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Optimized Framework Model for the Identification and Automated Detection of Multiple Grapes Leaf Diseases

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ABSTRACT: One of the popular fruit yields in India is the grape. The spread of numerous diseases on grapes fruit, stem, and leaves causes a decline in production. Bacteria, fungi, viruses, etc. are the principal culprits behind leaf diseases. Diseases are a significant influence in restricting the yield of fruit, and they are frequently challenging to control. Correct control measures cannot be implemented at the right time for a disease without an accurate illness identification. One of the most popular methods for identifying and categorizing plant leaf infections is image processing. This study uses the optimized svm classification approach to help identify and categorize grape leaf diseases and datasets taken from an online source like Kaggle. There are a total of 8500 images of grape leaves to use in this project work. Furthermore, an optimized SVM were evaluated in terms of their effectiveness in detecting illnesses in grape plants. The suggested Research model has an accuracy of 99% for detecting and classifying the tested grape leaf disease which has higher accuracy as compared to other models. An automated system has been implemented to take pictures of the disease affected leafs of grape plants and send them to the dedicated server for assaying. On the server side, the affected portion from the image will be segmented using customized thresholding formula based on segmentation. The consequential feature values will be extracted from the segmented portion for texture analysis using color co-occurrence methodology. The extracted values will be compared with the sample values stored in the pre-defined database which will lead the disease to be identified and classified using Multi-SVM

KEYWORDS: Grape leaf diseases Image processing SVM classification Disease identification Texture analysis Color co-occurrence methodology Segmentation Automated system Dataset Disease classification

I.INTRODUCTION

Grapes, a key ingredient in wine production, face significant threats from various diseases, impacting their quality and yield. These diseases, caused by fungi, viruses, and bacteria, can spread rapidly if not controlled, posing a challenge to grape production. Traditional methods of disease identification are labor-intensive and unreliable, especially given the expansive grape-growing areas globally. To address this, researchers are turning to machine learning-based visual recognition methods.

Machine learning approaches typically involve spot segmentation, feature extraction, and classifier recognition. Various studies have shown promising results using techniques like artificial neural networks (ANNs), probabilistic neural networks (PNNs), support vector machines (SVMs), and hyperspectral techniques to identify crop diseases. For

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instance, SVM classification techniques have been successfully applied to detect and classify grape leaf diseases with an accuracy of 88.89%. While these methods demonstrate feasibility, they can be complex and time-consuming.

Plant leaf diseases are broadly categorized into infectious (fungal, bacterial, viral) and non-infectious types. Fungal infections are prevalent and can enter plants through various sources, causing leaf spots and yellowing. Bacterial infections are harder to detect but can result in cankers, leaf spots, and wilting, spreading rapidly to nearby plants. Viral infections, though difficult to diagnose, exhibit symptoms like mosaic leaf patterns and decreased plant growth.

In summary, leveraging machine learning for disease identification offers a promising solution to the challenges faced in grape production. However, further advancements are needed to enhance efficiency and accuracy, ensuring the sustainable growth of this vital agricultural sector.

II.LITERATURE REVIEW

Recent advancements in agriculture have seen the application of various innovative techniques for diagnosing plant leaf diseases. Here's a concise summary of some notable methods:

Genetic Algorithm-based Image Segmentation: Singh et al. utilized genetic algorithms for image segmentation to detect and classify plant leaf diseases. Their technique demonstrated early-stage disease detection across various plant species.

Pattern Recognition with Gabor Wavelet Transform: Another study explored plant disease detection using pattern recognition integrated with Gabor Wavelet Transform (GWT). This method achieved an 89% accuracy rate in identifying plant diseases from crop images.

Hybrid Technique for Mobile Vision: Prasad et al. introduced an automated mobile vision approach for disease detection, combining GWT-GLCM (Gray Level Co-occurrence Matrix) with an optimized image processing algorithm for segmentation. Their hybrid approach achieved a high accuracy rate of 93% in identifying plant diseases.

FCM-KM and R-CNN for Rice Plant Diseases: Rapid identification of rice plant diseases was achieved using FCM-KM clustering and R-CNN (Region-based Convolutional Neural Network). This combined approach yielded an impressive accuracy of 96.71% in disease identification.

DeltaE Method for Citrus Fruit Diseases: Researchers proposed the DeltaE method for precise identification of citrus fruit diseases. They employed KNN and cubic SVM classifiers at both image and disease levels, achieving an overall accuracy of 97%.

Wavelet and Pyramid Histogram for Disease Detection: Ahmed et al. introduced a methodology combining wavelet transforms and pyramid histogram techniques for plant disease detection. They applied the Random Forest supervised learning algorithm to identify diseases with 95% accuracy.

Deep Learning-based Disease Detection: A study presented a disease detection approach based on deep learning techniques in image processing. By training a deep convolutional neural network with available dataset images, the system demonstrated promising results in disease identification.

These innovative approaches underscore the significance of leveraging advanced technologies like genetic algorithms, pattern recognition, deep learning, and hybrid techniques for accurate and efficient plant disease diagnosis in agriculture.
The plant disease detection system typically comprises four phases: Image Acquisition, Preprocessing, Image Segmentation, Feature Extraction, Feature Selection, and Classification.

III.EXISTING METHODOLOGY

Image Acquisition: Images of plant leaves are collected using digital media such as cameras, mobile phones, or from the web, forming a database for efficient classification.

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Preprocessing: Raw data is prepared to suit machine learning models. This step involves cleaning and formatting data to make it suitable for analysis.

Image Segmentation: This phase simplifies image representation for easier analysis. Methods like k-means clustering, Otsu's algorithm, and thresholding are used to segment images.

Feature Extraction: Features from areas of interest are extracted to determine the meaning of a sample image. Texture features, especially using methods like gray-level co-occurrence matrix (GLCM), are commonly employed for disease detection.

Feature Selection: Ensures that only relevant features are input into the model, reducing noise and improving model performance. It separates useful data from noise, contributing to faster and more accurate models.

Classification: Determines if the input image is healthy or diseased, and further classifies diseases if present. Common classifiers include k-nearest neighbor (KNN), support vector machines (SVM), artificial neural networks (ANN), Naïve Bayes, and decision tree classifiers, with SVM being commonly used due to its simplicity and robustness.

IV.PROPOSED SYSTEM

The proposed Plant Disease Detection Algorithm involves several phases:

1**. Image Preprocessing:**
Resize Image: Input images are resized to match the dimensions of the images stored in the database.
Enhance Image: Image intensity values are enhanced by adjusting the contrast, considering the top and bottom 1% of pixel values.
Noise Removal: Bilateral smoothing filters are applied to remove noise from the images.

2. **Hue-based Segmentation**:
Gray Conversion: Images are converted to grayscale for further processing.
Thresholding: A customized thresholding formula is applied to mask only the disease-affected parts of the leaf.
Blob Detection: Morphological analysis, including erosion and dilation, is performed to extract the largest connected component.
RGB Conversion: Segmented portions are converted back to RGB color space for analysis.

3. **Feature Extraction:**
- Color co-occurrence methodology using Grey-level Co-occurrence Matrices (GLCM) is employed.
- Thirteen feature values are calculated for each training and input image to perform texture analysis.

4. **Classification:**
- Extracted features are compared with pre-calculated dataset stored in a .mat file.
- Support Vector Machine (SVM) classifier is utilized for disease classification, as it's effective for both classification and regression tasks.
- A multi-class SVM classifier is used, with each disease corresponding to a class. The classifier with the highest output function assigns the class, thus detecting the disease.

The algorithm distinguishes between two cases for feature extraction for texture analysis from training images. Case 1 calculates features without applying hue-based segmentation, resulting in unsatisfactory classification. Case 2 segments the diseased portion from training images before feature extraction, leading to improved accuracy. Consequently, the approach from case 2 is chosen for further implementation based on its higher accuracy of around 86%.

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V. EXPERIMENTAL RESULTS

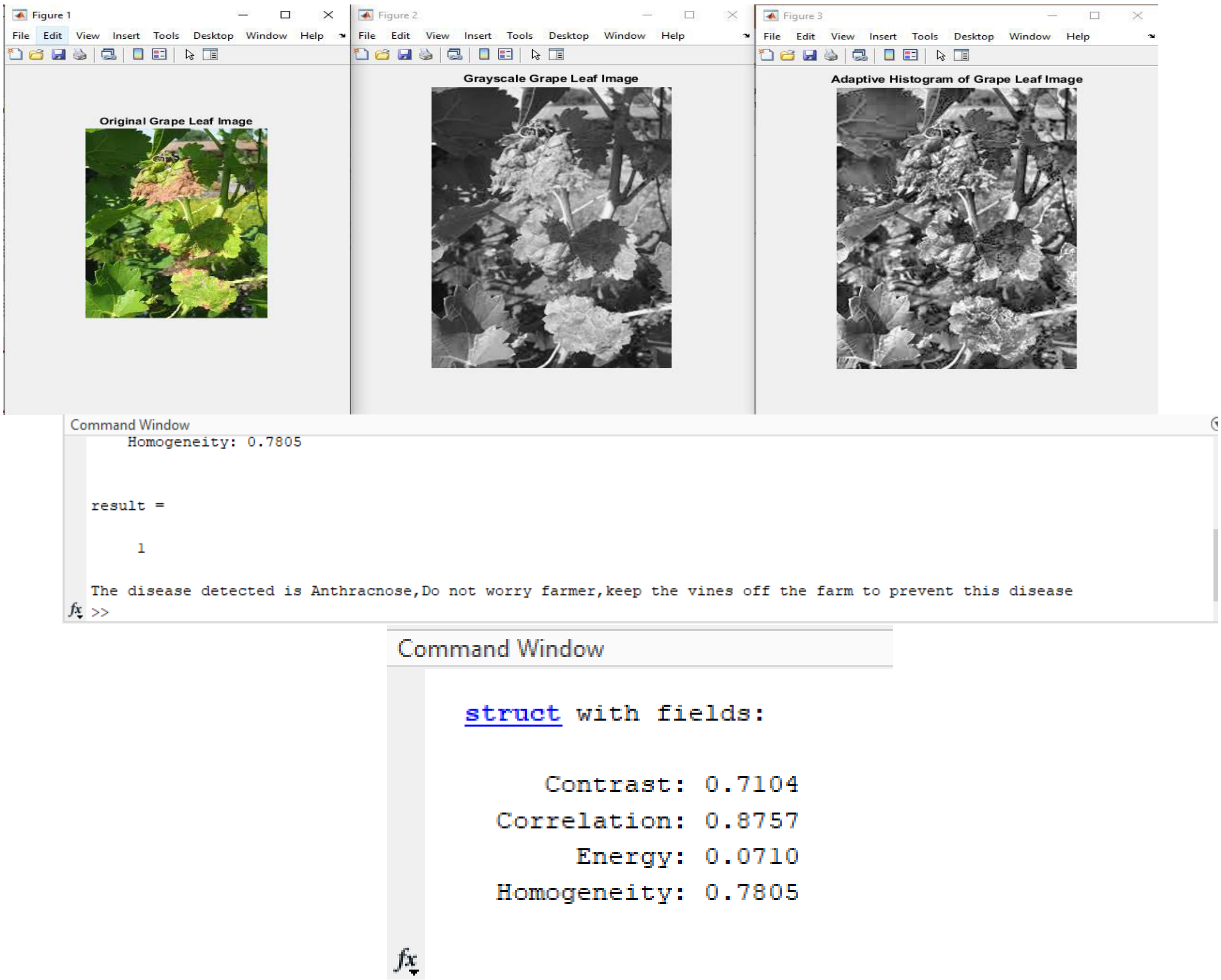
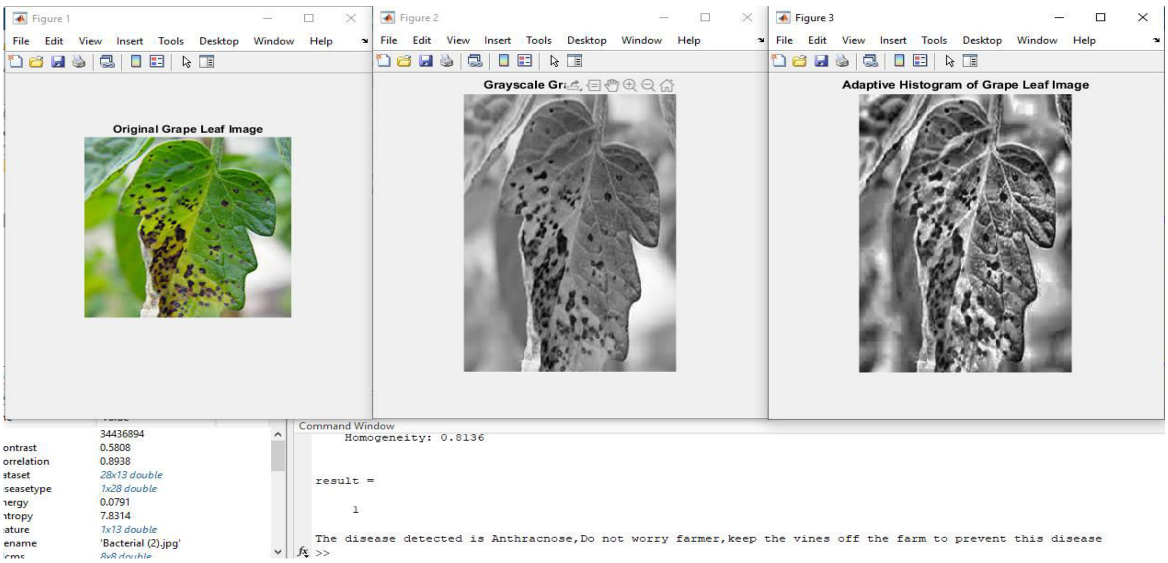


Fig. 4.9. Simulated experimental output detection of plant disease run1



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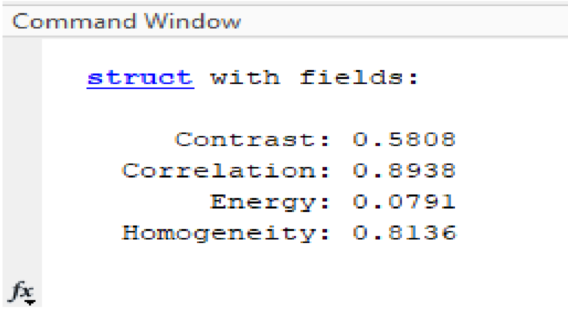
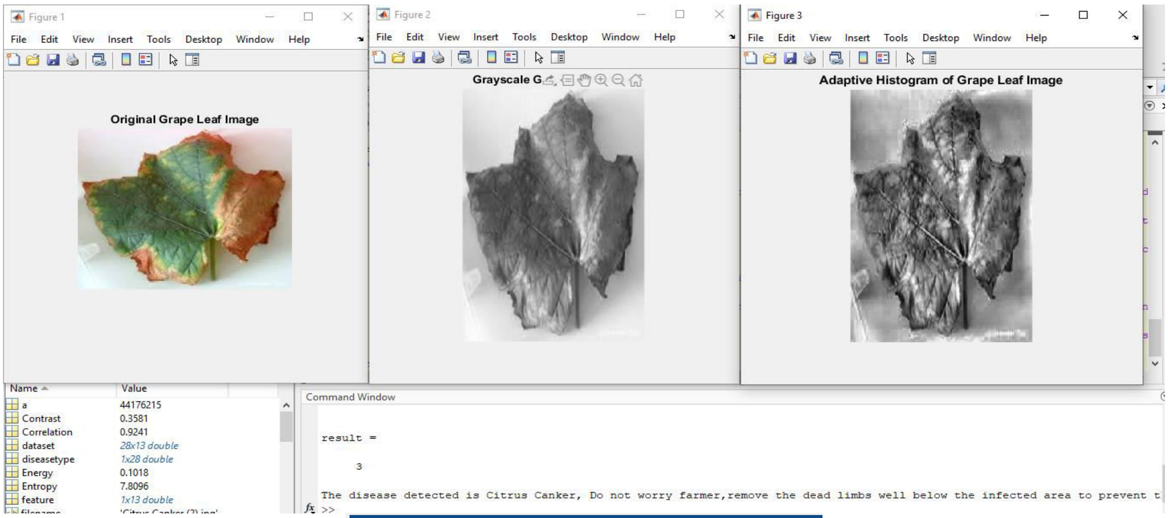


Fig. 4.10. Simulated experimental output detection of plant disease run 2



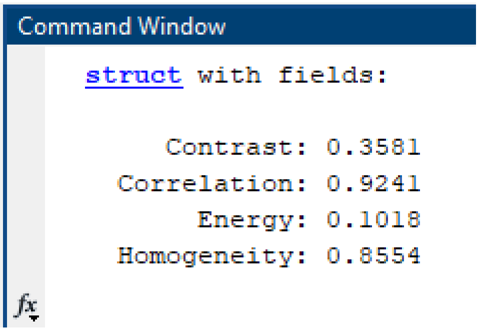


Fig. 4.11. Simulated experimental output detection of plant disease run 3

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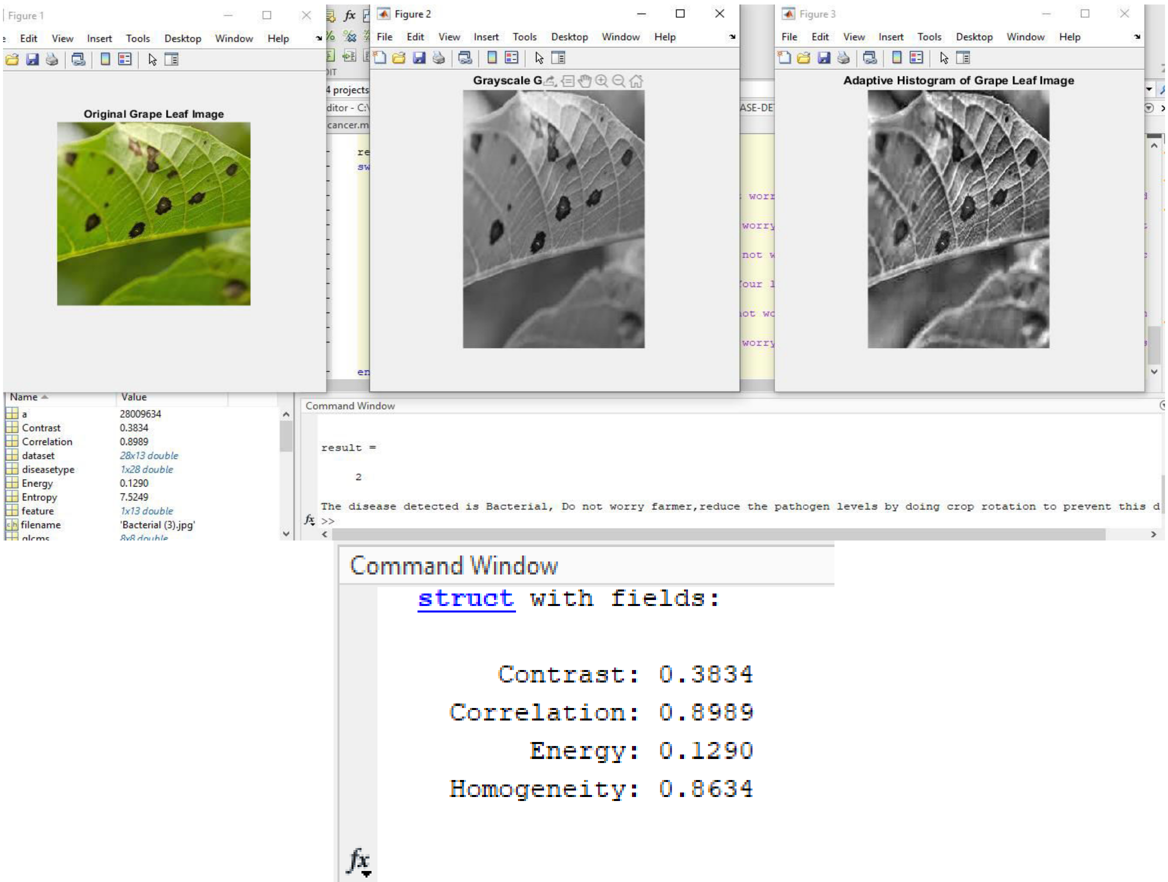
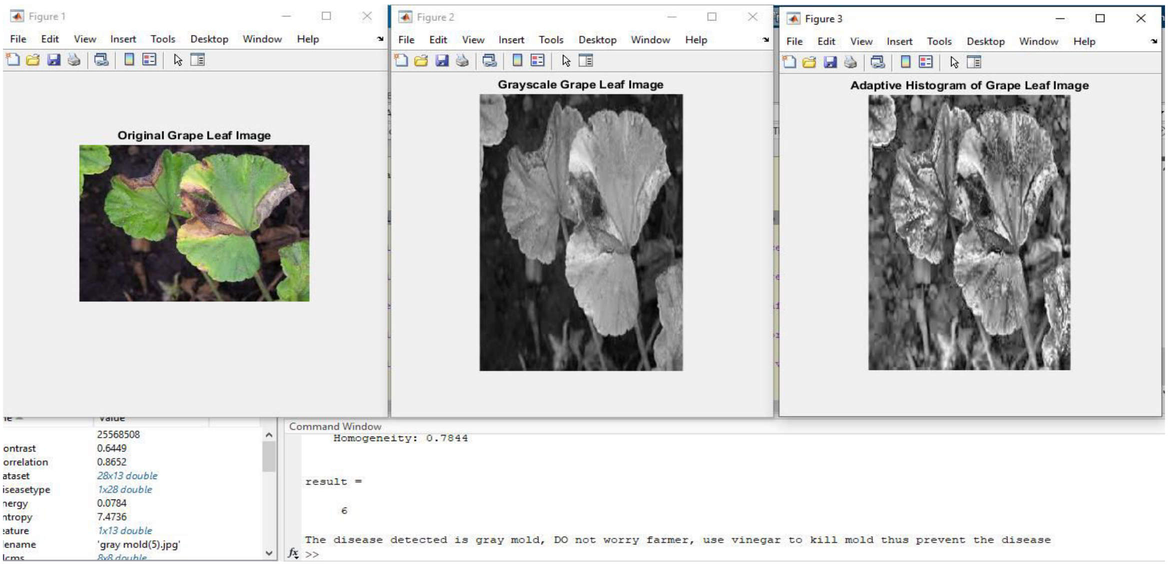


Fig. 4.12. Simulated experimental output detection of plant disease run 4



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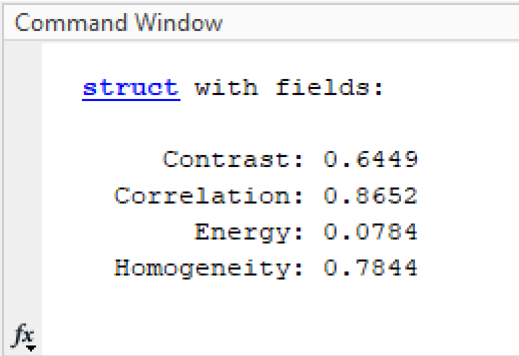

Fig. 4.13. Simulated experimental output detection of plant disease run 5

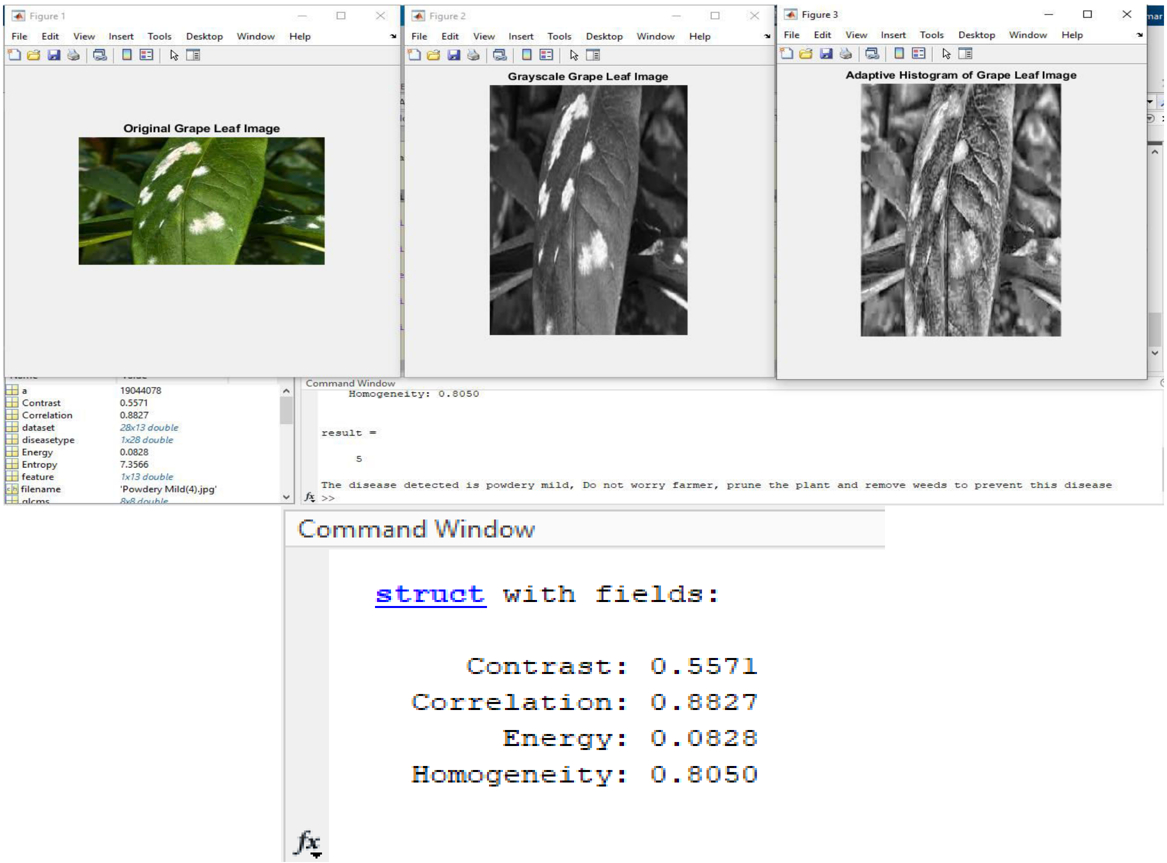

Fig. 4.14. Simulated experimental output detection of plant disease run 6

Figure 4.11 & 4.12 shows simulation result of Anthracnose Disease. The leaf disease obtained from the figure 4.13 is the detected Citrus Canker disease. Figure 4.14 portrays the Bacterial Disease. Figure 4.15 is the Gray Mold Disease detected during the testing and Figure 4.16 is the important and most widely seen Powdery Mild disease

Table. 4.1. Simulated Metrics

S.No.	Parameter	Anthracnose Disease	Citrus Canker Disease	Bacterial Disease	Gray Mold Disease	Powdery Mild Disease
1	Contrast	0.7104	0.3581	0.3834	0.6449	0.5571
2	Correlation	0.8757	0.9241	0.8989	0.8652	0.8827
3	Energy	0.0710	0.1018	0.1290	0.0784	0.0828
4	Homogeneity	0.7805	0.8554	0.8634	0.7844	0.8050

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The average outcome gained from the evaluation test provides an overall impression about the efficacy of the system where three out of five farmers preferred using this application to detect diseases along with manual inspection. Most importantly, the accuracy level obtained from the handson use (80%) almost matches the accuracy level measured from the test images (86%)

VI.CONCLUSION

In this paper, we have built an automated system to detect leaf-oriented diseases for grape plants using image segmentation and feature extraction with along with potential machine learning. Application of machine learning specially image analysis and texture analysis in practical cases are now more common and encouraged than ever before. Although visual analysis done by human is simpler technique but it cannot be accessible always. On the other hand, providing the farmers with an automated and reliable system for crop disease detection to be used from their mobile phone can bring an insurgency for agricultural industry. In future, it will be a great challenge for us to build a universal app that can be used to detect any sort of disease of the grape plants considering both plant and leaves.

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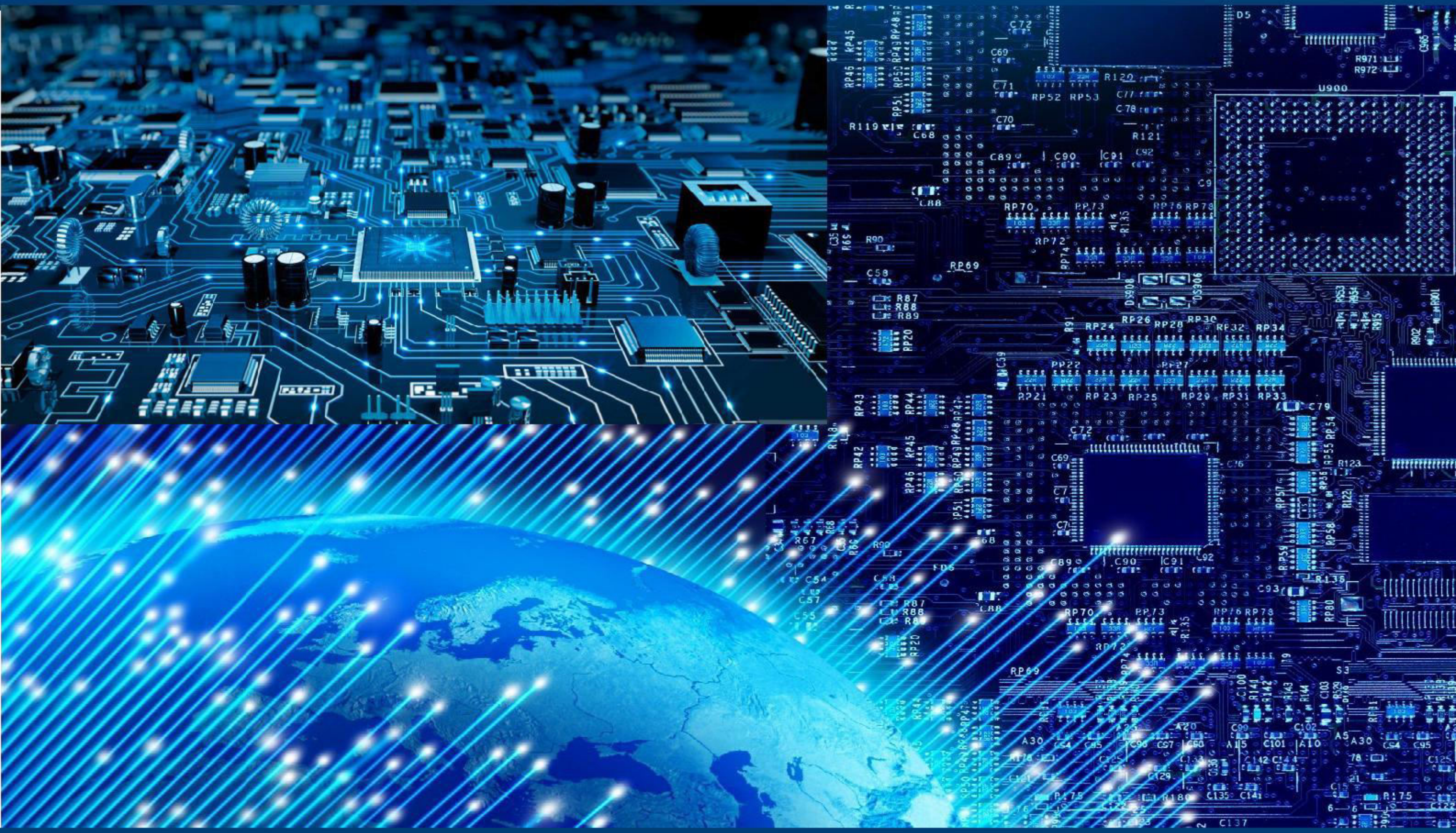

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