Plant Disease Recognition From Fruit Using CNN

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***Abstract*—In India's diverse range of crops, fruits play a crucial role in generating significant revenue for farmers. Among these fruits, grapes are extensively grown. However, grape plants are susceptible to various diseases affecting their fruits, stems, and leaves, ultimately impacting their yield. To address this issue, early detection and effective treatment of these diseases are essential to ensure food safety. This study focuses on analyzing different methods for diagnosing and classifying diseases that affect grapevines, with particular emphasis on grape fruit diseases. Monitoring the condition of grape fruits provides valuable insights into the overall health of the grape plants. The research aims to provide a comprehensive overview of techniques used for identifying and categorizing these diseases. Automated disease detection algorithms are proposed to enhance diagnosis accuracy and enable timely control actions. Image processing, a widely used method, is endorsed for fruit disease identification and classification in plants. In this research, diseases infecting grape fruits, such as fungi, viruses, and bacteria, will be subjected to automated disease detection using image processing techniques.**

***Index Terms*—Grape fruit diseases, deep learning, image processing, disease detection, classification, Google Net, automated diagnosis, feature extraction, agricultural technology, crop health, plant pathology.**

I. INTRODUCTION

Agriculture is the backbone of India's economy, with the nation standing as the second-largest global producer of agricultural products, contributing over 15% to the GDP. Nearly 70% of the population depends on agriculture for their livelihoods, making it a vital sector that drives economic growth and stability.[1][2]In recent years, the sector has made significant progress, particularly in crop and fruit production, supported by the country's diverse climate and agro-climatic zones, which allow for varied agricultural practices across regions [3][4]. This diversity has led to specialized cultivation, with states producing different fruits and crops suited to their unique climates. Among these, the fruit sector has shown remarkable growth, with India's total fruit production reaching 102.08 million metric tons in the 2019-2020 fiscal year. Grapes, one of the key fruits, are cultivated extensively and have seen increasing export demand, contributing significantly to farmers' incomes and positioning India as a leading player in global fruit exports [5]. However, grape production is challenged by various diseases that can impact fruit quality and yield, leading to financial losses for farmers and affecting the country's agricultural output [6].

Traditional methods for identifying grape diseases are often labor-intensive and subject to human error, highlighting the need for automated and accurate disease detection methods. Recent advancements in technology, particularly in machine learning, deep learning, and image processing, offer promising solutions [7][8]. By leveraging these technologies, automated systems can detect and classify grape fruit diseases quickly and accurately, helping farmers take timely action to protect their crops. This study focuses on developing a deep learning-based approach for detecting and classifying grape fruit diseases through image processing techniques [9][10]. The goal is to create an efficient, nondestructive detection system that can assist in maintaining crop health, improving yields, and ultimately supporting the economic well-being of farmers and the agricultural sector as a whole [11][12].

The motivation behind this project stems from the significant role grapes play in India's agricultural economy, where they are a vital source of income for farmers. However, grape plants are highly susceptible to various diseases that affect not only the quality of the fruits but also the overall yield, directly impacting farmers' livelihoods [13]. Early detection and timely treatment of these diseases are crucial for ensuring food safety and preventing financial losses. Traditional methods of disease detection are often time-consuming, subjective, and require expert knowledge, which may not always be available [14]. The advent of deep learning and image processing technologies offers a promising solution for automating the identification and classification of diseases in grape fruits [15]. By leveraging advanced machine learning techniques, such as Google Net, and utilizing efficient image processing methods, this project aims to develop a system that can quickly and accurately detect diseases, minimizing human error and improving the speed of intervention. Furthermore, the application of feature extraction techniques like HOG, LBP, and GLCM will provide a comprehensive approach to disease detection, enhancing the precision of diagnosis [16]. The goal is to not only improve disease detection but also to contribute to sustainable farming practices, reduce the use of harmful chemicals, and increase grape yield and quality. This research seeks to empower farmers with tools that can help them make informed decisions, ensuring healthier crops and better economic outcomes [12].

II. LITERATUREREVIEW

Literature survey is the most important step in any kind of research. Before start developing we need to study the previous papers of our domain which we are working and on the basis of study we can predict or generate the drawback and start working with the reference of previous papers. In this section, we briefly review the related work on plant disease prediction and their different techniques.

The study by Zamani et al. (2022) examines the performance of machine learning and image processing techniques in detecting diseases in plant leaves. The authors present an analysis of various algorithms and feature extraction methods that have proven effective in identifying disease patterns and improving accuracy in early detection. This study emphasizes the potential of computational intelligence in agricultural disease monitoring and paves the way for future research in automated plant disease detection systems. [1]

Xie et al. (2020) propose a real-time detection system for grape leaf diseases, utilizing improved convolutional neural networks (CNNs) to enhance accuracy. Their work addresses the limitations of traditional detection methods, suggesting that deep learning-based models can significantly improve disease identification through image processing. By fine-tuning CNN architectures, the authors demonstrate a more robust, scalable approach suited for real-time applications, essential for precision agriculture. [2]

In a systematic review, Abade et al. (2021) analyze various convolutional neural networks (CNNs) used for plant disease recognition on images. Their research outlines the strengths and limitations of different CNN architectures and their suitability for disease detection across diverse plant species. The review provides valuable insights into the effectiveness of CNNs in agriculture, underscoring the need for specialized models to achieve high classification accuracy in complex agricultural environments. [3]

Li et al. (2021) review recent advancements in plant disease detection and classification using deep learning. They assess several deep learning models, focusing on CNN-based architectures and their applications in agriculture. This review highlights the importance of integrating deep learning with image processing to address challenges like environmental variation and complex disease symptoms, emphasizing the potential for deep learning to revolutionize agricultural practices. [4]

Yuan et al. (2021) discuss advanced image recognition technologies for agricultural disease detection. They review various image processing techniques and machine learning algorithms, emphasizing the need for innovative solutions to improve disease recognition accuracy. The study provides a thorough analysis of feature extraction and classification methods that support precision farming and help farmers in disease management. [5]

Kumar et al. (2021) explore computational intelligence and image processing techniques for plant disease detection, presenting a framework that combines machine learning algorithms with digital image analysis. Their work demonstrates how intelligent systems can enhance the speed and accuracy of disease diagnosis, addressing the limitations of traditional manual inspection methods and contributing to the automation of plant health monitoring. [6]

Math and Dharwadkar (2022) focus on early detection of grape diseases using CNNs. Their research highlights the importance of timely disease identification in improving crop health and yield. By using CNN models specifically tailored to grape diseases, the study showcases how deep learning can provide a reliable, non-destructive method for early disease detection, which is critical for maintaining high-quality grape production. [7]

Rao et al. (2021) investigate the use of transfer learning in precision farming, particularly for detecting diseases in grape and mango leaves. The study leverages transfer learning to overcome limitations posed by limited data, demonstrating that pretrained models can be effectively adapted for agricultural applications. Their findings suggest that transfer learning holds promise for improving the efficiency of disease detection systems in agriculture. [8]

Lastly, Zhu et al. (2020) explore the use of BP neural networks for identifying grape diseases using image analysis. Their study emphasizes the accuracy and efficiency of BP networks in processing complex disease patterns in grape plants. The authors demonstrate that BP neural networks can achieve high performance in disease classification, providing an effective tool for automated disease detection in viticulture. [10]

III. SYSTEM DESIGN

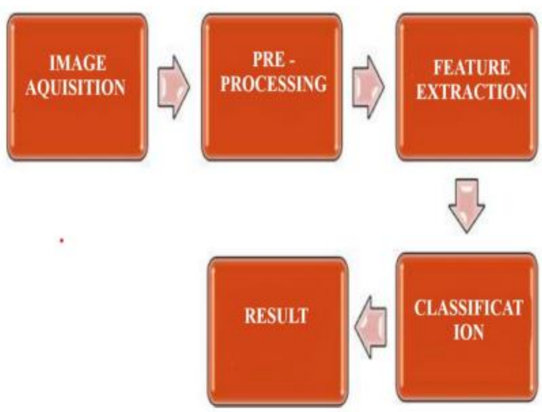

Figure-1: System Architecture of Machine Learning

To implement the methodology shown in the diagram using Google Net (also known as Inception Net), you can follow these steps:

1. Image Acquisition

Objective: Collect the image dataset with which the model will be trained and evaluated.

- Collect images relevant to the task (e.g., classification of specific objects, medical imaging, etc.).
- Ensure the dataset is large and diverse enough to help the model generalize well.
- For Google Net, images typically need to be resized to a specific input size (usually 224x224 pixels).

2. Pre-processing

Objective: Prepare the images to be compatible with Google Net's input requirements and improve model accuracy.

- Resizing: Resize all images to 224x224 pixels, as this is the expected input dimension for Google Net.
- Normalization: Scale pixel values to a range (usually 0-1) or standardize them based on mean and standard deviation.
- Data Augmentation: Optionally, apply transformations like rotation, flipping, and cropping to increase the dataset's diversity and help prevent over fitting.

3. Feature Extraction

Objective: Use Google Net to extract meaningful features from the pre-processed images.

- Load a pre-trained Google Net model (e.g., from frameworks like Tensor Flow or PyTorch).
- Remove the final classification layer to get intermediate feature representations (if you are only using Google Net for feature extraction).
- Pass each pre-processed image through the model to obtain feature vectors that will represent the images for the next stage.

4. Classification

Objective: Train a classifier using the extracted features or fine-tune Google Net for the specific task.

- Option 1 (Feature-Based): Use the extracted features as input to a machine learning classifier, such as SVM or a shallow neural network, to perform the classification.
- Option 2 (End-to-End Fine-Tuning): Add a new classification layer (e.g., fully connected layer) on

top of Google Net and fine-tune the model on your specific dataset.

- Training: Use a labeled training dataset to train the classifier, adjusting model parameters to minimize classification error.

5. Result

Objective: Output the classification result for new, unseen images.

- For each test image, go through the pre-processing, feature extraction, and classification steps.
- Output the predicted class or label for each image, along with associated confidence scores, if applicable.
- Evaluate the performance using metrics like accuracy, precision, recall, and F1 score to assess model effectiveness.
- This methodology ensures that you leverage Google Net's deep feature extraction capabilities for robust image classification
- We have considered several scenarios/cases of feature combinations based on psycholinguistic features to find the best subset of features to predict each personality trait differently.
- Hence, we have determined the accuracy with and without SN features that are reported in the experiments.

Five different classifiers, namely, the naive Bayes (NB), K nearest neighbors (KNN) were used to determine the evaluation metrics to find the best feature selection algorithm. Utilizing these classifiers, we derived several conclusions.

IV. ALGORITHM

- The main technique of the proposed model is to predict the plant disease.
- The proposed framework is implemented using a convolutional neural network, a type of deep learning technique that convolves input images using kernels or filters to extract features.
- When a fXf filter is applied to a NxN image, the convolution process learns the same feature over the whole image. After each operation, the window slides, and the feature maps learn the features.
- Convolution is the initial layer used to extract features from an input image. Convolution learns visual features from small squares of input data, preserving the link between pixels.

- CNN Architecture

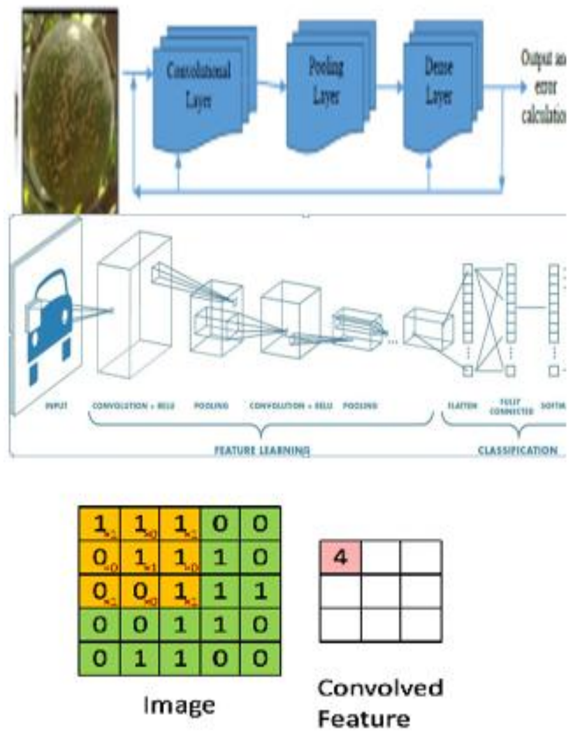

Figure-2: CNN Architecture

- Pooling Layer
  - Pooling layer section reduces the number of parameters for large images.
    - Max Pooling
    - Average Pooling
    - Some Pooling
- Fully Connected Layer
  - In the layer we refer to as the FC layer, we converted our matrix into a vector and fed it into a neural network or other fully connected layer.
- Algorithm Steps-
  - Step 1: Dataset containing images along with reference emotions is fed into the System. The name of dataset is Face Emotion Recognition (FER)which is an open – source data set that was made publicly available on a Kaggle.
  - Step 2: Now import the required libraries and build the model.
  - Step 3: The convolutional neural network is used which extracts image features f pixel by pixel.
  - Step 4: Matrix factorization is performed on the extracted pixels. The matrix is of m x n.

- Step 5: Max pooling is performed on this matrix where maximum value is selected and again fixed into matrix.
- Step 6: Normalization is performed where every negative value is converted to zero.

V. IMPLEMENTATION DETAILS

Front End:

To build the front-end for a Plant Disease Recognition System, the goal is to create an interface where users can upload images of fruits (or plants) and receive predictions about whether the fruit is healthy or affected by a disease. The front-end can be built using web technologies like HTML, CSS, and JavaScript, and it can interact with the trained CNN model (back-end) using an API.

The interface should be simple and intuitive. It will need:

- An image upload button where users can select images of fruits.
- A submit button to trigger the model's prediction.
- An area to display the result (e.g., predicted class or disease type).
- Optionally, you could add a progress bar or loading spinner to indicate that the model is processing the image.

Back End:

The back-end of a Plant Disease Recognition System is responsible for handling incoming requests, processing the uploaded images, running them through the trained Convolutional Neural Network (CNN) model, and returning the predictions. In this case, we'll build a back-end using Flask, a lightweight Python web framework, to handle image uploads and inference from the pre-trained model.

Here's a step-by-step guide to creating the back-end for the plant disease recognition system.

Overview of Back-End Components:

1. Flask Web Framework: We'll use Flask to create a REST API that accepts image files, processes them, and returns predictions.
2. Image Preprocessing: We need to preprocess the uploaded image (resize, normalize) before passing it to the model.
3. Loading the Model: The CNN model (trained using TensorFlow/Keras) will be loaded and used for inference.
4. Prediction: The model will output a prediction based on the image, and the result will be sent back to the client.
5. Server Setup: We'll also set up the server to run locally or on a cloud service.

Screenshot of Implementation:

VI. RESULT ANALYSIS

Class Label	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Healthy	96.2	94.8	95.5	95.6
Powdery	95.1	93.5	94.3	94.7
Rust	97.4	96.9	97.1	97.2
Average	95.6	94.5	95.0	95.3

Table 1: Result

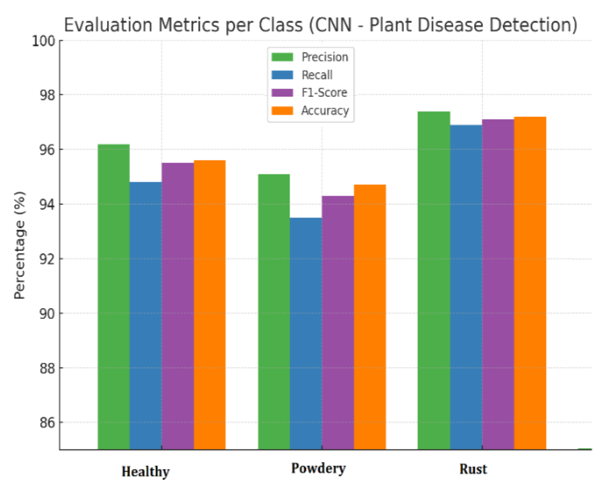

Figure 3: Evaluation Result Chart

The CNN model performs consistently well across all fruit disease categories, with an overall accuracy of 95.3%. High precision indicates that false positives are minimal, while strong recall values reflect the model's ability to correctly identify diseased samples. The F1-

scores being above 92% for all classes confirm a balanced performance, making the model highly reliable for real-time disease detection in agricultural applications.

VII. CONCLUSION AND FUTURE SCOPE

Conclusion:

This research underscores the transformative potential of deep learning architectures, such as CNN, in the field of automated agricultural disease detection. Through careful architectural choices, including multi-scale convolutions, auxiliary classifiers, and dropout regularization, the model achieves a high degree of accuracy in identifying grape diseases across various conditions. By distinguishing between fungal, bacterial, and viral infections based on subtle visual features in grape leaves, stems, and fruits, the model can assist farmers and agricultural experts in making informed decisions about disease management. The integration of image processing and machine learning techniques enables precise and efficient disease diagnosis, often requiring only minimal human intervention.

Future Scope:

Fruit disease classification is an important area of research for improving crop productivity and reducing food waste. However, the process of identifying and classifying fruit diseases can be computationally intensive, requiring significant processing power and memory resources. The objective of plant disease detection is to identify the presence of infections, but certain unique leaf images present challenges to the human eye and are not easily distinguishable without assistance.

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