behaviour for all training samples. In order to improve the images of cotton leaf, various environmental and lighting conditions were used while the significant features of cotton leaf disease, such as leaf spots, leaf discoloration, curled leaves and variations in leaf texture were highlighted by employing image enhancement techniques. To enhance the image quality and local contrast enhancement, Contrast Limited Adaptive Histogram Equalization (CLAHE) technique was used for the cotton leaf images. CLAHE enhanced the local contrast of the image, but not the noise in the homogeneous regions. This technique was found very useful to describe the subtle symptoms of the disease in cotton leaves infected and to differentiate among the different classes of the disease. Furthermore, the data augmentation technique was used to make the data more diverse and to make the proposed deep learning models more generalizable. The augmentations included rotation, horizontal flipping, zooming, changing the brightness of the images, and shifting the images. The augmentation process was used to simulate the changes (variations) in the appearance of cotton leaves that may occur in the field, to simulate

different camera angles, lighting conditions and environments in the field to reduce the over fitting problem. Overall, the pre-processed and standardized data pipeline enhanced the quality of data, feature extraction and diagnosis and monitoring of cotton crop diseases via deep learning and hybrid models.

2.4 Data Splitting

To make sure the proposed deep learning and hybrid models can be fairly and objectively assessed, the cotton leaf dataset split into train and test datasets. Equal number of each class (Bacterial Blight, Cotton Curl Leaf Disease, Healthy Leaf) was obtained by having a stratification split. This ensured that the data set used for training and that used for testing were evenly distributed so that there was no bias in model building and testing. A total of 700 images (70%) was allocated for training, and 300 images (30%) were kept for testing in each class. Hence, the training images and test images were 2100 and 900, respectively as shown in Figure 4. For consistency among class distributions, stratified split method was applied to both subsystems, while results from the different deep learning framework that were implemented and proposed for the hybrid models were compared. The training set was used only for learning and tuning parameters of the deep learning models and the testing set was used solely for testing and validating the deep learning models performance. The separation of the models was intended to test the models on unseen data records that would give a realistic indication of the models' ability to generalize in real world, cotton disease classification situations. The proposed evaluation framework is an effective tool to assess the performance of various deep learning and hybrid architectures to automatically diagnose and monitor cotton crop diseases.

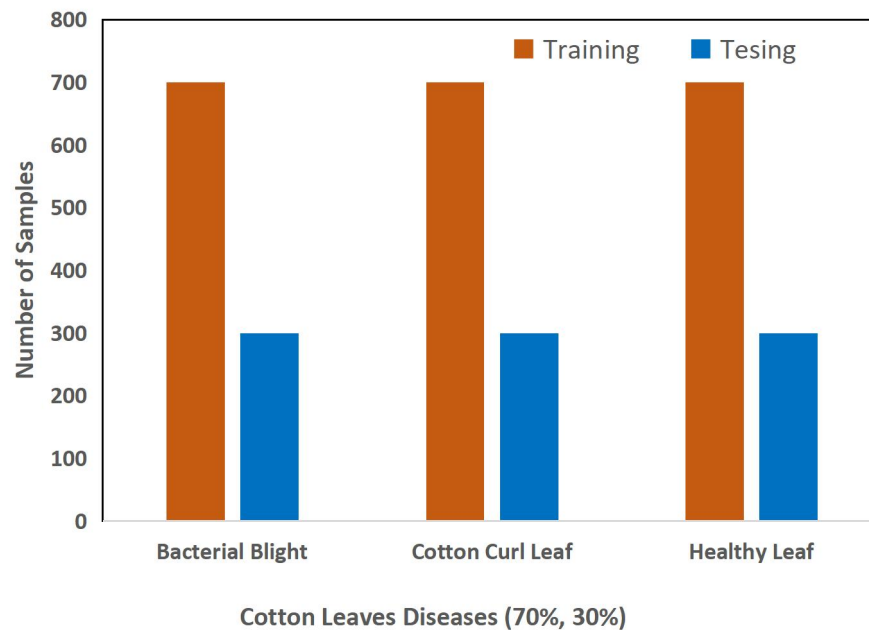


Figure 4: Distributions of samples in the training set vs. the testing set

2.5 Employed Machine Learning Models

Three models based on deep learning and machine learning were applied to classify the cotton leaves into Bacterial Blight, Cotton Curl Leaf Disease and Healthy Leaf. Different state-of-the-art deep learning architectures were designed & implemented to assess their capabilities on the automatic classification and monitoring of cotton diseases. The models which were employed were MobileNetV2, EfficientNetB3, EfficientNetV2S and Random Forest Classifier. In order to achieve efficient image classification, CNN architecture with less compute resources (MobileNetV2) and light weight CNN architecture (MobileNetV2) have been used. It uses effective feature extraction, and is also faster as it makes use of Depthwise separable convolutions and inverted residual blocks. MobileNetV2's lightness and good generalization capability has been shown to be effective in the cotton disease recognition problem. EfficientNetB3 is an improved deep learning model, which is better scaled by width, depth and image size. This model was chosen in this study because of its ability to detect features similar to the disease in the cotton leaves' image. Likewise, EfficientNetV2S is an improved version of

EfficientNet and an improved family of the EfficientNet, to enable faster training of the net and optimized learning performance with fused convolutional operations and progressive learning strategies. The Random Forest Classifier was implemented as it is a traditional ensemble machine learning algorithm. Random Forest is an ensemble of decision trees, which collectively make predictions while avoiding overfitting. The image features related to classification of cotton leaf disease were extracted and given to the cotton leaf disease classifier for training. The pre-trained weights of the ImageNet were used and the transfer learning methods were utilized to enhance the classification ability and feature learning capability. To classify cotton diseases, task-specific fully connected dense layers were employed instead of classification layers in the original deep learning architectures that are used for multi-class classification mode. In addition, global average pooling and dropout regularization techniques were used to alleviate overfitting and increase the model's generalisation. All models used the same testing condition and testing procedure, so that the results of the models performance can be compared. The results of the experiments

showed that the classification accuracy 85%; precision 86%; recall 85% and F1 86% were the best obtained by the MobileNetV2 model. The EfficientNetV2S model had moderate performance with 69.8% accuracy and Random Forest Classifier had 79.5% accuracy with balanced metrics in classification. The performance of efficientNetB3 on the chosen dataset was not so promising. Overall, the stand-

alone deep learning models were the best performing of the three models due to the lightweight architecture of MobileNetV2, efficient feature extraction of the model, and its great generalisation capability which proved beneficial in application to the proposed web-based monitoring and disease management platform for cotton crops.

Table 1: *Detail of Parameters of a proposed Deep Learning Model*

Layer Type	Configuration	Output	Activation
EfficientNetB0	Pretrained (ImageNet) include_top = False, input (224, 224, 3)	Feature map	ReLU (internal)
Global Average Pooling			
Flatten	Implicit	1280-d feature vector	
Random Forest Classifier	7000 estimators, random_state = 42	Class probabilities via voting	

2.6 Web-Based Deployment

The cotton crop disease classification system was implemented by developing an online deployment platform as in Figure 1 – system architecture. To evaluate the performance of the models, several deep learning and machine learning models are trained and evaluated, like MobileNetV2, EfficientNetB3, EfficientNetV2S, Random Forest Classifier, HybridEfficientMobiNet and HybridEfficientRForest models. The HybridEfficientRForest model was proposed as the most suitable model to be deployed to the proposed smart farming platform as all the

implemented architectures were validated with highest possible accuracy of 98% using proposed HybridEfficientRForest model. To allow real-time classification and monitoring of cotton leaf disease, the trained HybridEfficientRForest model was embedded into a web application. A user-friendly interface, which is intuitive, is provided in the system, which enables the farmers, agricultural experts and researchers to upload cotton leaf images straight from the web page as shown in Figure 5. The platform is designed in a way that it will be easily used and accessible to the users with less technical skills.

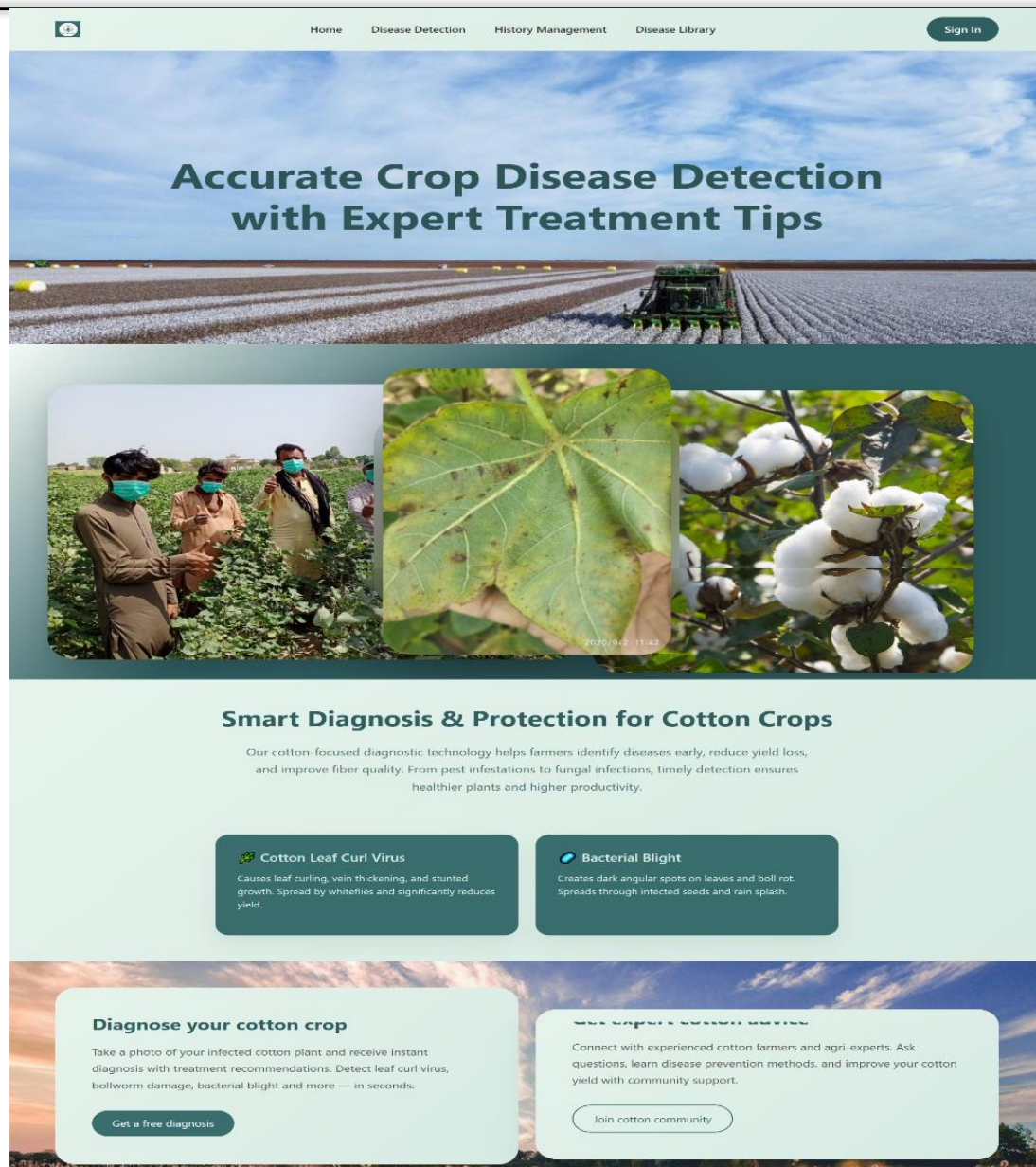


Figure 5: Main interface of the proposed AI web application

The same pre-processing steps as used during the training of the model are applied when using it, such as resizing and normalization, as well as any other pre-processing steps that are necessary to ensure consistency and better representation of features. The image is then sent to a trained MobileNetV2 model which extracts features and classifies the image into one of the labels in the dataset: benign or malignant lesions (as given in the data set). The decision supporting is instantly presented via the web interface, providing a fast, accurate and effective presentation of the

decision supporting. To load the model, preprocess the system coordination and run inference, it can be used to help the deep learning model to be correctly integrated to the user interface, using System backend. The trained model is then embedded in a diagnostic support tool in web, with which it can be used in real-life clinical situations. It makes it more user friendly, it enables real time decision making and it shows in practice how automated skin disease detection and classification can be achieved using AI, as shown in Figure 6.

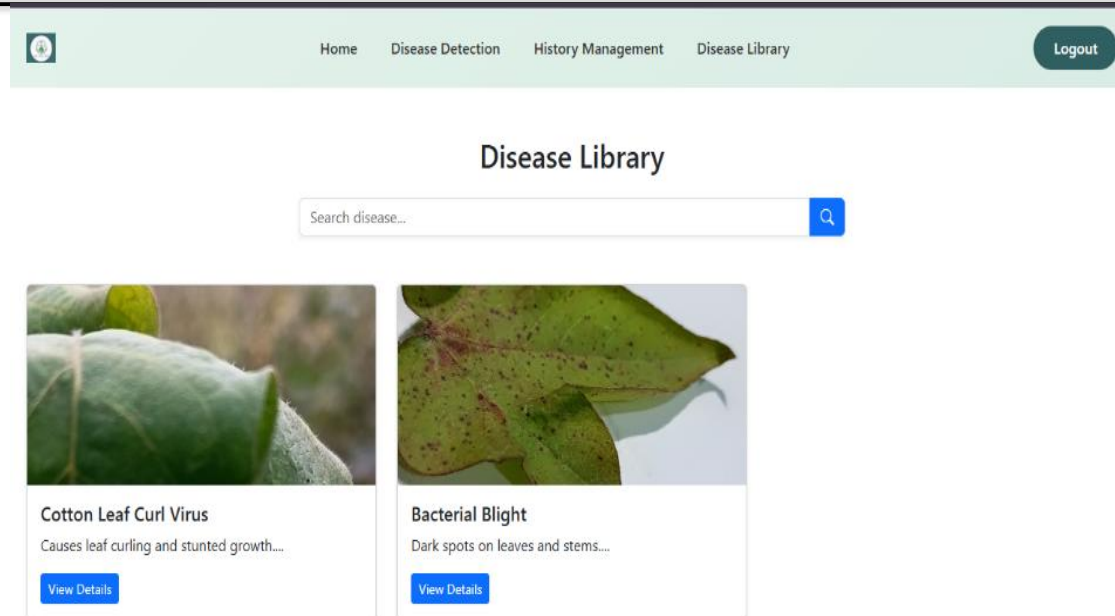


Figure 6: Cotton Plant Disease Output Generated by the Proposed Framework

3. Results and Discussion

The conclusions reached from the experiments conducted on classification of cotton leaf disease are summarised. Evaluation of the different deep learning models were assessed by using accuracy, recall, precision, and F1 score. EfficientNetB3 has been successful, but not as successful at the classification performance, likely because it was only able to get a small number of features from the chosen dataset. MobileNetV2 and EfficientNetV2S showed the highest level of disease classification accuracy and had a higher level of representation of features. Additionally, the balanced prediction accuracy of cotton disease is also satisfactory with the use of Random Forest Classifier. The proposed hybrid models displayed better level of classification accuracy and reliability as compared with individual models. Images successfully captured important features of cotton leaf disease, and HybridEfficientMobiNet was effective in capturing those features. The proposed model HybridEfficientRForest outperformed all the other models with 98% accuracy. The hybrid architecture was able to represent the deep feature extraction and machine learning based classification well. The results show the overall effectiveness of the hybrid deep learning methods

applied to automatic monitoring and management of cotton crop and disease in smart agriculture applications.

3.1 Experimental Setup

The experiments performed on cloud-based environment of Google collab which helps to perform deep learning computation and model training for cotton crop disease classification. Google Colab offered access to high-performance computational resources, such as GPU acceleration, allowing for efficient training and evaluation of deep learning models on the cotton leaf image datasets. The experimental setup was a combination of data storage space, efficient processing with NVIDIA Tesla GPUs and the equipment was equipped with all the necessary peripherals. All experiments were implemented in the programming language Python using popular deep learning and machine learning libraries like TensorFlow, Keras, Scikit-learn, NumPy, Pandas, OpenCV and Matplotlib. All the developed models such as MobileNetV2, EfficientNetB3, EfficientNetV2S, Random Forest Classifier and the proposed hybrid architectures were trained and tested in Colab environment. Before the model training, the data pre-processing techniques used were image resizing, image normalization, image

augmentation and contrast enhancement. Lastly, all cotton leaf images were cropped to fit the selected deep learning architectures: 224×224. The training time was significantly shortened due to GPU acceleration and computational cost for feature extraction and classification was significantly reduced. All the data preprocessing, training and validation, testing and performance evaluation of the model were carried out efficiently on the experimental setup. The proposed system for cotton crop monitoring and disease management based on artificial intelligence was developed in this cloud-based computational environment, which was suitable for the system and was reliable and scalable.

4.1 Performance of Classifiers

To classify cotton leaf disease, the accuracy, precision, recall and F1 score were used to evaluate the performance of the classifiers implemented. The comparison of the results obtained from the experiments showed that the performance of the models used, deep learning, machine learning and hybrid models, varies considerably as shown in Table 2. From the

Table 2: *The outcome of the performance measures related to the Deep Learning Models*

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score(%)
EfficientNetB3	33.0	11.0	33.0	16.6
MobileNetV2	85.0	86.0	85.0	86.0
EfficientNetV2S	69.8	76.0	69.0	67.0
HybridEfficientMobiNet	92.0	93.0	93.0	93.0
HybridEfficientRForest	98.0	98.0	98.0	98.0

The highest accuracy; recall; precision and F1-score of 98% was achieved by the proposed HybridEfficientRForest model as shown in Figure 7. The hybrid model achieved better performance than the individual deep learning model and machine learning model, indicating

standalone DL models, the MobileNetV2 model achieved excellent classification accuracy of 85%, precision of 86%, recall of 85% and F1 score of 86% that proved its efficiency in extracting cotton leaf disease related features. The performance of EfficientNetV2S was moderate with accuracy, precision, recall and F1 scores being 69.8%, 76%, 69% and 67% respectively. The performance of efficientNetB3 was relatively low, obtaining 33% accuracy, 11% precision, 33% recall and 16.6% F1 score, which do not show a good generality performance on the target data. The balanced classification accuracy of the Random Forest Classifier was 79.5 per cent, its precision was 80 per cent, its recall was 79 per cent and its f1 score was 79 per cent. The hybrid models achieved performance significantly better than the standalone models. The accuracy, precision, recall and f1-score obtained from HybridEfficientMobiNet were 92%, 93%, 93% and 93%, respectively, indicating the capability to extract features from the images and classify them with high accuracy.

that the addition of the deep learning classifiers for extraction of features and the machine learning model for classification further increases the accuracy and robustness of automated cotton crop monitoring and disease management systems for disease recognition.

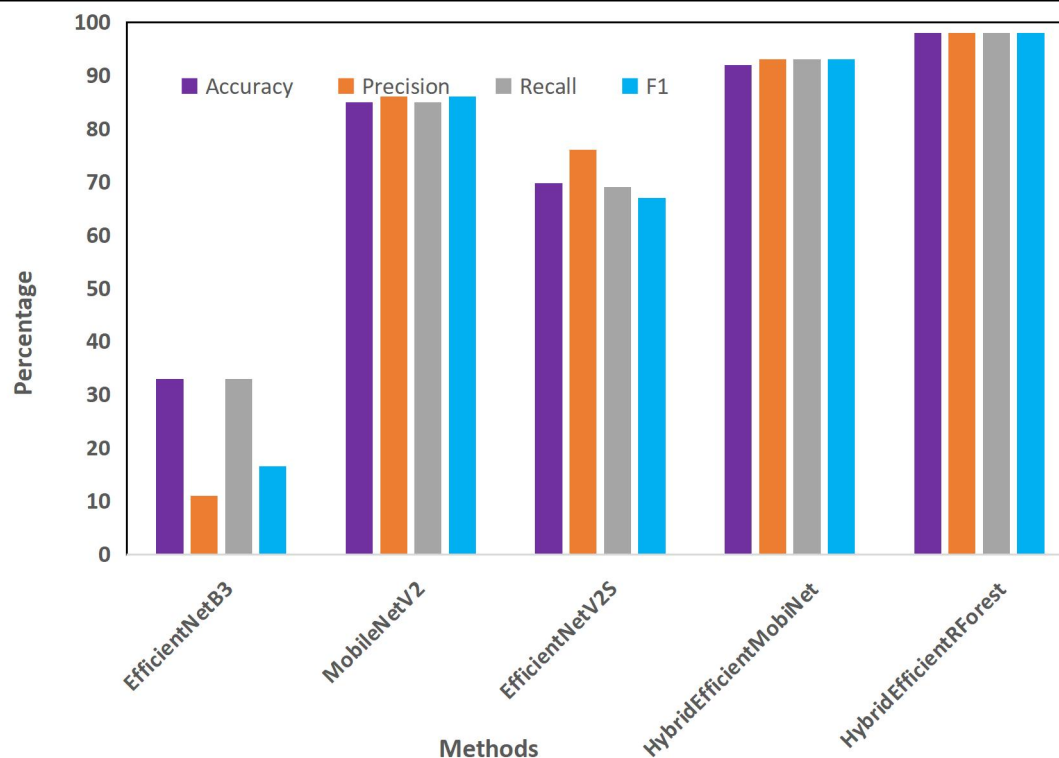


Figure 7: Visualization performance metrics of classifiers

4.2 K-Fold Cross-Validations Results

The proposed classifiers were evaluated on cotton leaf disease dataset using the K-Fold Cross-Validation technique to test the robustness and generalization power of the proposed classifiers.

The data set was partitioned into several folds, one-fold for validation while the rest were used for training in each iteration. In this process the developed Deep Learning and Hybrid models were assessed effectively and fairly.

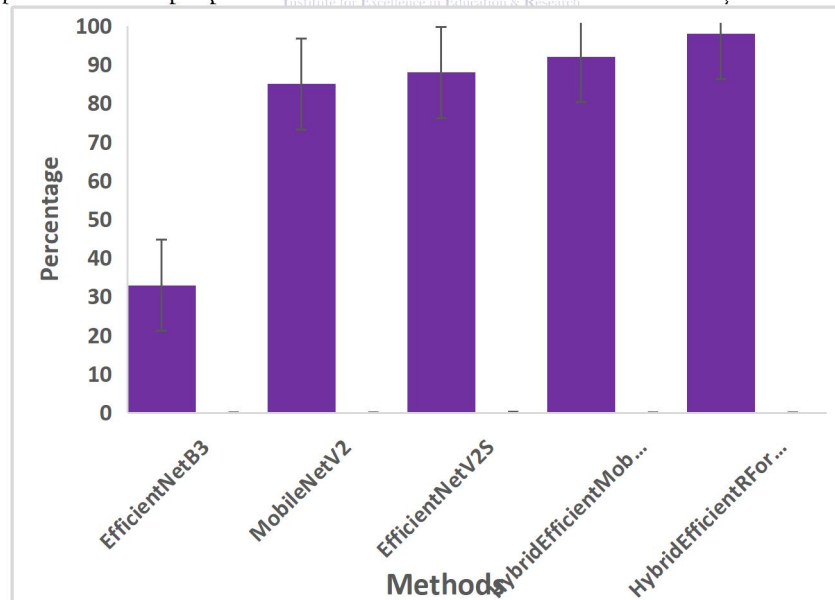


Figure 8: A cross-validated score represented by their standard deviation (SD) as a bar

The evaluation of the results of the cross validation has been made using the average accuracy and the standard deviation. Based on the average accuracy and standard deviation,

EfficientNetB3 obtained the worst performance of 33% with a standard deviation of 0.0308, which shows that it has low generalization ability in the evaluation of the selected cotton leaf

dataset. The accuracy of the MobileNetV2 was high (85%) and the standard deviation was very low (0.0245), showing the high consistency of the model in extracting features and making accurate classification in every fold. Lastly, EfficientNetV2S achieved the highest accuracy and lowest standard deviation in the classification task at 88% and 0.0575 respectively. The proposed HybridEfficientMobiNet model improved the classification performance as the accuracy is 92% and the standard deviation is 0.0134, indicating very stable classification

Table 3: Results of K-Fold validation

Method	Accuracy	Standard Deviation (+/-)
EfficientNetB3	33	0.0308
MobileNetV2	85	0.0245
EfficientNetV2S	88	0.0575
HybridEfficientMobiNet	92	0.0134
HybridEfficientRForest	98	0.0325

Based on the results of the proposed hybrid models, the system performance improves compared to the performances of the individual deep learning architectures and gets more accuracy, stability and generalization for automated monitoring and disease management applications for cotton crop management.

4.3 Discussion

Based on the experimental results it is concluded that deep learning and hybrid learning can be applied to automate the classification of cotton plant diseases. The models implemented achieved different performances based on the feature extraction and classification ability. The MobileNetV2 and EfficientNetV2S are isolated networks with efficient deep feature learning mechanisms, enabling them to achieve very good performance in the classification tasks. The results obtained from the MobileNetV2 yielded stable and good level of accuracy with a low standard deviation indicating the suitability of MobileNetV2 for light weight and real time farming applications. The efficientNetB3 has not performed very well in the dataset selected. The lack of feature generalisation and sensitivity to

performance in cross validation as shown in Figure 8. The overall best performance of the proposed model was obtained in the HybridEfficientRForest model with an accuracy of 98% and a standard deviation of 0.0325. The validation results show that the accuracy of the overall classification is high, and the differences between the validation folds are low, indicating the robustness and reliability of the cotton crop disease diagnosis system using a hybrid architecture as shown in Table 3.

changes in the cotton leaf disease pattern can explain this reduction in performance. EfficientNetV2S, on the other hand, offered enhanced feature representation and classification performance, showcasing the power of sophisticated EfficientNet models in agricultural image analysis. The hybrid models proposed, exhibited remarkable improvements in terms of classification of diseases and robustness as a stand-alone deep learning models. The accuracy of HybridEfficientMobiNet is high, with a low standard deviation as well, indicating that the algorithm is effective and there are not that many differences between the various folds in the validation set. Also, the efficient Net and Mobile Net are used for feature extraction which also contributed to the model to detect the discriminative features of the disease in the cotton leaves. The proposed HybridEfficientRForest model has achieved the best overall result, with the consistent cross-validation result of 98% classification accuracy. The above improved performance can be recommended that Deep Learning based feature extraction and Random Forest based

classification are better approach to improve the reliability of prediction to minimize classification error. Based on the advantages of deep learning and machine learning methods, the hybrid architecture was used to attain satisfactory results in the cotton disease identification. The trained model also demonstrates the feasibility of the proposed model for precision agriculture applications when deployed in a web platform. The platform has been designed with technical support facility to farmers and agricultural experts for real time disease diagnosis for farmers to ensure early detection of diseases and better agriculture management practices. Finally, the results validate the efficiency of the hybrid deep learning-based approaches to improve automated monitoring and disease management systems in cotton crops for smart agriculture.

Conclusions

A multi-deep learning and machine learning-based cotton crop disease classification system HybridEfficientNetB3, HybridEfficientNetV2S, HybridEfficientRForest, HybridEfficientMobiNet and MobileNetV2 was proposed in this research. The outcomes achieved in the experiments show the importance of the hybrid learning approach on reliability and accuracy of the cotton leaf disease diagnosis. The performance of all the models was examined and the proposed HybridEfficientRForest model delivered the best accuracy (98%), precision (98%), recall (98%) and F1-score (98%) with stable cross-validation results. Similarly, HybridEfficientMobiNet also has a good classification performance with high accuracy and low standard deviation. The results achieved demonstrate the validity of using deep learning-based feature extraction and machine learning classification methods to gain better capability in disease recognition and enhance the robustness of the model. The real time monitoring and management of cotton crop was then integrated with the proposed system using a Web based platform. The web application developed allows for uploading of the leaf image

of the cotton crop and an immediate diagnosis and classification of the disease is provided, without the need for any advanced infrastructure. This renders the proposed system viable and user friendly for smart farming applications, especially in remote and agricultural areas where expert consultations may be scarce. The proposed intelligent system can be useful as automatic decision support system in diseases detection of cotton and precision agriculture is expected. The system could be applied to improve the accuracy of disease diagnosis, reduce the amount of manual disease assessment, facilitate effective crop management at the proper time and minimize losses from plant diseases to agriculture. Future work will focus on adding more cotton diseases; introducing multimodal agricultural data; optimizing the EAI techniques and approaches; and extending the system in realistic smart agriculture scenarios, mobile and cloud platforms, to enhance the availability and applicability of the system.

Conflict of Interest: The authors state that there are no conflicts of interest.

Dataset link:

<https://data.mendeley.com/datasets/b3jy2p6k8w/2>

Abbreviations:

AI	Artificial Intelligence
CNN	Convolutional Neural
Network	
DL	Deep Learning
RF	Radom Forest
ML	Machine Learning
HybridEfficientMobiNet	Efficient + MobileNet
HybridEfficientRForest	Efficient + Random Forest

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