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LEAF DISEASE DETECTION USING MACHINE LEARNING

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Abstract: Agriculture provides food to all the human beings even in case of rapid increase in the population. Easily spreadable diseases can have a strong negative impact on plant yields and even destroy whole crops. It is recommended to predict plant diseases at their early stage in the field of agriculture. Traditional methods rely on lab analysis and human expertise which are usually expensive and unavailable in a large part of the undeveloped world. Since smartphones are becoming increasingly present even in the most rural areas, in recent years scientists have turned to automated image analysis as a way of identifying crop diseases. The idea behind this proposed system is to bring awareness amongst the farmers about the cutting-edge technologies to detect diseases in plant leaves. The approaches of machine learning and image processing with an accurate algorithm is used to detect the leaf diseases in the plants.
Keywords: Machine Learning, Image Processing, CNN Algorithm.

I. INTRODUCTION

Human population steadily continues to grow, and along with it the need for food production increases. According to the UN projections, human population is expected to reach 9.7 billion in 2050, 2 billion more than today. Considering that most of the population growth is to occur in the least developed countries (around 80% increase in the next 30 years), where the food scarcity is the main problem, it is easy to conclude that minimizing food loss in those countries is a primary concern. It is estimated that the yield loss worldwide is between 20 and 40 percent, with many farms suffering a total loss. Traditional methods for detecting diseases require manual inspection of plants by experts. This process needs to be continuous, and can be very expensive in large farms, or even completely unavailable to many small farm holders living in rural areas. This is why many attempts to automate disease detection have been made in the last few decades. One of the notable approaches is the use of hyperspectral imaging. Hyperspectral images are usually taken by satellites or airborne imaging devices and used for monitoring large areas. A downside of this approach is extremely high equipment cost, as well as high dimensionality and small number of samples which make them unsuitable for machine learning (ML) analysis. Because of the recent breakthroughs in computer vision and the availability of cheap hardware, currently the most popular approach is the analysis of RGB images. The other motive for analysing RGB images is that with the current smartphone usage these solutions have potential to reach even the most rural areas. RGB images can be analysed by classical ML algorithms or the deep learning (DL) approach. Classical methods rely on image pre-processing and the extraction of features which are then fed into one of the ML algorithms. Popular algorithm choices are Support Vector Machines (SVM), kNearest Neighbours (*k*-NN),

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Fully Connected Neural Networks (CNN), Decision Trees, Random Forests etc. In the last few years, the researchers shifted almost exclusively to the DL methods for image classification tasks. The reason is that they almost always outperform classical algorithms when given reasonably sized dataset, and can be implemented without the need for handengineered features. In this paper, we compare the DL approach with classical ML algorithms for the study case of plant disease classification.

II. LITERATURE SURVEY

Early information on crop health and disease detection may be obtained by implementing the proper management strategies, such as fungicide applications, disease-specific chemical applications, and vector control through pesticide applications[3]. This could help with illness management and boost output. In this article, the authors discuss the need for creating a quick, affordable, and dependable health-monitoring sensor that supports agricultural improvements. For the objective of building ground-based sensor systems to aid in monitoring plant health and illnesses in the field, they discussed the already employed technologies, including spectroscopic, imaging-based, and volatile profiling-based plant disease detection approaches. It was determined to employ image processing disease recognition strategy among other frequently used ways for plant disease diagnostics, such as double-stranded ribonucleic acid (RNA) analysis, nucleic acid probes, and microscopy, after study of their work and analysis offered by the authors[5].

Computer vision is now used in several techniques for plant disease identification. One of these, as described by the authors in, is illness detection using color feature extraction. Utilizing the YcbCr, HSI, and CIELAB color models allowed for the successful detection of disease spots in this study, which was unaffected by noise from other sources, such as camera flash [1]. The approach of obtaining form data might also be used to identify plant diseases. In their final tests, Patil and Bodhe employed this approach to identify illness in sugarcane leaves. They used threshold segmentation to calculate the leaf area and a triangle threshold to determine the infected area. The ability to extract textural features may also be utilized to identify plant diseases. Using texture features like inertia, homogeneity, and correlation discovered by computing the grey level co occurrence matrix on an image, Patil and Kumar proposed a model for plant disease detection [11].

They experimented with disease detection on maize leaves in conjunction with color extraction. Combining all of these features yields a rich feature set that may be used to enhance images and improve categorization. The authors have provided an overview of popular traditional feature extraction techniques [9]. The application of these approaches and strategies is the major emphasis of this paper's work because Artificial Intelligence (AI) science is moving along so quickly [2].There are several methods for recognising the species of leaf, pest, or disease that use feed-forward back propagation of neural networks with one input, one output, and one hidden layer; this model was put out by the authors in. To advise corrective actions for pest or disease control in agricultural crops, they created a software model [8].
The scientists also suggest a method that combines characteristics from forward neural networks and particle swarm optimization (PSO) in order to improve the accuracy of the system and identify cotton leaves that have been wounded, with a final accuracy of 95%.

Additionally, Support Vector Machine techniques may be used to identify and classify plant diseases[3]. This method was used for sugar beet illnesses and published in, where the classification accuracy ranged from 65% to 90%, depending on the kind and stage of the disease.

For the detection of plant diseases, there are techniques that combine feature extraction with Neural Network Ensemble (NNE). NNE provides a superior generalization of learning capacity by training a set number of neural networks and integrating their results afterwards. Only tea leaf illnesses were recognised using this approach, which had a 91% final testing accuracy.

The authors employed k-means as a clustering strategy in combination with another method based on leaf pictures and employing ANNs as a tool for an automated identification and classification of plant diseases. There were 10 secret layers in the ANN. The total number of outputs was 6, with each class representing one healthy leaf and five different illnesses. This method's categorization accuracy was 94.67% on average[10].

In their paper, the authors discussed deep learning techniques for tackling the most challenging problems in biology, bioinformatics, biomedicine, robotics, and 3D technologies. We use deep learning to identify plant diseases in our work, which is motivated by the development of deep learning techniques and their practical use. A thorough search of the most recent scientific literature turned up no proof that deep learning techniques were investigated for identifying plant diseases from leaf photos. The sections below show our approach to recognition using deep CNN[4].

III. ANALYSIS

EXISTING SYSTEM

The existing method for plant disease detection is simply naked eye observation by experts through which identification and detection of plant diseases is done. For doing so, a large team of experts as well as continuous monitoring of plant is required, which costs very high when we do with large farms.

PROPOSED SYSTEM

Digital camera or similar devices are used to take images of leaves of different types and then those are used to identify the affected area in leaves. Then different types of image-processing techniques are applied on them, to process those images to get different and useful features needed for the purpose of analyzing later. In the proposed method KNN (K-Nearest Neighbour), SVM(Support Vector Machine) and CNN(Convolutional Neural Network) are used to detect the plant disease at greater accuracy.

IV. DESIGN

UML DIAGRAMS

The system requirements, operating environment, system and subsystem architecture, files and database design, input formats, output layouts, user interfaces, detailed design, processing logic, and external interfaces are all covered in the System Design Document.

Use Case Diagram:

The Use Case diagram of the project disease prediction using machine learning contains of all the various aspects a general use case diagram requires. This use case diagram shows how to do from starting the model flows from one step to another like he enter into the system then enters all his information like symptoms that goes into the system. compares with the prediction model and if true is predicts the appropriate results otherwise it shows the details where the user if gone wrong while entering the information's and it also shows the appropriate messages for the user to follow. Here the use case diagram of all the entities are linked to each other where the user gets started with the system and in the end output will be presented.

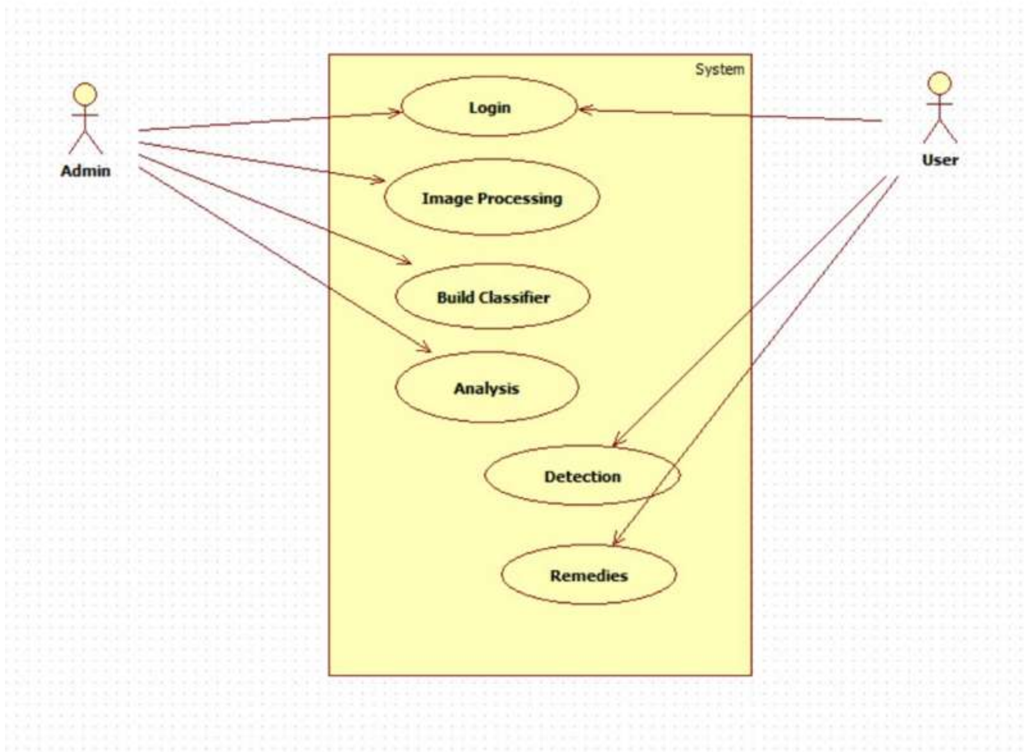


Figure 4.1.1 Use Case Diagram

Class Diagram:

Self diagnosable human disease prediction using machine learning (ML) consists of class diagram that all the other application that consist the basic class diagram, here the class diagram is the basic entity that is required in order to carry on with the project. Class diagram consist the data about all the classes that is used and all the related datasets, and all the other necessary attributes and their relationships with other entities, all these information is necessary in order to use the concept of the prediction, where the user will enter all necessary information that is required in order to use the system.

Purpose of Class Diagrams

- Analysis and design of the static view of an application.

- Describe responsibilities of a system.
- Base for component and deployment diagrams.
- Forward and reverse engineering

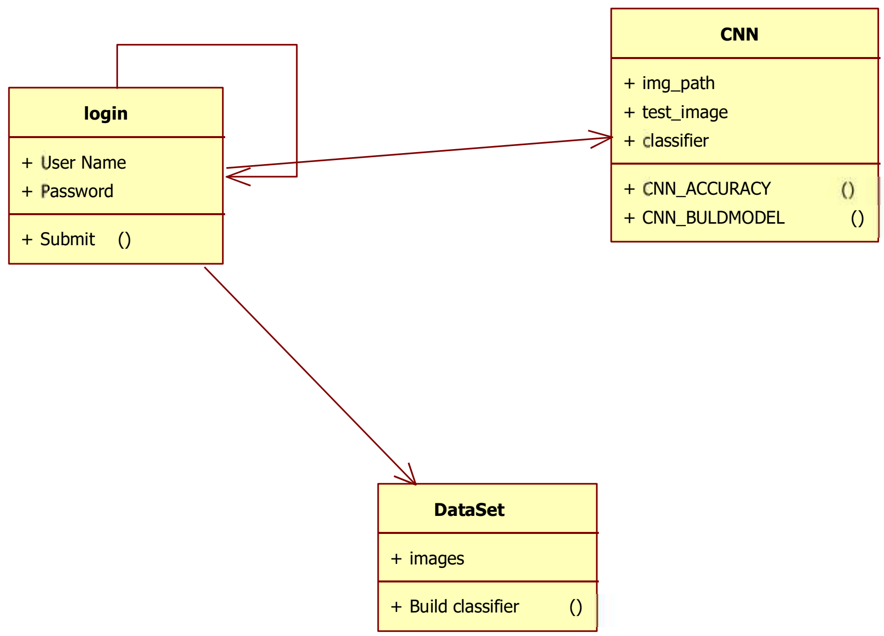


Figure 4.1.2 Class Diagram

Activity Diagram:

Activity diagram is an important diagram in UML to describe the dynamic aspects of any system. Activity diagram is a flowchart to show the flow from one activity to another. The activity can be explained as an operation of the system's execution. The control flow is taken from one operation to another operation. Here in this diagram the activity starts from user then the user proceeds to the prediction phase where the prediction happens. Then finally after processing the data from datasets the analysis will happen then the correct result or prediction will be displayed which is nothing but the Output.

Purpose of Activity Diagrams

The purpose of an activity diagram can be described as -

Draw the activity flow of a system.

- Describe the sequence from one activity to another.
- Describe the parallel, branched and concurrent flow of the system.

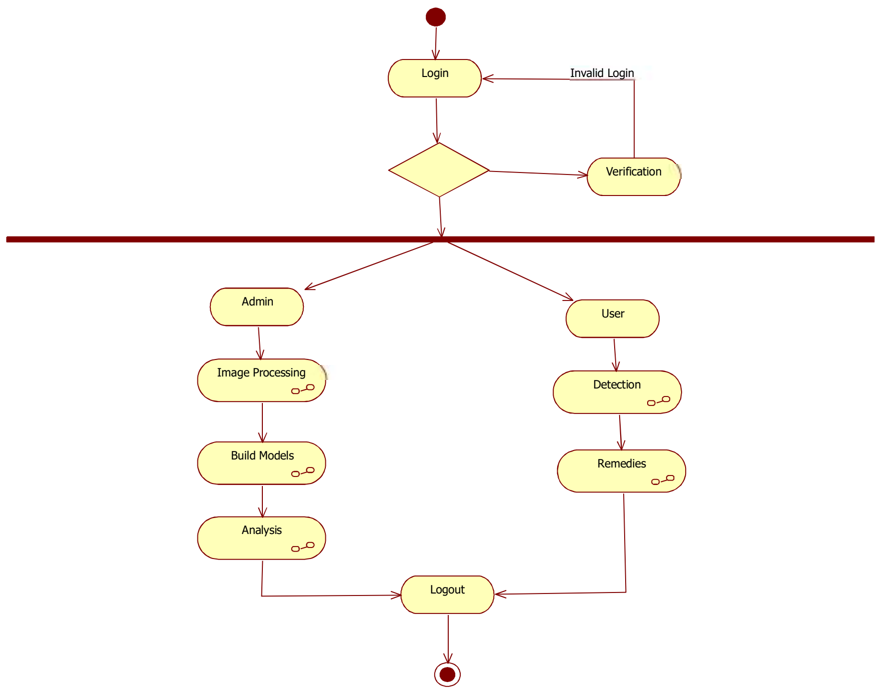


Figure 4.1.3 Activity Diagram

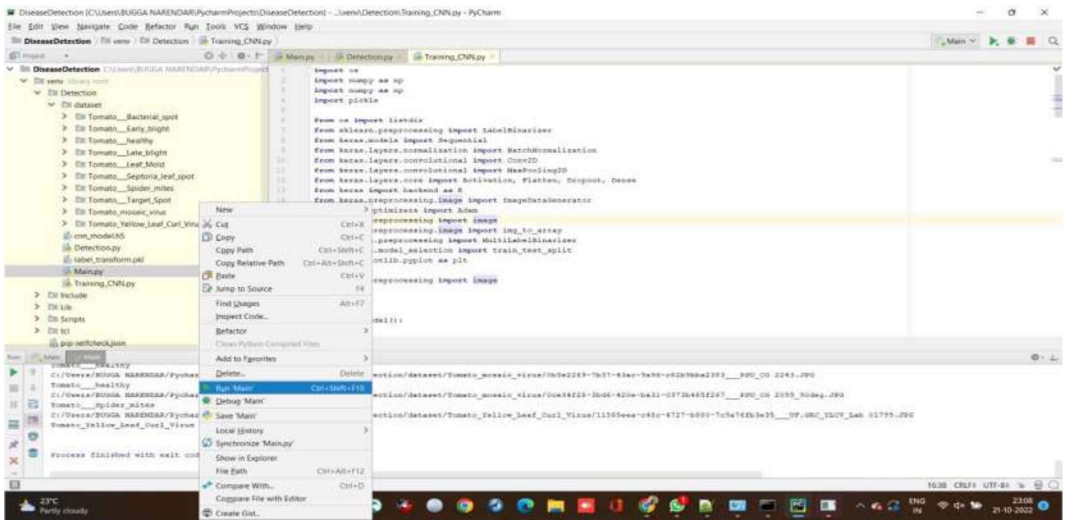
Sequence Diagram:

The Sequence diagram of the project self diagnosable human disease prediction using machine learning (ML) consist of all the various aspects a general sequence diagram requires. This sequence diagram shows how from starting the model flows from one step to another, like how a user enter into the system then enters all the information like symptoms that goes into the system, compares with the prediction model and if true is predicts the appropriate output will be shown otherwise it shows the details where the user gone wrong while entering the information and it also shows the appropriate precautionary measure for the user to follow. Here, the sequence of the entities are linked to each other where the user gets started with the system.

Purpose of Sequence Diagram

To model the flow of control by time sequence.

- To model the flow of control by structural organizations.
- For forward engineering.
- For reverse engineering.



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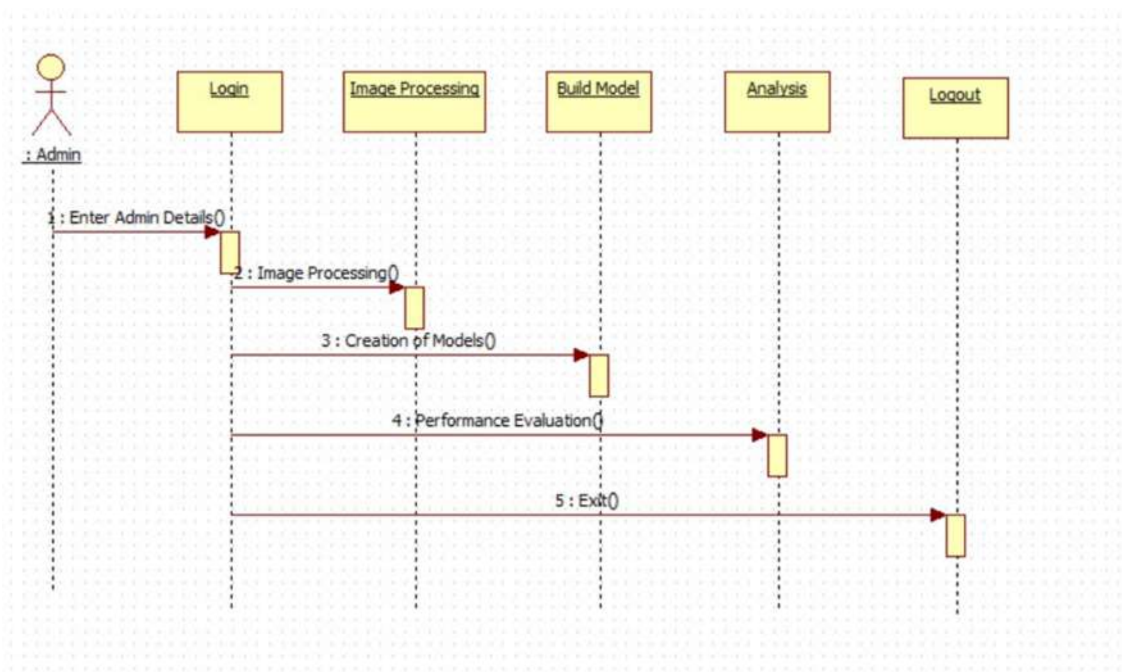
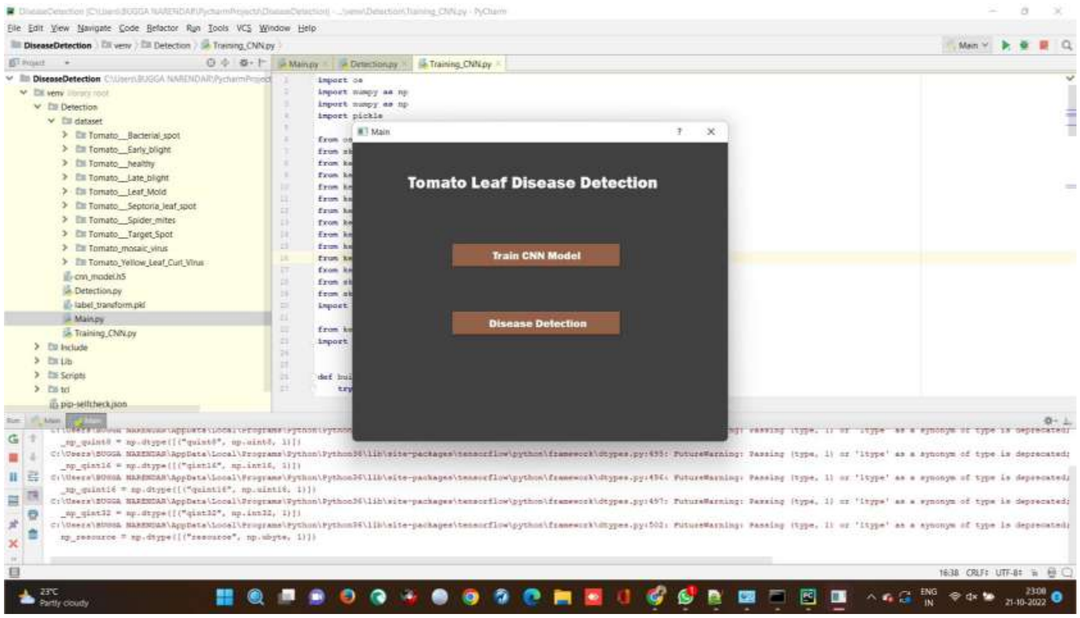


Figure 4.1.4 Sequence diagram

SCREEN SHOTS

Figure 7.1 Execution image



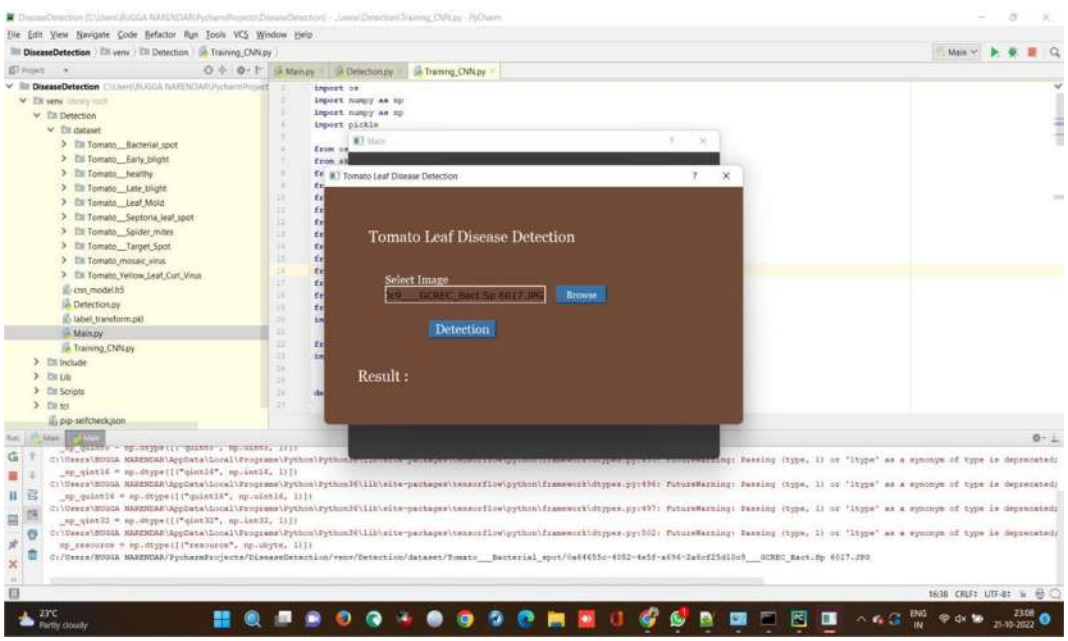


Figure 7.2 Home Page

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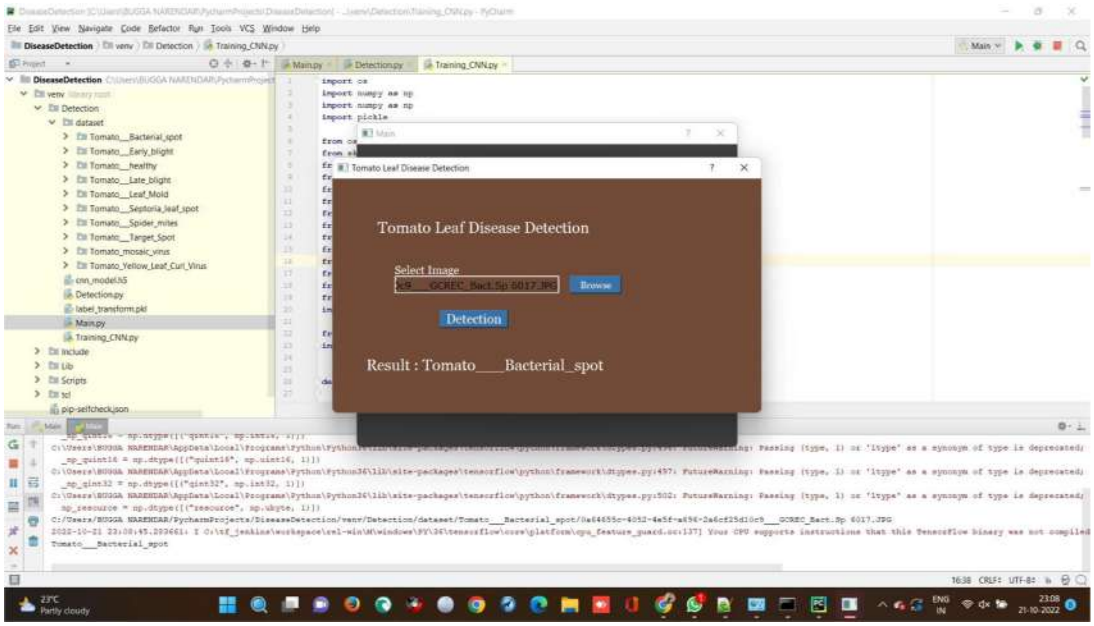

Figure 7.4 Disease Detection image

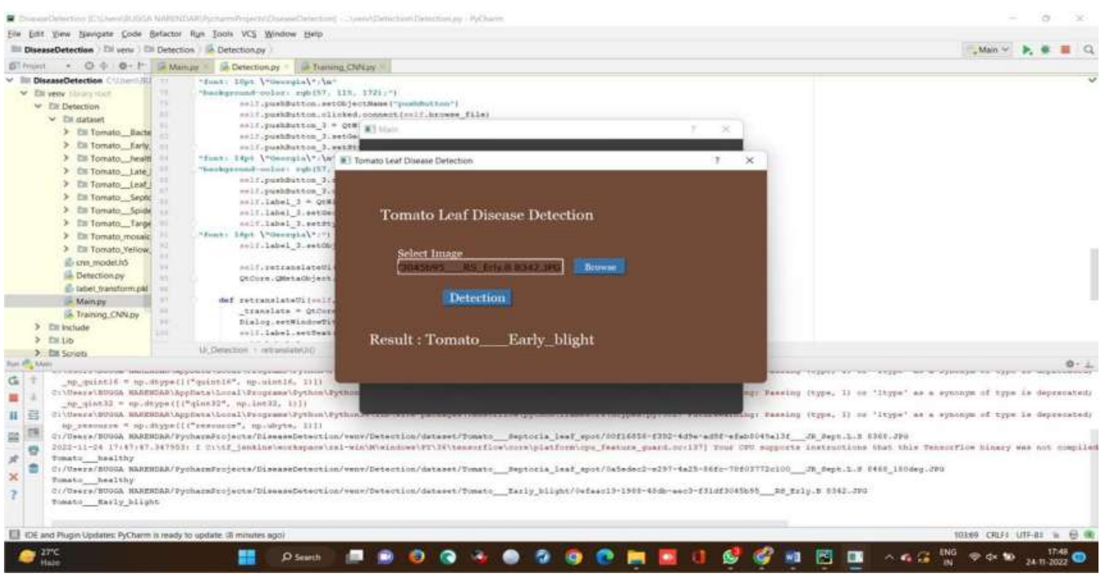

Figure 7.5 Result image

CONCLUSION

There are several techniques for computer vision or automated plant disease detection and categorization, however this area of study still needs improvement. Additionally, only those market-available commercial solutions that deal with plant species recognition based on pictures of the leaves In this study, a novel method for automatically classifying and identifying plant diseases from leaf photos was investigated. The created model was capable of identifying the presence of leaves and differentiating between healthy leaves and 10 distinct disorders that may be identified visually. The whole process was covered, starting with gathering the pictures needed for training and validation, moving on to image pre-processing and augmentation, and concluding with the training and fine-tuning of the deep CNN. Various experiments were run to evaluate the effectiveness of the newly developed model. More than 3,000 original photographs from sources on the Internet were used to start a new plant disease image collection, which was then expanded to more than 30,000 images by applying the necessary changes. For various class assessments, the experimental findings had a precision of between 91% and 98%.

The trained model's ultimate total accuracy was 96.3%. Overall accuracy has not changed significantly as a result of fine-tuning, but the augmentation procedure had a stronger impact on obtaining decent outcomes. There was no comparison with findings from similar experiments using the same methodology since, as far as we are aware, the proposed method has not been used in the field of plant disease detection.Comparable or even superior results were obtained when compared to other methods utilized and discussed in Section 2, particularly when taking into account the larger number of classes in the research under consideration.

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