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Plant Doctor: The Messiah for New-Age Farmers

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Abstract: Agriculture plays a major role in developing countries; however, food security remains a vital issue. Most crops get wasted due to a lack of storage facilities, transportation, and diseases. More than 15% of the crops get wasted in India due to diseases, hence it has become one of the major concerns to be resolved. There is a need for an automaticsystem that can identify these diseases and help farmers take appropriate steps to get rid of crop loss. Farmers have followedthe conventional method of identifying plant diseases with their naked eyes, and all farmers can't identify these diseases the sameway. With the advances in AI, there is a need to incorporate the facilities of computer vision in the field of agriculture. Deep Learning rich libraries and user as well as developer-friendly environment to work with, all these qualities make Deep Learning the favourable method to get started with this problem.

Abbreviations--
AI Artificial Intelligence
ANN Artificial Neural Networks CNN Convolutional Neural NetworkDP Disease Prediction
DT Decision Trees IoT Internet of ThingsIP Image Processing ML Machine Learning
RCNN Regions with convolutional neural networkDL Deep learning
KNN K-Nearest Neighbors PDD Plant Disease Detection PDI Plant Disease IdentificationPVD Plant Village Dataset
RAN Residual Attention NetworkRF Random Forest
SVM Support Vector MachinesTF Transfer Learning
WHO World Health OrganizationXGB Extreme gradient boosting VGG visual geometry group P2O2 Plant Pathology on Palms
GAN Generative Adversarial NetworkRESNET Residual Neural Network
ICSCDS International Conference on Sustainable Computing andData Communication Systems
INCET International Conference for Emerging Technology
ICOEI International Conference on Trends in Electronics andInformatics
ICACCS9th International Conference on Advanced Computing andCommunication Systems
SCEECS International Students' Conference on Electrical,Electronics and Computer Science
ICSCCC International Conference on Secure Cyber Computing andCommunications

I. INTRODUCTION

"In the continuously evolving field of agro-technology, the integration of plant disease identification, soil assessment, and weather prediction emerges as a fundamental frontier. Theharmonious synergy between these domains holds the promise of transforming the agricultural sector profoundly. In this era of precision agriculture, where data-driven decisions steer the course of farming practices, the integration of plant disease detection with soil and weather parameters heralds a new era of innovation.

As the global population burges, ensuring food security becomes not just a challenge but an imperative. Plant diseases, often exacerbatedby specific soil conditions and weather patterns, pose significant threats to crop yield and food production. Addressing this challengenecessitates a holistic approach, one that marries cutting-edge technology with the nuances of agricultural ecosystems.

In this context, the development and implementation of a comprehensive 'Plant Disease Detection System based on Weather and Soil' stand as a beacon of scientific advancement. Using machine learning, sensor technologies, and meteorological insights, this system aims to provide real-time, context-aware solutions to farmers. Understanding the intricate interplay between soil health, weather dynamics, and the onset of plant diseases, this innovative system not only identifies potential threats but also empowers farmers with actionable insights.

This introduction delves into the core of a pioneering research endeavour, underscoring the urgency and significance of integrating soil and weather data into the realm of plant disease detection. By illuminating the path toward a sustainable and resilient agricultural future, this research endeavour charts new territories in the domain of precision agriculture. Through this technical paper, we invite readers to embark on a journey where technology meets agriculture, shaping a future where data-driven decisions cultivate abundance amidst challenges."

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There are a variety of methods that can be used for leaf detection. One common approach is to use color-based segmentation. This involves identifying pixels in the image that are within a certain range of colors that are typical of leaves. Another approach is to use texture-based segmentation. This involves identifying pixels in the image that have a similar texture to that of leaves.

Once the leaf pixels have been identified, they can be grouped together into individual leaves using various clustering algorithms. Once the leaves have been grouped, their bounding boxes can be estimated using a variety of methods, such as convex hulls or minimum bounding rectangles.

Leaf detection is an important task in many computer vision applications. It has the potential to improve the efficiency and accuracy of a variety of agricultural and environmental monitoring tasks.

Plant disease detection using soil and climate data has several potential applications in agriculture, including Precision agriculture: Plant disease detection can be used to guide precision agriculture practices, such as targeted pesticide application and irrigation. Thiscan help to reduce the use of pesticides and improve the efficiency of water use. Crop yield forecasting: Plant disease detection can be used to improve crop yield forecasting by providing early warning of potential disease outbreaks.

This information can also be used by farmers to make informed decisions about crop management and marketing. Pest and disease management: Plant disease detection can be used to develop more effective pest and disease management strategies. For example, predictive models of plant disease risk can be used to identify areaswhere targeted surveillance and control measures are needed.

One of the key advantages of plant disease detection using soil and climate data is that it is non-invasive. This means that it does not require direct contact with the plants, which can be particularly beneficial for monitoring large areas of land or crops in difficult-to-access areas. Additionally, soil and climate data can be collected continuously, providing real-time information on the health of the plants. This allows for the early detection of diseases, which can help to minimize crop losses. Another advantage of plant disease detection using soil and climate data is that it can be used to developpredictive models of plant disease risk. This information can then beused to target preventive measures to areas where the risk of diseaseis highest. For example, farmers can use this information to adjust their irrigation practices or to apply pesticides more precisely.

Plant disease detection using soil and climate data is still in its earlystages of development, but it has the potential to revolutionize the way that plant diseases are managed. By providing early and accurate detection of diseases, this technology can help to reduce crop losses and improve food security.

It is crucial for detecting plant diseases early to curb the use of dangerous agronomic chemicals meant to induce crop growth and protect plants. Example, use of IoT techniques for plant health status diagnosis in a few cases and recent AI methods such as deep/machine learning and IP oriented in a few others. In recent days, several ways of appreciating AI applied in agriculture have been demonstrated, such as DL techniques useful in designingadvanced AI models for detecting plant diseases. However, there are problems of using AI methodology for plant infection diagnostics ofnatural environment. To trace and identify diseases, drones are deployed to detect plant health. Thus, despite their autonomous character, the use of these semi- or autonomous aircraft offers stronger vision techniques applicable to a variety of crops, rather than using regular digital cameras.

The study presents an extensive review of the latest disease recognition and PDD methods emphasizing the mostly utilized AI (ML and DL) and IP algorithm for disease recognition. It also critically analyses their weaknesses, advantages, and major peculiarities when applied in practice. This review analyzed a total of 1349 papers retrieved through a search in five prominent academic research sources including Springer, IEEE Xplore, Scopus, Google Scholar, and ACM. The key- words searched, are “Disease Classification”, “Disease Identification”, “Crop disease Detection”, “PDD”, “ML”, “DL” and “IP”. Based on the importanceof the latest reports conducted, and regarding their prominence.

II. LITERATURE SURVEY

‘Wasswa Shafik, Ali Tufail, and Abdallah Namoun’ are the authors of the paper titled "A Systematic Literature Review on Plant DiseaseDetection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends” They say that “plant diseases have a global effect on plant production. Therefore, farmers are supposed to attain expert knowledge and thorough training to distinguish early plant pests or viral symptoms and take appropriate action to prevent disease continuity. PDD control can help economic development by reducing hunger and saving the environment through reduced chemical fertilizer utilization. Environmental factors primarily cause plant diseases, and pathogens (like bacteria, worms, viruses, fungi, and protozoa) are defined as diseases in plant pathology. Several plant diseases commonly occur because of a variety of factors. For instance, depending on its nature, soil, seed, or air type, it can be caused by a pandemic, epidemic, or endemic. Other factorsinclude symptoms and significant causes such as blight, rots, and viruses, as shown in Fig. 1.

Early symptoms are essential in PDD because conventional traits for identifying in-field diseases are based on several factors, including the type of disease, its colour, pattern, appearance, and location on the plant. These symptoms on various sections of plants, like the stems, fruits, and leaves, among others, are primarily utilized in PDD. Farmers and agricultural experts use traditional surveillance to identify disease categories. High-tech agricultural systems that use vision-based learning approaches for PDD can effectively increase crop yields. There has been an improvement in efficiency in identifying plant diseases using AI for early diagnosis and smart inspection automation. Few valid case studies in third-world countries use automatic approaches in agriculture. Despite the contributions of the remarkable endeavours available, a few factors continue to make real-time PDD complex. The main objective of this review is to present techniques, available datasets, and challenges in plant disease detection that need to be addressed to develop comprehensive, intelligent agricultural methods for monitoring and diagnosing early plant detection." [1]

'Emmanuel Moupojou, Appolinaire Tagne, Florent Retraint, Anicet Tadonkemwa, Dongmo Wilfried, Hyppolite Tapamo, Marcellin Nkenl' are the authors of the paper titled "FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning" they say that "The "FieldPlant" dataset is a collection of images designed to enhance plant disease detection and classification using deep learning techniques. Captured from real agricultural fields, the dataset reflects diverse environmental conditions and contains images of various plant species afflicted with different diseases. Each image is annotated with accurate disease and plant species information, enabling effective model training and evaluation. With its emphasis on real-world scenarios and robust annotations, the "FieldPlant" dataset serves as a valuable resource for researchers and developers working on AI-driven solutions for plant disease detection, fostering advancements in agricultural technology and crop health management." [2]

'Md. Sakib Hossain Shovon, Shakrin Jahan Mozumder, and Osim Kumar Pal' are the authors of the paper titled "PlantDet: A Robust Multi-Model Ensemble Method Based on Deep Learning For Plant Disease Detection" They say that "The paper "PlantDet: A Robust Multi-Model Ensemble Method Based on Deep Learning For Plant Disease Detection" introduces a novel approach to enhance plant disease detection accuracy. The method, called "PlantDet," combines multiple deep learning models in an ensemble, addressing the limitations of individual models. The process begins with dataset collection and preprocessing, followed by training diverse deep learning models like ResNet, Inception, and EfficientNet as base classifiers. The ensemble aggregates predictions using techniques like majority voting, resulting in improved robustness and accuracy.

Techniques like data augmentation and fine-tuning enhance generalization. Evaluation metrics like accuracy and F1-score are used for performance assessment. The paper highlights "PlantDet" as a significant advancement in plant disease detection, demonstrating its potential for agricultural technology and sustainable crop management." [3]

'Mayank Agarwal, Ashish Kotecha, Atharva Deolalikar, Ritika Kalia, Ram Kumar Yadav, and Achamma Thomas' are the authors of the paper titled "Deep Learning Approaches for Plant Disease Detection" They say that "The paper "Deep Learning Approaches for Plant Disease Detection: A Comparative Review" presents a comprehensive analysis of various deep learning methods employed in plant disease detection. By systematically reviewing a diverse range of research papers, the study examines the efficacy of techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in identifying plant diseases. The paper meticulously compares their performance metrics, accuracy, and suitability across different datasets and disease types. The review serves as a valuable resource for researchers and practitioners by highlighting the strengths and limitations of each approach, offering insights into the most effective strategies for advancing plant disease detection using deep learning techniques." [4]

'Md. Ali–Al–Alvy, Golam Kibria Khan, Mohammad Jahangir Alam, Saiful Islam, Mokhlesur Rahman, and Mirza Shahriyar Rahman' are the authors of the paper titled "Rose Plant Disease Detection using Deep Learning" They say that "The paper "Rose Plant Disease Detection using Deep Learning" presents an innovative approach to identifying diseases in rose plants through the application of deep learning techniques. The study begins by collecting and preparing a dataset of images depicting various diseases affecting rose plants. Deep learning models, particularly convolutional neural networks (CNNs), are chosen for their image recognition capabilities. These models undergo training on the prepared dataset to learn distinctive features associated with different types of diseases. The trained models are then evaluated using standard performance metrics to assess their accuracy and effectiveness. The results indicate that the deep learning approach shows promise in accurately detecting diseases in rose plants. This research contributes to the field of agricultural technology by offering an automated and efficient method for disease identification, potentially aiding in the preservation of rose plant health and crop management." [5]

'P. Maragathavalli, and S. Jana' are the authors of the paper titled "A Review Of Plant Disease Detection Methods Using Image Processing Approaches" they say that "The paper titled "A Review Of Plant Disease Detection Methods Using Image Processing Approaches" provides an insightful overview of diverse techniques for plant disease detection through image processing. By systematically analyzing a range of research articles, the review covers methods including segmentation, feature extraction, and classification.

It evaluates their strengths and limitations, considering factors like accuracy and adaptability to various plant diseases and species. The paper's goal is to offer a comprehensive understanding of image processing's role in plant disease detection,laying a foundation for potential hybrid approaches and technological advancements to enhance crop health management.” [6]

‘V. Ebenezer, Arsha Anna Daniel, P. Getzi Jeba Lillipushpam, E.Bijolin Edwin, M. Roshni Thanka, Rosebel Devassy’ are the authors of the paper titled “Classification and Segmentation of Leaf Images based on Deep Learning for Peanut Plant Disease Detection” they say that “The paper "Classification and Segmentation of Leaf Images based on Deep Learning for Peanut Plant Disease Detection"presents an advanced approach to identifying and segmenting diseases in peanut plant leaves using deep learning. The study begins with collecting a diverse dataset of peanut plant leaf images and annotating disease labels. Deep learning models, particularly convolutional neural networks (CNNs), are selected for classification and segmentation tasks. The models are trained, utilizing techniques like transfer learning and data augmentation to enhance performance. The paper evaluates the models' accuracy andprecision metrics and explores hybrid approaches combining both classification and segmentation tasks. The research provides a comprehensive method for accurate peanut plant disease detection, with implications for improving crop management and disease prevention strategies.” [7]

‘R Jeevanantham, D Vignesh, Rahman A Abdul, Angeljulie J’ are the authors of the paper titled “Deep Learning Based Plant DiseasesMonitoring and Detection System” They say that “The paper titled "Deep Learning Based Plant Diseases Monitoring and Detection System" introduces an innovative approach to plant disease management. By harnessing the power of deep learning, the system employs convolutional neural networks (CNNs) to analyze plant images and accurately identify disease symptoms. The study emphasizes the importance of dataset preparation, model selection, and hyperparameter tuning to optimize model performance. The proposed system integrates real-time image capture with the trainedmodels, allowing for timely disease detection. This synergy oftechnology and agriculture offers a practical solution for earlydisease identification and prevention, contributing to improved cropyield and sustainable farming practices.” [8]

‘Muhammad Hammad Saleem, Johan Potgieter, and Khalid Mahmood Arif’ are the authors of the paper titled “A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand” They say that “The paper presents a performance-optimized deep learning approach for detecting plant diseases in horticultural crops specific to New Zealand. The study focuses on creating an effective model by curating a diverse dataset of healthy and diseased crop images. Leveraging deep learning techniques, a pre-trained model is fine- tuned to suit the unique disease patterns of New Zealand's crops. The methodology emphasizes data preprocessing, hyperparameter tuning, and post-processing techniques such as classification thresholding and non-maximum suppression. The model's performance is rigorously evaluated, showcasing its accuracy and robustness. The research highlights the potential for real-worlddeployment, providing valuable insights for sustainable agriculture in New Zealand through reliable disease detection andmanagement.” [9]

‘Shalinee Pareek, Awanit Kumar, and Sheshang Degadwala’ are the authors of the paper titled “Machine Learning & Internet of Things in Plant Disease Detection: A Comprehensive Review” They say that “The paper provides a comprehensive review of the synergisticapplication of Machine Learning (ML) and Internet of Things (IoT)in plant disease detection. It covers the integration of IoT devices for data collection, preprocessing, and the utilization of various ML algorithms for accurate disease identification and prediction. The review highlights the potential of this combined approach in achieving real-time monitoring and automated decision-making in agriculture. It also discusses challenges and suggests future directions for research, pointing toward a promising future forimproving plant disease management through advanced technologyintegration.” [10]

‘Biswajit Biswal, and Simien Chestnut’ are the authors of the paper titled “DeepTrac: Applying Artificial Intelligence in Plant Disease Detection” They say that “The paper presents "DeepTrac," an innovative approach applying Artificial Intelligence (AI) to plant disease detection. It outlines a methodology involving dataset collection, preprocessing, model selection, transfer learning, and performance optimization. The study highlights the potential of AI, particularly deep learning, in accurately identifying plant diseases. The paper emphasizes model validation, deployment, and continuous improvement through user feedback. The future scope involves advancements in AI techniques, model interpretability, andreal-world application. "DeepTrac" aims to revolutionize plant disease management and enhance agricultural practices throughtechnology-driven solutions.” [11]

‘B Mohith Kumar, K Rama Krishna Rao, P Nagaraj, K Muthamil Sudar, V Muneeswaran’ are the authors of the paper titled “TobaccoPlant Disease Detection and Classification using Deep Convolutional Neural Networks” They say that “The paper focuses on "Tobacco Plant Disease Detection and Classification using Deep Convolutional Neural Networks." It presents a methodology involving data collection, preprocessing, deep CNN selection, and transfer learning. The model's performance is validated and evaluated. A threshold-based classification approach is implemented. The paper emphasizes user-friendly deployment and continuous improvement through feedback.

The future scope involves advanced AI techniques, real-time monitoring, collaboration, and interpretability enhancement. Ultimately, the study aims to enhance tobacco plant disease management through efficient deep learning-based classification." [12]

'Divyanshu Varshney, Burhanuddin Babukhanwala, Javed Khan, Deepika Saxena, and Ashutosh Kumar Singh' are the authors of thepaper titled "Plant Disease Detection Using Machine Learning Techniques" They say that "The paper "Plant Disease Detection Using Machine Learning Techniques" presents a comprehensive exploration of leveraging machine learning for plant disease detection. It discusses data collection, preprocessing, and the application of various machine learning algorithms, highlighting their effectiveness. The paper underscores the significance of accurate feature extraction and model selection. Evaluation metrics demonstrate the models' performance and deployment strategies areconsidered for practical implementation. The study emphasizes the potential of these techniques in enhancing agricultural practices by aiding in early disease identification. However, it also acknowledgesthe need for continuous improvement and collaboration amongexperts to refine and expand the approach. Overall, the paper offersvaluable insights into the promising role of machine learning in plant disease detection." [13]

'Zhiyan Liu, Rab Nawaz Bashir, Salman Iqbal, Malik Muhammad Ali Shahid, Muhammad Tausif, Qasim Umer' are the authors of thepaper titled "Internet of Things (IoT) and Machine Learning Modelof Plant Disease Prediction–Blister Blight for Tea Plant" they say that "The paper "Internet of Things (IoT) and Machine Learning Model of Plant Disease Prediction–Blister Blight for Tea Plant" presents a novel and practical approach to predict blister blight disease in tea plants. By integrating IoT sensors to gather real-time environmental data and leveraging machine learning techniques, thestudy effectively addresses disease prediction. The paper's methodology is well-structured, encompassing data collection, preprocessing, feature extraction, and model training. The integration of IoT for continuous monitoring and prediction holds promise for early disease detection. The research contributes to enhancing agricultural practices and crop management by aiding intimely disease prevention. Overall, the paper offers a significant advancement in leveraging technology for plant disease prediction and demonstrates its potential impact in the field." [14]

'Junde Chen, Weirong Chen, Adan Zeb, Shuangyuan Yang, and Defu Zhang' are the authors of the paper titled "Lightweight Inception Networks for the Recognition and Detection of Rice PlantDiseases" They say that "The paper introduces "MobInc-Net," a lightweight neural network architecture for identifying rice plant diseases. This approach combines MobileNet and an optimized Inception module with depth-wise and point-wise convolutions. The model excels in real-world scenarios, handling complex backgrounds and varied lighting. The authors emphasize practicalitythrough experiments with actual field images, showcasing its adaptability. They plan to refine the model by fine-tuning it and aimto deploy it on portable devices for widespread crop disease monitoring. This innovation has the potential to greatly impact cropmanagement and food security." [15]

'A Khakimov1, I Salakhutdinov2, A Omolikov1 and S Utaganov3' are the authors of the paper titled "Traditional and current-prospective methods of agricultural plant diseases detection: Areview" They say that "Early detection of infection on plants is of crucial significance in the control and elimination of diseases (as well as in recording quarantine diseases of plants and in their eradication). Although each of the methods for diagnosing plant diseases and identifying pathogens has its specific shortcomings, these methods do not lose their importance in diagnosis. Because in most cases, traditional methods are sufficiently informative, cheap, universal, give reliable results, and do not require special expensiveequipment. According to the recommendations of leading mycologists and phytopathologists, in many cases the results of theuse of molecular identification methods are insufficient, and they are of course required to be used in conjunction with classical morphological identification (microscopy, study of macro- and micromorphological markers, artificial infestation of host plants, and implementation of the Koch's triad). The extensive introductionand application of new promising, modern, rapid and reliable methods does not mean that traditional methods should be ignored"[16]

'Vishvesh Trivedi, Vinay Sheth, Aakash Shah, and Uttam Chauhan' are the authors of the paper titled "ResTS: Residual Deep interpretable architecture for plant disease detection" They say that "With the cooperation of Deep Learning, the problem of early diagnosis of plant diseases can be resolved and food security can beensured. Numerous methods have been proposed for the same, making the agriculture sector one of the most active research areas in Machine Learning and Computer Vision disciplines [34], [35], [36]. In this research, we have worked on improving the results of the formerly proposed Teacher/Student architecture by introducing residual connections and carrying out batch normalization in all three components of it: Teacher, Decoder and Student. ResTS comprises an autoencoder (ResTeacher + Decoder) and ResStudent.ResStudent is guiding the entire architecture to train in a way that the reconstructed images by decoder contain only the discriminant regions. From the results of experiments performed, it was deduced that the Teacher/Student structure that used VGG16 is overfitting to the training set and performs poorly on the validation set (Validationloss: 0.123) while ResTS performs well on the training set as well as the validation set (Validation loss: 0.059). The visualizations from ResTS are precise and superior to those of Teacher/Student. The model's meticulous decisions can be explained by its unique design.

In the future, any other residual architecture can be fit to work as the ResTeacher or ResStudent. To use a residual classifier other than Xception, the layers in the Decoder have to be applied inan exact inverse manner as ResTeacher. The residual connections also need to be applied in the opposite order as ResTeacher.” [17]

‘Anuradgha Chugh’ are the authors of the paper titled “A novel framework for image-based plant disease detection using hybrid deep learning approach” They say that “The paper presents a new framework for plant disease detection using a hybrid deep learning approach. This technique combines various deep-learning methods to improve accuracy in identifying plant diseases from images. Thestudy highlights the framework's success in achieving precise disease detection and classification. Moving forward, the authors aim to refine the hybrid approach, explore cross-domain transfer learning, and adapt the framework for real-time use. This innovation has the potential to greatly enhance image-based plant diseasedetection and transform agricultural practices.” [18]

‘Sivasubramaniam Janarthan, Selvarajah Thuseethan, Sutharshan Rajasegarar, and John Yearwood’ are the authors of the paper titled“P2OP—Plant Pathology on Palms: A deep learning-based mobile solution for in-field plant disease detection” they say that “The paperintroduces "P2OP—Plant Pathology on Palms," a mobile solution for in-field plant disease detection using deep learning. The system enables real-time disease diagnosis by capturing images of plants using mobile devices. The authors leverage deep learning techniquesto achieve accurate and rapid disease identification. The paper underscores the significance of on-site disease detection for immediate action. The proposed solution's potential lies in its accessibility and quick response, contributing to improved crop management and disease control. However, challenges in real-world conditions and scalability need further exploration. Overall, the paper presents a promising approach to mobile-based plant disease detection, offering practical benefits for agriculture.” [19]

‘Raj Kumar, Gulsher Baloch, Pankaj, Abdul Baseer Buriro, and Junaid Bhatti’ are the authors of the paper titled “Fungal Blast Disease Detection in Rice Seed using Machine Learning” They saythat “Plant disease detection plays an essential role in the growth ofthe economy and healthy crop production. In the proposed work, thefungal blast disease is detected in the seed of a rice crop. This paperdiscussed the different image processing and machine learningtechniques to detect fungal blast disease in rice crops. Image processing is used for the extraction of multiple features and extracted 11 different features from the models such as texture, SURF, and BRISK. As per this research, the mentioned features arebeneficial for the detection of fungal blast disease, in which rice has brownish spots on its seed, shown in Fig. 2. In the machine learningportion, a comparative analysis regarding different machine learningalgorithms based on disease detection with varying accuracies has been made. Seven different classifiers are used, including traditionaland convolutional classifiers. After analyzing these traditional features and classifiers, the dataset has been used as input to transferlearning VGG-16 model, then trained the model with the unaugmented dataset and augmented dataset.” [20]

‘Avijit Bose, Debanjan Ghosh, Anish Banerjee, Debojyoti Saha, Pranita Ganguly & Satyajit Chakrabarti’ are the authors of the paper titled “Capsnet-VGG16 Architecture for Cassava Plant Disease Detection” They say that “This hybrid model combines the strengths of Capsule Networks (CapsNets) and the VGG16 convolutional neural network, offering improved accuracy and robustness in identifying diseases in cassava plants. Through its innovative use ofdynamic routing and feature extraction, the CapsNet-VGG16 architecture addresses some of the limitations of traditional CNN- based approaches. The results obtained from this architecture demonstrate its efficacy in accurately classifying cassava plant diseases, which is crucial for early disease detection and effective disease management in agriculture. This model has the potential to contribute significantly to improving crop yield and food security inregions heavily reliant on cassava cultivation.” [21]

III. METHODOLOGY REVIEWED

TITLE	YEAR	ALGO	ACCURACY	PLANT
Capsnet-VGG16 Architecture for Cassava Plant Disease Detection	2021	Capsnet VCG-16	97%	Cassava Plant
Attention embedded residual CNN for disease detection in tomato leaves.	2020	CNN	98%	Tomato Plant
An approach to Plant Disease Detection using Deep Learning Techniques	2022	Pddnet-cv	99%	Bell Pepper, Potato and Tomato
Plant Pathology Disease Detection in Apple Leaves Using Deep Convolutional Neural Networks: Apple Leaves Disease Detection using efficientnet and densenet	2021	Efficientnet densenet	99.75%	Apple Leaves
Fieldplant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning	2023	CNN	95%	Corn leaf Tomato leaf
Computer vision technology in agricultural automation —A review	2020	Yolov3 RCNN	79.19 75.92	Capsicum plant
Plantdet: A Robust Multi-Model Ensemble Method Based on Deep Learning For Plant Disease Detection	2023	Inceptionresnetv2	96.69%.	Betel leaf
Deeptrac: Applying Artificial Intelligence in Plant Disease Detection	2022	R-CNN CNN	98.49 97.53	Bell pepper
A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand	2022	Densenet-77	74.47	Kiwi leaf
Deep Learning Based Plant Diseases Monitoring and Detection System	2023	YOLO	96%	Tomato leaf
A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends	2023	Cnn Knn	99.33 98.7	Grapes, rice, apples, cucumbers, maize, tomatoes, wheat, and potatoes

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IV. ANALYSIS OF ALGORITHMS REVIEWED

CNN (Convolutional Neural Network) is a type of deep learning algorithm designed for image recognition and analysis. It's inspired by how the human brain processes visual information. CNNs use specialized layers to automatically and adaptively learn patterns from data. Key components include convolutional layers, pooling layers, and fully connected layers. CNNs are highly effective for tasks like image recognition, object detection, and even medical image analysis due to their ability to capture intricate patterns in visual data.

Support Vector Machine (SVM) is a machine learning algorithm used for classification and regression tasks. In classification, SVM finds the optimal hyperplane that best separates different classes in a high-dimensional space. It aims to maximize the margin between classes, making it a powerful algorithm for both linear and non- linear data. SVM works well for high-dimensional data and iseffective in scenarios with clear class boundaries.

ResNet, short for Residual Neural Network, is a deep learning architecture designed to tackle the vanishing gradient problem in very deep neural networks. It introduces "skip connections" or "shortcuts" that allow the gradient to flow directly backward through the network during training. This helps in training extremely deep networks effectively, leading to improved accuracy and faster convergence in tasks like image recognition and object detection.

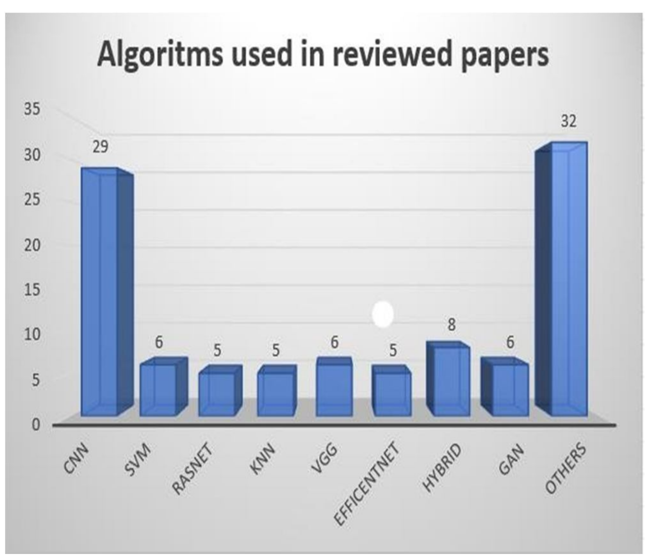
KNN, or k-Nearest Neighbors, is a simple and intuitive machine learning algorithm used for both classification and regression tasks. In classification, it assigns a class label to an input based on the majority class of its k nearest neighbors in the training data. In regression, it predicts a numerical value based on the average of thek nearest neighbors' values. The value of k represents the number ofneighboring data points considered for making predictions.

VGG, short for Visual Geometry Group, is a deep learning architecture designed for image recognition. It consists of several convolutional layers, making it deep, and is known for its simplicity and effectiveness. VGG's key idea is to use small 3x3 convolutional filters repeatedly, deepening the network, which has been shown to improve the model's ability to learn intricate patterns in images. Thearchitecture's simplicity and strong performance have made it a popular choice in computer vision tasks.

EfficientNet is a family of neural network architectures designed forefficient and effective deep learning. It achieves state-of-the-art performance by balancing network depth, width, and resolution. Unlike traditional models that scale these dimensions uniformly, EfficientNet uses a compound scaling method, optimizing each dimension differently to maximize accuracy while minimizing computational resources. This makes EfficientNet models highly efficient and suitable for various applications, including image recognition and classification tasks.

GAN, or Generative Adversarial Network, is a type of artificial intelligence algorithm consisting of two neural networks, the generator, and the discriminator, which work in opposition. The generator creates fake data, and the discriminator evaluates whether the data is real or fake. Through iterative competition, GANs learn to generate increasingly realistic and high-quality data, making thempowerful tools in generating images and videos.

Hybrid Deep Learning (DL) algorithms combine multiple machine learning techniques, such as traditional algorithms and neural networks, to leverage the strengths of each. By integrating differentmodels, hybrid DL algorithms can improve accuracy, efficiency, and the ability to handle complex data patterns, making them versatile solutions for various applications.



V. IMPLEMENTATION

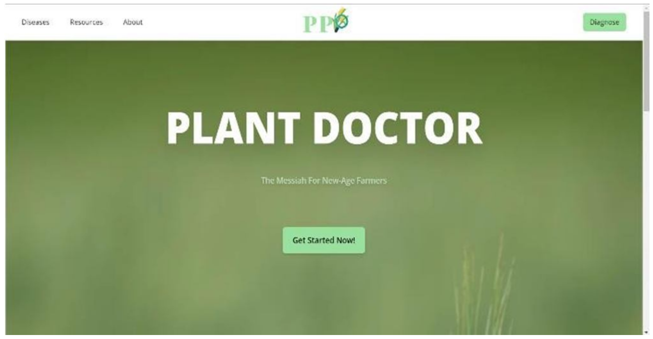


Fig1. Home page.

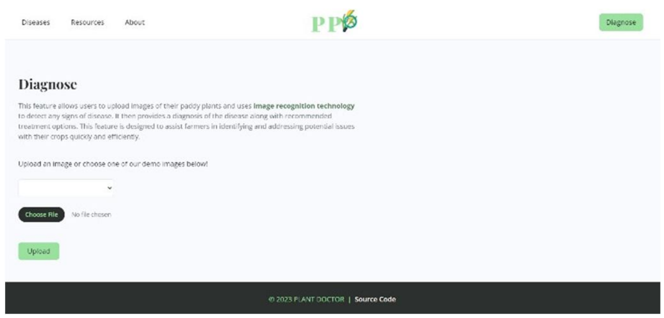


Fig2. Diagnose page.

Fig3. Uploading a stock image.

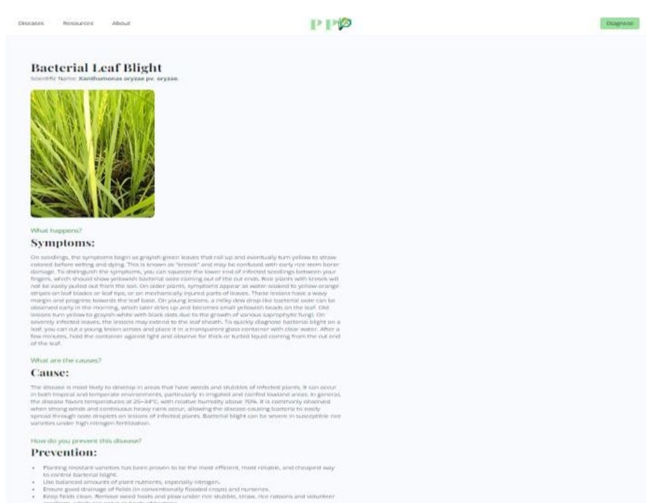


Fig4. Result page.

VI. CONCLUSION

"The integration of climate and soil data into a plant disease detection system signifies a revolutionary approach to agriculture. Powered by technology, data analytics, and machine learning, it transforms crop protection and fosters sustainable farming amidst climate change.

This unique system, delving into the intricate relationship between climate, soil, and plant health, empowers farmers and researchers with predictive insights, enabling informed decisions and proactive disease prevention. By minimizing crop losses and reducing harmfulpesticide use, it addresses global food security challenges, promoting environmentally friendly farming practices.

In a world threatened by climate change and reliant on productive soil, this innovative plant disease detection system offers hope and resilience. It not only helps us adapt to environmental shifts but alsocharts a promising course toward a sustainable agricultural future.

This research, leveraging Deep Learning and computer vision, presents a vital solution for enhancing food security in India. By combatting plant diseases effectively, it reduces crop wastage and aids farmers in preserving their harvests."

Finally, future improvement of techniques used in plant disease detection will revolutionize global agriculture. Use of novel technologies like IoT, machine learning and remote sensing has opened new doors towards early and accurate detection of plant diseases. These devices improve the speed and accuracy of diseasesdiagnosis as well, provide farmers with immediate data they need toact properly before loss is irrevocable.

With mobile application technology and easily usable screens, access to such technologies is also demystified thereby becoming more democratic in agriculture practice. With the passage of time, these apps will increasingly become developed and common with apotential to change how farmers handle their crops.

The sustainability and adaptability associated with a plant disease detection in its future perspective goes beyond mere technology. This encompasses continuous investigations into biotech ways e.g., genetic engineering for disease resistant plants as a responsive and ecofriendly approach. These methods help reduce dependence on chemicals in agriculture hence making the practices environmentally friendly and sustainable.

Thus, the nature of the detection of plant diseases in the future is comprehensive and collaborative one that combines technological innovation, evidence-based information, and sustainable farming. These factors come together with the aim of improving global foodsecurity, environmental preservation, and farmer adaptation towardsplant disease in a dynamic environment.

VII. FUTURE SCOPE

In the evolving agricultural technology, the integration of soil andweather parameters into plant disease detection systems marks a promising avenue for future research and innovation. Future research for plant disease detection can get advanced sensor technologies and data analytics techniques to produce real-time soiland weather data.

Machine learning algorithms, coupled with IoT (Internet of Things) devices, can provide a robust foundation for predictive modeling, enabling early detection of diseases based on environmental factors. Integration of satellite images and remote sensing technologies further expands the scope and will allow for large-scale monitoringand analysis.

Additionally, we can use blockchain technology to enhance the traceability of agricultural data to ensure the authenticity and integrity of collected information from various sources. Collaborative efforts between agricultural scientists, data analysts, and technology experts are essential to developing comprehensive models that consider regional variations in soil composition and weather patterns.

In the future, this technology will be useful for traceability in order to track the sources of diseases and implement specific control measurements to combat these health conditions. Smartphone-basedimage recognition apps coupled with artificial intelligence (AI) technologies provide a convenient solution for farming diseasediagnosis. Development of drought resistant crop varieties through biotechnology, especially in genetic engineering is a possible way of managing diseases by being proactive while environmentally sustainable practice.

With changing environmental conditions, in addition to adapting tothem, we shall need to implement such solutions. Plant diseases detection in the future is made up of collaboration and sharing of data by stakeholders together with education and building capacitiesfor farmers.

This overall objective is to establish an all-encompassing and technology driven environment, which not only detects and manages crop disorders, but which also promotes robust and resilient agriculture for global food safety.

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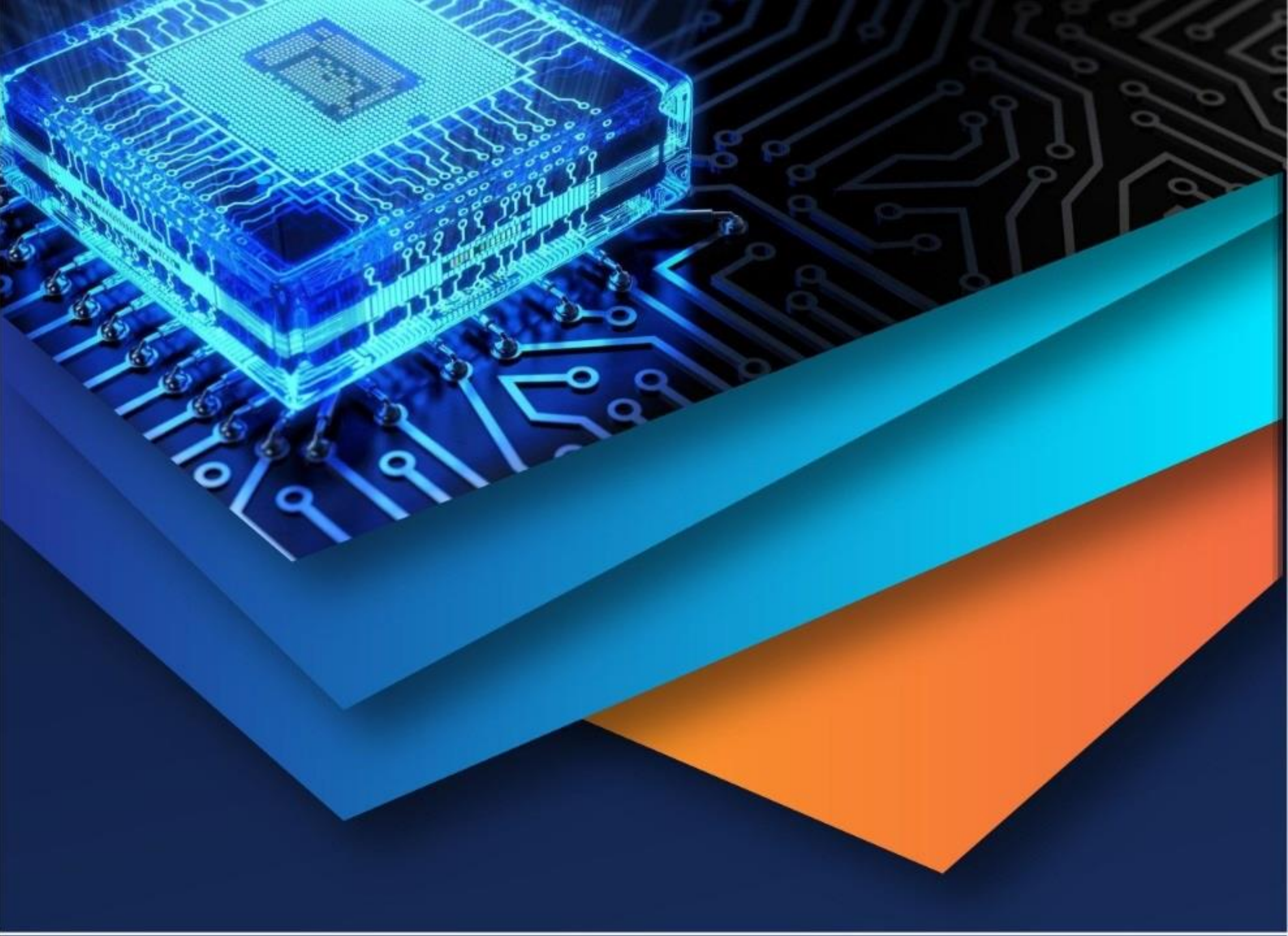

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