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AgriSense: Plant Disease Detection Model

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Abstract: This study focusses on the creation and use of AgriSense, a web-based tool for classifying and identifying plant diseases through the uploading of images. The program uses a CNN model trained on a library of plant leaf images to identify healthy, powdery mildew, and rust-infected plant leaves. It is also equipped with features where users can send pictures in ZIP format containing several photos and get a health percentage of all the files. This solution will help farmers and agricultural professionals use the method of early disease detection and monitoring to prevent loss and improve crop yield quality. It then focuses on examining the current state of the system, its efficiency, and recommendations for further enhancement.
Keywords: Machine Learning, CNN, Agriculture, VGG-16

I. INTRODUCTION

Agriculture sector is one of the most significant parts of people's lives as it is an essential aspect of food supply, economy, and environmentally friendly lifestyle. Nevertheless, the agricultural sector has numerous challenges, and among them is plant diseases. Some of the plant diseases may lead to significant losses in crop production, posing a menace to food security and producers. The conventional technique of diagnosing the diseases involves the identification by certified personnel, which can be expensive, time-consuming and less reliable since there are early and vague manifestations of the diseases.

Technological developments in machine learning and computer vision have provided directions to extend the technique of automated disease identification in plants in recent years. Specifically, there is an object called 'deep learning' which falls under the broad umbrella of Machine Learning, which excels when it comes to recognizing imagery; thus, it may be a good fit for agriculture. In essence, deep learning systems preserve the model trained on the large database of images with label information, enabling the model to detect regularities that indicate certain diseases.

This paper presents the AgriSense system, a novel web-based tool developed to help farmers and other related personnel to quickly diagnose and categorize aerial crop diseases. AgriSense utilizes a convolutional neural network (CNN), plant leaf images categorised into three groups: Blight, Mildew diseases referred to as Healthy, Powdery Mildew, or Rust. The application not only can make individual photo real-time prediction but also has a batch analysis space where the user can upload multiple image files packaged in a ZIP folder and get the overall picture health check results.

This is the main concept of this project, as it implies the possibility of using diagnostic equipment that can be available to all. The problem that AgriSense would solve is a challenging topic and this can be done through designing a simple platform, easy to use, but with the help of cloud computing and artificial intelligence behind the scenes. As a result there would be increased possibilities of early intervention with economic damage such as crop damage and improvement in the quality of the crop yields. Furthermore, it uses feedback mechanism that allow the user to correct classification errors hence enhancing improvements of the program models overtime.

The rest of this paper expounds on the methodology that was adopted in the development of AgriSense, a performance evaluation, the results and feedback received from its users, and the plan for the improvement of the innovation going forward. Through the use of advanced technology in synchronizing with the pragmatic requirements in the agricultural practices, AgriSense is a step towards better, sustainable, and productive system in farming..

II. LITERATURE REVIEW

The agricultural sector is increasingly embracing advanced technologies to raise productivity, efficiency, and sustainability. This review discusses a synthesis of ten research papers that focus on wide-ranging applications of Internet of Things (IoT), Artificial Intelligence (AI), and related technologies in agriculture. The studies summarized here touch on a wide range of issues from crop growth monitoring, detection of pests and diseases, precision farming, and the integration of renewable energy sources in agricultural systems.

Javaid et al. comprehensively covers the AI technologies and their applications in agriculture by stressing that AI holds vast potential in significantly influencing agricultural productivity and sustainability. The study points out the need for addressing key challenges related to data quality, cost, and integration for a complete benefit of AI in farming practices. Overcoming these obstacles, AI can transform the production of food on this earth and improve agriculture globally[1]. Effective detection of pests and diseases is vital for providing maximum safety to the crops so that there is a healthy yield with the finest quality of produce. Deepika and Kaliraj have concentrated on AI and deep learning-based crop pest and disease monitoring. According to their research, these technologies have proved to be very valuable both in terms of timeliness and accuracy of detection, a function which will play a critical role in preventing damage and loss in crops. However, the authors also come across challenges, like data quality, computational complexity, that would need to be overcome before these technologies can achieve full effect 2. Advanced monitoring and prediction systems have now become the need of the hour in sophisticated farming for dealing with environmental stressors and crop diseases. Enhancement of crop productivity: A crop can be made more productive using multisensory data fusion and machine learning. The technologies classify agricultural data and give crop recommendations to farmers, thus optimizing the practices of farming and increasing yield despite adverse weather conditions. This is a significant step forward in improving food security and sustainable farming [3]. HSI with deep learning is a strong and powerful tool in agricultural remote sensing. Alajmi et al designed a new frame of deep learning, named Dandelion Optimizer with Deep Transfer Learning-based Crop Type Detection and Classification (DODTL-CTDC), that uses the Xception model along with convolutional autoencoder (CAE) to be utilized for accurate crop monitoring. Their research shows that integrating HSI with advanced deep learning techniques provides great improvements in accuracy rates for crop type detection and classification, hence advancing better management and planning of agricultural activities [4]. Meng Ji-hua et al. introduced a global crop growth monitoring system designed to be able to meet the needs of global crop monitoring. It involves the use of remote sensing data for crop growth monitoring in real-time and for crop growing process monitoring. This method provides information necessary for the field's management and crop production estimation early, therefore allowing appropriate resource distribution and timely intervention [5].Internet of Things (IoT) technology in farming is currently changing the face of farming. IoT allows the collection of critical weather data, soil moisture, temperature, and soil fertility data, which accurately permits better and more precise agricultural practice. This article explores how IoT technology improves accuracy and sustainable agriculture, focusing on its applications, benefits, as well as potential challenges. The data obtained via IoT systems helps farmers make better decisions, thereby improving crop yields and sustainability [6]. Precision agriculture has become one of the most important notions in modern farming techniques, based on developments in WSN and IoT that improve monitoring and management systems in agriculture. Islam and Dey are the first to propose a green approach based on renewable sources of energy, specifically solar energy, in precision agriculture in combination with WSN and IoT technologies. This solution solves one of the most critical issues in efficient agricultural monitoring and management systems, especially crucially relevant in countries such as Bangladesh, where the sectors make an immense contribution to economic growth[7]. Singh et al. here propose an AI and IoT-based crop monitoring system for increasing crop yields, especially for marigold plants. The paper proposes to identify conditions for better plant growth to mitigate agricultural risk and promote smart farming practices. By monitoring key physical parameters such as humidity, temperature, soil temperature and moisture, and light intensity using IoT-based sensor units, the system extracts data crucial for plant growth analysis, thereby aiding in precision agriculture [8]. Ramaprasad et al. have proposed an Intelligent Crop Monitoring and Protection System for agricultural fields utilizing IoT technology. They focus on the most critical issue related to irrigation: water management in agriculture, which they emphasize is crucial because of population growth and urbanization factors. The article promotes a scientific approach towards irrigation, targeting the moisture content in soils for optimization of water use and better crop yield. This system ensures efficient water management, which is critical for sustainable agriculture [9]. It is within this context that Han et al. explore the challenges associated with remote sensing-based climate and crop monitoring. Noting the potential to use AI to overcome these complexities, they also bring out the profound impact of human-induced climate change on the biosphere and the importance of ecological as well as climate monitoring in comprehension of the intricate interplay between ecosystems and changing climate trends. Technical limitations, data integration challenges, scale differences and above all critical need for up-to-date information to be ensured for enhancing biosphere resilience are reviewed [10].One significant review by Trinchero and Fossa [11] discusses the convergence of smart sensors, IoT, and AI in precision agriculture, focusing on the possibilities it brings in optimizing crop management, resource use, and sustainability. Those developments support farmers to take better decisions and avoid the use and consequently the waste of resources in the pursuit of environmentally sustainable farming practices. Another prominent study by Alahmad, Neményi, and Nyéki [12] outlines how IoT sensors and big data are changing crop production.

The review introduces the reader to a process in which real-time data collected from sensors are analyzed to enhance the predictability of crop yield and agricultural practices, offering valuable insights into sustainable food production. Zhou et al. [13] explores the integration of AIoT (AI + IoT) in agriculture and explains how these technologies address challenges like pest management and post-harvest issues. The system can collect data, automatically analyze images, and carry out predictive analytics integrating AI with IoT to improve the decision-making processes in agriculture. Work in related domains point out that Applicon and WeSmart [14] make available an architecture of smart agriculture for the management of vineyards that integrates IoT sensors and unmanned aerial vehicles. Their findings prove how this system allows farmers to monitor the health status of their crops in real time, hence improving better resource management and optimizing crop yields. Advancement of edge computing in real-time soil assessment, Kalox et al. [15] discusses the application of edge computing with IoT in heavy metal contamination and soil health monitoring. An integration that not only supports decision making in real-time but provides more precise control over agricultural inputs ensuring sustainability. Finally, Gupta et al. [16] summarize a framework-based approach for precision agriculture using IoT, which employs wireless sensor networks (WSNs) to sense environmental data. The overall framework put forward by the author helps to enable smarter farming through the ability to monitor soil moisture, humidity, and temperature in real time; thus, it improves crop management and productivity.

Collectively, such studies have revealed the possibility of AI, IoT, and related technologies revolutionizing agriculture. Such technologies can be helpful in improving crop health monitoring and enhancing yield prediction capabilities and in accurately detecting and classifying crop types, among others. Major limitations include data quality, computational complexity, and integration with traditional farming practices. Tackling these challenges would, therefore be crucial in widespread adoption and success of these technologies in agriculture. In its current form, technology can drive highly sustainable agricultural practice and is expected to ensure world food security.

III. METHODOLOGY

The dataset used in this project consists of images of plant leaves categorized into three classes: Some of the identified diseases are; Rust, Powdery Mildew, and Healthy. These images were collected from the common agricultural references and labelled by hand for the purpose of checking the necessity and relevance. Due to this, the created dataset was further divided into 80:10:10 training, validation, and test datasets.

The dataset was preprocessed, where the images were all resized to 224x224 pixels and normalized by scaling pixel values to the interval 0–1. Data augmentation was also done to improve the generalization of the model through techniques such as random rotations, zooming, horizontal flipping, and shearing. These transformations created diverse training samples, reducing overfitting and enhancing the model's capacity to manage changes in plant leaf images under various circumstances. At the center of disease detection capability of its platform, AgriSense utilizes a Convolutional Neural Network (CNN).The CNN's architecture consists of the following layers:

1) *Convolutional Layers:* These layers add masks to the input image, identifying different elements in an image such as edges, texture, as well as shapes. The initial layers of the model consist of Convm2D layer with 32 filters, activation through ReLU and a subsequent measure of dimensionality Reduction through a MaxPooling layer. Further layers have a greater number of filters (64 and 128) to detect higher level features of the input image.
2) *Flattening Layer:* Thus, layer flattens the 2D feature maps to the equivalent one dimension feature vectors for full connected layers.
3) *Fully Connected Layers:* These dense layers then perform another layer of analysis on the feature vector. The first layer is a convolution layer with a density of 128 and rectification linear unit activation function, while the last layer is fully connected layer with three neurons and soft-max function that outputs probabilities for the three classes: Powdery Mildew, Healthy and Rust.

The model was trained with Adam optimizer, wherever the categorical cross-entropy loss function which ought to be applied for multi-class classification and learning rates fluctuate throughout the training process. Measurements with regards to the accuracy of the performance were used. Augmented training data was used for the model training that lasted for 10 epochs. The training process included:

Train Generator: Augmented images were generated in batches from the training folder.

Validation Generator: This generator created batches of normalized images from the validation folder.

For each epoch, the performance of the model was evaluated on the validation set. Loss and accuracy metrics, as well as information about generalization and over fitting were collected in the history.

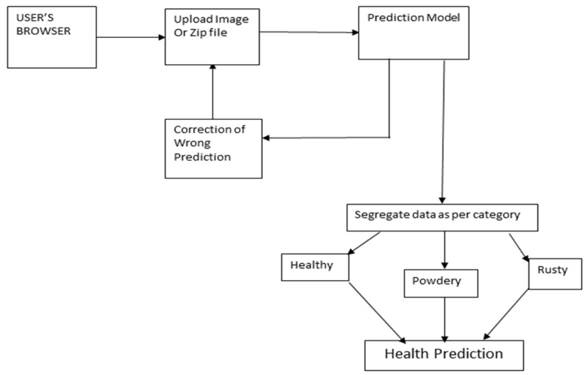

Figure 1: Backend Block Diagram

The disease detection and analysis app, AgriSense, is designed with Flask which is a lightweight web framework in Python. It has a user-friendly interface. The following are some of the most important functionalities:

Image Upload and Prediction: Single image upload and prediction by pre-trained CNNs. The result including, predicted disease class, is shown on the result page.

Analysing Batches by ZIP File Upload: Users can just send in multiple images via a zip file. Once it receives these images as input, the application will extract them and pass each one through the CNN for processing and then calculate health percentage as follows: (No_H + 0.5* No_P)/Total_Im where No_H (number of healthy plants), No_P(number of powdery mildew affected plants) and Total_Im(total number of images). Results also provide counts for each class and health percentage appearing at another result page.To ensure that the model improves user experience and gets more accurate with time, AgriSense has a feedback mechanism:

AgriSense uses visualisation approaches, such as Gradient-weighted Class Activation Mapping (Grad-CAM), to address the interpretability of deep learning models. The heatmaps that Grad-CAM creates highlight the areas of the input image that have the biggest influence on the model's decisions, so users could understand what features are really targeted during classification by the model. These visualizations are returned along with the predictions for transparency in decision making. Building trust and improving usability, particularly for non-expert users, by allowing the area of interest for each classification, AgriSense enables the system to interpret such data. Interpretability thus helps in determining errors and fine-tuning the model toward accuracy and reliability.

Correction Submission: For those who know how to correct wrong assignments of labels to pictures, this feature allows them to provide the right labels. These corrections are saved and utilized in training the model again periodically, thus increasing its precision.

IV. RESULTS AND DISCUSSION

A. Model Performance

The Convolutional Neural Network (CNN) model from AgriSense was assessed based on the accuracy metrics on the test and validation sets. The model eventually obtained an accuracy rate of 90% during validation and 88% during testing, almost perfectly predicting the outcomes of powdery mildew and rust infections. If the data also suggested that the reality corresponds to the model's prediction, then these results mean that the model draws conclusions that are accurate in 90% of the cases during validation. On the other hand, these results are concerned with the situation that the predicted label is actually the true label, namely, the actual label are also different from the predicted label in 10% of the cases.

This means that the true label cannot be predicted by the model with an absolute certainty. The confusion matrix above indicates that the model performed outstandingly across the different classes, however, the model quite often mistook mildew and rust for one another.

B. Single Image Prediction

It's really a single image prediction feature that was tested multiple times. The system processing time for classifying the image was achieved within a couple of seconds. There is no splash screen that pops up when you launch a prediction, so you can start immediately. The prediction accuracy for individual images was consistent with the overall model accuracy. Farmers could quickly run such a feature to assess the crops before returning to their homes, which was the most preferred activity carried out by them.

C. Batch Analysis

The batch analysis feature, where users upload a ZIP file containing multiple images, has been favorably accepted by the market, adding to the strength of the application. Generally, the processing time for a ZIP file was about 30 seconds. The health situation was assessed through some calculated parameters, such as healthy images, images that manifest a partial healthy state (powdery mildew), and so forth. This provided the farmers with a consistent report of the crops' physical condition.

D. Health Percentage Calculation

The health percentage is calculated as follows:

$$\text{Health Percentage} = \left(\frac{\text{Healthy Images} + 0.5 \times \text{Powdery Images}}{\text{Total Images}}\right) \times 100\%$$

This formula considers powdery mildew as a less severe condition compared to rust, thereby providing a nuanced health assessment. Users appreciated this detailed analysis, which allowed them to gauge the overall health of their crops quickly.

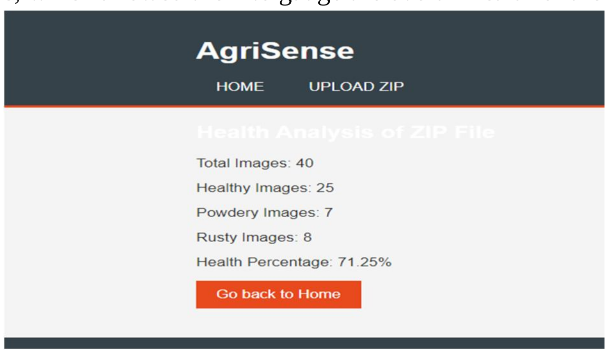

Figure 2: Health Percentage Output

E. User Feedback and Correction Mechanism

That is the mechanism where users can correct misclassifications if they occur. The users can enter the correct label for each image that is classified incorrectly, and the received corrections are stored to be used for the model retraining operation in the future. The model gets better each time it is retrained. The retraining process has resulted in the practice of very few and long sessions for the retraining of the model, thereby improving the efficiency of the system.

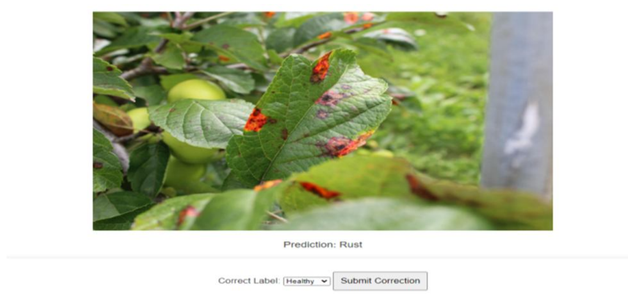

Figure 3: Feedback and Correction Option

The feedback mechanism of AgriSense sends corrections submitted by the users for misclassified images to a separate database providing the correct labels. It is periodically reviewed for retraining purposes. Though it is semi-automated, an automated retraining pipeline can be built in which corrected labels will be incorporated into the existing dataset seamlessly. The model may be retrained at predetermined intervals or after the occurrence of a certain number of user corrections. Thus, the model will continue to improve with time and achieve better accuracy with the effects of new disease patterns.

F. Deployment and User Experience

Cloud infrastructure, which is the platform where the application starts, allows the application to be accessed online and from anywhere that has an Internet connection. An auto-loading strategy is used in the deployment, which requires embedding the pre-trained machine learning model in the application runtime instance, thereby saving the need to retrain the model and hence reducing the startup time significantly.

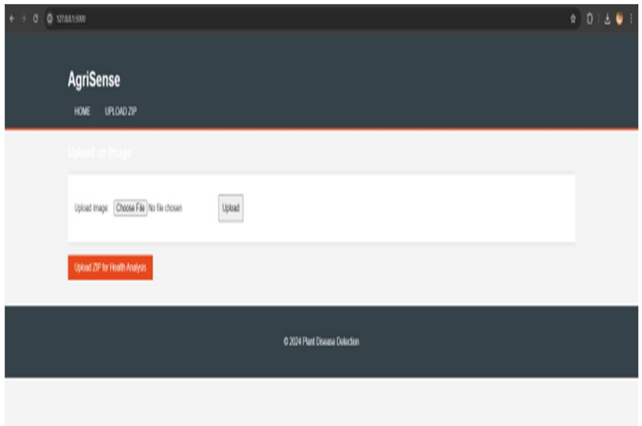

Figure 4: Home Page

The user interface, which is created using the Flask framework and stylized with CSS for a modern look, is an intuitive and attention-grabbing user experience. The company branding of the header and footer, with the title "AgriSense," gives a unified look to every single page in the index, upload zip, and result sections.

V. CONCLUSION

Designed by AgriSense, a combination of advanced deep learning with a user-friendly web interface is a special tool that can be employed for agricultural health monitoring and plant disease detection. Convolutional Neural Networks (CNNs) are used to the system does a fabulous job in the recognition of the healthy leaves, powdery mildew, and rust infections with high precision. Having a runtime capacity for prediction that is under two seconds long, it is essential for quick decision-making with awareness in the situation, which is critical for the stopping of disease dissemination and reduction of crop loss. One great purpose performed by AgriSense is the batch analysis feature that the product has added that allows the processing of a large set of images, thus the result is a detailed health check of the whole area in just a few seconds. There are benefits of scalability, both for small farms and large agricultural operations. There is also a mechanism for gathering user feedback in AgriSense, this feature gives the users the chance to make a judgement and to fix the classification as well if necessary. This way, the model keeps improving all the time, thus becoming more and more precise through each of the successive retraining cycles as well as adapting to new data and changing diseases. To sum up, the move from AgriSense to applying machine learning to agriculture is a significant breakthrough in the field as it presents farmers with accessible, scalable, and improving solutions. Agriculturalists are thus equipped with the ability to take care of their crops, reduce the prevalence of losses, and practice environmentally sustainable farming.

VI. FUTURE SCOPE

While AgriSense has demonstrated robust performance and user satisfaction, several limitations and areas for future work have been identified:

1) *Dataset Expansion:* The accuracy and adaptability of the model can be improved by expanding the dataset's size and diversity to include more plant disease kinds.
2) *Model Accuracy:* Continuous efforts to improve the model's accuracy, particularly in distinguishing between similar disease symptoms, are necessary
3) *Real-Time Data Integration:* Including real-time soil and weather data could provide disease forecasts additional context, increasing the tool's usefulness for farmers.
4) *Mobile Application:* Developing a mobile application could further enhance accessibility, allowing users to capture and upload images directly from the field.

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