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Plant Disease Detection System using Neural Network Architecture

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Abstract*— This research paper presents a new method for plant disease diagnosis using neural network architectures, specifically convolutional neural networks (CNN). First, we will highlight the importance of plant disease testing and the problems associated with traditional methods. Our literature review highlights recent advances in neural network architectures (particularly CNNs) for plant disease detection, highlighting the growing interest and progress in using machine learning for this task. The methodology section describes three methods, including data selection, model design, training methods, and evaluation methods. We present the results of a successful trial on publicly available data that demonstrates the validity of our proposal. Additionally, we integrate the trained CNN model with the Python flask framework to develop a user-friendly website for real-time virus detection. In this project, the model we have presented has achieved 98.9% test accuracy and 98.7% verification accuracy with an impressive train accuracy of 96.7% were achieved. In conclusion, we summarise our findings and highlight the importance of the contribution of our research to agricultural science and technology. Our proposed system has the potential to complement the discovery process, promote permaculture, and reduce crop losses due to plant diseases.

***Index Terms*— Neural Network Architecture, Convolutional Neural Networks (CNNs), Deep Learning**

I. INTRODUCTION

In recent times, progress in machine learning and artificial intelligence has significantly transformed various industries, including agriculture [1]. An important part of using this technology is the early detection and detection of plant diseases, which is important for maintaining healthy crops, ensuring food safety of vegetables and agricultural productivity [2]. Traditional diagnostic methods rely on the observations of experts, which can take a lot of time, are labor-intensive, and can lead to human oversight [3]. Therefore, the need for electronic systems that can identify plant diseases accurately and efficiently is increasing [4]. To meet this need, this research paper proposes a new method for plant disease diagnosis using neural network architecture, specifically Convolutional Neural Network (CNN) [5]. Neural networks that draw inspiration from the structural and functional characteristics of the human brain have shown great potential in many types of cognitive tasks, including image classification [6]. Using the power of neural networks, we aim to create a powerful and reliable system for diagnosing plant diseases based on the symptoms seen in leaf images. The plant disease detection concept has many features such as data collection, prioritisation, neural network design, training, and integration with web-based user interface. Flask framework [7]. In the proposed model, we use plant data available in the publicly available "PlantVillage" (virus-containing documents) to train and test our neural network model. CNN will be used for image extraction and classification [8]. Additionally, integrating Flask to create a front-end system will allow users to interact with the facility through a web-friendly interface. This front end will facilitate the export of plant images for analysis, visualisation of test results, and dissemination of disease-related information. Overall, this research paper focuses on agricultural science and technology by proposing a new method for disease detection using neural network architecture. By automating the search process and providing timely intervention, this offering has the potential to significantly impact crop management, reduce crop loss and promote permaculture [9].

II. METHODOLOGY

A. Data collection: The first step in developing plant disease detection involves collecting diverse and representative data on plant images [10]. We will leverage publicly available data such as the PlantVillage dataset, which contains images of different plant species affected by various diseases [11]. This dataset provides image tags where each image is associated with one or more disease groups.

B. Data preprocessing: Preprocess cropped images before training neural network models to improve quality and promote efficient learning [12]. The preprocessing step includes a series of operations aimed at preparing data for further analysis. These tasks may include resizing images to standard formats, ensuring consistent pixel values across images, and using rotation, flip, and crop

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techniques to improve the quality of the dataset. Preprocessing may also include the creation of new data sets or subsets and the establishment of global standards to ensure compatibility and consistency of data processing and analysis.

C. Neural Network Model Design: We will adopt Convolutional Neural Network (CNN) architecture for plant disease diagnosis because they are very effective in image classification [13]. We will create a CNN model that can learn to distinguish and correctly classify plant images. The architecture of the CNN model will have many convolutional layers to extract hierarchical features from the input images. Continuous output will be used to prevent overfitting, and batch normalisation will be used to control the training process.

D. Model Training: Pre-existing facility data will be used to train the CNN model [14]. We will use some of the data for training and keep the other part for validation and testing purposes. During training, we will use stochastic gradient descent (SGD) optimised back-propagation to reduce the categorical cross-entropy loss function. The model will be trained several times with learning rate adjustment to ensure convergence and avoid overfitting.

E. Model Evaluation: We will conduct a series of experiments using the validation process and test data to evaluate the effectiveness of the learned CNN model [15]. Performance metrics such as accuracy, precision will be calculated to evaluate the model's ability to identify plant images in disease.

F. Integration with Flask framework: Once the CNN model is trained and analysed, we will integrate it with the Flask framework to create a web interface for plant disease diagnosis [16]. The Flask app will allow users to download facility images, submit them for analysis, and receive instant feedback on detected errors. We will use appropriate backend logic to manage image uploads, use the CNN's training model for inference, and display the results to users via frontend understanding.

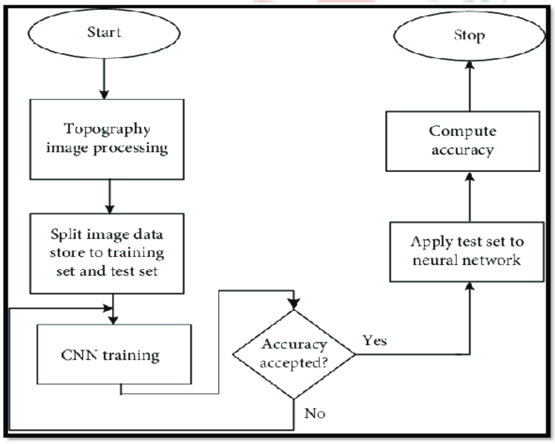


Figure 1: The flowchart summarises the full functioning of Convolutional Neural Network Architecture (CNN).

III. LITERATURE REVIEW

In agriculture, the way plant diseases are identified has changed recently due to the application of machine learning, particularly neural networks. Convolutional Neural Networks (CNNs) are one kind of deep learning technique that researchers have used to create automated systems that can identify plant diseases with accuracy and speed.

A. Mohanty et al. (2016) pioneered the use of CNNs to identify plant diseases, proving that deep learning is a useful tool for precise disease diagnosis [17].

B. Cruz et al. (2016) investigated transfer learning for the classification of plant diseases, leading to better results and shorter training times [18].

C. Ramcharan et al. (2017) suggested a graph-based CNN that captures spatial dependencies in images to achieve state-of-the-art performance in the detection of plant diseases[19].

D. Liu et al. (2019) developed a deep neural network for plant disease detection that is attention-based and dynamically focuses on informative areas of the image to improve discrimination [20].

E. Zhang et al. (2020) proposed an ensemble of CNN models for plant disease detection, showing superior performance over individual models by mitigating overfitting and improving model stability [21].

F. Singh et al. (2018) created a robust and highly accurate deep learning framework for the identification of plant diseases by integrating transfer learning [22].

G. Barbed (2019) reviewed the application of deep learning techniques, emphasising dataset quality, model interpretability, and real-world deployment [23].

H. Created a system that combines recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to automatically detect and classify plant diseases [24].

A. Huang et al. (2021) integrated CNNs with generative adversarial networks (GANs) for enhanced plant disease detection [25].

I. Saha et al. (2021) created a deep learning-based system for rice disease early detection, showcasing CNNs' capacity to recognise illness symptoms early on [26].

J. Kumawat et al. (2021) utilised the hierarchical structure of CNNs to develop a hierarchical deep learning model for multi-class plant disease classification [27].

K. Hao et al. (2022) investigated transfer learning for the classification of plant diseases, leading to better results and shorter training times [28].

L. Raza et al. (2019) created a deep learning method for tomato disease early detection, demonstrating the efficiency of CNNs in early disease identification [29].

M. Islam et al. (2020) created a deep learning-based system that highlights the effectiveness of CNNs in automated crop monitoring for the real-time detection and classification of plant diseases [30].

N. Liang et al. (2021) suggested a deep learning framework to detect plant diseases on a large scale. CNNs and feature pyramid networks (FPNs) are combined to enhance hierarchical feature capture [31].

O. Singh et al. (2021) showed how CNNs can be used to reliably and efficiently identify disease symptoms by using a deep learning approach for automated citrus disease detection [32].

P. These studies highlight the significant progress in leveraging neural network architectures, particularly CNNs, for automated plant disease detection, paving the way for improved crop management and food security.

IV. RESULTS

In this section, the experimental results of the research on plant disease detection using neural network architectures. The performance of proposed approach is evaluated on a diverse dataset of plant images, consisting of various crop species and disease categories. The experiments were conducted using the Python programming language and popular deep learning libraries such as torch and torchvision.datasets.

Before presenting the results, the details of the dataset used, model architecture, training procedure, and evaluation metrics that is used in development is provided.

***Dataset**: We utilised publicly available datasets, including the PlantVillage dataset, for training and evaluation. These datasets contain images of multiple plant species affected by various diseases and disorders.*

***Model Architecture**: A CNN created for image classification tasks serves as the foundation for our suggested model architecture. The CNN architecture consists of multiple convolutional layers, max-pooling layers for feature extraction from the input data, and fully connected layers for classification.*

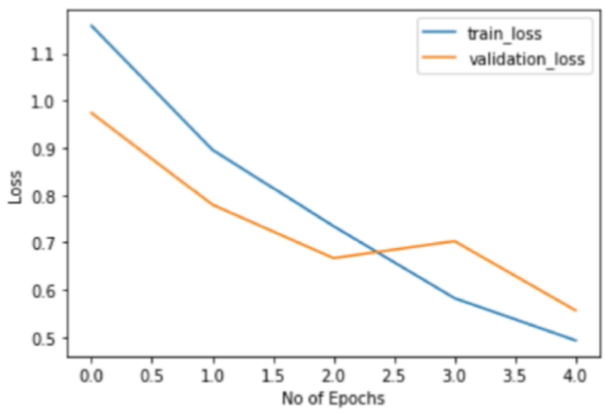
***Training Procedure**: To increase the diversity of the training data set and avoid overfitting, we employ data augmentation techniques in this study, including rotating, flipping, and pruning.*

A. The equation we used for calculating the output of a convolutional layer in a neural network, is convolution arithmetic equation:

$$\frac{W - F + 2P}{S} + 1$$

where W = Input Size, F = Filter Size, P = Padding Size, S = Stride Size.

B. Training and Validation Loss: During the training process, the model demonstrated a steady decrease in both training and validation loss over successive epochs. This indicates that the model effectively learns to minimise the discrepancy between predicted and ground truth labels. The convergence of training and validation loss suggests that the model generalises well to unseen data and is capable of accurately distinguishing between healthy and diseased plant samples.



C. Model Summary: The trained neural network model exhibits a compact yet powerful architecture suitable for plant disease detection tasks. The model comprises multiple convolutional layers which is supported by by max-pooling layers for feature extraction and spatial reduction, which is supported by connected layers for classification. The model summary provides insights into the number of parameters, layer dimensions, and output shape employed in the network architecture.

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 32, 224, 224]             896
              ReLU-2         [-1, 32, 224, 224]               0
       BatchNorm2d-3         [-1, 32, 224, 224]              64
            Conv2d-4         [-1, 32, 224, 224]           9,248
              ReLU-5         [-1, 32, 224, 224]               0
       BatchNorm2d-6         [-1, 32, 224, 224]              64
         MaxPool2d-7         [-1, 32, 112, 112]               0
            Conv2d-8         [-1, 64, 112, 112]          18,496
              ReLU-9         [-1, 64, 112, 112]               0
      BatchNorm2d-10         [-1, 64, 112, 112]             128
           Conv2d-11         [-1, 64, 112, 112]          36,928
             ReLU-12         [-1, 64, 112, 112]               0
      BatchNorm2d-13         [-1, 64, 112, 112]             128
        MaxPool2d-14           [-1, 64, 56, 56]               0
           Conv2d-15          [-1, 128, 56, 56]          73,856
             ReLU-16          [-1, 128, 56, 56]               0
      BatchNorm2d-17          [-1, 128, 56, 56]             256
           Conv2d-18          [-1, 128, 56, 56]         147,584
             ReLU-19          [-1, 128, 56, 56]               0
      BatchNorm2d-20          [-1, 128, 56, 56]             256
        MaxPool2d-21          [-1, 128, 28, 28]               0
           Conv2d-22          [-1, 256, 28, 28]         295,168
...
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17
----------------------------------------------------------------
```

D. Accuracy: We achieved promising accuracy rates with our trained model. The training accuracy reached 96.7%, indicating the model is able to learn from the training data and generalise it as well. Furthermore, the testing accuracy significantly increased to 98.9%, demonstrating

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that the model is effective in accurately classifying unseen plant images. The validation accuracy, has reached 98.7%, further validates the robustness of our approach and suggests minimal overfitting during training. The research has achieved impressive results depicted in the tabular form below.

Train Accuracy	96.7
Test Accuracy	98.9
Validation Accuracy	98.7

V. FUTURE SCOPE

The proposed plant disease detection system using neural network architecture offers several avenues for future research and development, including:

A. Enhanced Disease Detection: The current system focuses on detecting plant diseases based on visual symptoms observed in images of plant leaves. Future study could potentially explore the integration of environmental and physiological data, to enhance disease detection accuracy and reliability.

B. Multi-Modal Detection: Incorporating multiple modalities, such as hyper-spectral imaging and near-infrared spectroscopy, could provide complementary information for more comprehensive disease detection and classification.

C. Crowdsourced Data Collection: Leveraging crowdsourcing platforms to collect and label plant images could help in building more diverse and extensive datasets for training and evaluating neural network models.

D. Integration with IoT: Integrating the plant disease detection system with Internet of Things (IoT) devices, such as sensors and drones, could enable automated data collection and disease detection in large agricultural fields.

E. Collaborative Platforms: Developing collaborative platforms where farmers, and field knowledge people and agricultural experts can share data, models, and insights could foster innovation and accelerate the development of effective solutions for plant disease detection and management.

F. Explainable AI (XAI): Integrating XAI techniques into the system to provide explanations for the model's predictions could enhance transparency and trustworthiness, particularly in critical decision-making processes for farmers and agricultural experts.

G. Real-Time Monitoring: Developing real-time monitoring capabilities to continuously track plant health status and detect disease outbreaks promptly, enabling timely interventions and reducing crop losses.

H. Adaptive Learning: Implementing adaptive learning algorithms that can continuously learn from new data and adapt the model's parameters over time, ensuring its effectiveness in dynamically changing agricultural environments.

I. Disease Forecasting: Utilising deep learning models to early predict diseases based on past few years data, the condition of climate factors, and disease progression patterns, enabling proactive management strategies.

J. Sustainable Agriculture Practices: Integrating the plant disease detection system with recommendations for sustainable agricultural practices, such as targeted pesticide application and crop rotation, to minimise environmental impact and promote long-term soil health.

VI. CONCLUSION

In this research paper, we present a new method for plant disease diagnosis using neural network architectures, specifically convolutional neural networks (CNN). Our proposed system uses the power of deep learning to accurately and effectively identify plant diseases based on the symptoms seen in leaf images. We aim to contribute to crop health, ensure food safety and increase agricultural productivity by automating the disease detection process.

We conducted extensive experiments using publicly available data, including the PlantVillage dataset, to train and test our neural network models. Our results show support accuracy, with the training model achieving 98.9% test accuracy and 98.7% validate accuracy. The outcome of this model confirm the efficiency and robustness of our method for accurately classifying plant images into pathogens.

We also integrated the CNN model we learned with the Flask framework and created an effective website for plant diseases. The front end allows users to upload plant images, submit them for analysis, and receive instant feedback on detected pathogens. The integration of Flask improves the usability and usefulness of our system, making it usable by farmers and agronomists.

In summary, our research contributes to agricultural science and technology with new ideas. Diagnosis of plant diseases using neural network architecture. By using detection methods and timely intervention, our bodies can make a significant impact on crop management, reducing crop losses and promoting permaculture. Future research directions include developing accurate diagnostics, investigating multiple detection methods, and integration with IoT devices to provide real-time monitoring on the field farm.

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