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An Image Processing System for the Detection of Cotton Crop Diseases

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Abstract: The cotton sector is a significant part of Pakistan's industrial economy, substantially contributing to the nation's GDP. However, sustaining cotton yields has become increasingly difficult due to diseases exacerbated by climate change, which threaten both export revenue and local livelihoods. Traditional methods for identifying these diseases are often inaccurate and inefficient, resulting in significant crop losses and delayed responses. To address this critical issue, this study proposes an AI-driven system that leverages digital image processing and machine learning to provide a scalable, real-time solution for cotton leaf disease detection. By enabling early and accurate identification of diseases, the system facilitates proactive crop management and helps farmers make timely decisions. Integrating a mobile application with cloud-based analytics supports policymakers in effectively tracking disease outbreaks and allocating resources. While promising, future improvements should focus on enhancing data diversity and computational efficiency to ensure widespread adoption. This study offers a valuable contribution to improving agricultural sustainability and productivity in regions heavily reliant on cotton cultivation.

Keywords: Cotton Crop; Image Processing; Clustering; Segmentation; Threshold; Feature Extraction; Otsu's Method

1. Introduction

Pakistan is an agricultural country, where about seventy percent of the population depends on agriculture. Pakistan is the fourth-largest cotton-growing country to grow cotton in the world. Cotton is one of the most popular commercial crops of Pakistan and grows on 15 % of the nation's land during the period of monsoon from May to August [1].

Punjab and Sindh are two famous provinces for growing cotton on a large scale, as shown in Fig. 1. The Pakistan textile industry uses this cotton to make fabrics and provide a livelihood to thousands of people in Pakistan.

Cotton contributes 8-10% of Pakistan's GDP, and employs 40% of the industrial workforce, making it the backbone of the economy. However, despite being the world's fourth-largest cotton producer, Pakistan faces declining yields due to climate-induced diseases, threatening both local livelihoods and export revenues [2].

Rapid climate changes are the major causes of a gradual decrease in the yield of cotton because, with time, new viruses or diseases emerge that affect the crops, and farmers have no idea how to control these diseases. They are still working with traditional methods to control diseases of cotton crops. They get help from experts for the identification of the disease and its remedy. Sometimes the availability of experts is not confirmed; in this case, farmers must wait for them. Late remedies become the cause of a decrease in both the quality and quantity of cotton yield.

Insect infestations and virus diseases are becoming a bigger hazard to cotton harvests; therefore, farmers are looking for practical ways to reduce these risks. Due to a lack of agricultural specialists, farmers currently rely on visual inspection, which is frequently inefficient and prone to mistakes, delaying diagnosis. In extreme circumstances, yield losses may amount to 30–40%. Furthermore, resistant infections brought forth by climate variability make conventional pesticides useless. Creating a smartphone application that allows farmers to take pictures of cotton plant leaves and submit them, together with farm coordinates, to a cloud-hosted disease detection system is one suggested way to address these issues [3].

Although there is laboratory testing, it is expensive and time-consuming. AI-enabled automated image-based systems provide scalable, real-time solutions that enable proactive disease containment and cut down on diagnosis times from days to minutes [4]. The device helps farmers take prompt action by identifying the ailment and suggesting an appropriate pesticide through digital picture processing. Future preventive actions and thorough aerial reporting are also made possible by the coordinates and disease data gathered. Farmers may increase cotton production, prevent crop damage, and lessen their dependency on antiquated techniques by implementing this technology [5].

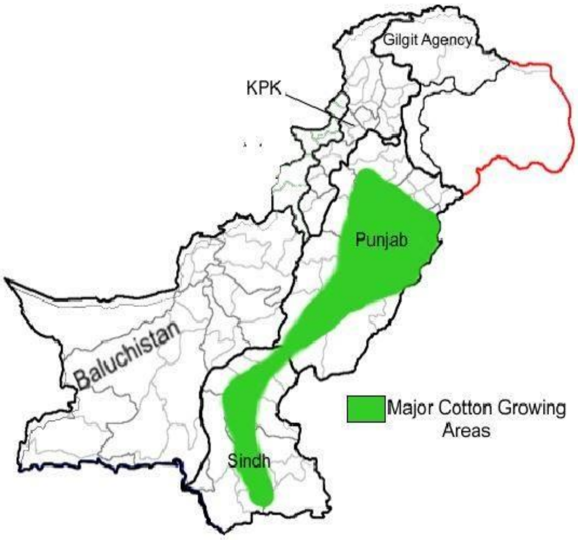

Figure 1. Map showing the major cotton-growing Area in Pakistan

To separate disease-affected leaf patches in real-field conditions, the proposed method uses K-means clustering and Otsu's thresholding to account for lighting and background noise variations. When paired with an ANN-based classifier, the technique achieves an accuracy of over 90%, surpassing both manual inspection and lab-based tests. Low-quality smartphone images are handled efficiently by mobile applications, which were developed with rural accessibility in mind, even in situations where internet connectivity is limited. By crowdsourcing geo-tagged disease data and enabling predictive analytics for large-scale crop management, the platform transforms reactive farming into a proactive, data-driven strategy.

By implementing this approach early on, cotton yields might be increased by 20–25%, protecting $2 billion in export revenue annually. It also helps policymakers allocate resources to areas affected by epidemics by tracking outbreaks.

In this paper, Section 2 presents a literature review, which discusses various diseases affecting cotton plants. Section 3 describes the proposed solution, detailing the system's workflow for disease detection. Section 4 describes the Process of testing and training, and Section 5 covers the results and discussion, including an analysis of different image preprocessing filters. Finally, the conclusion summarizes the paper's key contributions and objectives.

2. Literature Review

Plant disease detection has been transformed by recent developments in artificial intelligence, which have overcome the drawbacks of manual techniques. Plant diseases in a variety of crops can be accurately classified using machine learning and deep learning approaches, especially Convolutional Neural Networks (CNNs).

Using deep learning methods like CNNs, research has concentrated on automating the categorization and detection of cotton leaf diseases. These initiatives acknowledge how important early disease diagnosis is to preserve cotton crops and bolstering the agricultural economy, especially in areas where manual disease identification is challenging. Major Cotton leaf diseases, which can be difficult to treat if not discovered early, can be categorized and identified using methods that have been established [6].

The necessity to minimize disease-related losses in cotton cultivation, particularly in regions where conventional identification methods are impractical, has driven research into automated solutions. For instance, [7] developed a CNN-based model using Keras and TensorFlow to classify bacterial blight, spider mite, and leaf miner diseases in cotton leaves. Their model employed a 5-fold cross-validation strategy on a dataset of 2,400 images. This strategy's drawback is that the models need more processing power to train and run, which could prevent adoption in settings with limited resources. Rapid response to disease outbreaks the computing intensity, which may limit real-time processing capabilities.

A CNN framework called CNN8GN was used for the automated classification of three critical cotton leaf diseases. Architecture combines eight convolutional layers with GlobalAveragePooling and dropout regularization to prevent overfitting. The model was trained on a dataset of 3,000 annotated cotton leaf images. While demonstrating high precision for early-stage disease detection, the authors note that real-time deployment requires substantial GPU resources due to the model's 15M parameters, which may limit accessibility for small-scale farmers. [8].

An in-depth study employed transfer learning with multiple deep learning architectures, including VGG16, ResNet50, DenseNet201, GoogleNet, and TLResnet152V2, to predict cotton leaf diseases using a large, normalized, and augmented image dataset. The approach involved extensive preprocessing, feature extraction, and fine-tuning of pre-trained models to enhance classification accuracy across various disease conditions. The study further explored integrating CNN-based detection into smart agriculture frameworks, enabling real-time disease classification via mobile and IoT devices. However, challenges remain in computational complexity and the need for lightweight models to facilitate deployment in resource-constrained environments [9].

A deep learning-based automated method, CNNs, is suggested for the classification and differentiation of cotton leaf diseases. The reliance on high-quality, representative image datasets for training is a limitation of such automated systems, despite their encouraging results. Performance may be impacted when these systems are used in real-world situations with variable lighting, image quality, or disease presentations that have not yet been observed. By providing a dependable means of identifying cotton leaf diseases that are hard to manage if not detected early, this approach seeks to enhance crop management [10].

Because early and accurate disease diagnosis is essential to preserving cotton harvests, research has concentrated on using deep learning techniques to automatically identify and detect cotton leaf diseases. Research on neural networks has shown promise in precisely identifying and classifying important cotton leaf diseases. However, the availability of large, high-quality datasets of diseased leaves, which may be scarce or skewed toward particular disease stages or environmental conditions, is a critical component in the efficacy of these CNN-based solutions. When used in a variety of real-world agricultural contexts, training data that is not sufficiently diverse may result in decreased accuracy and dependability [11].

The ability to offer accurate and fast disease identification, which is crucial for preserving cotton crop yields, is what drives the study's emphasis. CNNs are frequently used in methods to automatically identify and classify various cotton leaf diseases. These systems' sensitivity to changes in data quality could be a disadvantage; the models usually call on constant lighting, viewing angles, and image resolution. The precision and dependability of the disease categorization could be diminished if actual conditions differ from the training data [12].

Table 1. Summary of the Recent Studies

References	Methodology	Contributions	Limitations
[6]	CNN-based multi-SVM classifiers for disease categorization	Achieved 95% accuracy in classifying bacterial blight, anthracnose, and leaf curl diseases	Limited to specific diseases; lacks real-world deployment validation
[7]	ResNet50 + KNN for bacterial blight and curl	Achieved 86% accuracy with KNN and Integrated	Small dataset, computational

		UAV/drone data for scalable detection; provided actionable remedies	constraints in resource-limited settings
[8]	CNN8GN architecture (8 layers + dropout) on 3,000 annotated images	Achieved 98% test accuracy: outperformed VGG16/ResNet50 in early-stage detection	High GPU dependency (15M parameters); impractical for small-scale farmers
[9]	Transfer learning with TLResnet152V2, ResNet50, VGG16	Achieved 92.03% accuracy	Computational complexity limits edge deployment; requires lightweight models for scalability
[10]	CNN-based classification using comprehensive dataset	Highlighted dataset quality impact on model generalization; proposed standardized data collection protocols	Performance drops under variable lighting/image quality; limited field validation
[11]	Analysis of CNN performance across diverse disease stages/environments	Identified bias in training data as critical failure point; proposed dynamic dataset updating framework	Requires continuous data curation; computationally intensive for real-time updates
[12]	Sensitivity analysis of CNNs to image resolution/viewing angles	Quantified accuracy degradation (12-18%) under suboptimal field conditions	Requires specialized imaging hardware for consistent input quality

The CNNs can be used to automatically classify and detect cotton leaf illnesses, according to a method found in several research projects. Models based on small or biased datasets may not translate well to real-world situations with different lighting, picture quality, or disease presentations.

3. Categories of plants Diseases:

3.1. Fungal Diseases

Leaf Spot: Leaf spot is primarily a leaf disease, but symptoms may also develop on cotyledons and bolls. The fungus survives on undecomposed trash from the previous cotton crops and is spread by airborne spores as shown in Fig 2.

Figure 2. Leaf Spot Source: [13]

Ascochyta blight: Small, round, and whitish spots up to two diameters first appear on the cotyledons and lower leaves of the seedlings. These spots have a deep purplish brown border, they later enlarge, and the Centre becomes light brown, papery, and bears conidiomata [14].

3.2. Viral Diseases

Leaf Curl: Leaf Curl disease is a serious disorder of cotton crops that belong to the family of Malvaceae. Plants affected by the disease exhibit very unusual symptoms, consisting of vein swelling, upward or downward cupping of the leaves, and the formation of enations on the main veins on the undersides of leaves. Fig 3 shows a leaf curl.

Figure 3. Leaf Curl Source: [15]

Blue Disease: Cotton blue disease is caused by aphid-transmitted viruses. Cotton blue disease has similarities with other diseases of cotton, such as cotton bunchy top, anthocyanosis, and cotton leaf roll, and all are spread by the cotton aphid, Aphis gossypii. CBD-affected leaves tend to be small, thick, more brittle, and leathery than healthy leaves and have an intense green to bluish color with yellow veins [16].

3.3. Bacterial Diseases

Crown Gall: This disease caused by the bacterium Agrobacterium tumefaciens. Thousands of plant species are susceptible. Symptoms include roundish, rough-surfaced galls (woody tumorlike growths), several centimeters or more in diameter, usually at or near the soil line, on a graft site or bud union, or on roots and lower stems [17].

Lint Degradation: It causes internal necrosis and the roots of immature cotton balls. Usually, no external ball damage can be observed. In sensitive varieties, the damage can be significant [18].

3.4. Insects

Whitefly: Several whitefly species infest cotton – sweet potato whitefly [Bemisia tabaci (Gennadius)] Biotypes A & B, silverleaf whitefly (B. argentifolii Bellows and Perring), banded-winged whitefly [Trialeurodes abutilonea (Haldeman)], and the greenhouse whitefly [T. vaporariorum Westwood)]. Of these, the sweet potato whitefly Biotype B is the most serious economic pest of cotton [19].

Figure 4. Whitefly

Jassids: The cotton jassids are serious sucking pest of cotton in Pakistan. Adults are small, like the tip of a lentil, and flat. Adults are usually yellowish-green or white with black spots on the front wings. They jump and fly away at the slightest disturbance [20]. The cotton jassids sucks sap from the underside of leaves and leaf buds. When jassids are abundant, cotton growth is stunted, the leaves turn downwards, and heavy fruit loss may occur on pre-flowering plants. Leaves turn pale and a rust-red color develops at the edges.

Thrips: The most consistent insect-related challenge for Kansas cotton growers is thrips as shown in Fig 5. These tiny, barely visible, splinter-like insects are important pests during the first couple of weeks after plants emerge. They can retard growth but also are sometimes blamed for more damage than they cause [21].

Figure 5. Thrips

4. Proposed Solution

The Cotton Crops Disease Detection System is an overly complex system that requires highly computable servers for deployment. A mobile application will be provided to the farmer as a remote control. By using this application, the farmer will capture the image of cotton life that is defective cotton and send it to the server for disease diagnosis. The farmer not only sends the image of the infected leaf, but he also sends the coordinates of the affected area. These coordinates help the system to gather statistics of cotton disease from different regions, which are further used for compiling reports for decision-making, i.e., which region is most affected by which disease, what is the most common disease among different regions, and which is the most repeated disease each season. With the help of these statistics, the system marks the infected areas as shown in the picture below.

The disease is diagnosed automatically by using Digital Image Processing, and the result is sent back to the farmer. The Figure 6 explains how client-server communication is done. In the system, the process begins when a farmer uses a mobile application to capture an image of a cotton leaf along with its precise plant location. This information is then transmitted over the internet to a remote server to store a comprehensive database of local disease images and run advanced image processing algorithms. The server analyzes the incoming leaf image, compares it with the stored disease data, and generates a detailed diagnostic report. This report is then sent back to the farmer through the mobile app, providing real-time, location-specific disease identification and management recommendations. By integrating mobile technology, cloud connectivity, and AI-driven analysis, my system enables timely and accurate disease detection, ultimately supporting more effective crop management for farmers.

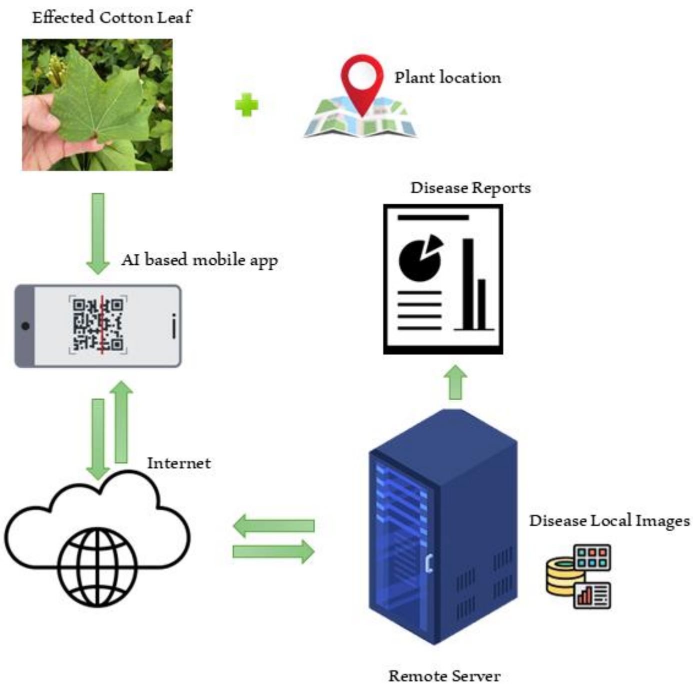

Figure 6. Flow diagram of the system

A digital agricultural monitoring system that tracks and evaluates cotton plant health, with an emphasis on leaves, is depicted in the image. The procedure starts at the factory, where information is gathered, potentially using sensors or photos. Detailed reports on plant health, disease detection, or growth conditions are then produced using this data, especially about cotton leaves. Farmers and agronomists may enter data, examine reports, and get relevant insights using a mobile app. The application establishes an internet connection with a distant server, where sophisticated processing, including analysis powered by artificial intelligence, occurs. Precision agriculture improves crop management and productivity by facilitating real-time monitoring and decision-making through this integrated system.

5. Process of Detecting Disease in Cotton Leaf

This system consists of two steps. The first step is training, and the second is testing.

5.1. Training

In this step, training is done through the system for the detection of a specific disease. In the training phase, a data set is stored in the system database after applying digital image processing steps on it that as mentioned below.

5.1.1. Image acquisition

RGB images of cotton leaves are collected in JPEG format. The images are acquired by the system administrator using external storage devices such as DVDs or flash memory to ensure a diverse and representative dataset.

5.1.2. Image Preprocessing

To enhance image quality and facilitate accurate analysis, preprocessing techniques are applied. These may include noise reduction, resizing, normalization, and color space conversion, which help in standardizing the images and removing irrelevant information.

5.1.3. Image Segmentation

Segmentation isolates the region of interest (ROI) - the diseased portions of the leaf - from the background. This step improves the focus on affected areas by separating them from healthy leaf regions, enabling more precise feature extraction.

5.1.4. Feature Extraction

Critical features such as texture, color, shape, and edge information are extracted from the segmented images. These features serve as the input variables for the classification model, helping it distinguish between different disease types.

5.1.5. Save in DB

The processed images,s along with their extracted features and corresponding disease labels are stored in the system database. This curated dataset forms the foundation for training the machine learning model.

5.2. Testing

In the testing phase, the disease will be evaluated after training, which will be provided by the system. Send the image of a cotton plant leaf to a system that is defective due to disease, the system classifies it with a stored dataset that is stored in the system database during the training phase and sends results back to the farmer.

5.2.1. Image acquisition

Using an Android mobile, capture an image of the plant leaf. Give camera and GPS permission in the Android manifest file that allows the app to use the camera and GPS. Capture the image and store the bitstream image in a Bitmap variable for further use.

Using web REST services, send the plant leaf image to a remote server for disease diagnosis, where the Cotton Crops Disease Detection System is hosted using the HTTP protocol (HttpURLConnection), pass the Bitmap variable in JSON Object parameters, and write the buffer using DataOutputStream. Read the buffer on the server side and write these bitstreams in the cotton jassids in the JPEG file using a loop. Data communication between client and server is in JSON format.

5.2.2. Preprocessing Image

Filter the blur or enhance the image using a histogram and the median filter [22]. We are using a median filter because it is better than a mean filter.

Figure 7. Blur Image

Figure 8. Feature enhancement in preprocessing using a median filter

5.2.3. Clustering

A. *Color-based image Segmentation (For bacteria, fungi, and insects)*

The leaf image is being segmented into three clusters in this project.

In this paper color-based segmentation technique is used, K-means clustering. Set the parameters of k-means clustering. K is a constant value, and the image will be divided into how many clusters? This takes the meaning of color pixels in an image and divides one object into many objects. At the end, it returns indexes, and each index contains the object. Results of the segment cotton plant leaf image.

Figure 9. Input Image

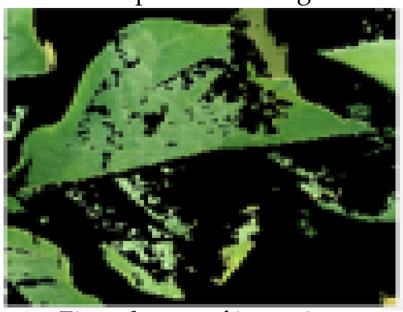

Figure 10. First cluster of input image

Figure 11. Second cluster of input image

Figure `12. Feature extraction through clustering

B. *Edge Detection*

Classifying viral diseases in cotton leaves can be challenging using traditional image segmentation techniques because viral infections often cause distinctive morphological changes, such as curling or deformation of leaf edges. To capture these subtle shape variations, an edge detection algorithm is employed. The Sobel edge detection method is used to extract the contours and boundaries of the leaf edges from the images. By highlighting these edge patterns, the algorithm effectively isolates the characteristic curling and irregularities caused by viral infections. The extracted edge features are then quantitatively analyzed and compared against a labeled dataset of known diseased leaf edge profiles. This comparison enables the system to differentiate viral diseases based on the unique edge deformation patterns, thereby improving the accuracy of disease classification beyond what conventional segmentation methods can achieve.

Figure 13. Sobel edge detection

C. Feature extraction

After image segmentation, mask green pixels using a threshold value of 0, and get relative information that has some valuable information for further processing.

Figure 14. Extracted features

D. Classification & Recognition using neural networks

ANN is used for the compression of the training dataset and the testing image. ANNs are known for their high capacity for classification of data in a nonlinear domain. Based on a multi-layered architecture, the input layer analyzes previously processed leaf pictures to extract properties including texture, color variations, and lesion forms [23]. To find disease-specific traits, hidden layers that are outfitted with nonlinear activation functions such as Sigmoid or ReLU gradually hone these properties. A Softmax function is then used by the output layer to classify the disease, producing probabilistic findings that show the most likely infection. The processes of testing and training are shown in Figure 15.

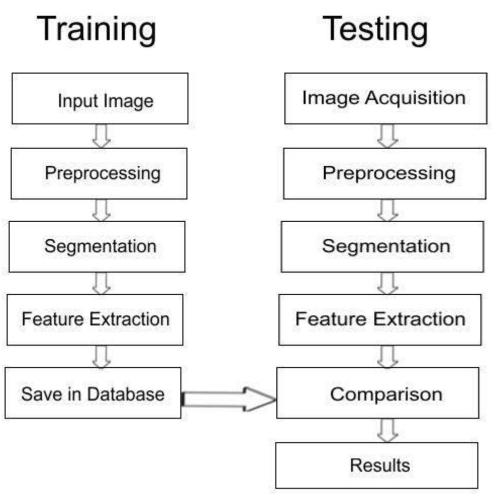

Figure 15. Flowchart of Cotton Disease Detection System

Backpropagation is used to train the ANN, in which optimization methods such as stochastic gradient descent are used to minimize a loss function (such as cross-entropy), causing the network to modify its weights. As the model gains knowledge from a growing collection of labeled cotton disease photos, this process takes place over several epochs, enabling the model to become more accurate. ANNs' resilience to noise is one of their main advantages in this application since it allows them to deal with real-world fluctuations in image quality, like variations in lighting, angles, or partial obstructions.

6. Results and Discussion

6.1. Image comparison of disease-trained and disease-tested images

A cotton leaf that has been subjected to an ANN-based disease detection system is depicted in the figure, emphasizing characteristics including texture, color variation, and lesion shapes—all of which are important markers of infection. Accurate disease presence classification is made possible by the multicolored regions, which indicate places that the model discovered during feature extraction. The ANN exhibits robustness by successfully identifying disease-specific characteristics despite potential image noise or low light levels. The visual output most likely comes from a hybrid model that combines ANN classification with CNN-based spatial feature extraction. The system's capacity to evaluate both training and test images is demonstrated in this comparison, enabling accurate and timely diagnosis in agricultural applications.

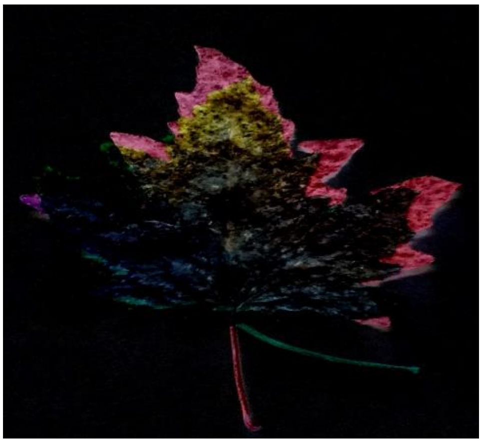

Figure 16. Comparison of trained and tested images

Simple Histogram applied on the diseased image for high intensity values. The cotton leaf in the figure has been grayscale and has had high-intensity pixel values highlighted using straightforward histogram enhancement. By adjusting the image's contrast, this approach helps to highlight abnormalities like lesions, inconsistencies in texture, or infected areas. The histogram procedure improves visual clarity by dispersing the intensity values throughout the grayscale spectrum, especially in areas where disease signs could otherwise get obscured. Because it increases the visibility of important information, this preprocessing step is essential in automated illness detection systems.

Figure 17. Enhanced image from histogram

6.2. Laplace filter for edge detection of viral diseases

Applying the Laplace filter to the leaf picture allows it to discern abrupt changes in intensity, which makes it a very useful tool for edge identification, especially for seeing patterns of viral illness. By identifying locations where pixel intensity abruptly changes, which frequently correlates to disease-affected zones on the leaf surface, this filter draws attention to the borders of lesions or infected regions.

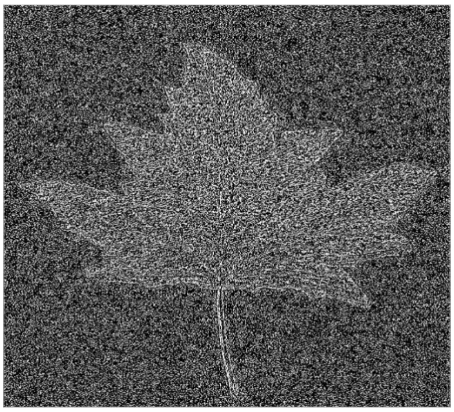

Figure 18. Laplace filter

6.3. Prewitt and Sobel's edge detection of viral diseases

The leaf image is subjected to Prewitt and Sobel edge detection algorithms, which use gradients in pixel intensity to determine the boundaries of viral infections. These techniques highlight vertical and horizontal edges, which makes them helpful for emphasizing disease-related structural alterations, such as vein distortions or lesion outlines. The Sobel filter gives pixels nearer the center more weight, resulting in more accurate edge details, whereas the Prewitt operator offers a more straightforward, noise-tolerant method. When combined, they improve feature extraction for classification systems based on neural networks by making disease-affected areas more visible [24].

Figure 19. Edge Detection

6.4. Weighted median filter applied on the diseased image to enhance the image

The diseased leaf image is improved by applying the weighted median filter, which lowers noise while maintaining crucial edge features. In contrast to conventional median filters, the weighted version gives certain pixels greater weight, enabling more precise smoothing without obfuscating important details like lesion borders.

Figure 20. Weighted median filter

7. Conclusion

This study demonstrates how AI-driven solutions can be utilized to address Pakistan's pressing issue of detecting cotton leaf disease. The suggested system provides a scalable and real-time approach to disease identification by utilizing digital image processing and machine learning, allowing for initiative-taking crop management. In addition to helping farmers make timely decisions, the combination of a mobile application and cloud-based analytics helps policymakers track disease outbreaks and allocate resources. Although the system has potential, future developments should concentrate on increasing data diversity and computing efficiency to guarantee broad adoption. In areas where cotton cultivation is a major industry, this strategy greatly improves agricultural sustainability and productivity.

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