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Plant Disease Detection using CNN

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***Abstract*—Diseases that infect plants and crops pose a substantial threat to agricultural productivity within a nation. Traditionally, farmers or experts monitor plants closely to detect and identify diseases, a process often characterized by its time-consuming nature, high cost, and lack of precision. A common method for plant disease detection involves visually inspecting the leaves of diseased plants for characteristic spots. The aim of this research is to develop a Disease Recognition Model using leaf image classification to improve the effectiveness of disease detection. Employing image processing techniques, we deploy a Convolutional Neural Network (CNN) to detect plant diseases. CNNs are a specialized type of artificial neural network designed for analyzing pixel input and are commonly used in tasks related to image recognition.**

***Index Terms*— CNN, Deep Learning, Image recognition and ANN.**

I. INTRODUCTION

Agricultural production has been a fundamental means of sustenance for humanity since ancient times, serving as a vital source of food and income worldwide. The significance of plants extends beyond human consumption, as they provide essential resources such as oxygen and habitat for various life forms. Governments and experts are continuously striving to enhance food production to meet the growing demands of global populations.

The widespread occurrence of plant diseases presents a major challenge to agricultural productivity and food security as well. When a plant becomes infected, the entire ecosystem is impacted, affecting not only crop yields but also the livelihoods of farmers and the availability of food for consumption. Plant diseases can manifest in various parts of the plant, including the stem, leaves, and branches, and can be caused by factors such as bacteria, fungi, or environmental conditions.

The consequences of plant diseases are particularly severe for regions with high levels of food insecurity, where insufficient crop output exacerbates the problem. Climate change further compounds these challenges, leading to unpredictable shifts in plant development and susceptibility to diseases. Early detection of plant diseases is essential for preventing widespread crop losses and minimizing the need for excessive pesticide use, which can harm both crops and the environment.

Traditionally, farmers rely on visual inspection to detect plant diseases, but this approach is limited by its subjectivity and dependence on human expertise. The emergence of automated disease detection tools offers a promising solution to this challenge, leveraging advancements in deep learning and neural networks to achieve precise and efficient detection of plant diseases.

This study introduces the development of a Disease Recognition Model, which is reinforced by leaf image classification. It employs a Deep Convolutional Neural Network (CNN) to differentiate between infected and

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healthy leaves and to identify diseases in affected plants.. By harnessing the power of deep learning techniques and image processing algorithms, our goal is to create a reliable and user-friendly tool that enhances agricultural efficiency by enabling accurate and timely detection of plant diseases. Through this study, our goal is to contribute to enhancing global food security and promoting the sustainability of agricultural practices.

II. Literature Review

In the Plant leaf disease detection using computer vision and machine learning algorithms Research Paper by Sunil S. Harakannanavar, Jayashri M. Rudagi , Veena I Puranikmath Ayesha Siddiqua , R Pramodhini, the publication makes use of combinations of various machine learning models to improve the accuracy of the result , but the model can be improved using fusion techniques for extraction of significant features and examined for other leaf samples of datasets.

The literature review provides a comprehensive overview of recent advancements in plant disease detection using both machine learning and deep learning techniques. Authored by Muhammad Shoaib et al., the review delineates the potential applications of advanced models in this domain and succinctly outlines the challenges that may arise during their implementation. However, a notable gap in the literature is the absence of real-world implementation examples. While the paper adeptly identifies the practical implications and hurdles of deploying such models, it lacks concrete demonstrations of their efficacy in actual agricultural settings. Closing this gap by incorporating empirical studies or case studies would enhance the credibility and applicability of the review, providing valuable insights for researchers and practitioners alike.

The literature review examines recent progress in utilizing advanced deep learning models for plant disease detection, as discussed by Muhammad Shoaib et al. The authors highlight the positive impact of image recognition technologies, facilitated by deep learning (DL) and machine learning (ML), in effectively identifying complex diseases and pests affecting plants. However, a notable gap identified in the research is the predominant focus on laboratory-based studies and the heavy reliance on collected images of plant diseases and pests. To overcome this constraint and enhance the strength and applicability of the models, the review underscores the significance of diversifying the dataset by including images from different plant growth stages, seasons, and geographical regions. These endeavors would not just improve the reliability and usefulness of the models but also aid in advancing plant pathology research by encompassing a broader spectrum of environmental and agricultural conditions.

The literature review explores an innovative approach to plant disease detection utilizing image processing and machine learning techniques, as demonstrated by Pranesh Kulkarni et al. The authors have undertaken a commendable effort to analyze various image parameters and features to effectively identify different plant leaf diseases, ultimately striving for optimal accuracy. However, a significant gap addressed in the literature is the traditional reliance on visual inspection or chemical processes by experts for disease diagnosis. This conventional method necessitates a considerable investment in both manpower and resources, particularly for large-scale farming operations. By introducing an automated and data-driven approach, the reviewed project offers a promising solution to mitigate these challenges and revolutionize the field of plant pathology. Yet, further validation and real-world implementation studies would be valuable to ascertain the practical viability and scalability of the proposed methodology, thereby bridging the gap between theoretical innovation and tangible impact in agricultural practices.

The literature review offers insights into the application of deep learning (DL) techniques for plant disease detection and classification, as discussed by Muhammad Hammad Saleem et al. The authors commendably elucidate various DL approaches employed in this domain and provide a comprehensive summary of visualization techniques for recognizing disease symptoms in plants. However, a notable gap identified in the research is the need for a more efficient method of visualizing disease spots on plants. Introducing such a method would not only enhance the accuracy of disease detection but also contribute to cost savings by minimizing the unnecessary application of fungicides, pesticides, and herbicides. Addressing this gap would not only optimize agricultural practices but also promote sustainable farming methods, underscoring the importance of continual innovation in plant pathology research.

III. Proposed System

Users initiate the process by accessing the website and clicking on the "Choose Image" button to upload a plant leaf image through the designated interface. Once the image is selected, it is then transmitted to the Convolutional Neural Network (CNN) analyser for further processing.

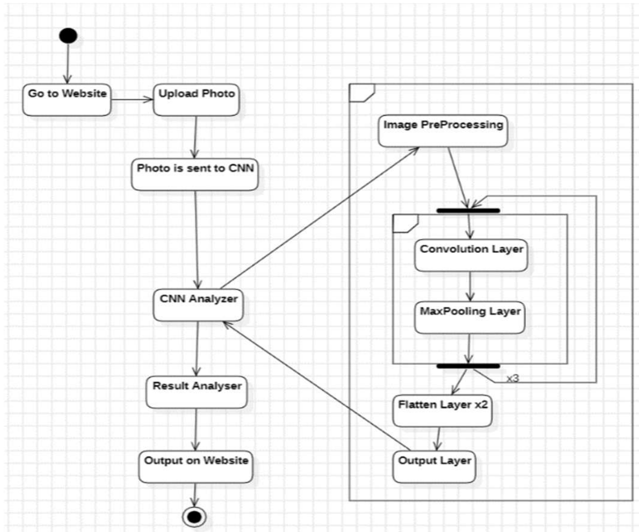


Figure 1. Proposed System Block Diagram

Upon receiving the image, the CNN analyser preprocesses the image data to enhance its suitability for analysis. This preprocessing step involves various techniques to normalize, resize, and enhance the image, ensuring optimal input for the subsequent layers.

Following preprocessing, the image data passes through a series of layers within the CNN architecture. The convolutional layers extract relevant features from the input image through convolution operations. Subsequently, max-pooling layers reduce the spatial dimensions of the feature maps while retaining the most significant features, further enhancing computational efficiency.

The output from the max-pooling layers is then passed through a flatten layer, which converts the multidimensional feature maps into a one-dimensional vector. This flattened representation of the features is fed into the output layer of the CNN, where the final classification of the image is performed.

Simultaneously, the image data is sent to the result analyser, which processes the output from the CNN to interpret the disease classification. This results analyser module decodes the output from the CNN and maps it to a specific plant disease category.

Finally, the results from both the CNN analyser and the results analyser are consolidated and presented to the user when they click on the "Predict Image" button. This user-friendly interface provides users with instant access to the detected plant disease, facilitating timely interventions and decision-making in agricultural practices.

IV. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

Convolutional Neural Network is structured with three key layers: a convolutional layer, a max pooling layer, and a fully connected layer (See Fig. 2).

A. Convolutional Layers

Convolutional layers serve as the fundamental components of CNNs. They contain a series of adaptable filters or kernels that undergo convolution with the input data (such as images or text). Every filter extracts unique features from the input by performing element-wise multiplication with local regions of the input and then combining the results. This mechanism enables the network to acquire hierarchical representations of the input data.

B. Max Pooling Layers

Max pooling serves as a down sampling technique frequently utilized following convolutional layers. It segments the input feature maps into non-overlapping rectangular regions and picks the maximum value from each region. This action efficiently reduces the spatial dimensions of the feature maps while maintaining the most important features. Max pooling aids in attaining translation invariance, diminishing the network's sensitivity to minor variations in the feature positions within the input.

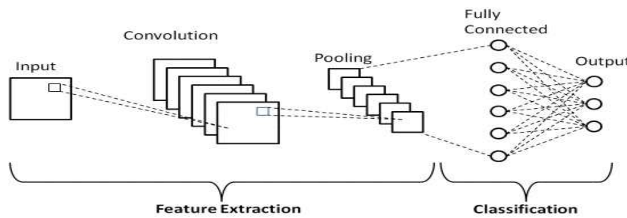


Figure 2. Convolutional Layers

Pooling Size: Max pooling is commonly conducted using small windows, such as 2x2 or 3x3, with a stride (step size) equivalent to the window size. For instance, a max pooling operation with a 2x2 window and a stride of 2 will halve the spatial dimensions of the feature maps.

Pooling Layers: Max pooling is commonly used after convolutional layers, often alternating with convolutional layers within the architecture of a CNN. This combination of convolutional layers and max pooling layers helps capture hierarchical features of growing complexity while decreasing the spatial dimensions of the feature maps.

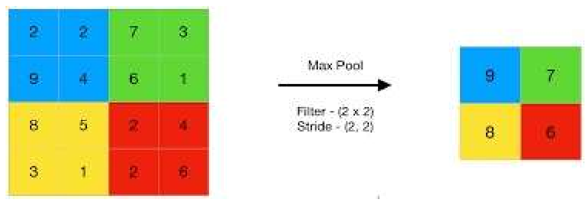


Figure 3. Max Pooling Example Diagram

C. Flatten Data

Data flattening is a preprocessing technique frequently employed in machine learning, especially in neural networks, to convert multi-dimensional data structures into a one-dimensional array. This conversion is typically required when transferring data from convolutional layers (or any other multi-dimensional layers) to fully connected layers, which demand one-dimensional input.

D. Fully Connected Layer

Fully connected layer 1-

Following the convolutional and pooling layers in a convolutional neural network (CNN) architecture, the fully connected layer 1 is typically situated. Its role is to accept the high-level features acquired by the convolutional layers and convert them into a format appropriate for making predictions.

Fully connected layer 2-

Fully connected layer 2 is frequently introduced following fully connected layer 1 to enhance the refinement of features learned in the preceding layers and extract more abstract representations of the input data.

In a neural network architecture, both fully connected layers 1 and 2 serve to extract and refine features learned from earlier layers, while the output layer generates final predictions based on these features. Each layer plays a critical role in enabling the network to learn from the input data and make precise predictions for the assigned task.

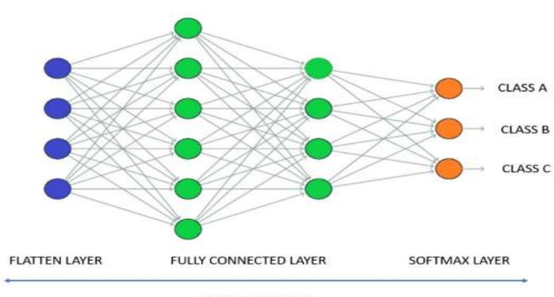


Figure 4. Fully Connected Layers

E. Output Layer

The output layer is the ultimate layer of the neural network and is tasked with generating the model's predictions. Its configuration varies based on the nature of the task, such as classification or regression.

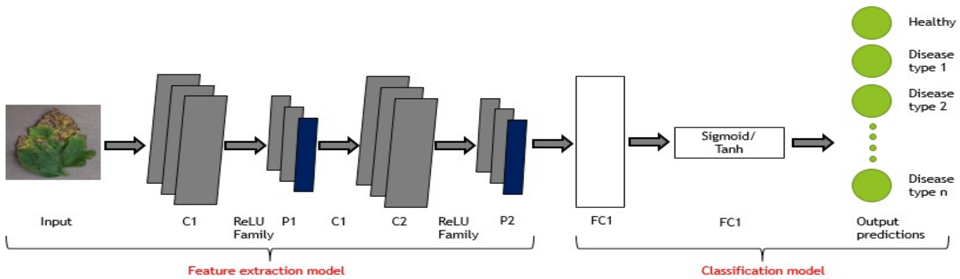
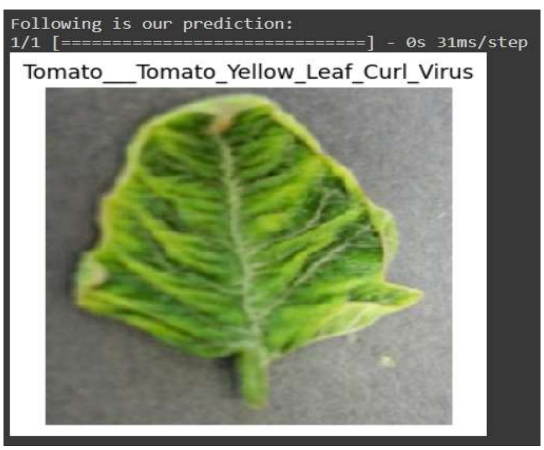


Figure 5. Classification Layers

V. RESULTS

The CNN achieved an overall accuracy of 95.04% in correctly identifying diseased and healthy leaves while training the model on 7 epochs. Such a high level of accuracy demonstrates the model's robustness in distinguishing between various types of plant diseases. The outcome of detecting and recognizing a tomato plant is illustrated in Figure 6 and of a Tulsi plant in Figure 8.



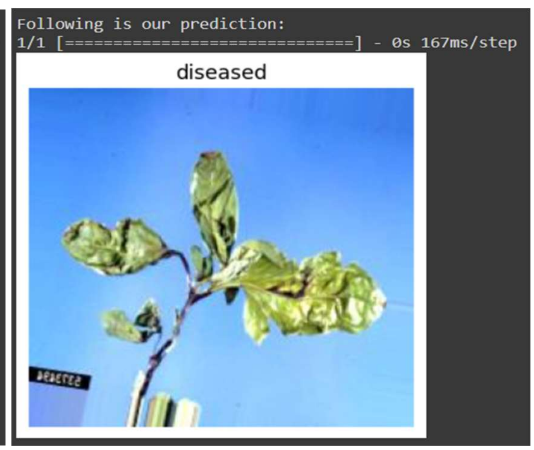


Figure 6. Tomato Leaf Output

Figure 7. Tulsi Leaf Output

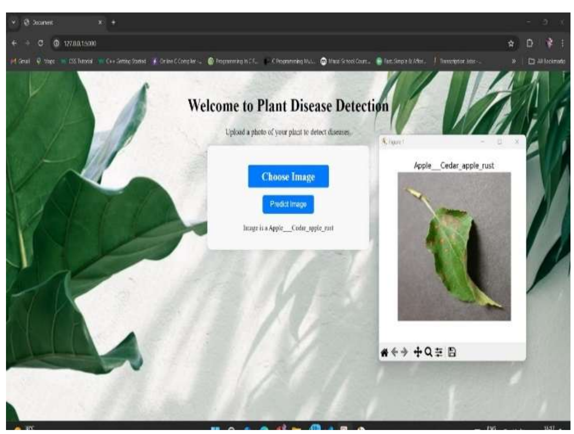


Figure 8. Website Output Screenshot

VI. CONCLUSION

In this study, we've developed a deep learning model using Convolutional Neural Networks (CNN) to automatically identify and classify plant leaf diseases. Through rigorous experimentation, our CNN model has shown promising results in accurately recognizing diseased leaves and distinguishing between various plant diseases. This disease classification technique offers a dependable solution for agricultural practitioners. By leveraging deep learning and image processing techniques, our model enables early detection of plant diseases, allowing for timely intervention to prevent extensive crop losses. Future research will focus on refining the CNN model, expanding the dataset to include more plant species and disease types, and exploring real-time implementation in field settings. Our goal is to enhance agricultural efficiency and food security by providing farmers and agricultural professionals with effective tools for managing plant diseases.

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