IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 13, Issue 4, April 2024

DOI: 10.17148/IJARCCE.2024.13495

IMPLEMENTATION PAPER ON ADVANCE PLANT DISEASES DETECTION USING VGGNET WITH CONVOLUTIONAL NEURAL NETWORK

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Abstract: The integration of IoT, automation, and advanced technologies such as artificial intelligence (AI) and deep learning has sparked a significant transformation in modern agriculture. In particular, the utilization of deep learning techniques, notably convolutional neural networks (CNNs), has emerged as a promising approach for disease detection in crops. This paper presents a comprehensive review of recent advancements in using deep learning, specifically focusing on the application of convolutional neural networks like VGG-16 in identifying plant diseases from leaf images. By harnessing the power of deep learning and leveraging tools like PyTorch, this study aims to revolutionize disease identification processes in agriculture. The automatic learning and feature extraction capabilities of deep learning offer a more objective and efficient means of detecting plant diseases compared to traditional methods. Moreover, the implementation of deep learning in agricultural settings promises faster and more accurate detection, enabling timely interventions for disease management. The review also addresses current challenges and future directions in the field, providing valuable insights for researchers and practitioners working on disease detection and pest control in agriculture.

Keywords: - Convolutional neural network, Deep neural networks, Deep structured learning, Machine learning.

I .INTRODUCTION

Since ancient times, agriculture has been the bedrock of human existence, sustaining roughly 70% of the global population. Even amidst modern advancements, its importance remains paramount, addressing the challenge of feeding a burgeoning world. However, amidst its critical role, agriculture faces numerous threats, with plant diseases emerging as a formidable adversary, jeopardizing both crop health and productivity. For generations, farmers have relied on visual inspection to detect diseased plants – a method prone to inaccuracies and inefficiencies, particularly in large-scale operations. Recognizing these limitations, there has been an increasing interest in harnessing the power of machine learning and computer vision technologies to automate disease detection processes.

This shift represents a promising avenue for revolutionizing plant disease detection in agriculture. By leveraging algorithms capable of analysing plant images and identifying disease patterns, farmers can swiftly pinpoint afflicted plants and implement necessary measures to mitigate disease spread. Notably, advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable efficacy in accurately classifying plant diseases from imagery data, surpassing traditional machine learning approaches.

In this context, this paper delves into the valving landscape of plant disease detection in agriculture, emphasizing the pivotal role of machine learning and computer vision technologies. By examining the challenges posed by plant diseases and the limitations of manual inspection methods, we aim to underscore the transformative potential of advanced technologies for safeguarding crop health and enhancing agricultural sustainability. Through a comprehensive exploration of recent research and developments, we illuminate the promising prospects and imminent challenges

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associated with utilizing machine learning for plant disease detection, ultimately contributing to the advancement of agricultural practices worldwide.

This paper aims to provide a comprehensive review of the state-of-the-art techniques for plant disease detection using deep learning, with a focus on CNNs. We discuss the key steps involved in the process, including image acquisition, pre-processing, feature extraction, and classification. Various CNN architectures and their performance on different plant disease datasets are reviewed. Additionally, we highlight the challenges and future research directions in this field.

II. LITERATURE SURVEY

1.In this paper deep learning techniques, particularly convolutional neural networks (CNN), are extensively employed in agricultural applications to enhance quality and productivity. A significant challenge for farmers is combating crop diseases and fungal or bacterial infections, which can substantially impact yield despite the use of costly fertilizers. Early detection of these issues is crucial for effective mitigation.
In this study, various CNN architectures including AlexNet, LeNet, GoogLeNet, VGGNet, ResNet, and DenseNet were evaluated for their effectiveness in identifying and classifying diseased tomato plant leaves using a dataset from a plant village. The results showed that DenseNet outperformed other models, achieving validation accuracies ranging from 90% to 99%. Notably, DenseNet exhibited superior performance in resolving the gradient vanishing problem and required more epochs for training. These findings suggest that the DenseNet model is highly efficient for early detection of tomato plant diseases, offering promising results for practical implementation in agricultural settings**.[1]**
The findings of this study suggest that the VGG-16 deep learning model provides an excellent solution for image classification tasks. Unlike traditional methods, CNNs like VGG-16 automatically learn essential features such as shape, texture, color, size, and defects, reducing the need for manual feature extraction and minimizing errors significantly.
CNNs utilize kernel matrices as local feature extractors to extract distinctive features. Tuning the model involves adjusting hyperparameters to identify a set of kernels that can extract useful discriminative features effectively. Deep learning emerges as the most efficient approach for classifying fruit images and determining their nutritional content, achieving an accuracy of 98%.
Moreover, this research proposes a systematic and non-destructive method for addressing cotton leaf disease, which could be beneficial for farmers in preventing crop loss. The potential development of mobile applications, coupled with user education, could empower end-users, including farmers, to detect cotton leaf disease effectively, thus mitigating potential losses**.[2]**

III. WORKING METHODOLOGY

These codes describe the process of developing deep learning models for detecting diseases in different plants: tomatoes, apple, etc. Each segment follows a similar pattern using **Pytorch**, a leading deep learning framework, to implement a **Convolutional Neural Network (CNN) model** for image classification. Here's an overview of the workflow and technologies used across these examples:
Data Preparation:
The first step involves organizing and preprocessing the image data. Images of plant leaves, each showing various health conditions (like bacterial spot or early blight in tomatoes), are collected into a dataset. The dataset is divided into training and validation sets, with images resized to 224x224 pixels and normalized to have pixel values between 0 and 1. This standardization helps the model learn more efficiently.
Data Augmentation:
To improve model robustness and counteract the limited size of datasets, data augmentation techniques such as random flips and rotations are applied. This creates a more diverse training dataset, enabling the model to learn from a broader range of image variations.
Model Architecture and Transfer Learning:
The models leverage a CNN, VGG16, as their base. VGG16 is known for its efficiency and is pertained on a large dataset (ImageNet), allowing it to recognize a wide variety of features. The top layers of the model are customized to classify images into the specific classes of plant diseases. The base model's weights are frozen during training, ensuring that the learned features are retained, while the new layers are trained to adapt to the specific task.
Training and Evaluation:
With the architecture in place, the models are trained using the training dataset. **The optimizer, loss function**, and metrics are defined to guide the training process towards minimizing the classification error. After training, the models' performances are evaluated on a separate validation dataset, providing insights into how well the models generalize to new, unseen data.

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Prediction and Deployment:

Once trained and validated, the models can predict the disease class of new plant images. An image is preprocessed (resized and normalized) before being fed into the model, which outputs the predicted class and the confidence level of the prediction.

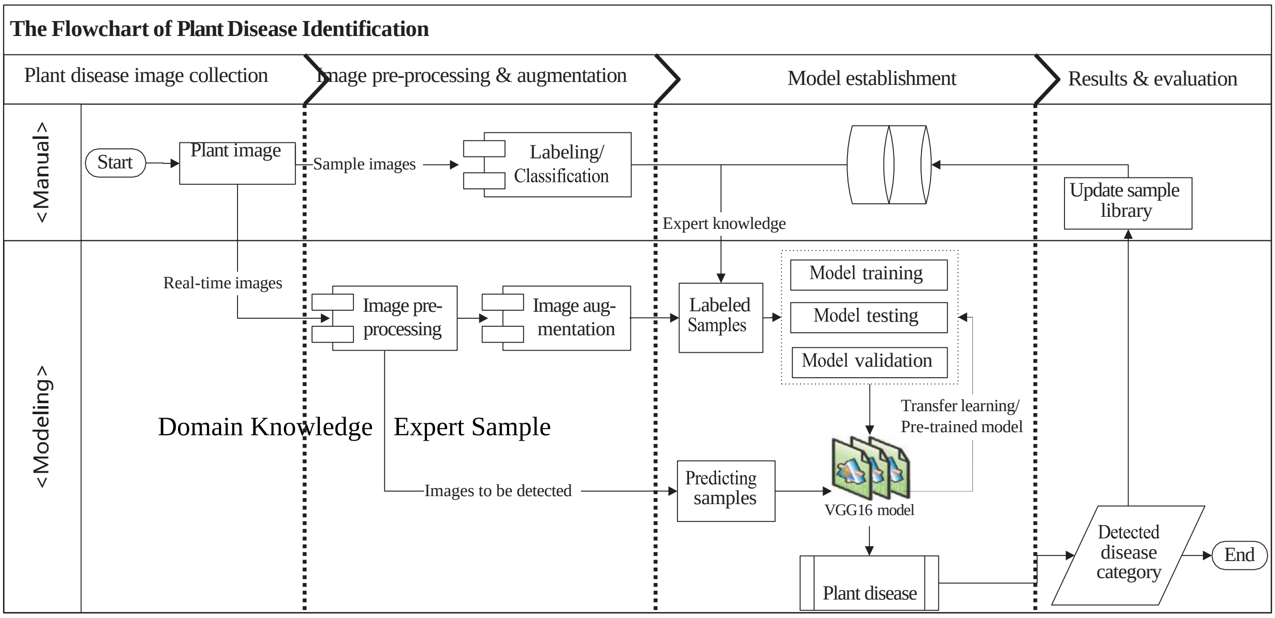

Fig. 1. The overall flow of plant disease identification

As illustrated in Figure 1, our approach to plant disease identification can be outlined as, plant disease images are collected and labeled by domain experts. Subsequently, image processing techniques, such as grey transformation, image filtering, sharpening, and resizing, are applied to the collected images. Additionally, data augmentation methods, including random rotation, flipping, and translation, are employed to generate new sample images and enrich the dataset.

Following data preprocessing, the sample images are fed into the proposed method for model training. Once trained, the model is utilized to predict the classes of unseen images, resulting in the identification of plant diseases.

Convolutional neural networks:

Convolutional neural networks (CNNs) stand out among neural network architectures specifically tailored for tasks like image recognition and classification, consistently delivering impressive results. Unlike conventional approaches, CNNs possess the ability to directly discern high-level features from raw images without the need for manual feature extraction. This inherent capability proves particularly advantageous in tasks such as identifying plant species and diseases, where CNNs consistently outperform traditional feature extraction methods.

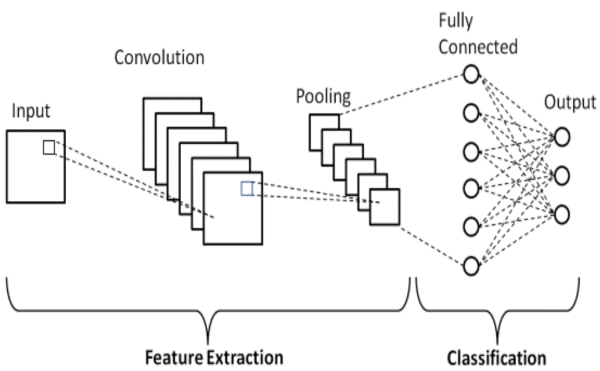

Fig 2: CNN Architecture

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A standard CNN architecture typically comprises convolution layers, pooling layers, and fully connected layers. These components work synergistically to analyze and extract meaningful patterns from input images, enabling the network to make accurate classifications.

VGGNet:

VGGNet, developed by researchers at Oxford University and Google DeepMind, is a type of convolutional neural network. It's characterized by its cascaded network structure, typically featuring 16 or more layers consisting of convolution, pooling, and fully-connected layers. In VGGNet, after every 2 or 3 convolution layers, there's a pooling layer employing small 3 × 3 convolution filters.

There are two main models in VGGNet: VGG-16 and VGG-19, pretrained with 16 and 19 weight layers respectively, trained on the ImageNet dataset. In our experiments, we utilize VGG-16 as the base model, adapting it to create new networks. These networks are then trained and fine-tuned using labeled sample images.

Transfer learning:

Transfer learning is a method in machine learning where we leverage the knowledge gained from training a Convolutional Neural Network (CNN) on one task and apply it to another task. Rather than starting from scratch with randomly initialized weights, we utilize a pre-trained network that has learned patterns from large labeled datasets, like ImageNet. In our study, we focus on using pre-trained models from ImageNet and adapting them to our specific task using our own dataset

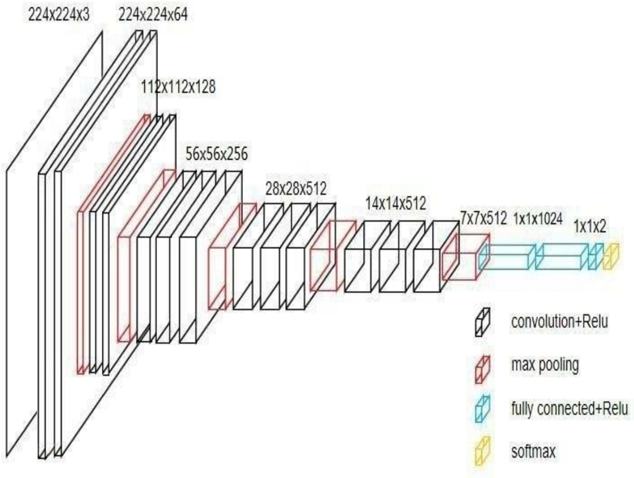

Fig 3. VGG16 Architecture

Model Creation:

In PyTorch, we need to manually manage the shape on each layer since it's not automatically calculated. Specifically, when transitioning to the first fully connected layer, we must determine the output size based on the shape of the convolutional layer. This process is often referred to as Convolutional Arithmetic.

The equation for Convolutional Arithmetic is:

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where

$$H_{out} = \left\lfloor \frac{H_{in} + 2 \times \text{padding}[0] - \text{dilation}[0] \times (\text{kernel\_size}[0] - 1) - 1}{\text{stride}[0]} + 1 \right\rfloor$$

$$W_{out} = \left\lfloor \frac{W_{in} + 2 \times \text{padding}[1] - \text{dilation}[1] \times (\text{kernel\_size}[1] - 1) - 1}{\text{stride}[1]} + 1 \right\rfloor$$

We build our model using a convolutional neural network. Below the image, we outline the layers of the model, specifying the filter size for both the Convolutional and Pooling layers, along with the shape of each layer, represented as (channels, height, width).

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```
----------------------------------------------------------------
        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
             ReLU-23          [-1, 256, 28, 28]               0
      BatchNorm2d-24          [-1, 256, 28, 28]             512
           Conv2d-25          [-1, 256, 28, 28]         590,080
             ReLU-26          [-1, 256, 28, 28]               0
      BatchNorm2d-27          [-1, 256, 28, 28]             512
        MaxPool2d-28          [-1, 256, 14, 14]               0
          Dropout-29                [-1, 50176]               0
           Linear-30                 [-1, 1024]      51,381,248
             ReLU-31                 [-1, 1024]               0
          Dropout-32                 [-1, 1024]               0
           Linear-33                   [-1, 39]          39,975
================================================================
Total params: 52,595,399
Trainable params: 52,595,399
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17
----------------------------------------------------------------
```

Fig 4. Layered Model

Dataset:

Fig 5. Dataset Collection

This dataset comprises 39 distinct classes of plant leaf and background images, totalling 61,486 images. To augment the dataset and enhance its diversity, we applied six different techniques: image flipping, gamma correction, noise injection, PCA colour augmentation, rotation, and scaling.

Our objective is to predict the class of the plant leaf among the 39 available classes using a Convolutional Neural Network (CNN) model.

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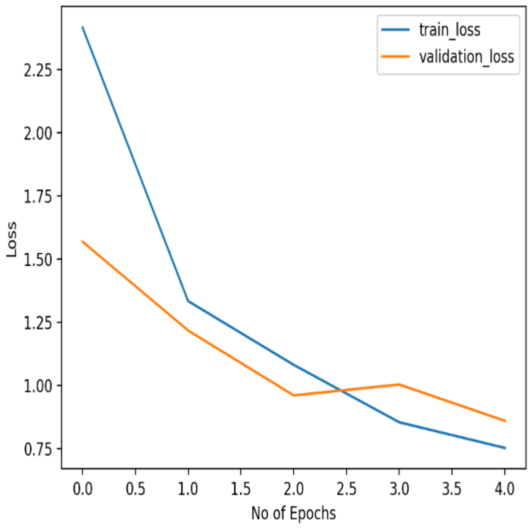
Epoch Graph:



The achieved accuracies for training, testing, and validation on the plant disease dataset are impressive. With a training accuracy of 83.09%, the model effectively learns from the data. The test accuracy of 82.89% indicates its ability to perform well on unseen data, while the validation accuracy of 82.31% confirms its robustness during training. These results underscore the model's efficacy in accurately classifying plant diseases, crucial for agriculture's practical applications.

The training process utilized batch gradient descent (batch_gd) for five epochs, tracking both training and validation losses. Throughout the training, the model's performance steadily improved.At the end of the first epoch, the training loss was 2.416, while the validation loss was notably lower at 1.568.

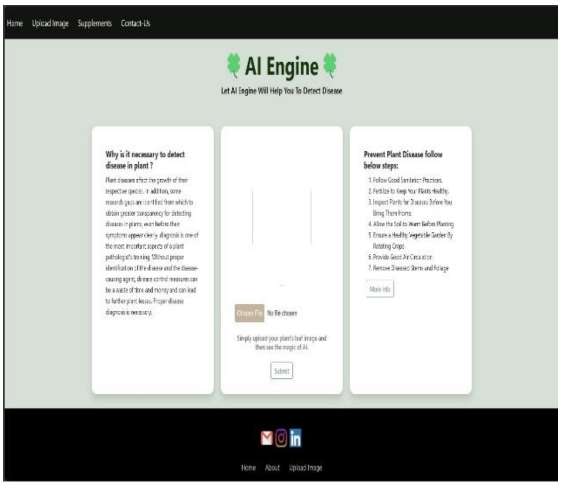
By the second epoch, both losses decreased, with the training loss dropping to 1.333 and the validation loss to 1.217.

The trend continued in the subsequent epochs, with further reductions in both training and validation losses: 1.081 and 0.960 in the third epoch, 0.854 and 1.003 in the fourth, and 0.752 and 0.860 in the final fifth epoch.

These results demonstrate the model's ability to learn from the training data, reflected in the decreasing training loss. Additionally, the relatively low validation losses indicate the model's generalization capability, suggesting its effectiveness in accurately predicting outcomes on unseen data. Each epoch's duration ranged from approximately 1 hour and 22 minutes to 1 hour and 33 minutes.

RESULT:

1. Home Page



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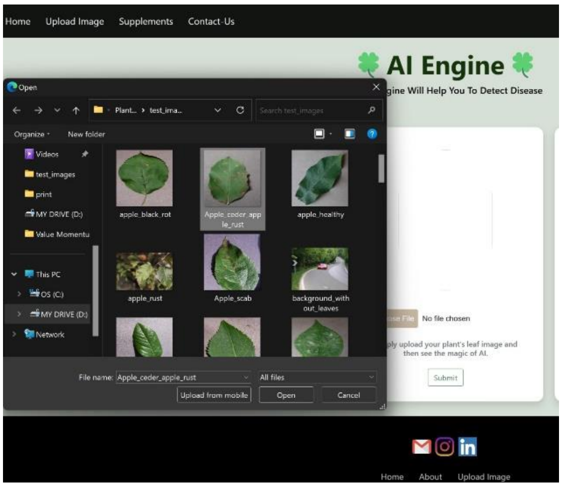
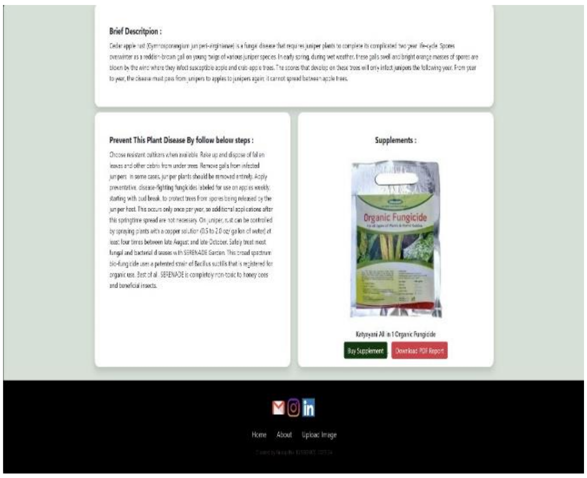
2. Upload Image



3. System Execution & Prediction

4. System Result



V. CONCLUSION

In conclusion, this paper presents advance plant disease detection using CNN In conclusion, using machine learning holds great promise for revolutionizing agricultural practices. By leveraging ML techniques, the project aims to develop automated systems capable of accurately detecting and diagnosing diseases in these crops, thereby improving

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productivity, sustainability, and food security. While there are challenges and limitations associated with ML-based approaches, the advantages outweigh the disadvantages, highlighting the potential impact of this technology on the agricultural sector.

VI. ACKNOWLEDGEMENT

I am deeply grateful to my guide Assistant Professor, **Shrijeet B. Pagrut,** whose guidance and supervision have been invaluable throughout this endeavor. I owe a profound debt of gratitude for the consistent inspiration and invaluable direction provided during the course of this work.

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