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Plant Disease Identification Using a Novel Convolutional Neural Network

S.Saila, Manish V

Dept of CSE Engineering, Jyothi Institute of Technology, Bangalore, India

Abstract: Earlydetectionofplantdiseasesavoidstheadverseeffectsoncrops.Convolutionalneural network,intensivelearning, is appliedextensively inmachinevisionandpattern recognitionapplications.Butthedeeplearningmodelstakealotofparameters, and thus, the training time required is longer and hard to execute onsmalldevices. The model proposed has beentrained & testedonthree plant diseasedatasets.

Keywords: Plantdisease, machinelearning, deeplearning, depthwise convolution, pointwise convolution.

I. INTRODUCTION

Diseases in crops caused mainly by bacteria and fungi negativelyimpacttheproductionandqualityofcrops [1]. The reason behind the CNN-based popularity is the automatic extraction of appropriate features from the dataset. Several popular deeplearning-based models, such as AlexNet [10], GoogleNet [11], VGGNet [12], ResNet[13], DenseNet[14], have been developed for the identification of plant diseases. Real-time applications and disease identification using deep learning architectures are gaining more importance in the Current scenario. Therefore, there will be issues in applying to small devices having limited resources [15]. Utilizing sophisticated devices with GPUs is not feasible in agriculture as they are costly. Therefore, there is a shortage of demand for applications with fewer parameters, less power consumption, and computation [16]. Based on the above consideration, we have proposed anew, lightweight deeplearning model for disease detection in the field. Inception architecture utilizes improved features with multiple convolutions of varying filter sizes. Rather than conventional con-con- convolution, we have employed depth-wise separable convolution, which reduces the size of parameters and computational complexity without affecting performance.

Toverify the robustness, the performance of the model is checked three different on plant disease data sets.Wehavetakenthreedifferentconditioned images. In the PlantVillage data set, the images were taken on a uniform background and under laboratory setup conditions. The photos in the rice disease dataset werecapturedinactual field conditions, and in the cassavaplantdataset,thephotos weretakeninthe field,andthephotoscontainseveralleaves.We havecomparedtheperformanceofour proposed method withother state-of-the-artdeep learningmethods on three different sets. The outcome indicates thatourproposed method thodexcelscompared toother deep learning methods. The restof the paper isorganized as follows: Section 2 presents existing detection of plant diseases with deep learning models.Materialsand methodsaredescribed literature on the inSection3.lightweightdeeplearningmodel to identify the diseases in the plant. The Inception architecture extracts better features using multiple convolutions of different filtersizes. Instead of standard con- con-convolution, we have used depth-wise separable convolution, which reduces the parameter size and the computational complexity without affecting performance. The model has been trainedonthreedifferentdatasets, and the performances are Evaluated. The main contribution of the paper is summarized as follows:

- A new CNN architecture is proposed usingInceptionand Residual connection, whichextractsbetter feature sandproduceshigherperformanceresults.
- In this paper, the standard convolution isreplaced withdepth-wiseseparable convolution, which reduces the parameter number by a large marg inwithout affecting performance.
- To check the robustness, the model's performance is evaluated on three different plantdiseasedatasets. Wehaveconsideredthreedifferentconditionedimages.Inthe PlantVillage dataset, the images werecaptured on auniform background and under laboratorysetupconditions.Theimagesin thericediseasedatasetwerecapturedin real-time field conditions, and in the cassava plant dataset, the ima

II. RELATED WORK

This section reviews recent research on plant disease detection using deep learning models. Mohanty et al. [5] used Alex Net and Google Net to classify 26 diseases across 14 plants pecies, achieving 99.34% accuracy with Google Net.



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Ferentinos [7] used five pre-trained models like VGG and GoogleNet to classify 58 plant leaf diseases. Geetharamani and Pandian [17] built a nine-layer CNN and achieved96.46% accuracy. Liuetal. [18] modifiedAlexNet by adding an inceptionlayer to classify apple leaf diseases with 97.62% accuracy. Ahmad et al. [19] used VGG16, VGG19, ResNet, and InceptionV3 to classify tomato leaf diseases, achieving 99.60% for lab images and 93.70% forfield images withInceptionV3. Rangarajanand Purushothaman [20] used VGG16 and multiclass SVM to classify eggplant diseases, achieving 99.4% accuracy withRGB mages. Tooetal. [21] fine-tunedmultiplemodels, with DenseNet reaching 99.75% accuracy. Sethy et al. [1] combined deep CNN features with SVM to detectriced iseases, with ResNet50 achieving an F1-score of 98.38%. RangarajanAravindandRaja[22]usedsixpre-trained models andfoundVGG16 gavethebestresultof90%.

Ramacharanetal.[23,24]appliedInceptionV3and MobileNet for cassava disease detection, achieving better accuracywithsingle leafimages(80.6% for images and 70.4% for video files). Oyewola et al. [25] showed that deep residualnetworksoutperformbasicCNNsforcassavadiseasedetection.Piconetal.[26]useda50layerResNetforwheatdiseases, achieving96 % accuracy. Durmusetal. [27] used SqueezeNet to detect tomato diseases with a much smaller model size. Hu et al. [28] improved a Cifar10 CNNwith depthwise separable convolution to detect tea diseases, reaching 92.5% accuracy. Atilaetal. [29] used EfficientNetB4 for crop disease detection, achieving 99.97% accuracy with fewer parameters. Chen et al. [6] built INC- VGGN by adding inceptionlayers to VGGNetfor rice and corn disease classification, achieving 92% and 80.38% accuracy, respectively. Li et al. [30] used a shallow VGG16- basedCNNwithPCA and achieved an F1-score of 94% using SVM and RF classifiers. Finally, Zeng and Li [31] employed as elf-attention CNN to focus on important regions for better crop disease detection. Table 1 summarizes these studies and their results.

III. MATERIAL SAND METHODS

A. Convlutional Neural Network

Convolutional Neural Network (CNN) is a Neural network that is highly efficient in many computer vision applications like pattern recognition and classification.CNN has the benefit of learning and extracting the features automatically from the training images, while in the conventional method, manual feature extraction from the images is required. CNN comprises various layers: a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer is the most central and important one among CNN's layers, which detects features of the input image. Convolution layers comprise a tiny array of figures known as kernels spread across the input, which creates an output named feature maps. Various convolutional kernels are used for detecting varying kinds of features. There are many convolutional layers, depending on the input image size. Following the convolutional layer are converted into a one- dimensional vector where each input is associated with each output by weight. There can be multiple fully connected layers, and the last fully connected layer contains the same number of classes.

B. Residial Network

The convolutional neural network canhave highperformance onclassification problems. As the network depthincreases, the accuracy of performance gets saturated and deteriorates sharply.



Figure1.basicblockdiagramofresidualnetwork.



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Toaddressthisissuein2015,Heetal.[13]introduced a deep residual learning network known as ResNet. In deep learning, using the residual connection in the network, we can train a large network and solve the vanishinggradientproblem,whichusuallyoccursdue to the increasein network depth.Figure 1 shows the basic block diagram of the ResNet model. ResNet introduced a skip connection known as "identity mapping" which combines the previous layer's output with the forthcoming layer. To performidentitymapping,itdoesn'tgenerateanyparameters.Therefore,theResNecantotrainsadeepernetwork with lower complexity thanother networks, suchas VGG.

C. Depthwisese Parable Convolution

Depthwiseseparableconvolution, introduced by Chollet in the X ception model and lateradopted in Mobile Net by Howard et al., breaks down standard convolution into two operations: depthwise convolution and 1×1 pointwise convolution. This significantly reduces computational cost compared to traditional convolutions. The cost for depthwise separable convolution is much lower, as shown by the formula where DFD_FDF is the input size, DKD_KDK is kernel size, MMM is input channels, and NNN is the number of filters. In this paper, a lightweight CNN model is proposed using Inception and Residual connections, drawing from the Inception-V3 architecture by Szegedy et al. The original Inception blocks perform multi-scale convolutions in parallel and concatenate the outputs. In our model, computationally expensive convolutions in Inception-A and Inception-B blocks are replaced with depthwise separable convolutions. For instance, 3×3 and 5×5 convolutions in Inception-A are replaced with 3×3 depthwiseseparable convolutions, while 7×7 convolutions in Inception Barereplaced similarly. These modifications reduce parameters while maintaining high performance.

D. Proposed Novelcnn Approach For Plant Disease Identification

In this paper, we have proposed a novel light-weight CNN based on Inception and Residual connections with fewer parameters compared to Inception V3, ResNet50, as well as other deeple anning approaches. The reduction A 3×3 convolution layer was substituted with 1×1 convolution layer and a 3×3 depthwise separable convolution. In block reduction B, we substituted the 3×3 and 7×7 convolution with a 1×1 convolution layer and a 3×3 depthwiseseparableconvolution layer Tablese 2 and 3 illustrate the parameter comparison of the original inception-Ablockwith the modified inception-A block having depthwise separable convolution. From Table3, one can observe that the parameter utilized in the modified inception-A block is significantly smaller than compared of the original inception-A blocks. Figure 5 illustrates the proposed CNN architectureemployedtodetectdiseasesinplants. The implemented model proposed comprises a convolutionlayer, abatchnormalizationanactivation layer, a depthwise separable convolution layer, inception blocks, a pooling layer, and a fullyconnected layer. In this structure, we have substituted the standard convolution with depthwise separable convolution. We have employed onestandard convolution, three depthwise separable convolutions, two max-pooling, and one globalaveragepoolingoperation, threemodified inception A blocks with residual connection, followed by modified reduction Ablocks, three modified inception Bblocks with residual connection, followed by modified reduction B Following eachoftheconvolutionlayers, we have applied Batch Normalization and activation. We applied blocks. ReLUasthe activation function. Batch Normalization and activation function enhance the performance and accelerate theprocess. Following global average pooling, wehave applied dropout, which decreases the likelihood of overfitting themodel. The number of parameters required in our proposed model is 428,100 w, whereas the parameters utilized in the conventional inception V3 model are 23,851,784, which is even greater than the proposed model. It is seen that the proposed model employs 770% fewer parameters compared to the Inception V3 architecture.

TABLE 1.

table1.summaryofr	relatedworksor	nidentification	of plantdiseases.
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Author	Deep learning model	Dataset	Results
Mohanthy et al.(2016) [5]			99.35%(Training acc.)
Sladojevic et al.(2016) [32]			96.3%(Precision)
Fuentes et al.(2017) [33]	Faster R-CNN	Own	83%(Testing acc)
Ferentinos et al.(2018) [7]	Multiple CNN	PlantVillage	99.53%(Training acc.)
Geetharamani et al. (2019) [17]	Nine Layer CNN	PlantVillage	96.46%(Testing acc.) 97.87%(Validation acc.)
Foo et al. (2019) [21]	Multiple CNN		99.75%(Testing acc.)
Sethy et al.(2020) [1]	Multiple CNN with SVM		98.38%(†1-score)
		MK-D2 AES-CD9214	95.33%(Testing acc.) 98%(Testing acc.)



Zeng et al.(2020) [31]	Self Attention CNN		
J Chen et al.(2020) [6]	INC-VGGN	PlantVillage	97.57%(Training acc.) 91.83%(Validation acc.)
Yan Li et al.(2020) [30]	Shallow CNN	PlantVillage	94%(Precision) 94%(Recall) 94%(f1-score)
Oyewola et al.(2021) [25]	Deep residual CNN	Cassava	96.75%(Testing acc.)

IV. RESULTS ANDDISCUSSION

A. Dataset

To evaluate the proposed model, three plant diseasedatasets were used:

- PlantVillage Dataset: Contains corn, potato, and tomatodiseaseimages, captured under controlled, uniform background conditions.
- RiceDiseaseDataset:Includes5,932field images divided into four classes bacterialblight,blast,brownspot,andtungro.
- Cassava Disease Dataset: Consists of 5,656 field images with complex backgrounds and multiple leaves; five classes including healthy and various diseased leaves.

All images were resized to 256×256 pixels and datasets weresplitinto80% training and 20% testing.

B. Experimental Results

Themodelwasevaluatedusingaccuracy, precision, recall, and F1-score:

Keyresultsafter50epochs:

- PlantVillage Dataset: Training accuracy of 99.81%, validation accuracy of 99.39%.
- RiceDataset:Trainingaccuracyof99.94%, validation accuracy of 99.66%.
- CassavaDataset:Trainingaccuracyof98.17%, validation accuracy of 76.59%.

Due to complex backgrounds and class imbalance, the Cassavadatasetshowedcomparativelylower performance. However, overall the model demonstrated highaccuracy withfewer parameters.

Figures7-9 depict the training and validation accuracy and loss trends for the datasets, showing fast convergence and stability.





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Figure2:Inceptionarchitectureof(A)Originalinception-Bblock(B) Modifiedinception-Bblock

C. Model Robustness

- To test robustness, 5-fold cross-validation was performed:
- PlantVillage:Accuracybetween99.29% and 99.37%.
- Rice:Accuracybetween99.33% and 99.66%.
- Cassava: Accuracy between 76.42% and 76.58%.

Minimalvariationacrossfolds indicates consistent model performance across different splits.



FIGURE 5



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Figure4:Sampleimagesof Plantvillagedataset,riceandcassavaplant dataset.

D. Performance Comparisonwithpre- Trained Networks

We compared the proposed model with VGG16, VGG19, Inception V3, ResNet50, and DenseNet201:

- Ourmodelachievedhigheraccuracy(upto 99.66% on Rice) with significantly fewer parameters(428,100).
- Pre-trained models showed lower accuracybecause they used weights trained on the ImageNet dataset, which is not specialized forplant diseases.
- The proposed model benefited from using Inception layers, residual connections, batch normalization, and depth-wise separable convolutions, leading to better feature extraction, reduced vanishing gradients, and faster training.

Training time wassignificantly lessfor theproposed model compared to DenseNet201 and others due to its lightweight structure.

	table2.datadescriptionoicassavadataset.							
Class	Plant Name	Disease Name	Disease Scientific Name	Type of Disease	No of Image			
CI	Cassava	-	*	-	316			
C2	Cassava	Bacterial blight	Xanthomonas axonopodis pv. manihotis	Bacterial	466			
C3	Cassava	Brown streak	Cassava brown streak viruses	Bacterial	1443			
C4	Cassava	Green mite	Mononychellus tanajoa	Pest	773			
C5	Cassava	Mosaic disease	Cassava mosaic disease	Viral	2658			

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table3.Summaryofdeeplearningbasedimplementedmethods.



Figure 5. (a) training & validation accuracy (b) training & validation loss on plant village dataset.





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a China San San	279.7

Table4.Performancemetricoftheproposedmodelontestingimages.

Dataset	Accuracy	Recall	Precision	F1-score
Rice Dataset	99.66	99.67	99.66	99.67
PlantVillage	99.39	99.19	99.17	99.18
Cassava	76.59	72.63	62.03	66.91



 $\label{eq:Figure8} \ensuremath{\mathsf{Figure8}}\xspace. \ensuremath{\mathsf{Figure8}}\xspace \ensurema$



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E. Comparison Withexistingliterature

Finally, the proposed CNN model was compared against existing deeplearning models reported in the literature:

- Themodelachievedhigheraccuracy, lower parameter count, and faster training time.
- Unlike many previous works focusing only on controlled datasets like PlantVillage, our model was tested on real-world field images (Rice and Cassava datasets), demonstrating robustness under practical conditions.

Thus, the proposed lightweight CNN shows advantages interms of efficiency, accuracy, and practical usability in plant disease detection.

TABLE 9.

table5.ResultofproposedCNNbsedonk-foldcrossvalidation.

No of		Accuracy	
Fold	PlantVillage	Rice Dataset	Cassava
1-fold	0.9931	0.9966	0.7649
2-fold	0.9929	0.9954	0.7645
3-fold	0.9937	0.9951	0.7642
4-fold	0.9934	0.9933	0.7658
5-fold	0.9931	0.9959	0.7652

Table6.Performancecomparisonwithpre-trainednetwork.

Models	VGG16	VGG19	InceptionV3	ResNet50	DenseNet201	Proposed
Parameter	138,357,544	143,667,240	23,851,784	25,636,712	20,242,984	428,100
Accuracy (PlantVillage)	0.9565	0.9887	0.9727	0.9798	0.9975	0.9939
Training Time						
(sec/epoch)	2135	2463	2742	5475	9626	883
(PlantVillage) Accuracy (Rice)	0.7931	0.7888	0.7931	0.7888	0.7991	0.9966
Training Time (sec/epoch) (Rice)	490	608	697	1434	2582	227
Accuracy (Cassava)	0.6355	0.6813	0.7143	0.7439	0.7567	0.7659
Training Time (sec/epoch)	477	598	673	1412	2556	221
(Cassava) Average	0.9932		0.9952		0.7649	

TABLE 11.

table7.Performancecomparisonwithdifferentdeeplearningmodels.

Deep learning model	Dataset used	Parameter required	Training acc	Testing acc	Testing loss	Epoch	Training time (sec/epoch)
VGG [7]	PlantVillage	138 million		98.87	0.0542	49	4208
AlexNet [5]	PlantVillage	60 million	99.35	93.88	-	30	-
INC-VGGN [6]	PlantVillage	more than 138 million	97.57	91.83	0.2409	30	-
GoogleNet	PlantVillage	7 million	-	97.3	-	20	-
ResNet50+SVM [1]	Rice	23 million	-	98.38	-	-	69.04
Nine layer CNN [17]	PlantVillage	-	97.87	96.46		3000	~
Shallow CNN+ RF [30]	PlantVillage	0.26 million	-	94	-	-	-
Deep Residual CNN [25]	Cassava	-	-	58.39	-	80	-
Proposed CNN	PlantVillage	0.42 million	99.73	99.39	0.0549	50	883
Proposed CNN	Rice	0.42 million	99.94	99.66	0.0041	50	227
Proposed CNN	Cassava	0.42 million	98.17	76.59	0.4465	50	221

V. CONCLUSION

Deeplearning is also proven to be a good approach tofinding plant diseases. In this research work, we proposed alightweight CNN model with Inception modules, Residual connections, and depthwise separable convolutions that reduced parameters by 70% and accelerated the training process. The developed model recorded astounding test accuracies of 99.39% on PlantVillage, 99.66% on Rice, and 76.59% on the imbalanced Cassava dataset compared to the traditional models such as CNN and ResNet. The model performs with higher accuracy and efficiency compared to pastresearch. Our future work will involve its application for the detection of weeds and pests and the assessment of performance onvarious datasets and location



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