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# Betel Leaf Disease Classification Using Data Augmentation and Convolutional Neural Network

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***Abstract*— Identification of betel leaf disease at an early stageandaccuratelywillincreasetheproductivityofthecropandav oidfinanciallossforthefarmers.Multifariousmachinelearningalg orithmsandmultipledeeplearning-basedmodelshave been developed to improve image classification accuracy.This paper primarily discusses data collection of real field betelleafimagedatasetsundervariousclimateconditions.Then,ac quiringmoretrainingimagedatainplantleafdiseaseclassification and identification is highly challenging and time-consuming. Soimage augmentation techniques, such as imageflipping,shearing,cropping,androtationtechniques,areaug mented on betel leaf image datasets. Finally, the augmentedimages were trained using a simple convolutional neural networkandVGG16.TheaccuracyofVGG16modelwithdataaug mentation performed well, and the accuracy increased up to86.67%.**

***Keywords*— *Betel leaf, Deep Learning, convolutional neuralnetwork,Dataaugmentation, VGG16.***

## I. Introduction

Plant diseases directly impact agriculture and can change thesocial, economic, and natural balance. Plant leaves disease canoccur due to various reasons such as lack of water, excesswater, excess heat, climate change, nematodes, pollution, soilquality, etc., The symptoms of plant leaf disease are mostlyvisiblelikechangesinleafcolor,shape,growthsize,andpa ttern based on the symptom, the category of disease can bedetermined such as viral, bacterial, or fungal disease. In thispaper, the image of plant diseases is classified based on pestattack, leaf burn, and healthy leaf. Deep learning in agricultureis a current and trending technique with high performance inthe agriculture domain. One of the most significant challengesis enhancing the model performance on data it has previouslyseen(trainingdata)vs.dataithasneverseenbeforeism easured(testingdata).Poorinferencesmodelshavetooverfit the training set. Plotting the training and validationaccuracy at each epoch during training is one technique toidentify overfitting. This may be accomplished very well withdataaugmentation.Dataaugmentationisaprocedurethatinc reases the size of any dataset that is already accessible sothat it can also be used with deep learning models. This iscrucial work in boosting entire performance. The dataset canbe increased by the method and input into a learning model training through changing parameters like anepoch, batch, and optimizer.

## II. Literature Review

In the study to combat the problem of over-fitting, the authorexperiments with the test and train data ratio and found thattrainingononly20% ofthedataofauthenticimages andtesting on the remaining 80% of the image data, the model stillattains a final result with an accuracy of 98.21%for GoogleNeuralNetwork[1].Fortheobjectiveofdetectingplantdi seases, a model based on transfer learning and ResNet50 isrecommendedsinceitperformsbetter,strengthensfeatureprop agation,andhashigheraccuracywhencomparedtoMCNN in terms of training time [2].CNN does a good job ofprocessing visual information. There are different layers, suchas "input,""hidden," and "output,"in thearchitecture of aneural network. A group of hidden layers, including Convo,pooling, and fully connected layers with the normalizing layer,are synchronized and complete the task of securing the dataand images spatially [3]. The author made a comparative studyof the models and the result of the existing work and soybeandiseases using AlexNet and GoogleNett[14]. In this paper,the author built small neural networks of various depths fromfundamentalstepsonthebasisofaminimalnumberoftrainin gsamplesandimprovedfourcutting-edgemodelssuchasVGG16, ResNet50, and VGG19. According to comparativework and results of these networks, pre-trained deep modelscan be fine-tuned to increase significantly performance withfewerdata.TheoptimizedVGG16modelperformsbest,wit hatest set accuracy of 90.4%, proving that deep learning is anovel and updated technology for completely automated plantdiseasedeductionandseverityclassificationbasedonthesy mptomsfromtheactualleafimages[10].Theproposedmethod in this paper using MobileNet-V2on the field andpublic dataset performed with good results. It can be deployedto mobile devices to automatically observe and analyze theoutcome from a wide range of plant disease classifications [4].The author uses the ANN algorithm to detect plant diseaseusing python tool based on the observation of symptoms of thedisease class and the field images with the real background aretrained and choose a machine learning algorithm to predict thediseaseandtherecommendationofthesolution.Based onfeature extraction parameters, the algorithm predicts the croppest ordisease[7].Inthispaper,modelsuchas Inception,Alexnet, Resnet, and Densenet enhanced the training process results. Consequently, a trained machine thatcandiagnoseplant disease quickly and accurately has the potential to boostthe agricultural sector. If the technology is widely used, it willstop plant illnesses before they spread and relieve farmers andspecialistsfromhavingtoobserveplantsintheirareas.Althou ghthemodelperformedexceptionallywellinitsevaluation of the validation set, its high computational demandprevents it from being ready for usage in actual applicationsjust yet. The goal of future studies should be to reduce

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thenumberofparameterswhileretainingaccuracy.Whencompared to the outcome of the previous method, the stackingmethod'saccuracyrateof87%representsamajorimprovement[5]. The suggested augmentation technique performs changesintheimagesofhealthyandunhealthyleavesandmakesuseofattentional mechanisms to produce images that reflect moreobvious disease textures[15]. We did an experiment to see ifthisdataaugmentationstrategymightfurtherenhancetheperformanceofaclassificationalgorithmfortheearlydiagnosisofplants.Throughtheseadvancements,weproduceda more convincing diseased leaf image compared to existingmethods ResNet-18, MobileNet-v2, and EfficientNet were themodels that were tested; they were all adjusted using weightsthathadalreadybeenlearned.Accordingtoexperimentalfindings,whentheEfficientNetandthesuggesteddataaugmentation strategy were combined, the greatest F1 scorewasobtainedforallthreeplantleaves[6].Themodelpresentedusing CNN performs well on detection and classification withgood results using simple disease leaves and healthy leaves[11]. In this paper author used AlexNet and VGG16 models toidentify tomato disease and compare the result of the modelwhichismorethan90%ofaccuracy[12].

## III. METHODOLOGY

### A. *Data collection*

Thecollectionofthebetelleafdiseasedatasetischallenging. A dataset of 1089 images of betel leaf used forthis study is collected directly from the betel vine farm. Thereal field images were taken using a camera and smartphones.Thedatasetobtainedisclassifiedunderthreeclasses:leafburn,pestattack,andhealthyleaf.

(a) (b) (c)

Fig.1.(a)LeafBurn (b)Pestattack,and (c)Healthy Leaf

### B. *Preprocessingofthedataset*

There were many issues while collecting the dataset,such as poor lighting, shadow, background, etc. The image ispreprocessed in two stages such as the actual stage and themodel training set. In the essential step, the image is resized to400x400x3.Inthemodeltrainingstage,dataaugmentation,suchasrotation,shear,flip,fill,etc.,isappliedtothedatausingKerasdeeplearning libraryinpython.

### C. *Dataaugmentation*

Dataaugmentationisamethodforintentionallyboostingtheproportionsoftrainingdatasets. Theproportionofthetrainingandtestingdatasetissplitinto80:20. Forimposinga deep learning model with good classification accuracy, alarge image of samples is essential[8]. It is accurate to say thatthe resurgence of artificial intelligence is solely a result of theavailability of powerful processing resources (GPUs) and asizableamountofinformationonline.Scaling,turning,shifting, androtationaresomestandardaugmentationtechniques[6]. Understanding these functions that can affectthe efficacy of the model is sound. Shear is one of the manyaugmentationmethodsaccessible[13].ThekerasImageDataGenerator class was used to increase data, and thebestresultwasobtainedbysettingthebelowparameters.

a) She arrange=0.2
b) Horizontal flip=True
c) rotation range=40
d) zoom range=0.2
e) fill mode=nearest
f) width shif trange= 0.2
g) height shif trange=0.2

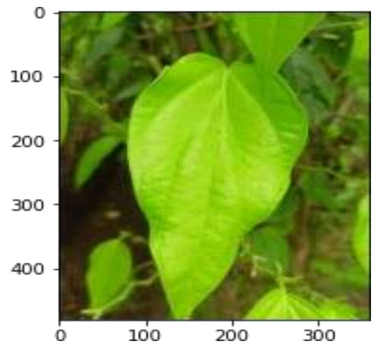


Fig.2.Sampleofhealthybetelleafimageafteraugmentation

### D. *Experiment*

To study the impact of the augmentation method, wepropose a simple convolutional neural network (CNN) andVGG16 model for betel leaf disease classification. We use ourdatasetcontainingthreeclassesofleafimages:Pestattack,leafburn,andhealthybetelleaves.Itissplitintotwoparts:trainingand testing.OurmodelwasimplementedusingtheKerastensorflow

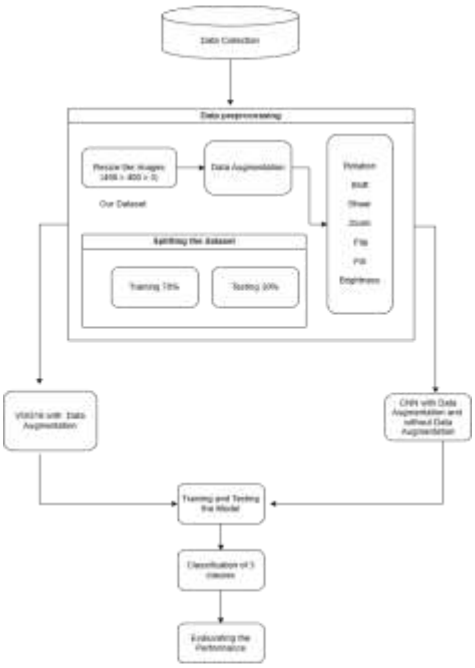

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Fig.3.Flowofworkofproposedmodel

## E. CNNModel

TheConvolutionneuralnetworkusedtoextractcharacteristics from a massive and varied dataset of images,CNN is the deep neural architecture class that has received themost adoption. The images will be transformed into arrays ofmatrices after the image augmentation process is finished, andthen they will be trained. A deep CNN design has multiplelayersandtypicallybeginsfromsingleordoubleconvolutionallayers to extract multiple attributes from the pictures given asinput data. These layers produce a feature map, which is thengiven to further layers for feature analysis. It concludes withmultiplepoolingandactivationlayersfollowing.Thesummaryofthemodelismentionedin Fig.4.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d 4 (Conv2D) | (None, 148, 148, 64) | 1792 |
| max pooling2d 4(MaxPooling2D) | (None, 74, 74, 64) | 0 |
| conv2d 5 (Conv2D) | (None, 72, 72, 64) | 36928 |
| max pooling2d 5 (MaxPooling 2D) | (None, 36, 36, 64) | 0 |
| conv2d 6 (Conv2D) | (None, 34, 34, 128) | 73856 |
| max pooling2d 6 (MaxPooling 2D) | (None, 17, 17, 128) | 0 |
| conv2d 7 (Conv2D) | (None, 15, 15, 128) | 147584 |
| max pooling2d 7(MaxPooling2D) | (None, 7, 7, 128) | 0 |
| flatten 1 (Flatten) | (None, 6272) | 0 |
| dropout 1 (Dropout) | (None, 6272) | 0 |
| dense 2 (Dense) | (None, 512) | 3211776 |
| dense 3 (Dense) | (None, 3) | 1539 |

Total params: 34,73,475
Trainable params: 34,73,475
Non-trainable params: 0

Fig.4.ModelsummaryofCNNwithdataaugmentation

## F. VGG16MODEL

VGG16pretrainedmodelusedforimprovingtheclassification accuracy of the tiny image data. The result hasgoodperformancewhencomparedwiththeearliermodeldiscussedabove.InVGG16[9].VGG16hasimprovedtheperformance accuracy above 80 on betel leaf images for 3diseaseclassesandthehyperparameterswiththelearningrate0.001 through the epochs of25because of the small dataset..The convolution block with the layer of CONV2D and thesame block can flip ofany 2layers of the similar dimensionfollowed by maxpooling. The total parameters are 14,714,688andasummaryofthemodelisdisplayedinFig.5.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input_1 (InputLayer) | [(None, 224, 224, 3)] | 0 |
| block1_conv1 (Conv2D) | (None, 224, 224, 64) | 1792 |
| block1_conv2 (Conv2D) | (None, 224, 224, 64) | 36928 |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64) | 0 |
| block2_conv1 (Conv2D) | (None, 112, 112, 128) | 73856 |
| block2_conv2 (Conv2D) | (None, 112, 112, 128) | 147584 |
| block2_pool (MaxPooling2D) | (None, 56, 56, 128) | 0 |
| block3_conv1 (Conv2D) | (None, 56, 56, 256) | 295168 |
| block3_conv2 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_conv3 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256) | 0 |
| block4_conv1 (Conv2D) | (None, 28, 28, 512) | 1180160 |
| block4_conv2 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_conv3 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512) | 0 |
| block5_conv1 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv2 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv3 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_pool (MaxPooling2D) | (None, 7, 7, 512) | 0 |

Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0

Fig.5.ModelsummaryofVGG16 withdataaugmentation

## IV. RESULTS AND DISCUSSIONS

The classification accuracy of the real field betal leaf datasetandthelossofthemodelontheepochusingdataaugmentationarecomparedinthebelowtable.After25epochsoftrainingthe model,theaccuracytestingoftheproposed approach achieves 85.67% and the loss is 0.23, Themodel with VGG16 improves on its performance as displayedin Table I.

TABLEI. COMPARISONOFCNNANDVGG16WITHDATAAUGMENTATION

| Datasets | Models | Depths | Loss | Accuracy |
|---|---|---|---|---|
| Ourreal-fielddataset | CNNwithoutDA | 10 | 0.36 | 76.42 |
| | CNNwithDA | 10 | 2.52 | 82.36 |
| | VGG16with DA | 25 | 0.23 | 86.67 |

Finally based on the above experimental result VGG16 withdataaugmentationachievedbetterperformanceontheclassification ofthe diseaseinthe betel leaf dataset.

Figures 6 and 7 show the result of the classification of diseaseclassfortrainingandtestaccuracyagainstthenumberofepochs. With the data augmentations we offer in our work, toincrease the quantity of data collectionand it is discoveredthatthisimprovementisratherconsiderableusing VGG16.

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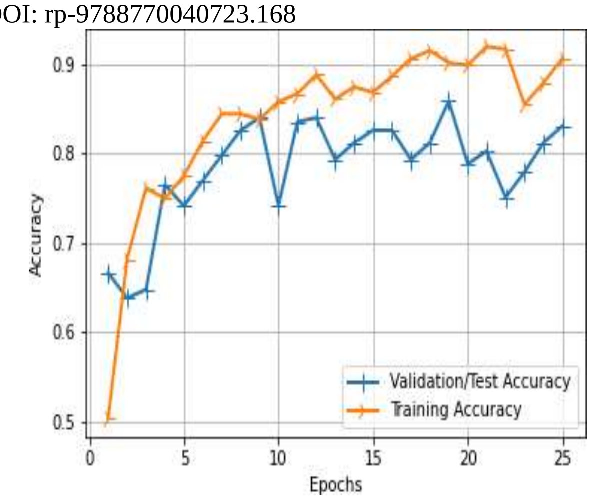


Fig.6.PlotofaccuracyandepochsofVGG16Model

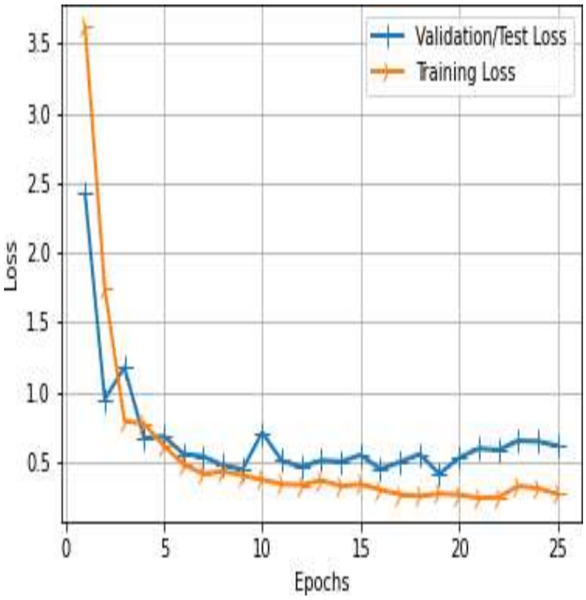


Fig.7.PlotoflossandepochsofVGG16Model

## V. Conclusion

Inthispaper,therealfieldimagesofbetelleafareaugmented by creating the output images with 3 classes ofdisease to multiply the image data using a different augmentedtechnique such as brightness, shear, rotation, etc., Eventually,compared the result with augmented images implemented totrainthesimpleconvolutionalneuralnetworkmodelandVGG 16model.Inourexperiment,theaccuracyofmodelVGG16 with data augmentation improves the accuracy rate inthe betel leaf dataset. Our future direction of work can beproceed on exploring how the model performs on increasingthe disease class, enhance the quantity ofdataset to improvetheaccuracyfurtherontherealfieldimagedataset.

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