Analysis of Diseases in Farm Crops Using Image Processing and Machine Learning Techniques

C. Siva kumar[1*], Kodadala Charishma Reddy[2], Mounika Annam[3], Ch Govardhan Reddy[4], Enamala Pujith[5]

[1]Associate Professor, Dept. of CSSE, Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College), Tirupati.India
[2,3,4,5] UG Scholar, Department of Computer Science and Systems Engineering, Sree Vidyanikethan Engineering College, Tirupati, India

[*1]sivakumar.c@vidyanikethan.edu
[2]kodadalacharishmareddy@gmail.com
[3]mounikaannam319@gmail.com
[4]chgovardhanreddy2310@gmail.com
[5]enamalapujith@gmail.com

Abstract: The existence of plant diseases is a matter of considerable health apprehension for all forms of life. Timely identification of diseases enables farmers to promptly implement the required remedies, thereby enhancing agricultural productivity. Machine learning stands at the forefront of modern technology, serving as the foundation for precision agriculture by facilitating the creation of sophisticated techniques for disease detection and classification. This project delves into the detection of plant diseases through the use of visual recognition technology. Upon uploading an image of the infected leaf to our application, it will undergo analysis. The application will then promptly identify the disease and provide recommended preventive methods directly within the application. Managing diseases poses a formidable challenge. Diseases are predominantly observed on the leaves or stems of plants. Accurately measuring diseases, pests, and traits that are visually observed has not been thoroughly explored due to the intricate nature of visual patterns. This paper introduces an approach for identifying leaf diseases through the utilization of advanced machine learning and image processing methods, addressing the escalating demand for enhanced and accurate image pattern recognition in this context. Using image processing and CNNs for detecting plant diseases involves capturing and preprocessing plant images, extracting relevant features, and then using a CNN to learn and identify patterns indicative of diseases. Image Processing involves Image Acquisition, Pre-processing and Feature Extraction, whereas CNN involves Convolutional Layers, Activation Function, Pooling Layers, Fully Connected Layers and Output Layers.

Keywords: Image processing, Image Acquisition, Pre-processing, Feature Extraction, Neural networks, Activation Function and Pooling Layers.

1 INTRODUCTION

Agriculture is the cornerstone of global sustainability, providing the foundation for food security and economic stability. However, the persistent threat of crop diseases poses a formidable challenge to the agricultural sector, jeopardizing crop yields and food production. Ensuring timely and precise identification of crop diseases is imperative for deploying successful mitigation measures. In recent times, the amalgamation of image processing and machine learning methodologies has surfaced as a revolutionary strategy to tackle this challenge. The thorough investigation of applying machine learning techniques and image processing helps in analyzing the diseases affecting farm crops by predicting disease. Leveraging advancements in technology, methodology aims to enhance the efficiency and accuracy of disease identification, enabling early detection and proactive management strategies. By harnessing the power of computational algorithms, the proposed approach seeks to provide farmers and agronomists with a robust tool for real-time monitoring and diagnosis, ultimately contributing to the resilience and sustainability of agricultural practices. The combination of these innovative technologies has the potential to completely transform disease analysis in farm crops, marking a significant stride towards ensuring global food security in the face of evolving

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_35

agricultural challenges. In this endeavor, the focus lies on creating a seamless synergy between image processing and machine learning techniques. Convolutional Neural Networks (CNNs) will be employed to decipher intricate patterns within crop images, enabling a nuanced understanding of disease characteristics. The utilization of a diverse and well-annotated dataset will serve as the cornerstone for training these models, ensuring adaptability across various crops and diseases. Furthermore, the proposed methodology extends beyond mere disease identification, delving into the realm of disease severity assessment.

2 RELATED WORK

The exploration of image processing and machine learning in the context of agricultural disease analysis has generated a significant body of related works, reflecting the increasing recognition of the importance of leveraging technology for sustainable agriculture. One notable area of related research focuses on the development and application of specific image processing techniques for crop identification of diseases, block diagram shown in Fig 1.Literature Survey encompasses a framework that combines machine learning and image processing to analyze diseases affecting farm crops. Various methods can be employed to recognize and categorize diseases affecting plants and fruits.
Suhaili Kutty et al. categorized as conditions affecting watermelon leaves, such as Anthracnose and Downey mildew, are noteworthy leaf diseases. To accomplish the task, it is essential to pinpoint the region of interest within an infected leaf sample by leveraging the RGB color components. Writers have employed mean filters for the purpose of eliminating noise in the input data. Dubey and R. Jalal conducted research on various apple diseases, including scab, apple rot, and apple blotch.

Dipali Majumder et al. reported that BTH (benzothiadiazole) offers systemic protection to wheat from powdery mildew infection by disrupting various phases of the pathogen's life cycle. Rong and colleagues successfully detected early cercospora leaf spot in sugar beet by employing a hybrid approach that integrated template matching and support vector machine techniques. Revathi et al. suggested employing fuzzy curves and fuzzy surfaces for the selection of image features in the diagnosis of cotton leaves disease.

Mohanty and colleagues conducted training on AlexNet and GoogLeNet to detect 26 diseases across 14 different crop species. This training utilized the PlantVillage dataset, comprising a total of 54,306 images. Amara et al. employed the LeNet architecture in their study to categorize diseases found in banana leaves into three distinct classes. In the preprocessing phase, the images underwent a resizing operation to achieve dimensions of 60×60, and concurrently, they were converted into grayscale. The suggested framework underwent evaluation using the dataset named PlantVillage, which demonstrates a precision range between 82% and 89%.

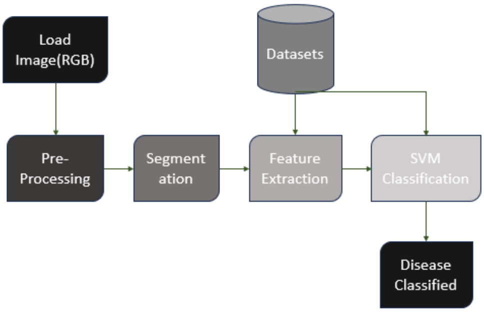

Fig 1: Block diagram for existing system

Liu et al. used the AlexNet model to recognize and classify diseases in apple leaves, demonstrating its effectiveness in identifying and distinguishing various disease patterns. Their study involved a collection comprising a total of 13,689 pictures, encompassing four distinct diseases: mosaic disease, brown spot disease, rust disease, as well as Alternaria leaf spot disease. Before conducting the classification process, they were involved in preprocessing images, which included rotating and enhancing the images. This method yielded a total accuracy rate of 97.62%. Researchers developed a multi-level convolutional neural network (ConvNet) architecture inspired by AlexNet with the aim of identifying diseases in rice crops.

The researchers gathered visuals required for their investigation through a database dedicated to agricultural pests and insect pests, in addition to sourcing images through a book that featured illustrations of infected vegetation. The visuals were resized to 512 by 512 pixels and subsequently utilized the ZCA-Whitening method for preprocessing, to enhance data independence.

Oppenheim and Shani employed a Convolutional Neural Network (CNN) utilizing the VGG architecture to partition potatoes into five distinct categories, comprising quadruple categories for infected potatoes and another one class for healthy potatoes. They obtained 400 photographs of tainted potatoes through the utilization of three basic digital cameras, and expanded the dataset by incorporating augmented versions through image flipping and cropping techniques. During the preprocessing phase, the images were resized to dimensions of 224 × 224 and transformed into grayscale. They performed experiments using different ratios of training and test sets, with the CNN achieving accuracy levels ranging from 83% with only 10% of the data used for training to 96% when 90% of the data was utilized for training.

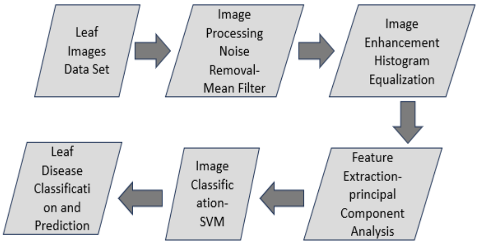

Fig 2: .Block diagram for leaf disease detection by image processing and machine learning

Barbedo conducted a study examining the key elements that impact the design and effectiveness of Convolutional Neural Networks (CNNs) in the context of recognizing plant diseases. To predict corn diseases, researchers employed the PDDB dataset, which comprises 50,000 images and encompasses information on 171 distinct diseases affecting corn crops. They examined nine factors that play a role in the detection of diseases in maize fields. The model underwent training using four distinct datasets, achieving its highest accuracy of 87% when utilizing a subdivided dataset.

3 PROPOSED WORK

Leveraging cutting-edge technologies, specifically image processing and machine learning, to develop a robust system for the analysis of diseases in farm crops. By harnessing the power of computational methods, we intend to create a solution that not only identifies the presence of diseases but also offers insights into their severity, enabling farmers to take timely and targeted actions to protect their crops. Process shown in Fig 2, CNN model is shown in Fig 3 and training and testing model shown in fig 4.

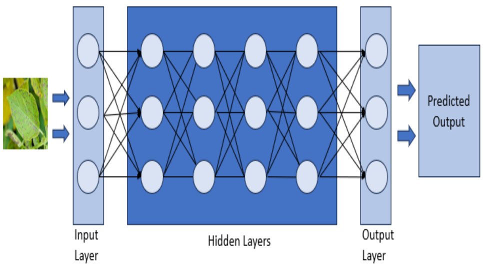

Fig 3: Convolutional Neural Network with four hidden layers

To address the limitations of traditional methods of disease detection in crops, various alternative technologies and approaches can be employed, leveraging advancements in imaging, sensing, and data analytics. The proposed system seeks to address these limitations by providing an automated and objective approach to disease analysis. The integration of image processing techniques and deep learning algorithms promises a level of accuracy and efficiency that is not easily achievable through manual methods.

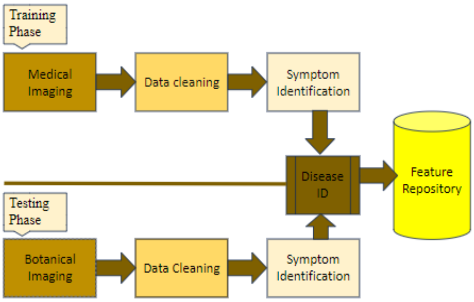

Fig 4: **Training and Testing Model**

Various images are acquired that form a dataset representing diseased crops shown in Fig 5. The images are annotated to create a labeled dataset for training and validating the models. Image preprocessing techniques are performed to enhance the quality of images, including normalization, resizing, and noise reduction as in Fig 6. Data augmentation is explored to artificially increase the diversity of the training dataset. A suitable machine learning architecture is chosen for image classification tasks (e.g., Convolutional Neural Network - CNN). Pre-trained models are considered for transfer learning to leverage knowledge learned on large datasets.The dataset is partiti into training, validation, and test subsets, followed by training the selected machine learning model using the training dataset.Deployment and Testing:The developed system is deployed in a real-world setting, collaborating with farmers or agricultural institutions. Collecting feedback and continuously improving the system based on user experiences.

Fig.5. Potato leaf Tomato leaf Pepper leaf

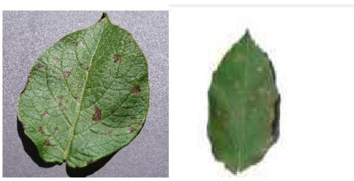

Fig 6. Original image pre-processed image

Proposed work plan outlines the key steps involved in developing a robust system for disease analysis in farm crops using image processing and machine learning.

Steps to implement the Plant Leaf Disease Prediction project-

1) Start
2) A connection is established to Google Drive within the Google Colab Notebook and proceeds to import the dataset.

3) The required libraries are imported.
4) Visualizing the images and images are resized.
5) The images are transformed into a NumPy array format and normalization is done to standardize the pixel values.
6) The class count is visualized and Checked for class imbalance.
7) The dataset is splitted into training, validation and testing sets.
8) The model architecture is defined, compiling the model, and training it by fitting it to the training data.
9) The accuracy is plotted and found loss against each epoch
10) Predictions are made on testing data.
11) Visualizing the original and predicted labels for the test images.
12) Stop

Convolution Operation:

Given an input image I and a filter/kernel K, the convolution operation is calculated as:

$$(I*K)(i,j) = \sum_m \sum_n I(m,n) \cdot K(i-m, j-n)$$

Operation involves element-wise multiplication of the filter with overlapping regions of the input image followed by summation.

RELU Activation Function

The Rectified Linear Unit (RELU) activation function is commonly used in CNNs to introduce non-linearity. It is defined as:

$$F(x) = \max(0,x)$$

The anticipated outcomes of research include an accurate and efficient system for disease analysis in farm crops. By harnessing the capabilities of image processing and deep learning, we aim to significantly reduce the time between disease onset and intervention, ultimately improving crop yield and sustainability.

4 RESULTS AND COMPARISON

The analysis of diseases in farm crops utilizing a CNN achieved promising results, with a training accuracy of 97% indicating robust performance shown in Fig 8. Furthermore, the model demonstrated generalization capabilities, maintaining a commendable testing accuracy.

Training Accuracy: 97%
Testing Accuracy: 92%

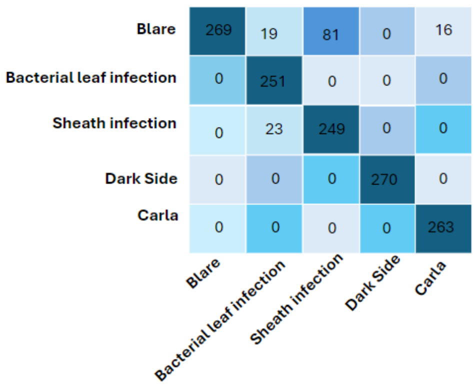

Fig 7: Confusion Matrix for CNN classifier

Performance Metrics:

The performance metric is assessed through various measures including accuracy, precision, recall, and F1-score, shown in fig 8.. These metrics provide detailed insights into different aspects of the model's performance.

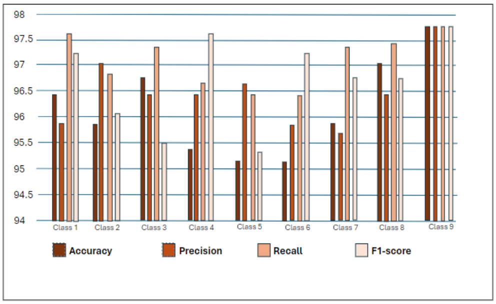

Fig 8: Performance Analysis of CNN Classifier

5 CONCLUSION AND FUTURE WORK

In conclusion, the fusion of image processing and machine learning in farm crop disease analysis represents a transformative leap towards sustainable agriculture. This approach, employing advanced algorithms and Convolutional Neural Networks, not only ensures early disease detection but also enables nuanced severity assessment. The system's user-friendly interface empowers farmers with real-time insights, optimizing resource allocation and fostering proactive management. This research signifies a crucial step in leveraging technology to fortify global food security, illustrating the potential of precision agriculture in addressing evolving challenges and contributing to resilient, efficient farming practices.Future work should focus on integrating multispectral imaging, enhancing model adaptability through advanced transfer learning, and developing a real-time decision support system. Additionally, exploring edge computing, collaborative data sharing, and climate impact analysis will contribute to more robust and adaptable solutions for crop disease analysis in diverse agricultural settings.

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