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Deep Learning Approach for Cotton Plant Disease Identification and Severity Evaluation

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Abstract: Cotton productivity plays a crucial role in the global agricultural economy; however, various leaf diseases significantly threaten crop yield and fiber quality. Early and accurate disease detection is essential for effective crop management, yet traditional inspection methods are time-consuming, labor-intensive, and dependent on expert knowledge, often leading to inconsistent results. Conventional machine learning approaches also face limitations in real-world agricultural environments due to variations in lighting conditions, complex backgrounds, and similarities between disease symptoms. To address these challenges, this research proposes an intelligent framework called Cotton Plant Disease Identification Using ResMobNet with Attention-Guided Localization and Severity Analysis (CPDI-RMN).

The proposed system integrates advanced image preprocessing, hybrid feature extraction, deep learning classification, and attention-based localization to create a comprehensive disease detection framework. Initially, cotton leaf images are collected from a comprehensive dataset and preprocessed through image resizing, noise removal, contrast enhancement, and Min–Max normalization to improve visual quality and ensure stable model training. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied to enhance dataset diversity and improve model robustness against overfitting.

For feature enhancement, contour visualization and geometric feature representation are combined with texture analysis using the Gray-Level Co-occurrence Matrix (GLCM) and Laplacian filtering. The core of the framework is the ResMobNet hybrid architecture, which integrates ResNet-50, EfficientNet-B3, and MobileNet-V2 to capture multi-scale spatial and texture features while maintaining computational efficiency. Gradient-Weighted Class Activation Mapping (Grad-CAM) is employed to generate attention maps for disease localization, followed by segmentation to isolate infected regions. Disease severity is then quantified by calculating the percentage of infected leaf area and classifying it into mild, moderate, and severe categories. Experimental results using five-fold cross-validation demonstrate that the CPDI-RMN model achieves 98.85% classification accuracy, outperforming CNN, ANN, ResNet, and MobileNetV2 models. Additionally, the attention-based localization achieves 96.8% Intersection over Union and 98.0% Dice Score, indicating highly accurate disease region detection. Overall, the proposed framework provides a reliable and scalable solution for intelligent cotton disease monitoring and supports precision agriculture through data-driven crop management.

Keyword: ResMobNet, CNN, ANN, Gradient-Weighted Class Activation Mapping, Gray-Level Co-occurrence Matrix, Attention-Guided Localization and Severity Analysis.

I. INTRODUCTION

A. Overview

Cotton isn’t just another crop—it’s a lifeline for millions of farmers around the world. Every year, people plant, tend, and harvest cotton, and those fluffy white fibers end up everywhere, from your favorite T-shirt to the towels in your bathroom. Beyond clothing, cotton shapes entire economies, especially in developing countries.

It gives people jobs—not just in the fields, but also in factories, spinning mills, and textile plants. It’s a big deal for rural communities and global trade.

But growing cotton isn’t easy. The plants face a constant battle with diseases. Fungi, bacteria, and viruses are always lurking, waiting for a chance to strike. When they do, the results aren’t pretty—plants might stop growing, their leaves yellow and curl, and the cotton fibers can turn out weak or unusable. When disease hits hard, harvests shrink and farmers lose out.

B. Types of Cotton Diseases

Cotton plants are prone to various bacteria, fungi and virus diseases. There are five prevalent cotton diseases as discussed below

1) Bacterial Blight

Figure 1 Cotton leaves affected by Bacterial Blight showing dark spots and wilting.

2) Fusarium Wilt

Figure 2 shows Cotton plant infected with Fusarium Wilt Fusarium wilt is a fungal infection that is caused by Fusarium oxysporum vasinfectum

Figure 2 Cotton plant infected with Fusarium Wilt

3) Verticillium Wilt

Figure 3 Cotton plant showing Verticillium Wilt with leaf yellowing and wilting.

Fig 3 shows Verticillium wilt is caused by verticillium dahliae. The fungus invades the roots and vascular tissues of the cotton plants.

4) Root Rot

Figure 4 Cotton plant affected by Root Rot

Figure 4 shows Root rot is a soil-borne fungus caused by *Rhizoctonia solani and Pythium species*. It mostly attacks young seedlings and roots. Symptoms are brown or blackening of roots, retarded growth, wilting, and eventual death of the plant. The severity of the disease is usually increased by waterlogged soils and poor drainage conditions.

5) Cotton Leaf Curl Disease (CLCuD)

Figure 5 Cotton leaves affected by Cotton Leaf Curl Disease

Figure 5 shows the *begomovirus* is the cause of cotton leaf curl disease which is transmitted by whiteflies. It impacts the leaves, stems and bolls of the plant. The symptoms are curling, thickening, distortion of leaves, retarded growth of plants and decreased development of bolls. Unless it is managed in a proper way, this viral disease can lead to huge losses in cotton production [1].
Traditionally, spotting disease has meant walking the fields and checking plants by eye. Farmers or experts look for yellow patches, spots, weird leaf shapes—anything out of the ordinary. While this old-school approach has worked for generations, it's far from perfect. It takes a lot of time and effort, and even the best observers can miss early warning signs, especially when symptoms are faint. On big farms, checking every plant is almost impossible. Sometimes, people make mistakes—misidentifying a disease can lead to the wrong pesticide, wasted money, and even harm to the environment [2].

Now, things are changing. Artificial intelligence, machine learning, and deep learning are opening up new ways to spot plant diseases automatically. Computers can analyze images of cotton leaves, pick up on patterns, and identify diseases with impressive accuracy. Machine learning models like Support Vector Machines and Random Forests do a decent job by looking at features like color and texture, but they still need humans to tell them what to look for [3].

Deep learning, especially with Convolutional Neural Networks (CNNs), takes things further. These models learn directly from images, catching even the tiniest signs of disease that people might miss. Pre-trained networks like ResNet, MobileNet, and EfficientNet—thanks to transfer learning—can classify diseases accurately, even when there aren't tons of images to train on [4].

This study jumps in right here. The goal is to build a smart, deep learning–based system that can automatically detect cotton plant diseases and figure out how severe they are. By combining sharp image preprocessing, texture analysis, and advanced CNN models, the system aims to boost accuracy and catch problems early. Tools like this can help farmers keep a closer eye on their crops, cut losses, and support more sustainable, efficient agriculture by catching diseases before they get out of hand.

II. PROPOSED METHODOLOGY

The Cotton Plant Disease Identification framework (CPDI-RMN) assists in detecting, identifying, and assessing the severity of diseases on cotton leaves using deep learning. Initially, it processes a set of cotton leaf images from a large dataset, performing preprocessing steps such as resizing, removing Gaussian noise, enhancing contrast through histogram equalization, and normalizing the data with Min–Max scaling. Next, data augmentation is applied, incorporating rotations, flips, zooms, and brightness adjustments to expand the dataset and improve the model's ability to handle various real-world scenarios [5].

For feature extraction, the system combines contour–geometric features with GLCM-Laplacian texture analysis. This approach captures not only the changes in shape but also the subtle texture variations caused by diseases. These extracted features are then input into the ResMobNet ensemble, which integrates ResNet-50, EfficientNet-B3, and MobileNet-V2, enabling the model to learn from a wide range of disease patterns, both prominent and subtle. To localize infected areas, Grad-CAM highlights the affected regions. Finally, the framework evaluates the severity of the infection by measuring the infected area on each leaf. following steps are involved [6].

A. Data Collection

Initially the input data is gathered from A comprehensive Dataset of Cotton Plant Disease Identification and Treatment and Guidance a curated collection of images created to aid with the correct identification and classification of cotton leaf diseases.

B. Preprocessing

Data preprocessing is an important aspect that can enhance the quality of images and ensure stable learning performance for deep learning models. The collected images of the cotton leaf undergo rigorous preprocessing techniques such as image resizing, noise elimination, contrast enhancement, and normalization [7].

1) Image Resizing: To guarantee a constant input size for the deep learning model, all cotton leaf images are reduced to a fixed resolution of 224 × 224 pixels due to variations in spatial dimensions
2) Noise Removal Using Gaussian Filtering: Following resizing Gaussian filtering is used to eliminate noise produced during image acquisition such as sensor noise and illumination variations. Gaussian filtering reduces the image by convolution using a gaussian kernel efficiently decreasing high frequency noise while retaining important structure information.
3) Contrast Enhancement Using Histogram Equalization: To enhance the visibility of patterns and texture information, histogram equalization is performed on the denoised images. Histogram equalization is a technique used to enhance the contrast of images by altering the intensity values of pixels
4) Min-Max Normalization: Finally, Min-Max normalization is used to scale pixel intensity data to a specific range, typically $[b, a]$ where $b = 0$ and $a = 1$. This normalization improves numerical stability and accelerates convergence during deep learning model training

C. Data Augmentation

To improve the robustness of the model, overcome class imbalance issues, and boost the generalization ability of the model, a set of data augmentation operations are performed on the cotton leaf images during the training process.

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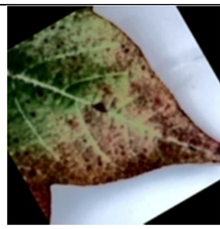
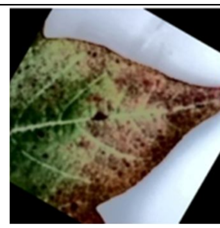
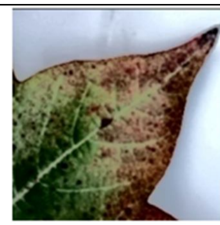
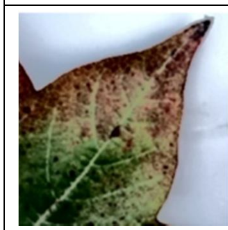
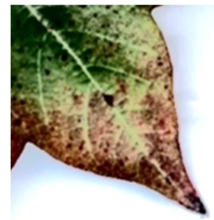
Table 1 Input and Output Images after Data Augmentation

Input	Rotate 30	Rotate 60	Rotate 90	Horizontal Flipping
				
Vertical Flipping	Both	Zoom	Brightness 0.7	Brightness 1.3
				

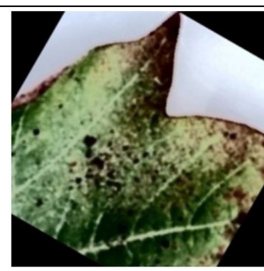
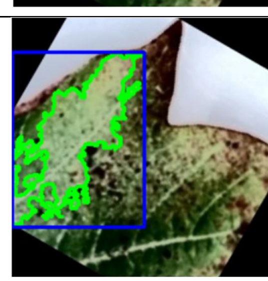
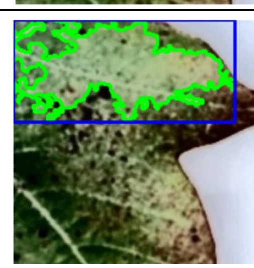
D. Feature Extraction

Feature extraction is a process of finding the most informative visual features from the augmented images of the cotton leaves to enable accurate disease classification. After the augmentation process, the images have varied spatial, structural, and texture features that need to be measured efficiently.

1) Contour and Geometric Feature Visualization

Contour and geometric feature visualization is utilized to identify the leaf borders and identify the disease affected regions inside the leaf. By isolating the leaf shape from the background and assessing border abnormalities this approach clearly displays the regions where disease symptoms affect the leaf inherent geometry [8].

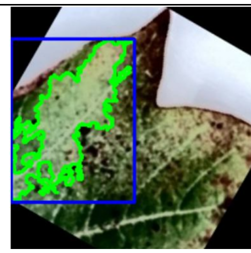
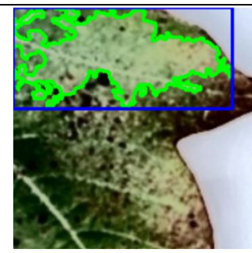
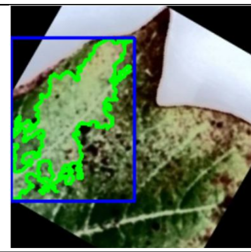
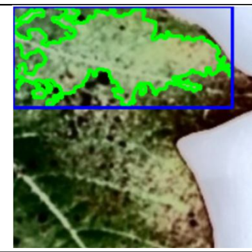
Table 2 Input and Output Images after Contour and Geometric Feature Visualization

Feature Extraction	Contour and Geometric Feature Visualization		
Input Images			
Output Images			

2) GLCM with Laplacian Texture Overlay

While contour analysis concentrates on specific disease locations the GLCM with Laplacian texture overlay improves overall image texture by combining statistical texture connections with fine structural detail.

Table 3 Input and Output Images After GLCM with Laplacian Texture Overlay

Feature Extraction	GLCM + Laplacian Texture Overlay		
Input Images			
Output Images			

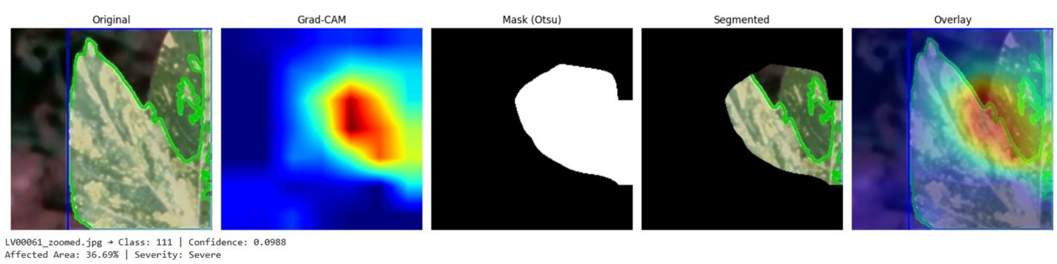
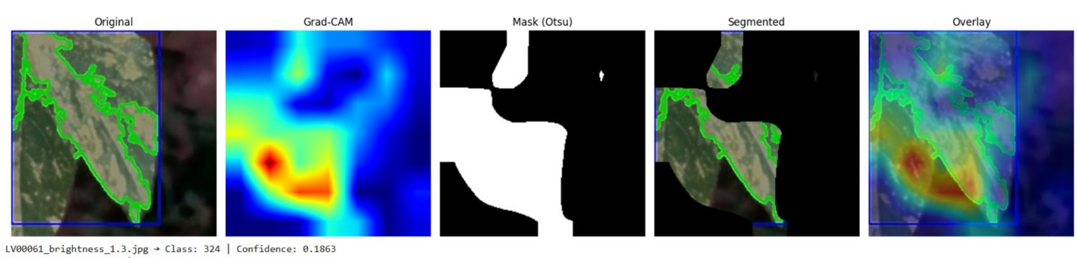
3) Disease Localization

After determining whether a cotton leaf is diseased or healthy using the proposed ResMobNet model the next essential step is to localize the specific affected patches on the leaf surface. Because pixel-level annotations are nor available the Gradient-Weighted Class Activation Mapping (Grad-CAM) method is used for weakly supervised disease localization.

E. Infected Region Segmentation

After disease localization with the Grad-CAM approach the resulting heatmap indicates that have a significant impact on disease prediction. To precisely segment infected patches from the leaf surface the Grad-CAM heatmap is converted into a binary infection mask. This phase allows for the accurate separation of sick areas from healthy tissue without requiring pixel-level ground truth annotations.

Table 4 Input and Output After Segmentation

Input Image	
Output Image	

F. Affected Area Percentage Calculation

Based on the accurate segmentation of the infected areas, the severity of the disease is then measured by determining the percentage of the leaf area that is infected. This is done by overlaying the infected area mask with the leaf mask, such that only the infected areas within the leaf area are taken into account.

G. Disease Severity Level Estimation

After disease localization and segmentation of the infected region, the subsequent phase involves disease severity analysis, which measures the severity level of the cotton leaf infection. This phase is very essential in determining the progression of infection and hence agricultural decision-making. Table 5 illustrate the performance results of the proposed CPDI-RMN method. It also shows metrics being compared to existing methods such as, CNN, ResNet, ANN and MobileNetV2 respectively.

III. RESULT AND DISCUSSION

Here we describe the actual findings of the projected CPDI-RMN. Several performance parameters were assessed, including accuracy, precision, F1-score, sensitivity, specificity, NPV, MCC, FPR, and FNR. The performance of the proposed CPDI-RMN is compared with existing approaches such as CNN, ResNet, ANN and MobileNetV2. Table 3.9 shows the experimental setup for the proposed model.

Table 5 Five-fold cross-validation accuracy comparison between existing and the proposed approaches

Methods	Fold-1 (%)	Fold-2 (%)	Fold-3 (%)	Fold-4 (%)	Fold-5 (%)	Mean Accuracy (%)
CNN	94.1	95.2	94.75	95.05	95.15	94.85
ResNet	96	96.85	96.3	96.55	96.3	96.4
ANN	92.1	93.4	92.65	92.9	92.7	92.75
MobileNetV2	96.75	97.45	97.05	97.3	96.95	97.1
Proposed	98.4	99.05	98.7	99.1	98.95	98.85

The five-fold cross-validation accuracy comparison for cotton plant disease classification is shown in Table 3.10. The Proposed model performs the best in all folds with 98.4%, 99.05%, 98.7%, 99.1%, and 98.95% accuracy, and has the best mean accuracy of 98.85%. MobileNetV2 comes next with 96.75%, 97.45%, 97.05%, 97.3%, and 96.95% accuracy in all folds, giving a mean accuracy of 97.1%. ResNet gives a mean accuracy of 96.4%, while CNN and ANN give 94.85% and 92.75% mean accuracy, respectively. The results show that the Proposed method is capable of providing stable and accurate performance for cotton leaf disease classification.

The proposed CPDI-RMN model always performs better than the existing approaches for all evaluation metrics, datasets, and validation methods. This makes it highly accurate, with minimal error rates, and a strong generalization capability to ensure the reliability of the model for accurate cotton leaf disease detection and severity assessment.

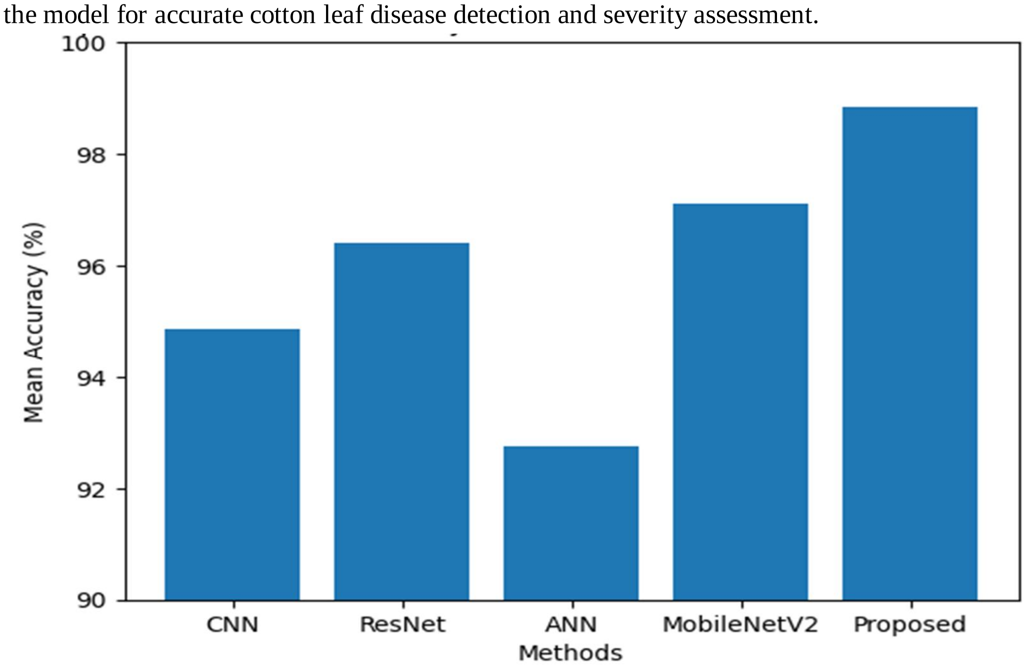


Figure 6 Comparison of Mean Accuracy Across Models for Cotton Disease Detection

REFERENCES

[1] S. Chohan, R. Perveen, M. Abid, M. N. Tahir, and M. Sajid, “Cotton Diseases and Their Management,” Springer Singapore, 2020, pp. 239–270. doi: 10.1007/978-981-15-1472-2_13.

[2] A. A. Alatawi, S. M. Alomani, N. I. Alhawiti, and M. Ayaz, “Plant Disease Detection using AI based VGG-16 Model,” IJACSA, vol. 13, no. 4, Jan. 2022, doi: 10.14569/ijacsa.2022.0130484.

[3] R. Sujatha, S. Krishnan, J. M. Chatterjee, and A. H. Gandomi, “Advancing plant leaf disease detection integrating machine learning and deep learning,” Sci Rep, vol. 15, no. 1, Apr. 2025, doi: 10.1038/s41598-024-72197-2.

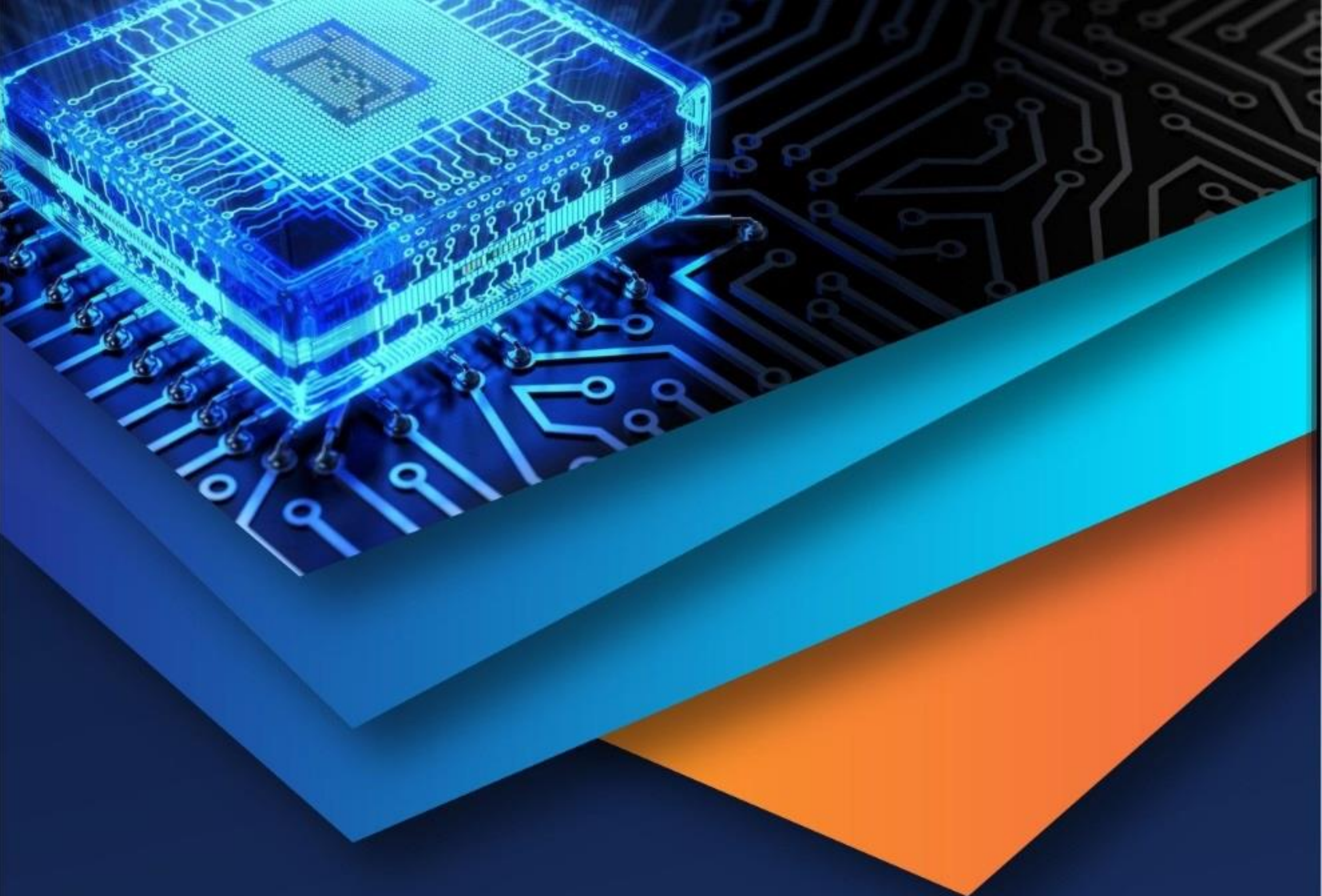
[4] Ö. Özaltın, “Early Detection of Alzheimer’s Disease from MR Images Using Fine-Tuning Neighborhood Component Analysis and Convolutional Neural Networks,” Arab J Sci Eng, vol. 50, no. 10, pp. 7781–7800, Jan. 2025, doi: 10.1007/s13369-024-09954-y.

[5] P. Bishshash, A. S. Nirob, H. Shikder, A. H. Sarower, T. Bhuiyan, and S. R. H. Noori, “A comprehensive cotton leaf disease dataset for enhanced detection and classification,” Sept. 10, 2024, Elsevier. doi: 10.1016/j.dib.2024.110913.

[6] P. Johri et al., “Advanced deep transfer learning techniques for efficient detection of cotton plant diseases.,” Front. Plant Sci., vol. 15, Dec. 2024, doi: 10.3389/fpls.2024.1441117.

[7] T. Kalpana et al., “An Image Based Classification and Prediction of Diseases on Cotton Leaves Using Deep Learning Techniques,” Institute Of Electrical Electronics Engineers, Jan. 2023. doi: 10.1109/iccci56745.2023.10128306.

[8] N. Sofina and M. Ehlers, “Building Change Detection Using High Resolution Remotely Sensed Data and GIS,” IEEE J. Sel. Top. Appl. Earth Observations Remote Sensing, vol. 9, no. 8, pp. 3430–3438, Aug. 2016, doi: 10.1109/jstars.2016.2542074.



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