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E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

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CLASSIFICATION OF LEAF DISEASE USING CNN

Y Jalajakshi , [2]Ch Ranjith, [3]D Naresh

Abstract—Inthefieldofagriculturalinformation, the automatic identification and diagnosis ofmaizeleafdiseasesishighlydesired.Toimprovetheidentification accuracy of maize leaf diseases and reducethenumberofnetworkparameters,theimprovedGoogLeNet and Cifar10 models based on deep learning[10]areproposed for leaf disease recognition in this paper. Twoimproved models that are used to train and test nine kindsofmaizeleafimagesareobtainedbyadjustingtheparameters, changing the pooling combinations, addingdropoutoperationsandrectifiedlinearunitfunctions,andreducing the number of classifiers. In addition, the numberofparametersoftheimprovedmodelsissignificantlysmaller than that of the VGG and Alex Net structures.Duringtherecognitionofeightkindsofmaizeleafdiseases, the GoogLeNet model achieves a top - 1 averageidentification accuracy of 98.9%, and the Cifar10 modelachieves an average accuracy of 98.8%. The improvedmethods are possibly improved the accuracy of maize leafdisease, and reduced the convergence iterations, which caneffectivelyimprovethemodeltrainingandrecognitionefficiency.

IIntroduction

Maize is an important food and feed crop. Its plantarea and total output are the largest in the world except forrice and wheat [1]. However, in recent years, the number ofspeciesofmaizediseasesandthedegreeofharmtheycausehavein creased,mainlyduetochangesincultivationsystems, the variation of pathogen varieties, and inadequateofplantprotectionmeasures.Generally,thereareeightty pesof common leaf diseases, including Curvularia leaf spot,Dwarf mosaic, Gray leaf spot, Northern leaf blight, Brownspot,Roundspot,Rust,andSouthernleafblight[2-6].Mostseriously, maize leaf disease is hazardous and will affectmaizeproductionandpeople'slives.

Maizeleafdiseaseshavevarioussymptoms.Itmaybemore difficultforinexperiencedfarmerstodiagnosediseases than for professional plant pathologists [7]. As averificationsystemindiseasediagnostics,anautomaticsystemtha tisdesignedtoidentifyplantdiseasesbytheplant's appearance and visual symptoms could be of greathelptofarmers.Manyeffortshavebeenappliedtothequickand accurate diagnosis of leaf diseases. By using digitalimage

Assistant Professor,Department of ECE, Samskruti College of Engineering and Technology

, Assistant Professor, Department of ECE, Samskruti College of Engineering and Technology,

, Assistant Professor, Department of ECE, Samskruti College of Engineering and Technology

processingtechniques,supportvectormachine(SVM), neural networks, and other methods, we can detectandclassifyleaf diseases[8]. An SVM- basedmulti -classifier was proposed

by Song et al. and was applied toidentify a variety of maize leaf diseases. The best recognitionaccuracy was 89.6%. The method of classification usingSVMisonlyapplicabletosmallsamples,foralargenumberofsamples,itcannotachievehigh recognitionaccuracy.

II LiteratureSurvey

L. Chen and L.Y. Wang proposed a method for theidentificationofmaizeleafdiseasesbasedonimageprocessing technology and a probabilistic neural network(PNN)[9].Thebestrecognitionaccuracyofthismethodwas90.4%. However, for the PNN classifier, the identificationaccuracyandspeedofthismethoddecreaseasthenumberoftraining samples increases. A method of maize leaf diseaseidentification based on adaptive weighting multi-classifierfusion was proposed by L. F. Xu [10]. Seven common typesof maize leaf disease were tested by this method. The averagerecognitionratewas94.71%.N.Wang.[11]Z.Qietal.[11] and F. Zhang [11] proposed different methods using digitalimage processing techniques based on Fisher discriminant,Retinexalgorithmcombinedwithprincipalcomponentanalysis(PCA)andSVM[8],andquantumneuralnetwork(QNN) and combination features for identification of maizeleafdisease.Thehighestrecognitionaccuracyofthesestudies was 95.3%, but fewer maize

diseases were involvedin these methods. Different methods are used to identifymaizediseasesandthebestrecognitionaccuracywas95.3

%,whichcannotmeetthecurrentrequirementsforhighrecognition accuracy. Therefore, in the follow-up study, weshould focusonhow to improve identification accuracy.

Deeplearninghasmadetremendousadvancesinthepast few years.It is now able to extract usefulfeaturerepresentationsfromalargenumberofinputimages.Deeplearningprovidesanopportunityfordetectorstoidentifycropdiseasesinatimelyandaccuratemannerwhichwillnotonlyimprovetheaccuracyofplantprotection but also expand the scope of computer vision inthe field of precision agriculture. Y. Lu et al. [9] useddifferent pooling operations, filter sizes, and algorithms toidentify10commonricediseases.Theproposedconvolutional neuralnetworks(CNNs)-basedmodelachieved an accuracy of 95.48%. C. Dechant et al. [11]trained CNNs to automatically identify the northern leafblight of maize. This approach addressed the challenge oflimited data and the myriad irregularities that appear inimages of field-grown plants. The identification schemeachievedanaccuracyof96.7%.Someresearcherscanimprove the identification accuracy of plant diseases to acertain extent by using different convolution neural networkmodels and changing the ratio of training set size to testingset size [9]. These studies have obtained better results,butmoreparametersandlongertrainingconvergencetimes have a negative effect on the recognition rate. To obtain ahighlymaizeleafdiseaseidentificationaccuracy,itishighly significant to design a recognition model with fewerparametersandhigherrecognitionaccuracy.

III ProposedModel

Inthisstudy,twoimproveddeepconvolutionneuralnetwork models, GoogLeNet and Cifar10, are presented toincreasetherecognitionaccuracyofmaizeleafdiseasesandimprove the traditional identification methods with longconvergencetimesandlargenumbersofmodelparameters.The two models that are used to train and test 9 kinds ofmaizeleafimages areobtainedbyadjustingthemodelparameters, changing the pooling combinations, adding thedropout operation and rectified linear unit (Relu) function,andreducingthenumberofclassifiers.Finally,theexperimentalresultsarecomparedwiththoseoftheunmodified model.

AGoogleModel

The initial learning rate of the original GoogLeNetmodelis 0.001, using the ‘‘step’’ method to attenuate the learningrate. After 100000th iterations and classified by the threeclassifiers, the top - 1 testing accuracy are 98.8%, 98.6%,98.2%;top-5testingaccuracyare99.6%,99.6%,99.6%;theloss of the system is 15.8%. Fig.1 (a) shows the changes ofpartial top - 1 test accuracy and Fig.1 (b) shows the curve ofthe system loss. We can see that the top - 1 identificationaccuracyandsystemlossgraduallyconvergeafter40000thiterations. The training time and the convergence time of theoriginal model are longer. The original model also has alarger numberofparameters.

The first classifier of the GoogLeNet model is usedto perform 50000th iterations on 9 samples of the maize leafdataset in this test. After each 100th iteration, the top - 1accuracy and the model loss are measured. Fig.2 (a) showsthe changes in top - 1 test accuracy and Fig.2 (b) show thecurve of the model loss. In this study, the initial learning rateof the GoogLeNet model is 0.001, and the ‘‘step’’ methodattenuatesthelearningrateby0.96timesevery2000thiterations. As seen from Figure, after 10000th iterations, thetop-1testingaccuracygraduallytendsto1,thelossgraduallyapproaches0,andbothstatesarestable.Experimentsshowthattheaveragetop-1accuracyis98.9%and the loss is 1.6%, after using the improved GoogLeNetmodeltotrainandtestthe maize leaf image dataset.

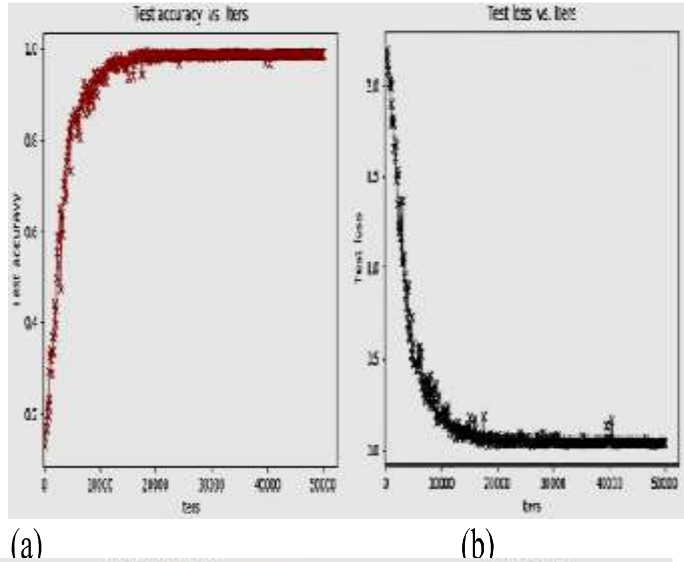


Fig1:ExperimentalresultsoftheoriginalGoogLeNet model.

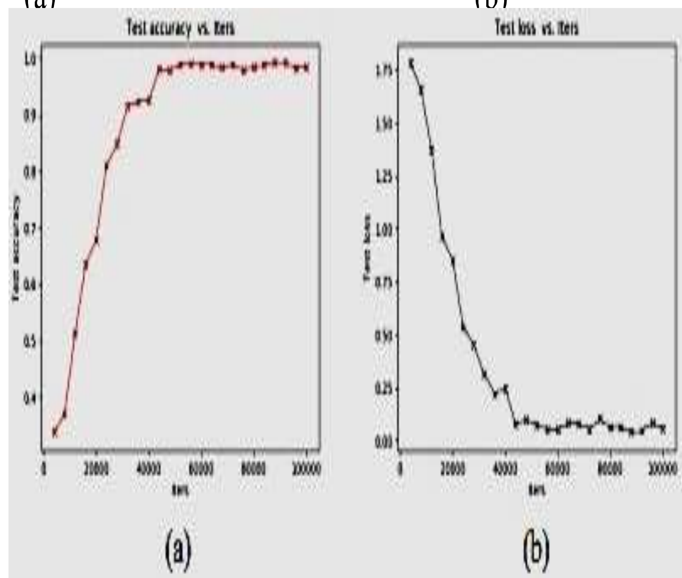


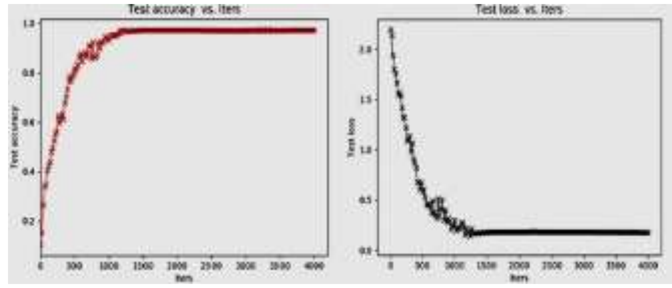
Fig2:ExperimentalresultsoftheimprovedGoogLeNet model.

BCifar10 Model

The Relu function and dropout operation will beaddedbetweenthetwofullyconnectedlayersoftheCifar10model.Relufunctioncanadaptivelylearntheparametersoftherectifierandincreaseaccuracywithnegligibleadditionalcost.Foraninputx,theReluactivationfunction.

elu(x) =0,if x $\leq$00,if x> 0

Thedropoutoperationworksbyrandomlysuppressingacertainnumberofneurons.Thesuppressedneuronsaretemporarily not involved in the forward communication ofthe network. Optimizing the model-related parameters andtheninitializingthethreepoolingcombinations:Max-Max - Ave (By taking the maximum of the kk neighbourhood inthe feature graph, max-pooling can calculate the maximumvalueofthenon-overlappingrectangularareaforeachconvolution kernel output. The mean pooling is averagedover all the sampling points in the locally accepted domain.Itispossibletoreducethe errorofthevarianceoftheestimated variance increases due to the limited size of theneighbourhood, which can retain more image backgroundinformation.). Considering the fact that different dropoutparameters will affect the recognition accuracy, in this test,the relationship between the dropout probability value andthe testing accuracy of the improved model is studied. Themaximum testing accuracy of the model is 97.8% when thedropout probability value is 0.65. We fix this value and thenexperimentwithfourpoolingcombinationsofthreeconvolutions: Max/Ave/Ave, Max/Max/Ave,Max/Max/Max, and Ave/Ave/Ave. The learning rate of thismodel is fixed at 0.0002. The accuracy and the loss of themodel is measured after every 20th iteration, for a total of50000th iterations. The model's testing accuracy and losscurves are shown in graph. As seen in graph, the preferredpoolingcombinationisMax-Max-Ave.Theoriginalmodel's testing accuracy and loss are shown in Fig.3. Theimprovedmodels'testing accuraciesareshown in Fig.4 .



(a) (b)

Fig3:ExperimentalresultsoftheoriginalCifar10 model.

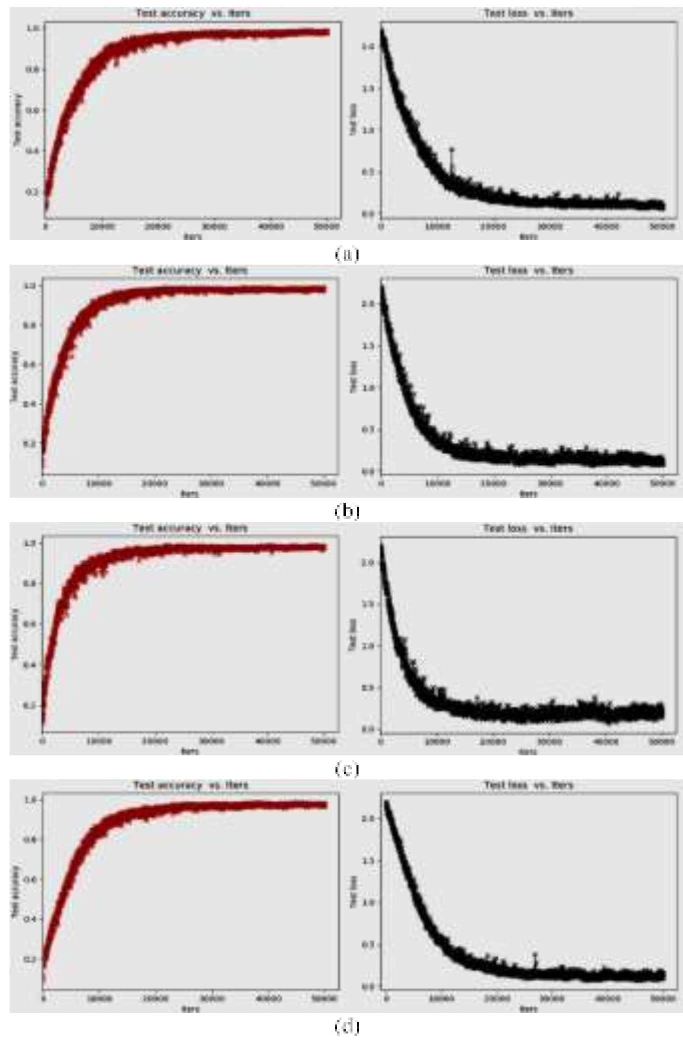


Fig 4: Experimental results of the four pooling layercombinations of the Cifar10 model (a) Max-Ave-Ave. (b)Max-Max-Ave.(c) Max-Max-Max.(d)Ave-Ave-Ave.

Methodology

A. DATASET:

An appropriate dataset is required at all stages ofobjectrecognitionresearch,startingfromthetrainingphaseto evaluating the performance of recognition algorithms. Atotal of 500 images are collected from different sources,such as the Plant Village and Google websites, includingdifferent periodsofoccurrencesofmaizeleafdiseases,which are divided into 9 different categories. There are 8categories representing infected maize leaves and a categoryrepresentinghealthyleaves.Eightkindsofmaizeleafdiseases are shown in Fig.5: Curvularia leaf spot, Dwarfmosaic, Gray leaf spot, Northern leaf blight,Bbrown spot,Round spot, Rust, and Southern leaf blight; these are themain diseasesinvestigatedin thisstudy.

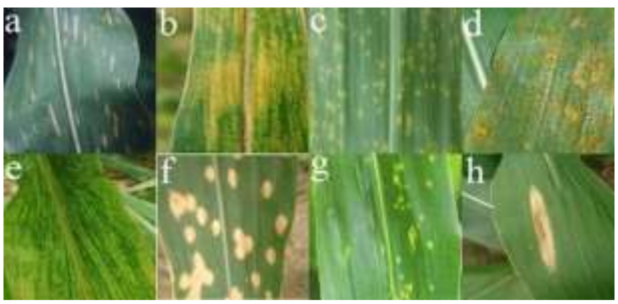


Fig 5:Eight common maize leaf diseases a: Southernleaf blight; b: Brown spot; c: Curvularia leaf spot; d:Rust; e: Dwarf mosaic; f: Gray leaf spot; g: Round spot;h:Northernleafblight.

B. AUGMENTATION:

TrainingCNNsrequiressubstantialdata.Themoredatathe CNNshavetolearn,themorefeaturesitcanobtain.Since the original leaf image dataset collected in this studyis not sufficient, it is necessary to expand the dataset bydifferentmethodstodistinguishthedifferentdiseasecategories. Aftertheoriginalimagesareinitialized,additional versions are created by rotating the images 90˚,180˚, and 270˚; by mirroring each rotated image; by cuttingthe center of the image by the same size; and by convertingall processed images to grayscale. The dataset is expandedby the above methods, which helps in reducing over fittingduring the training stage. Partially converted images areshown in Fig.6. In total, the maize leaf dataset contains 3060images2248(80%)for training and612(20%)fortesting.

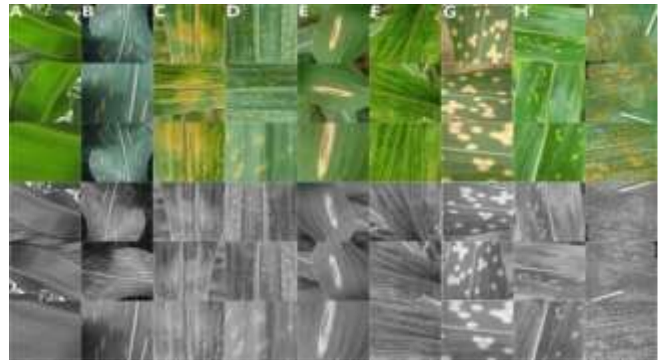


Fig 6: Part of the image samples after the augmentationprocess Part A shows a healthy maize leaf after rotation,cutting, and grayscale. Part B-I shows eight kinds of maizeleaf disease images

C. IMAGEPREPROCESSINGANDLABELLING:

Toimprovefeatureextractionandincreaseconsistency, the images in the dataset for the deep CNNsclassifierarepre-processedbeforethemodelistrained.Oneof the most significant operations is the normalization ofimagesizeandformat.Inthisstudy,allimagesareresizedto224x 224pixelsand32x32dotsperinch,whichareautomaticallycomputedbyPythonscriptsbasedontheOpenCVframework.

In the interest of confirming the accuracy of theclassesinthe dataset, agricultural experts examinedleafimages grouped by a keyword search and labeled all theimageswiththeappropriatediseaseacronym.Itiswellknown that it is essential to use accurately classified imagesfor the training and validation dataset. Only in that can mayan appropriate and reliable model be developed. In this stage,various classes of the dataset, as well as the training set andthetestingset, are marked.

D. CONVOLUTIONALNEURALNETWORKS:

ArtificialIntelligencehasbeenwitnessingamonumentalgrowthinbridgingthegapbetweenthecapabilitiesofhumansandmachines.Researchersandenthusiasts alike, work on numerous aspects of the field tomakeamazingthingshappen.Oneofmanysuchareasisthedomain of Computer Vision. The agenda for this field is toenablemachinestoviewtheworldashumansdo,perceiveitinasimilarmannerandevenusetheknowledgeforamultitude of tasks such as Image & Video recognition, ImageAnalysis&Classification,MediaRecreation,Recommen

dation Systems, Natural Language Processing,etc.TheadvancementsinComputerVisionwithDeepLearninghasbeenconstructedandperfectedwithtime,primarily over one particular algorithm — a ConvolutionalNeuralNetwork[16-20].

A Convolutional Neural Network (ConvNet/CNN)[20] is aDeep Learning algorithm which can take in an input image,assign importance (learnable weights and biases) to variousaspects/objects in the image and be able to differentiate onefrom the other. The pre-processing required in a ConvNet ismuch lower as compared to other classification algorithms.Whileinprimitivemethodsfiltersarehand-engineered,withenough training, ConvNets have the ability to learn thesefilters/characteristics.TheOperationsdonebyCNN[8]are:Convolution,ActivateFunction,Pooling,Dropout,LossFunction.

E. HYPERPARAMETER:

TheimprovedCifar10andGoogLeNetmodels'hyperparameters are shown in Tablecompared with theoriginal one in Table 2. By changing the base learning rate,it can affect the identification accuracy of the network. AllexperimentsaredoneusingtheGPUs.Themodelsareoptimized bythestochasticgradientdescent(SGD)algorithm. The method of batch training is to divide thetraining set and the testing set into multiple batches. Eachbatchconsistsoftraining10images.Theinitiallearningrateof the Cifar10 model is fixed at 0.0002. The initial learningratefortheGoogLeNetmodelis0.001anddecrementedby 0.96 times.

V CONCLUSION:

In this study, when identifying 9 types of maizeleaves,thetwoimproveddeepconvolutionalneuralnetwork models,GoogLeNetandCifar10,canachievehighidentificationaccuracy,98.9%,and98.8%,respectively.When the train-test set is 80 - 20 (80% of the whole datasetused for training, and 20% for testing), the classificationalgorithms used in this study allow the systems to acquire adiversityofsampleconditionswithstrongrobustness.Experiments show that it is possible to improve recognitionaccuracy by increasing the diversity of pooling operations,thereasonableadditionofaRelufunctionanddropoutoperations,and including multipleadjustmentsof themodelparameters. In future research, we will identify more typesofmaizediseasesandpestsandcombinenewalgorithmsandother deep learning structures for the training and testing ofthemodel.Meanwhile,inordertoenableagriculturalproducers to make quick and reasonable judgments aboutcropdiseaseinformation,thetrainedmodelcanbecombined with mobile devicesinaflexible manner.

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