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Plant Disease Identification Using a Novel Convolutional Neural Network

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***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 proposedhas beentrained &testedonthree plant diseasedatasets.*

***Keywords:** Plantdisease,machinelearning,deeplearning,depthwiseconvolution,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.Severalpopulardeeplearning-basedmodels, such as AlexNet [10], GoogleNet [11], VGGNet [12], ResNet[13],DenseNet[14],havebeendevelopedfor theidentificationofplantdiseases.Real-time applicationsanddiseaseidentificationusingdeep learning architecturesare gainingmoreimportance in the Currentscenario.Therefore,therewillbe issues in applying to small devices having limitedresources[15].UtilizingsophisticateddeviceswithGPUs 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 haveproposedanew,lightweightdeeplearningmodel 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 sizeof parameters and computationalcomplexitywithoutaffecting performance.

Toverifytherobustness,theperformanceofthe model is checked on three different 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 werecapturedinactualfieldconditions,andinthe cassavaplantdataset,thephotos weretakeninthe field,andthephotoscontainseveralleaves.We havecomparedtheperformanceofour proposed method withother state-of-the-artdeep learningmethods on three different sets. The outcome indicates thatourproposedme thodexcelscompared toother deep learning methods. The restof the paper isorganized as follows: Section 2 presents existing literature on the detection of plant diseases with deep learning models.Materialsand methodsaredescribed inSection3.lightweightdeeplearningmodel to identify the diseases in the plant. The Inception architecture extracts better features using multiple convolutionsofdifferentfiltersizes.Insteadof standard con- con-convolution, we have used depth-wise separable convolution, whichreduces theparameter sizeand the computational complexitywithout affecting performance. The model has been trainedonthreedifferentdatasets,andtheperformancesareEvaluated.Themain contributionofthe paperissummarizedasfollows:

- A new CNN architecture is proposed usingInceptionand Residual connection, whichextractsbetter feature sandproduceshigherperformanceresults.
- In this paper, the standard convolution isreplaced withdepth-wiseseparable convolution,whichreducestheparameter number byalargemarg 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

Thissectionreviewsrecentresearchonplantdiseasedetectionusingdeeplearningmodels.Mohantyetal.[5]usedAlexNetandGoogleNettocla ssify26diseasesacross14plantspecies,achieving99.34%accuracywith GoogleNet.

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 aninceptionlayer to classify apple leaf diseaseswith 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% forfieldimageswithInceptionV3. Rangarajanand Purushothaman [20] used VGG16 and multiclass SVM to classify eggplant diseases, achieving 99.4% accuracy withRGBimages.Tooetal.[21]fine-tunedmultiplemodels, with DenseNet reaching 99.75% accuracy. Sethy et al. [1] combined deep CNN features with SVM to detectricediseases, with ResNet50 achieving an F1-score of 98.38%. RangarajanAravindandRaja[22]usedsixpre-trained modelsandfoundVGG16gavethebestresultof90%.

Ramacharanetal.[23,24]appliedInceptionV3and MobileNet for cassava disease detection, achieving better accuracywithsingle leafimages(80.6%forimagesand 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, reaching92.5%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- basedCNNwithPCAandachievedanF1-scoreof94% using SVM and RF classifiers. Finally, Zeng and Li [31] employedaself-attentionCNNtofocusonimportantregionsforbettercropdiseasedetection.Table1summarizesthesestudiesandtheirresults.

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 andclassification.CNNhasthebenefitoflearning and extracting the features automatically from the training images, while in the conventional method, manualfeatureextractionfromtheimagesis required. CNN comprises various layers: a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer is the most centralandimportantoneamongCNN'slayers, whichdetects features of theinputimage.Convolution layers comprise a tiny array of figures known as kernels spread across the input, whichcreates an output named feature maps. Various convolutional kernels are used for detecting varying kindsoffeatures.Thereare manyconvolutional layers, depending on the input image size. Following theconvolutionallayer,poolingisdone,whichis used to decrease the dimension of the convolutional feature map. The feature maps of the convolution the pooling layer are converted into a one- dimensional vectorwhereeachinputisassociatedwitheach outputbyweight.Therecan be multiple fully connected layers, and the last fully connected layer containsthesame numberof outputsasthenumber of classes.

B. Residial Network

The convolutional neural network canhave highperformance onclassificationproblems. As the network depthincreases, the accuracy of performance getssaturated and deteriorates sharply.

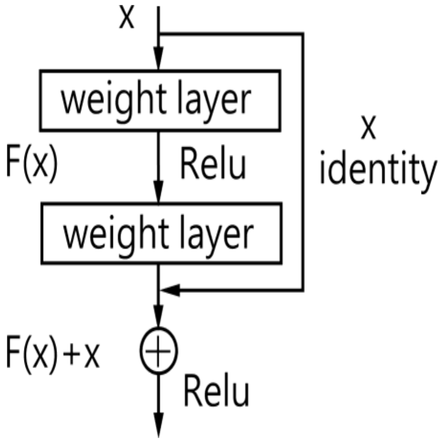


Figure1.basicblockdiagramofresidualnetwork.

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

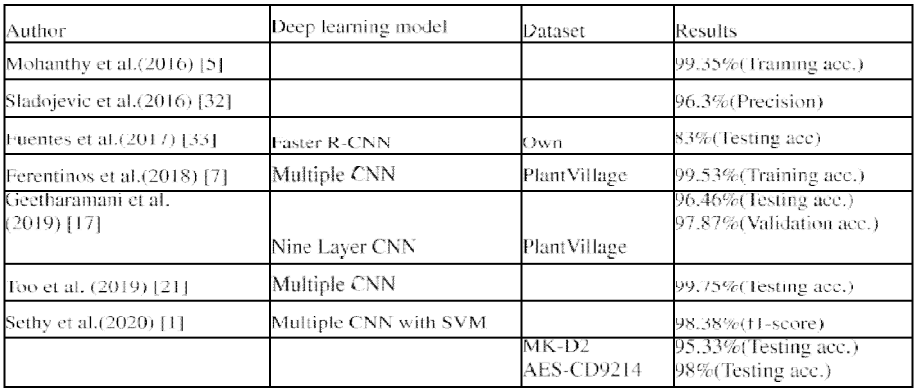
Depthwiseseparableconvolution,introducedbyChollet intheXceptionmodelandlateradoptedinMobileNet by Howard et al., breaks down standard convolution into twooperations:depthwiseconvolutionand1×1pointwise convolution. This significantly reduces computationalcostcomparedtotraditional convolutions. The cost for depthwise separableconvolution is muchlower,as shownby the formula where DFD_FDF is the input size, DKD_KDK is kernel size,MMMisinputchannels,andNNNisthenumber of filters.In this paper, a lightweight CNN model is proposed using Inception and Residual connections, drawingfromtheInception-V3architecturebySzegedy et al. The original Inception blocks perform multi-scale convolutions inparalleland concatenate theoutputs.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 depthwiseseparableconvolutions,while7×7convolutionsinInceptionBarereplacedsimilarly.Thesemodificationsreduceparameterswhile 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 connectionswith fewer parameters compared to InceptionV3, ResNet50,aswellasotherdeeplearningapproaches. The reduction A 3 × 3 convolution layer was substitutedwitha 1 × 1 convolutionlayer and a 3× 3 depthwise separable convolution. In block reduction B, we substituted the 3 × 3 and 7 × 7 convolution with a 1×1convolution layer and a 3×3 depthwiseseparableconvolutionlayerTablese2and3 illustrate the parameter comparison of the original inception-Ablockwiththe modifiedinception-A block having depthwise separable convolution. From Table3,onecanobservethattheparameter 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,threemodifiedinception A blocks with residual connection, followed by modifiedreductionAblocks,threemodified inceptionBblockswithresidualconnection, followed by modifiedreduction B blocks. Following eachoftheconvolutionlayers,wehaveappliedBatchNormalizationandactivation.Weapplied ReLUasthe activationfunction. Batch Normalization and activation function enhance the performance and accelerate theprocess. Following global average pooling, wehave applied dropout,whichdecreases the likelihood of overfitting themodel. The number of parameters required in our proposedmodelis428,100w,whereasthe parameters utilized inthe conventional inception V3 model are 23,851,784, which is even greaterthan the proposed model. It is seen that the proposed model employs 770% fewer parameters compared to the Inception V3 architecture.

TABLE 1.

table1.summaryofrelatedworksonidentificationof plantdiseases.



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.)
Too et al. (2019) [21]	Multiple CNN		99.75%(Testing acc.)
Sethy et al.(2020) [1]	Multiple CNN with SVM		98.38%(f1-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,capturedundercontrolled,uniformbackgroundconditions.
- 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;fiveclassesincludinghealthyandvarious diseased leaves.

All images were resized to 256×256 pixels and datasets weresplitinto80%trainingand20%testing.

B. Experimental Results

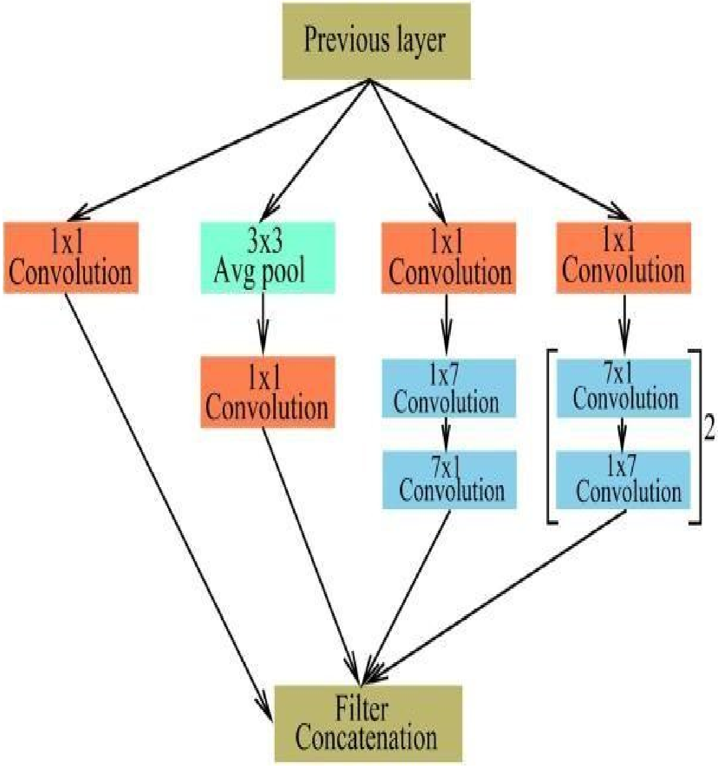
Themodelwasevaluatedusingaccuracy,precision, recall, and F1-score:

Keyresultsafter50epochs:

- PlantVillage Dataset:Trainingaccuracy 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 depictthe training and validationaccuracy andlosstrendsforthedatasets,showingfast convergence and stability.



(a)

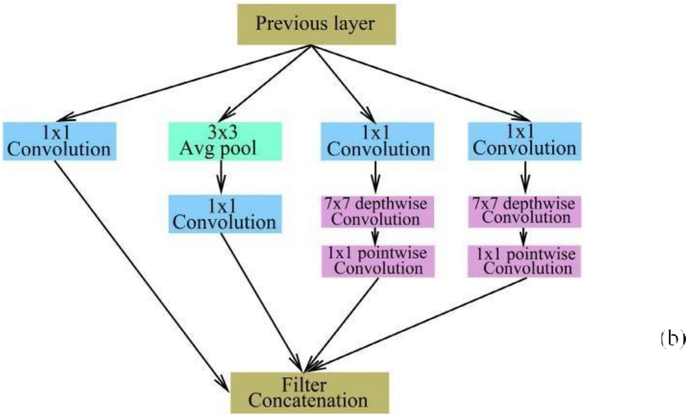


Figure2:Inceptionarchitectureof(A)Originalinception-Bblock(B) Modifiedinception-Bblock

C. Model Robustness

To test robustness, 5-fold cross-validation was performed:

- PlantVillage:Accuracybetween99.29%and99.37%.
- Rice:Accuracybetween99.33%and99.66%.
- Cassava: Accuracy between 76.42% and 76.58%.

Minimalvariationacrossfoldsindicatesconsistentmodel performance across differentsplits.

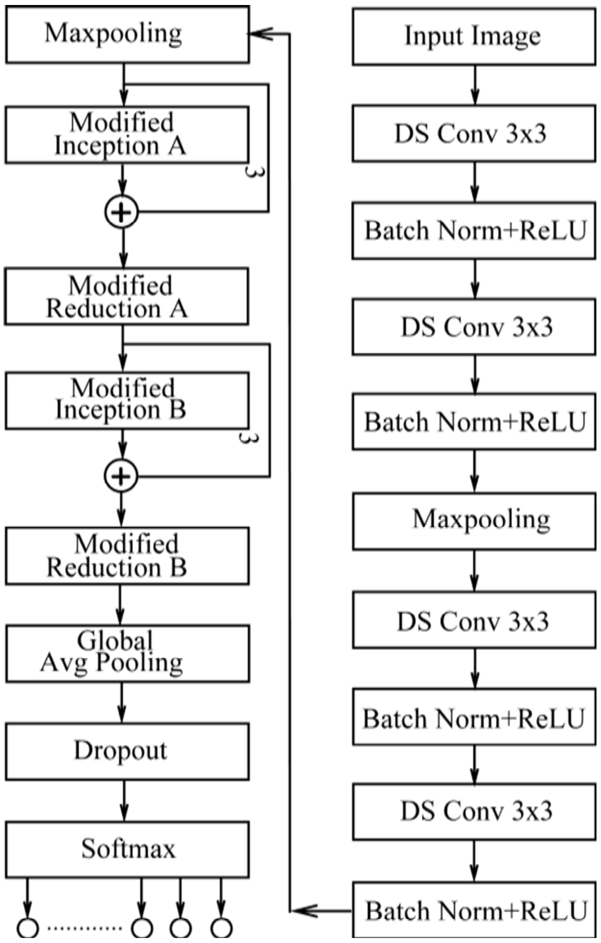


FIGURE 5.

figure 3: Proposed CNN approach in identification of plantdiseases.

Figure4:Sampleimagesof Plantvillagedataset,riceandcassavaplant dataset.

D. Performance Comparisonwithpre- Trained Networks

WecomparedtheproposedmodelwithVGG16, VGG19,InceptionV3,ResNet50,andDenseNet201:

- Ourmodelachievedhigheraccuracy(upto 99.66%on Rice)with significantlyfewer parameters(428,100).
- Pre-trained models showed lower accuracybecause they used weights trained on theImageNet dataset, which is not specialized forplant diseases.
- The proposed model benefited from using Inception layers, residual connections, batch normalization, and depth-wise separable convolutions,leadingtobetterfeatureextraction,reducedvanishinggradients,and faster training.

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

table2.datadescriptionofcassavadataset.

Class	Plant Name	Disease Name	Disease Scientific Name	Type of Disease	No of Image
C1	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

table3.Summaryofdeeplearningbasedimplementedmethods.

	30 epochs				50 epochs				Training time (sec/epoch)	Testing accuracy (%)
	Training acc	Training loss	Val acc	Val loss	Training acc	Training loss	Val acc	Val loss		
PlantVillage	0.9981	0.0273	0.9891	0.0864	0.9973	0.0015	0.9939	0.0549	883	0.9939
Rice	0.9970	0.0085	0.9823	0.0452	0.9994	0.0030	1.00	0.0041	227	0.9966
Cassava	0.9545	0.1201	0.6793	0.6732	0.9817	0.0508	0.7659	0.4465	221	0.7659

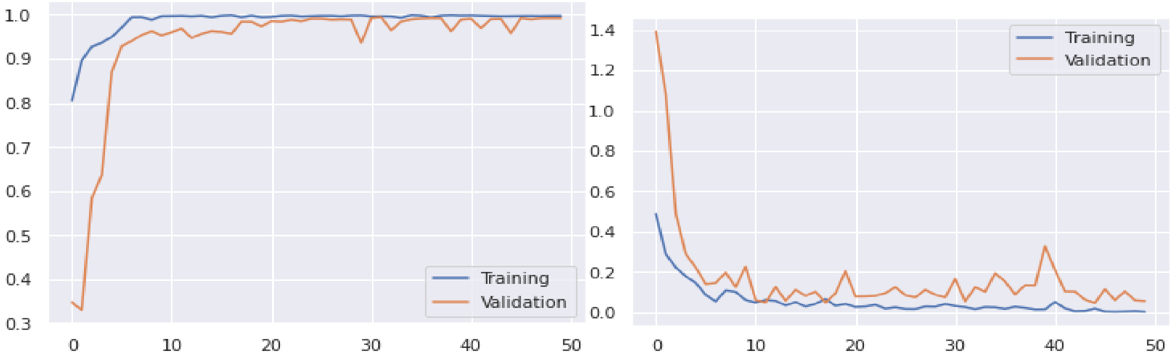


Figure5.(a)training&validationaccuracy(b)training&validationlossonplantvillagedataset.

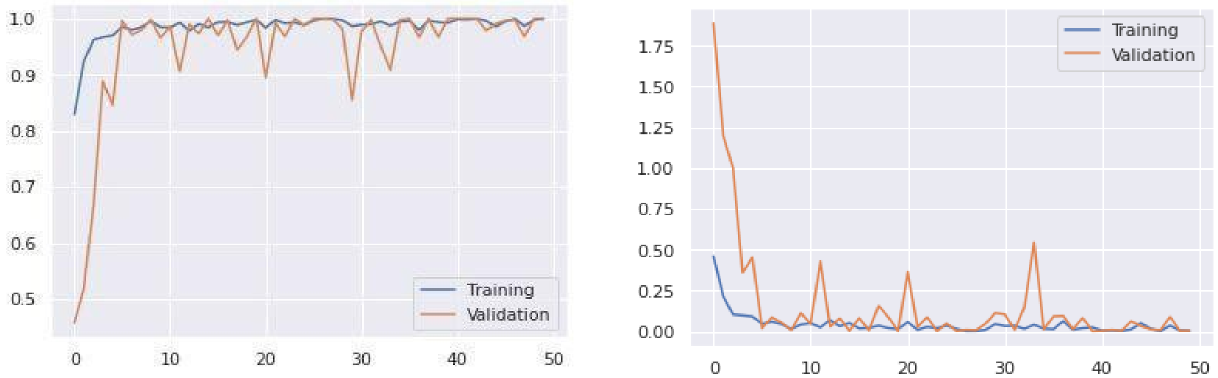
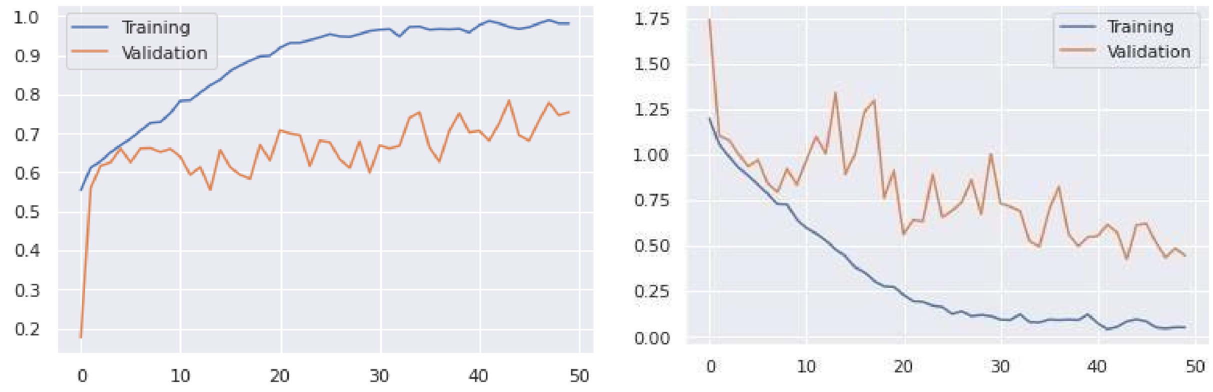


Figure6.(a)training&validationaccuracy(b)training&validationlossonricediseasedataset.



(a) (b)

Figure7.(a)training&validationaccuracy(b)training&validationlossoncassavaplantdataset.

TABLE 8.

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

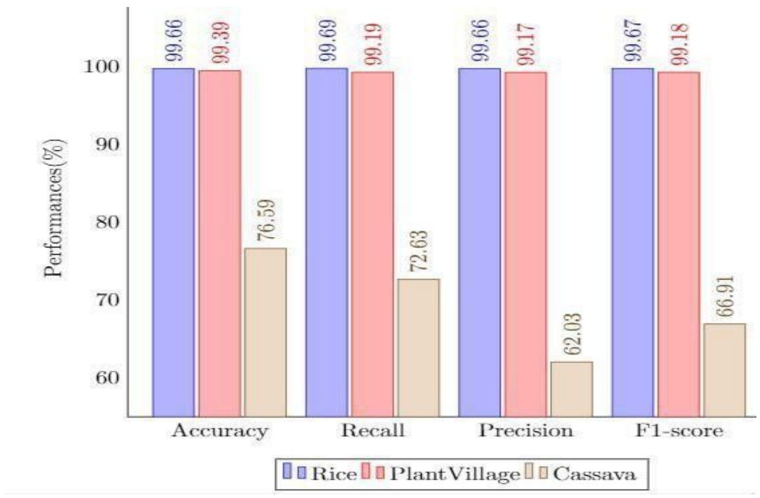


FIGURE 1 Figure8.Performancemetricofproposedmodelondifferentdataset.

E. Comparison Withexistingliterature

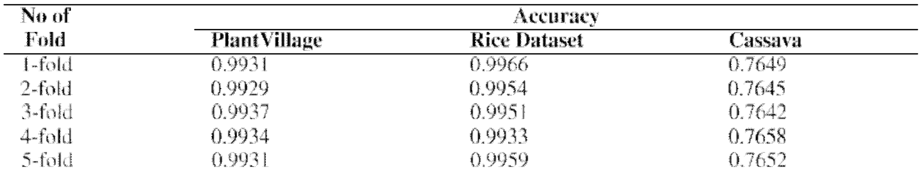
Finally, the proposed CNN model was compared against existingdeeplearningmodelsreportedintheliterature:

- Themodelachievedhigheraccuracy,lower parametercount,andfastertrainingtime.
- 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.

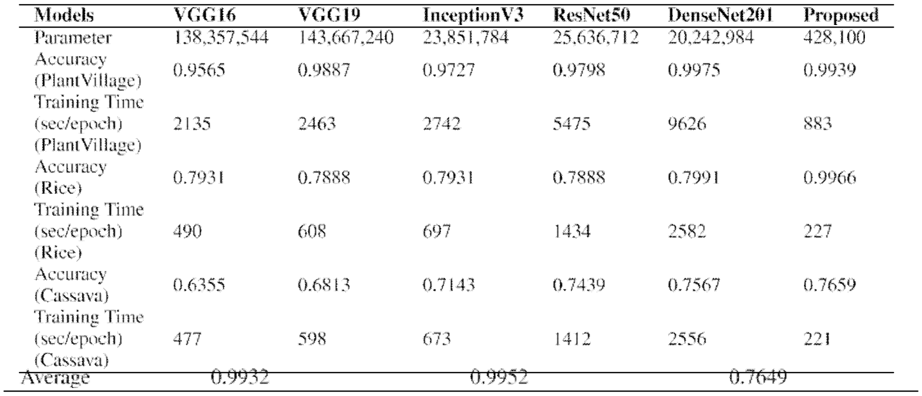
TABLE 9.

table5.ResultofproposedCNNbsedonk-foldcrossvalidation.



No of Fold	Accuracy		
	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

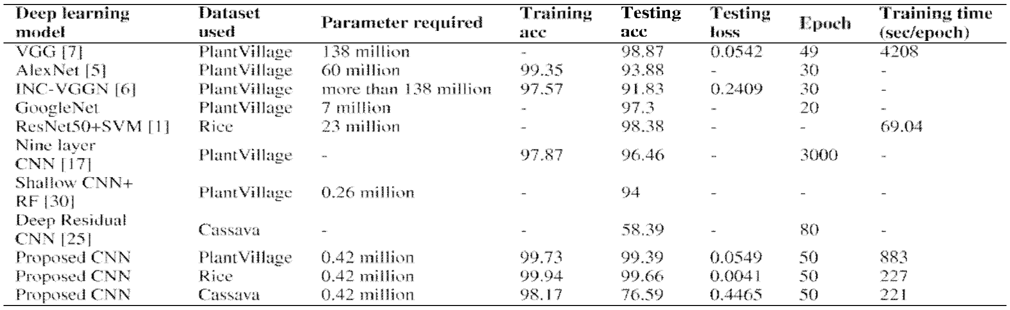
Table6.Performancecomparisonwithpre-trainednetwork.



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) (PlantVillage)	2135	2463	2742	5475	9626	883
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) (Cassava)	477	598	673	1412	2556	221
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 thatreduced 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 performswith higher accuracyand efficiencycompared to pastresearch.Ourfutureworkwillinvolveitsapplication for the detection of weeds and pests and the assessment of performanceonvariousdatasetsandlocation

REFERENCES

[1] P.K.Sethy,N.K. Barpanda,A. K.Rath, and S.K. Behera, ‘‘Deep feature based Rice leaf disease identification using support vector machine,’’ Comput. Electron. Agricult., vol. 175, Aug. 2020, Art. no. 105527.
[2] V. Singh and A. K. Misra, ‘‘Detection of plantleaf diseases using image segmentation and soft computing techniques,’’ Inf. Process. Agricult., vol.4, pp. 41–49, Mar. 2017.
[3] S. H. Lee, C. S. Chan, S. J. Mayo,and P. Remagnino,‘‘Howdeeplearningextractsandlearns leaf features for plant classification,’’ Pattern Recognit., vol. 71, pp. 1–13, Nov. 2017.
[4] G. Farjon, O. Krikeb, A. B. Hillel, and V. Alchanatis, ‘‘Detection and countingof flowers on apple trees for better chemicalthinning decisions,’’ Precis.Agricult.,vol.21,pp.1–19,Aug.2019.
[5] S. P. Mohanty, D. P. Hughes, and M. Salathé, ‘‘Usingdeeplearningforimage-basedplantdisease detection,’’ Frontiers Plant Sci., vol. 7, p. 1419, Sep. 2016.
[6] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, ‘‘Using deep transfer learning forimage-based plant disease identification,’’ Comput. Electron. Agricult., vol. 173, Jun. 2020, Art. no. 105393.
[7] K. P. Ferentinos, ‘‘Deep learning models forplant disease detection and diagnosis,’’ Comput. Electron.Agricult.,vol.145,pp.311–318,Feb. 2018.
[8] V.HoangTrong,Y.Gwang-hyun,D.Thanh Vu, and K. Jin-young, ‘‘Late fusion of multimodal deep neural networks for weeds classification,’’ Comput. Electron. Agricult., vol. 175, Aug. 2020,Art. no. 105506.
[9] F. Ren, W. Liu, and G. Wu, ‘‘Feature reuse residualnetworksforinsectpestrecognition,’’IEEE Access, vol. 7, pp. 122758–122768, 2019.
[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ‘‘ImageNet classification with deep convolutional neural networks,’’ inProc. Adv. Neural Inf. Process.Syst.(NIPS),vol.25,Dec.2012,pp.1097–1105.