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Review Paper On Crop Disease Diagnosis Model Using Deep Hybrid Architecture With A New Segnet-Based Segmentation Model

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Abstract– *Crop diseases are a serious risk to the world's food supply, reducing agricultural productivity and causing substantial economic losses each year. Crop disease management, yield loss reduction, and sustainable farming practices all depend on early and precise diagnosis. Conventional approaches of disease diagnosis, which frequently depend on Visual examination and professional expertise, can be lengthy and prone to human error. In recent years, technological developments, including machine learning, image processing, and remote sensing—have revolutionized the field, offering more precise, rapid, and scalable solutions. This work explores current methodologies for crop disease diagnosis, highlights emerging technologies, and discusses the potential of integrating artificial intelligence to improve accuracy and accessibility in agricultural disease management.*
Keywords–*Crop Disease Diagnosis, Deep Learning, Hybrid Architecture, SegNet, Image Segmentation, Precision Agriculture*

OVERVIEW

As the global population grows, the amount of agricultural food demand also increases. To meet the food demands, the production of food should be increased. On the other hand, challenges like weeds and increasingly volatile weather are mainly faced by agriculture [9][10]. Numerous methods are developed for controlling the weeds that grow ups in the agricultural field, and share all the things which are required for the main crop. Along with weeds, a crucial factor which affects the crop yield is that crop diseases [11][12].

For identifying the crop disease in the initial phase, the automatic disease detection method is more useful. In the traditional crop disease detection method, experts observe them with the bare eye. However, a crop's continuous monitoring along with a huge team of experts is required for this traditional crop disease detection method, which leads to higher cost for large forms [13][14][15]. Moreover, in several countries, farmers don't have appropriate facilities or idea about that they can make contact in with experts [16][17][18]. Because of this reason, consulting the experts becomes more time consuming and expensive. In such conditions, to monitor the huge fields of crops, automatic detection is proven to be helpful. In addition, only just by seeing the symptoms on the the plants' foliage, the disease can be discovered in automatic detection, which makes it inexpensive and easier. Machine vision also supported by this approach to offer image dependent process inspection, and control along with robot guidance [19][20][21].

At the same time, identifying the plant disease leveraging a visual way is a less accurate, more laborious task, and only in limited areas can be conducted. Whereas, the utilization of automatic detection techniques resulting to less effort and less time requirement along with more accurate detection. In some plants, generally diseases might be seen as yellow and brown spots, early and late scorch. In this context, to measure the disease-affected region, and identify the variation in the affected area's color, image processing can be utilized [22][23].

Furthermore, for identifying the plant diseases at early stage before they damage the whole crop, computerized image processing methods are important. To address this, Several Deep Learning (DL), Machine Learning (ML) and image processing techniques are created to detect the disease using the plant leaf images. Furthermore, the process of grouping or separating an image into diverse parts is named as image segmentation. Many different ways are there to perform the image segmentation, which are ranging from typical thresholding approach to advanced color image segmentation techniques [4][24][25]. Especially, depend on the diverse features found in the image; the segmentation process can be conducted. This features includes, color data, segment or boundaries of an image [3][26][27]. Motivated by that, we have introduced novel crop disease detection with the utilization of DL model.

LITERATURE REVIEW

Some recent papers associated with plants or crop identification of disease has been reviewed underneath. An automatic crop diagnostic system was introduced by R. Abbasi et al [1] in 2023, to detect the biotic stresses along with controlling the diseases in 4 leafy green drops such as basil, lettuce, parsley, and spinach that are grown in aquaponics facility. The developed disease detection works in 3 phases which were initially, a crop categorization system, afterwards a disease identification system, and finally, a system for disease detection was presented. Through a cloud-dependent application, an ontology model was incorporated with the final disease identification system.

In 2023, Sushruta Mishra et al [2] proposed an improved DL accompanied Astute disease recognition system for the millet plants. From the millet farmlands, the data are gathered. Afterwards, the crop data readings were transferred towards the Raspberry Pi as well as cloud server. A Customized CNN (Convolutional Neural Network) works with Raspberry Pi for detecting the blast as well as rust disease symptom's existence in millet. Customized CNN attained the recall of 97.4%, accuracy of 98.8%, exactness of 98.2%, and f-score of 97.7%, respectively.

A DL-based was introduced by Nidhi Kundu et al [3] in 2022, which includes the steps such as input pre-processing, automatic disease detection, prediction of severity and estimation of crop loss. For RoI (Region of Interest) extraction, it leveraged the K-Means clustering algorithm. For disease detection, prediction of severity and estimation of crop loss, a model named MaizeNet was introduced, which attained the accuracy of 98.50%. To offer a user-friendly interface, this model was integrated with a web application.

For the identification of leaf disease along with its source, CNN models were utilized by Md. Manowarul Islam et al [4] in 2023. For leaf condition detection, several models including ResNet-50, VGG-16, VGG19 and CNN architecture are utilized. From these models, better accuracy of 98.98% was attained by ResNet-50 model. So, to detect the plant disease correctly, ResNet-50 model was utilized in web app development.

In 2023, Nipuna Chamara et al [5] introduced AICropCAM, which was a field-deployable imaging framework. This framework integrates the edge image processing, IoT, and LoRaWAN to attain the lower-power along with long-range communication. This AICropCAM's core component was a stack of 4 DCNN (Deep CNN) models running sequentially, crop type categorization using CropClassiNet, canopy cover measurement using CanopySegNet, plants and weeds count using PlantCountNet with insect identification using InsectNet.

In light of disease detection and categorization in diverse crops Ananda S. Paymode et al [6] utilized the CNN. To extract the features also CNN-based model was utilized. This work's main goal was to detect and categorize the crop diseases that affect the tomato and grape leaves at the initial stage. For the performance measure enhancement, CNN based VGG (Visual Geometry Group) model was utilized.

In 2024, Theofrida Julius Maginga et al [7] introduced a technique for Northern Leaf Blight (NLB) detection at early stage using IoT (Internet of Things) sensors. Total Volatile Organic Compounds' (VOC's) non-visual measurements and maize plant's ultrasound emissions are captured with the utilization of CNN and LSTM prototypes. This With wavelet data preprocessing, this hybrid CNN-LSTM model was improved and which obtained F1 score of 0.96 and AUC (Area under the ROC Curve) of 1.00.

For efficient plant disease recognition, Andrew J. et al [8] employed CNN-based pre-trained model in 2022. This aimed to improve the well-liked pre-trained model's hyperparameters. Here models including VGG - 16, ResNet-50, InceptionV4 and DenseNet-121 were utilized and their hyperparameters were tuned. The experiment was conducted leveraging Using Plant Village dataset. Highest classification accuracy of 99.81% was attained by DenseNet-121 model.

METHODOLOGY

For the global food supply, the crop's growth is essential. Moreover, the production loss can be caused by diverse plant diseases. However, monitoring crop diseases manually by botanists and agriculture experts

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are challenging, error-prone as well as time consuming and. To enhance the disease detection, machine vision technology can be beneficial. Consequently, a novel crop disease detection system has been proposed which includes the following working phases.

a) **Data Acquisition:** Initially, in the data acquisition phase, data is collected from the benchmark datasets.

b) **Pre-processing:** The acquired data get pre-processed using Gaussian filtering process, which effectively smoothers out noise and reduces sharp transitions among the pixel values.

c) **Segmentation:** Pre-processed image get subjected to segmentation, where Improved SegNet is utilized to divide the pre-processed image into multiple segments.

d) **Feature Extraction:** From the segmented images, features such as Improved Local Gabor Directional Pattern (LGDip), PHOG (Pyramid Histogram of Oriented Gradients) and shape features are extracted.

e) **Classification:** Using extracted features, the crop disease is classified in this phase with the utilization of proposed hybrid model, which is the combination of both Modified CNN (Convolutional Neural Network) and Bi-LSTM (Bi directional Long Short-Term Memory). The overall architecture of proposed work crop disease detection system has been provided in Fig 1.

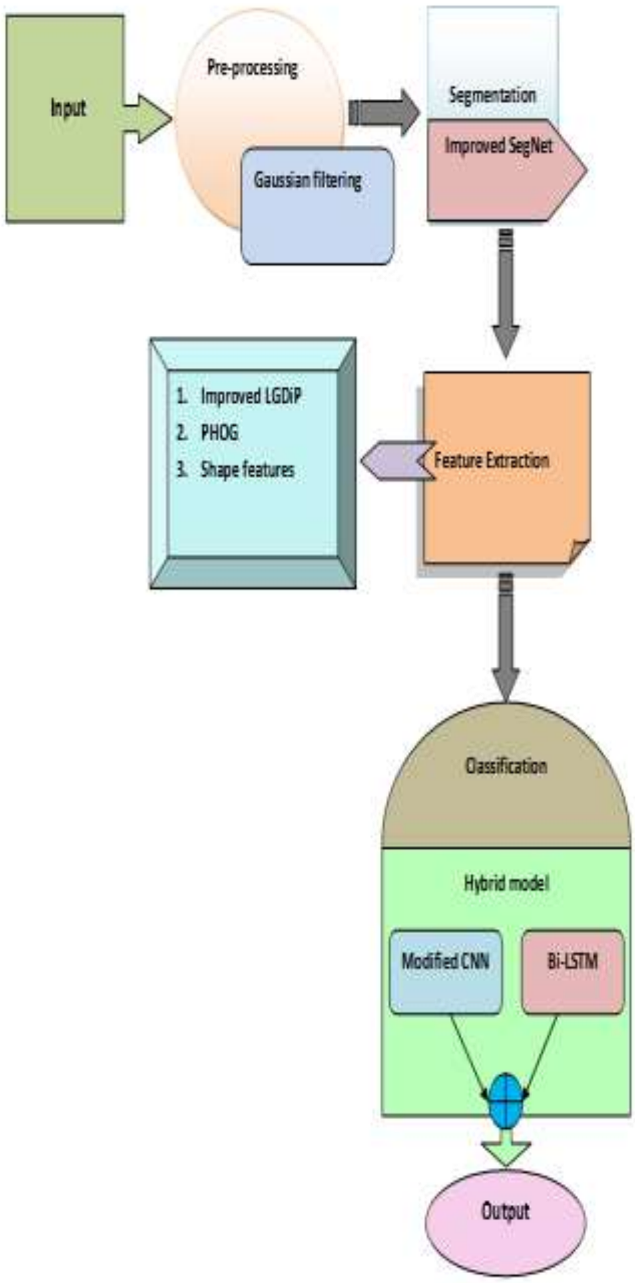

Fig. 1. Architecture of proposed work crop disease detection system

RELATED WORK

TABLE I

Citation	Techniques	Advantages	Challenges
R. Abbasi *et al* [1]	ResNet 50, YOLO v5s	Along with disease detection, this also helps in making decisions about the treatment for that detected disease.	Model is not secure, privacy issues can occur.
Sushruta Mishra *et al* [2]	Customized-CNN	Highest accuracy can be produced even with limited dataset	Model has higher computational complexity along with limited generalization
Nidhi Kundu *et al* [3]	MaizeNet	Since it utilizes least number of parameters, takes only less training time	Model needs to be generalized for any other crop's loss estimation.
Md. Manowarul Islam *et al* [4]	DL models	Better accuracy rating of 98.98% was attained by ResNet-50	Utilized only for the potato leaf diseases.
Nipuna Chamara *et al* [5]	AICropCAM	Only a short time was required to run each DCNN that increases the system's suitability in real-time applications.	Lower accuracy ratings that are 94.5 % and 92.83 % are attained by classification and segmentation models.
Ananda S. Paymode S *et al* [6]	CNN (VGG-16)	Attained 98.40% and 95.71% accuracy for grapes and tomatoes disease detection.	Model was computationally expensive and it requires large count of parameters
Theofrida Julius Maginga *et al* [7]	Hybrid CNN-LSTM model	Along with maize, for other crops also it was more suitable	For adopting these models to new domains, extensive retraining and fine-tuning was required.
Andrew J. *et al* [8]	Pre-trained CNN models	DenseNet-121 attained 99.81% categorization accuracy.	Only a single leaf was utilized for disease detection.

MOTIVATION

The increasing impact of climate change on agriculture, coupled with the rising global population, has intensified the urgency for efficient crop management practices. Crop diseases can lead to significant yield losses, threatening food security and farmers' livelihoods. Traditional methods of Disease identification is frequently a labor intensive and slow, making timely intervention difficult. By harnessing advancements in machine learning and image processing, this research aims to provide farmers with an automated, cost-effective solution for early disease detection. This approach not only empowers farmers to take proactive measures but also enhances overall agricultural productivity, contributing to a more sustainable food supply.

SCOPE OF PROJECT

This project focuses on developing a comprehensive framework for crop disease detection that integrates advanced machine learning techniques, specifically an improved SegNet model for image segmentation and a hybrid classification architecture combining Modified CNN and Bi-LSTM. The scope includes data acquisition from benchmark datasets, preprocessing of images to enhance quality, effective segmentation of plant leaf images, extraction of relevant features, and accurate classification of diseases. Additionally, the project will evaluate the Performance of the suggested model in comparison to current state-of-the-art techniques, aiming to provide a robust solution is easily applicable in actual agricultural environments. Ultimately, this research seeks to contribute valuable insights and tools for enhancing agricultural productivity through technology.

RESEARCH GAPS IDENTIFIED

Despite recent advancements in crop and plant disease detection methods, several critical gaps persist that hinder their practical application. Many existing models face security and privacy issues, particularly in cloud-based systems, which can undermine user trust and limit adoption among farmers. Furthermore, these models often exhibit higher computational complexity, making them difficult to implement in resource-limited settings. Many approaches also suffer from limited generalization, proving effective only for specific crops or conditions, which restricts their utility in diverse agricultural environments. Additionally, a common shortfall is the reliance on data from only a single leaf for disease detection, which may not adequately represent the overall health of a crop and can lead to inaccurate assessments. To truly benefit the agricultural community, there is a pressing need to enhance the generalization capabilities of these models, allowing them to function effectively across various crop types and conditions. Addressing these gaps will be essential for developing robust, efficient, and widely applicable crop disease detection systems that can support farmers in managing their crops more effectively.

RESEARCH HYPOTHESIS

The central hypothesis of this research is that the integration of an improved SegNet model with a hybrid classification architecture will significantly enhance the precision and effectiveness of crop disease detection compared to traditional approaches. Specifically, we propose:

Sub-hypothesis:

(i) Improved Segmentation Accuracy: The enhanced SegNet model will yield more precise segmentation of plant leaf images, reducing misclassification rates and improving disease detection reliability.

(ii) Enhanced Feature Extraction: Utilizing advanced techniques like Improved Local Gabor Directional Pattern (LGDip) and Pyramid Histogram of Oriented Gradients (PHOG) will provide a richer feature set, enabling the model to identify subtle disease symptoms effectively.

(iii) Superior Classification Performance: The hybrid model, combining Modified CNN and Bi-LSTM, is expected to outperform traditional classifiers in accuracy, specificity, and sensitivity by capturing both spatial and temporal features.

(iv) Robustness in Diverse Conditions: The proposed system will demonstrate robustness across various environmental conditions and crop types, addressing limitations of existing models that rely on narrow datasets.

(v) Cost-Effectiveness and Accessibility: Automation of disease detection will reduce time and labor costs, making advanced detection technology more accessible to farmers, particularly in resource-limited settings.

Thus, this research hypothesizes that the combination of improved segmentation, enhanced feature extraction, and advanced classification will make a more efficient crop disease detection system, empowering farmers and contributing to better agricultural practices.

EXPECTED OUTCOME

The effectiveness of the proposed work is contrasted with over the conventional models in relation to accuracy, specificity, sensitivity, etc.

CONCLUSION

In this proposed system we provide the integration of an improved SegNet model with a hybrid classification architecture will significantly enhance The precision and effectiveness of crop disease detection in contrast to conventional techniques

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