ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 1, 2024

AI Powered farmer friendly insecticide recommendation systems and learn to decrease diagnosis

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Abstract: Crop diseases, predominantly caused by bacteria and fungi, impose a substantial threat to global crop production and quality. Timely identification of these diseases is particularly challenging in developing countries due to the labor-intensive and costly nature of manual expert inspection. The potential of smart devices for automated disease detection offers a promising solution to reduce expenses and enhance efficiency. In the context of a changing climate, evolving disease strains, and increasing food demand, agriculture, the bedrock of human civilization, faces contemporary challenges. Regrettably, accessible tools for proactive disease detection and management are lacking. Our proposed solution, CropGuard, revolves around the creation of an integrated chatbot system for plant disease detection, harnessing the power of AI and deep learning technologies. CropGuard comprises essential components, including a user-centric frontend developed with Streamlit, backend deep learning models, conversational AI powered by GPT-3.5 Turbo, and dynamic learning mechanisms. Recognizing the ever-evolving landscape of agriculture and technology, our approach integrates feedback loops and data-driven insights. This dynamic learning framework enables the chatbot to continuously enhance its responses and diagnostic accuracy, aligning with the evolving needs of agriculture and technology.

Keywords: *Plant Disease Detection, Agricultural Tech, AI-2 Chatbot, Crop Management, Sustainable Agriculture.*

1. Introduction

Modern agriculture faces the pressing challenge of ensuring global food security amidst a backdrop of climate change and evolving disease patterns in plants. In response to this critical issue, our research presents "CropGuard," an in-innovative approach that leverages the power of artificial intelligence (AI) to revolutionize plant disease detection and agricultural knowledge dis-semination. By integrating state-of-the-art technologies, our study combines image classification, conversational AI, and data-driven insights to create a comprehensive solution for farmers and agricultural enthusiasts.

The foundation of CropGuard rests on a robust methodology that encompasses several key phases. First, we carefully curated and pre-processed a diverse dataset of plant images, incorporating both healthy and diseased specimens from potato and tomato plants. These images were meticulously labelled to create a reliable training set for our AI model. Data augmentation techniques were then employed to enhance the model's ability to generalize and accurately identify plant diseases in real-world scenarios.

Our research includes an exploratory data analysis, which offers valuable insights into the dataset's class distribution and image dimensions, aiding in the model's optimization. The heart of CropGuard lies in the development of a deep learning model based on the ResNet50 architecture, which achieved impressive training and vali-dation accuracies of 95.3% and 88.2%, respectively.

To ensure the accessibility of our innovation, we designed a user-friendly Streamlit-based web application, allowing users to upload images of plants displaying disease symptoms. The application utilizes a TensorFlow Lite model for real-time disease detection and delivers results with high accuracy and confidence levels.

Beyond disease detection, our research extends into the realm of knowledge dissemination by integrating conversational AI capabilities. Our chatbot agent, enhanced by cutting-edge language models and the Wolfram Alpha API, serves as a bridge between users and the vast world of agricultural information. It facilitates engaging and informative conversations while providing structured data on plant diseases, cures, and preventive measures.

In essence, CropGuard embodies a pioneering effort to empower agriculture with AI-driven solutions. By amalgamating image classification, conversational AI, and a wealth of agricultural knowledge, our research equips farmers and enthusiasts with an indispensable tool for crop protection and sustainable farming practices, ultimately contributing to global food security in a changing world.[17][18][19]

2. Related Work

Agriculture is one of the major research areas in todays world because it generates food for most of the worlds population. In this section we will discuss the research work done in this field and the use of technology in the same.

2.1. Plant Disease Detection

2.1.1. Deep Learning-Based Approaches

Deep learning techniques have gained prominence in plant disease detection due to their ability to learn intricate patterns from large

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 1, 2024

datasets. [1] employed a convolutional neural network (CNN) architecture for the identification of crop dis-eases. Their model was trained on a substantial dataset of plant images and achieved an impressive 95% accuracy in classifying various diseases. This study exemplifies the power of deep learning in automating disease identification processes, thereby enabling timely interventions to protect crops.

2.1.2. Transfer Learning

Limited data availability in the agricultural domain can pose a challenge for training deep learning models. To address this, [2] explored transfer learning, where a pre-trained model is fine-tuned for dis-ease detection in fruit trees. Their work demonstrated the advantages of leveraging pre-trained models such as Inception and ResNet, showing significant improvements in disease classification accuracy. This approach is particularly valuable in scenarios where collecting extensive labelled data is impractical.

2.1.3. Spectral Imaging

Spectral imaging techniques, which capture the electromagnetic spectrum beyond visible light, have been used for disease detection in crops. [3] delved into hyper-spectral and multispectral imaging in agriculture. They developed a system that combined spectral imaging with machine learning algorithms to enable the early and accurate detection of diseases. This technology allows for the identification of subtle spectral changes in plants, even before visible symptoms appear, enabling proactive disease management.

2.2. AI In Agriculture

2.2.1. Precision Agriculture

The application of AI in precision agriculture is a promising avenue for optimizing resource use and crop yield. [4] investigated precision agriculture systems that utilize AI algorithms to fine-tune irrigation, fertilization, and pest control. By analysing various data sources, including soil moisture sensors and weather forecasts, their system could make data-driven decisions in real-time, improving crop quality and reducing resource wastage.

2.2.2. Robotic Farming

Robotics integrated with AI is transforming agriculture by automating labour-intensive tasks [22]. In [5]'s research, autonomous robots equipped with computer vision and machine learning algorithms were employed for activities such as planting, weeding, and harvesting. Their study highlighted the potential of robotics to increase efficiency, reduce labour costs, and enhance farm productivity.

2.2.3. Crop Monitoring

AI-driven crop monitoring systems offer continuous insights into crop health and growth stages. [6] developed a system that integrates data from satellite imagery, drones, and IoT devices. Their AI algorithms process this data to provide farmers with detailed information on crop conditions, enabling timely actions to

protect and optimize yield.

2.3. Chatbot Applications in Agriculture

2.3.1. Information Dissemination

Chatbots have emerged as valuable tools for disseminating real-time information to farmers. [7] designed a chatbot that delivers weather forecasts, market prices, and best agricultural practices through natural language conversations. This enables farmers to make informed decisions and adapt their strategies to changing conditions.

2.3.2. Pest and Disease advisory

Some chatbots, like the one developed by [8], specialize in pest and disease advisory. These chatbots use natural language processing and image recognition to diagnose issues and recommend suitable treatments. They engage with farmers in interactive conversations, offering guidance on managing agricultural challenges effectively [23].

2.4. Existing Research

The section on current research provides a methodical and comprehensive analysis of several studies, which is a vital part of the evolution of agricultural technology. A well-organized summary is given in Table 1, which includes pertinent information about the approaches used, the research articles' strengths and limitations, and other pertinent details. This evaluative method makes a substantial contribution to our collective knowledge of the condition of agricultural technology development today.

Through a thorough evaluation of methods, researchers can identify strategies and tactics that work well for tackling particular agricultural problems. Comprehending the merits of every research study offers valuable perspectives on efficacious approaches, techniques, or innovations that might be employed in subsequent investigations or expanded for pragmatic implementation.

Finding the studies' shortcomings after review is just as crucial. This critical analysis aids researchers in identifying constraints, possible biases, or potential weak points in their methodology. It is imperative to acknowledge these limits to improve study designs, refine research methodology, and make sure that subsequent work builds upon the knowledge gained from previous mistakes.

Researchers can use the thorough review as a guide to help them navigate the current agricultural technology ecosystem. By using this method, researchers can identify regions that still need investigation and knowledge gaps. By recognizing these gaps, the scientific community may focus its efforts on finding answers to open issues, which will further our understanding of technology's application in agriculture.

Furthermore, determining the direction of next contributions to the area depends on this iterative process of evaluating current research. The evaluation's conclusions can be used by researchers to plan investigations that advance our understanding while also building on earlier discoveries. A dynamic and changing environment is produced by the ongoing cycle of assessment, gap identification, and research initiatives. This encourages innovation and propels the ongoing improvement of agriculture through technological breakthroughs.

In conclusion, the part on current research is crucial in determining the direction that agricultural technology development will go. It offers a basis for well-informed decision-making, pointing researchers in the direction of significant contributions that tackle pressing issues and advance agricultural practices globally.

Title	Strengths	Drawback	Findings
Fertilizers Recommendation for disease prediction in tree leaves	The proposed method is compared with the existing CNN-based leaf disease prediction. The proposed SVM technique gives a better result when compared to existing CNN.	The CNN-based code was taken from GitHub instead of implemented from scratch	F-Measure for CNN is 0.7 and 0.8 for SVM, the accuracy of identification of leaf disease of CNN is 0.6 and SVM is 0.8.
Soil-Based Fertilizer Recommendation System for Crop Disease Prediction System	The main advantage of our proposed system is that it is user-friendly and highly efficient. The proposed system maintains privacy and also predicts accuracy.	The proposed method was carried out with five different crops	The proposed system was able to analyse the soil nutrient type efficiently, the kind of leaf disease present in the crop, and predict the fertiliser in a proficient manner. The approach was flexible and could be extended to the needs of the users in a better manner.
An advanced deep learning models-based plant disease detection: A review of recent research	The main advantage of this paper is that it elaborates and gives deeper insights on how deep learning models can be used for plant disease detection along with the drawbacks of each type of models.	There is no drawback as such since this is a theoretical research paper	This paper gives us an overview of various deep learning models like CNN, DGVGNet, and Multitasking Learning Networks. This also gives us background knowledge of how plant disease detection from images actually works.
AI Chatbot for Plant and Animal Disease Detection Using Convolutional Neural Network	CNN is used, which is found to be more reliable than other deep learning techniques. The pre-processing required for ConvNet is far lower when compared to other classification algorithms	The drawbacks are that the number of plant diseases detected correctly is quite low, and their future scope includes adding new data images. Performance and Accuracy of the Model can be improved.	This paper utilises deep learning techniques for Plant and Animal Disease Detection. It emphasises the use of Convolutional Neural Networks (CNN). Image Augmentation plays an important role.
Plant Disease Detection and Classification by Deep Learning	Provides direction for future research. The authors experimented with a large dataset. They also checked for techniques with and without visualization. They also experimented with an emerging technology known as Hyperspectral Imaging.	We need a more efficient way of visualising plant disease as it would save costs for fertilisers. As we are aware that the severity of plant diseases changes over time therefore, we must develop a model which can detect the diseases throughout all stages.	The authors used various architectures of CNN like AlexNet, GoogleNet, and ResNet to detect the plant diseases when compared, ResNet was best for tomato leaves.
Crop Harvest Prediction and Disease Detection Using Machine Learning	The crop prediction and disease detection system is built with the help of various machine learning algorithms such as Random Forest and convolution neural network	The lack of database to store visitor's information is a limitation	Random forest has maximum accuracy.

Table 1. Literature Survey of Existing Studies

3. Methodology

In this section, we discuss the crucial work of identifying plant diseases as well as the methodology used to achieve our study goals. Our study's success was dependent on a methodical, well-organized approach that combined several methods and resources.

Figure 1 represents the overall methodology of our proposed model.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

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Vol 18, Issue 1, 2024

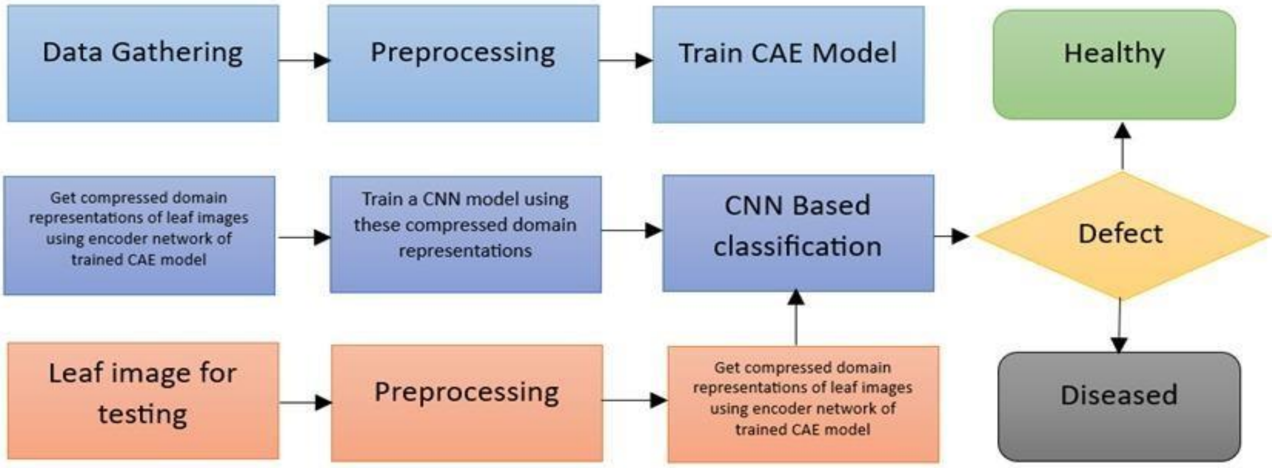

Fig 1. Proposed Methodology

4. Structure of Paper

4.1. Dataset Preparation

In the first stage of our study, a dataset that had been specially curated for the goal of identifying plant diseases was prepared and extracted. We used the Plant Village Dataset, a useful tool that has a broad assortment of leaf picture data, to accomplish this [9]. These photos show a range of plant leaves, with a main emphasis on tomato and potato plants. Each image in the dataset we used was pre-classified and labeled according to its state, whether it was a healthy leaf or one displaying symptoms of disease [9]. Our efforts to develop and test machine learning models for the precise identification of plant diseases relied heavily on this pre-labeling and classification. We were able to access a vast amount of visual data that covered a wide range of plant health issues by using the PlantVillage Dataset [9]. Because of this diversity, our model was exposed to a wider range of disease kinds and severity levels, which improved its capacity to recognize and distinguish between healthy and diseased leaves.[24][25] Fig 2. Below displays the kind of images present in the dataset used.

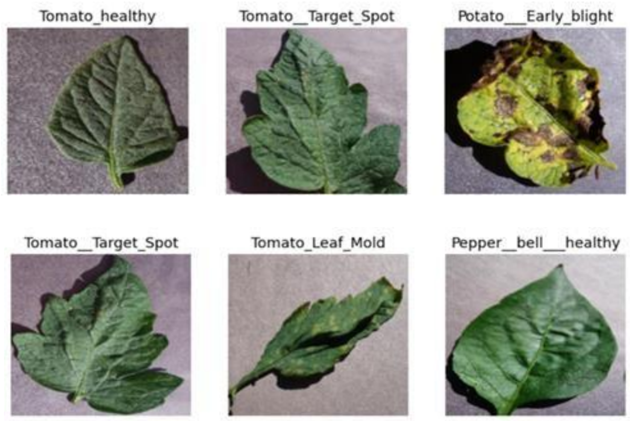

Fig 2. Dataset Preview

4.2. Data Preprocessing

Data preprocessing is a critical phase in preparing the plant disease classification dataset for model training. Preparing the plant disease classification dataset for model training requires important data preprocessing steps [10]. The first step in the procedure is to remove the photos from the dataset that is kept in Google Drive. Following that, these photos go through several modifications, such as scaling to a standard dimension of 224x224 pixels and normalization using mean and standard deviation values from the ImageNet dataset [10]. The training dataset is also subjected to data augmentation methods such as rotation, width and height changes, shearing, zooming, and horizontal flipping [10]. These additions broaden the training set, which enhances the model's capacity to generalize to new examples. The deep learning model is more resistant to fluctuations in the input images thanks to the preprocessing, which also improves the model's overall performance during training and inference. Fig 3. Displays the classes present in the dataset.

```
Class names in the training directory:
Tomato_healthy
Tomato__Tomato_YellowLeaf__Curl_Virus
Tomato_Septoria_leaf_spot
Tomato_Spider_mites_Two_spotted_spider_mite
Tomato_Leaf_Mold
Tomato__Target_Spot
Pepper__bell___Bacterial_spot
Pepper__bell___healthy
Potato___healthy
Tomato_Late_blight
Potato___Late_blight
Tomato_Early_blight
Potato___Early_blight
Tomato__Tomato_mosaic_virus
Tomato_Bacterial_spot
```

Fig 3. Different Classes present in the dataset

4.3. Exploratory Data Analysis

Exploratory data analysis (EDA) is a vital element in the data analysis process that is essential for comprehending and learning from datasets, particularly when applied to tasks like the categorization of plant diseases [3]. In this situation, EDA aids data scientists or analysts in understanding the dataset, evaluating its quality, and making defensible choices regarding the preprocessing and modeling of the data.

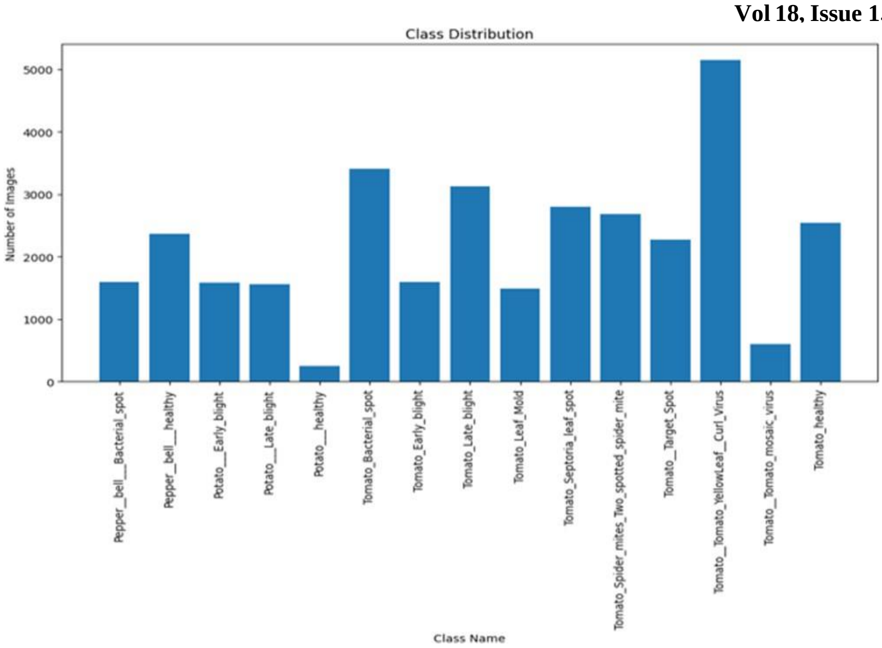

Fig 4. Displays the number of images in each class

Model Building

Plant disease detection often begins with data preparation, and a key source for such data is the PlantVillage Dataset [9]. The dataset offers a diverse collection of leaf images, primarily focused on tomato and potato plants. Each image within this dataset is pre-classified and labelled according to its health state. This meticulously labelled dataset serves as the foundation for developing and testing machine learning models for precise plant disease identification. The diversity within the PlantVillage Dataset exposes the model to a wide range of disease types and severity levels, enhancing its ability to distinguish between healthy and diseased leaves.

Additionally, the work of Nasir and Salleh provides insights into the use of deep learning techniques in plant disease detection [12]. Their com-prehensive review discusses the various approaches and methods that have been applied to this field, providing valuable context for the model building process.

4.3.1. Splitting the dataset into training and validation

The training and validation process is a crucial phase in model development, and it often involves splitting the dataset into these two sub-sets [13]. In our study, we used an 80/20 split ratio, dedicating 80% of the data to model training. This allocation ensures that a substantial amount of data is available for training, while reserving 20% for evaluating the model's performance. During this process, we extracted class labels from the 'plantvillage/train' subdirectories, each representing a distinct category of plant diseases. This method provides valuable insights into the dataset's diversity, paving the way for subsequent model building and evaluation.

4.3.2. Model Training

Model training was a critical step in creating a reliable plant disease categorization system. ResNet50, a deep convolutional neural network (CNN) architecture, forms the foundation of the model's design [14]. A wide range of image classification jobs can be handled by this architecture, which is well known for this property. In this situation, pre-trained weights from the ImageNet dataset are employed with the ResNet50 model. These pre-trained weights give the model a head start because they have already taught it useful features from the many millions of photos in ImageNet. The model can successfully recognize pertinent patterns and characteristics in photos of plant diseases by utilizing these pre-trained weights.

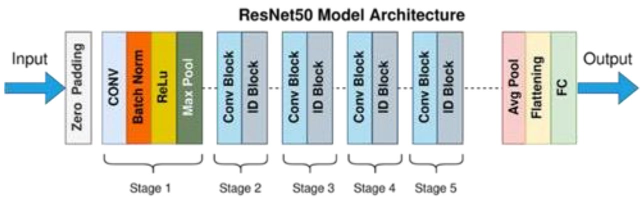

Fig 5. ResNet50 Model Architecture

Each training epoch covers a complete run of the training dataset and is made up of several epochs. In this instance, the model underwent seven epochs of training. The model learns to generate predictions and adjust its internal parameters to minimize the training loss when it is exposed to batches of training photos. The model's weights are updated using optimization strategies like gradient descent during a series of forward and backward sweeps when the model's predictions are compared to the actual labels.

Early stopping is used to prevent overfitting. When a model becomes overly focused on learning the training set of data and struggles to generalize to brand-new, untried data, it is said to be overfit. Early halting keeps track of the model's effectiveness on a different validation dataset. To prevent overfitting, the training process is stopped whenever the validation loss stops improving. In this instance, early stopping was configured to halt training after a predetermined number of epochs (in this case, five epochs) if the validation loss did not decrease.

Accuracy, a standard performance indica-tor for classification tasks, is used to assess the model's effectiveness. 95.3% training accuracy means that 95.3% of the training dataset's photos could be classified

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 1, 2024

correctly by the model. The validation accuracy of 88.2% demonstrates that the model generalizes to fresh, untried images with good accuracy. These accuracy ratings provide assurance that the model can correctly classify plant diseases in practical applications.

In conclusion, the model used the potent ResNet50 architecture with learned weights to achieve excellent classification accuracy for plant diseases. The model's robustness was increased, and early halting was used to avoid overfitting. The combination of these elements helped the model be successful in accurately classifying plant diseases with high accuracy.

Table 2. Displays Accuracy of each epoch

Epoch	Training Accuracy	Validation Accuracy
1/7	74.29%	9.24%
2/7	88.15%	41.41%
3/7	91.75%	53.52%
4/7	92.74%	69.05%
5/7	93.90%	89.54%
6/7	94.88%	86.47%
7/7	95.15%	89.55%

4.4. Streamlit Frontend Methodology

The creation of a user-friendly web application for plant disease detection involved a systematic pro-cess using Streamlit and a pre-trained TensorFlow Lite model [13]. To build this application, several key libraries were imported, including TensorFlow for deep learning, NumPy for numerical operations, and PIL (Pillow) for image processing. We designed a list of class labels, defining various plant disease types and health conditions for accurate interpretation of model predictions. The pre-trained TensorFlow Lite model specifically tailored for plant disease detection was loaded, and its input-output details were configured. Two essential helper functions for image preprocessing and prediction were established to ensure that up-loaded images were correctly processed and analysed. The Streamlit app was set up, enabling users to easily upload images of plants suspected to have diseases. An intuitive "Detect" button was implemented, allowing users with minimal machine learning knowledge to trigger the disease detection process. Upon clicking the "Detect" but-ton, the code executed image processing and analysis using the TensorFlow Lite model. The results, including the predicted disease class label and an associated accuracy score, were displayed for users in a user-friendly interface.

In addition to the above resources, the paper by A. Smith and his collaborators provides a practical guide on building user-friendly plant disease detection applications using TensorFlow Lite and Streamlit [13].

4.4.1. Importing Libraries

We started by importing essential libraries, including Streamlit for the web application, TensorFlow for deep learning, NumPy for numerical operations, and PIL (Pillow) for image processing.

4.4.2. Define Class Labels

A list of class labels was defined to represent different types of plant diseases and health conditions for plants. These labels were used to interpret the model's predictions.

4.4.3. Load TensorFlow Lite model

The pre-trained TensorFlow Lite model for plant disease detection was loaded. The model path was specified, and an interpreter was created to work with the model. Input and output details were obtained from the model.

4.4.4. Define Helper Function

Two helper functions were defined for image preprocessing and making predictions. These functions ensured that the uploaded images were appropriately processed and analysed by the model.

4.4.5. StreamLit app setup

The Streamlit application was set up, and the user interface was designed. Users could upload plant images with suspected disease symptoms for analysis.

4.4.6. Image Upload

A file uploader widget allowed users to upload images of plants with potential disease symptoms.

4.4.7. Detection Button

A "Detect" button enabled users to initiate the disease detection process.

4.4.8. Model Interface

When the "Detect" button was clicked, the code opened and processed the uploaded image using the TensorFlow Lite model.

4.4.9. Prediction Display

The predicted class label for the disease was displayed in the sidebar, based on the highest probability from the model's output. Additionally, an accuracy value represented the confidence level of the model's prediction.

Fig 6. Streamlit Integrated Frontend

4.5. Integration of API's

Our research extended beyond disease detection to include the integration of language models and APIs, enhancing user interactions and knowledge access. This integration comprised several com-ponents:

4.5.1. LangChain

A cutting-edge language model that elevated natural language understanding and generation for seamless interactions.

4.5.2. OpenAI's Language Model

We employed state-of-the-art language models such as GPT-3 to empower our chatbot with hu-man-like conversational capabilities, facilitating engaging and informative con-versations.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 1, 2024

4.5.3. Wolfram Alpha API

Integration with this API enabled structured data retrieval regarding plant diseases, cures, and preventive measures, enriching the user's informational experience.

4.6. Chatbot Integration

At the core of our research lies the integration of a chatbot agent, fortified by LangChain and OpenA-I's language model. This chatbot exhibits adept understanding of user queries, engages in human-like conversation, and provides comprehensive information about plant diseases, their cures, and prevention strategies. The chatbot operates as the user's intermediary, enhancing the quality of interactions and enriching the user's knowledge.[20][21]

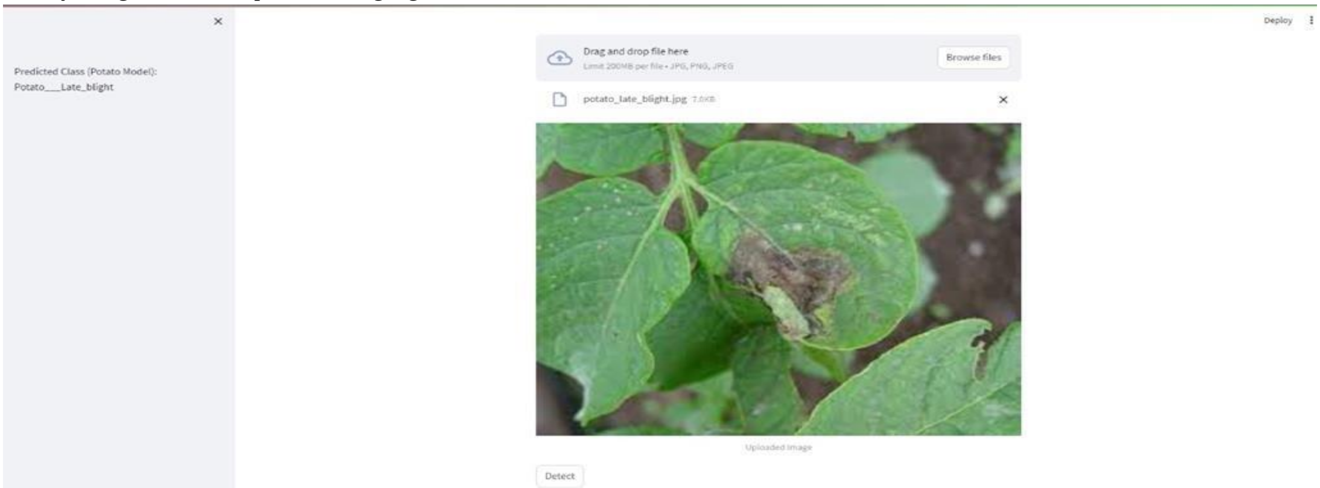

Fig 7. Chatbot Predicted Image

Fig 7. Displays the input image and as we can see that the chatbot has correctly detected the disease as displayed on the top left corner.

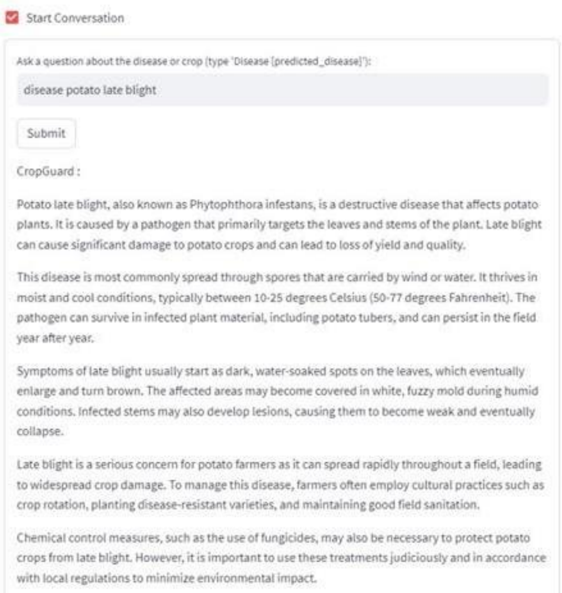

Fig 8. Conversation with Chatbot

Fig 8. Displays the conversation with the chatbot regarding the detected disease. As we can see it displays the details of the disease and gives measures which can be taken to treat it

5. Conclusion and Future Work

Future research stemming from the paper "CropGuard: Empowering Agriculture with AI-driven Plant Disease Detection Chatbot" should focus on improving disease detection models, potentially integrating sensor technologies for real-time monitoring. Additionally, developing predictive models for disease forecasting and enhancing user experience are important objectives. Collaborations with experts from various fields can lead to a holistic approach to disease management and sustainability. Ensuring global accessibility, ethical considerations, and data security are essential for responsible and widespread technology deployment in agriculture.

In conclusion, "CropGuard: Empowering Agriculture with AI-driven Plant Disease Detection Chatbot" introduces an innovative stride to-wards the modernization of agriculture through AI technology. The system's current achievements mark substantial progress, yet its potential for future development is vast. Beyond technical enhancements, forthcoming efforts must address real-world applicability, encompassing scalability, usability, and interdisciplinary collaboration. Ethical considerations and data security are paramount to ensure responsible AI integration in agriculture. Furthermore, a focus on sustainability, eco-friendly disease management, and global accessibility is imperative. This research's profound impact extends to global food security and sustainable agricultural practices, promising a bright-er and more secure future for agriculture and food supply worldwide.

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