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Botanic Shield: A Deep Learning Solution for Early Detection of Plant Disease

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Abstract: Plant diseases threaten both food security and the botanical system of the environment which canlead to low- grade food quality and life style. Early detection of plants diseases is the key feature in plantproduction which increase the better growth of plant, results in best yield and better food quality andquantity. The plant condition can be determined by using the photos of the plant which will be in the formof jpg using digital image processing and the current emerging technology Deep Learning. DeepLearning has made breakthroughs in the field of digital image processing, far superior to traditional methods. The Digital image processing process happens through convolution neural network (CNN) and computer vision techniques, the image recognition technology based on deep learning does not need to extract specificfeatures, and only through iterative learning can find appropriate features, which can acquire global andcontextual features of images, and has strong robustness and higher recognition accuracy. By inputting a test image into the classification network, the network analyses the input image and returns a label that classifies the image. The added feature is thatit also suggeststhe required pesticides after the detection
Keywords: Plant disease Detection, Digital imageprocessing, Deep learning, Convolutional neural network (CNN), Computervision Pesticide recommendations, Ag riculture automation, Image recognition.

I. INTRODUCTION

The global agricultural landscape faces a persistent threat from plant diseases, jeopardizingboth food security and environmental stability. With the potential to degrade food quality and compromise crop yields, the timely detection and management of these diseases are imperative for sustainable agricultural practices. Traditional methods of diseaseidentification often fall short in terms of accuracy andefficiency, necessitating innovative approaches to address this critical issue.

In recent years, significant strides have been madein the realm of plant disease detection through the convergence of digital image processing and deep learning technologies. Leveraging the power of convolutional neural networks (CNNs) and computer vision techniques, these advancements have revolutionized the field by offering unparalleled precision and reliability in disease diagnosis.

II. LITERATURE REVIEW

In India about 70% of the populace relies on agriculture. Identification of the plant diseases is important in order to prevent the losses within the yield. It's terribly troublesome to observe the plant diseasesmanually [6]. Farmers require continuous monitoring of experts which might be prohibitively expensive and time consuming [3] Detection of plant disease has a crucial role in better understanding the economy of India in terms of agricultural productivity [1]. Researchers have proposed several techniques to accurately detect and classify plant infections. Some use traditional image processing techniques that incorporate hand-crafted—that is, manual—feature extraction and segmentation [2]. Garima Shrestha et Al. deployed the convolutional neural network to detect the plant disease [5]. With the advent of machine learning and deep learning techniques, the progress made in plant disease recognition has been enormous and represents a massivebreakthrough in research. This has made it easy for automatic classification and feature extraction to express the original characteristics of an image. Furthermore, the availability of datasets, GPUmachines, and software supporting complex deeplearning architectures with lower complexity has made it feasible to switch from traditional methods to the deep-learning platform. In recent times, convolutionneural networks(CNNs) have gained wide attention for their recognition and classification abilities, which work by extracting low-level complex features from images. Hence, CNNs are preferred for the replacement of traditional methods in automated plant disease recognition as they achieve better outcomes [1]. A CNN-based predictive model has been proposed bySharma et al. The analysis of the methodology of the proposed work has been presented using images inFigure 1. Image datasets are collected from the rice dataset [5] and the Kaggle plant village dataset [6].

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These images go through preprocessing called filtering.After the pre-processing step, Deep and machine learning on plant diseases 493 different texture and colorfeatures are collected. The features obtained are fed as an input in DL to correctly classify the disease of a givenplan [2]. . The performance of the work can be updatedby large datasets.[1]

III. PROBLEM STATEMENT

The main difficulties in agriculture field such as difficulty of early detection, reliance on labor- intensive manual inspection methods, losses in crop yield and quality, limited access to resources for farmers, environmental concerns related to pesticide use, the complexity of disease dynamics, and the needfor scalable and cost-effective solutions. By addressing these challenges, such as deep learning systems for detections and best user-friendly site canhelp improve agricultural productivity, reduce environmental impact, and promote sustainable farming practices

IV. METHODOLOGY

To address the challenges outlined in the problem statement, a comprehensive methodology integrating multiple components is proposed:

1) *Data Collection and Annotation:* Acquire high-resolution images of diseased and healthy plant samples across various crop species and environmental conditions. Annotate the images with ground truth labels indicating the presence and type of disease, as well ascontextual information such as location, weather conditions, and agronomic practices.
2) *Dataset Curation and Augmentation:* Curate a diverse dataset comprising annotated images representative of different crop diseases and environmental factors. Augment the dataset using techniques such as image rotation, flipping, and scaling to enhance model robustness and generalization capabilities.
3) *Model Development:* Design and implement deep learning-based models, such as convolutional neural networks (CNNs), tailored for plant disease detection. Explore state-of-the-art architectures and techniques for feature extraction, including transfer learning from pretrained models to leverage knowledge from related domains. Train the models using the curated dataset, optimizing hyperparameters and regularization techniques to minimize overfitting and maximize classification performance.
4) *Evaluation and Validation:* Evaluate the trained models using metrics such as accuracy, precision, recall, and F1- score on independenttest datasets. Validate the models under real-world conditions by deploying them in field trials and comparing their performance against traditional disease diagnosis methods. Assess the robustness and reliability of the models acrossdifferent crop species, geographical regions, and environmental variations.
5) *Integration with Decision Support Systems:* Develop decision support systems (DSS) capable ofintegrating disease detection models with agronomic knowledge and environmental data. Incorporate algorithms for pesticide recommendation based on disease severity, crop susceptibility, andecological considerations. Validate the efficacy of the DSS through simulationsand field trials, ensuring alignment with sustainable agricultural practices and socio-economicconstraints.
6) *Deployment and Adoption:* Deploy the developed models and decision support systems through user-friendly interfaces accessible to farmers, agronomists, and agricultural extension workers. Provide training and capacity-building programs to facilitate the adoption of the technology and promoteits integration into existing agricultural workflows. Monitor and evaluate the impact of the deployed solutions on crop productivity, disease management practices, and environmental sustainability metrics.
7) *Continuous Improvement and Iteration:* Continuously refine and optimize the models and decision support systems based on feedback from end- users and stakeholders. Incorporate new data sources, sensor technologies, and machine learning techniques to enhance the performance and scalability of the solutions overtime. Foster collaboration and knowledge-sharing within the research community to drive innovation and accelerate the adoption of best practices in plant disease detection and management. By following this methodology, it is envisaged that significant strides can be made towards overcoming the challenges associated with plant disease detectionand management, ultimately contributing to enhancedagricultural productivity, food security, and environmental sustainability.

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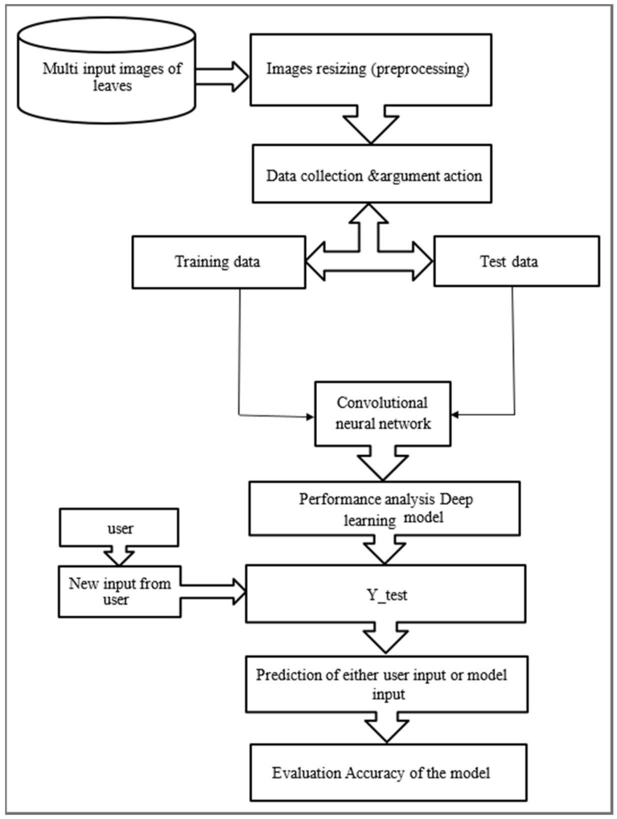
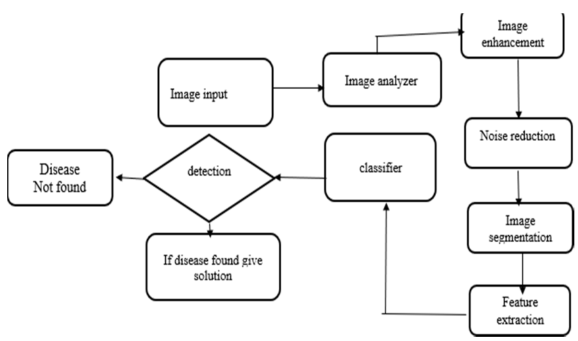
V. ARCHITECTURE

The Architecture includes both model training usingimages, building website and taking input from the user.This kind of architecture helps to implement the deep learning solution in real time.



VI. ER DIAGRAM



The E-R diagram for a plant disease prediction system would typically include image analyzer image enhancement, image segmentation, feature extraction,classifier and detection.

The datasets contain the images classified according to their plant health in different folders and these folders areused accordingly to train the CNN.

VII. EXPERIMENTAL RESULTS

In our experimental evaluation of Botanic Shield, weconducted extensive testing to assess its performance in detecting plant diseases across various crops andenvironmental conditions. We utilized a diverse dataset consisting of thousands of high-resolution images representing a wide range of plant species and disease types.The results of our experiments demonstrate the efficacy of Botanic Shield in accurately identifying plant diseases with a high degree of precision and recall.

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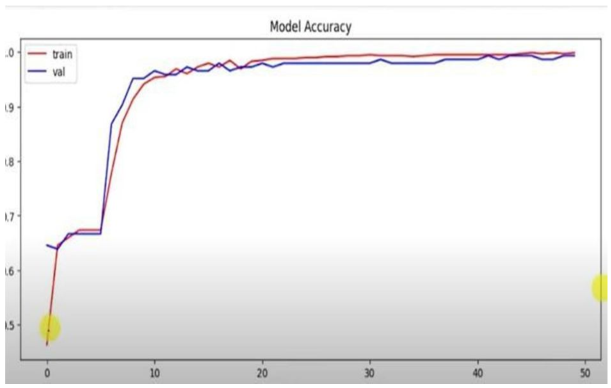
A. Model Implementation and Training

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 256, 256, 32)      896

 max_pooling2d (MaxPooling2  (None, 85, 85, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 85, 85, 16)        4624

 max_pooling2d_1 (MaxPoolin  (None, 42, 42, 16)        0
 g2D)

 flatten (Flatten)           (None, 28224)             0

 dense (Dense)               (None, 8)                 225800

 dense_1 (Dense)             (None, 3)                 27

=================================================================
Total params: 231347 (903.70 KB)
Trainable params: 231347 (903.70 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

B. Model Accuracy



C. GUI'S Development

```
Anaconda Prompt - streamlit

(base) C:\Users\akankshaonteddu>cd "C:\ADPROJECT\StreamlitAPP"

(base) C:\ADPROJECT\StreamlitAPP>streamlit run "C:\ADPROJECT\StreamlitAPP\main_app.py"

  You can now view your Streamlit app in your browser.

  Local URL: http://localhost:8501
  Network URL: http://182.182.191.120:8501

2024-05-02 11:54:09.545534: I tensorflow/core/util/port.cc:113] oneDNN custom operations a
fferent numerical results due to floating-point round-off errors from different computatio
t the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
```

VIII. CONCLUSION

In conclusion, Botanic Shield represents a significantadvancement in the field of agriculture through theapplication of deep learning technology for early detection of plant diseases. Throughout the course of this project, we have successfully developed and implemented a robust deep learning solution capable ofanalyzing images of plants to identify signs of disease or stress with high accuracy.

Our research and development efforts have demonstratedthe effectiveness of Botanic Shield in detecting plant diseases at an early stage, enabling farmers to take proactive measures to mitigate the spread of disease andminimize crop losses. By harnessing the power of deep learning algorithms, Botanic Shield has the potential to revolutionize crop management practices, leading to more sustainable and resilient agricultural systems.

IX. FUTURE WORK

1) *Enhanced Dataset Collection:* Expand the dataset used for training Botanic Shield to include a broader range of plant species, disease types, and environmental conditions. This will improve the model's ability to generalize across diverse agricultural settings.
2) *Real-Time Deployment:* Develop methods for deploying Botanic Shield in real-time agricultural settings, such as on drones or automated monitoring systems. This will require optimizing the model for efficient inference and integrating it with hardware platforms capable of capturing and processing image data in the field.
3) *Multi-Spectral Imaging:* Explore the use of multi- spectral or hyperspectral imaging techniques to capture additional information about plant health beyond visible light. Integrating these data modalities into Botanic Shield could enhance its ability to detectsubtle signs of disease or stress that may not be visibleto the naked eye

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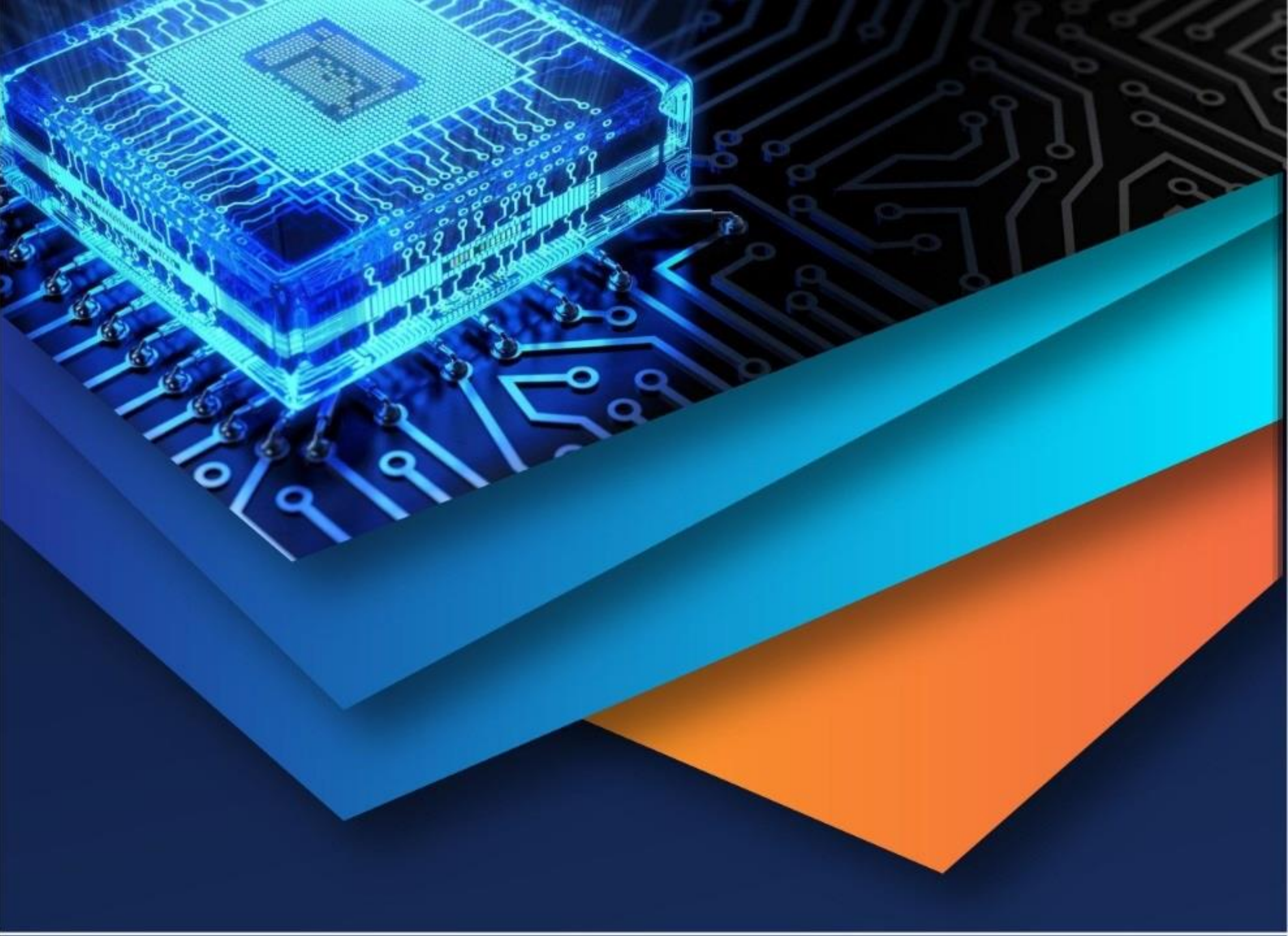

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