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Plant Leaf Disease Detection and Automatic Pesticide Recommendation Using Deep Learning

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Abstract: Defoliating plant diseases are critical and still remains a significant threat on the world's agricultural production, foodsecurity and economies. The older models for disease detection and diagnosis are inefficient, error-prone, and labor extensive, allowing for delays in action and mistimed pesticide application. Recent improvements in deep learning (DL) and image processing technologies appear to allow the use of automated plant disease detectionsystems that canassist in recommending suitable and more effective pesticides. This work assesses various deep learning methods for their capabilities for plant leaf diseases detection, focusing on their functionality, accuracy and ease of use in real field setting. It also focuses on the methods for implementing the automatic recommendation systems interpolating between CNN and machine learning methodologies. It was shown that the most effective architectures are implemented on the basis of CNN, giving the best results in disease diagnosis precision. Also, the hybrid methods allow combining the recommendation for the use of pesticides. A number of possible avenues for research aimed at enhancing efficiency of the models in real time field application are outlined.

Keywords: Plant leaf disease detection, Deep learning, Pesticide recommendation, Convolutional neural network, Crop management, Agricultural productivity

I. INTRODUCTION

Agriculturalproductivity food security wellas sustainabilityoftheglobalpopulation. is vital for as economic With the global population on the increased a yin dayout, it is becoming more and more critical to have a steady supply of food. This, however, begsthequestionhowtodealwith one of the most notorious factors reducing crop yield, quality and profitabilityplantdiseases. Theimpactisdevastating when compared to the losses in agricultural production across the globe. The Food and Agriculture Organization (FAO) records more than 20-40% of annual global crop losses caused by plant diseases. Such problems not only decrease the quantities and quality of the goods produced, but also hinder prices and chances for selling products abroad, thus disrupting the chain of supply of food.

Leaves are a primary focus of disease detection strategies since plants9diseasesappearprominentlyonleaves.Thetypicalmethod for detectingplants9 infections is the routine practice of plant specialists whoscrutinizetheaffectedleafforabnormalitiessuch as discoloration, spots, or other irregularities. However, this manual approach cut across agricultural practices, though being very painstaking, is time consuming and also susceptible to errors, especially in large-scaleagricultural settings where rapidandprecisediagnoses of diseases are essential. Some farmers can also misread the symptoms and apply wrong or too much pesticides which can be harmful to the crop, the soil and the ecosystemand thesurrounding areas. Therefore, it is essential develop efficient, dependable, and cost-effective systems for the earlydiagnosis of diseases and precisedosageof pesticides.

Artificial intelligence (AI) tools including machine learning algorithms notably deep learning techniques are fast revolutionizing the pace and the accuracy in which disease detection can be done. Among the many deep learning models that are available, convolutional neural networks (CNNs) have been shown to work exceptionallywell for imageclassification tasks, proving their capabilities in handling leaf images. Different CNNs can learn diverse and complex patterns associated with a variety of diseases and classify disease from leaf images without human assistance or manual feature extraction. This has, as a consequence, resulted in growing interest in the application of CNNs for determining plant diseases in a variety of crops, for example, corn, mango and citrus plants. It is evident from these studies that, for example, certain CNN models achieved above 90% accuracy in some instances and could prove useful in disease diagnosis.

It is not enough to detect plant diseases; disease management also involves taking active measures to protect the crops from potential threats. It is this aspect that calls for the recommendation of pesticides. So when a plant disease is detected, an integrated systemcould suggest suitablepesticides incorporated to the pathogen detected allowing farmers to know the appropriate one to apply and thus minimizing the chances of overuse. With that however, most of the pesticide recommendation systems are basic and are manual – expert knowledge and experience which at times is not available most particularly in the countryside areas.



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On the other hand, CNN based disease detection together with an automated recommendation system can address both identification and treatment of the disease in one broad sweep. Combining these two functions would reduce human input, lower the risk of errors being made, and encourage best agricultural practices by promotingaccurate applicationofpesticides to avoid pollution in the environment.

Some of these studies have looked at enhancing integration of machine learning (ML) together with CNNS in undertaking disease detection and even carrying out recommending other tasks such as spraying pesticides. For instance, it has been noted that ML algorithms analyses the prevalent climate conditions and the severity of the diseases so as to suggest themost suitable pesticides for plants which have been infected with diseases that have already been identified with CNN-based treatment. Such hybrid systems combine ML and DL and enhance both accuracy and efficiency allowing crop disease management to be multi-dimensional.



Even with these instated procedures, there are limitations in the application of deep learning techniques in diagnosing disease and recommending pesticides in the actual farming unit. Considering the amount of pictures taken by a model, CNNs are demandable in terms of computational capacity making them difficult to be integrated intoresource limited usage like smart phones or field devices. Moreover, external forces such as changes in lighting, presence of occlusions such as leaves and environmental distractions can also impact the model 9 seffectiveness when released into the field. Diversity in plants



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diseases is another challenge because that varies across crops, areas, and the time of the year. There are often limited or no available datasets that include these variations for a model to generalize across severaltargets.

Theseframings of theproblemallow us toformulate research goals in three directions: what are, and which current deep learning models are themost promising for plantleaf disease detection and how could they be integrated into an automated pesticide recommendation system? We concentrate on the effectiveness of CNN-based systems; their accuracy, computational resource consumption, and possibilities for scaling. Additionally, we evaluate hybrid models which also incorporate machine learning algorithms for pesticide recommendation enhancements. This paper enhances researching the creation of actionable, cost effective methods capable of wide scale automated detection and management of crops diseases in contemporary agriculture.

II. LITERATURE REVIEW

Research on plant disease detection and automated pesticide recommendation systems has grown significantly in recent years. This literaturereview covers several relevant studies, categorized into the key areasofdeep learning techniques, CNN-based architectures, hybrid ML- DLapproaches, and theapplication of the setechnologies in real-world agriculture.

1) ImageProcessingTechniquesinDiseaseDetection

- Earlystudies laid the groundwork by using traditional image processing techniques for detecting diseases in plant leaves. While not as accurate as deep learning methods, these techniques are computationally simpler and have been foundational in developing automated systems:
- BananaPlantDiseaseDetectionUsingImageProcessing- This study investigates thresholding and segmentation methodstodetectdiseasesymptomsonbananaleaves, laying the foundation for automated detection in other crops.
- DetectionofDefectedMaizeLeafUsingImageProcessing Techniques Explores edge detection and color feature analysis for identifying defects, demonstrating the applicability of imageprocessing in maizediseasedetection.
- Disease Detection in Pomegranate Plant Using Image ProcessingTechniques Utilizescolorand textureanalysis to identify disease symptoms on pomegranate leaves, showcasingimageprocessingasacost-effectiveapproachfor diseasedetection.



$2) \quad Deep Learning and CNN-Based Disease Detection$

With the advent of CNNs, disease detection accuracy has improved significantly due to the deep networks9 ability to learn complex features from images without manual feature engineering: accuracy and indicating CNNs' effectiveness for disease prediction.

- GrapeLeafDisease Recognition: ADeepLearningand Machine Learning Techniques Overview Compares different CNN architectures for grape leaf disease detection, identifying the most suitable models for grape leaf disease classification.
- Identification of Various Diseases in Plant Leaves UsingImageProcessingandCNNApproach –Employs CNNs for highaccuracy classification of plant diseases across multiple crops, illustrating the potential of deep learning in agricultural applications.

3) CNNArchitecturesforImprovedAccuracyand Efficiency

DifferentCNNarchitectureshavebeen exploredtooptimize modelperformanceandcomputationalefficiency, especially for deployment in resource-constrained environments:

- AnAutomatedandFine-TunedImageDetectionand Classification System for Plant Leaf Diseases Investigates finetuningCNNslikeVGG16andResNet to improve classification accuracy while reducing computation time.
- FieldPlant:ADatasetofFieldPlantImagesforPlant Disease Detection and Classification With Deep Learning Highlights the importance of dataset diversity in improving model robustness in real-world conditions.
- Advanced Citrus Disease Analysis Integrating ML and DL for Improved Identification and Classification-ComparesCNNslikeInceptionV3and ResNet for identifying citrus diseases, with a focus on improving generalization to diverse field conditions.
- A Survey on Automated Disease Diagnosis and Classification of Herbal Plants Using Digital Image Processing Provides a comparative analysis of CNN models, showing that deepernetworks like Efficient Net yield higher accuracy for herbal plant diseases.
- MachineLearning-BasedPlantDiseaseDetectionfor Agricultural Applications: A Review Reviews the effectiveness of CNN architectures in agricultural applications, especially focusing on MobileNet for its computational efficiency.

4) HybridModelsIntegratingMLandDLforDisease Detection and Pesticide Recommendation

Several studies combine CNN-based detection with traditionalmachine learningalgorithms to enhancepesticide recommendations and disease management capabilities:

- 5) ComparativeAnalysisofSmartPesticide
- ApplicationofDeepCNNforImage-Based
 RecommendationSystemUsingML& AI-Explores integrating
- Identification and Classification of Plant Diseases Demonstrates that CNNs achieve over 90% accuracyin distinguishingbetween differenttypesofplantdiseases.CNNsfordiseasedetectionwithMLforpesticiderecommendation, demonstrating improved accuracy in providing tailored pesticide options.
- Development of Plant-Leaf Disease Classification
- LeafDiseasesPrediction,PestDetection,andPesticides
- ModelUsingConvolutionalNeuralNetwork-Studies the use of CNNs for classification in various crops, showing promising results in model adaptability across different types.
- Recommendation Using Deep Learning Techniques Investigates a system that combines CNN-based disease detection with decision tree-based pesticide recommendation, yielding high accuracy and relevant recommendations.
- AccuratePredictionofLeafDiseaseinPepperBell
- EffectiveClassificationofPlantDiseaseUsingImageProcessing
- Using Deep LearningAlgorithm –AppliesCNNs to identifydiseasesinpepperleaves, achievinghigh and MachineLearning Combinesimageprocessing and machinelearning to improve the classification accuracy of plant diseases, focusing on efficient and targ etedpesticide use.
- Earlier Detection of Plant Disease and Recommending Pesticides Using Convolutional Neural Network Proposes an endto-end system that combines disease detection and pesticide recommendation, enhancing early intervention.
- A Web-Based Agriculture Recommendation System Using DeepLearningforCrops,Fertilizers,andPesticides–Develops acomprehensiverecommendationsystem, incorporatingCNNfor disease detection with other ML algorithms for making tailored crop and pesticide suggestions.



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• PesticideRecommenderSystemforDetectingthePaddyCrop Diseases Through SVM – This system uses SVM for disease classification followed by a pesticide recommendation module, showcasing the utility of ML in disease management.

6) Real-TimeDiseaseDetectionandFieldApplications

- Real-timedetectionsystemsareessentialforpracticaldeployment in thefield, wheretimelyintervention can prevent diseasespread. These studies emphasize optimizing models for real-time performance and robustness in diverse environments:
- ACombinedArchitectureofImage Processing Techniques and Deep Neural Network for the Classification of Corn Plant Diseases–Usesahybridapproachtoincreasemodelrobustnessin field conditions, allowing for real-time disease detection.
- A Mango Disease Prediction for Smart Agriculture Using Machine Learning Algorithms Demonstrates a real-time detection and prediction system for mango diseases, supporting practical application in agriculture.
- Disease Detection of Citrus Plants Using Image Processing Techniques–Thisstudyhighlights theuseoffast-processingCNN models optimized for field deployment in citrus farms.
- Detection of Diseases in Cardamom Leaves Using Digital Image Feature Selection Techniques Optimizes feature selection for real-timedisease classification incardamom, illustrating potential for field applications.
- Cotton Leaf Disease Classification and Pesticide Recommendation Integrates CNN with optimized image preprocessing for real-time classification and recommendation in cotton fields.

7) ComprehensiveReviewsandSurveysonPlantDiseaseDetection

The following papers provide an overview of the advances in plant disease detection, summarizing and analyzing various techniques:

- A Review of Plant Disease Detection Methods Using Image Processing Approaches Covers different image processing techniques, from traditional methods to CNNs, for plant disease detection.
- A Survey: Machine Learning and Deep Learning in Wheat Disease Detection and Classification Provides a detailed survey of ML and DL methods in wheat disease detection, emphasizing CNN architectures for high accuracy.
- A Review on Various Plant Disease Detection Using Image Processing Reviews numerous disease detection techniques, highlighting the strengthsandlimitations of CNN-based approaches.
- A Review on Coconut Tree and Plant Disease Detection Using Various Deep Learning and Convolutional Neural Network Models Summarizes CNN models' applicability to disease detection in coconut and other plants.
- e-Farmer: A Study of How Image Processing Tools May Be Used to Detect Plant Disease Reviews image processing tools used in digital agriculture, focusing on CNN and ML applications in plant disease detection.

III. COMPARATIVE PERFORMANCE ANALYSISOFEXISTINGSYSTEMS

1) EffectivenessforDiagnosingDisease

- Models based on CNN: Convolutional neural network (CNN) architecture is the most standard and extensively used architectureindiseaseidentificationviaimageswithsomecrops exceeding 90 % accuracy. For example, 8Detection of Banana PlantDiseasesusingArtificialIntelligenceandDelimitatedLeaf Section9 applies a CNN based analysis for classification of bananaplant9sdiseasesfromleafdiscolorations andothervisible symptoms.Itiswellknownthatalargeamountofimageswould enhancetheaccuracyoftheconvolutionalneuralnetworkasthe task of recognizing pattern is inherent to CNNs.
- Hybrid ML-DL Models: Integrated models or multi-thematic models will have added advantage by incorporating image features and additional datarelated to the disease or site such as Marked features. The study 8C omparative Analysis of Smart Pesticide Recommendation System using ML & AI9 confirms the findings, stating that ML enhances the ability of the models trained already with the CNN enhancing specificity of the recommended pesticides to the disease classified.

2) Computational EfficiencyandModelComplexity

• DeeperlayeredarchitecturessuchasResNetandEfficientNet areconsideredcomplexandcomputationallycostlybutyield high accuracyin detection methods. <Automatic Diagnosisof PlantLeafDiseasesBasedonDeepLearningApproach=this sentencecanbeomittedtheconstructionisformoreaccurate models obtained higher performance in terms of operational efficiency, still sites the challenge of making these models deployableinfieldsituations.MobileNetandSqueezeNetare lightweight architectures but they are less accurate models. They can, however, provide a useful solution.



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• Image Processing Techniques: More typically, such systems involve matrix-based processes, such as thresholding and edge detection, which are less computationally intensive. Fadila et al. in <Detection of Defected Maize Leaf using Image Processing Techniques=alsofocusontheseapproachesandreport thatsuchsystemsarenotasaccurateasCNNbasedbut the computational requirements are lowermakingthemsuitableforlowresourcerealtimeapplication.

3) FieldApplicability andReal-timePerformance

- RobustnesstoFieldConditions:Thisiscriticalasmostofthetimes inlighting,weatherandstagesofplantdevelopmentallinfluencing awidervarietyofimagesorsetsofsignificantvariablesisnotedin Disease Detection and Classification With Deep Learning=.
 oftheyear,theconditionsaremostlynot theclarityof images. ThenecessityofexposingCNANmodels to researchlike"FieldPlant:ADatasetofFieldPlantImagesforPlant
- Timely Suggestion of Pestors9 Synthetic Substances: In "Earlier Detection of Plant Disease and Recommending Pesticides Using ConvolutionalNeuralNetwork,"anautomaticfullloopisoffered, whereCNNdetects and recommends for usein diseased crops in optimal timing to provide efficiency towards crop diseases.CNN is able to deliver and recommend to farmers in a timely way suitableforpesticidesthatmaysuitspecifictypesofinfected disease based on the model and synthesis encountered together with a pre-processing stage that is real time or near time.

IV. CONCLUSION

As a result of this research, existing frameworks have been evaluated and analyzed that focus on plant leaf microbialdisease detection and automatic pesticide recommendation through deep learning, theiressential changes, strengths, and weaknesses. Deep learning-based new generation systems, including convolutional neuralnetworks (CNN), have drastically increased the accuracy of disease diagnosis, improving even the existing image processing techniques. Efficient and lightweights tructures for Mobile Net and Efficient Net have shown their potential for field applications which require real time operation of resource constrained systems. It can be noted that hybrid models of CNN-based disease diagnosis and machine learning algorithms for recommendation systems are more versatile innature, how ever, they are still a work in progress with regards to their applicability on new diseases and varied agricultural practices.

In as much as the advances have been achieved, actual implementationinpracticalscenariosisstilladauntingtask. Many models exhibit reduced efficiency in field settings due to the presence of lighting differences, obstruction and the diversity of theleaves alone. Also, dataset diversity must be emphasized as a veryimportant aspect when seeking to develop intelligent models because asystem designed using a small set of conditions will not be able to work over many crops, diseases and environments. These are the two factors which if incorporated will help create an umbrella model that will ultimately improve performance, reliability and increase usability in real world settings.

Going forward there is a clear demand for systems that can improve n the existing limitations and that will make use of low operational resources to detect diseases at high efficiency standards.

The advancement of plant protection measures will be facilitated by extending the research on hybrid and multi-model strategies, developing extensive agricultural databases, and enhancing the abilitytocopewithchangesinrealtime.Suchadvancementsmay bebeneficialfordecreasingcroplosses, reducing the dependency on pesticides, and promoting agriculture9s sustainable development. The integration of these systems, therefore, can revolutionize agricultural disease management through deep learning for plant disease detection and pest control, ultimately transforming agricultural productivity and the global environment for the better.

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