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Revolutionizing Plant Disease Detection: A Review of Deep Learning and Machine Learning Algorithms

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ABSTRACT

The food industry has led the agricultural economy of the state all India to prosperity. India has historically been the largest producing nation having identity of Agricultural Land. Grains , fruits , Vegetables , such as potatoes, oranges, Tomato ,sugarcane and other specially grains and cottons are the chief crops of the India. Citrus and cotton industries have been a driving force behind Maharashtra's impressive economic growth.. The situation has created job opportunities for many people, boosting the state's economic potential. To maintain the prosperity of citrus and cotton industries, Government has been concerned about disease control, labour cost, and global market.

During the recent past, citrus canker and citrus greening, Black spot-n cotton has become serious threats to citrus in Maharashtra. Infection by these diseases weakens trees, leading to decline, mortality, lower yields, and decreased commercial value. Likewise, the farmers are concerned about costs from tree loss, scouting, and chemicals used in an attempt to control the disease. An automated detection system may help in prevention and, thus reduce the serious loss to the industries, farmers and Economy of country.

This research aims to the development of disease detection with pattern recognition approaches for these diseases in crop. The detection approach consists of three major sub-systems, namely, image acquisition, image processing and pattern recognition. The imaging processing sub-system includes image preprocessing for background noise removal, leaf boundary detection and image feature extraction. Pattern recognition approaches will be use to classify samples among several different conditions on crops. In order to evaluate the classification approaches, results will be compared between classification methods for the different induvial fruits, vegetable, grains disease detection. Obtained results will help in demonstration of classification accuracy which is targeted as better than existing for proposed model as high as 97.00%. This study aimed to assess the potential of identifying plant diseases by examining visible signs on fruits and leaves. These data collection and initial knowledge acquisition is plan in offline approaches. By implementing this simple model, we can achieve a more favourable cost-to-production ratio compared to complex solutions.

Keywords: Convolutional Neural Network (CNN), Image Recognition, Plat Disease Detection

I. INTRODUCTION

Crops become stressed when any infections, such as viral infections, or physiological factors, such as air pollution, adversely affect growth, development, and yield. These stresses are expressed in various ways. For example, problems in the water balance control can slow down photosynthesis, reduce evapotranspiration, and raise leaf surface temperature (Nilsson, 1995).

Because of these observable symptoms, humans could easily assess the conditions of their crops. However, the large size of current farms and the decrease of farm labor make it impossible to assess the whole field. Furthermore, the symptoms of some diseases do not show up in the visible range (400 -700 nm), which is the sensitivity of the human eyes.

Pattern recognition and colour co-occurrence texture method is proposed for research approach in detection of crop disease. Digitized RGB images from various disease conditions will be obtained using an image acquisition system. Texture features containing useful information for diseases classification will be extracted from the pre-processed RGB images that will convert into hue, saturation, and intensity (HSI) colour space representation.

For each HSI image, three spatial Gray-level dependence matrices (SGDMs) will be generated, and texture features will be obtained from each image sample. A stepwise discriminant analysis is proposed in finding useful texture features from three colour combinations including 1) hue, saturation, and intensity (HSI), 2) hue and saturation (HS), and 3) intensity (I).

The food industry plays a critical role in India's agricultural and economic achievements. Maharashtra's economic growth benefits from industries like citrus and cotton. These sectors create jobs and contribute to the state's prosperity. The government emphasizes crop disease management to ensure the continued success of these industries and their impact on both Maharashtra's growth and India's agricultural sector.

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In general, back-propagation based on neural network method has good performance above 93% for accuracy. The support vector machine had good classification results but poor accuracy. Backpropagation offers a powerful approach to disease detection due to its ability to learn complex patterns from medical data. This method proposed to obtain better performance and the implementation of algorithms also simple for a detection system.

I. LITERATURE REVIEW

1) Muhammad Hammad Saleem, Johan Potgieter, And Khalid Mahmood Arif authored research paper titled, **"A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand [2022]"** This research addresses gap in deep learning-based plant disease detection, encompassing diseases in five significant New Zealand horticultural crops. Various factors, such as data augmentation techniques, image resizers, weight initializers, batch normalization, and deep learning optimizers, are evaluated for their impact on performance. The study demonstrates proposed approach's robustness through stratified k-fold cross-validation and external dataset testing. RFCN model achieves a mean average precision of 93.80%. Optimizes region-based fully convolutional network model for achieving a mean average precision of 93.80%. However, limitations include potential biases in the dataset, generalizability issues to other plant species, and need for real-world validation in agricultural settings.[1]

2) Wasswa Shafik, Ali Tufail, Abdallah Namoun, Liyanage Chandratilak De Silva and Rosyzie Anna Awg Haji Mohd Apong are author to the **"A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends [2023]"** This study addresses global threat of plant pests and diseases to food security by exploring smart agricultural practices employing AI, ML, and DL methods for disease detection. These studies primarily focus on crops like grapes, rice, apples, and others, using vision-based approaches. Support Vector Machines (SVMs) and Logistic Regression (LR) classifiers show promise in achieving higher accuracy. Challenges include disease localization, and there's a need for standardized model performance assessment, larger datasets, and models optimized for small devices to ensure robust disease detection systems. The study, is limited by the focus on a specific subset of crops and vision-based approaches, potentially overlooking diseases in other plant species and alternative detection methods. Additionally, challenges related to disease localization, lack of standardized model performance assessment, limited availability of large datasets, and optimization of models for small devices underscore need for further research and development in this area.[2]

3) Zhiyong Xiao, Yongge Shi, Gailin Zhu, Jianping Xiong, And Jianhua Wu authored the research paper titled, **"Leaf Disease Detection Based on Lightweight Deep Residual Network and Attention Mechanism [2023]"** In leaf disease detection, achieving high accuracy is crucial. This study introduces SE-VRNet, a lightweight model based on advanced residual networks and attention mechanisms, designed to enhance accuracy in recognizing leaf diseases. SE-VRNet combines a deep variant residual network (VRNet) with a squeeze-and-excitation (SE) module to address challenges posed by dispersed lesions. The model achieves impressive results with top-1 and top-3 accuracy rates of 99.73% and 99.98% on NewData and 95.71% and 99.89% on SelfData, respectively. It outperforms other state-of-the-art methods on datasets like PlantVillage, OriData, NewData, and SelfData, demonstrating its effectiveness and suitability for identifying leaf diseases using mobile devices. While SE-VRNet demonstrates outstanding accuracy in leaf disease detection, its limitations include the lack of information on the generalizability of the model to diverse environmental conditions and different plant

species, as well as potential challenges in real-world deployment, such as processing time and computational resource requirements, especially when implemented on resource-constrained mobile devices.[3]

4) Emre Özb˙ilge, Mehtap Köse Ulukök, Önsen Toygar, And Ebru Ozb˙ilge titled **"Tomato Disease Recognition Using a Compact Convolutional Neural Network [2022]",** This study focuses on early disease detection in tomatoes to enhance production efficiency and quality, benefiting both farmers and consumers. It introduces a compact six-layer convolutional neural network (CNN) for disease identification, trained on the PlantVillage tomato crop dataset with ten classes. The proposed network achieves impressive accuracy, F1 score, Matthew's correlation coefficient, true positive rate, and true negative rate of 99.70%, 98.49%, 98.31%, 98.49%, and 99.81%, respectively, on 9,077 unseen test images, outperforming or matching state-of-the-art methods while maintaining computational efficiency. Its limitations include the lack of evaluation in diverse environmental conditions and with different tomato varieties, potentially affecting the model's generalizability. Additionally, the study does not provide insights into the network's robustness against adversarial attacks or its performance in real-time applications, which are essential considerations for practical implementation in agricultural settings.[4]

5) Aanis Ahmad, Aly El Gamal and Dharmendra Saraswat has researched on **"Toward Generalization of Deep Learning-Based Plant Disease Identification Under Controlled and Field Conditions [2023]"** This study addresses the challenge of identifying corn diseases under field conditions and evaluates the generalization performance of deep learning (DL) models across different datasets and environmental conditions. Five datasets of foliar disease images in corn were used: PlantVillage, PlantDoc, Digipathos, northern leaf blight (NLB) dataset, and a custom CD&S dataset. Multiple DL-based image classification models were trained using various pre-trained DNN architectures, achieving the highest generalization accuracy of 81.60% when trained on RGBA images from the CD&S corn disease dataset with removed backgrounds. The study's limitations include the relatively moderate generalization accuracy of 81.60%, suggesting room for improvement in accurately identifying corn diseases under diverse field conditions. The study lacks detailed exploration of potential biases and limitations inherent in the training datasets, raising questions about model's robustness across varying environmental and geographical factors, which are crucial for real-world applications in different agricultural settings.[5]

6) Khalid M. Hosny, Walaa M. El-Hady, Farid M. Samy, Eleni Vrochidou, And George A. Papakostas paper titled **"Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern [2023]"** This research addresses the pressing issue of plant diseases affecting agricultural production by introducing a novel lightweight deep convolutional neural network (CNN) model. It is evaluated on three publicly available datasets (Apple Leaf, Tomato Leaf, and Grape Leaf), achieving impressive validation accuracies of 99%, 96.6%, and 98.5%, and test accuracies of 98.8%, 96.5%, and 98.3%, respectively. These results highlight the model's potential as an effective solution for early detection and control of plant diseases, supporting healthier plant production. The study's limitations include the lack of information about the model's performance in real-world field conditions. Additionally, the evaluation on publicly available datasets might not fully represent the diversity of plant diseases and environmental variations, indicating the need for testing the model on more extensive and diverse datasets to assess its robustness and generalizability across various agricultural scenarios.[6]

7) Xueqian Fu, Qiaoyu Ma, Feifei Yang, Chunyu Zhang,

Xiaolong Zhao, Fuhao Chang, Lingling Han wrote this paper **"Crop pest image recognition based on the improved ViT method "[2023]** This study addresses the significant challenge of crop pests and diseases in agriculture, which can lead to reduced crop yields and lower produce quality, affecting macroeconomic stability and sustainable development. Traditional manual and instrument-based recognition methods are subjective and inefficient. To overcome these limitations, the study introduces an improved Vision Transformer (ViT) method for crop pest image recognition. The experiment, conducted with data containing seven classes of examples, demonstrates high accuracy, showcasing the potential of this approach for precise crop disease and pest classification. The study's limitations include a lack of potential challenges faced during the real-world implementation of improved Vision Transformer (ViT) method, such as computational resource requirements and processing time, which are crucial factors for practical adoption in agricultural settings. Additionally, it focuses on a specific classes and lesion areas might not encompass full spectrum of crop diseases and pests, raising questions about the method's effectiveness in handling diverse and evolving pest and disease scenarios in agriculture.[7]

8) Ang Liu, Guoqin Gao and Zhenhui Zhang titled **"Crop Disease Recognition Based on Modified Light-Weight CNN with Attention Mechanism [2022]"** This study addresses the challenge of classifying the severity of crop diseases, a critical step in disease prevention and control strategies. It focuses on the subtle differences between disease severity levels in the same crop disease, which can be challenging to detect, especially at the early stages when lesions are not prominent. The model is evaluated using the AI Challenger 2018 plant disease recognition dataset, achieving an accuracy of 91.94%, outperforming the original SqueezeNext model by 3.02 The study's limitations include potential challenges related to the generalizability of the modified lightweight convolutional neural network (CNN) to diverse and evolving crop disease scenarios outside the specific dataset used for evaluation, raising concerns about its performance in real-world agricultural settings with varying environmental conditions. Additionally, study does not discuss model's robustness against noise, variations in lighting, or other environmental factors, uncontrolled field conditions, suggesting need for further testing and validation in different agricultural contexts.[8]

9) Akila Begum H, Yasmin A, T. Ashmi wrote **"Automatic Field Monitoring and Detection of Plant Diseases Using IoT [2023]"** This research introduces a GSM-based system for automatic plant disease diagnosis, contributing to the development of an Automated Crop Protection System (ACPS). To address this, the study employs a Convolutional Neural Network (CNN) model trained to analyze crop images captured by a health maintenance system. Agricultural robots, or "agribots," The system also incorporates plant disease prediction technology and intelligent irrigation controls, streamlining crop monitoring and irrigation processes while reducing energy consumption by combining these functions. The limitations include challenges in the real-world implementation of the GSM-based system, such as issues related to network coverage, connectivity reliability, and transmission speed, which might affect system's responsiveness and effectiveness in remote or rural agricultural areas. Additionally, the study does not provide detailed information on the system's accuracy and reliability in disease diagnosis, prediction, and irrigation control, raising questions about its precision and performance under various environmental conditions and with different crop types, indicating the need for comprehensive field testing and validation.[9]

10) SK Mahmudul Hassan and Arnab Kumar Maji titled the paper **"Plant Disease Identification Using a Novel Convolutional Neural Network [2022]"** This paper addresses the crucial need for timely plant disease

identification to safeguard crops. It introduces a novel deep learning model that combines inception layers and residual connections while reducing parameter count through depth wise separable convolution. The model is trained and tested on three distinct plant disease datasets, achieving impressive accuracy rates of 99.39% on the PlantVillage dataset, 99.66% on the rice disease dataset, and 76.59% on the cassava dataset. Despite having fewer parameters, the proposed model outperforms existing state-of-the-art deep learning models, demonstrating its efficiency and effectiveness in plant disease identification. The limitations include the need for further evaluation in real-world agricultural settings, considering factors such as diverse environmental conditions, variations in lighting, and different stages of disease progression, which may impact the model's performance and generalizability. Additionally, it focuses on specific plant disease datasets, highlighting the necessity for testing its robustness across various crop types and diseases to assess its practical applicability.[10]

II. OBJECTIVES

1) To enrichment of available dataset and addressing to limitation of dataset problem, the visits to Plant Village project / centres is planned for collecting tens of thousands of images of healthy and diseased crop plants . Searching and data collection from existing database sources and from farmers for detection of the presence of disease by Online and offline approaches.
2) Pattern detection and extraction Using ANN. This study introduces a novel method for extracting features from leaf images. The method captures information about each point along the leaf's contour by analysing the distribution of distances between these points, visualized through a length histogram.
3) To detect fertility and enhancing the accuracy Using Machine Learning. To enhance the accuracy of healthy plant detection by image processing technology in low cost. Several factors can limit plant productivity and quality, including inadequate fertility, poor management practices, and unsuitable plant varieties for the growing site.
4) Pattern Classification and Prevention Analysis of productivity

III. LIMITATIONS

1) While the "Agriculture Suit" project offers an array of advantages, it's essential to acknowledge certain limitations. The project's reliance on technology may pose challenges for users with limited access to smartphones or the internet, potentially limiting its reach in regions with limited tech infrastructure. This limitation highlights the need for complementary strategies to ensure that the project can benefit a diverse audience.
2) Language barriers are another consideration. The project has been designed to be user-friendly, but language diversity in agricultural communities may present challenges for some users. While efforts have been made to offer multilingual support, ongoing work may be required to cater to the linguistic diversity of the target audience.
3) Furthermore, the accuracy of disease recognition, while generally high, may vary based on the quality of the images and specific disease variations. This variability may result in occasional misclassifications, emphasizing the importance of clear and high-quality images for optimal results.
4) Another potential limitation is the initial dataset's size and diversity. The effectiveness of the image recognition system depends on the volume and diversity of data. While efforts have been made to establish a comprehensive dataset, it may take time to accumulate a dataset that encompasses a wide array of crop diseases and their variations. Ongoing data collection and user contributions are essential to overcoming this limitation.

IV. CONCLUSION

In conclusion, this review delves into the potential of deep learning and machine learning for plant disease detection mobile applications. The studies explored here showcase the promise of convolutional neural networks (CNNs), lightweight CNNs, and transformers, achieving impressive accuracy in controlled settings. However, several challenges hinder the widespread adoption of these technologies in mobile apps. Generalizability remains a key concern.

Evaluations were often conducted on limited datasets or specific crops, raising questions about their effectiveness in handling the vast diversity of environmental conditions, plant species, and disease variations encountered in real-world agriculture. Furthermore, real-world validation involving factors like processing time, computational limitations of mobile devices, and robustness against variations in lighting, noise, and uncontrolled field conditions is scarce. Additionally, the lack of standardized evaluation metrics makes it difficult to objectively compare the performance of different models. Moving forward, research should prioritize developing models with superior generalizability for accurate disease identification across various crops, environments, and disease stages. Real-world testing in agricultural settings is crucial to validate the effectiveness and robustness of these models in practical scenarios.

Finally, establishing standardized evaluation metrics would enable a more comprehensive comparison of different approaches, accelerating the development of reliable and efficient plant disease detection mobile applications. By addressing these challenges, researchers can empower farmers with powerful tools for early and accurate disease detection, ultimately contributing to improved crop health, yield, and food security.

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