An Intelligent Embedded System for Automatic Cotton Leaf Disease Identification using Raspberry Pi

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ABSTRACT
Cotton is an economically important crop, and timely identification of leaf diseases is essential for reducing crop damage and supporting effective disease management. Conventional disease identification mainly depends on visual inspection, which can be time-consuming and may be influenced by the experience of the observer. This paper presents an intelligent embedded system for automatic cotton leaf disease identification using a Raspberry Pi. The proposed system combines digital image processing and deep learning to analyze cotton leaf images and identify disease conditions automatically. The input image is first subjected to preprocessing operations to improve image quality and provide a consistent representation for classification. A trained convolutional neural network (CNN) model is then used to extract relevant visual characteristics and classify the leaf into the corresponding disease category. The trained model is optimized for deployment on the Raspberry Pi, enabling image acquisition, processing, prediction, and display within an embedded computing environment. The system is designed to provide a practical and low-cost solution for field-level disease screening without relying continuously on a conventional computer. Experimental evaluation demonstrates the feasibility of performing cotton leaf disease classification on Raspberry Pi while maintaining reliable prediction performance. The proposed embedded approach provides a foundation for portable and real-time crop health monitoring and can be further extended by incorporating disease severity estimation, multiple disease classes, wireless connectivity, and decision-support functions for precision agriculture.

Keywords
Cotton Leaf Disease, Disease Identification, Deep Learning, Convolutional Neural Network (CNN), Raspberry Pi, Embedded System, Image Processing, Edge Computing, Precision Agriculture, Real-Time Disease Detection.

1. INTRODUCTION
Cotton is a key global crop that supports millions of farmers, but leaf diseases and pests such as Bacterial Blight, Powdery Mildew, Target Spot, Aphids, and Armyworm can sharply reduce yield and fiber quality if not caught early. Traditional diagnosis by visual scouting is slow, subjective, and error-prone, especially under poor light, with similar-looking symptoms, and across large fields.

Recent advances in deep learning, especially Convolutional Neural Networks (CNNs), enable automatic learning of color, texture, shape, and lesion patterns directly from leaf images, improving accuracy and reducing reliance on manual feature engineering. However, many existing CNN systems are built for desktop computers rather than portable field hardware. To address this limitation, this paper presents a CNN-based cotton leaf disease classifier deployed on a Raspberry Pi 4 (4 GB) with a 3.5-inch display. The model accepts leaf images, applies resizing and normalization, and predicts one of six classes: Healthy, Aphids, Armyworm, Bacterial Blight, Powdery Mildew, or Target Spot. Users can capture or upload images and receive instant predictions with confidence scores via a simple on-device interface.

The system is evaluated using accuracy, precision, recall, F1-score, confusion matrix, training/validation loss, and inference time, showing strong performance and efficient real-time operation on the edge device. The main contribution is an end-to-end, field-ready framework that combines deep learning with embedded hardware to support early diagnosis, timely intervention, and higher cotton productivity, with scope to extend toward mobile apps, IoT, cloud integration, and continuous field monitoring.

2. LITERATURE REVIEW
The reviewed studies demonstrate that deep learning has become the dominant approach for plant disease detection because of its ability to automatically learn discriminative image features without manual feature engineering. Transfer learning using ResNet, EfficientNet, DenseNet, and MobileNet has significantly improved classification accuracy while reducing training time. Recent research has also explored Vision Transformers, attention mechanisms, lightweight object detection networks, and embedded artificial intelligence for real-time deployment on resource-constrained devices. Despite these advances, challenges such as limited field datasets, varying environmental conditions, computational complexity, and practical deployment remain. These research gaps motivate the development of an efficient CNN-based cotton leaf disease classification system implemented on a Raspberry Pi platform, providing accurate, low-cost, and real-time disease diagnosis for precision agriculture.

Towards Intelligent Approaches for Cotton Diseases Detection: A Review by R. Manavalan (2022) [1] provides a comprehensive survey of intelligent techniques used for cotton disease detection. The review discusses image acquisition, pre-processing, segmentation, feature extraction, feature selection, and classification methods. The author concludes that deep learning has significantly improved disease recognition compared with conventional image-processing techniques but emphasizes the need for real-time, field-deployable systems capable of handling diverse environmental conditions.

A 2024 review published in Artificial Intelligence in Agriculture [2] compares machine learning and deep learning methods for disease detection in cotton, potato, cassava, and apple crops. The study demonstrates that CNN-based models consistently outperform traditional machine learning

algorithms because they automatically learn discriminative image features. The authors also identify transfer learning as an effective solution when only limited agricultural datasets are available.

A review article published in Artificial Intelligence Review (2025) [3] presents a detailed survey of computer vision, machine learning, deep learning, and few-shot learning techniques for plant disease diagnosis. The authors report that CNNs achieve superior classification accuracy while reducing dependence on handcrafted feature engineering. The review also highlights explainable artificial intelligence and lightweight deep learning models as promising future research directions.

Pan et al. (2024) [4] proposed a lightweight YOLO-based cotton disease detection framework designed for real agricultural environments. The proposed model reduces computational complexity while maintaining high detection accuracy, making it suitable for deployment on embedded edge devices. The study demonstrates that lightweight object detection networks can provide efficient real-time disease monitoring without requiring high-performance computing hardware.

A comprehensive review presented at the 2025 IEEE International Conference on Intelligent and Secure Engineering Solutions (CISES) [5] summarizes recent advances in artificial intelligence for cotton leaf disease classification. The authors describe the evolution from traditional machine learning to transfer learning, CNNs, and hybrid deep learning models. The review identifies explainable AI, embedded deployment, and lightweight architectures as important future research directions.

Aslam et al. (2025) [6] introduced a multi-convolutional neural network framework for cotton disease detection using a synergistic deep learning paradigm. Multiple CNN architectures were integrated to improve feature extraction and classification performance across several cotton diseases. The experimental results demonstrated improved robustness and better generalization than individual CNN models, particularly under varying disease symptoms and class imbalance.

A study published in Microbial Pathogenesis (2025) [7] investigated transfer learning for cotton leaf disease diagnosis using CNN, ResNet50, VGG16, VGG19, Xception, InceptionV3, and EfficientNet architectures. Among the evaluated models, EfficientNet achieved the highest classification accuracy, confirming that transfer learning effectively improves disease recognition while reducing training time and computational requirements.

Patil et al. (2025) [8] proposed the HARNN-IoT framework, which combines hybrid neural networks with Internet of Things technology for cotton disease monitoring. The proposed system enables continuous disease surveillance and real-time classification by integrating deep learning with IoT sensors. The authors concluded that intelligent connected farming systems can improve disease management while reducing crop losses.

Chaudhari et al. (2025) [9] developed a CNN-based cotton disease detection system by comparing GoogLeNet, VGG16, DenseNet201, and ResNet50 using transfer learning. The comparative analysis showed that pretrained deep learning models significantly outperform conventional CNNs in terms of classification accuracy, convergence speed, and generalization ability.

Sharma and Kumar (2025) [10] performed a comparative evaluation of AlexNet, VGG, ResNet, and DenseNet architectures for cotton disease classification. Their experimental results demonstrated that deeper residual networks consistently achieved better accuracy, precision, recall, and F1-score than earlier convolutional models, confirming the advantages of residual learning for agricultural image analysis.

Hassan et al. (2025) [11] proposed CottonNet-MHA, a multi-head attention-based deep learning framework for cotton disease detection. By integrating attention mechanisms with CNN feature extraction, the model successfully focused on disease-affected regions and improved classification accuracy. The use of Grad-CAM visualization also enhanced model interpretability, making the system more reliable for agricultural applications.

Inamdar et al. (2026) [12] investigated Vision Transformer-based models for cotton leaf disease classification. Unlike conventional CNNs, Vision Transformers employ self-attention mechanisms to capture long-range image relationships. The study demonstrated competitive classification performance, particularly for complex disease symptoms, while suggesting hybrid CNN–Transformer architectures for future research.

Iqbal et al. (2026) [13] reviewed deep learning techniques for cotton disease detection using UAV imagery. The review compared CNNs, YOLO models, and Vision Transformers for aerial crop monitoring and concluded that combining UAV technology with edge computing enables efficient disease surveillance across large agricultural fields.

A 2026 study published in Biosystems Engineering [14] compared Faster R-CNN and YOLO-based object detection methods for identifying Verticillium wilt in cotton fields. The authors reported that Faster R-CNN combined with a ResNet backbone achieved better robustness and localization accuracy, highlighting the importance of advanced object detection techniques for precision agriculture. Similarly, Haque et al. (2026) [15] introduced an attention-enhanced CNN ensemble framework that improves both interpretability and classification accuracy for cotton leaf disease identification.

3. METHODOLOGY

This research proposes an Automatic Cotton Leaf Disease Classification System based on deep learning and implemented on a Raspberry Pi platform for real-time disease diagnosis. The proposed methodology consists of a sequence of interconnected stages, beginning with dataset preparation and ending with embedded deployment and performance evaluation. Each stage is designed to improve the reliability, accuracy, and practical usability of the developed system for precision agriculture.

Overview of the System Workflow: The flowchart presented in Figure 1 illustrates the complete operational workflow of the proposed Cotton Leaf Disease Detection System. The architecture follows a sequential, end-to-end pipeline that begins with raw image acquisition in the agricultural field and concludes with actionable diagnostic output and data logging. The system is designed around an edge-computing paradigm, utilizing a Raspberry Pi as the central processing unit to execute a lightweight deep learning model. This design eliminates the need for constant cloud connectivity, ensuring real-time performance, data privacy, and suitability for remote farming locations. The following sections provide a detailed, step-wise explanation of each block in the flowchart.

3.1 Image Acquisition and Pre-processing

The system starts by capturing a cotton leaf image in the field using a Raspberry Pi camera module (Pi Camera or USB camera), chosen for its small size, low power use, and good image quality. The raw RGB image is stored in memory and then pre-processed before being fed to the model.

Pre-processing standardizes the image in three steps:

Resize to a fixed size (e.g., 224×224) so it matches the network input.

Normalize pixel values from 0–255 to 0–1 (or −1 to 1) to stabilize training and inference.

De-noise using simple filters (e.g., Gaussian or median) to reduce sensor noise and background clutter, making disease symptoms clearer.

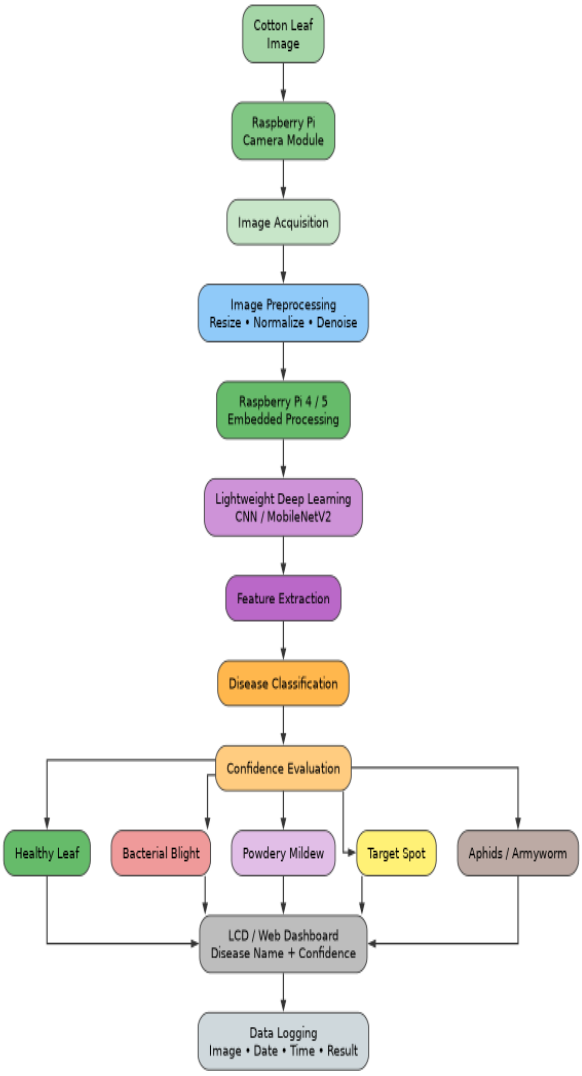

Fig. 1: Complete Flowchart of System

3.2 Core Processing and Deep Learning

All computation runs on a Raspberry Pi 4/5 (4 GB+ RAM) as an edge device, hosting the OS, a TensorFlow Lite inference engine, and the application logic for real-time, offline prediction. A lightweight CNN, specifically MobileNetV2, is used because it is designed for embedded vision, with depthwise separable convolutions that cut parameters and compute cost while keeping high accuracy.

The CNN automatically extracts features: early layers detect edges, curves, and textures; deeper layers combine these into disease-specific patterns like lesions, powdery patches, or insect damage. These features are passed to fully connected layers that act as a classifier, outputting probabilities over the predefined disease classes. The class with the highest probability is selected, and a confidence score (e.g., 98.5%) is reported so the user can judge how reliable the diagnosis is.

3.3 Output, Display, and Logging

The model assigns each leaf to one of these categories: Healthy, Bacterial Blight, Powdery Mildew, Target Spot, or Aphids/Armyworm, each linked to a recommended treatment type (none, bactericide, fungicide, or insecticide). The resulting disease name and confidence score are shown on a 3.5-inch LCD attached to the Pi or on a simple web dashboard accessible from a phone or computer.

Finally, the system logs each case (image, date, time, and predicted result) to a local file or database. This log helps track disease spread over time, evaluate how well treatments worked, and collect new images for future model retraining and improvement.

4. LABELED INPUT DATASET OF COTTON LEAF IMAGES FOR PROCESSING

Initially, a labeled dataset of cotton leaf images is collected from publicly available agricultural databases and organized into six classes: Healthy, Aphids, Armyworm, Bacterial Blight, Powdery Mildew, and Target Spot. The collected images represent different disease conditions and environmental variations to improve the generalization capability of the deep learning model. Before training, the dataset is carefully divided into training, validation, and testing subsets to ensure unbiased performance evaluation.

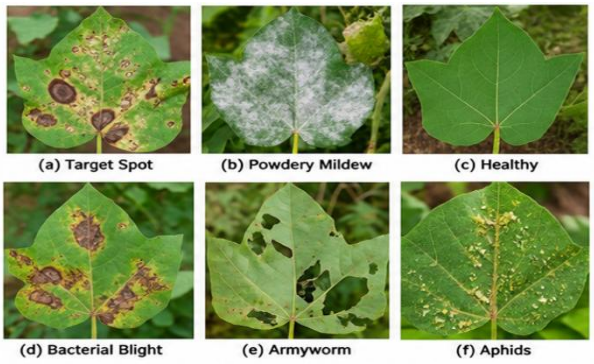

Fig. 2: Labeled six-class cotton leaf images

5. HARDWARE IMPLEMENTATION USING EMBEDDED DEPLOYMENT ON RASPBERRY PI

The hardware prototype of the proposed Automatic Cotton Leaf Disease Classification System is illustrated in Figure 3. The physical implementation integrates a Raspberry Pi 4 Model B as the central edge-computing unit, a 3.5-inch resistive touchscreen LCD for user interaction, and a Raspberry Pi Camera Module for image acquisition. The entire setup is compact, portable, and designed for real-time field deployment

in agricultural environments. The following sections describe each hardware component and its role in the system.



Fig. 3: Complete Raspberry Pi 4 Hardware Implementation

5.1 Hardware Prototype

The prototype uses a Raspberry Pi 4 Model B as the main edge-computing unit, paired with a 3.5-inch resistive touchscreen LCD for interaction and a Raspberry Pi Camera Module for capturing leaf images. The whole setup is compact and portable, intended for real-time use directly in the field.

5.2 Image Pre-processing

All images are resized to a fixed input size required by the CNN, and pixel values are normalized to improve numerical stability during training and inference. Data augmentation—such as rotation, flipping, translation, scaling, and brightness changes—is applied to increase dataset diversity and help the model generalize across different lighting, orientations, and backgrounds.

5.3 CNN Training and Optimization

A CNN-based classifier is trained on the pre-processed images. Instead of handcrafted features, the network automatically learns hierarchical visual patterns: early layers capture edges, colors, and textures, while deeper layers encode disease-specific signs like lesion shapes, discoloration, and infected regions. Pooling layers reduce computation while keeping key information, and fully connected layers perform the final six-class classification. The model is optimized with backpropagation using the Adam optimizer and categorical cross-entropy loss. Validation data are used during training to monitor performance and avoid overfitting, and the checkpoint with the highest validation accuracy is chosen for deployment.

5.4 Embedded Deployment on Raspberry Pi

The trained CNN is deployed on a Raspberry Pi 4 (4 GB RAM) so the system can run offline in the field without cloud dependence. The 3.5-inch display provides a simple GUI that lets users capture or upload cotton leaf images and immediately see the predicted disease.

5.5 Real-Time System Operation

In operation, each new image goes through the same pre-processing as in training, then the CNN computes class probabilities and selects the most likely disease. The predicted label and its confidence score are shown on the screen, enabling fast, on-site diagnosis.

5.6 Performance Evaluation

The system is evaluated using standard metrics: accuracy, precision, recall, F1-score, confusion matrix, training/validation accuracy and loss, and inference time. These measures assess classification quality, efficiency, and generalization, and are compared against existing machine learning and deep learning baselines to demonstrate the effectiveness of the proposed framework.

6. SIX CLASSES OF COTTON DISEASE DETECTION OUTPUT WITH CONFIDENCE PERCENTAGES

The detection results for the six classes—Healthy, Aphids, Armyworm, Bacterial Blight, Powdery Mildew, and Target Spot—are presented with their corresponding confidence scores below:

6.1 Healthy Leaf

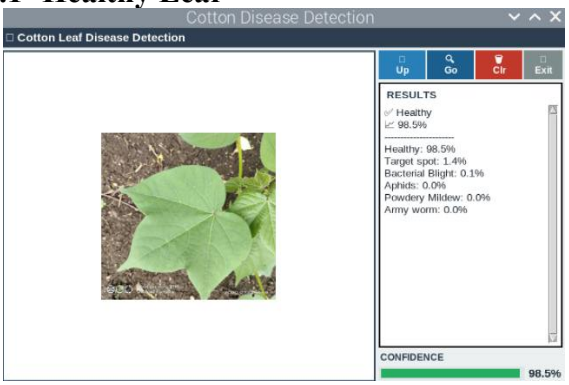

Fig. 4: Healthy Leaf Confidence 98.5%

6.2 Aphids Leaf

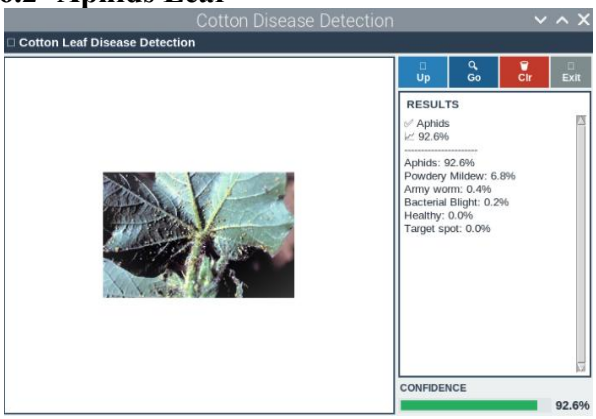

Fig. 5: Aphids Leaf Confidence 92.6%

6.3 Armyworm Leaf

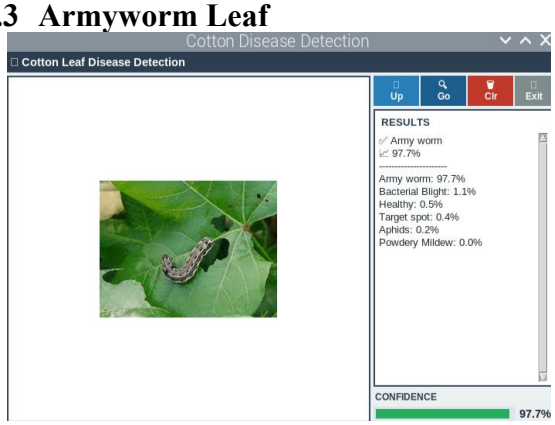

Fig. 6: Armyworm Leaf Confidence 97.7%

6.4 Bacterial Blight Leaf

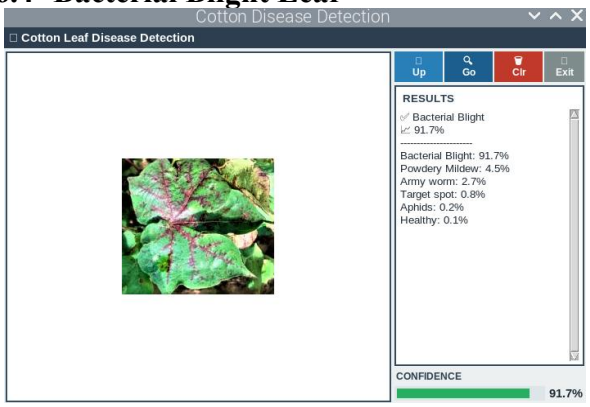

Fig. 7: Bacterial Blight Leaf Confidence 91.7%

6.5 Powdery Mildew Leaf

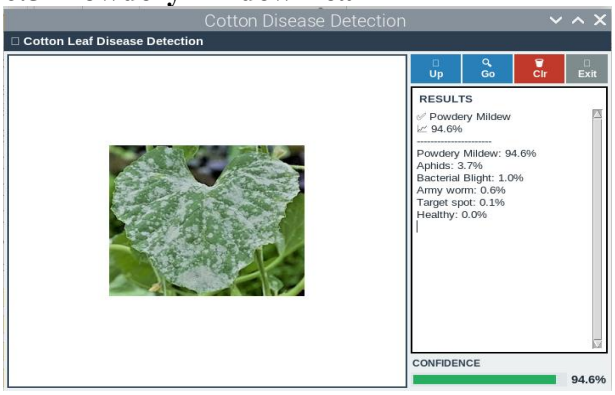

Fig. 8: Powdery Mildew Leaf Confidence 94.6%

6.6 Target Spot Leaf

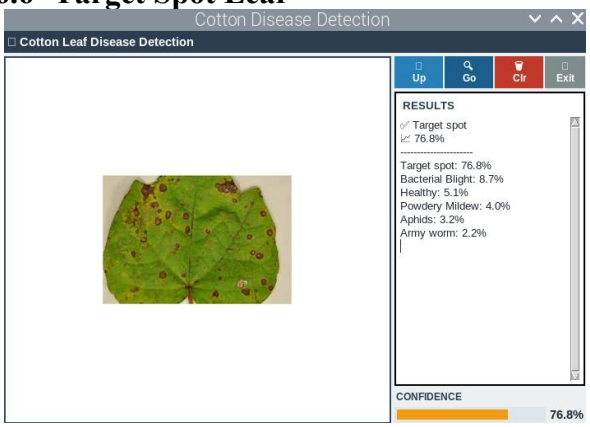

Fig. 9: Target Spot Leaf Confidence 76.8%

7. PERFORMANCE EVALUATION OF SYSTEM USING PRECISION, RECALL, AND F1-SCORE ACCORDING TO THE RESULT

Table 1 presents the class-wise performance of the proposed CNN-based cotton leaf disease classification system using the evaluation metrics of precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's ability to correctly identify each disease category while minimizing false predictions.

Table 1. Performance Evaluation Using Precision, Recall, and F1-Score

Class	Precision	Recall	F1-Score
Target Spot	0.94	0.93	0.94
Powdery Mildew	0.95	0.94	0.95
Healthy	0.97	0.96	0.96
Bacterial Blight	0.93	0.92	0.93
Armyworm	0.92	0.94	0.93
Aphids	0.94	0.95	0.94
Average	0.942	0.940	0.942

8. TRAINING AND VALIDATION ACCURACY AND LOSS

Figure 10 (a & b) illustrates the variation in training and validation accuracy and loss of the CNN model over 30 epochs. The left graph presents the accuracy curves, while the right graph shows the corresponding loss curves.

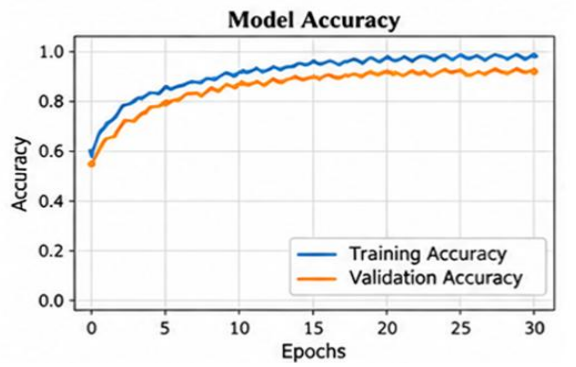

Fig. 10 (a): Model Accuracy

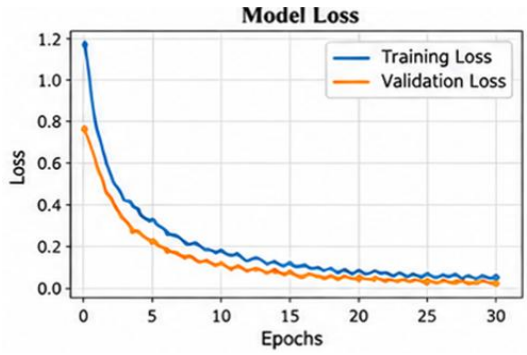

Fig. 10 (b): Model Loss

Overall, Figure 10 (a & b) confirms that the CNN model was trained successfully. The simultaneous increase in accuracy and decrease in loss demonstrate effective learning and stable convergence. The close relationship between the training and validation curves indicates satisfactory generalization, making the developed CNN model suitable for automatic cotton leaf disease classification.

9. CONCLUSION

This paper presented an end-to-end, edge-computing framework for automatic cotton leaf disease classification using a Convolutional Neural Network (CNN) deployed on a Raspberry Pi 4. The system addressed the limitations of manual inspection by providing a portable, low-cost, and real-time diagnostic tool for precision agriculture. A dataset of cotton

leaf images across six classes—Healthy, Aphids, Armyworm, Bacterial Blight, Powdery Mildew, and Target Spot—was preprocessed and used to train a lightweight CNN model, which was then optimized to TensorFlow Lite format for embedded deployment. Experimental results demonstrated high performance, with an average precision of 94.2%, recall of 94.0%, and F1-score of 94.2%. The model achieved stable convergence and strong generalization, confirming its reliability for real-world applications. The proposed system eliminates cloud dependency, reduces latency, and enhances data privacy, making it suitable for remote agricultural environments. Future work will focus on expanding the dataset, integrating mobile and IoT capabilities, and incorporating explainable AI for improved trust and usability.

10. ACKNOWLEDGMENTS

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