An Accurate Plant Disease Detection Technique Using Machine Learning

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Abstract. Plant diseases have a major detrimental effect on agricultural output, resulting in large crop losses and financial losses for the farming sector. Modern technical technologies have been established to precisely monitor plant health and identify illnesses early in their life cycle in order to solve this problem. It is suggested that plant diseases may be precisely predicted using image processing techniques, more especially a Convolutional Neural Network (CNN) approach. The goal of this novel strategy is to offer an automated and dependable disease detection system, assisting professionals and farmers in acting promptly to prevent infections and minimize crop losses. The agricultural business has a lot of potential to increase profitability and production via the integration of cutting-edge technologies.

Keywords: Agriculture, Plant diseases detection, Image processing, Machine learning.

1. Introduction

Plant sickness detection is a vital element of agriculture that plays a vital position in making sure crop fitness, minimizing losses, and keeping meals security. Traditional strategies of disorder detection regularly rely upon manual inspection and visible commentary, which may be time-consuming, subjective, and liable to human errors. With the advancements in machine gaining knowledge of and synthetic intelligence, there's an opportunity to increase computerized structures that could appropriately come across and classify plant illnesses.

Technological advancements have led to the discovery of applying system mastering techniques in plant ailment detection and class. By leveraging algorithms along with CNNs, to expand a machine that may examine plant pictures, become aware of disease symptoms, and offer accurate disorder diagnosis. The predicted effects of this observation will provide treasured insights into the prospects of the usage of machine mastering for plant disease detection, presenting enthusiasts with a higher understanding of the suitability of numerous algorithms for this mission.

Patel et al. [1] (2020) had proposed a solution for identifying and categorizing leaf diseases in which deep learning and image processing methods are frequently utilized. These methods include image preprocessing, CNN, MRCNN, and FRCNN.

Monigari et al. [2] (2021) had presented an innovative solution for plant disease detection using leaf photographs. Their approach involved utilizing image processing techniques like acquisition, filtering, segmentation, feature extraction, and classification. They trained a deep CNN on a dataset comprising 20,639 images from 15 folders of healthy and diseased plant leaves. The main goal of their study was to develop a precise and effective method for identifying plant diseases through leaf image analysis. By employing modern image identification technologies like CNNs, the researchers aimed to provide a quick and accurate tool for disease detection, facilitating timely interventions in agriculture.

Sai et al. [3] (2021) had developed a novel disease detection system was introduced, utilizing color and texture-based analysis with deep learning techniques. The system employs DenseNet for image classification and 1D-CNN for semantic segmentation to distinguish healthy and defective leaf pixels. By evaluating pixel values, the model accurately identifies disease types and measures the extent of infection. The system generates valuable outputs, including disease categorization, infection stage, damaged area segmentation, and tailored recommendations for suitable remedies. This innovative approach shows promising potential in facilitating timely interventions and targeted treatments to improve crop health and enhance agricultural productivity.

Lili et al. [4] (2021) had carried out a study identifying plant diseases from leaves. This review presents the research progress in crop leaf disease identification, highlighting developments and difficulties in the use of deep learning and sophisticated imaging methods to identify plant leaf diseases. The study acts as a valuable resource for researchers studying plant disease sensing and insect pests.

1.1. Objective

This paper aims to explore the application of machine learning techniques for the accurate sensing and classification of plant diseases. The primary focus is to develop an automated system capable of analyzing plant images, detecting disease symptoms, and classifying plants as healthy or disease-affected.

- Plant disease diagnostics helps in identifying the integrity and life span of the plant leaves without difficulty for the farmers to know the name, integrity and life span.

- It provides insights into the benefits and applications of developed plant disease detection systems, including early disease detection, precision agricultural practices, and effective disease management strategies

2. Literature Survey

Nabobi et al. [5] (2022) had examined on the detection of plant leaf diseases, highlighting the limitations of manual visual inspection. They addressed these challenges by utilizing image processing and artificial intelligence algorithms. Their research was organized into three parts: the first part explored various image processing and AI techniques, the second part evaluated different frameworks and their accuracy, and the third part provided a detailed explanation of the disease detection and classification performance. Through their work, they contributed valuable insights into automated approaches for disease recognition, promising to advance agricultural practices and crop management.

Pranesh et al. [6] (2021) had presented an intelligent and effective method for crop disease detection, employing computer vision and machine learning techniques. Their system demonstrates an impressive 93% accuracy in detecting 20 diseases across 5 common plants. To accomplish this, the researchers utilized the Plant Village dataset, a publicly available collection of 87,000 RGB images of healthy and diseased plant leaves. The algorithm was rigorously tested across 25 different classes to validate its performance.

Rahul et al. [7] (2022) had described the significance of India's agriculture industry. Their research study demonstrated methods for identifying plant illnesses using image processing in leaves in an effort to provide a solution to the query of whether the grains and crops are chemical-free and healthy.

Kelothu et al. [8] (2023) had utilized a dataset comprising of 9127 images to perform a study on the detection of plant diseases. The study employed VGG16, VGG19 and CNN models. The outcome of the study favors VGG16 model with an accuracy of 0.96. Their work stated both the advantages and limitations of deep learning like automatic feature extraction and scalability, overfitting, need for sophisticated computational resources, and high-quality annotated data.

Bharath et al. [9] (2020) had carried out smart farming systems to improve agricultural production quality and quantity by addressing plant leaf disease, which is an important threat to food safety. They employed deep learning and computer vision for disease diagnosis in plant leaves. CNNs have been successful in classifying various plant leaf diseases using neuron-wise and layer-wise visualization methods. These neural networks can catch colors and textures of lesions, acting as human decision-makers during disease diagnosis.

Vikki et al. [10] (2023) had proposed a solution to the challenges faced by agriculturist like diagnosing plant leaf diseases and destructive insects. The work employed models such as sequential model, InceptionV3, AlexNet and MobileNet to find out the plant leaf diseases by processing the images. The trained model was found to be effective as an early warning tool and a strategy for a real-world unified plant disease detection system.

Tariqul et al. [11] (2020) had introduced a system that utilized image processing and CNN to increase crop production and alleviate plant disease and insect attraction. The model is trained with the dataset to achieve an accuracy rate of 94.29%. This research helped universal cultivators increase crop production and alleviate plant disease and insect attraction.

Prakanshu et al. [12] (2021) had established an innovative method for disease recognition in plants using deep convolutional networks for leaf image classification. Leveraging advancements in computer vision, their approach provides a fast and accurate means of detecting plant diseases. By training a deep CNN on a diverse dataset of plant leaves, the model successfully distinguished between healthy and diseased leaves. The results showed promising potential for disease recognition, offering valuable insights for agriculture and food security, with the possibility of improving crop yield and managing plant diseases on a global scale.

Husnul et al. [13] (2020) had stated the importance of agriculture mentioning it is critical for satisfying basic food demands and supporting a healthy global economy. Their study suggested a method for identifying plant leaf diseases and taking preventative actions using image processing and the CNN models ResNet-50 and AlexNet. The technique achieves 97% and 96.1% accuracy for ResNet-50 and 96.5% and 95.3% accuracy for AlexNet. The method also offered a visual representation of how to prevent leaf diseases and promote plant health.

Jasmeet et al. [14] (2016) had proposed a new method combining BP, PCA, and SVD to improve plant disease detection accuracy. BPA enables training networks with hidden units in layers without layer organization, while PCA converts correlated and uncorrelated observations. SVD is a reliable orthogonal matrix decomposition method popular in signal and image processing. Its relation to matrix rank and ability to estimated matrices of a given rank is crucial. The proposed methods aim to improve plant disease detection accuracy and efficiency.

Gidudu et al. [15] (2016) had concentrated on land cover mapping employing Support Vector Machines (SVM). It is a new organized classification technique in land cover mapping, gaining popularity due to their robustness, accuracy, and effectiveness. They are essentially binary classifiers, but can handle multiple classification tasks in remote sensing studies. The study evaluated the impact of One-Against-One (1A1) and

One-Against-All (1AA) techniques on land cover mapping. The choice of a suitable technique depends on personal preference and dataset uniqueness.

Ko et al. [16] (2018) had carried out the research on Myanmar's agricultural sector. Their research work presented a SVM classifier algorithm using MATLAB R2017a for leaf disease classification. The algorithm converted RGB color space into HSI, used k-means clustering for defect selection, extracted features using GLCM, and used a median filter for noise-free results and achieved a maximum accuracy of 83%.

Godliver et al. [17] (2018) had presented a research work for segregating healthy and affected parts using spectral data from leaves. Results show significant improvement in performance and early detection of diseases before crops become visibly symptomatic.

Mahmudul et al. [18] (2021) has diagnosed plant diseases by focusing the leaves. The approach utilized deep CNN models for the same. The models replaced the conventional depth-separable convolution technique, thereby it lowers the cost involved in computation and the number of parameters. Training was given to the model by using a dataset which considers 14 categories of plants, 38 categories of illness etc. By employing InceptionV3 an accuracy of 98.42% was obtained while Mobile NetV2, InceptionResNetV2 and EfficentNetB0 attained the accuracy level of 97.02%,99.11% and 99.56%.

Gobalakrishnan et al. [19] (2020) had conducted a survey highlighting the importance of predicting plant diseases in their lifetime, particularly those affecting leaves. The survey focused on some well-known image processing technique to diagnose and check the illness of the plants. The study also concentrated on the identification of the infection on the plant by comparing various machine learning algorithms.

Saleem et la. [20] (2022) has carried research on Deep learning-based plant disease identification has gained popularity but has not been tested in horticulture settings. This study uses the NZDLPlantDisease-v1 dataset to identify plant diseases using an improved region-based fully convolutional network model. The model achieves a mean average precision of 93.80%, 19.33% better than default settings. This study may serve as a standard for automated disease management in diverse plant species.

Hassam et al. [21] (2022) has developed research on Fruit disease detection is an important area in computer vision since it lowers fruit yield and has an effect on the economy. To address problems with duplicated features, CNN model selection, low contrast pictures, and processing delays, a single stream CNN architecture is put forth for the detection of citrus illnesses.

Shafik et al. [22] (2023) has carried out research on Global food security is being threatened by plant pests and diseases. These problems are managed using techniques from AI, machine learning, and deep learning. With an emphasis on hyperspectral images and vision-centered methodologies, a systematic literature review examined 1349 publications. But before using AI techniques successfully, there are still several unresolved problems.

Vishnoi et al. [23] (2022) had proposed a research work using CNN for identifying plant diseases using leaf pictures. The model is suited for portable devices since it has a classification accuracy of 98% and uses less storage and processing power.

Moupojou et al. [24] (2023) has conducted a survey on o United Nations Food and Agriculture Organization’s goal to enhance global food production by 70% by the year 2050, a significant challenge arises due to the substantial losses incurred from plant diseases, accounting for one-third of potential growth wasted. In addressing this issue, various plant disease databases have been employed to train deep learning models. Notably, while both Plant Village and PlantDoc contribute valuable data, recent studies have indicated that the Field Plant dataset, consisting of 5,170 images, outperforms PlantDoc in terms of its efficacy in classifying photographs.

3. Existing System

Previous studies in this area used the Chan – Vese (CV)algorithm for detecting plant illnesses. Plants can showcase illness by considerable versions of their signs, such as color changes, spots, lesions, and deformations. These variations make it tough to develop strong system learning models that could correctly locate and classify illnesses throughout distinct plant species and environmental situations. The algorithm utilizes the standards of lively contours and level set techniques to iteratively optimize the segmentation based on a predefined electricity useful. The extracted features are used to classify the detected sicknesses. Machine gaining knowledge of strategies inclusive of SVM, decision trees, or neural networks can be hired for this cause. The class version is educated by the use of classified statistics that accomplice particular features with known diseases. The extracted features are used to classify the detected sicknesses. Machine getting to know strategies along with SVM, selection timber, or neural networks can be employed for this reason. The type model is skilled the usage of categorized facts that accomplice particular capabilities with recognized diseases.

3.1 Drawbacks of existing system

In most of the existing systems for plant sickness detection the use of gadget learning regularly war with generalizing their performance to unseen facts and different environmental conditions. The models skilled on particular datasets and may have difficulty detecting illnesses in flowers that exhibit versions in symptoms or come from exclusive regions or climates.

Some current structures may also require specialized hardware or technical understanding to set up and function successfully. This restricted accessibility can pose obstacles for farmers, agricultural workers, or people in aid-confined settings who may also advantage from such disease detection systems.

Most existing structures depend on outstanding snap shots for accurate disease detection. However, in actual-international scenarios, taking pictures wonderful pix might not always be feasible because of elements which includes lighting situations, digicam barriers, or photograph noise. This dependency on terrific photographs can restrict the sensible applicability of those systems.

4. Proposed Method

To overcome the issues of the prevailing methodologies, machine regression and classification algorithms may be used. The CNN considering the system learning model. This System Architecture is Shown in Figure 1. The CNN model shows the accuracy level properly and the set of rules additionally enables to distinguish between the affected leaves and unaffected leaves. The proposed system's intention is to overcome the shortcomings of the existing one. The gadget's requirements were advanced primarily based on input from prior metrics device users in addition to flaws that had been previously documented. The following dreams for the cautioned gadget are listed:

- Farmers can easily recognise the name of the plant disease, accuracy level and life time.
- There is no need to look for a solution for the affected leaves separately since the web application shows the ailment and prevention.
- It saves the time for the farmers by providing the required information from their whereabouts without going to the agriculture office to test.

4.1 System Architecture

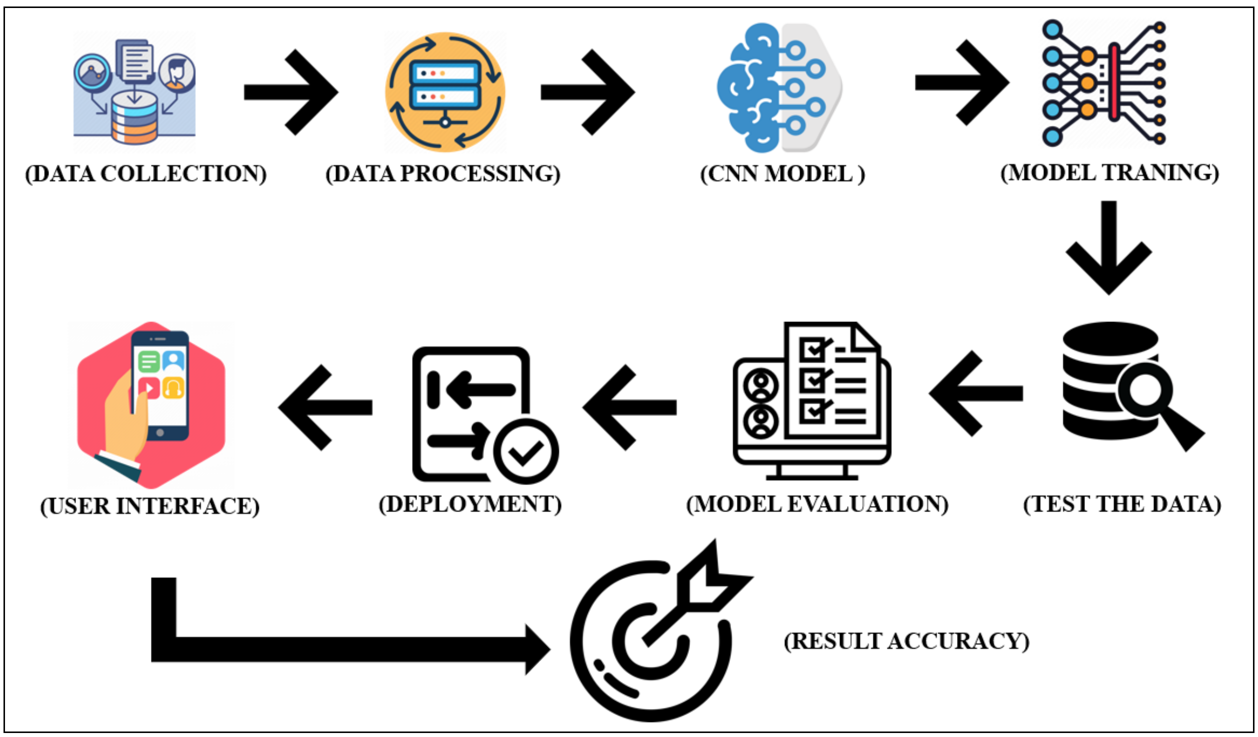

Fig. 1. System architecture.

4.2 Data collection

The dataset would not encompass any duplicate rows or lacking cells; hence no education is vital to dispose of duplicates and impute missing data.

4.3 Data Pre-Processing

Preprocessing involves cleaning raw information by amassing statistics within the real world and then changing them into error-free datasets. This part of the conversation is known as statistics preprocessing," while a specific operation is performed to transform the data into a free information set that is barely decreased and appropriate for evaluation.

The following are some examples of crucial pre-processing strategies:

- Missing data handling

- Dimensionality Reduction
- Dimensionality Reduction
- Data Partitioning.

If the set of rules' facts is simply too large to ever be processed it will very quickly become an extra complex feature set. To reduce the complexity, the feature selection, which specifies a subset of the authentic features. Relevant records from the statistics must be added to the selected functions to complete a better task. The use of this truncated representation rather than the entire starting records curtails the difficulty in handling the complexity of the dataset. The reduced description of complicated record structures is an advantage of the function.

Withdrawals: This avoids clustering estimates with the intention to over-converge for guidance and poor convergence for other activities. Highlight extraction is a common time period for techniques of combining factors to resolve those troubles, but to build a successful version, the use of more advantageous element extraction display records extra accurately. When testing with a couple of factors, it calls for loads of memory and processing electricity.

4.4 Model Selection

The process of selecting the final AI model from a list to train for plant disease from images is called model selection. Model selection is a cycle that can be used to compare different models and unique models set with different model hyperparameters, so, it is used a CNN to train the data set.

4.5 CNN

A CNN is a deep learning algorithm worn for image recognition and computer vision tasks. It integrates multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers detect local patterns and features in images, while pooling layers reduce spatial dimensions and improve robustness to fetching variations. Activation functions introduce non-linearities, such as ReLU and sigmoid functions, and fully connected layers make predictions based on learned features. During training, CNNs optimize parameters using techniques like backpropagation and gradient descent.

They are particularly effective in object detection, image classification, and semantic segmentation, as they automatically learn and extract hierarchical features from images. Researchers have developed various variations and architectural modifications to improve performance and address specific challenges.

CNNs are ideal for plant disease detection due to their ability to capture local patterns, translation invariance, robust feature learning, handling variability and complexity, scalability, transfer learning, real-time and non-invasive detection, and their suitability for real-time and non-invasive applications. These algorithms capture local patterns, extract relevant features from input images, and are translation invariant, allowing them to accurately identify disease symptoms on leaves. They also learn hierarchical representations of features, enabling them to distinguish between healthy and diseased plant leaves. CNNs are suitable for real-world plant disease detection scenarios due to their ability to generalize well to diverse examples and handle large datasets efficiently. Additionally, CNN-based systems can be deployed in real-time applications, enabling timely identification and response to disease outbreaks. Furthermore, their non-invasive nature enables efficient and non-destructive monitoring of plant health at scale. Overall, CNNs have the potential to revolutionize precision agriculture and contribute to sustainable crop management.

4.5 Training and Testing data

To train and test a machine learning model. While testing data assesses the model's performance on hidden data, training data is used to create training worms. Depending on the size and complexity of the dataset, a typical split is 80% training and 20% testing. This makes it easier to evaluate how well the model performs in actual situations and how well it generalises to fresh samples.

A training dataset for a CNN algorithm in plant disease detection consists of labelled images representing samples of plant leaves or parts affected by various diseases. The CNN algorithm will learn to extract features from the images and classify them into disease categories. The quality and representativeness of the training data significantly influence the model's performance.

The test data for a CNN algorithm in plant disease detection is a set of labelled images not used during the training phase. These images evaluate the model's performance and generalization ability on unseen data, ensuring it is representative of real-world scenarios and includes the same disease categories as the training data. This ensures an unbiased evaluation of the CNN algorithm's performance as shown in Figure 2 and provides a more accurate assessment of the model's ability.

```
history = model.fit_generator(
    aug.flow(x_train, y_train, batch_size=BS),
    validation_data=(x_test, y_test),
    steps_per_epoch=len(x_train) // BS,
    epochs=EPOCHS, verbose=1
    )
```

Fig. 2. Training and testing data.

5. Evaluation of the proposed model

A classification model's performance is measured using a variety of metrics, including precision, F1-score, recall, AUC, confusion matrix, cross-validation, ROC curve, and accuracy. These metrics can be used to identify the strengths and weaknesses of a model, and to select the right metric for the specific application. By understanding how these metrics work, it is possible to improve the performance of a model.

5.1. Performance metrics

The performance metrics provide insights into the model's accuracy, erudition to identify diseased samples, and its robustness in handling imbalanced datasets. It is important to consider multiple metrics and assess them collectively to get a comprehensive understanding of the CNN algorithm's performance in plant disease detection.

- Convolution operation: The output feature map size can be calculated using the formula: ((input_size - kernel_size + 2 * padding) / stride) + 1.
- Max Pooling operation: The output size is calculated similarly to the convolution operation using the formula above.
- Softmax activation: The softmax function is defined as softmax(x) = e^x / sum(e^x) for each class, where e is the base of the natural logarithm.

6. Results and discusion

The output of the performance metrics of the model:

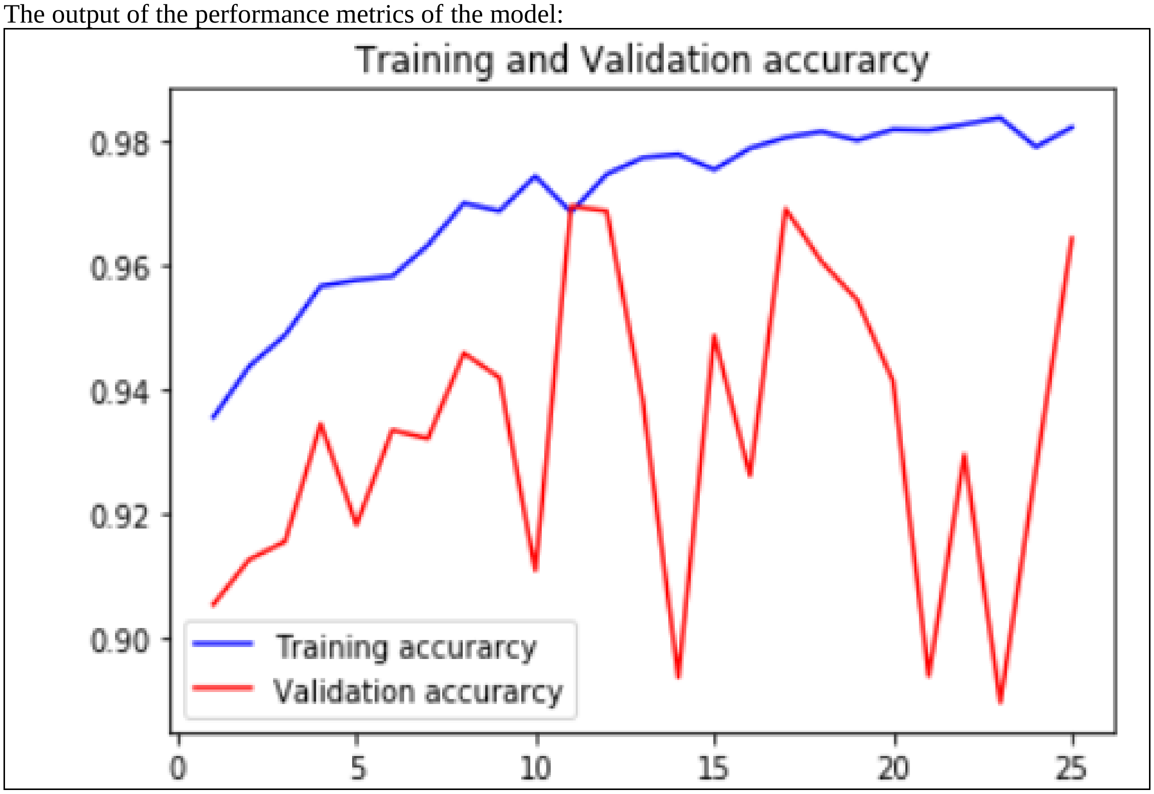

Fig. 3. Accuracy of CNN model

Training accuracy is a measure of how well a machine learning model performs on the training dataset. It is calculated by comparing the model's predicted labels with the true labels in the training dataset. Great precision while training indicates that the model is able to fit the training data well and learn the underlying patterns. The Figure 3 represents Training and validation accuracy.

Utilized a validation dataset to determine the validation accuracy.

6.1. Model accuracy

```
scores = model.evaluate(x_test, y_test)

print(f"Test Accuracy: {scores[1]*100}")

Test Accuracy: 96.67230919129554
```

Fig. 4. Model accuracy.

Model accuracy is a metric used to measure how well a machine learning model performs on a given task. It represents the proportion of correct predictions made by the model out of all predictions. Model accuracy refers the ratio of the accurate prediction to the total number of predictions made an accuracy of 96.67 using the model which was shown in Figure 4.

6.2. Deployment of the model

The web interface is developed using Flask, a popular web application framework written in Python. The integration of the model and the web page is achieved through the use of the pickle library. The Various Pages of Web Application is shown in Figures 5,6,7,8,9,10,11.

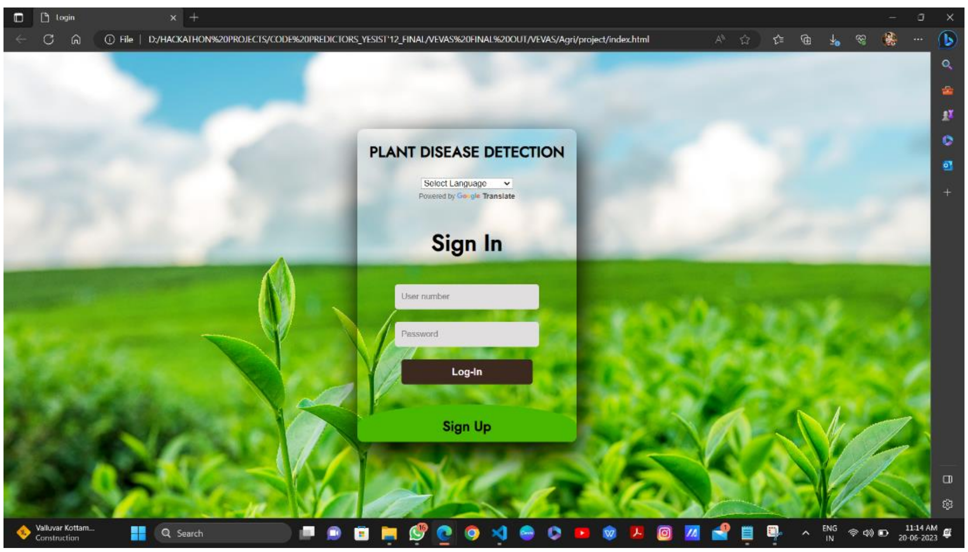

Fig. 5. Login page.

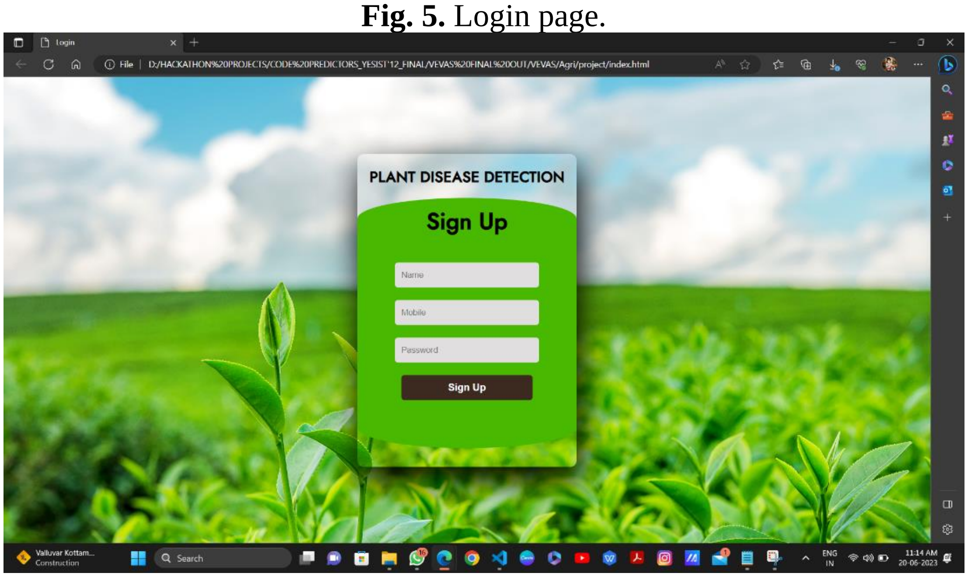

Fig.6. Signup page.

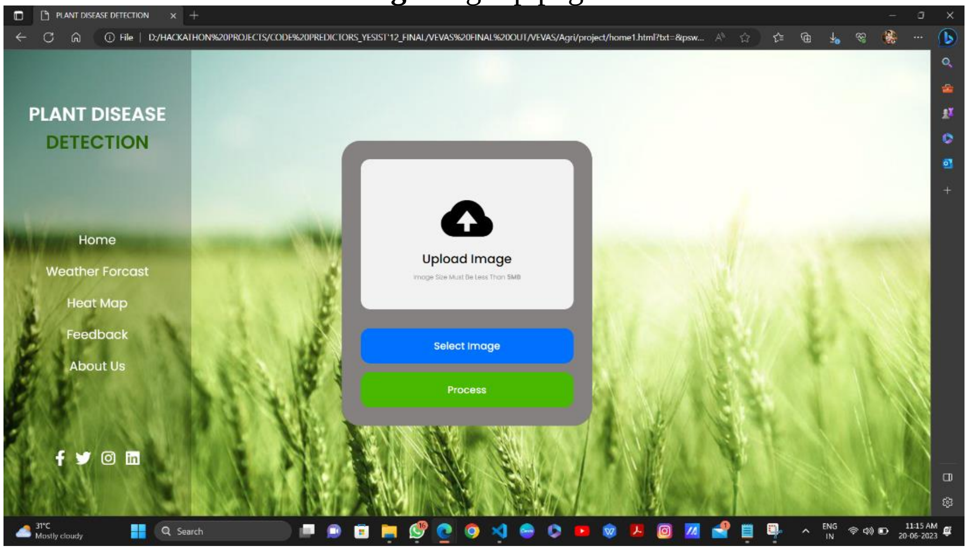

Fig. 7. Home page.

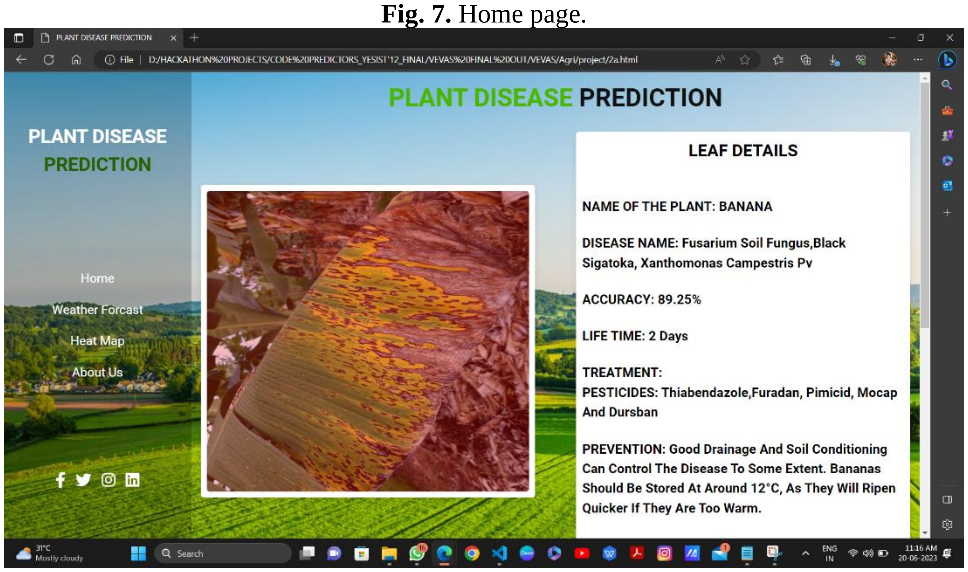

Fig.8. High level detection page.

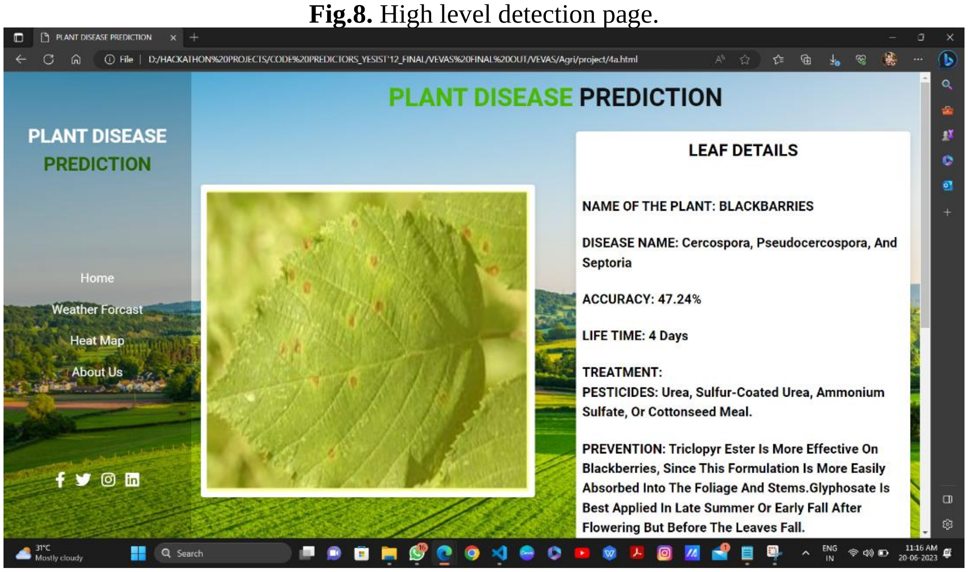

Fig. 9. Low level detection page.

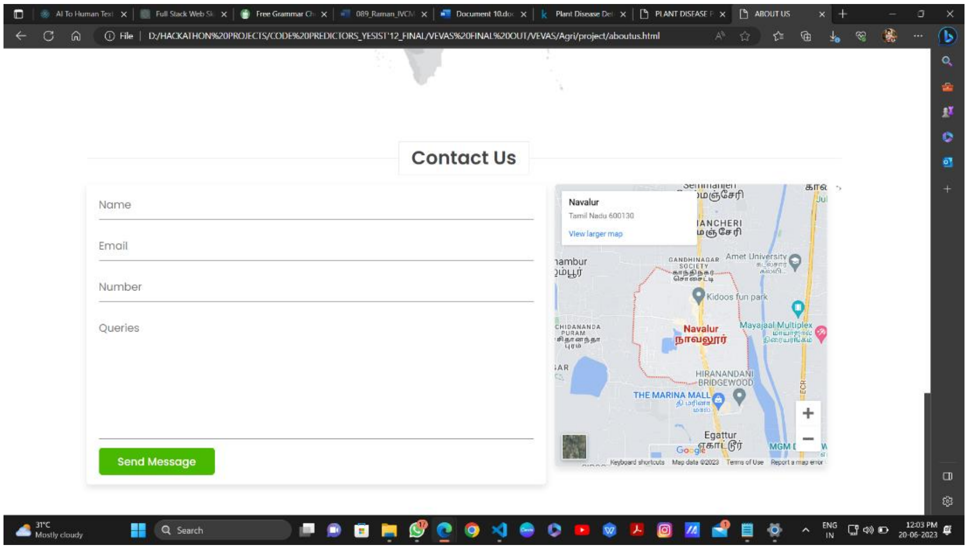

Fig.10. Contact us page.

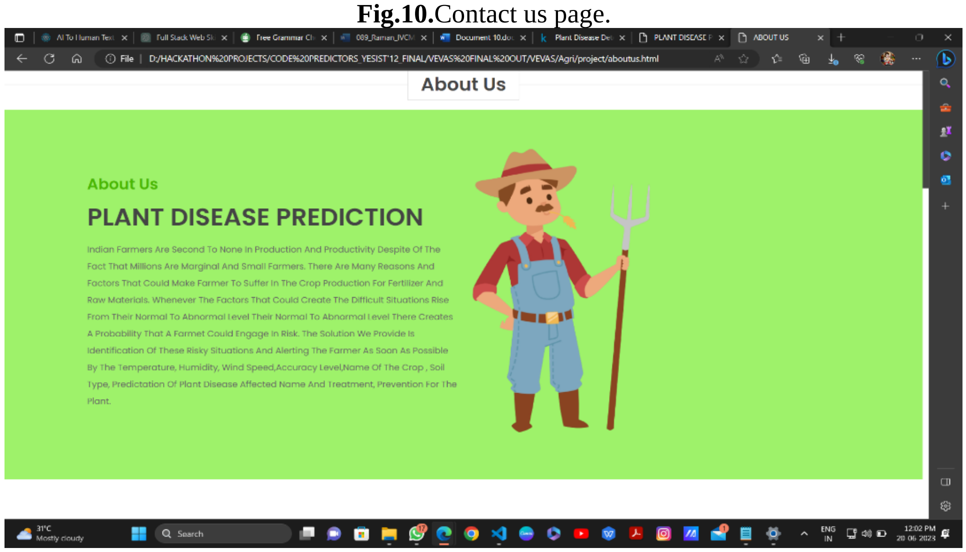

Fig.11. About us page.

7. Conclusion

The paper utilized a CNN algorithm to accurately predict plant disease. A web application is created utilizing loads of technologies, including python, HTML, CSS, JavaScript, sklearn, matplot, numpy, pandas, Flask and other libraries, to make the consumer interface (UI) extra accessible and easy. With the deployment of the proposed version, farmers can access via web application easily which is user friendly. The application lists out the name of the plant disease, its life time, preventive and treatment measures to the farmers after they had uploaded the picture of the affected leaves. Finally, by detecting illnesses at an early stage, farmers can take appropriate remedial steps to curb sicknesses and crop losses.

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