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MULTI-CLASS CLASSIFICATION OF PLANT LEAF DISEASES USING FEATURE FUSION OF DEEP CONVOLUTIONAL NEURAL NETWORK AND LOCAL BINARY PATTERN

Mr. R. Ramesh Babu[*1], R. Ravindhra Naidu[*2], M. Mounish[*3], Y. Nithin[*4], SK. Md. Suhel[*5]

[*1]Assistant Professor, Department Of Electronics And Communication Engineering, Vasireddy Venkatadri Institute Of Technology, Nambur, Guntur, Andhra Pradesh, India.

[*2,3,4,5]Department Of Electronics And Communication Engineering, Vasireddy Venkatadri Institute Of Technology, Nambur, Guntur Andhra Pradesh, India.

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ABSTRACT

This study presents a multi-class classification approach for identifying plant leaf diseases using a combination of deep convolutional neural networks (CNN) and Local Binary Pattern (LBP) feature fusion. The method first classifies the plant species, such as Apple, Tomato, or Grape, and then classifies the specific disease affecting the plant, including Black Rot, Scab, Cedar Rust, and others. The process begins with an input image, which undergoes noise removal and restoration. LBP features are then extracted from the image, and the data is organized into a datastore, with labels split by proportion. Augmented image data is generated in batches to enhance training. A CNN is employed with various layers and training options to classify the plant species. After determining the plant species, the CNN undergoes additional training to classify the specific disease type. This dual-stage classification system improves accuracy by leveraging both deep learning and texture-based features, offering a robust solution for early and precise detection of plant diseases.

Keywords: Plant Disease Dataset, Pre-Processing, Convolutional Neural Networks, Deep Learning, Feature Extraction, Classification, Accuracy.

I. INTRODUCTION

Plant diseases pose significant challenges to agriculture, impacting crops such as tomatoes, grapes, and apples. Effective and timely disease detection is crucial for maintaining plant health and yield. This study introduces a multi-class classification method designed to identify plant leaf diseases using a combination of deep convolutional neural networks (CNN) and Local Binary Pattern (LBP) feature fusion. The approach first classifies the plant species—Apple, Tomato, or Grape—and then identifies specific diseases like Black Rot, Scab, and Cedar Rust. The process starts with preprocessing the input image to remove noise and restore quality. LBP features are extracted and organized into a datastore, with augmented image data used to enhance model training. A CNN is employed to classify the plant species and, once identified, undergoes further training to pinpoint the disease. This dual-stage classification system improves accuracy by integrating deep learning with texture-based features, providing a robust solution for the early and precise detection of plant diseases. This method not only enhances disease identification but also aids in the timely implementation of control measures, thereby supporting effective crop management.

II. METHODOLOGY

The methodology for multi-class classification of plant leaf diseases using feature fusion of a deep convolutional neural network (CNN) and Local Binary Pattern (LBP) involves a structured approach to first classify the plant species and then identify the specific disease affecting it. The process begins with the input image, which undergoes noise removal and image restoration to enhance quality. LBP features are then extracted from the preprocessed image to capture essential texture information. The image data, along with their labels, is stored in a datastore, and labels are split by proportions to ensure balanced representation. To improve model generalization, batches of augmented image data are generated. The CNN is then structured with layers designed to learn and classify the plant species such as Apple, Tomato, or Grape using these processed images. After successful classification of the plant species, the CNN is further trained to classify the specific disease type, such as Black Rot, Scab, or Cedar Rust. This two-stage classification process, combining the power of CNNs with LBP texture features, enhances the model's accuracy and effectiveness in diagnosing plant diseases, providing a comprehensive solution for early detection and intervention.

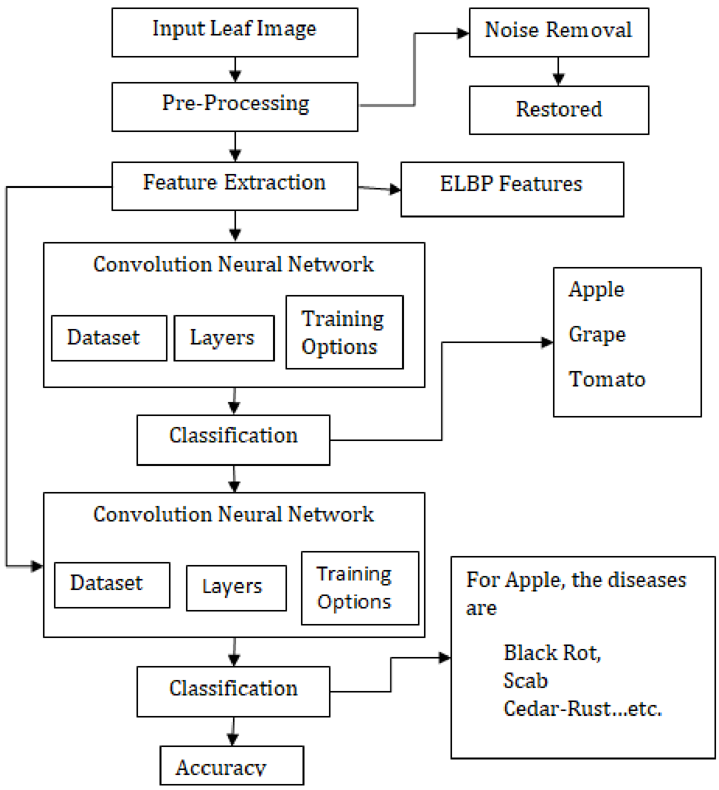
Advantages:

- The combination of CNN and LBP features improves classification accuracy by leveraging both deep learning and texture-based analysis, capturing more relevant details for precise disease identification.
- The initial noise removal and image restoration steps ensure that the input data is of high quality, making the model more robust to variations and noise in real-world scenarios.
- The two-step process accurately identifies plant species and diseases, making it useful for many crops.

Applications:

- Agricultural Monitoring
- Smart Farming Systems.
- Crop Health Assessment.
- Research and Development.
- Pest control.

III. MODELING AND ANALYSIS



Input & Preprocessing: The process starts with an input leaf image. It's then preprocessed, including noise removal, to improve image quality for further analysis.

Feature Extraction: Extended Local Binary Patterns (ELBP) are extracted from the preprocessed image. ELBP is a technique used to capture texture features, which are important for distinguishing different leaf patterns.

First-Stage Classification (Plant Type): A CNN is used to classify the leaf image into a general plant type (e.g., Apple, Grape, Tomato). This stage utilizes a dataset, specific layer architecture, and training options to achieve the classification.

Second-Stage Classification (Disease Detection): Based on the plant type identified in the first stage, another CNN is employed to detect specific diseases associated with that plant. For example, if the leaf is classified as "Apple," this stage aims to identify diseases like Black Rot, Scab, or Cedar-Rust.

Accuracy Evaluation: The final step involves evaluating the overall accuracy of the system by comparing the predicted disease with the actual disease present in the leaf image

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IV. RESULTS AND DISCUSSION

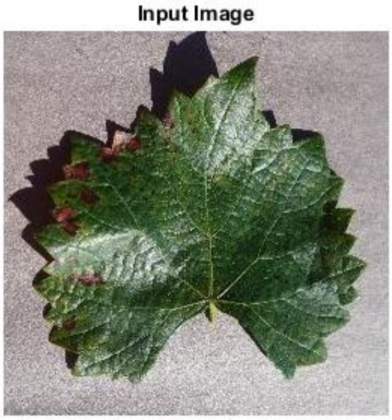


Fig 1: Input image

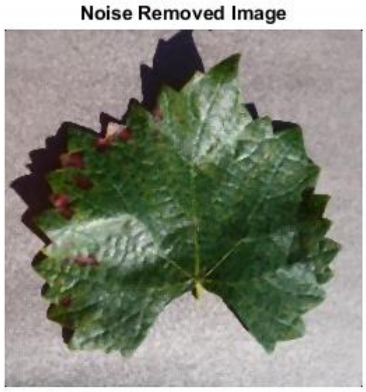


Fig 2: Noise Removed Image

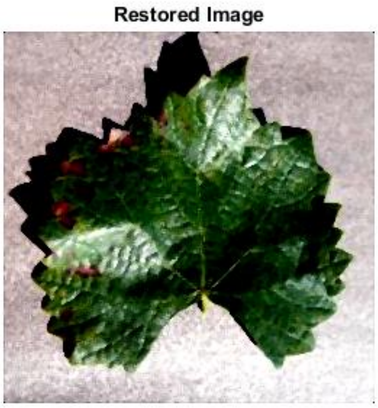


Fig 3: Restored Image

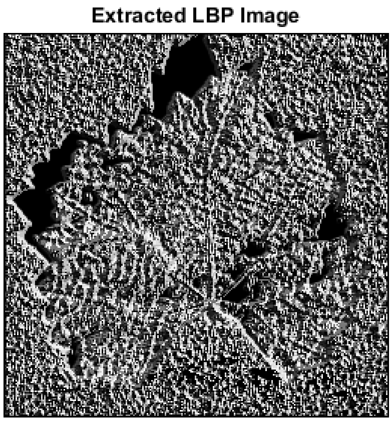
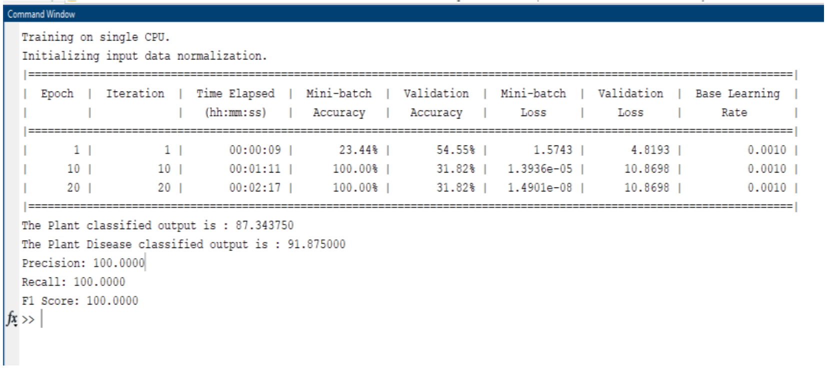


Fig 4: Extract LBP features Image


Command Window

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Training on single CPU.
Initializing input data normalization.
|========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|========================================================================================================|
|       1 |           1 |       00:00:09 |       23.44% |       54.55% |       1.5743 |       4.8193 |          0.0010 |
|      10 |          10 |       00:01:11 |      100.00% |       31.82% |   1.3936e-05 |      10.8698 |          0.0010 |
|      20 |          20 |       00:02:17 |      100.00% |       31.82% |   1.4901e-08 |      10.8698 |          0.0010 |
|========================================================================================================|
The Plant classified output is : 87.343750
The Plant Disease classified output is : 91.875000
Precision: 100.0000
Recall: 100.0000
F1 Score: 100.0000
fx >>
```

Fig 5: Training Iterations

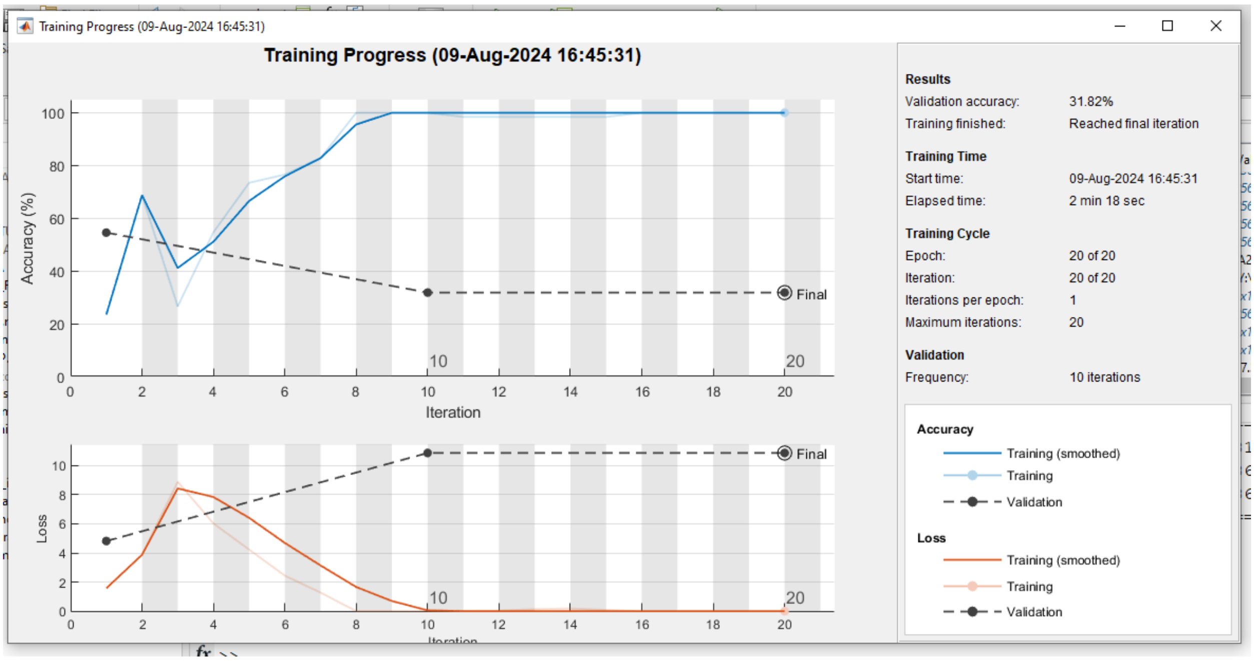

Fig 6: Training Progress

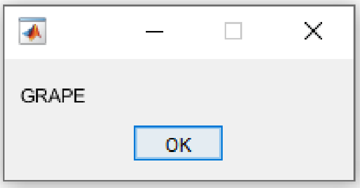

Fig 7: Plant Classification Result

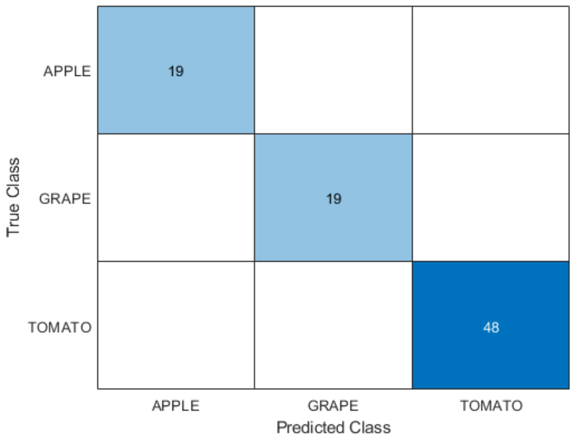

Fig 8: Plant Related Confusion matrix Image

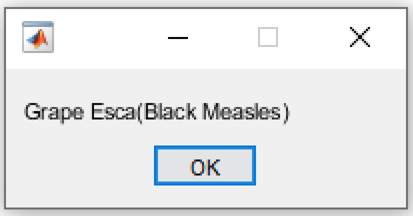

Fig 9: Plant Disease Classification

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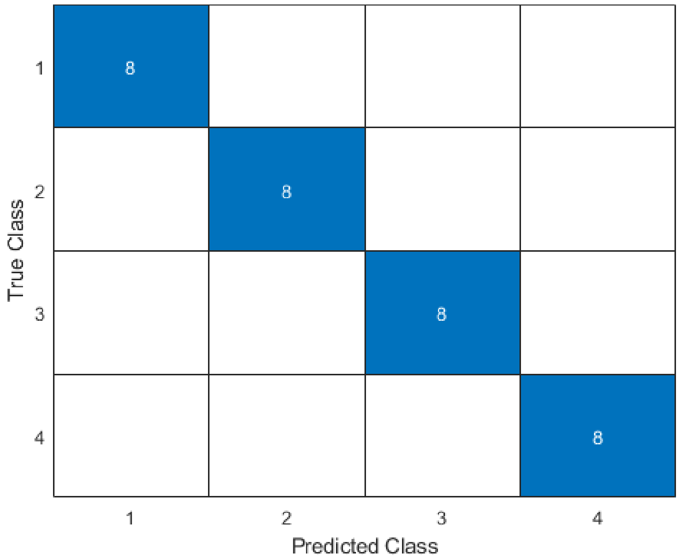

Fig 10: Plant Disease Related Confusion matrix Image

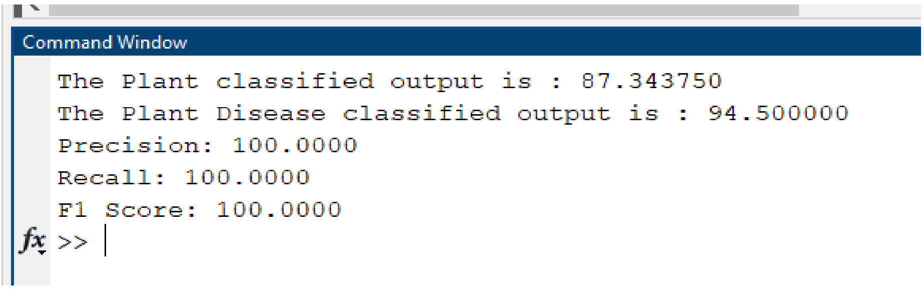

Fig 11: Accuracy and Metric Values

V. CONCLUSION

In conclusion, this study demonstrates the efficacy of a dual-stage classification approach for accurately identifying plant leaf diseases, leveraging the strengths of deep convolutional neural networks (CNN) and Local Binary Pattern (LBP) feature fusion. By first classifying the plant species, such as Apple, Tomato, or Grape, and subsequently identifying specific diseases like Black Rot, Scab, or Cedar Rust, the method ensures a comprehensive analysis that enhances diagnostic precision. The integration of noise removal, image restoration, and feature extraction from LBP, combined with augmented data, contributes to the model's robustness. The CNN's layered architecture and iterative training further refine the classification process, enabling high accuracy in disease detection. This approach not only advances the field of plant pathology by providing a reliable tool for early disease identification but also underscores the potential of combining deep learning with traditional feature extraction techniques to address complex classification tasks in agricultural domains.

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