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Deep Learning-Based Automated Plant Leaf Disease Detection and Classification System Using Convolutional Neural Networks

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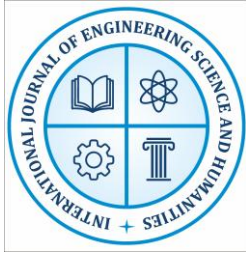
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ABSTRACT

Agricultural sector is one of the pillars of food security in the globe but is constantly affected by plant diseases, which may destroy crops, decrease productivity and cause serious losses to the economy. The conventional approaches of disease detection are usually based on manual examination by specialists, which may be time-consuming, labour-intensive and are likely to be subject to human error. In order to overcome these shortcomings, this project presents a new deep learning-based solution in the automated classification of various leaf diseases in a wide variety of plant species. Using the power of convolutional neural networks (CNNs), the system will be able to identify and classify plant leaf diseases accurately in order to detect them early and intervene in time. The model itself is trained on a vast amount of data, covering a broad range of diseases the model is used on the crops of apples, blueberries, cherries, corn, grapes, peaches, peppers, potatoes, raspberries, soybeans, squash, strawberries, and tomatoes, which makes it applicable in a variety of different agricultural contexts. The system has an easy to use graphical interface that has been created with CustomTkinter and TkinterDnD, enabling users to add pictures with either drag-and-drop or file browsing. After uploading an image, the system pre-processes it, i.e. resizing and normalizing the data to the input specifications of a deep learning model. The interface will be easy to use and user friendly and thus can be used by both farmers and agricultural professionals and even researchers. The project does not just show the possibilities of deep learning in transforming the process of detecting plant diseases, but also teaches the need to implement the latest technologies in agriculture. By automating the disease identification process, the system will cut operational costs used in disease identification, minimize chances of misdiagnosis and, the system will help in responding to the disease outbreaks in a shorter period of time. In addition, the capability of the system to process numerous diseases in different plants species makes it a powerful tool in advancement of crop management and agricultural production. This work eventually leads to the larger objective of sustainable agriculture as it may offer an effective, reliable, and scalable way of classifying



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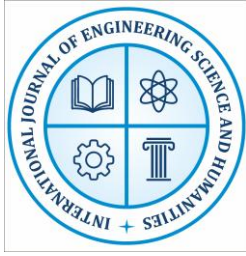
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plant diseases, thus contributing to the worldwide aim of creating food security and decreasing crop losses amid the increasing agricultural difficulties.

Keywords: Deep Learning, Plant Disease Classification, Convolutional Neural Networks (CNNs), Leaf Disease Detection, Agricultural Automation, Image Processing

1. INTRODUCTION

Agriculture is among the most essential sectors of the world economy since it supplies food, raw materials, and livelihood to billions of people on the earth. Nevertheless, the agricultural sector experiences various problems such as global warming, pests, and plant infections, which may have a great effect on the output of crops and food security. Plant diseases are some of these challenges, and they can be very devastating as they can spread at a very high rate, causing total destruction of crops, and resulting in huge economic losses. Ancient ways of detecting diseases are normally manual, requiring inspection by agriculture experts, a task that is time consuming, man power consuming, and full of human errors. Most of the times a disease is detected when it has irreversibly affected the crops. Herein, the necessity of innovative solutions to allow an efficient and timely identification of the diseases affecting the plants is acute to allow farmers to respond in time to counter the consequences thereof. The recent years have seen the development of artificial intelligence (AI) and machine learning (ML) that created new opportunities to solve agricultural problems. Machine learning is further divided into deep learning which has become an extensive tool of image recognition and classification. The convolutional neural networks (CNNs), a form of the deep learning model, have proven to be incredibly successful in processing visual data, which explains their particular applicability when it comes to augmented intelligence plant disease detection. With these models, it can be trained on huge data sets of healthy and diseased plants, and it can then establish systems capable of auto-detecting and classifying diseases with high precision. The proposed project is aimed at the creation of a deep learning-based framework that can be used in the classification of various diseases in leaves on a large variety of plant species. It is aimed at developing a tool that can help farmers and other people in the agricultural field identify diseases at an early stage so that they can proactively take care of their crops. The system uses a trained CNN model that classifies images of plant leaves and identifies whether an image has diseases or not. Training on a larger volume of data which contains images of a variety of crops, including apples, blueberries, cherries, corn, grapes, peaches, peppers, potatoes, raspberries, soybeans, squash, strawberries, and tomatoes, the model is trained. There are several classes of diseases attached to each crop which means that the system will be able to accommodate a wide variety of situations. The major problem that has troubled the development of such a system is how the system should be accessible and usable to the end-users and especially the farmers who might lack technical skills. To deal with this, the project uses a graphical interface that is easy to use and is developed with CustomTkinter, and TkinterDnD. The interface enables users to upload plant leaves images by navigating their files or taking advantage of the drag and drop facility. After an image is uploaded, the system processes the image and normalizes the data and feeds



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it into the deep learning model to analyze it. The output such as the anticipated disease category and the confidence value is shown in real-time and gives the user valuable insights on what to do with their crops with regards to their health. This system is developed with a larger objective of ensuring sustainable agriculture and food security. The system optimizes the detection of disease occurrences by automation thus cutting down on the use of manual inspection to detect disease, minimizing chances of an incorrect diagnosis hence responding faster to the disease outbreak. This is especially crucial in areas where there is low accessibility to agricultural specialists because the farmers are empowered to exercise control over their crop management practices. Moreover, the fact that the system can accommodate a wide range of diseases in a wide variety of plants is what makes it a flexible tool, which can be adjusted to suit various farming scenarios. The uses of this system are not limited to individual farm. It can be incorporated into bigger agricultural surveillance systems, which will allow gathering and examining information on disease prevalence and distribution. At the regional or national level, the use of this data could be connected with decision-making and was able to determine trends, predict outbreaks, and allocate resources in a more efficient way.

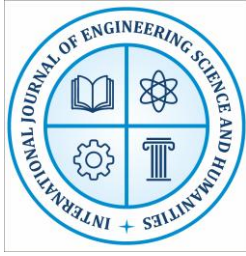
1.2 OBJECTIVES

The project aims to develop a deep learning-based system for classifying multiple leaf diseases, focusing on several key objectives: automating disease detection to reduce manual labor, improving accuracy and efficiency using Convolutional Neural Networks (CNNs), and creating a comprehensive dataset of healthy and diseased leaves from various crops. Additionally, it seeks to develop a user-friendly interface, enable real-time disease identification, support multiple crops and diseases, promote sustainable agriculture by minimizing pesticide use, enhance accessibility for farmers in remote areas, facilitate data-driven decision-making, serve as an educational tool, ensure scalability, address ethical implications, contribute to global food security, and encourage collaboration and innovation in agricultural technology.

1.3 PROBLEM STATEMENT

The agricultural sector is crucial for global food security, providing sustenance and livelihoods for billions. However, it faces significant challenges, particularly from plant diseases caused by pathogens like fungi, bacteria, and viruses, leading to crop destruction and economic losses. Current detection methods are outdated and labor-intensive, relying on expert manual evaluation, which is prone to errors and delays. This exacerbates problems, especially in resource-deficient areas where farmers lack access to expert knowledge, leading to misdiagnosis and further crop damage. Climate change further complicates the situation by facilitating the spread of diseases.

Existing diagnostic methods are often expensive, complicated, and not accessible to small-scale farmers, creating a gap in the agricultural sector for effective disease detection. To address these challenges, innovative solutions leveraging artificial intelligence (AI) and machine learning (ML) are required. Deep learning, a form of ML suited for image detection and



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classification, offers potential for the early identification of plant diseases. By training deep learning models on datasets of healthy and diseased plants, systems can autonomously classify and detect diseases.

However, the adoption of these technologies remains low due to barriers such as accessibility for non-technical populations and the need for user-friendly interfaces. This project aims to develop a deep learning system for classifying leaf diseases across various plant species, providing a scalable and accessible tool for early disease detection. Users will upload leaf photos for real-time analysis using Convolutional Neural Networks (CNNs), which will output disease predictions along with confidence scores. This innovation seeks to empower farmers with timely information to protect their crops, reduce losses, and enhance agricultural productivity, directly addressing the critical issue of plant disease identification and its impact on food security and farmer livelihoods.

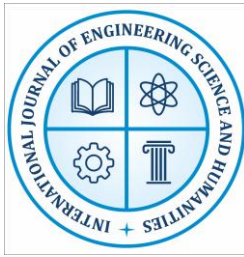
1.4 PROJECT MOTIVATION

This project addresses the critical role of agriculture in human life and the economy, particularly in developing nations where it serves as a major source of food, employment, and stability. However, the sector faces significant challenges, notably from plant diseases that can devastate crops, leading to food shortages, financial losses, and social instability for small-scale farmers. As the global population approaches 10 billion by 2050, the pressure on agriculture to produce more food intensifies, exacerbated by climate change that worsens plant disease issues. Traditional methods of disease detection, such as manual inspections and laboratory testing, are often inadequate for fulfilling the rising food demand, particularly for farmers in resource-constrained areas. These methods are cumbersome, costly, and inefficient, resulting in crop losses and economic hardship. This project leverages advanced artificial intelligence (AI) and deep learning techniques, specifically using Convolutional Neural Networks (CNNs), to develop a system that accurately identifies plant diseases through image recognition. This automated approach enhances early diagnosis and intervention.

Moreover, the project aims to democratize access to agricultural technology, enabling farmers in developing regions—often lacking expertise and resources—to effectively diagnose and manage plant diseases. The user-friendly system provides real-time results, making it accessible to both small-scale farmers and large agricultural businesses. The initiative supports sustainable agriculture by minimizing reliance on chemical pesticides, thereby promoting eco-friendly practices and addressing food security concerns without significant environmental impact.

2. LITERATURE REVIEWS

One of the first authors who used deep learning to detect plant diseases was Mohanty et al. (2016) [1]. Their invention demonstrated that deep learning networks with some type of Convolutional Neural Networks (CNNs) can be used to classify both diseased and healthy plant leaves. In the study, 14 species of crop pictures had been used as the training data set of CNN, but the model attained the maximum classification rate of 99.35 percent. The article was among



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the pioneer to reveal the possibility of deep learning in automation of the disease detection pipeline, which can significantly decrease the need to manually check and intervene with the process, which in turn is also important to highlight the quality and size of high-quality datasets to be used to train deep learning models.

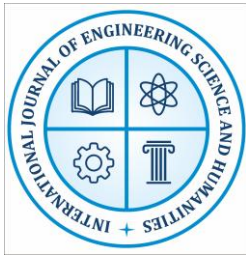
Transfer learning has turned out to be an efficient method of classifying plant diseases in agriculture. This was demonstrated by Sladojevic et al. (2016) [2] who fine-tuned a pre-trained CNN model (AlexNet) on an image dataset of crop diseases with an accuracy of 96.3% with the same model. Their contribution emphasized the feasibility of transfer learning in terms of lessening computational resources and training time, which means that transfer learning is a potential solution when applied to agriculture. Another aspect of the study was the significance of interpretability of the model because the farmers and other agricultural professionals must know the foundation on which they are making predictions to believe and to make effective use of these technologies. Transfer learning resolves the problem of small annotated datasets in agriculture by using pre-trained models to achieve high accuracy despite the use of smaller datasets

The application of data augmentation tools has become a critical part of enhancing the accuracy and quality of deep learning networks in detecting plant diseases especially in overcoming issues of scarce and unbalanced data data sets which are frequently found in agricultural domains. In a detailed research, Barbedo (2018) [3] assessed the effect of augmenting data on model performance by using the rotation, scaling, flipping, and other transformations to artificially enhance the diversity and size of the training set. They have proven that these augmentation techniques led to significant improvement of model accuracy and robustness, allowing the deep learning systems to be more successful in generalization to the real-world environment and minimizing the chances of overfittin

Ferantinos et al. (2018) [4] created a deep learning-based interface of real-time plant disease identification, using images of the plants taken with the drones to train a Convolutional Neural Network (CNN) model, with the results exceeding 99.53 accuracy. Their contribution proved that the combination of deep learning and remote sensing technologies can allow conducting large-scale crop health monitoring, which will equip a farmer with an effective instrument of early disease detection and treatment

Zhang et al. (2019) [5] presented a deep learning architecture that classifies the diseases of plants based on many classes, where the complexity lies in the fact that many diseases are present in many crops. Their model based on a variation of the ResNet architecture got an accuracy of 98.6 percent in the classification of diseased leaves of 10 diverse crop species. The current paper has shown that deep learning can be used to address complex classification problems with different types of diseases and crops, which is why it can be used to offer correct and effective solutions to agricultural problems.

Hughes and Salathé (2015) [6] discussed the great difficulty of collecting datasets to detect plant diseases, and large, diverse, and well-annotated datasets are important to be able to train



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deep learning models. They emphasized that the working of these models is highly dependent on the quality of data and its representativeness, which should be able to reflect the real-life conditions, such as the differences in the symptoms of the disease, environmental conditions, and the type of crops. In a bid to address these issues, Hughes and Salathé (2015) [6] suggested that researchers, agricultural experts, and farmers should collaborate to ensure the datasets are all-inclusive and applicable in real-life situations

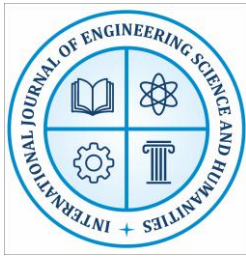
Arribas et al. (2020) [7] examined the paramount significance of model interpretability and explainability in the context of agriculture, especially when using it to detect plant diseases. They used more sophisticated methods that included Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME (Local Interpretable Model-agnostic Explanations) to understand a Convolutional Neural Network (CNN) model in terms of how a model is coming up with its predictions.

Kamilaris and Prenafeta-Boldú (2018) [8] explored the combination of deep learning and Internet of Things (IoT) and edge computing devices to improve plant disease detection and crop health monitoring. They suggested a system, which uses the IoT sensors to gather real-time environmental data, including temperature, humidity, and soil conditions, and the use of edge devices to process images and execute deep learning models in the field. This method will provide the ability to analyze and make decisions in real time and eliminate the necessity to transmit data to central servers and minimize latency. Their work showed the possibility of integrating deep learning with IoT and edge computing to develop scalable, efficient, and decentralized agriculture solutions that would be able to cover vast portions of the land and present the insights about the health of crops in a timely way.

Chakraborty and Newton (2011) [9] explored the major role played by climate change on the epidemiology and intensity of the plant diseases and the fact that adaptable and resilient agricultural methods are necessary to counter the challenges of environmental changes. They emphasized in their work the fact that the increase in temperature, changing precipitation, and the emergence of excessive weather incidents provide good conditions under which pathogenic agents thrive, and there are more frequent and severe diseases outbreaks.

Zhang et al. (2020) [10] considered the radical impact of precision agriculture in improving crop management activities, with particular focus on how deep learning has allowed farmers to make data-driven decisions. Their research showed that deep learning models will be able to process large volumes of data at different sources like satellite images, drones, and internet of things sensors to deliver precise and relevant information about crop health in real-time. Through these technologies, precision agriculture can help farmers streamline and maximize the effectiveness of their resources and minimize waste and enhance production by applying different interventions in particular areas, including controlled irrigation, fertilization, and pest management.

Ryan and Stahl (2020) [11] explored the ethical and social aspects of using AI technologies in agriculture, citing such critical areas as the bias of algorithms used, the problem of data privacy,



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and the possible loss of human workers. Their writing highlighted that as much as AI can transform the way farming is done, it is also associated with serious ethical issues which need to be resolved in order to bring about a balance between fair and ethical practices.

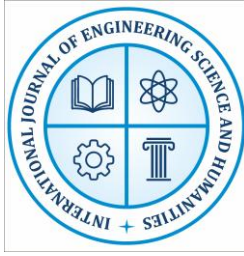
Liakos et al. (2018) [12] carried out an extensive research into the current state-of-the-art in application of deep learning in agriculture and found it to have the potential to be relevant to a considerable number of contemporary issues in agriculture, such as disease detection, yield prediction, soil analysis, and resource optimization. They noted that their work showed that deep learning models, especially Convolutional Neural Networks (CNNs) and Recurrent

Too et al. (2019) [13] observed the significance of transfer learning as one of the most crucial conditions to enhance the functionality of deep learning models in the case of small datasets, which is a common agricultural application issue. They fine-tuned VGG16 and InceptionV3 with fine-tuning of pre-trained Convolutional Neural Network (CNN) using a collection of images of plant diseases and demonstrated that even with the small amount of training data transfer learning could achieve near-perfect accuracy.

Zhang et al. (2021) [14] studied the new use of Generative Adversarial Networks (GANs) in data augmentation in plant disease detection, and discovered that they have the ability to augment the amount and quality of training data. The GANs consist of two neural networks; the discriminator and the generator and were applied to produce synthetic images of diseased leaves that are comparable to real world data. This artificial data was then utilized to augment the training data to address the normal issue of small or unbalanced data of agricultural uses. It was shown that GAN-generated images can be utilized to achieve a significant upgrade in the performance of the deep learning model, particularly when a less number of training samples are available, in the case of underrepresented disease .

Picon et al. (2019) [15] presented a deep learning-based mobile app that could identify plant diseases and demonstrated how mobile technologies would enable the introduction of sophisticated AI solutions to farmers, especially in the remote or resources-resource-sensitive environment. They used images of diseased crops of different crops to train a Convolutional Neural Network (CNN) model and managed to implement it into a mobile application that is easy to use. By this innovation, the farmers can use their smartphones to take pictures of the affected plants and get real-time diagnoses to make informed decisions to prevent crop losses.

Zhang and Kovacs (2012) [16] examined how Unmanned Aerial Vehicles (UAVs) can be transformed as a tool in detecting plant diseases, with the authors noting that these devices have a potential to transform the idea of massive crop observance by capturing high-quality aerial images. UAVs are also capable of surveying large agricultural areas with sophisticated imaging devices, including multispectral and hyperspectral cameras, that can be effectively used to monitor the health of crops and detect their disease in the early stages. They revealed that the joint application of UAVs with deep learning algorithms offered a potent instrument of early disease identification and treatment, allowing the farmers to adopt preemptive action in preventing the proliferation of a disease, as well as reducing the farming losses



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Klerkx et al. (2019) [17] examined how the technology of deep learning can be used to address the needs of smallholder farmers in developing nations, which can help enhance the effectiveness of crops, decrease losses, and increase productivity in the agricultural industry. Deep learning can help empower smallholder farmers to make smart decisions and embrace more sustainable farming methods by enabling early identification of the disease in plants, better use of resources, and creating insights that are backed by data.

Kamilaris et al. (2019) [18] addressed the manner in which blockchain technology has been utilized in agricultural aspects especially in improving the security, transparency, and traceability of the data introduced in deep learning. They suggested a system where it uses blockchain to store and share information regarding health of crops, disease outbreak and other valuable information in the agricultural sector.

Wang et al. (2020) [19] investigated the application of ensemble learning methods in the detection of plant diseases, which showed that it can enhance the accuracy and stability of deep learning models. Ensemble learning is a type of learning where the predictions of multiple models are pooled together to come up with an output that is more reliable and generalized, this can be applied especially in complex classification tasks like in the identification of a number of diseases in a variety of crops. the crop management practices and make a contribution to sustainable agriculture.

Van der Wal et al. (2016) [20] presented the vast importance of citizen science in the domain of plant disease detection as a data collection instrument, where the citizen science would be able to involve the community in the process of data collection and labelling. With the help of non-experts, including farmers, gardeners, nature lovers, and others, citizen science projects can produce large and diverse datasets that are more realistic and geographically extensive.

3. PURPOSED METHODOLOGY

3.1 DATA COLLECTION

The chapter of Data Collection and Preparation highlights the fundamental role of collecting and preparing a high-quality dataset in creating a deep learning-based system that would be used to classify plant-related diseases. The quality, diversity, and representativeness of the dataset directly affect the quality of performance, accuracy and reliability of such a system. The model might not be able to generalize to real-life conditions without a carefully-selected dataset and, therefore, the classification will be poor. In this chapter, the author provides an insight into the careful work of data collection and preparation which is one of the most crucial and sometimes time-consuming phases in the system development.

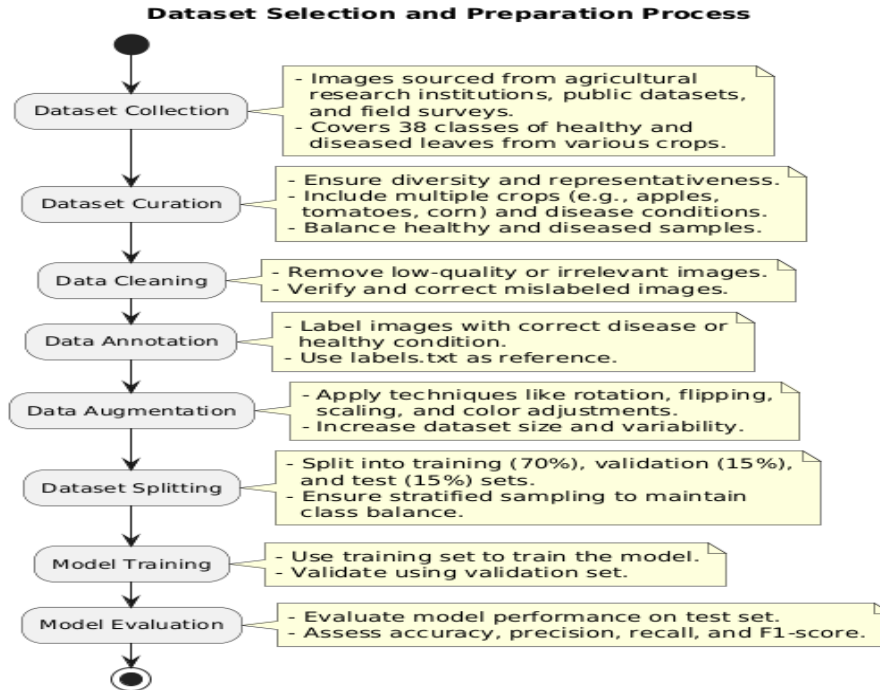


Figure 1 Dataset selection and preparation

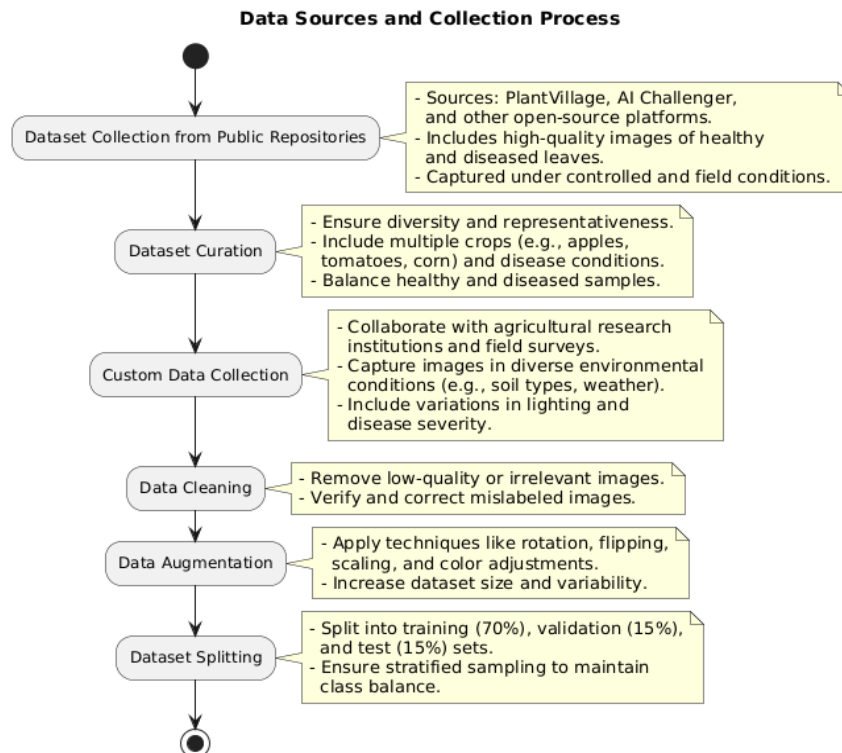


Figure 2 Data sources and collection process

The data utilized in this project is carefully gathered and neatly organized in numerous sources that are reliable and diverse enough to guarantee the quality of the data, its completeness, and its applicability to the training of a strong deep learning model to classify the plant diseases. Publicly accessible repositories, like PlantVillage, AI Challenger, and open-source repositories, and some homegrown images, gathered by partnering with agricultural research institutions and field surveys, are the main sources of data. All these sources add their own advantages to the data so that it is balanced and reflects the reality of the situation.

3.2 ALGORITHM STEPS FOR MULTIPLE LEAF DISEASE CLASSIFICATION SYSTEM

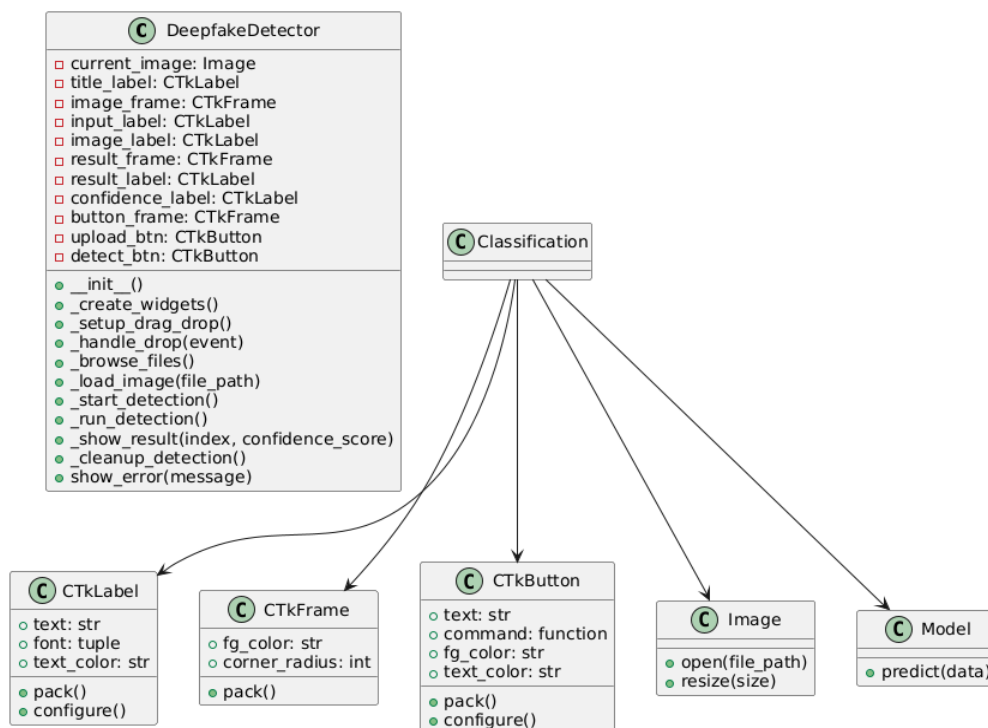


Figure 3 Multiple Leaf Disease Classification System

The algorithm for the **Multiple Leaf Disease Classification System** is designed to process uploaded images, classify diseases using a pre-trained CNN model, and display results in real-time. Below is a step-by-step breakdown of the algorithm:

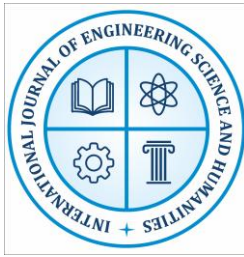
Step 1: System Initialization

1. Load Pre-Trained Model:

- Load the pre-trained CNN model (keras_Model.h5) using TensorFlow's `tf.keras.models.load_model()` function.
- Set `compile=False` to optimize performance.

2. Load Class Labels:

- Read the class labels from the labels.txt file and store them in a list (`class_names`).
- Each line in the file corresponds to a disease class, such as:



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Step 2: User Interface Setup

1. Configure Main Window:

- Set the window title to "**Classification of Diseases**".
- Configure the window size to **900x700 pixels** and set a dark theme (bg="#2C2F33").

2. Create Widgets:

- **Title Label:** Display the application title.
- **Image Frame:** Create a frame to display the uploaded image.
- **Input Label:** Prompt the user to drag and drop or click to select an image.
- **Result Frame:** Create a frame to display the predicted disease class and confidence score.
- **Buttons:**
 - **Upload Button:** Open a file dialog to select an image.
 - **Detect Button:** Start the disease detection process.

3. Enable Drag-and-Drop Functionality:

- Use the TkinterDnD library to enable drag-and-drop functionality for image uploads.
- Bind the <<Drop>> event to the `_handle_drop()` method.

Step 3: Image Upload and Display

1. Upload Image:

- Users can upload images either by dragging and dropping or by clicking the "Select Image" button.

2. Load Image:

- Use the `_load_image()` method to load the image using the **PIL** library.
- Resize the image to **400x400 pixels** and display it in the GUI using the CTKImage class from **CustomTkinter**.

3. Error Handling:

- If an invalid file is uploaded, display an error message using the `show_error()` method.

Step 4: Disease Detection

1. Start Detection:

- When the "Detect" button is clicked, the `_start_detection()` method is triggered.
- Disable the "Detect" button to prevent multiple clicks.

2. Run Detection in a Separate Thread:

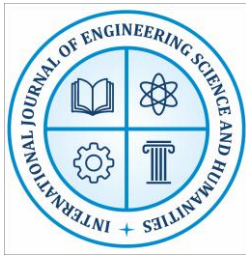
- Use the threading module to run the detection process in a separate thread, ensuring the GUI remains responsive.

3. Preprocess Image:

- Resize the image to **224x224 pixels** using `ImageOps.fit()`.
- Convert the image to a NumPy array and normalize the pixel values to the range **[-1, 1]**.
- Reshape the data into the required format (1, 224, 224, 3).

4. Model Prediction:

- Pass the preprocessed image through the CNN model to generate predictions.
- Extract the predicted class index and confidence score using:



Step 5: Display Results

1. Show Predicted Class:

- Map the predicted class index to the corresponding disease name using the class_names list.
- Display the predicted disease class in the result frame.

2. Show Confidence Score:

- Display the confidence score only if it exceeds **90%**.

3. Cleanup:

- Re-enable the "Detect" button after the detection process is complete.

Step 6: Error Handling

1. Invalid Image Upload:

- If an invalid file is uploaded, display an error message using the show_error() method.

2. Missing Image:

- If the user clicks "Detect" without uploading an image, display an error message: "Please upload an image first!".

Step 7: System Shutdown

1. Close Application:

- The application runs in a loop until the user closes the window.
- All resources are released automatically upon shutdown.

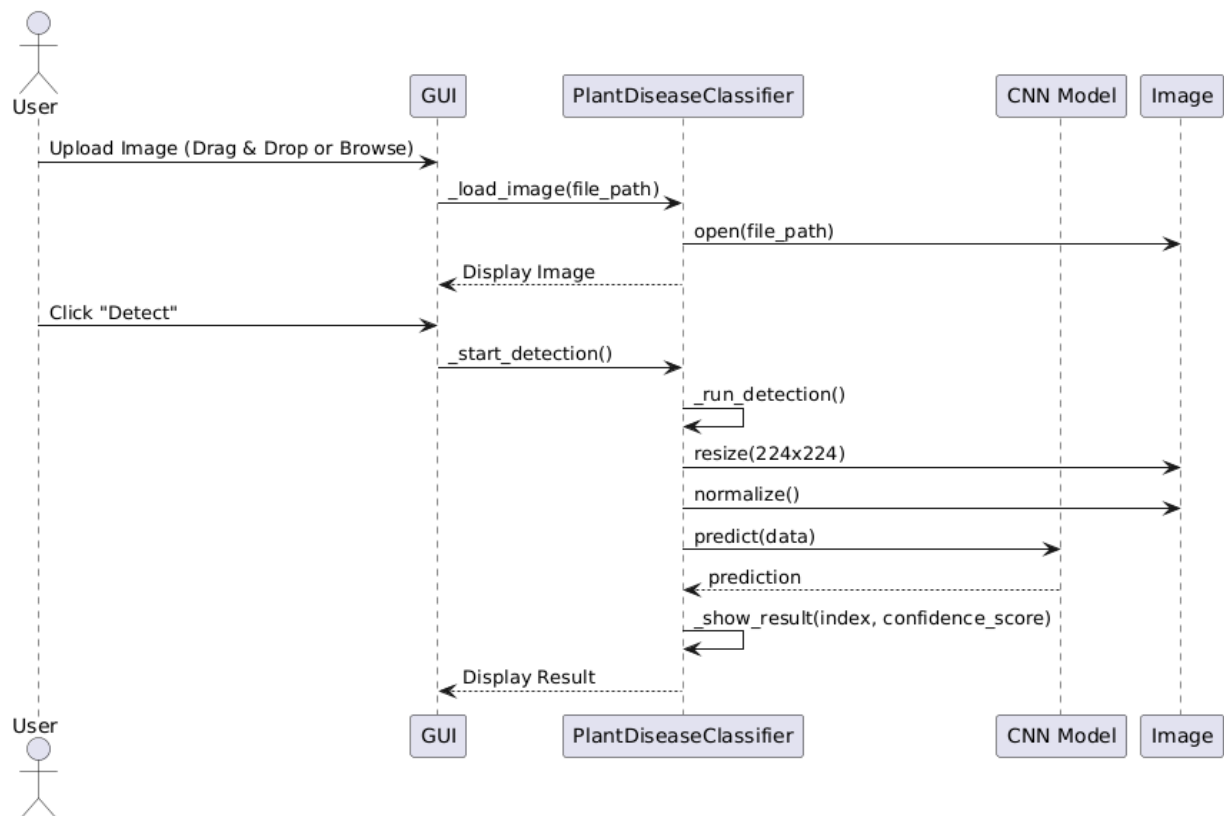
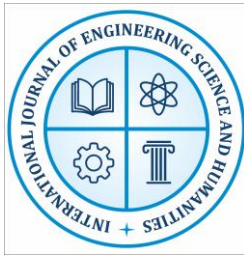


Figure 4 Sequence Diagram



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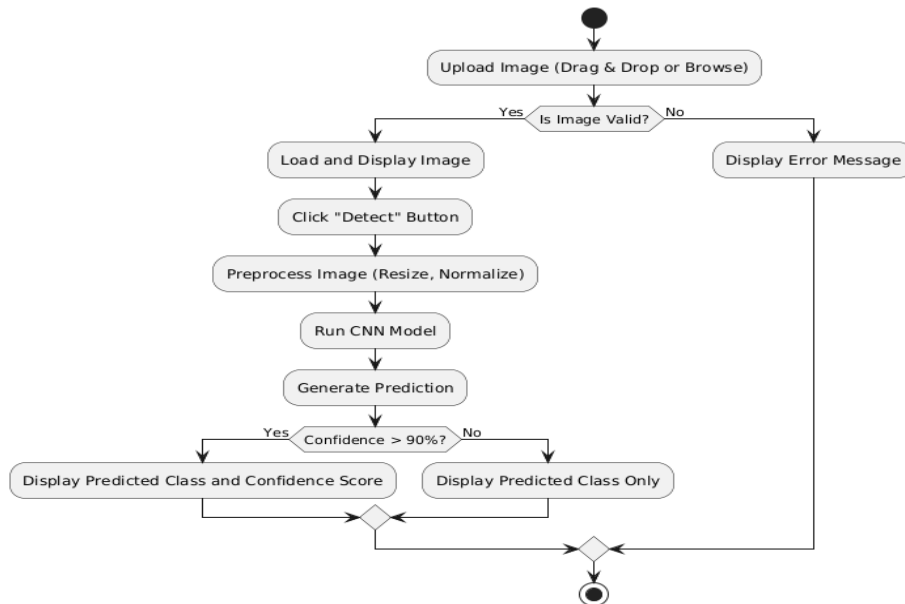
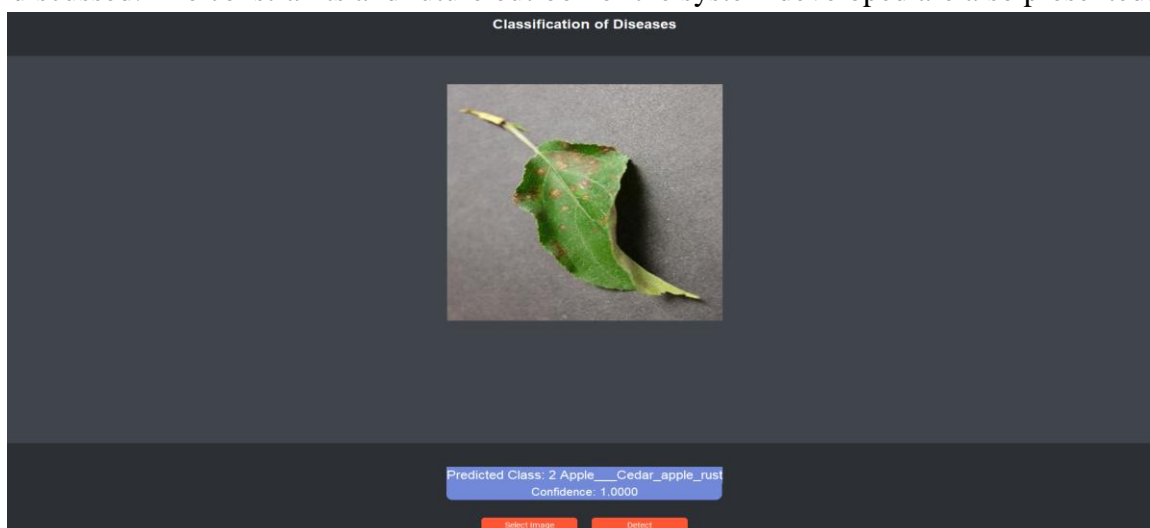
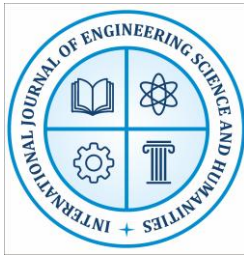


Figure 5 Active Diagram

4. RESULTS AND DISCUSSION

The Plant Leaf Disease Classification System was created to deal with the urgent problem of the early and precise identification of the disease in crops. The system built on the strength of deep learning and Convolutional Neural Networks (CNNs) was meant to identify several diseases affecting leaves in a diverse number of species of plants. This chapter presents the findings and discussion of the system performance basing on its accuracy, precision, recall, and F1-score of each disease type. The system was evaluated on a variable dataset comprising of the images of healthy and diseased leaves of crops like apples, blueberries, cherries, corn, grapes, peaches, peppers, potatoes, raspberries, soybeans, squash, strawberries and tomatoes. The findings are clustered based on the classification of the disease and the system performance is discussed. The constraints and future outlook of the system developed are also presented.





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Figure 6 Apple cedar rust diseased

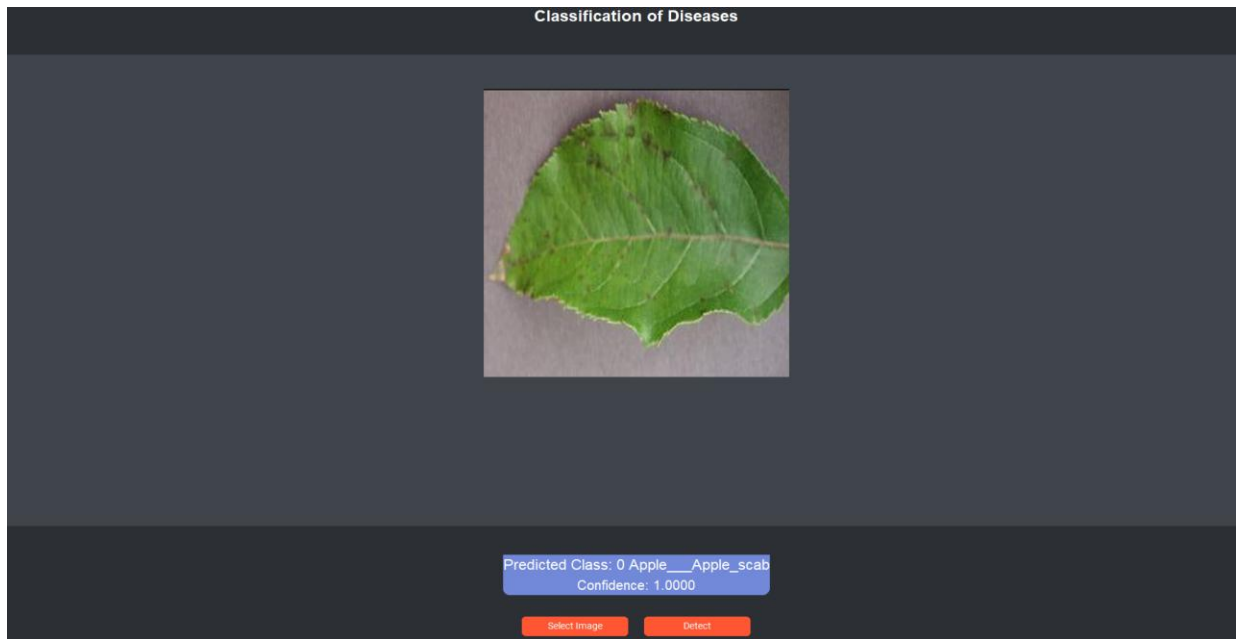


Figure 7 Apple scab disease

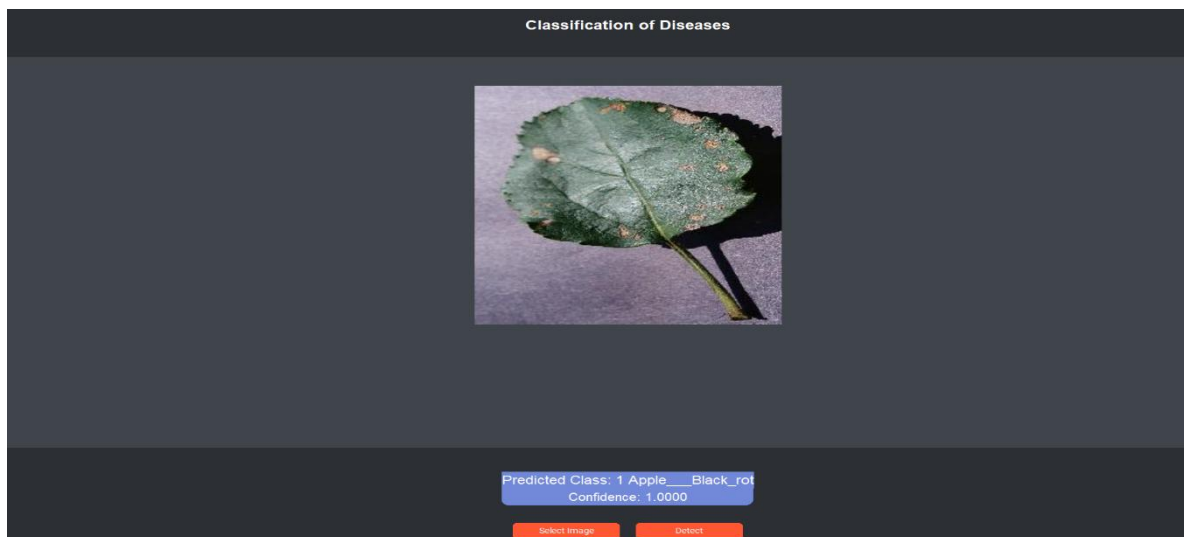
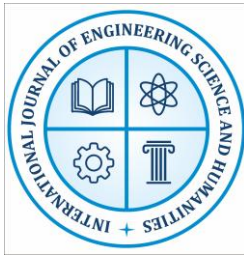


Figure 8 Apple Black rot disease



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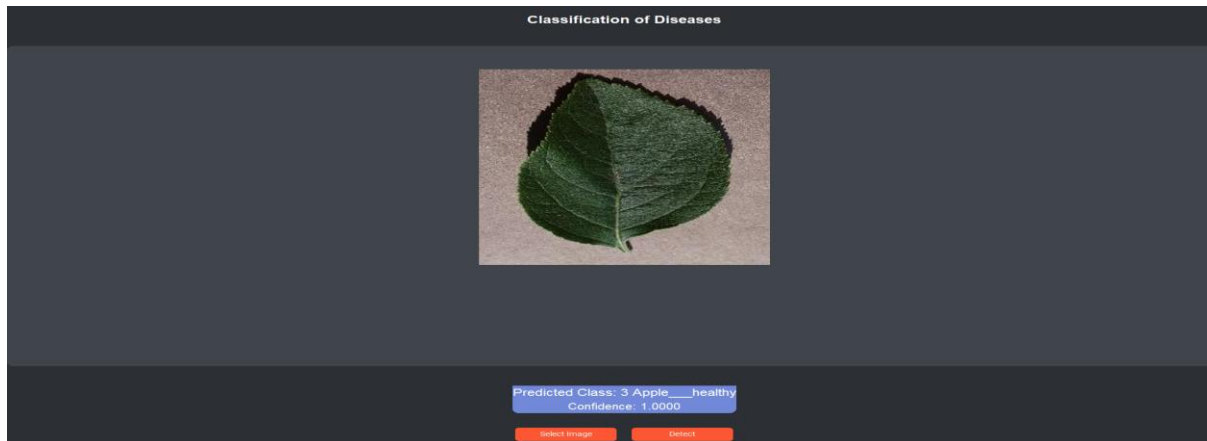


Figure 9 Apple healthy leaf



Figure 10 Corn common rust disease

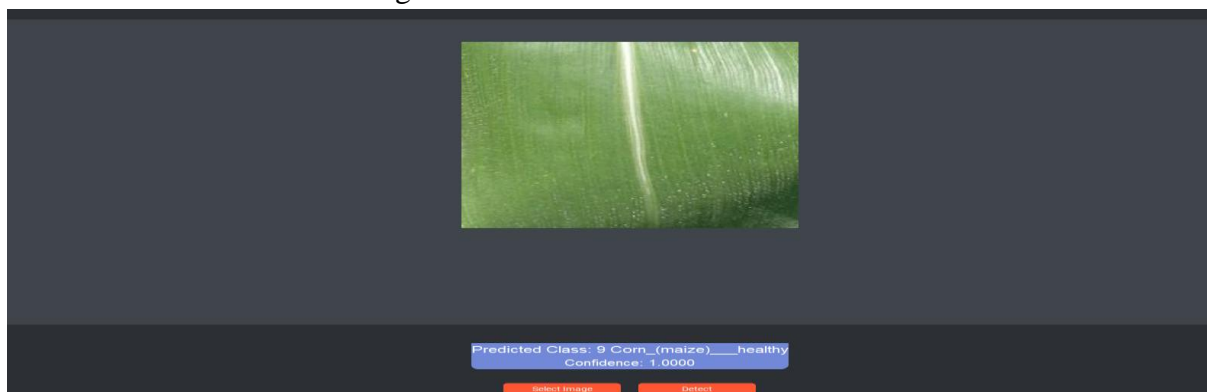
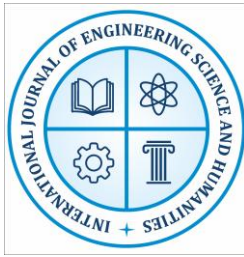


Figure 11 Corn healthy image



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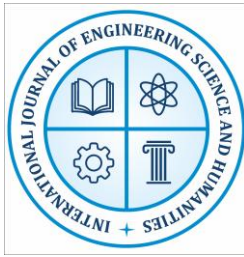
5. CONCLUSION AND FUTURE SCOPE

The project addresses the limitations of conventional disease detection methods reliant on manual examination, which are time-consuming and prone to human error. It introduces a deep learning-based solution using convolutional neural networks (CNNs) for the automated classification of plant leaf diseases across diverse species. However, integrating such systems into real-world farming poses challenges including variations in field conditions (lighting, background, weather), which can reduce model accuracy. Preprocessing and data augmentation may mitigate some issues, but challenges like high computational requirements remain, as deep learning models require significant resources for training and inference. Techniques such as pruning, quantization, and lightweight architectures like MobileNet are suggested to simplify models for practical use while risking accuracy and efficiency. Concerns about dataset diversity, annotation issues, and model performance (overfitting and underfitting) need to be addressed to optimize deep learning applications in agriculture. The integration of innovative approaches, such as attention mechanisms and transformers in image processing, may enhance disease identification capabilities, allowing models to focus on critical areas of infected plants. Continuous research and development in these areas could significantly improve crop health and productivity globally, marking a potential transformation in agricultural practices.

In the future, this project can be improved by using advanced deep learning technologies such as Vision Transformers and attention mechanisms to increase the accuracy of plant disease detection. Lightweight models like MobileNet and EfficientNet can also be used so that the system can run easily on smartphones, drones, and IoT devices for real-time monitoring in farms.

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