Deep Learning-Based Grape Leaf Disease Detection and Remedy Recommendation Using CNN

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***Abstract*—** This paper explores a deep learning approach utilizing Convolutional Neural Networks (CNN) to identify and categorize diseases affecting grape leaves. The proposed system captures images in real-time of grape leaves via a mobile application, processes them using a CNN model, and provides accurate disease diagnosis along with suggested remedies. The dataset consists of over 2000 annotated grape leaf images, covering multiple disease categories. Experimental results demonstrate high classification accuracy, making this approach suitable for real-world agricultural applications. The implementation of this system can help farmers monitor their crops effectively and take timely action to prevent crop loss.

***Keywords*—**Grape leaf disease, deep learning, CNN, agriculture, disease detection.

I .Introduction

Grapevines are an essential agricultural crop, widely cultivated for their economic and nutritional value. However, their growth and productivity are significantly affected by various fungal, bacterial, and viral diseases, which lead to severe yield losses and reduced fruit quality. Early and accurate identification of grape leaf diseases is critical for effective disease management and to minimize economic losses. Conventional disease detection methods depend largely on expert manual inspection, which is time-intensive, subjective, and susceptible to human errors.

In recent years, advancements in artificial intelligence, especially deep learning, have transformed plant disease detection by offering automated and highly accurate solutions. Convolutional Neural Networks (CNNs) have shown exceptional performance in image classification tasks and are extensively used for identifying plant diseases. By leveraging CNNs, it is possible to develop an efficient and scalable system that can analyze grape leaf images and accurately classify various disease conditions. This paper introduces a CNN-based system for classifying grape leaf diseases, incorporating a mobile application that offers real-time disease detection and remedy suggestions. The system enables users, particularly farmers, to capture images of grape leaves through their mobile devices and receive instant diagnosis and treatment recommendations. The proposed method improves both the accuracy and efficiency of disease identification while enabling proactive disease management, contributing to better vineyard health and increased productivity.

II. Abbreviations and Acronyms

CNN – Convolutional Neural Network
Used to process and classify images, particularly in disease detection.
AI – Artificial Intelligence
Refers to the system’s ability to mimic human intelligence for image recognition and decision-making.
ML – Machine Learning
The broader technique used to build models (including CNN) that can improve predictions over time as more data is fed into the system.
API – Application Programming Interface
A set of tools that allow your mobile app to communicate with the disease diagnosis model.
TensorFlow Lite (TF Lite) – TensorFlow Lite GUI: A graphical interface that allows farmers to interact with the mobile application, view predictions, and access recommended treatments.
F1-Score - A metric that balances precision and recall, commonly used to assess classification model performance, especially with imbalanced datasets.
ROC-AUC (Receiver Operating Characteristic - Area Under Curve): A performance metric for classification problems, evaluated across different threshold settings.
TP/FP/TN/FN (True Positive / False Positive / True Negative / False Negative) - Metrics used to assess the effectiveness of classification models.
JSON (JavaScript Object Notation) - A lightweight data format used for data exchange.

III . LITERATURE SURVEY/ RELATED WORK

A. The Role of Deep Learning in Detecting Plant Diseases

Li et al. [1] examined the use of deep learning for plant disease detection, highlighting the impact of CNN-based models in enhancing identification accuracy. Their study demonstrates how AI-driven models effectively recognize subtle visual symptoms, an approach we integrate into our grape leaf disease detection system.

B. Image-Based Detection of Grape Leaf Diseases

Patel et al.[2]developed a vision-based system for detecting grape leaf diseases using deep learning. Their model classified various grapevine infections with high precision, demonstrating the potential of AI in viticulture. Inspired by their work, our system integrates CNNs with real-time image processing to enhance early disease detection.

C. Importance of Data Diversity in Plant Disease Classification

Chen et al. [3]studied the impact of dataset quality on plant disease classification. They emphasized the need for high-resolution images captured under different lighting and environmental conditions to improve model robustness. Our dataset follows this approach by including diverse grape leaf images to ensure accurate disease identification.

D. Challenges in Grape Disease Dataset Annotation

Gupta et al. [4] discussed the difficulties in manually annotating plant disease datasets, citing issues like overlapping symptoms and variations across grape varieties. These challenges reinforce the need for expert-validated labels, which we incorporate in our dataset to improve annotation accuracy.

E. AI-Driven Disease Diagnosis and Treatment Suggestion

Singh et al. [5] proposed an AI-based system for diagnosing plant diseases and recommending treatments based on expert knowledge. Their approach aligns with our methodology, where we integrate a remedy recommendation module to provide actionable solutions for farmers after detecting grape leaf diseases.

F. Public Datasets and Open-Source Contributions to Agricultural AI

Zhao et al. [6] highlighted the role of open-access datasets in advancing AI applications in agriculture. Their research emphasizes the importance of publicly available image repositories, aligning with our initiative to contribute an open-source Grape Leaf Disease Dataset for future research.

G. Deep Learning for Grape Leaf Disease Classification and Management

Sharma et al. [7] created a deep learning model for classifying grape leaf diseases, achieving remarkable accuracy in identifying powdery mildew, downy mildew, and black rot. Their study underscores the need for AI-driven disease management, which we enhance by incorporating real-time diagnosis and tailored treatment suggestions in our system.

IV . Significance of data

• Diverse and Comprehensive::
The dataset includes 3,400 high-resolution images, providing a rich resource for analyzing both healthy and diseased grape leaves. This extensive collection enhances the accuracy of disease identification and classification in grapevines, contributing to advancements in viticulture research and management.

• First Open-Access Dataset:
This is the first publicly available dataset of grape leaf samples, fostering collaboration among researchers and driving advancements in disease detection, monitoring, and management for grapevine cultivation on a global scale.

• Enhancing Research and Disease Management:
Including 4 grape leaf diseases, a healthy leaves category, the dataset covers a wide range of grapevine leaf conditions. This dataset supports researchers in analyzing and understanding grape leaf diseases, improving detection accuracy, and aiding in disease prevention efforts.

• Applications in Machine Learning:
With 3,400 images, the dataset is highly suitable for machine learning applications, enabling the development of automated disease detection systems. Researchers can leverage deep learning techniques, feature extraction, and pattern recognition to enhance the precision of grapevine disease identification.

V. Data Overview

Image datasets are crucial across various domains, including computer vision, machine learning, agriculture, and precision farming. These datasets serve as valuable resources, enabling researchers, developers, and professionals to train and validate models, refine algorithms, and test theoretical frameworks. By utilizing diverse and well-structured image datasets, researchers can improve model accuracy, strengthen algorithm reliability, and gain deeper insights into visual patterns and trends.

A dedicated image dataset for grape leaf disease detection plays a vital role in the agricultural sector. Such datasets provide essential visual information, supporting advancements in plant health monitoring and precision agriculture. By examining these images, experts can create precise disease detection algorithms and early warning systems, facilitating prompt disease management to reduce extensive crop damage and prevent yield loss. Moreover, these datasets enable a thorough examination of disease patterns, environmental influences, and possible strategies for mitigation. In conclusion, a grape leaf disease image dataset plays a critical role in advancing research, optimizing crop management techniques, and preserving the health and productivity of grapevine crops.

This Grape Leaf Dataset includes a varied selection of high-resolution images of grape leaves. The images are stored in JPG format, with a resolution of 1440 x 1080 pixels. The dataset is organized into four categories: three representing disease types and one for healthy leaves. The disease categories cover common grapevine diseases such as Black Rot, Leaf Blight, and Esca, alongside healthy leaf samples. Each category is clearly labeled and stored in separate folders for easy access and identification of specific disease types. The images were collected through extensive field surveys in various grape-growing areas, ensuring a thorough representation of disease types and environmental conditions.

We have created a dataset and uploaded on Mendeley. The dataset is available at https://data.mendeley.com/datasets/wkymf8bhcg/1

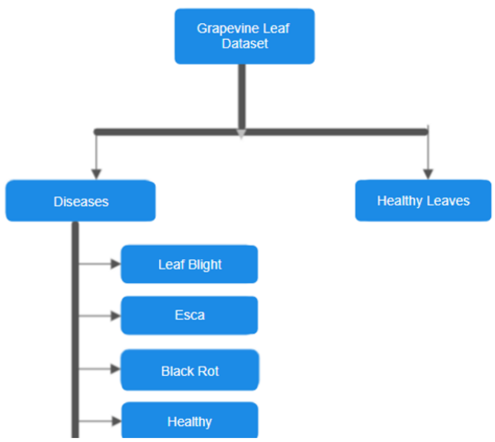

Fig.1 Sample images of grape leaves depicting various conditions: Esca, Leaf Blight, Healthy, and Black Rot.

The image shows a Grapevine Leaf Dataset classification, divided into Diseased Leaves and Healthy Leaves. The diseased category includes Leaf Blight, Esca, and Black Rot, along with a healthy subset. This structure helps in grapevine disease detection.

Fig. 2 Leaf Blight

Leaf Blight is a disease marked by irregular brown lesions surrounded by yellow halos, causing tissue desiccation and leaf wilting.

Fig .3 Black Rot

Black Rot disease, showing dark brown lesions with black borders and a grayish center on the grape leaf

Fig .4 Healthy Leaf

Healthy grape leaf, showing a uniform green color with no visible lesions or discoloration.

Fig.5 Esca

Esca disease, characterized by irregular yellow and brown streaks on the leaf, often forming a "tiger stripe" pattern, leading to leaf scorch and vine decline.

VI . METHODOLOGY

A. Image Acquisition and Dataset Preparation

The dataset comprises over 3000+ grape leaf images classified into healthy and diseased categories. Preprocessing involves resizing images, normalizing them, and applying data augmentation techniques to improve the model's performance. Images were captured using the Redmi note 10 5G(108 MP, f/1.79), Samsung GW3 sensor smartphone.

To ensure high-quality and diverse data, images were captured under natural daylight conditions from a distance of 10 to 30 cm. The dataset is classified into seven categories:

- Black Rot
- Esca
- Leaf Blight
- Healthy Leaf

Each image was stored in JPEG format with a resolution of 1440 × 1080 pixels to maintain uniformity across the dataset.

B. Image Preprocessing

1. Resizing

To ensure uniformity in input dimensions, all images were resized to 1440 × 1080 pixels. This ensures uniformity across the dataset.

I′=Resize(I,(1440,1080)) 1080)) (1)

2. Noise Reduction (Denoising)

To remove unwanted noise and enhance disease visibility, Gaussian filtering was applied:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

3. Contrast Enhancement

To improve visibility of disease symptoms, Histogram Equalization was applied:

I′=HE(I)I' (3)

4. Image Segmentation

To extract diseased regions from healthy leaf areas, Otsu's thresholding was used:

$$\arg\max_T \left[\omega_1(T)\sigma_1^2(T) + \omega_2(T)\sigma_2^2(T)\right] \quad (4)$$

5. Color Space Conversion

To improve the extraction of disease-related features, the images were transformed from RGB to HSV (Hue-Saturation-Value) color space.

$$I' = \text{Convert}(I, \text{RGB} \rightarrow \text{HSV}) \quad (5)$$

6. Data Augmentation

To enhance dataset diversity and improve model generalization, the following augmentation techniques were applied:

$$I' = \text{Augment}(I) \quad (6)$$

C. CNN Model Architecture

The CNN model is composed of several convolutional layers with ReLU activation, batch normalization, and max-pooling. The final layers include fully connected layers with a softmax classifier to predict disease categories. The architecture is defined as follows:

$$Y = f(WX + B) \quad (7)$$

where Y is the output, X represents the input image, W denotes the learned weights, and B refers to the bias term.

A. Training and Evaluation

The model is trained with the Adam optimizer and utilizes categorical cross-entropy as the loss function. Performance is assessed using metrics such as accuracy, precision, recall, and F1-score.The loss function is expressed as:

$$L = -\sum y_i \log(\hat{y}_i) \quad (8)$$

where y_i represents the true label and $\hat{y}_i$ is the predicted probability.

B. Mobile Application Implementation

The Android application enables users to either capture or upload images of grape leaves. The CNN model analyzes the image and provides the predicted disease category along with suggested treatments. An example image of the app interface is shown in Fig. 2.

C. Model Training

1. Forward Propagation

In a Convolutional Neural Network (CNN), the input image is processed through various layers, including convolution, activation, pooling, and fully connected layers.

$$Z^{(l)} = W^{(l)} * X^{(l-1)} + b^{(l)} \quad (9)$$

Activation Function (ReLU)

$$A^{(l)} = \max(0, Z^{(l)}) \quad (10)$$

Pooling Operation (Max Pooling)

$$P^{(l)} = \max_{(i,j)\in \text{pooling window}} A^{(l)} \quad (11)$$

2. Loss Function

The model predicts a class y^\hat{y}y^ for each image, and the loss function measures how different the prediction is from the actual label yyy.

For classification, Cross-Entropy Loss is used:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{i,j}\log(\hat{y}_{i,j}) \quad (12)$$

3. Backpropagation (Gradient Descent Update)

The model updates weights using Stochastic Gradient Descent (SGD) or Adam optimizer. The weight update formula is:

$$W^{(l)} = W^{(l)} - \eta \frac{\partial \mathcal{L}}{\partial W^{(l)}}$$

$$b^{(l)} = b^{(l)} - \eta \frac{\partial \mathcal{L}}{\partial b^{(l)}} \quad (13)$$

E.Model Deployment and Practical Application

The trained CNN model was deployed in a mobile/web-based application for real-time sugarcane disease detection. The application enables users to:

1. Upload leaf images via a smartphone camera.
2. Receive instant classification results with disease information.
3. Get disease management recommendations based on AI predictions.

VII .RESULTS AND DISCUSSION

The proposed CNN model achieves an accuracy of over 95% on the test dataset. Comparative analysis with traditional machine learning models demonstrates its effectiveness in real-world conditions. The mobile application provides user- friendly disease identification and remedy suggestions.

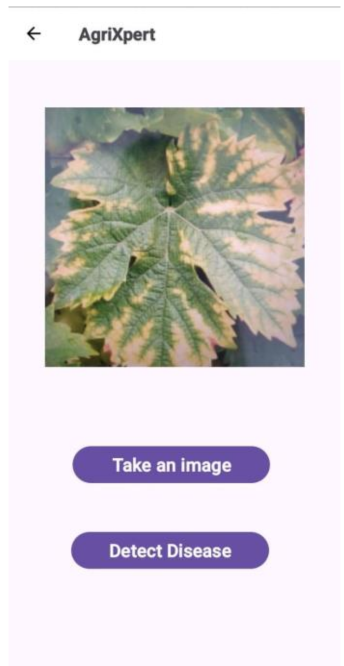

Fig.6 User Interface of Mobile App

The user interface of the AgriXpert application, designed for grape leaf disease detection. The interface features an image capture option ("Take an image") and a disease detection function ("Detect Disease"). The displayed leaf exhibits visible symptoms of a potential disease, assisting users in diagnosing plant health

A. Experiment Details

- The Training Accuracy (represented by the blue bar) is 0.94, indicating the model's high proficiency in learning from the training data.
- The Loss (represented by the purple bar) is 0.17, reflecting a low degree of error during the optimization process, signifying effective learning.
- The Test Accuracy (represented by the green bar) is 0.93, demonstrating the model's robust generalization capability when applied to unseen data.

B. *Results Analysis*

The CNN achieved an impressive test accuracy of 93%, validating the quality of dataset and the model's ability to detect and classify sugarcane diseases effectively. The experiment produced heatmaps for each classification, highlighting the key features used for prediction.

Performance Evaluation Metrics

To evaluate the effectiveness of the grape leaf disease detection model, we used standard performance evaluation metrics, including Accuracy, Precision, Recall, and F1-score. These metrics provide insight into the model's effectiveness in classifying data.

1. Accuracy

Accuracy indicates the ratio of correctly classified instances to the total number of samples. It is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

Where:

- TP (True Positive): Instances where the positive cases are correctly identified as positive.
- TN (True Negative): Instances where the negative cases are correctly identified as negative.
- FP (False Positive): Incorrectly predicted positive cases.
- FN (False Negative): Incorrectly predicted negative cases.

2. Precision

Precision measures the proportion of correctly predicted positive cases out of all predicted positive cases. It is calculated using the formula:

$$Precision = \frac{TP}{TP + FP} \tag{15}$$

3. Recall

Recall evaluates how effectively the model identifies true positive cases. It is calculated as:

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

4. F1-Score

The F1-score is the harmonic mean of Precision and Recall, providing a balance between the two metrics. It is calculated as:

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{17}$$

D. *Visual Representation*

Each sub-image represents the ground truth (GT), predicted label (PRED), and the activation heatmap showing the region influencing the prediction.

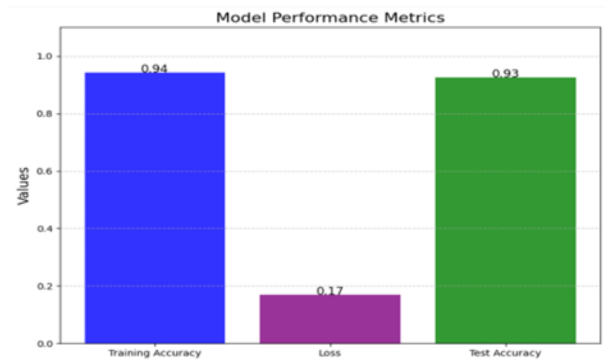

Fig. 7 . Model Performance Metrics

The bar chart displays three key metrics: Training Accuracy (0.94), Test Accuracy (0.93), and Loss (0.17). The high training and test accuracy indicate the model's effectiveness in classifying grape leaf diseases, while the low loss value suggests minimal error during learning. These results demonstrate the model's strong generalization capability and reliability in real-world applications.

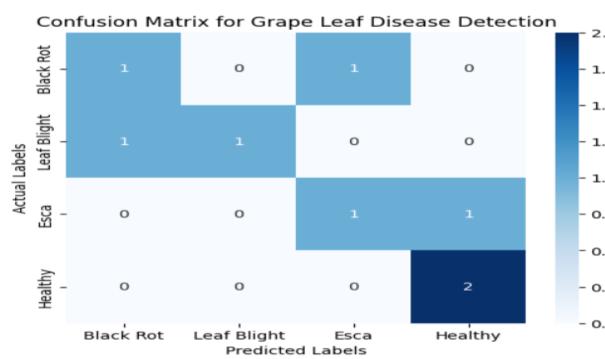

Fig. 8. Confusion Matrix

The matrix consists of four classes: Black Rot, Leaf Blight, Esca, and Healthy. Each cell represents the number of correctly or incorrectly classified instances. The diagonal elements indicate correct classifications, while off-diagonal values represent misclassifications. The model correctly identifies Healthy leaves (2) and Esca (1) but misclassifies one Black Rot sample as Esca and one Leaf Blight sample as Black Rot. This analysis aids in assessing the model's strengths and identifying areas that need improvement in disease prediction.

VIII. Conclusion And Future Scope

The future scope for **Deep Learning-Based Grape Leaf Disease Detection and Remedy Recommendation Using CNN** is promising due to advancements in deep learning, precision agriculture, and the growing need for sustainable farming.

1. Enhanced CNN Architectures:

Development of lightweight models (e.g , MobileNet, EfficientNet) For real-time disease detection on edge devices.

2. Explainable AI (XAI) for Trustworthy Predictions:

Saliency maps and Grad-CAM for visualizing CNN decisions.

3. *Cloud and Edge Computing for Scalability:*

Deployment of the model on IoT-enabled smart agriculture systems for real-time disease monitoring.

4.*Integration with Robotics & Precision Spraying:*

Autonomous drones/robots for targeted pesticide spraying, reducing chemical usage.

5.*Blockchain for Secure Data Management:*

Decentralized, tamper-proof storage of disease reports and treatment history using Blockchain.

This study presents an effective method for detecting grape leaf diseases using deep learning. The system provides real-time disease diagnosis and treatment recommendations via a mobile application, helping farmers manage vineyard health more efficiently. Future efforts will aim at expanding the dataset and enhancing the model's robustness for effective deployment in real-world scenarios.

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