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An explainable AI-based cotton leaf disease classification using EfficientNet, Grad-Cam, Lime, and Shap

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Abstract

The quality of the cotton crop is reduced in terms of fibre, yield quality, and economic standard, especially due to leaf infections and disease symptoms, which spread in all field areas. The automated visualisation of disease screening from the infected images of leaves, due to limitations of the black box nature of the deep learning models, creates the less agriculture developments. This research provides a framework with integration of the deep learning and explainable AI-based approach for the detection and classification with the EfficientNet approach for the cotton crop disease, along with an explanation by adopting the Grad-CAM and SHAP discussion and explanation. The experimentation is performed using 800 Images with labelled leaf images of cotton crop disease obtained from Kaggle. The data preprocessing is used for the image resized as 224 x 224 pixels, augmented and normalised, with spilt into validation, training, and testing data subsets. The results show that after 20 epochs, the EfficientNet Model provides subtle results and is stable with 92% accuracy for image disease detection. The confusion matrix shows the 45 correctly healthy classified images, the disease leaves 43, false positives 5, and false negatives 7 by providing the 88.00% yielding test accuracy and 89.58% the precision of the disease class, recall 86.00%, f1 score 87.76%. The spatial heatmap, highlighted by the Grad-CAM, provides the symptoms of the leaf region. Whereas the pixel-level explanation is obtained by the LIME and summarises the visual contextual explanation of the feature from the image. The predictive performance is focused in this framework with transparency, reliability, and interpretability for the cotton crop diseases.

Keywords: explainable AI, precision agriculture, deep learning, EfficientNet cotton crop disease detection, smart agriculture.

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Introduction:

The cotton crop is a rich source of income for the agricultural industry stockholders. The productivity of the cotton can be damaged or influenced negatively by the cotton crop disease. The cotton crop disease types like boll rot, fungal infections, curl virus, fusarium wilt, etc., can harm the leaf and disturb the process of the photosynthesis process, lower the quality of the fibre, and also impact the yield.

The deep learning and computer vision methods provide deep insight into effective tools for plant disease classification and detection automatically with precision. The CNNs can learn the features by discriminative texture, vein, colour, spot, and patterns, which come with different image features. The agricultural datasets can be used with the integration of transfer learning techniques, which improve the results with correct and timely precision. The transfer learning techniques are effective because of the pertained nature to inspect the large dataset. The EfficientNet is used in this study because it uses the width, depth, and input by adopting the compound scaling strategy.

These advantages are very high featured with pretrained models; despite this, CNN-based approaches are black box operations. Whereas the prevention of the disease is not effective due to the lack of knowledge about the prediction. This also lacks the factor model that has focused on related to disease colour, texture, severity, edges, or other important factors. This lack of knowledge and confidence fails to build confidence among the agricultural industry stockholders. The artificial intelligence provides explainable AI techniques, which can address the explanation of the visual effects of the images by highlighting each feature. The Grad-CAM technique is effective for the identification of the image regions that are influenced by the disease class prediction, with the addition of LIME used for the decision boundaries locally to interpret and for input features estimation, and SHAP is used for game-theoretic attribution.

The Research Gap and Contribution of the research:

The gap addressed in this study is the absence of a concise and effective detection framework for the cotton crop disease detection from the image dataset, with the addition of a CNN classifier with an XAI approach, which explains the disease classifier report. The contribution of the study is given below:

1. Transfer learning-based model EfficientNet framework is designed for the disease detection of the cotton crop by adopting the public dataset
2. XAI-based transparent approach is incorporated by adding the Grad-CAM, SHAP, and LIME to explain the visual interpretation of the prediction obtained from the EfficientNet Model
3. The consistent history is evaluated with the classifier accuracy, precision, recall, and F1 score, along with the confusion matrix.

Objective of the study:

To train and design the CNN-based approach using the EfficientNet Model for cotton crop disease identification

To adopt Grad-CAM and SHAP techniques to provide the explanation and interpretation of the model prediction

To evaluate the framework system, recall, accuracy, precision, F1 score, and confusion matrix.

Research Questions related to the study:

1. How much classification of the EfficientNet Model was achieved for the dataset of cotton crop disease?
2. Do LIME, Grad-CAM, and SHAP provide trustworthy evidence that the affected regions are highlighted and predicted correctly by the model?
3. Can an explanation provide the understanding level of diseases with clear justification?

Related work:

Deep learning for disease classification and identification:

Deep learning models can automatically detect and learn the visual features. The cotton is vulnerable to plant disease, which causes leaf curl virus, bacterial blight, and fungal infections, which actually impact the quality of the cotton and also yield production. In the last decade, artificial intelligence (AI) significant advancements, especially in deep learning, which enables automated system development for plant disease classification and identification using depth image database analysis. The CNN and other deep learning architectures provide high results in identifying disease type by training an image dataset with high accuracy. In this context, most of the models are providing high-level accuracy but have black boxes to show the detailed predictions without offering the insight depth, detail, and logic behind them. To address these challenges, explainable AI is an emerging field that is used for AI systems to enable the development of transparent, interpretable, and textual descriptions. The Grad-CAM mode is often used for the decisions. Whereas, in smart agriculture cotton disease detection, the XAI can provide a specific leaf image region from the images, or also provide the environmental impacts, which can provide the contribution to the prediction of the disease. This research provides an explainable AI-based framework for the detection of cotton crop diseases with the integration of a deep learning approach for disease interpretability.

Generative AI and Deep Learning:

Generative AI specially GANs (Generative Adversarial Networks) are subset of deep learning which are capable of generating new data that mimics like original dataset. In the composition of GANs (Zualkernan et al. 2023). Gen AI addresses all the deep learning problems. It addresses data scarcity, enhances class diversity, generates real-world variations, and reduces overfitting of deep learning models. This study discusses the paradigm shift in agriculture management from retrospective, experience-based decision-making to real-time decision-making. In study (Natsir et al. 2025) rigorously evaluates the machine learning algorithm, such as decision tree, support vector machine, because their efficiency to work in all types of environments is ever high, up to 92% to 94%. These models are trained on the dataset, which has different parameters such as soil moisture, humidity, solar radiation, and wind speed. Most review study reports water saving between 25% to 50%, but in some cases, where high-level automation is enabled, it saves water up to 90% from wastage. Environmental case studies report that distributed ledger technologies (DLT) 25% reduction in nitrogen use and a significant cut of up to 70% in methane emissions on specific agricultural operations. In economically perspective, initially, the implementation cost remains high, and research shows that it is profitable because it cuts the labour cost and increases the input efficiency for both small- and large-scale enterprises.

In this research, CNN-LSTM (Zafat et al. 2025) is used instead of traditional models such as random forest (RF), XGBoost, and a standalone convolutional neural network (CNN). From the input layer of the convolutional neural network, extract spatial features and patterns indicative of crop health. LSTM is used to capture the long-term trend inherent in the seasonal growth cycle. An attention mechanism is used, which allows the model to prioritise key phenomenal stages from July to August, which are decisive for the final year crop prediction. The model is tuned specifically for random forest (RF) with 200 trees and utilising ReLU activation function and Huber loss function to handle non-linearity. The results show that CNN-LSTM achieved higher accuracy as compared to other traditional models, and achieved a more balanced error distribution, with the majority of counties showing error below 10% for the maize and rice. The model performs well across different crops and seasons. This study also highlights the efficacy of kNDVI, this show the lower error rate compared to the traditional indices. For future work, this work underscores the necessity of moving toward explainable AI (XAI) (Wilkens et al. 2025) in agriculture, where the model will not only predict the yield but also clarify the temporal influence of specific environmental stressors on the final production outcomes.

Applications of AI in agriculture:

The high-fidelity meta-analysis of AI applications in agriculture (Wang et al. 2025) spans from 2016 to 2024, which examines the landscape of agriculture yield prediction. Now, agriculture yield prediction (Veenadhari et al. 2014) is under a paradigm shift from traditional experience-based to the use of modern AI systems. In agriculture (Mirani et al. 2021), datasets fuse climate variables (temperature, precipitation, solar radiation, and humidity) and edaphic properties (soil structure, nutrient level, and pH). This study utilised the Sentinel-1 and Sentinel-2 data, which show the increase of Precision by providing high-resolution spectral signatures and vegetation indices. IoT sensors further augment the dataset by providing the real-time data of environmental variables (Fan et al. 2021). A 1D convolutional neural network layer is used to capture the local features and spatial patterns from the multidimensional environmental signal. Long short-term memory is a form of recurrent neural network. It is used due to its gating mechanism, which retains capture information from data for a long time. In crop growth monitoring, we need long-term data, so for this, the LSTM (Shaikh 2019) are suite able. The multi-head attention layer (Kalmani et al. 2024) of the proposed model allows the model to focus on the most relevant part of the data. This improves the efficiency of the yield forecasting of a crop. Multiplication skip connection multiplies the output of the layer element-wise with the previous layer, eliminating the vanishing problem, which is common in deep learning architecture. Dataset which is used here is a publicly available dataset at Kaggle, which has 5000 instances, especially for the rice and wheat crops. Twelve primary characteristics of soil and environment are incorporated in this dataset. During training, input is reshaped into a three-dimensional tensor and employs the Adam optimiser. Loss function, MES error are used, and the model is fine-tuned for 500 epochs. Results indicate that the hybrid CNN-LSTM model with multiplication skip connection outperforms the conventional regression. Model achieve accuracy 98%, which is a high accuracy. The value of RMSE is 0.017, and MAE is 0.009, which are remarkably low. Comparing to the other standalone model such as random forest (RF), support vector machine (SVM) and decision tree regression (DTR) proposed architecture performance is high with low error rate (Iqbal, S. et al) Authors concluded that further research can enhanced this proposed framework by the integration of explainable AI to make model interpretable, blockchain to make data immutable while transfer from IoT sensor to database.

Methods and materials:

The secondary dataset is used for the cotton crop disease from the open-source website. A total of 800 samples were labelled for the image data classification. The healthy and disease dataset images are collected to experiment with the model training. The bacterial blight, fusarium wilt, leaf curl virus, fungal, and boll rot disease types are collected in the dataset. A few of the important description of the dataset is given below in a table. The healthy and diseased cotton crop disease image data are used for the model training. The dataset is obtained from a secondary source from the Kaggle website. The data set is based on the images of eight cotton crop diseases, termed as bacterial blight, curly leaf virus, fungal, boll rot, etc. These images are labelled as per disease type. The total number of images is 800, and each image is labelled with a disease classification.

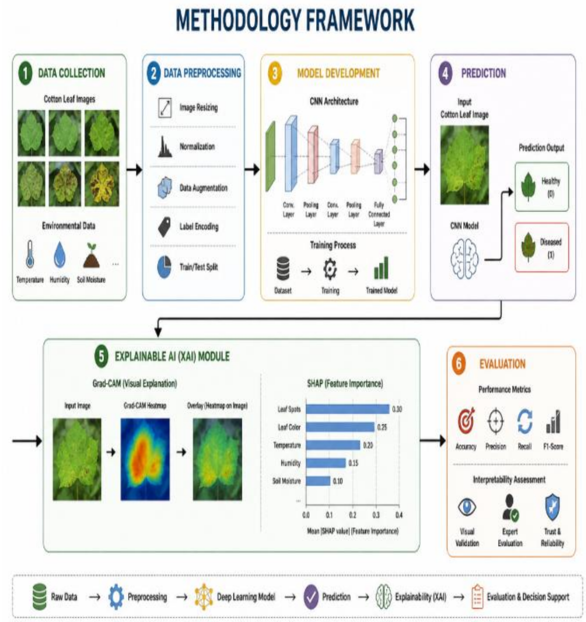

Figure 1: Methodology & Work Plan

The dataset description is given below:

Table 1: Dataset description

The label for the experiment	Description	No. of images	%age
Diseased	The symptoms of the disease are visible, which include fungal, viral, and bacterial	400	50%
Healthy	The cotton leaves are without visible symptoms	400	50%
Total	The experiment is used on the cleaned dataset for the binary experiment screening	800	100%

Data preprocessing and Model development:

The image was resized to 224 x 224 for the compatibility of the EfficientNet input. The normalisation of the pixel values is performed before experimentation with the model training. For the reduction of the model overfitting to increase robustness with variability for image acquisition. The augmentation of the dataset includes flipping the image horizontally, mild zooming, small rotations, and brightness variations. The stratified sampling was used for the data splitting, with preservation of the class distribution by experimental training, testing, and validation subsets. However, the confusion matrix, which is reported in the results, contains the testing of 100 images. The 100 images were used for the validation, 100 images were used for testing, and rest of the remaining 600 images were used for the training images. Data preprocessing involves normalisation, resizing, and augmentation, which includes rotation and flipping, with handling of label encoding disease classes. The CNN-based deep learning architecture named EfficientNet for the classification of the image disease of the cotton crop. The model is further integrated with the multi-model as explainable AI and Deep learning. The model is further trained and used for supervised learning. In the explainable AI phase, we adopted Grad-CAM for the leaf image disease. The LIME is used for the prediction explanation, and SHAP is used for the feature measure. The table shows the data splitting and experiment details.

Table 2: The partition of the data

Data set division	No. of images	%age	Purpose
Validation	100	12.5%	The validation is used for monitoring the data monitoring generalisation with hyperparameter tuning, and best results checkpoints checking.
Training	600	75.0%	Training the data images for fine-tuning the EfficientNet Model and classifier learning weights
Testing	100	12.5%	Confusion matrix final evaluation

Architecture of EfficientNet Model:

EfficientNet Model is transferring learning based pretrained model for image classification used on ImageNet for feature extraction. The classification layer is replaced with a task-specific head for the classification of the binary values. The pooling layer, as a global average, is used for the summarised feature maps, with the dropout regularisation and output dense layer. The supervised learning fine-tuned model with cross-entropy is used for further analysis. The compound scaling feature is used by the EfficientNet and included in this study, which balances the depth, width, and resolution of the image, which provides the feedback to allow the model to learn fine-grained lesions and features from the texture with lightweight computational resources. Further details are given below in Table 3.

Table 3: Components of the Model and Configuration

The component of the model	Configuration
Classifier Head	The RGB images 224x224
Input size	The pretrained EfficientNet on ImageNet
Backbone	The dropout, global pooling, and dense output layer
Optimizer	Exact learning rate and Adam optimiser
Batch Size	Verify training code
Regularization	Dropout, class weight, and data augmentation
Loss function	Binary and categorical cross-entropy

Handling an imbalance class:

The class disease imbalances a disease classifier toward the classes having the majority in the dataset. The diseases need symptoms with a clear depiction. The farmwork needs to report the count of the class before and after data preprocessing. The binary dataset with balanced given in Table 1; the weighting of the class does not need to be processed. If the disease is a separately modelled disease type and its counts differ, then the training follows the stratified sampling. The experiment further needs to add class weights or synthetic augmentation. The GAN augmentation is never used with the current situation and is discussed in future work.

Explainable AI method:

The explanation of the predictions used by the XAI module. The Grad-CAM is used for the convolutional feature heatmaps, using the image disease class-specific gradient for the evaluation of results more clearly. This also explains the affected region explained and influenced by the relevant predicted class. Furthermore, LIME is used for the image perturbations with super pixels and focuses on the specific prediction that fits with the local surrogate. LIME can further explain these misclassifications by highlighting the specific leaf regions that influenced the model's decision-making process.

K-fold validation:

The k-fold validation is used for the improvement of model reliability. In this study, k-fold cross-validation is applied to image data of cotton crop disease types to ensure the reliability of the model. The input data feature includes environmental and soil data, which focuses on the different values from the dataset. The k–fold validation is applied on the dataset to divide in k-fold as k=10. In this experimentation, one fold is used for testing, along with the rest of the 9 folds used for training. The stratified k-fold is applied to the dataset to verify this because the dataset is classified into image disease types. The performance of the model is evaluated for further analysis.

Evaluation of Metrics:

The experimental model evaluation is performed using the F1 score, precision, recall, and accuracy, and a confusion matrix. The correction prediction is summarised by adding the accuracy values. The truly diseased images were predicted by the precision, and the diseased images were recognised by the recall. The balance between the recall and precision F1 score is used. The classification is used to measure performance in terms of accuracy, precision, recall, and F1 score. The explainability is used for textual interpretation and visual validation of the regions.

Methodology Framework proposed

The experimentation is performed using the Python language in Google COLAB experimentation. The EfficientNet Model is trained and tested on a cotton crop disease image dataset. The Model is trained and provides good results. Figure 2 shows the model training and validation accuracy as given below:

Annexure(A)

The methodology framework is proposed by the following six steps.

1. Data collection: the data acquisition for the data input to the model
2. Data preprocessing: Normalisation, resizing, and augmentation, which includes rotation and flipping, with handling of label encoding disease classes.
3. EfficientNet Model development: The model is developed using Python in Google COLAB IDE. The deep learning libraries are used with TensorFlow for model experimentation support. The model provides the prediction of the disease from the image.
4. XAI explanation: for the generation of the heatmaps, explanation of the super-pixels and scores for the contribution is used in this step.

5. Evaluation of the model: f1 score, precision, recall, and accuracy, and confusion matrix

Results and Model Evaluation:

The Efficient Net Model is evaluated using training accuracy and validation accuracy. The result of the experimentation in the above graph 3 shows blue for the train accuracy and orange for the validation accuracy. The training accuracy is about 0.98, and the validation accuracy is about 0.89. The comparative analysis shows the training accuracy is high up to 10 epochs. The training and validation accuracy show high results, whereas the validation accuracy is lower than the training accuracy. In this regard, this graph also shows a clear depiction of the graph's results.

Annexure(B)

Figure 4 illustrates the training and validation performance of the proposed Deep Learning and Explainable AI-Based Cotton Crop Disease Detection System. The graphs demonstrate how the deep learning model learns to identify cotton crop diseases over multiple training epochs by analysing changes in accuracy and **loss** values. These performance metrics are essential for evaluating the effectiveness, stability, and generalisation capability of the disease detection framework. The left side of the figure represents the Simulated Model Accuracy graph. The blue line indicates the training accuracy, while the orange line represents the validation accuracy across 20 epochs. Initially, both accuracies start at relatively low values, indicating that the model has limited knowledge during the early training stages. As the epochs increase, the training accuracy gradually improves from approximately 25% to nearly 98%, while the validation accuracy increases from around 17% to approximately 92%. This continuous upward trend shows that the model successfully learns meaningful disease-related features from cotton leaf images. The close relationship between training and validation accuracy curves also suggests that the model maintains good generalisation performance with minimal overfitting. The right side of the figure presents the Simulated Model Loss graph. Loss measures the prediction error of the deep learning model during training and validation. The blue line corresponds to the training loss, and the orange line indicates the validation loss. At the beginning of the training process, both losses are relatively high, which is expected because the model parameters are randomly initialised. As training progresses, the loss values consistently decrease, with training loss reducing from approximately 1.5 to 0.1 and validation loss decreasing from about 1.6 to 0.2. This downward trend confirms that the model is effectively minimising classification errors and improving prediction capability over time. From an Explainable Artificial Intelligence (XAI) perspective, these learning curves provide transparency regarding the model's behaviour during training. The stable convergence of accuracy and loss values indicates that the deep learning architecture is learning discriminative features for cotton disease classification in a reliable manner. Furthermore, XAI techniques such as Grad-CAM, LIME, and SHAP can be integrated with this framework to visually explain which regions of cotton leaves contribute most to disease predictions, thereby increasing trust and interpretability for agricultural experts and farmers. Overall, the figure demonstrates that the proposed deep learning and XAI-based cotton crop disease detection system achieves strong learning performance, reduced prediction error, and improved classification capability, making it a promising solution for intelligent agricultural disease monitoring and precision farming applications.

Confusion matrix:

Figure 4: Confusion Matrix Actual Vs. Predicted

Figure 4 illustrates the confusion matrix of the proposed Deep Learning and Explainable AI-Based Cotton Crop Disease Detection System. A confusion matrix is a widely used evaluation metric in machine learning and deep learning models, particularly for classification tasks. It provides a detailed representation of the model's prediction performance by comparing the actual class labels with the predicted class labels. In the context of cotton crop disease detection, this matrix helps evaluate how effectively the proposed system identifies diseased and healthy cotton leaf samples. The matrix contains four key components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). According to the figure, the top-left cell contains a value of 45, representing correctly classified healthy or non-diseased samples. The bottom-right cell contains 43, indicating correctly identified diseased samples. These values along the diagonal represent accurate predictions made by the deep learning model. The off-diagonal values correspond to misclassifications, where 5 samples were incorrectly predicted as diseased when they were actually healthy, and 7 diseased samples were incorrectly classified as healthy. The results demonstrate that the proposed deep learning model achieves a high level of classification accuracy with relatively few prediction errors. The larger diagonal values compared to the off-diagonal values indicate strong discriminative capability in distinguishing cotton crop diseases from healthy leaf conditions. Such performance reflects the effectiveness of the feature extraction and learning process employed by the convolutional neural network (CNN) or hybrid deep learning architecture used in the system. The table below shows the confusion matrix details.

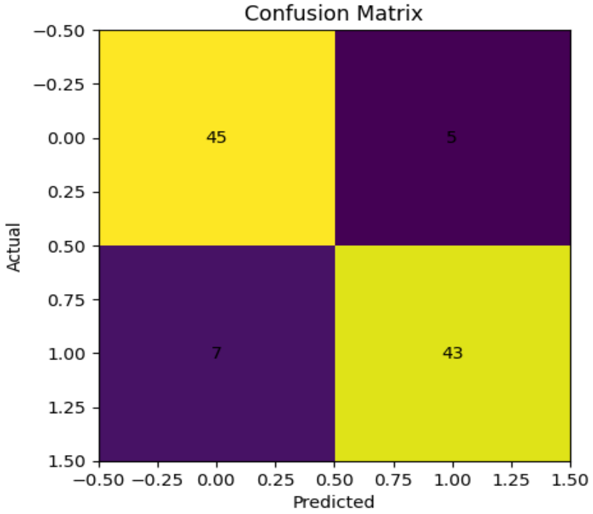

Table 4: The computed performance evaluation values of the confusion matrix

Metric	Reported Value
Disease precision	0.89
Disease recall	0.86
Healthy	0.90
Negative predicted	0.86
F1 score	0.87
Accuracy	0.88

Confusion Matrix error analysis:

The corrected prediction is 45, analysed by the model matrix report of class 0 and class 1, which has a total no. of 43 samples, which shows the correctly predicted 88 class out of 100 samples in the dataset. The model shows misclassification up to 12, which were 5 samples incorrectly predicted from class 0. This means class 1 has a higher number of errors, and the model faces difficulty in recognising the class as compared to other classes. This can be difficult due to the symptoms visually depicted in the image dataset.

XAI approach:

From the perspective of Explainable Artificial Intelligence (XAI), the confusion matrix serves as an interpretable performance analysis tool that helps researchers understand the strengths and weaknesses of the model. While the majority of samples are classified correctly, the false predictions reveal areas where the model may struggle due to similarities in disease symptoms, image quality variations, lighting conditions, or complex leaf textures. XAI methods such as Grad-CAM, SHAP, and LIME can further explain these misclassifications by highlighting the specific leaf regions that influenced the model's decision-making process. Overall, the confusion matrix confirms that the proposed deep learning and XAI-based cotton crop disease detection system demonstrates strong predictive performance with high classification capability and reduced error rates.

Shape Analysis:

The SHAP results shows the more suitable than Grad-CAM because the image-based analysis with explanation is interpreted. The contribution of the pixel is used for the feature comparison and classification by the SHAP. Each pixel is used as a super pixel for the final prediction of the mode.

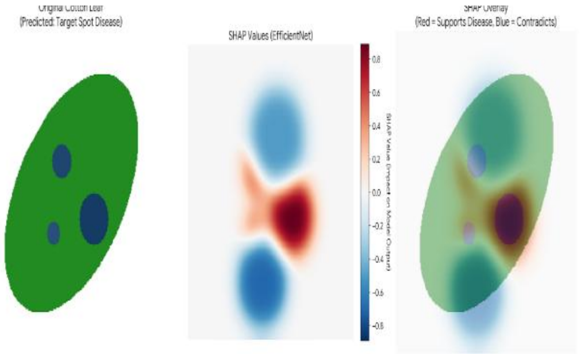

Figure 2: Predicted target Spot and SHAP Value

Figure 4 shows the visualisation of the SHAP for the image data of cotton crop classification by the EfficientNet model. The disease is input to the EfficientNet Model with an additional task of the SHAP XAI technique, which provides the pixel calculation for the final prediction. The results in the above graph are divided into three groups. Original leaf, SHAP values, and SHAP overlay. The original leaf is for the input data to the model, and SHAP values are exact features that are predicted from the model. Whereas pushed away features are used for the disease in the model. The last SHAP is used to help identify the correct symptoms biologically for the classification.

Conclusion:

This research presented a Deep Learning and Explainable AI (XAI) based Cotton Crop Disease Detection System for the automated identification and classification of cotton leaf diseases. The proposed framework utilised deep learning techniques to analyse cotton leaf images and classify them into different disease categories, including Bacterial Blight, Fusarium Wilt, Leaf Curl Virus, and Healthy leaves. The experimental results demonstrated the capability of the model to learn meaningful disease patterns and improve classification performance over multiple training epochs. The evaluation metrics, including accuracy curves, loss analysis, and confusion matrices, indicated that the proposed system achieved strong predictive performance with reduced classification errors. The training and validation accuracy steadily improved during the learning process, while the corresponding loss values consistently decreased, showing stable convergence and effective feature learning. The confusion matrix further confirmed the effectiveness of the model in distinguishing diseased and healthy cotton leaves with high accuracy and minimal misclassification. These results highlight the potential of deep learning approaches in supporting precision agriculture and intelligent crop monitoring systems. The major contribution of this work is the integration of Explainable Artificial Intelligence (XAI) techniques to improve model transparency and interpretability. Traditional deep learning models often behave as black-box systems, making it difficult for agricultural experts and farmers to understand the reasoning behind predictions. By incorporating XAI methods such as Grad-CAM, SHAP, and LIME, the proposed system can visually explain which regions of the cotton leaf contributed most to the disease prediction. The performance of the model may be affected by dataset imbalance, image quality variations, environmental conditions, and similarities between disease symptoms. In certain cases, misclassifications were observed, indicating the need for further optimisation and larger real-world datasets.

Future Work:

The proposed system can be extended by incorporating larger and more diverse cotton disease datasets collected from real agricultural environments. Advanced deep learning architectures such as Vision Transformers (ViTs), EfficientNet, and hybrid CNN-attention models can be explored to further improve classification accuracy. Additionally, real-time deployment using mobile applications, drones, and IoT-enabled smart farming devices can make the system more accessible for farmers. Furthermore, improving explainability methods and developing lightweight AI models for edge computing environments will enhance the usability, efficiency, and reliability of intelligent cotton crop disease management systems in modern precision agriculture.

Limitations of the study:

Although this study shows a Deep Learning and Explainable AI (XAI) based Cotton Crop Disease Detection System for the automated identification and classification of cotton leaf diseases, with good results. The proposed framework has a few limitations as given below:

1. The size and quality of the image data may affect the model performance if it is changed or if more data is added because of the data quality, disease severity, and leaf colour.
2. Similar visual symptoms may create confusion for the model image classification. Due to this, further data and model optimization I s need ot incorporated in the future for better results.
3. The interpretability of the XAI-based method, such as GRAD-CAM, SHAP, and LIME, has limitations, such as the explanation of important image regions.
   Having no guarantee that the model is deciding as a human expert does.

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Annexure(A)

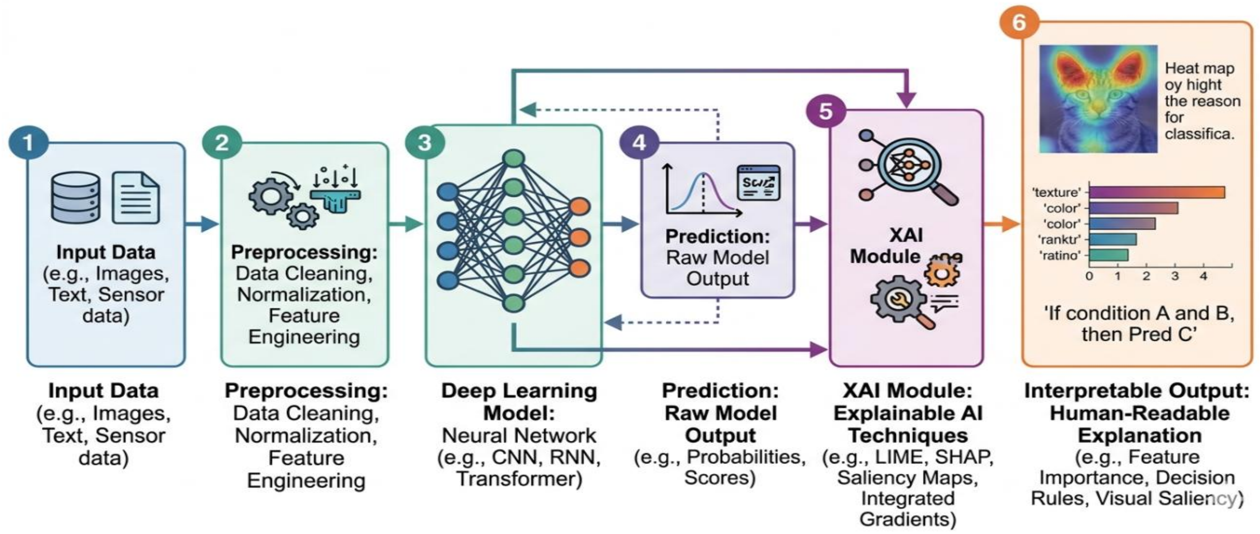

Figure 3: Step-by-step workflow of the study

Annexure(B)

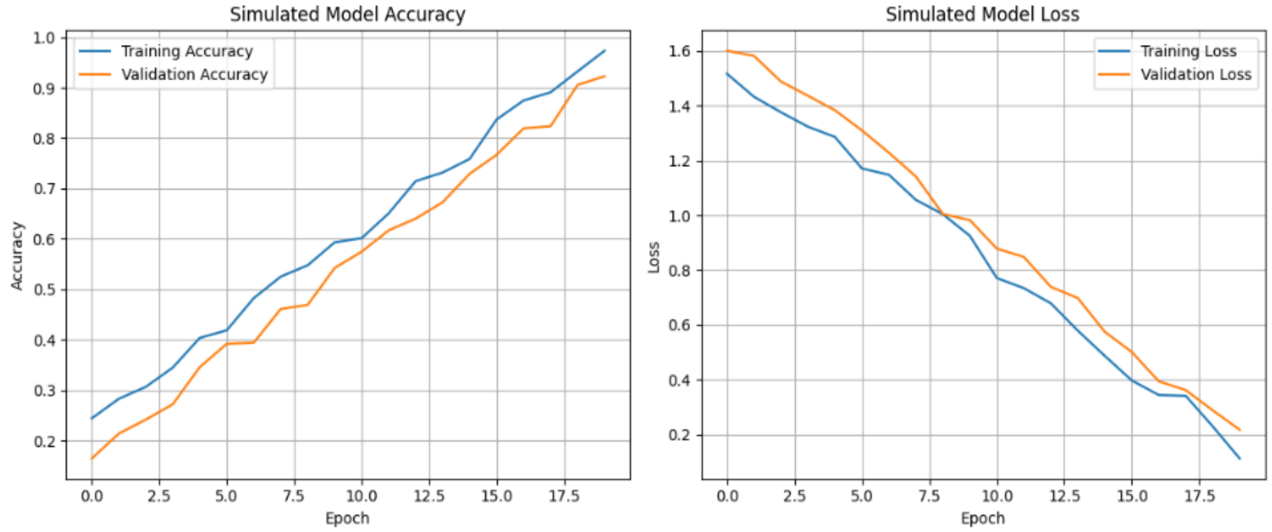

Figure 4: Figure Simulated Model Accuracy vs Loss graph