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REVOLUTIONIZING CITRUS AGRICULTURE USING DISEASE FORECASTING THROUGH CONVOLUTIONAL NEURAL NETWORKS FOR LEAVES AND FRUITS

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ABSTRACT

Citrus crops are vital contributors to the global agricultural economy. However, they are susceptible to various diseases that can significantly impact yield and quality. Early detection and management of these diseases are crucial for maintaining healthy citrus orchards. In this study, we propose a deep learning-based approach for the automated prediction of diseases affecting citrus leaves and fruits using the VGG16 convolutional neural network model. The proposed model leverages transfer learning, utilizing the pre-trained VGG16 model, which has demonstrated effectiveness in image classification tasks. We assemble a dataset comprising images of healthy citrus leaves and fruits, along with images depicting common diseases such as citrus canker, citrus greening, and citrus blackspot. These images are preprocessed and augmented to enhance model generalization and robustness. The VGG16 model is fine-tuned on the citrus dataset, where the last few layers are replaced with custom fully connected layers for disease classification. During training, the model learns to extract discriminative features from citrus images, enabling it to differentiate between healthy specimens and those affected by diseases. We employ data splitting techniques to ensure rigorous evaluation of the model's performance, including validation on separate datasets. The efficacy of the proposed model is evaluated through comprehensive experiments, including accuracy assessment, confusion matrix analysis, and comparison with existing methodologies. The results demonstrate the potential of the VGG16-based approach in accurately predicting citrus leaf and fruit diseases, thus facilitating timely intervention and management practices in citrus cultivation.

Keywords: Citrus Family, Deep Learning, Fertilizer recommendation, Transfer learning, Disease Prediction

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1. INTRODUCTION

With the increasing world population, the place of agricultural production in the world economy has become much more important. Considering that the world population is on an increasing trend and its global resources are decreasing, it is obvious that agricultural production will be more important in the next century. On the other hand, factors such as global climate change, the destruction of arable land, pests, and new diseases are important obstacles to agricultural production. These barrier sposea significant risk to global food security and the worldeconomy. These risks directly affect the yield and quality of crops worldwide. It is an extremely important issue to keep both the quality and quantity of the produced crop under control. Because the need for food of the world population is increasing day by day. For this reason, meeting the food demand is becoming more and more important every day. In this, the quality and quantity of the production should be strictly followed and no faultshouldbegivenintheproduction.Some methodshavebeenusedintheliteraturefor this subject. The first of these is plant breeding. Plant breeding, which is a difficult method, aims to develop more resistant plant speciesagainstdiseases.Thismethodiscostly and not accessible to all manufacturers. In addition,someproblemsmaybe experienced in breeding works. Another way to control diseases is to monitor disease conditions by observing plants and to apply agricultural pesticides directly in any adverse situation. This method is more preferred around the world and it is a method that manufacturers can easily apply. The disadvantage of this method is that some manufacturers use chemical pesticides unconsciously. The most common problem in unconscious drug use is that the diseases in plants cannot be detected correctly and the wrong drug is used. Unconscious drug use also directly threatens human health. The most common diseases in citrusproductionareBlackspot(CitrusBlack Spot (CBS), Canker (Citrus Bacterial Cancer (CBC),) Greening (Huanglongbing (HLB)). Especiallycommercialcitrusproductionis highly susceptible to these diseases. For this reason, necessary intervention should be made when disease formation is detected. Otherwise, there is a loss of quality and efficiency in the products.

CBC is a disease that affects many commercialcitrusvarietiesaroundtheworld, includinggrapefruit,lemons,limes,andsweet oranges. This disease is more common in humid-wetclimatessuchashightemperature, precipitation and windy conditions. In this disease, early leaf and fruit shedding, brown spotsonthe leavesandbubble-like lesionsin variouspartsofthetreeareseen.CBSusually appearsasfrecklespotsontheleavesandfruit of citrus plants. It is also seen as spots of lesion in the branches of the plant. It is a disease that is more prominent in warm regions, such as in CBC. CBS is a fungal pathogen-based disease called Phyllosticta citricarpa. This disease affects both quality and yield

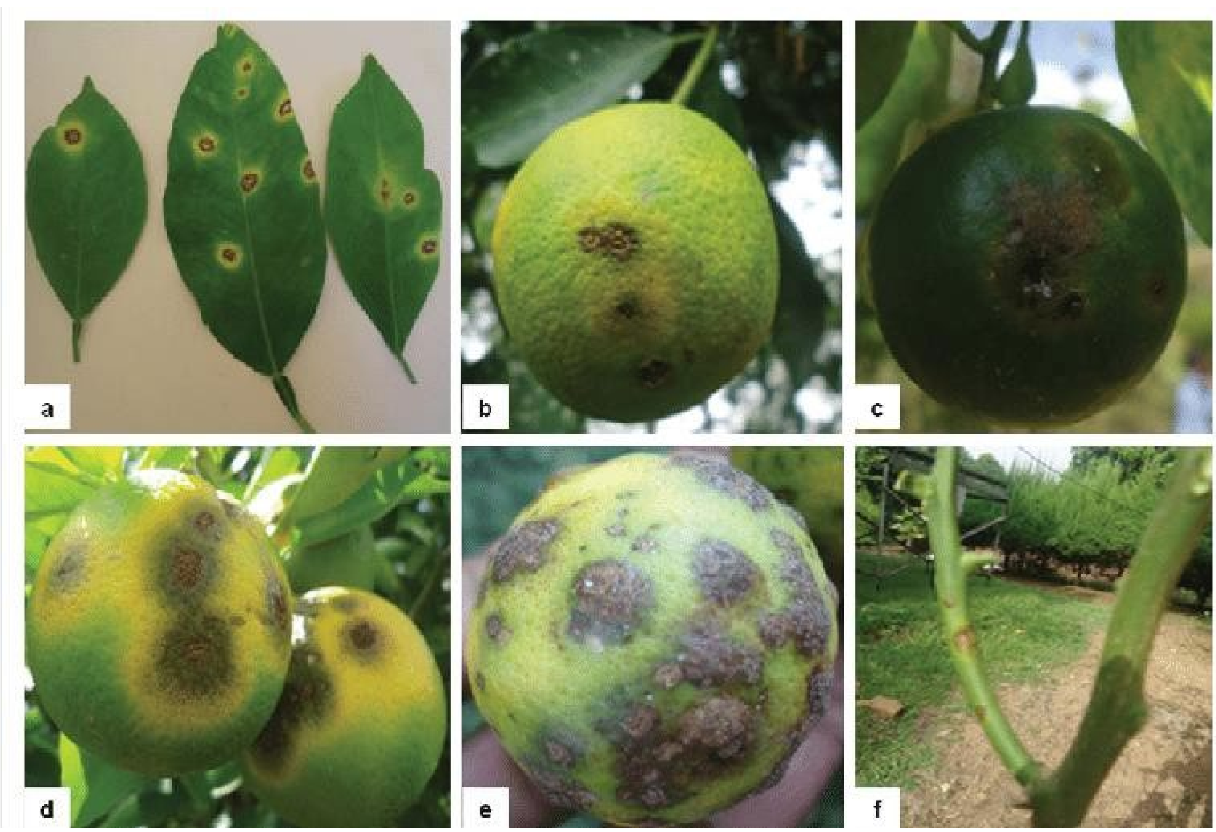

FIG1 CITRUSLEAFANDFRUITDISEASE

2. RELATEDWORK

JiangchuanFan,et.al,…[1]designthe system for rapid development of gene sequencingtechnologyandthecompletionof a variety of plant genome sequencing, plant phenotype has become a bottleneck to study the relationship between plant genotype- phenotype-environment type. At present, various plant phenotypes are high-throughput.Researchondetectiontechnology has received extensive attention. Plant phenomics research hopes to conduct high- throughput quantitative studies on specific genotypes of massive phenotypic parameters based on genome-wide sequencing. Moreover, these phenotypic parameters are not only morphological data, but also a large number of physiological and biochemical data, as well as deeper mechanistic data, enabling scientists to further identify and predict heritable traits through controlled studies of phenotypes and genotypes. At present, the vast majority of the world'sfood is still produced in the field environment. Therefore, research on plant phenotypic detectiontechniquesandmethodsinthe field environment is the focus and hotspot for future research on breeding and plant yield.

ShrikrishnaKolhar,et.al,…[2]dealed with issues of global interest like rapidly growing human population, climate changes, scarce rain falls, soil conditions and various plantdiseases,newinnovativemethodologies need to be designed. These new methods can be used to identify, classify, quantify and predict effects of these factors to enhance production and nutritional value of crop. Therefore, there is need for automatic integrativeanalysis of plantcharacteristics to speedupcropvarietyselectionsthatarebetter suited for local climatic conditions. Plant phenotyping is also used to study plant diseases. It gives quantitative analysis of pathogen infection on plant physiology. These methods have ability to keep track of physiological functions such as photosynthesis and transpiration, in infected plants.Advancedimagingtechniquesoutside visiblelightspectrumenableustoidentify

and quantify disease symptoms that are otherwise not visible by naked eye. RGB imagingislowcostandsimplestmethod that increases both speed and accuracy in plant phenotyping.Thoughvisibleimagingismost commonly used method, it can only provide structural information of the plants. The factors like overlapping leaves, circadian movement of leaves, similarity in brightness and color between plant and background, canopy shadow and influence of light pose challengesin plantphenotyping using visible imaging and need be addressed using other techniques.

Dr. V. Anantha Natarajan, et.al,…[3] adopted for more than two decades in the automation of certain agricultural practices. The images captured by remote sensing devices are used for the detection and classification of plant diseases. In recent years, deep learning techniques are used in combination with plant disease detection from leaves, fruits, stem of the plants. Deep learning uses several layers to extract high- level features from real-time input images without using hand-crafted features and then extracted features are passed to different classifiers such as k-nearest neighbours, support vector machines and fully connected neuralnetworkfordiseaseclassification.The present work is to develop an automated mechanismforanalysingtheimagescaptured fromsimplecameradevicesinreal-timeusing a combination of image processing and deep learning techniques and detect the four categories of tomato plant diseases namely early blight, bacterial spot, septoria leafspot, and leaf curl.

Jingyao Zhang, et.al,…[4] developed a novel identification approach of cucumber leaf diseases based on small sample size and deep convolutional neural network. The lesionimageswereacquiredbyonetwo-stage segmentation method that offered strong discriminationability to extract disease spots from cucumber leaves with little human intervention. The high-quality training samples were generated under the operation ofrotation,translation,andAR-GAN.With

the improvement in convolutional layers, the proposed DICNN exhibited powerful feature extraction and fast convergence ability. Experimental results demonstrated that the proposed approach could effectively identify cucumber leaf diseases. The research explored a feasible way for field agricultural IoTstotimelyimplementtheidentificationof plantleafdiseases,whichisofgreatpractical significance. Hence, the selection of raw diseased leaf images needed conducting in addition to annotation, whereas both image selectionandannotationprocesseswereoften difficult, laborious, and time-consuming, as well as requiring a high level of expertise to avoid misclassification or other errors.

Therefore, although there were lots of cucumber leaf images stored in the image repository of IoT system, 200 raw diseased leaf samples for each type of cucumber leaf diseases were chosen from the stored image repository, and the size of each sample was adjusted to 1024 3 682 pixels in order to improve processing efficiency before conducting image analysis. The overall goal of this study was to evaluate the dynamic variations in soybean due to the salt stress using an imaging-based plant phenotyping system in a greenhouse environment. This study was based on our previous work with the focus on developing an imaging processing pipeline to automatically segment singleplantsfromimagesandtranslateimage information to crop phenotypes that were sensitive to salt stress

ShuiqinZhou, et.al,…[5] implemented an automated procedure was developedtofacilitateplantsalinitytolerance studies through image stitching, automatic segmentation and trait extraction. Results fromthisstudyshowedthatthegreenchannel in RGB color space and the value channel in HSV color space were effective in removing image background while effectively preserve salt damages. In addition, RGB based vegetation index ExG could effectively segmentsingleplantsofsoybeanfromimages automatically. The developed procedure was abletoidentifytheuniqueimagefeaturesthat

associated with symptoms of soybean leaves withsaltdamages.Theresultsshowedthatthe phenotypic traits of five soybean genotypes under salt stress can effectively differentiate their salt tolerance. This procedure provides the possibility to automatically analyze the stitchedimagestakenfromthetopview.With the size and color calibration, the procedure can be adaptedto analyze other plant species recorded by a high-throughput phenotyping platform. This approach enabled us not only to generate biologically relevant outputs at both image and pot levels at one time on the same day, but also to analysis the growth procedure and salinity tolerance variation. It is concluded that the saturation and blue values can be used to extract salt stress characteristics such as curly leaf, salt spots and yellow leaf, which can be well distinguished from the normal green leaves. The salt damage features were visually identifiedforeachplantandthethresholdsin saturation and blue channels were manually determinedtoextractthem.Resultsindicated that two image features, i.e. canopy area and ExV (the difference of excess green and excess red) were highly correlated with salinitytolerance traitofsoybean.The image saturation and blue channel values were able to extract salt stress characteristics and identify different types of salt stress characteristics. In addition, the ratio of damaged leaf area to canopy area was extractedasanovelimagefeaturetoquantify the salinity tolerance grade. The overall results indicated that the automatic plant phenotypingsystembasedonlow-costimage sensors and automation platform was able to quantify plant stress due to salt stress and would be useful in soybean breeding programs.

3. EXISTINGMETHODOLOGIES

Even though the botanical categorization was not founded on their qualities, leaves are the most obvious and mostusedmethodofidentifyingtreespecies. They can be found practically all year, are simple to photograph, and their shapes have well-studiedcharacteristicsthatmake

identification possible, if not simple. It uses high-levelgeometriccriteriainspiredbythose used by botanists to classify a leaf into a list of species, with the goal of being an instructional tool. By removing noise and other undesired pixels and extracting additionalinformationfromtheimage,digital image processing will increase the image's quality.Imagesegmentationisatechniquefor analysing images that can be used to classify or cluster an image into numerous discontinuous portions by grouping pixels to produceahomogeneousregionbasedonpixel attributes such as grey level, colour, texture, intensity, and other factors.

- K-Means Clustering for Leaf Segmentation: We first segment the tomato leaf images into distinct regionsusingtheK-MeansClustering algorithm. This step helps isolate the leaf parts from the background and other non-leaf elements, facilitating more accurate disease classification.
- Feature Extraction: We extract color- based histogram features from the segmentedleafregions.Histogramsof color distributions provide valuable information about the color composition of the leaf, whichcan be indicative of disease presence.

Support Vector Machine Classification: The extracted features are then fed intoa Support Vector Machine (SVM) classifier. SVM is a powerful machine learning algorithm known for its effectiveness in binary classification tasks. We train the SVM model on a dataset of annotated tomato leaf images, where each imageis labeledas either healthy or diseased

4. PROPOSEDMETHODOLOGIES

The proposed system aims to automate the detection of diseases affecting citrus leaves and fruits using the VGG16 convolutional neural network (CNN) model. Citruscropsarevulnerabletovarious diseases, which can have detrimental effects onfruityieldandquality.Traditionalmethods of disease diagnosis rely on manual inspection, which is time-consuming and prone to human error. By leveraging deep learning techniques, our system offers a promising solution to this challenge. We begin by collecting a diverse dataset comprising images of healthy citrus specimens and those exhibiting common diseases such as citrus canker and citrus greening. This dataset undergoes preprocessing to ensure consistency and enhance model performance. The pre-trained VGG16model,knownforitseffectivenessin image classification tasks, serves as the foundationofoursystem.Weemploytransfer learning to adapt the VGG16 model to our specifictask,fine-tuningitslastlayersonour citrus disease dataset. During training, rigorousvalidationprocedures,includingdata augmentation and cross-validation, are applied to ensure the model's robustness and generalization. The trained model is then evaluated on a separate testing dataset to assess its ability to accurately detect citrus diseases. Performance metrics such as accuracy, precision, recall, and F1-score are computed to quantify the model's effectiveness.Ultimately,oursystemoffersa reliable tool for early disease detection and management in citrus orchards, potentially contributing to sustainable citrus production andimprovedcrophealthmonitoring.Central to our approach is the utilization of the VGG16 architecture, a widely recognized CNNmodelwithprovencapabilitiesinimage classification tasks. Leveraging transfer learning, the pre-trained VGG16 model is fine-tuned on our citrus disease dataset, enabling it to learn discriminative features specific to disease pathology. Fine-tuning involves adjusting the model parameters to adapt to the nuances of citrus diseases while retaining the foundational knowledge gained from its pre-training on large-scale image datasets.

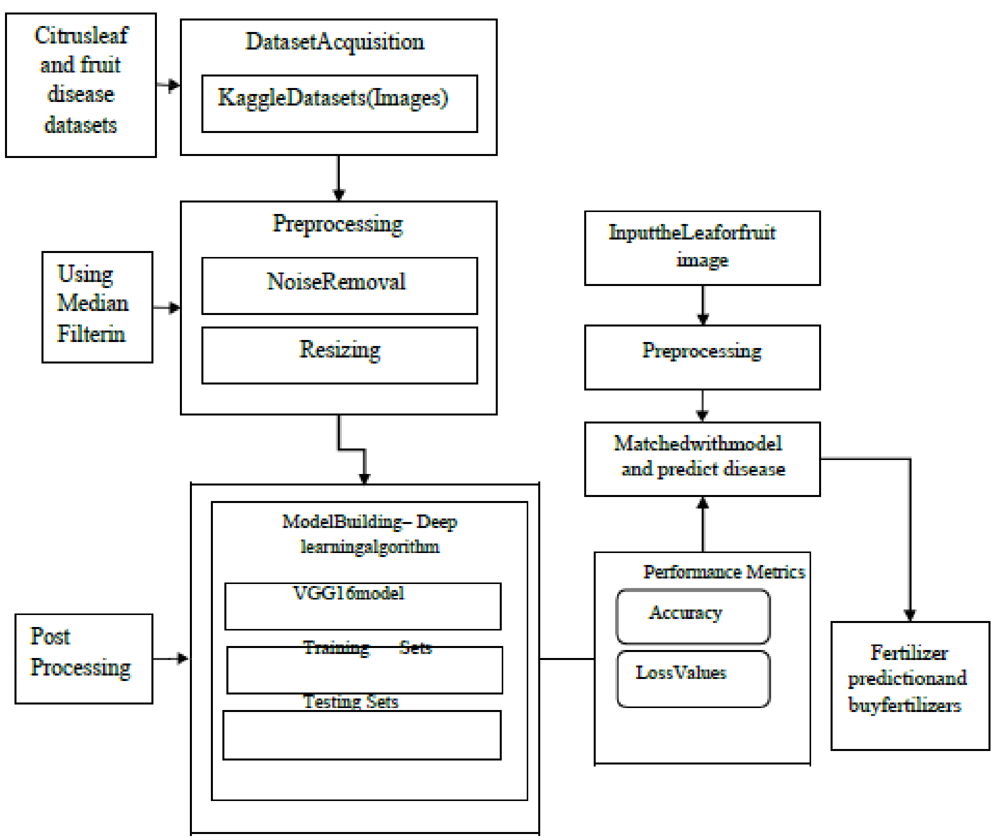

FIG2: BLOCK DIAGRAM

Implement Neural classification named as Convolutional neural network algorithmwithtransferlearningmodelnamed as VGG16 to predict the diseases. Predict diseasesasbacteria,fungiandotherdiseases. Annotate the images with corresponding labels indicating the type of citrus and the state of the fruit or leaf (e.g., healthy, diseased). Save the model file for both leaf and fruit as Model.h5 vector file.

Convolutional Layers: VGG16 consists of 13 convolutional layers, each followed by a rectified linear unit (ReLU) activationfunction,whichintroducesnon linearity to the model. These layers are responsibleforextractingfeaturesfrominput images, gradually capturing increasingly complex patterns as the network deepens.

Max Pooling Layers: After every two convolutional layers, VGG16 incorporates max-pooling layers to downsample the feature maps, reducing spatial dimensions whileretainingimportantfeatures.Thishelps in achieving translation invariance and reducing computational complexity.

Fully Connected Layers: Following the convolutional and max-pooling layers, VGG16includesthreefullyconnectedlayers

for high-level feature representation and classification. These layers are typically accompanied by dropout regularization to prevent overfitting.

Softmax Layer: The final layer of the network is a softmax activation function, whichoutputsprobabilitiesforeachclassina multi-class classification problem. It ensures thatthepredictedprobabilitiessumuptoone, enabling interpretation as class probabilities.

5. EXPERIMENTAL RESULTS

In this study we can input the citrus leaf and citrus fruit images that are collected fromKAGGLEsource.Thenbuildthemodel using VGG16 framework. Finally predictthe performance in terms of accuracy metricsfor both leaf and fruit model.

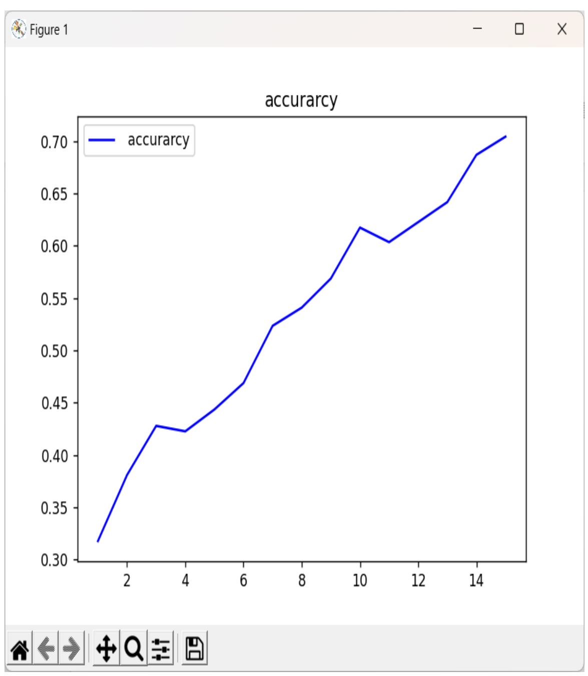

FIG3: Accuracy parameter forLeaf model

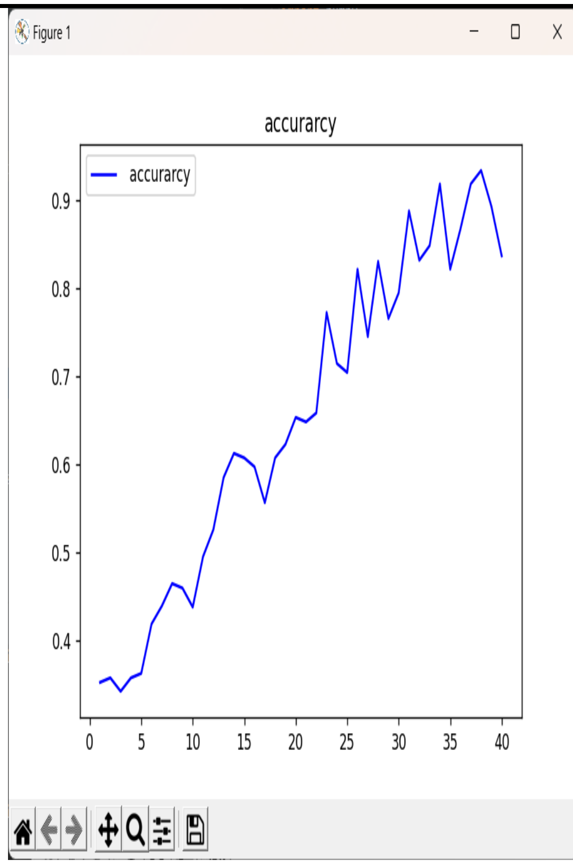

Fig 4: Accuracy parameter for fruit model Fromtheaboutfigures3and4**,**

proposedalgorithmachieves80%accuracyin leaf disease prediction and 91% accuracy in fruit disease prediction

6. CONCLUSION

In conclusion, the development of a citrus leaf-based disease prediction system holds immense potential for revolutionizing agricultural practices and ensuring the sustainability of citrus cultivation. Through the utilization of advanced deep learning techniques, particularly convolutional neural networks like VGG16, we can automate the detectionanddiagnosisofcitrusleafdiseases with unprecedented accuracy and efficiency. By leveraging large datasets containing images of both healthy citrus leaves and leaves affected by various diseases, we can train robust models capable of distinguishing between different disease types and accuratelypredictingtheirpresence.Through techniquessuchastransferlearningandfine- tuningofpre-trainedmodelslikeVGG16,we can capitalize on the wealth of knowledge learned from extensive image datasets like ImageNet, thereby accelerating the training process and enhancing the model's performance. The deployment of such a system in real-world agricultural settings has the potential to revolutionize disease management practices. By providing farmers and agronomists witha reliable tool forearly diseasedetection,thesystemempowersthem to take proactive measures to mitigate the spread of diseases, optimize resource allocation, and maximize crop yield. Additionally, by enabling timely interventions, the system can contribute to reducingtheeconomiclossesassociatedwith citrus diseases and ensuring the long-term sustainability of citrus production.

CONFLICT OF INTERESTS

None.

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None.

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