Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Statistical Analysis of Deep Learning Models for Diabetic Macular Edema Classification using OCT Images

Roopa B S*, Yogitha N*, Indhu TB*,Chandana K*,Suhana A*,

Mrs. Roopa B S, Asst. Prof.,ECE Dept., JNN College of Engg, shivamogga
and
*(Electronics and communication Engg, JNN College of Engg, shivamogga)

Abstract:

Diabetic macular edema (DME) is a potentially blinding complication of Diabetic retinopathy (DR) and indeed the main cause of visual impairment in diabetic patients. DME can indeed be diagnosed in varying levels of severity by employing Optical Coherence Tomography (OCT), which is a standard imaging modality to capture the 3D view of the retina. Computerized detection of DME is beneficial, and automated identification can assist doctors in their daily activities. Deep Learning (DL), a widely recognized method in this regard, has contributed to improving the effectiveness of classification algorithms. The focus of this research is to use a standard OCT dataset to test and analyse two DL models, Optic Net and DenseNet for DME classification. A statistical analysis of the accuracy measures collected during the experiments is performed to evaluate the performance of the two models. The statistical findings suggest that the model Optic Net (Accuracy-98%, Specificity-100%) outperforms DenseNet (Accuracy-94%, Specificity-96%) in terms of accuracy, and the results could be used to choose an optimal model for DME detection.

*Keywords:*Optical coherenceTomography,DeepLearning,DiabeticMacularEdema.

I. INTRODUCTION

Diabetesischaracterizedbychronichyperglycemiathatoccurs whenever the pancreas fails to produce insulin or whenthe existing insulin in the body is not being used effectively[1].Hyperglycemiaisattributedtoanelevatedlevelofglucosein the blood. An excessive amount of glucose over time caninduce diseases of the kidney, eye, heart, and blood vessels.Thedelicatebloodvesselsintheretinacanbeimpairedbyahigherconcentrationofglucose.There mayoccurleakageor blockage of blood vessels leading to an eye complicationknownasDiabeticRetinopathy(DR)[2]. DR is characterized by the lesions such as microaneurysms,hemorrhages, hard and soft exudates, etc [3]. Microaneurysmsoccurbecauseofthebloodvesselwalldamageduetoanexcessiveamountofglucoseinthebody.Theyappearliketinyred dots on the blood vessels and may lead to hemorrhageswhen ruptured. Protein and lipids deposited on the retina leadtotheformationofhardandsoftexudates.Alarge amountof fluid accumulated in the retina causes it to swell. And thisswelling, which when occurs at the crucial part of the retina,themacula,isnamedDiabeticMacularEdema.[2],[4].

DMEisaseveremaculardisorderthatcanbeapparentat any level of DR. DME, being an important component ofDR, may lead to complete vision loss where the lost visioncannot be recovered. Macula, being located in the middle ofthe retina, a common and noticeable characteristic associatedwith DME is the rise in the macular thickness. A safer optionfor preventing vision loss is early detection and treatment ofDME.AsthenumberofDMEpatientsisincreasing atadrastic speed, we need automated methods for faster detection.Among different eye imaging techniques available to date,Fundus photography and Optical Coherence Tomography arethe most used. Fundus images can provide 2D images of theeyeretina,whichlackquantitativestatistics[5][6] .

WiththeOpticalCoherenceTomographyimaging tech-nique,infraredlightisutilizedtoproduceresolutioncross-sectional photographs of active body tissues. OCTmachinecancapturevolumetricinformationofretinallayerssuchas the thickness. The presence of edema can be seen withfundus images but the quantity of fluid accumulated can bebetter visualized with the OCT scans. The OCT images of anormalandDMEaffectedretinaaredepictedinFigure1.

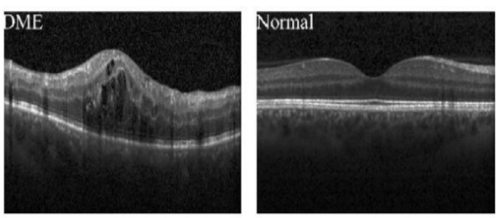


FIG.1.OCTIMAGESOFDMEANDNORMALRETINA.

II.RELATEDWORK

Manyresearchers have used pre-trained and custom-designed DLmodels to classify OCT images to identify a multitude of eyedisorders. Among the journal papers where DL-based CNNs are usedfortheclassificationofDME,themajorityofmodelsaretrained and tested on private data sets which are not accessibleinthepublicdomain.Noattempthasbeenmadeintheliterature to compare different DME detection models usingOCT images. To cross-validate any newly built DL model,thereisaneedtohaveacommondatasetthatservesasabenchmarkforthestudy.Noattempthasbeen madetocompare the performance of a set of DL classifiers for DMEdetection against a common OCT dataset. Also, most of themodels have employed very huge public datasets for training.Although most eye clinics possess smaller OCT datasets, anyDLclassifierthatperformswellwithasmallerdatasetisappreciated. In this case, a quantitative analysis of the performancemetrics of the DL models can be useful. The outcome of theproposed work is expected to meet the identified research gap.Therefore, the main objective of the research to be accomplished,involvestheanalysisofDLmodelsfor DMEdetectionusingacommon,smallOCTdataset. VGG-16 network is fine-tuned for OCT image categorizationbyLietal.[13]todemonstratetheeffectivenessoftheTLmethod. Leyuan et al. [14] adopted an iterative fusion tech-nique, where features from the current convolutional layer arefused with previous layers to improve classification accuracy.Tsuji et al. [15] incorporated the positional information fromthe OCT images by using a capsule network to enhance themodel prediction. Ibrahim et al. [16] attempted the fusion offeatures obtained by the DL model with handcrafted featuresextractedfromOCTimages.Intermsofthenumberofparameters,accuracy,andmemorysize,themodelbyKamran etal. et[17]outperformstheexistingmethods.TheCNNmodelwasbuiltfromscratchandevaluatedontwopublicdatasets.Junetal.[21]trainedaCNNwithmorethanonelakhOCTimagesemployinganattentionmechanismalongwithapre processingmodule.Nithyaetal.[18],Alietal.[19],Taimuretal.[20]andSunijaetal.[22]developedCNNmodelstogrademultipleclassessuchasDME,AMDandNormalin corporatinglargepublicOCTdatasets.

III.PROPOSEDMETHOD

Themethodologyprovidesthetheoreticalframework oftheproposedstudytoaddresstheresearchgapsidentifiedusingengineeringsolutions.Theproposedmethodaimstoanalyze the state of art DL models for DME screening usingOCT images. The proposed system incorporates a quantitativeapproach to research. The research intends to use ex-perimental methods for the DL model evaluation. The studyemploysanepistemologicalstancetoanswerRQ1andanontological stance to answer RQ2. And hence the proposedresearch follows a positivist paradigm with experimentation toarrive at the expected results. The complete block illustrationoftheproposedmethodisillustratedinFigure2.The proposed research aims to train two DL models ResNetandDenseNetforDMEclassificationusingOCTimagesonGoogleColab.Hypothesistestingisused toperformstatistical analysis on the findings of the two models. Finally,the results of the hypothesis testing and model findings areusedtoinferthebest-performingmodelonthegivendataset.

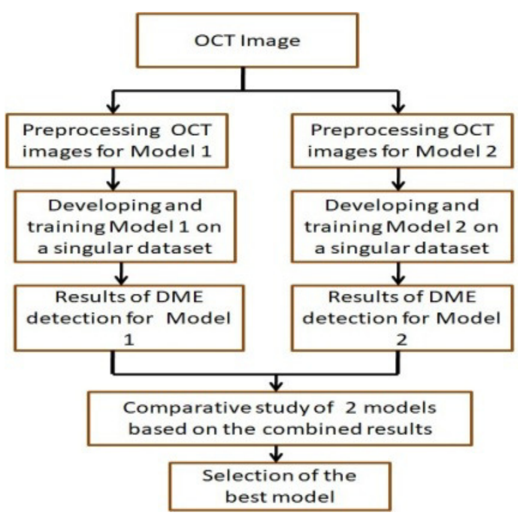


Fig.2.AdoptedMethodology

The steps taken in the analysis of the models are depicted inFigure3.In Deep Learning, CNNs are the distinct class of networksusedforcategorizingimagesbelongingtothe medicaldomain.The proposed implementation aims at classifying DME andNORMALOCTimagesusingMendeleydataset.TwoCNNarchitecturesResNetandDense Netfordiscriminating between two classes of OCT images are trainedsuccessfully. The OCT dataset consists of DME and NOR-MAL images with the original individual size specification of1024*496 pixels. Figure 4 depicts the architecture of a standard convolution where the input OCT image is passed overseveral convolution operations to extract the image featureswhicharehighlevel.Convolutional layersareusedinatypicalCNN, followed by fully connected and pooling layers. Filtersare included in every convolution layer to facilitate the featureextractionprocess.The experimental method uses a DenseNet201 architecturewhichmakesuseofaCNNwhichisawidely usednetworkfor medical image classification.

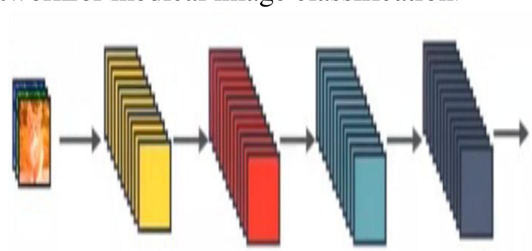


Fig3.Diagramdescribingstandardconvolution[26]

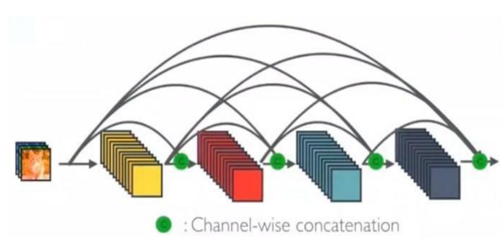


Fig.4.ResNetconceptusedinOpticNet

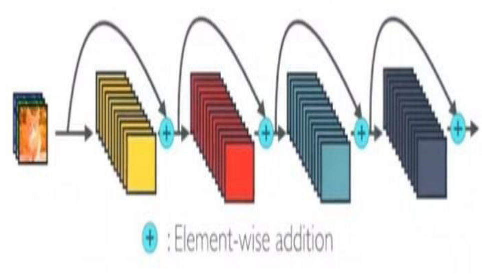


Fig5: Structure ofthe DenseNet block

The pre-trained CNN on the ImageNet dataset is used for classification. Image Net dataset consists of 1000 different sets of classes with a total of 1.2 million images. During the retraining process, different parameters of CNN were updated across multiple layers of the model. This fine-tuning is expected to help enhance the output of the model. The model incorporated a categorical-cross entropy loss function with a learning rate of 0.001. The optimizer used to reduce the loss function is the Adam optimizer. Dataset was trained in 50 different epochs with a batch size of 32 .An important feature of DenseNet is that feature maps of all the preceding layers in the network are provided to every other layer of the network, as additional input during processing. Also, every layer forwards its feature maps to The subsequent layers. Concatenation operation is performed to process the inputs. Collective knowledge from all the layers is taken into consideration during the processing performed at an individual layer. With this feature, the number of channels required by the network is less and the network becomes thinner and more compact. Figure 5 demonstrates the architecture of DenseNet. Figure 6 illustrates the architecture of the ResNet architecture is modified by proposing a few changes to be the Optic Net model. Additionally, aresidual unit is used for subsuming atrous separable convolution. The model incorporated a method to avoid gradient loss. To eliminate gradient degradation, the identity mapping techniqueisused withelement-wiseadditioninResNet.Skipconnectionsareincorporatedtomatchtheinputofonelayertothenextlayerwithoutapplyingmodificationsto theinput.. Figure 7showsdifferencesbetweenResNetand OpticNet.Compared toResNet,Optic Netrequiresminimalparametersandlessmemory .The optimizerused to reducethelossfunctionistheAdam optimizer.Dataset was trained in 50 differentepochswithabatchsizeof32.

A.OCTdataset

The primary step in OCT image analysis is image acquisition.Theresearchfocusesontheuseofthesecondarysourcefordatacollection.A public OCT image dataset “Large”DatasetofLabeled Optical Coherence Tomography (OCT) and Chest X-Ray Images” [10] is used for the evaluation of DL models.
Theresearchmakesuseof450OCTimagesconsisting oftwoimageclasses DME and NORMAL from the public dataset. The twoclasses ofimagesvarydrasticallyintheirappearance

IV.RESULTSANDDISCUSSION

The models ResNet and DenseNet are trained on a GoogleCollabenvironmentwith864DMEand864 NORMALimages.Thetestdatasetforboththemodelscontained50OCTimageswith216DMEand216NORMALimages.

A.ExperimentalResultsandInferences

The experimental results obtained for the DME classificationusingthe2modelsontheMendeleydatasetalongwiththegraphs are illustrated. Both the models ResNet and DenseNetwere tested over 216 NORMAL and 216 DMEimages. ResultsshowthatthemodelDensNetperformsbett erwithanaccuracyof 98.6%. The graphobtainedforloss during training andvalidationisillustratedinFigure8.The graph obtained for accuracy values during training andvalidationisillustratedinFigure9.

Fig.6.Trainingandvalidationloss

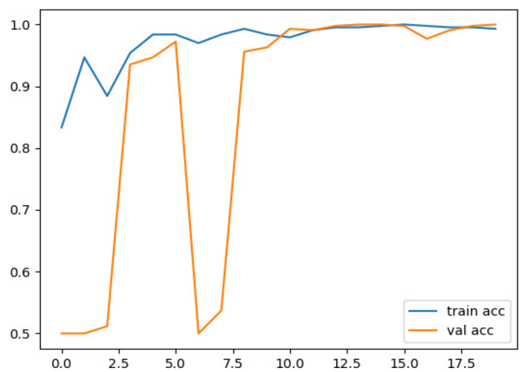


Fig.7.TrainingandvalidationAccuracy

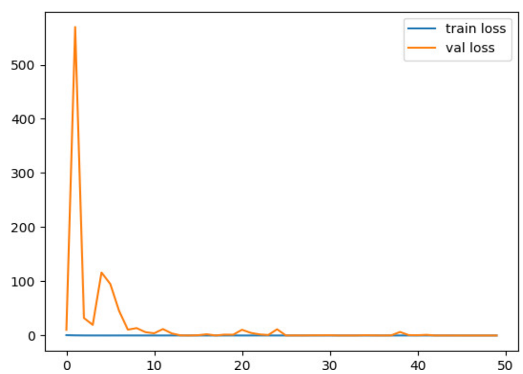
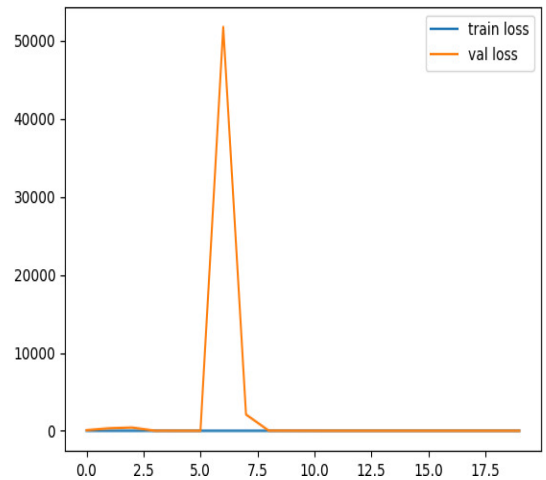


Fig.8.Trainingandvalidationloss



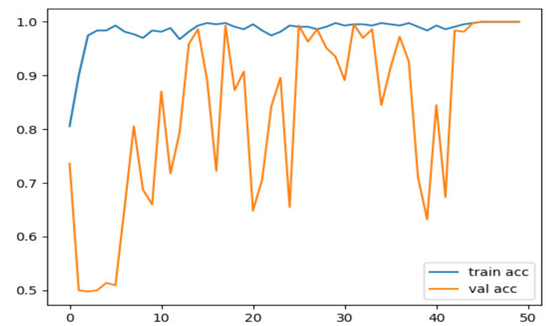


Fig.9.TrainingandvalidationAccuracy.

TABLE I

ACCURACY VALUESFOR OPTIC NET AND DENSENET

SL.No.	Accuracyvalues forRes Net	SL.No.	Accuracyvalues forDenseNet-
10	98	10	98
20	93	20	98
30	83	30	99
40	91	40	98
50	93	50	100

Dense Net obtains accuracy 98.6%.The graph obtained for lossduring training and validation is illustrated in Figure 6. Thegraph obtained for accuracy values during training and validation isillustratedinFigure7.TheDensNetmodelperformsefficientlywithanoverallachievedaccuracyof98.6%.Thegraphsobtainedfor the loss and accuracy seem more stable for DensNet than thegraphsthatareobtainedforResNetThe Optic Net model performs efficiently with an overallachievedaccuracyof98%,whichmeansthatthe misclassification rate is very low. One OCT image out of 50 OCT imagesgot classified wrongly. The model achieved a sensitivity of95%,whichmeans23DMEimagesgotclassifiedcorrectlyoutof24OCTDMEimages.Themodelachievedaspecificityvalue of 100%, which means that it could detect all the TrueNegatives (NORMAL class). DenseNet performed satisfacto-rilywithanoverallaccuracyof94%,whichshowsthat3out of 50 OCT images got misclassified by the model withsatisfactoryvaluesforsensitivityandspecificity.Thegraphs obtainedforthelossandaccuracyseemmorestableforOpticNetthanthegraphsthatareobtainedforDenseNet.

V.CONCLUSIONS

Toobtaingoodaccuracy,DLclassifiersentailahuge volumeoflabeledinformationfortraining.Since,mostoftheprimaryeyecarecenterspossesssmallerOCTimagedatasets,developingaDLmodelseemsdifficultbecauseofthescarcityofimages.Inthisstudy,asmallDMEOCTdataset is considered to evaluate the performance of two DLmodelsOpticNetandDenseNetwithpre-trainedweights.TheOpticNetModelwithnearaccurateresultsisfoundtobethebestperformingmodelonasmallpublicdatasetofOCTimages.Thismodelmaywellbetransformedintoastandalone application that ophthalmologists could use to helpthem detect and diagnose DME disease on a routine basis.Automated detection of retinal disorders can help in the fasterdiagnosis of the disease by helping doctors in providing earlyand timely treatment for the patients. The crucial point here isthat the disease detection system must be accurate, fast, andcost-effective. The design of a novel model built using theadvantages provided by the Optic Net model is appreciated.Along similar lines, an attempt can be made to identify theDME disease severity levels. The Optic Net model featurescan be used to detect various other eye disorders such as DR,Myopia,andage-relatedmaculardegeneration.

REFERENCES

[1] M. Ghazal, Y. Al Khalil, M. Alhalabi, L. Fraiwan, and A. El-Baz, “Early detection of diabetics using retinal oct images,” in Diabetes and Retinopathy, A. El-Baz, S. and J. Suri, S., Eds. Elsevier, 2020.

[2] S. A P, S. Kar, G. S, V. Gopi, and P. Palanisamy, “Octnet: A lightweight cnn for retinal disease classification from optical coherence tomography images,” 2021.

[3] “Review: DenseNet — Dense Convolutional Network (Image Classification)”, on 06/09/2022.

[4] T. Hassan, M. Akram, Usman, and I. Basit, “5 - analysis of optical coherence tomography images using deep convolutional neural network for maculopathy grading,” in Diabetes and Retinopathy, A. El-Baz, S. and J. Suri, S., Eds. Elsevier, 2020.

[5] N. Rajagopalan, V. Narasimhan, S. Vinjimoor, J. Aiyer, ”Deep cnn framework for retinal disease diagnosis using optical coherence tomography images,” Journal of Ambient Intelligence and Humanized Computing, 2020

[6] M. Ibrahim, K. Fathalla, and S. Youssef, “Hycad-oct: A hybrid computer-aided diagnosis of retinopathy by optical coherence tomography integrating machine learning and feature maps localization,” Applied Sciences (Switzerland), vol. 10, no. 14, 2020.

[7] D.Kumar,A.Goyal,A.Truhan,G.Abrams,andR.Manwar,“1-complementary capabilities of photoacoustic imaging to existing opticalocular imaging techniques,” in Diabetes and Retinopathy, A. El-Baz, S.andJ.Suri,S.,Eds.Elsevier,2020,vol.2,ch.1,pp.1–17.

[8] S. Karri, D. Chakraborty, and J. Chatterjee, “Transfer learning basedclassificationofopticalcoherencetomographyimageswithdiabeticmacular edema and dry age-related macular degeneration,” BiomedicalOpticsExpress,vol.8,no.2,pp.579–592,2017

[9] P.P. Srinivasan, L.A. Kim,P. S. Mettu, S. W.Cousins, G. M. Comer, J.

[10] D. Kermany, M. Goldbaum, and e. t. al, “Identifying medical diagnosesand treatable diseases by image-based deep learning,” Cell, vol. 172, no.5,pp.1122–1131.e9,2018

[11] C. W. Kermany D, Goldbaum M, ““large dataset of labeled opticalcoherence tomography (oct) and chest x-ray images”, mendeley data,”2018

[12] W.Lu,Y.Tong,Y.Yu,Y.Xing,C.Chen,andY.Shen,“Deeplearning-based automated classification of multi-categorical abnormalities fromopticalcoherencetomographyimages,”TranslationalVisionScienceandTechnology,vol.7,2018.

[13] J. De Fauw, J. Ledsam, and e. t. al, Nature Medicine, vol. 24, no. 9, pp.1342–1350,2018.

[14] F.Li,H.Chen,Z.Liu,X.Zhang,andZ.Wu,“Fullyautomateddetectionof retinal disorders by image-based deep learning,” Graefe’s Archive forClinical and Experimental Ophthalmology, vol. 257, no. 3, pp. 495–505,2019/

[15] L. Fang, Y. Jin, L. Huang, S. Guo, G. Zhao, and X. Chen, “Iterativefusion convolutional neural networks for classification of optical coher-ence tomography images,” Journal of Visual Communication and ImageRepresentation,vol.59,pp.327–333,2019.

[16] M.Ibrahim,K.Fathalla,andS.Youssef,“Hycad-oct:Ahybridcomputer-aided diagnosis of retinopathy by optical coherence tomogra-phyintegratingmachinelearningandfeaturemapslocalization,”AppliedSciences(Switzerland),vol.10,no.14,2020.

[17] S. Kamran, S. Saha, A. Sabbir, and A. Tavakkoli, “Optic-net: A novelconvolutionalneuralnetworkfordiagnosisofretinaldiseasesfromopticaltomographyimages,”pp.964–971,2019

[18] N.Rajagopalan,V.Narasimhan,S.Vinjimoor,J.Aiyer,”Deepcnnframeworkforretinaldiseasediagnosisusingopticalcoherenceto-mography images,” Journal of Ambient Intelligence and HumanizedComputing,2020.

[19] A.Alqudah,“Aoct-net:aconvolutionalnetworkautomatedclassificationof multiclass retinal diseases using spectral-domain optical coherencetomographyimages,”vol.58,no.1,pp.41–53,2020

[20] T. Hassan, M. Akram, Usman, and I. Basit, “5 - analysis of opticalcoherence tomography images using deep convolutional neural

networkfor maculopathy grading," in Diabetes and Retinopathy, A. El-Baz, S.andJ.Suri,S.,Eds.Elsevier,2020,vol.2,ch.5.

[21] J.Wu,Y.Zhang,J.Wang,J.Zhao,D.Ding,N.Chen,L.Wang,X.Chen,C.Jiang,X. Zou,X.Liu,H.Xiao,Y.Tian,Z.Shang,K.Wang,X.Li,G. Yang, and J. Fan, "Attennet: Deep attention based retinal diseaseclassificationinoctimages,"vol.11962LNCS,pp.565–576,2020.

[22] S.AP,S.Kar,G.S,V.Gopi,andP.Palanisamy,"Octnet:Alightweightcnn for retinal disease classification from optical coherence tomographyimages,"vol.200,2021.

[23] W. Creswell, J., Research design : qualitative, quantitative, and mixedmethodsapproaches.

[24] A. Suzuki and Y. Suzuki, "Deep learning achieves perfect anomalydetectionon108,308retinalimagesincludingunlearneddiseases," 2020.

[25] S. Chiu, M. Allingham, P. Mettu, S. Cousins, J. Izatt, and S. Farsiu,"Kernel regression based segmentation of optical coherence tomographyimages with diabetic macular edema," Biomedical Optics Express, vol.6,no.4,pp.1172–1194,2015.

[26] "Review:DenseNet—DenseConvolutionalNetwork(ImageClassification)", https://towardsdatascience.com/review-densenet-image-classification-b6631a8ef803,(Accessedon06/09/2022).

