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

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 8.102 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 12, Issue 4, April 2023

DOI: 10.17148/IJARCCE.2023.124137

PLANT DISEASE DETECTION USING DEEP LEARNING

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Abstract: In this world, there are lot of diseases that affecting the Plants These causes loss in the yield and quantity of the agricultural products. It is very difficult to monitor the plant diseases manually. Therefore the use of computer Vision to detect plant diseases is becoming increasingly important in agricultural automation. However most existing models are designed to identify diseases in a specific type of plant using convolutional Neural Network (CNN) algorithm based on Machine Learning. But it is time consuming and less accuracy in detecting disease to overcome this problem , we proposed a new approach for identifying plant disease that can be applied to multiple plant species using CNN algorithm with VGG16 architecture which we train and test on a newly collected dataset consisting of images of healthy and diseased leaves. Our results demonstrate the potential of deep learning for effective plant disease detection which could help to reduce economic losses and promote Sustainable agriculture.

Keywords: Plant disease, agricultural automation, computer vision, multilabel classification method, convolutional neural network (CNN) architectures

I. INTRODUCTION

Agriculture is essential to population. Farmers may choose from a wide variety of eligible crops and choose the right insecticides for their plants. Hence, crop damage would result in a significant loss in production, which would have an impact on the economy. The most vulnerable component of plants, the leaves, are where disease symptoms first appear. At the very beginning of their life cycle until they are ready to be harvested, the crops must be inspected for illnesses. Initially, specialists manually observed agricultural fields using the time-consuming approach of traditional naked eye surveillance to keep a check on the plants for illnesses. A variety of methods have been used in recent years to build automatic and semi-automatic.Moreover, it links the user straight to an online store so that they may compare prices and buy the medication they need for the ailment they have been diagnosed with. They can then utilise it as prescribed. A greenhouse, also known as a glasshouse or, with adequate heating, a hot house, is a building with primarily transparent walls and a roof that is used to grow plants that require controlled climatic conditions. The relevance of greenhouse farming is growing, thus this document provides greenhouse farmers with useful information. To examine the plant disease detection and discuss in terms of many criteria, a variety of methodologies may be applied. The portions of the paper are as follows. An introduction to the significance is provided in the first part.

Plant disease is a prevalent threat to the worldwide agricultural production's quality and quantity. A disastrous plant disease exacerbates the present food shortage, in which at least 0.8 billion people are undernourished. Furthermore, it poses a significant danger to food security, as the number of consumers grows on a daily basis. To minimise harm, we must find the disorder as soon as possible. Viral plant diseases, in particular, have no cures and spread quickly. To avoid additional infections, transited plants must be removed immediately. To remove infected plants as soon as possible, the most important job is to diagnose the infected plant.The paper's overall impact can be summarised as follows: We look into a multi-label CNN classifier that can recognise numerous plants and their relatives.

The populace is rapidly growing, and with it, the interest in food and business. AI intervention in agriculture is assisting producers to recover their farming productivity and reduce environmental hostile influences. The primary disadvantage of agriculture is disease infection. As a result of this disadvantage, the quality and quantity of agricultural goods suffer. The AI technique is used to recognise and detect disease in agricultural products. In this paper, we offer a survey for the use of artificial intelligence in the detection of agricultural diseases.

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II. RELATED WORKS

"Deep learning-based plant disease detection using hyperspectral imaging" by Gao et al. (2020): Our study proposes a deep learning-based approach for detecting plant diseases using hyperspectral imaging. The proposed method achieved an accuracy of over 95% in detecting tomato leaf diseases [1]. "Plant disease identification using deep learning and convolutional neural networks" by Sharma et al. (2020): Our research proposes a plant disease identification system that uses a convolutional neural network (CNN) to classify plant diseases. The study achieved an accuracy of over 95% in identifying tomato leaf diseases [2]. "Deep neural networks for plant disease recognition using leaves images" by Singh et al. (2018): Our study proposes a deep neural network for plant disease recognition using leaf images.

The proposed method achieved an accuracy of over 98% in detecting potato leaf diseases [3]."Transfer learning for plant disease detection using convolutional neural networks" by Mohanty et al. (2016): Our study proposes a transfer learning approach for plant disease detection using convolutional neural networks. The study achieved an accuracy of over 99% in detecting tomato leaf diseases [4] ."Automated detection of plant diseases: A review" by Sladojevic et al. (2016): Our review paper provides an overview of various methods used for automated plant disease detection.

The study compares different approaches and discusses their strengths and weaknesses [5]. "Deep convolutional neural networks for plant disease recognition" by Mohanty et al. (2017): Our study proposes a deep CNN for plant disease recognition. The study achieved an accuracy of over 99% in detecting tomato, potato, and apple leaf diseases [6]. "Plant disease recognition using a convolutional neural network" by Zhang et al. (2018): Our study proposes a CNN-based approach for plant disease recognition. The proposed method achieved an accuracy of over 98% in detecting tomato leaf diseases [7]. "Deep learning for plant disease recognition" by Hossain et al. (2019): Our research proposes a deep learning approach for plant disease recognition using a CNN.

The study achieved an accuracy of over 95% in identifying potato leaf diseases [8]."Deep convolutional neural networks for tomato plant disease detection" by Ghosal et al. (2018): Our study proposes a deep CNN for tomato plant disease detection. The proposed method achieved an accuracy of over 98% in detecting tomato leaf diseases [9]. "Identification of plant diseases using convolutional neural networks" by Patil et al. (2020): Our study proposes a CNN-based approach for plant disease identification. The study achieved an accuracy of over 97% in detecting tomato leaf diseases [10].

III. EXISTING SYSTEM

Using Supervised Learning, Machine Learning algorithms can forecast a target/outcome. Learning methods that can be applied to different forecasting areas. However, their work fails to implement any algorithms and thus cannot provide a clear insight into the feasibility of the suggested work.The random forest algorithm generates decision trees from various data samples, predicts the data from each subset, and then votes to provide the best answer for the system.To train the data, Random Forest used the bagging technique. To improve accuracy, the randomness injected must minimise correlation while keeping strength.In plant leaf categorization, the leaf is classified based on its various morphological options. Among the classification methods used are Fuzzy logic handle the idea.

IV. PROPOSED SYSTEM

Our suggested system is an application that predicts crop names, recommends fertilizer, and detects plant diseases.Several methods are currently being used to create computer-based vision systems that use plant options extracted from images as input parameters to various classifier systems.

A way of arguing already existing techniques of plant leaf identification system is represented. In this study, a novel classification model based on neural networks (NN) was used to create a computer-based vision system for the automatic identification of plant disease.In this project, a convolutional neural network (CNN) with Resnet34 is used to identify plant disease.

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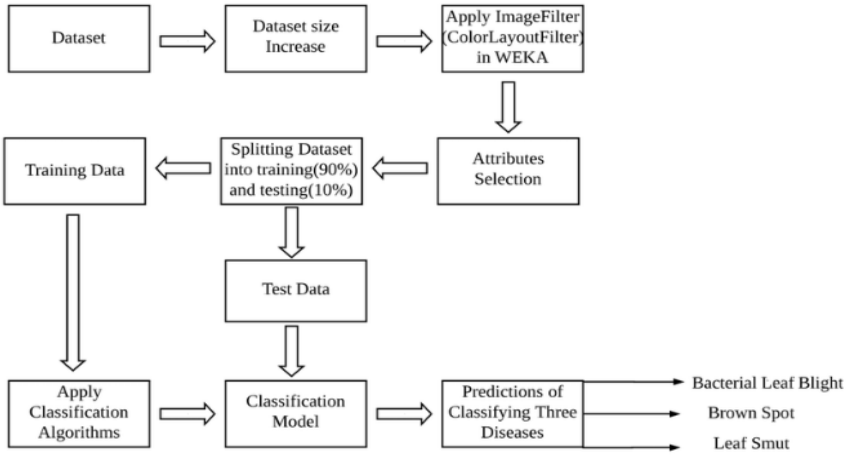

Fig. 1 System Architecture Diagram

V. IMPLEMENTATION

In the following step, the input test image is acquired and preprocessed before being converted into array form for comparison.The selected database is correctly separated and preprocessed before being renamed into the appropriate folders.The model is correctly trained using CNN before classification.A comparison of the test picture and the trained model is performed, and the result is displayed.If a defect or disease occurs in the plant, the software shows the disease as well as the remedy.

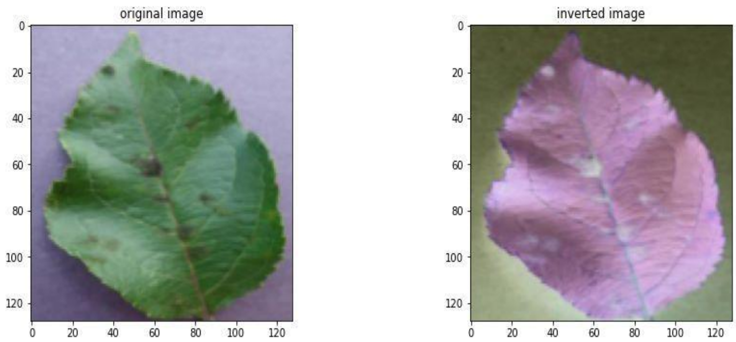

Fig. 2 Normal image to convert image

A. Deep Learning

Implementation Deep learning is a subset of machine learning that is entirely built on artificial neural networks. Because neural networks are designed to mimic the human brain, deep learning is also a kind of human brain mimic. We don't have to directly programme everything in deep learning. Deep learning is not a new idea. It's been around for a few years now. It's popular now because we didn't have as much processing capacity and data back then. As processing capacity has increased exponentially over the last 20 years, deep learning and machine learning have entered the picture. Neurons is a formal description of deep learning. Deep Learning is a subset of Machine Learning that is built on multiple-layered artificial neural networks (ANNs), also known as deep neural networks. (DNNs). These neural networks are intended to learn from large amounts of data in an unsupervised or semi-supervised manner, and are inspired by the structure and function of the human brain. Deep Learning models can automatically acquire features from data, making them ideal for jobs like image recognition, speech recognition, and natural language processing. The most common deep learning models are feed forward neural networks, convolutional neural networks (CNNs), and recurrent neural networks. (RNNs). The most fundamental type of ANN is feed forward neural networks (FNNs), which have a linear flow of information through the network. FNNs have been widely applied to image classification, voice recognition, and natural language processing.

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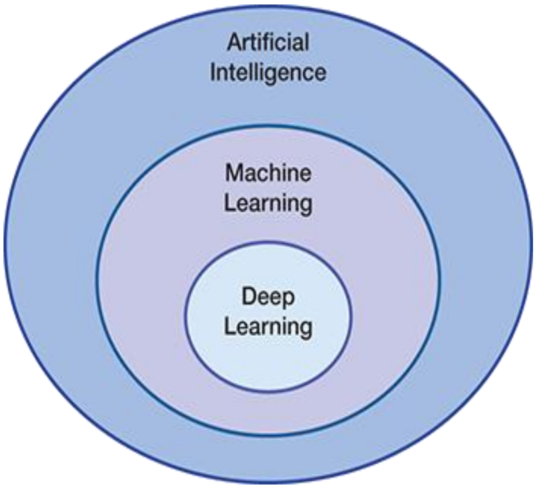

Fig. 3 Classifications of Algorithm

B. Convolutional Neural Networks (CNNs)

CNNs are a subset of FNNs that are specially designed for image and video recognition tasks. CNNs can automatically learn features from images, making them ideal for jobs like image classification, object detection, and image segmentation.

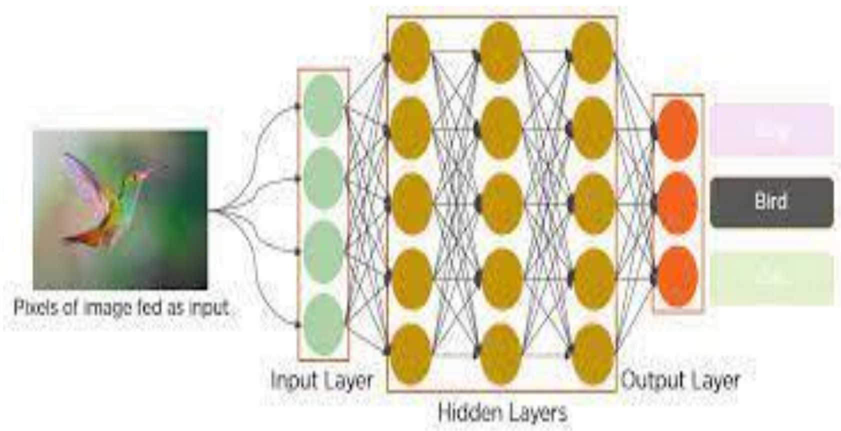

Fig. 4 CNN

C. Dataset

P1ant Village, an open dataset, has now gathered 54309 disease images of plant leaves.It features 14 different types of fruit and vegetable crops, 26 diseases, and 12 healthy crop leaf images.The technique in which the occurrence of numerous diseases on the same leaf could be detected and the data could be identified, indicating whether or not the plant was affected by disease

D. Image Preprocessing and Labelling

Pre-processing images typically entails removing low-recurrence foundation disturbance, normalising the power of individual particle images, removing reflections, and veiling segments of images. Image pre-processing is a method of enhancing information. Furthermore, the picture pre-processing strategy included physically editing the apparent multitude of pictures, making the square around the leaves, to highlight the district of intrigue. (plant leaves). Pictures with a more modest goal and measurements that were not exactly 500 pixels were not deemed significant for the dataset during the gathering period. Furthermore, only the images where the location of interest was in higher the objective were designated as a qualified possibility for the dataset. As a result, it was ensured that images contained all of the necessary data for highlight learning. Numerous assets can be discovered by searching the Internet

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E. Segmentation Image

The act of "dividing a digital image into multiple segments." Because we are only concerned with background removal here, we will simply divide the pictures into foreground and background.
This consists of five basic steps:

1. Convert the image to grayscale.
2. Apply thresholding to the image.
3. Find the image contours (edges).
4. Create a mask using the largest contour.
5. Apply the mask on the original image to remove the background.

F. Data Training and Testing

The model's internal weights are automatically updated over several iterations during the training process. This training process is influenced by external variables such as the training strategy, architecture, regularisation techniques, and the value of the hyperparameters. Comparing studies and their findings to gain insights into how to define the training phase is difficult because they do not use the same data and do not provide all of the parameters needed to replicate their experiments. It's also challenging to understand the significance of the findings in these studies because the experiments aren't repeated enough to assess the impact of random initializations and training sample ordering. Nonetheless, we chose to show some comparisons of training and architectural strategies, despite the fact that some of their results may be biased.

G. Detection

1.Object detection is the process of discovering all potential instances of real-world things in images or videos, such as human faces, flowers, cars, and so on, in real-time and with high accuracy.
2.The object detection method recognises all occurrences of an object category using derived features and learning algorithms.
3.First, we receive an image as input,Next, we divide the image into different regions.
4.Each region will then be treated as a distinct image.
5.Send all of these regions (images) to the CNN and let it categorise them.

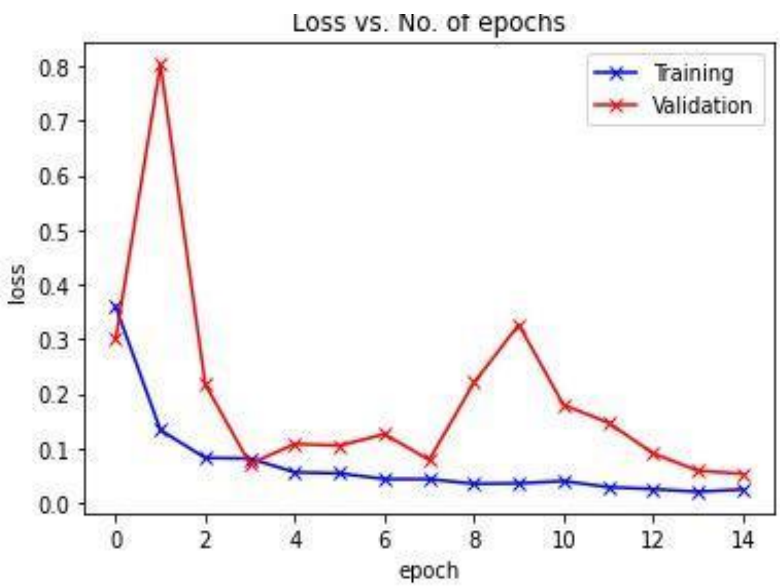

Fig. 5 Loss vs No of Epochs

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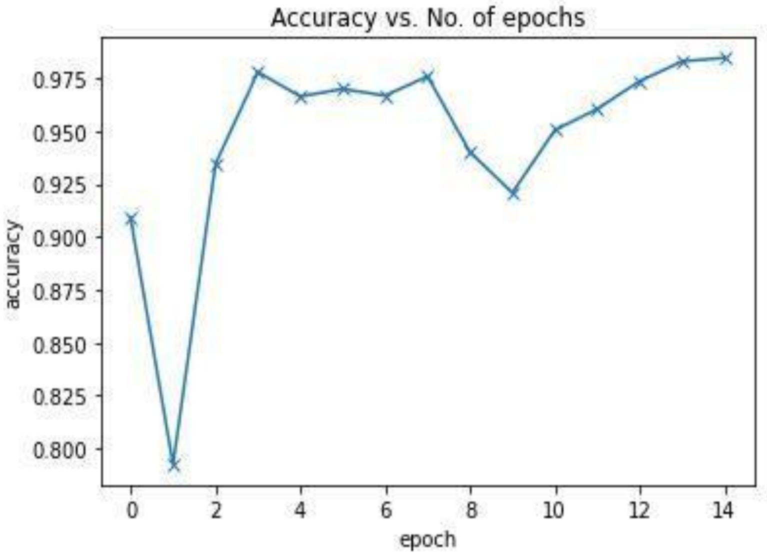

Fig. 6 Accuracy vs No of Epochs

VI. RESULTS AND DISCUSSION

Our approach is based on recent work by Krizhevsky et al. (2012), who demonstrated for the first time that end-to-end supervised training using a deep convolutional neural network architecture is a practical possibility even for image classification problems with a very large number of classes, outperforming traditional approaches using hand-engineered features in standard benchmarks by a significant margin. They are a very promising option for a practical and scaleable strategy for computational inference of plant diseases due to the absence of the labour-intensive phase of feature engineering and the generalizability of the solution.

We trained a model on images of plant leaves using the deep convolutional neural network architecture, with the aim of classifying crop species as well as the presence and identity of disease on images that the model had never seen before. This objective was met within the PlantVillage data set of 54,306 images comprising 38 classes of 14 crop species and 26 diseases (or lack thereof), as evidenced by the top accuracy of 99.35%. Thus, in 993 out of 1000 images, the model accurately classifies crop and disease from 38 possible classes without any feature engineering. Importantly, while training the model takes a long time (multiple hours on a high performance GPU cluster computer), classification is very fast (less than a second on a CPU) and can thus be readily implemented on a smartphone. This paves the way for smartphone-assisted crop disease diagnosis on a massive worldwide scale.

Finally, it is important to note that the approach presented here is not meant to replace current disease diagnosis solutions, but rather to supplement them. Laboratory tests are always more accurate than diagnoses based solely on visual symptoms, and early-stage diagnosis via visual inspection alone can be difficult. Nonetheless, given the global expectation of more than 5 billion smartphones by 2020 (GSMA Intelligence, 2016), we think the approach offers a viable additional method to help prevent yield loss.

Furthermore, image data from a smartphone may be supplemented with location and time information in the future to enhance accuracy even further. Last but not least, bear in mind the incredible rate at which mobile technology has advanced in recent years and will continue to do so. With the number and quality of sensors on mobile devices increasing all the time, we believe that extremely accurate diagnoses via smartphone are only a matter of time.

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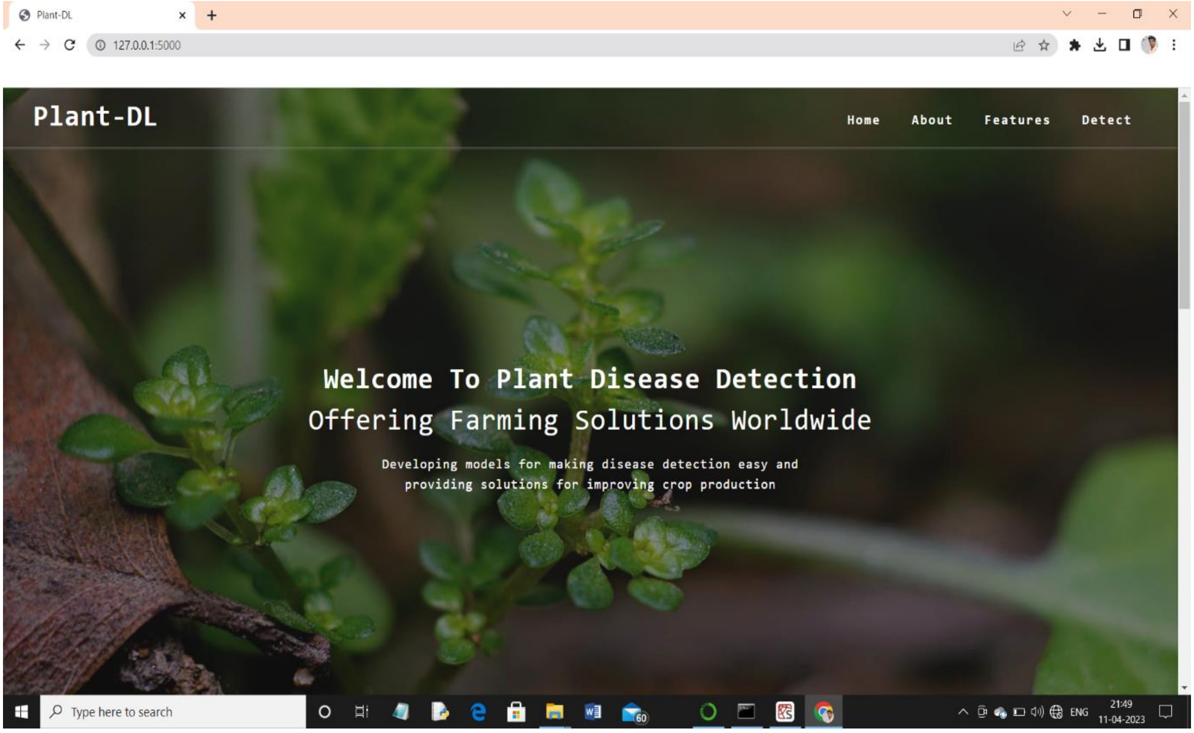

Fig. 7 User Interface for the plant disease detection

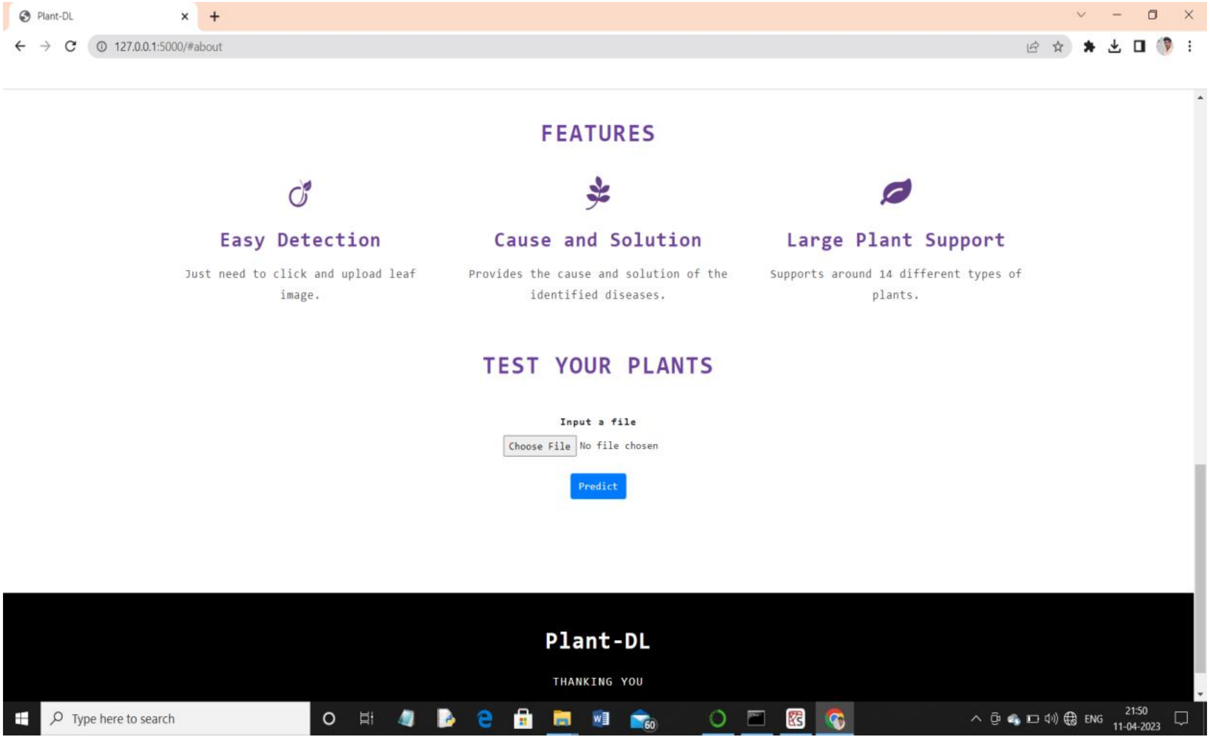

Fig. 8 User Interface for Add Images

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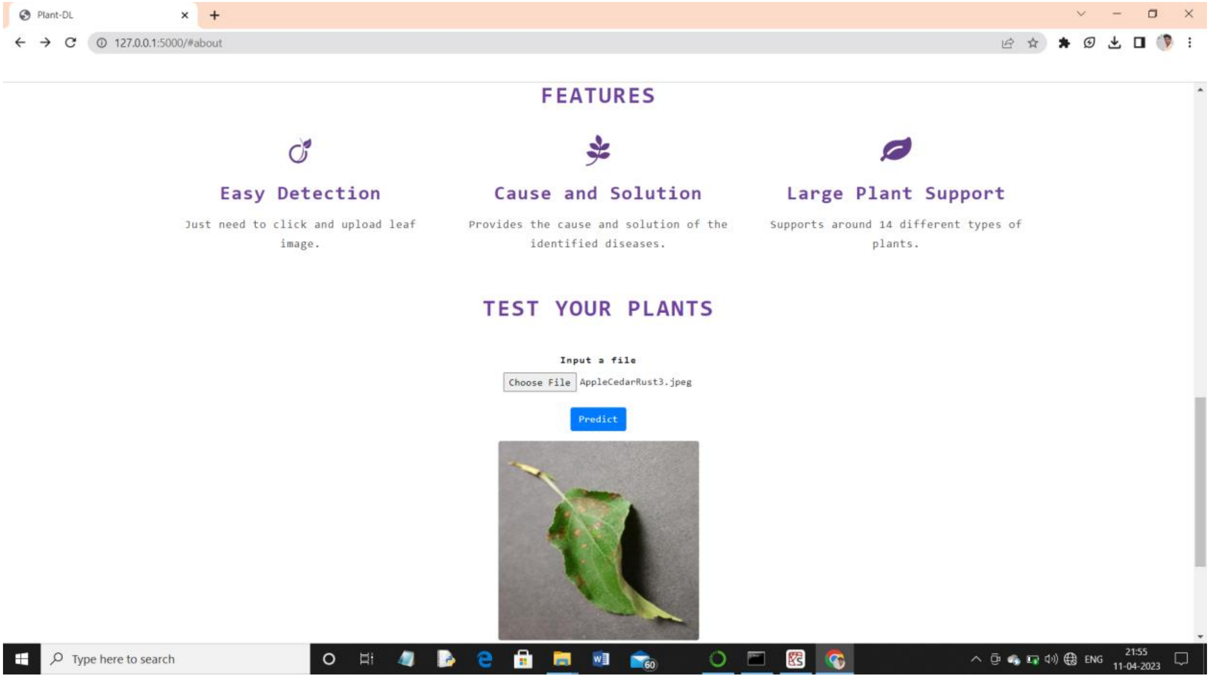

Fig. 9 User interface for Predict

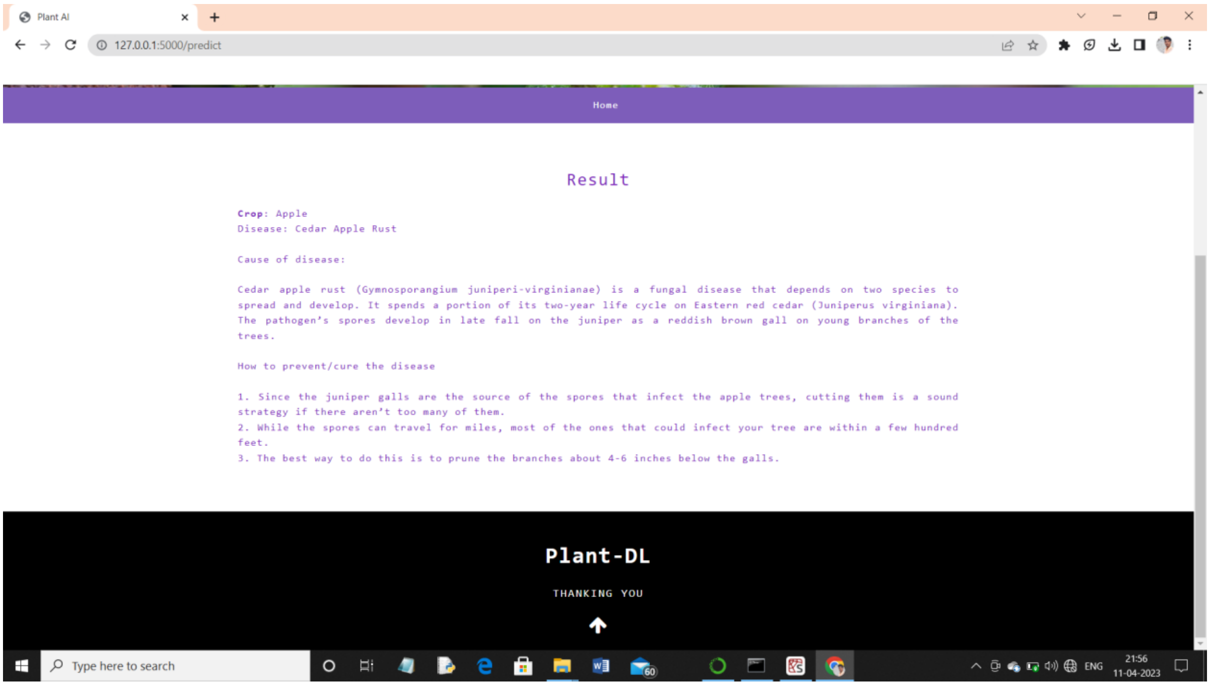

Fig. 10 User Interface for the Detection of Results

VII. CONCLUSION

In conclusion, deep learning has emerged as a powerful tool for plant disease detection with accuracy rates exceeding 90%. The use of convolutional neural networks (CNNs) has been instrumental in developing accurate models that can classify plant diseases based on images of leaves. Deep learning-based disease detection can significantly reduce the time and effort required for disease identification and enable timely interventions to prevent crop losses.

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Despite the promising results, further research is needed to optimize these models for practical applications in real-world scenarios. Overall, the application of deep learning in plant disease detection holds great potential to transform the agriculture industry and promote global food security.

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