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Smart Soybean Plant Disease Detection and Control

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---***ABSTRACT***---

This research presents the development of a Smart Soybean Plant Disease Detection and Control System, designed to accurately identify various soybean leaf diseases and recommend appropriate treatments. The system utilizes a machine learning model trained on a comprehensive dataset of leaf images, capturing both diseased and healthy leaves, to classify conditions with high accuracy. The model is a convolutional neural network trained on 224x224 RGB images. It was trained on a dataset of over 1000 soybean leaf images.The percentage training accuracy of the model was 95%. The testing phase demonstrated the system's capability to accurately detect four specific leaf conditions: Yellow Mosaic, Bacteria Pustule, Frogeye Leaf Spot, and healthy leaves. Upon detecting a disease, the system offers targeted treatment recommendations based on established scientific research. If the leaf is healthy, the system reassures farmers that no treatment is needed. This research contributes to the growing field of precision agriculture by providing a smart, automated tool for early disease detection, enabling farmers to take proactive measures to manage crop health. The recommendations are rooted in sustainable agricultural practices, aiming to reduce excessive pesticide use and promote environmental responsibility. The system's success in accurately detecting diseases and offering tailored treatment options underscores its potential to improve crop yields, reduce losses, and contribute to a more sustainable farming future.

KEYWORDS: Machine Learning, Smart System, internet of Things, Decision Support System

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I. INTRODUCTION

The agricultural industry faces significant production and economic losses due to infectious diseases on a global scale. In the United States, these losses accumulate to approximately five billion dollars annually [25]. Developing countries experience even higher rates of yield loss, with reports of more than 50% attributed to diseases and pests [9].

A large portion of crops are lost to plant diseases each year worldwide[4]. Crop plant diseases have been a recurring challenge throughout the history of agriculture. As crops are cultivated in monoculture systems, where large areas are planted with the same crop, pathogens find ideal conditions to spread rapidly and infect susceptible plants. Factors like climate change, globalization, and the movement of goods and people have also contributed to the emergence and spread of new and more virulent plant pathogens.

Soybean, an essential oil crop and plant protein source originating from China [29], plays a crucial role in agriculture. However, soybean diseases have a significant impact on its yield and quality [2]. Detecting and understanding phenotypic traits related to these diseases is of paramount importance for various aspects of soybean farming, including high-quality breeding, scientific cultivation, and fine management.

According to research based on relevant investigation data, soybean diseases result in an annual yield loss of approximately 10% and can even exceed 30% in severe cases [3] [7]. In recent years, environmental pollution has intensified, leading to increased disease stress on soybean crops. Consequently, the timely and accurate recognition and monitoring of soybean diseases have become critical in the morphological-physiological phenotypic detection system of soybean growth. Achieving precise disease control and variable application, as well as reducing pesticide residues based on the specific situation, can ultimately enhance crop quality and yield.

The advancement of deep learning in smart agriculture has revolutionized disease and pest detection, flower and fruit recognition, plant species classification, and other related fields [28]. By harnessing these technologies, farmers can significantly improve their disease management strategies, optimize resource allocation, and ensure sustainable and efficient soybean production.

Soybean, a major global crop, is susceptible to various diseases that can significantly impact its yield and overall productivity. These diseases are caused by pathogens such as fungi, bacteria, viruses, and nematodes. Diseases and insect pests are the major problems in Soybean production. These require careful diagnosis and timely handling to protect the soybean crops from heavy losses. The major problem of soybean plant leaf diseases like Bacterial pustule, Bacterial blight, Rust, Frogeye leaf spot, Downey Mildew, Mung bean yellow mosaic [23].

The literature has introduced various image processing techniques for plant disease recognition. These techniques encompass visible light image processing methods such as classification, real-time monitoring, and neural networks [1]. In a separate study, [21] evaluated the performance of two deep convolutional neural networks, namely AlexNet and GoogLeNet, using a vast training set comprising thousands of images. The results demonstrated an impressive accuracy exceeding 98%.

In the face of climate change, intensified global trades, and recent epidemic events, the quest for effective diagnostic tools for plant pathogen detection and management encounters new challenges. The urgency of this search is underscored by the proliferation of harmful "alien" species, including viruses, phytoplasmas, bacteria, fungi, insects, nematodes, and weeds, which are unwittingly transported worldwide through human and goods movement, including plant materials. These invasive species pose serious threats to agriculture on a global scale. Consequently, the early detection of plant pathogens becomes increasingly crucial for plant health monitoring. By identifying disease infections at various developmental stages, the risk of disease spread can be minimized, and the introduction of new pathogens can be prevented [20].

This research titled ‘A Smart Soybean Plant Disease Control System’ refers to an advanced technological approach that utilizes various tools and techniques to detect, and manage diseases in soybean crops. Due to soybean's rising popularity, its numerous benefits, the soaring demand for plant-based proteins and sustainable farming practices, it has become paramount for farmers to seize this golden opportunity.

Our visionary research project aims to revolutionize Nigeria's agricultural landscape by creating an innovative application designed to empower soybean farmers in Hong Local Government Area, Adamawa State, which is the case study. Imagine having access to critical information about different soybean plant diseases and effective control methods, right at your fingertips.

The problem with the existing system is that, smart system developed by [28] could detect soybean leaf diseases, and allow farmers to figure out solutions themselves. The accuracy of the developed systems was impressive; however, farmers are not given a clue or methods on how to control the diseases detected. It is on this account therefore, that we propose a smart system that could equally and adequately detect plant diseases, and also on the other hand, recommend adequate solutions/treatment to the disease detected which the existing system could not provide. Therefore, the proposed system would further serve as a decision support system to aid farmers with the best methods of disease control.

The aim of this research is to develop a Smart Soybean Plant Disease Detection and Control System. The specific objectives are to:

1. Design a model that will automatically classify soybean plant leaves disease using convolutional neural network (CNN)
2. Develop a system that will use CNN model to detect soybean plant diseases from its leaf images
3. Build a decision support system that will recommend treatments for the diseases detected by the model to the farmers.
4. Test and Validate the proposed system for efficiency and effectiveness

By leveraging the power of machine learning in this domain, this research could contribute to more sustainable and efficient agricultural practices, safeguarding soybean crops and ensuring food security for the future.

II. LITERATURE REVIEW

Research in the agriculture domain aims to enhance the quality and quantity of agricultural products while minimizing costs and maximizing profits. However, farmers often require expert monitoring, which can be both expensive and time-consuming. To address these challenges, various systems have been proposed that leverage image processing and automatic classification tools [11].

[14] discussed the main steps of image processing to detect and classify plant diseases, including image acquisition, pre-processing, segmentation, feature extraction, and classification. K-means clustering was found to yield accurate segmentation results. The proposed work used methods like Artificial Neural Network and Back Propagation Neural Network for classification.

In recent literature, convolutional neural networks (CNN) have been extensively employed for various tasks related to plant species recognition and disease identification. [32] utilized CNN training models, including SqueezeNet, ResNet, InceptionV3, and DenseNet, to identify similar rose flowers.

[8] achieved impressive results by utilizing a multi-feature fusion CNN to identify and classify 32 kinds of leaves in the Flavin database and 189 kinds of leaves in the MEW2014 database with average correct

recognition rates of 93.25% and 96.37%, respectively. [18] established and trained a CNN model with two convolutional layers using MNIST datasets on the TensorFlow platform.

[12] proposed and validated two training methods, TOTV and TVTV convolutional neural networks, using MNIST and CIFAR10 standard image datasets. [16] constructed an extended CNN model successfully applied to handwritten digit recognition using Mnist datasets. [34] designed an 8-layer CNN to effectively identify plant species in the PlantNet leaf library and self-collected leaf images with both simple and complex backgrounds.

[10] introduced a method for grape leaf disease identification based on multi-scale ResNet. [31] proposed an improved multi-scale ResNet lightweight disease recognition model based on the ResNet18 architecture. [17] established a plant species recognition method based on ResNet101 and transfer learning for an expanded wild plant dataset.

[5] built weed classification models using ResNet50, VGGNet, and AlexNet networks with 10 common weed images in tea gardens as data samples. [26] adopted an attention module in a residual network to recognize plant diseases, achieving a recognition accuracy of 92.08% for 60 kinds of diseases across various crops.

[33] constructed a parallel pooled attention module and proposed a residual attention network model based on ResNet50 to identify four potato diseases in the Plant Village Dataset with an accuracy of 93.86%. [19] embedded an attentional module into the ResNeXt50 structure to propose a tomato leaf disease recognition method based on a 3-channel attentional mechanism network.

Drawing inspiration from the recent advancements in Convolutional Neural Networks (CNNs) for object detection and recognition, numerous deep learning-based techniques have been proposed for plant disease detection. Most of these methods are built upon well-established CNN architectures originally designed for object recognition tasks, including AlexNet[15], GoogLeNet[30], and VGG [27].

[22]introduces a mobile phone application designed for plant disease diagnosis. The application utilizes a disease signature, consisting of rules related to color, spot shape, historical weather data, etc., to detect plant diseases. This format enables agriculturists, who act as end-users of the application, to expand or tailor the supported range of plant diseases according to their needs. The application's effectiveness has been demonstrated through testing on different plants, including citrus and grapevines, with consistent performance. Experimental results on grape diseases reveal a remarkable accuracy of over 90% in plant disease classification.

These studies demonstrate the significant contributions of CNN-based models in revolutionizing plant species recognition, disease identification, and agricultural applications. Moreover, Soybean plant leaf detection conducted in the literature review showed that the techniques adopted have demonstrated great performance, beating that of humans in object recognition and image classification problems. However, identifying a disease to farmer without providing treatment could still leave many farmers stranded on what to do. Thus, this research proposed an approach that will modify the existing system by adding a function that could classify, detect soybean plant leaf diseases and recommend treatments accordingly. This research will focus on soybean plant disease detection as well as provide the farmers with well informed decision on how to control these diseases.

III. METHODOLOGY

Convolutional Neural Networks (CNN) are a type of deep feed forward neural network that have the remarkable ability to process multidimensional data, such as images, videos, and speech signals. The main idea behind CNN is to reduce images into an easier processing form, without altering their important features that are crucial for obtaining accurate predictions.To classify diseases in soybean plants in a precise and efficient manner, images of the plants are provided as input to the CNN model. The convolutional layer of the CNN is used for extracting the relevant features from the input images. The pooling layer then computes the feature values from the extracted features, while also reducing the dimensionality of the data.

The CNN model typically consists of multiple convolutional and pooling layers that are stacked on top of each other to obtain more detailed features from the input data. The fully connected layer of the CNN uses the output of the previous layers and transforms them into a single vector that will be used as input for the next layer.

Finally, the output layer of the CNN classifies the soybean plant disease based on the extracted features and recommends the appropriate treatment accordingly. This advanced technology holds significant potential in improving the accuracy and efficiency of disease diagnosis in soybean plants, and has the potential to significantly benefit the agricultural industry.

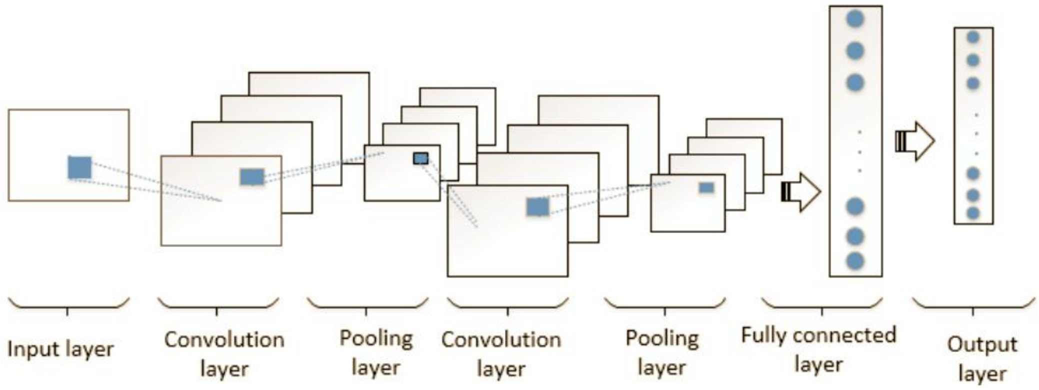

Fig. 1: The Architecture of CNN Model

The following are key stages for analyzing and building the system:

i. **Data Collection and Preprocessing**:
   a. Sufficient number of samples for each of the leaf conditions was collected to avoid imbalanced data.
   b. Data augmentation techniques to artificially increase dataset was considered, to improve the robustness and accuracy of the model.

ii. **Feature Selection and Model Training**:
   a. Different features that contribute most to model's accuracy was explored. These include color, texture, shape, or other characteristics of the leaves.
   b. Experiment with different machine learning algorithms (e.g., Convolutional Neural Networks for image data) to see which gives the best results.

iii. **Evaluation Metrics**:
   a. Assessed model's performance using various metrics like accuracy, precision, recall, and F1-score to get a more comprehensive view of its effectiveness.
   b. Used confusion matrices to understand how well the model is distinguishing between different leaf conditions.

iv. **Testing and Validation**:
   a. Validates model on a separate test set to ensure its generalizability.
   b. Perform cross-validation to check for model robustness and to prevent overfitting.

v. **Deployment and Application**:
   Explore deployment options for the model, laptop computer is chosen and no other means.

vi. **Continuous Improvement and Updates**:
   a. Continuous model Update as we gather more data and receive feedback from users.
   b. Update with the latest research in machine learning and plant pathology to ensure system remains state-of-the-art.

3.1 Data Set

The soybean leaf diseases dataset was collected from selected soybean farms in different locations of Hong Local Government Area, Adamawa State, Nigeria. Real time soybean plant leaves were collected and split into train, test and validation datasets. The collected data was cleaned and saved to train the model. 80% of the data collected was used for training the model, while 10% each for testing and validating the model.

3.2 The System Architecture of the Process Model

Figure 2 depicts the architecture of the process model for soybean plant disease detection and control support system with the following stages:

Image Acquisition: The first stage of the process is Image Acquisition, where images of soybean plants are obtained using a camera. This involves physically going to the site or soybean farm to capture the images.

Image Pre-processing: The second stage is Image Pre-processing, which involves transferring the plant leaf image to a digital system to remove any unwanted areas and noise. This is achieved by resizing, noise removal, enhancement, and smoothing of the images to ensure that the images are of good quality and can be easily analyzed.

Image Segmentation: The third stage is Image Segmentation, which partitions the image into significant components based on similar characteristics. This helps to separate the plant from the background and other irrelevant elements, making it easier to analyze.

Feature Extraction: In the fourth stage, Feature Extraction, various features such as texture, color, edges, and morphology were extracted from the image to detect soybean plant diseases. The color co-occurrence method is used for feature extraction.

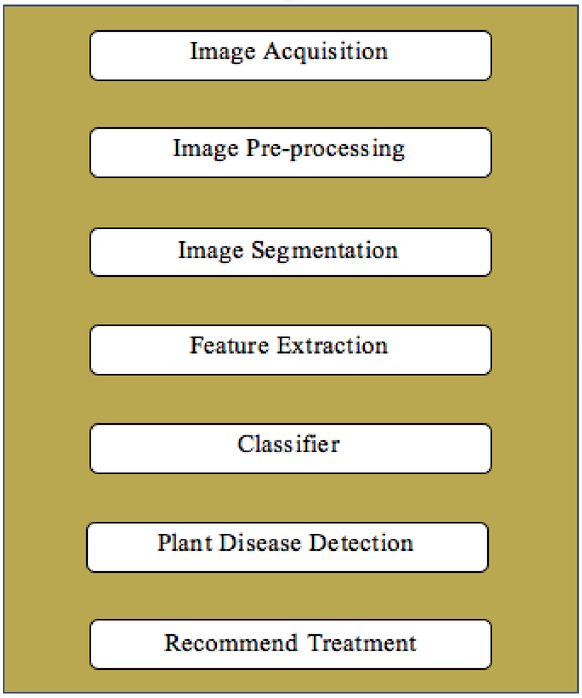

Fig. 2: Soybean Plant Disease Detector and Control Support System Architecture

Classifier and Detector: The fifth stage involved using Classifiers and Detectors to identify and categorize the different diseases that occur on plant leaves based on the obtained features. CNN classifiers were used to detect diseases in soybean plants.

Recommend Treatment: Finally, the last stage was to Recommend Treatment, where the best type of pesticide or disease control method was specified to treat the infected plants based on the identified disease taking into account the global best practice.

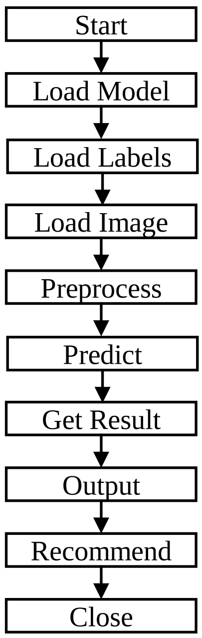

Fig. 3: The Model Process Flow Diagram

Model Design for Soybean Leaf Disease Detection

i. **Input Layer**
Source: Receives input from image files or live video streams.
Image Capture: If using live video, capture frames from a webcam or other camera device.

ii. **Preprocessing Layer**
Image Loading: Load the image or video frame.
Image Resizing: Resize the image to the required input dimensions (224x224 pixels).
Image Normalization: Normalize the pixel values to a suitable range for the model.

iii. **Model Prediction Layer**
Load Model: Load the pre-trained Keras model for soybean leaf disease detection.
Model Prediction: Use the model to predict the class of the preprocessed image.
Extract Prediction: Identify the class with the highest confidence score and extract the corresponding class name.

iv. **Output Layer**
Text Output: Display the predicted class name and confidence score.
Bounding Box: If applicable, create a bounding box around the detected area and display it on the image.
Treatment Recommendation: Based on the predicted class, read and display the corresponding treatment recommendation.
Image Display: Display the final image with the bounding box and class label.

v. **User Interaction Layer**
Control Interface: Allow the user to control the visualization (e.g., close the window, proceed with a new image, or quit).
Resource Management: Release resources and close windows when done.

vi. **Resource Management Layer**
Clean-Up: Properly manage and release resources like video capture objects and open image windows.

vii. **Handle Errors**: Ensure error handling for smooth user experience.

The Visual Representation of this model design is depicted in Figure 4

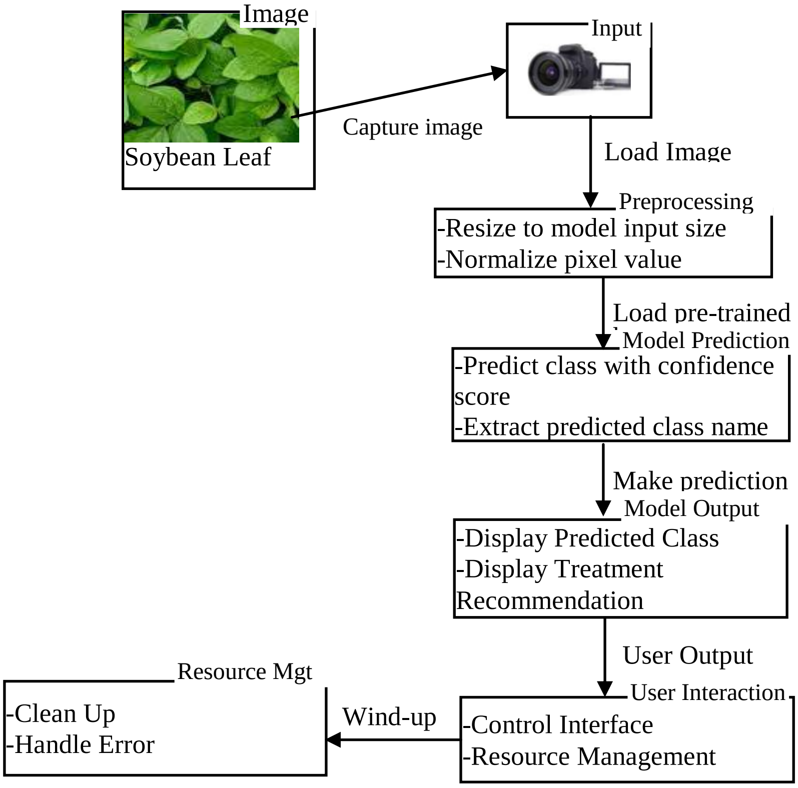

Fig. 4: Model Design for Soybean Leaf Disease Detection

IV. RESULTS

The research project titled Smart Soybean Plant Disease Detection and Control System, aimed to develop a robust system capable of accurately detecting various soybean leaf diseases and providing treatment recommendations. The results obtained from the system's testing phase demonstrated that it could successfully identify four distinct leaf conditions: Yellow Mosaic, Bacteria Pustule, Frogeye Leaf Spot, and Healthy leaves. The following discussion elaborates on these findings and the recommended treatment options.

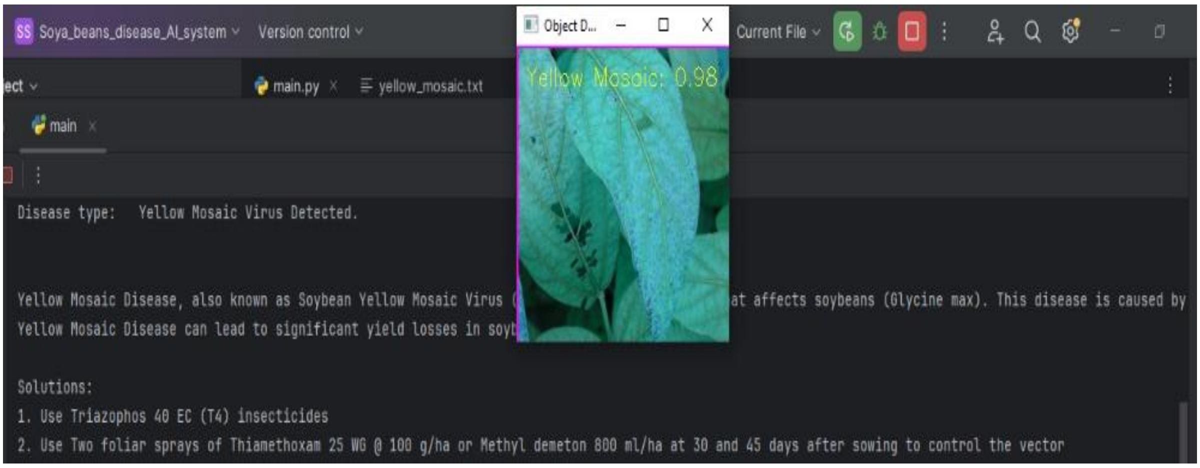

Fig. 5: Yellow Mosaic Virus Detected

Figure 5 depicts the result of a virus detected on a soybean leaf during testing. The result showed that the soybean leaf is infected by a virus called 'Yellow Mosaic'.

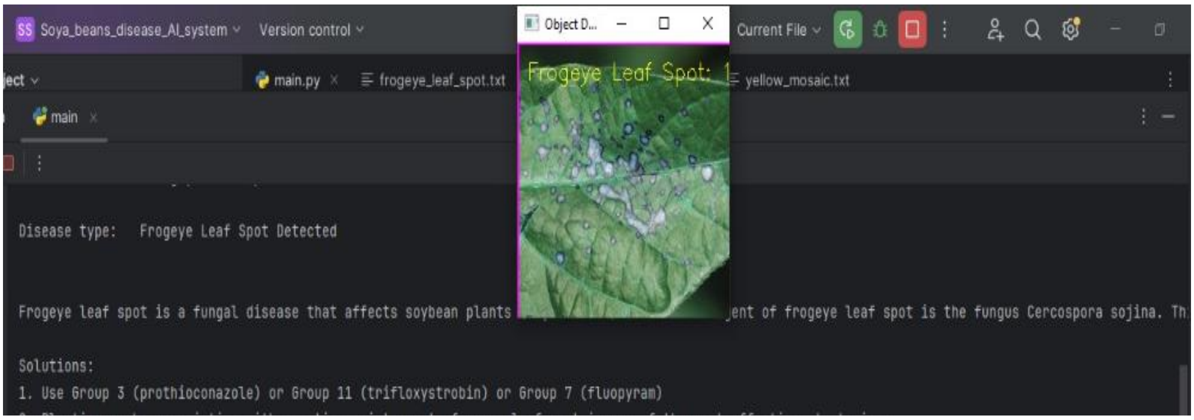

Fig. 6: Frogeye Leaf Spot Detected

Figure 6 shows the result of a disease detected on a soybean leaf during testing. The result showed that the soybean leaf is infected by a virus called 'Frogeye Leaf Spot'.

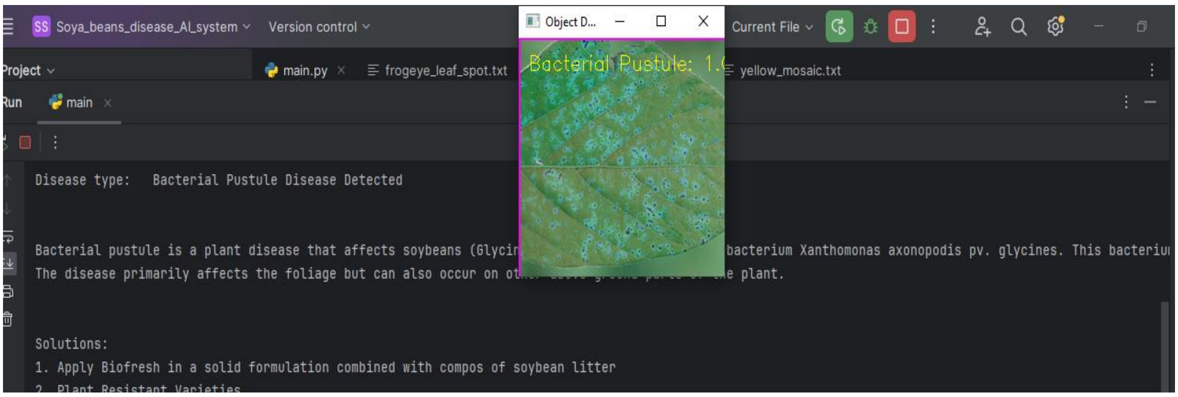

Fig. 7: Bacterial Pustule Disease Detected

Figure 7 elucidate the result of a bacteria detected on a soybean leaf during testing. The result depicts that the soybean leaf is infected by some bacteria called 'Bacteria Pustule'.

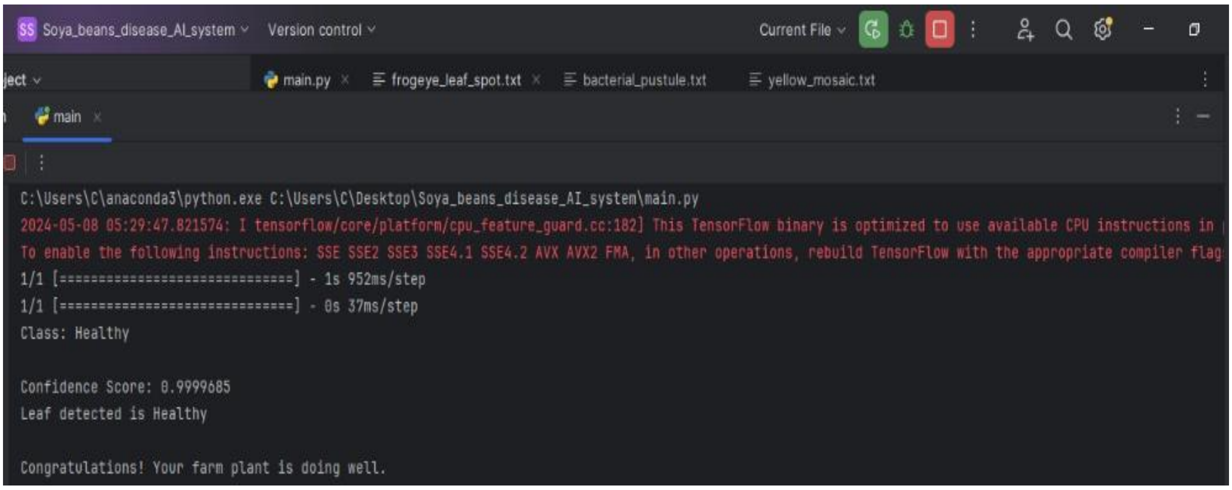

Fig. 8: A Healthy Soybean Leaf is Detected

Figure 8 depicts the result of a no disease of any kind was detected on a soybean leaf during testing. The result showed that the soybean leaf is healthy and does not require any treatment as to that regard.

V. DISCUSSION

The research project Smart Soybean Plant Disease Detection and Control System aimed to create an automated system that could detect various soybean leaf diseases and offer appropriate treatment recommendations. The system was designed to be user-friendly, providing farmers with practical insights to manage plant health. This discussion delves into the results, highlighting the significance of each detected condition, the recommended treatment approaches as discussed below.

Yellow Mosaic Disease Detection

Yellow Mosaic is a common disease affecting a range of crops, characterized by yellow spots or patches on the soybean leaves as depicted in Figure 5. The system accurately identified this condition, indicating the robustness of the model in recognizing specific patterns and discolorations typical of Yellow Mosaic. To address this disease, the system recommended using Triazophos 40 EC (T4) insecticides and two foliar sprays of Thiamethozam 25 WG at 100 grams per hectare. This treatment protocol, based on the research by [6], has proven effective in reducing Yellow Mosaic's impact. The system's ability to offer specific treatment guidance demonstrates its potential to streamline farmers' decision-making processes, potentially reducing crop losses and improving yields.

The accuracy in detecting Yellow Mosaic is particularly significant, as this disease can spread quickly if not addressed, leading to reduced plant growth and productivity. By providing early detection and targeted treatment recommendations, the system helps prevent the spread of the disease, promoting healthier crops and reducing the need for broader pesticide application.

Bacteria Pustule Detection

Bacteria Pustule, another condition identified by the system, is caused by bacterial infection, leading to small pustules on the soybean leaf surface, as seen in Figure 6. This condition can weaken the plant, impacting its overall health and yield. The system recommended using Biofresh in a solid formulation combined with compost derived from soybean litter. This treatment recommendation, based on [13], not only targets the bacterial infection but also promotes sustainable practices through the use of compost.

The model's ability to accurately detect Bacteria Pustule is critical, as this disease can spread through water splash and contact, leading to outbreaks in large areas. By identifying the disease early and recommending an effective treatment, the system helps farmers take timely action, reducing the risk of further contamination and promoting a more sustainable approach to disease management.

Frogeye Leaf Spot Detection

Figure 7 elucidate a Frogeye Leaf Spot, caused by a fungal infection, presents as small circular spots on the soybean leaves, often with a dark margin and lighter center. The system's detection of this condition is noteworthy, given the visual similarities to other fungal diseases. The recommended treatments for disease is

Group 3 (Prothioconazole), Group 11 (Trifloxystrobin), or Group 7 (Fluopyram), are based on [24], providing farmers with a choice of fungicides that have been proven to be effective against Frogeye Leaf Spot.
The specificity of the recommendations demonstrates the system's potential to guide farmers toward targeted fungicide applications, which can reduce unnecessary pesticide use and lower costs. Accurate detection of Frogeye Leaf Spot also helps prevent the spread of the fungus to other plants, maintaining overall crop health and yield.

Healthy Leaf Detection

The detection of healthy soybean leaves by the system plays an important role in reassuring farmers about the state of their crops. By indicating that no immediate treatment is necessary, the system helps reduce the risk of unnecessary pesticide use, promoting a more sustainable approach to agriculture. This capability is essential in reducing farming costs and environmental impact while ensuring crops remain healthy, this is elucidated in Figure 8.

Implications for Agricultural Practices

The successful detection of these distinct leaf conditions, coupled with specific treatment recommendations, suggests that machine learning-based systems can significantly benefit agricultural practices. By providing early detection and targeted treatment guidance, farmers can take proactive measures to manage crop health, reducing the risk of widespread disease and promoting higher yields. Moreover, the system's ability to offer recommendations based on established research ensures that farmers are adopting best practices, contributing to sustainable agriculture.

Future iterations of the system could expand the range of detectable diseases, integrate real-time monitoring, and incorporate additional environmental factors such as temperature and humidity. This would further enhance the system's effectiveness, providing farmers with a comprehensive tool for managing crop health and improving agricultural outcomes.

VI CONCLUSION

The development and testing of the Smart System Leaf Disease Detection Using Machine Learning indicated that machine learning technologies could play a significant role in modern agriculture. The system's high accuracy in detecting soybean leaf diseases suggests that it can serve as a valuable tool for farmers, allowing them to take early action to prevent the spread of diseases. Additionally, by recommending specific treatments based on established research, the system promotes best practices in agricultural management.

The study's successful results highlight the potential for broader application of machine learning in agriculture. The system's capability to accurately distinguish between different soybean leaf conditions and recommend appropriate treatments suggests a pathway toward smarter, data-driven farming practices. This can lead to increased crop yields, reduced pesticide use, and a more sustainable approach to farming.

VII. RECOMMENDATIONS

Based on the results and conclusion of this research, the following recommendations are made:

i. **Integration with Agricultural Systems**: The system should be integrated with existing agricultural systems to facilitate real-time monitoring and data analysis. This could involve incorporating IoT devices, drones, or other sensors to collect real-time data from fields.

ii. **User-Friendly Interface**: To ensure wide adoption, the system should have a user-friendly interface that allows farmers to easily input data and receive recommendations. This could involve developing a mobile application or web-based platform for accessibility.

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REFERENCES

[1] Barbedo, G. C. A. (2013).Digital image processing techniques for detecting quantifying and classifying plant diseases. Springer Plus 2013, 2, 660.

[2]. Cen, H. Y., Zhu, Y. M., Sun, D. W., Zhai, L., Wan, L., and Ma, Z. H. (2020). Current status and future perspective of the application of deep learning in plant phenotype research. Trans. Chin. Soc. Agric. Eng. (Trans. CSAE). 36, 1–16. doi: 10.11975/j.issn.1002-6819.2020.09.001

[3]. Chang, K. F., Hwang, S. F., and Ahmed, H. U. (2018). Disease reaction to Rhizoctoniasolaniand yield losses in soybean. Can. J. Plant Sci. 98, 115–124. doi: 10.1139/cjps-2017-0053

[4]. Fuang, N. H., Khoon, T. H., Chih-Yang, L., Hang., L. K. & Huang, C. J. (2021). Plant Disease Detection Mobile Application Development using Deep Learning. International Conference on Computer & Information Sciences (ICCOINS).

DOI:10.1109/ICCOINS49721.2021.9497190
[5]. Gao, Q.J., Li, C.B., Jin, X., Li, Y.Y., & Wu, H.P. (2021). Research on the traceability system of tea quality and safety based on blockchain. J. Anhui Agric. Univ. 48, 668–673. doi: 10.13610/j.cnki.1672-352x.20210824.002
[6]. Gehlot, J., Gupta, K. N., kumar, S., Jain, A., Chouksey, V., Mohit and Parmar, R. (2023). Managing the insect vector and soybean yellow mosaic virus can be achieved through the utilization of different insecticides and resistant cultivars. The Pharma Innovation Journal 2023; 12(10): 370-374
[7]. Guo, D., Zhang, H., Yang, J. T., Yu, L. Y., Wu, B. J., Li, M. M., et al. (2021). Occurrence status and green control counter measure for diseases and insect pests of soybeans in Shandong Province. Soybean Sci. Technol. 4, 27–30. doi: 10.3969/j.issn.1674-3547.2021.04.006
[8]. Han, B., and Zeng, S. W. (2021). Plant leaf image recognition based on multi-feature integration and convolutional neural network. Comput. Sci. 48, 113–117. doi: 10.11896/jsjkx.201100119
[9]. Harvey, C., Rakotobe, Z., Rao, N., Dave, R. &Razafimahatratra, H. (2014). Extreme vulnerability of small holder farmers to agricultural risks and climate change in Madagascar.Philosophical Trans. of the Royal Society B: Biological Sciences, vol. 369: 20130089.
[10]. He, X., Li, S. Q., and Liu, B. (2021). Identification of grape leaf diseases based on multi-scale residual neural network. Comput. Eng. 47, 285–291. doi: 10.19678/j.issn.1000-3428.0057818
[11]. Kanjalkar, H. P. &Lokhande, S. (2013). Detection and Classification of Plant LeafDiseases using ANN. International Journal of Scientific & Engineering Research, ISSN: 2229 5518.
[12]. Kannojia, S. P., and Jaiswal, G. (2018). Effects of varying resolution on performance of CNN based image classification an experimental study. Int. J. Comp. Sci. Eng. 6, 451–456. doi: 10.26438/ijcse/v6i9.451456
[13]. Khaeruni, A., Johan, E. A. Wijayanto, T., Taufik, M. Syafar, A. A. R. and Sutariati, G. A. K. (2018). Induction of soybean resistance to bacterial pustule disease (Xanthomonasaxonopodispv. glycines) by rhizobacteria and organic material treatment. International Conference on Agriculture, Environment, and Food Security IOP Publishing IOP Conf. Series: Earth and Environmental Science 122 (2018) 012052 doi :10.1088/1755-1315/122/1/012052
[14]. Khirade, S. &Patil, A. B. (2015). Plant Disease Detection Using Image Processing. IEEE, International Conference on Computing Communication Control and Automation, Pune, pp 768-771. https://doi.org/10.1109/ICCUBEA.2015.153
[15]. Krizhevsky, A., Sutskever, I. & Hinton, G. E. (2017). Imagenet classification with deep convolutional neural networks. Commun. ACM, vol. 60, pp. 84–90.
[16]. Lei, X., Pan, H., and Huang, X. (2019). A dilated CNN model for image classification. IEEE Access. 99, 1. doi: 10.1109/ACCESS.2019.2927169
[17]. Li, L. P., Shi, F. P., Tian, W. B., and Chen, L. (2021). Wild plant image recognition method based on residual network and transfer learning. Radio Eng. 51, 857–863. doi: 10.3969/j.issn.1003-3106.2021.09.003
[18]. Liang, Y., Li, B. B., and Jiao, B. (2019). Research and implementation of CNN Based on TensorFlow.IOP Conf. Ser. Mater. Sci. Eng. 490, 558–564. doi: 10.1088/1757-899X/490/4/042022
[19]. Ma, Y., Shan, Y. G., and Yuan, J. (2021). Tomato leaf disease recognition based on three-channel attention network. Sci. Technol. Eng. 21, 10789–10795. doi: 10.3969/j.issn.1671-1815.2021.25.031
[20]. Miller, S. A., Beed, F. D., & Harmon, C. L. (2009). Plant disease diagnostic capabilities and networks. Annu. Rev. Phytopathol. 47, 15–38.
[21]. Mohanty, S. P., Hughes, D. P. &Salathé, M. (2016).Using Deep Learning for Image-Based Plant Disease Detection. Front. Plant Sci. 2016, 7, 346.
[22]. Petrellis, N. (2017). Mobile Application for Plant Disease Classification Based on Symptom Signatures. PCI 2017: Proceedings of the 21st Pan-Hellenic Conference on Informatics, 1–6 https://doi.org/10.1145/3139367.3139368
[23]. Rajput, A. S., Shukla, S. & Thakur, S. S. (2020). Soybean Leaf Diseases Detection and Classification Using Recent Image Processing Techniques.International Journal of Students' Research in Technology & Management, 8(3): 01-08 https://doi.org/10.18510/ijsrtm.2020.831
[24]. Reese, M. (2020). Will fungicide resistant frogeye be an issue for Ohio in 2020? Retrieved from: https://ocj.com/2020/02/will-fungicide-resistant-frogeye-be-an-issue-for-ohio-in-2020/
[25]. Savary, S., Ficke, A., Aubertot, J. N. &Hollier, C. (2012). Crop losses due to diseases and their implications for global food production losses and food security. Food Security, 4(4): 519-537,
[26]. Shang, Y. H., Yu, Y. J., and Wu, G. (2021). Plant diseases recognition based on mixed attention mechanism. J. Tarim Univ. 33, 94–103. doi: 10.3969/j.issn.1009-0568.2021.02.013
[27]. Simonyan, K. & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. International Conference on Learning Representations (ICLR).
[28]. Singh, A., Ganapathysubramanian, B., and Singh, A. K. (2016). Machine learning for high-throughput stress phenotyping in plants. Trends Plant Sci. 21, 110–124. doi: 10.1016/j.tplants.2015.10.015
[29]. Sun, Y. Y., Zhao, L. M., Zhang, W., and Zhang, C. B. (2021). Research progression utilization of soybean heterosis. Soybean Sci. Technol. 6, 26–35. doi: 10.3969/j.issn.1674-3547.2021.06.006
[30]. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. &Rabinovich, A. (2015). Going deeper with convolutions," In CVPR, 2015.
[31]. Wang, C. S., Zhou, J., Wu, H. R., Teng, G. F., Zhao, C. J., and Li, J. X. (2020). Identification of vegetable leaf diseases based on improved Multi- scale ResNet. Trans. Chin. Soc. Agric. Eng. (Trans. CSAE). 36, 209–217. doi: 10.11975/j.issn.1002-6819.2020.20.025
[32]. Wang, X. Y., Zhang, C., and Zhang, L. (2021). Recognition of similar rose based on convolution neural network. J. Anhui Agric. Univ. 48, 504–510. doi: 10.13610/j.cnki.1672-352x.20210628.001
[33]. Xu, Y., Li, X. Z., Wu, Z. H., Gao, Z., and Liu, L. (2021). Potato leaf disease recognition via residual attention network. J. Shandong Univ. Sci. Technol. (Natl. Sci). 40, 76–83. doi: 10.16452/j.cnki.sdkjzk.2021.02.009
[34]. Zhang, S., &Huai, Y. J. (2016). Leaf image recognition based on layered convolutions neural network deep learning. J. Beijing Forest. Univ. 38, 108-115. doi: 10.13332/j.1000-1522.20160035