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Predicting Breast Cancer by Applying Deep Learning to Mammograms

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ABSTRACT--
Cancerisstillamajorthreattoindividualstodaybecauseithasthehighestmortalityrateontheglobe.Thisisduetoalackofearlycancerdetection.Breastcancercarcinomaisoneofthemostdeadlydiseasesforwomenworldwideandthemostcommonlydetectednon-skincancerinwomen.Diagnostictestingforthislife-threateningdiseaseincreasesthelikelihoodofasuccessfultreatmentsignificantly.Thetraditionalmethodofcancerdiagnosisreliesheavilyonthetechnician'sordoctor'sabilitytodetectanomaliesinthehumanbody.Breastcancerdevelopswhenthecelltissueinthebreastbeginstodivideirregularlyandaggressively.Furthermore,theabilitytomoreaccuratelypredicttheonsetofamalignantinfectionwillhelpbreastcancerpatientsplantheirfuturecourseoftreatmentunderthesupervisionoftheirdoctor.Becauseofitsgreatheterogeneityandcomplicatedfeatures,breastcancerisparticularlydifficulttopredict.TheaccuracyofmultipleCNNmodelsisinvestigatedinthisproject,whichfocusesonthepredictionofbreastdiseaseusingmammographyimages.Inthisproject,weexplorevariousCNNmodelsusing3datasetsfromvarioussourcesandcombining,themtoidentifymalignancyinmammographyscansimages.Fine-tuningisperformedincludingResNet-50,VGG-16,AlexNet,andGoogleNet.Additionally,wearegoingtobuildauniqueXceptionmodelwith92.8%accuracytodiagnosebreastcancerandcompareeachmodelforearlyprediction
ofabnormality.
IndexTerms—
AlexNet,BreastCancer,Carcinoma,CNN-ConvolutionalNeuralNetwork,DeepLearning,Diagnose,DDSMMammography, GoogleNet,Mammogram, Malignant infection,Machinelearning,ResNet-50,Tuning,VGG-16.

I. INTRODUCTION

Malignancyhasbeendefinedasacollectionofinfections,abnormalcellformation,andthepossibilityofuncontrolledcelldivisionandtissuedissemination.AccordingtotheGLOBOCANproject,14.1millionnewcasesofmalignantgrowthoccurredworldwidein2012alone(excludingskindiseasesotherthanmelanoma),accountingfor14.6%ofmortality.Tobeeradicated,malignantdevelopmentmustbeidentifiedanddiagnosedinitsearlystages.Duringtheprecedingyears,anongoinginvestigationintothedevelopmentofcancerwasconducted.Oneofthemostcriticaltasksfortheexpertisaccuratesicknessprediction.

Mammogramimagesallowustodetectcancerinitsearlystages.Professionalshavetraditionallydonethisbyphysicallyexaminingmammographyimages,butwecannowbuildamodelusingpatientdatafromthepast.Cancerthatisdetectedearlycanbeeffectivelytreated.Inthisstudy,wefocusonaComputer-AidedDiagnosisandDetection(CAD)frameworkthatusesseveralDeepLearning(DL)designmodelsto

classifysafeandunsafemasssoresfrommammographyimagetestsandestimatestheirperformance.Inthiscase,ResidualNetworks,alsoknownasResNet,VGG,GoogleNet/Inception,andAlexNet,willbeused.Inadditiontothesemodels,wewilldeveloponethatusesXceptiontopredictcancer.

DATASET:Thedatasetusedinthisprojectisacombinationof3datasetstoextractabnormalcellformationandpredictbreastcancerlevels.

1. DatasetsfromtheDigitalDatabaseforScreeningMammographywereutilizedinthisproject(DDSM).Link:-
https://wiki.cancerimagingarchive.net/display/Public/CBIS-DDSM#space-menu-link-content

2. CBIS-DDSM:BreastCancerImageDatasetCuratedBreastImagingSubsetDDSMDataset(Mammography).Link:-
https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset

3. DDSMMammographyfromKaggledatasets.Thedatasetcontains55,890trainingexamples,ofwhich14%arepositiveandtheremaining86%arenegative.

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Link:-
https://www.kaggle.com/datasets/skooch/ddsmmammography

Thedatasetisdividedintothreecategories:benign,cancer, and normal.

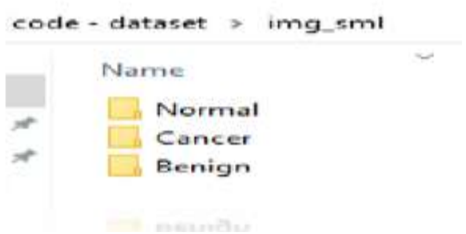

Fig. (A). Dataset Attribute

Thefirstoneisnormal,whichindicatesthatnomore

"workingup"isnecessary.
Thesecondcategoryisbenign;itisinthesuspiciousstageandpathologicalresultsarenotrequired.
ThethirdoneisMalignancy;Cancerfallswithinthelast category;pathologicalevidencesupportsitspresence.
Thereare4differentimagesofanglesinthedataset.

- LeftCC-LeftCraneCaudal.
- LeftMLO-LeftMediolateralOblique.
- RightCC-Rightcranecaudal.
- RightMLO-RightMediolateralOblique.

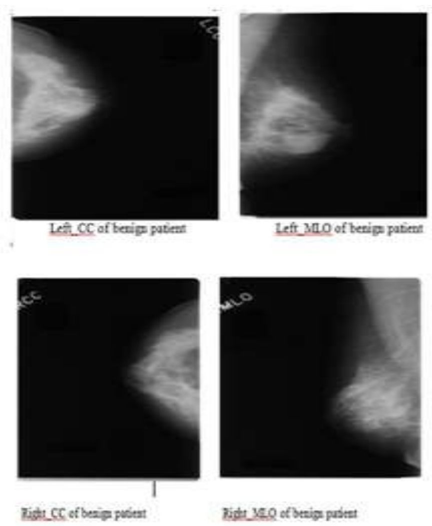

Fig. (B). Scan Images

Inadditiontotheseangleimages,itincludespatientinformationandmaskingimages.Maskingimagesareusedtodelineatethe necessary portionofthebreastfromthemammographyimage.Thepatientinformationandmaskingimagesarenotrequiredforourproject.Onlythefour-anglepicturesareneeded.

II. LITERATURESURVEY

Table1providesasummaryofthereferencepapersusedforthisproject.Itmentionstheauthor'snameaswellastheapplications.TheDDSMdatasetwasusedinthemajorityofthesepapers.Wecanseewhichmethodsareusedindifferentpapers,aswellastheiraccuracy.

III. EXISTINGSYSTEM

Cancerisdetectedbasedonthephysician'sexperiencebyanalyzingthemammogramscanreport.Thismethod's accuracyisverylow,andittakesalongtime.

IV. METHODOLOGY

4.1MODULEDESCRIPTION

Intermsofmanuscripts,thiscompositionpresentsaComputer-AidedDiagnosisandDetection(CAD)frameworkfororganizingnormalanddangerousmasssoresfrommammogramimagetestsandevaluatingtheirperformanceusingvariousDeepLearning(DL)designmodels.Inthiscase,ResidualNetworks,alsoknownasResNet,VGG, GoogLeNet/Inception,andAlexNet,willbeused.
Figure(a)showsdigitallystoredmammogramimagesfromthepubliclyaccessibleDDSMdatabase(DigitalDatabaseforScreeningMammography).Thenextstepin theprojectistopre-processthemammogramimages.Duringtheimagepreprocessingstep,undesirablearticlessuchasimageexplanations,marks,andnoiseintheimageareremovedfromthemammogramimages.Thepreprocessingstepallowstheareatobesearchedforirregularities to be localized.

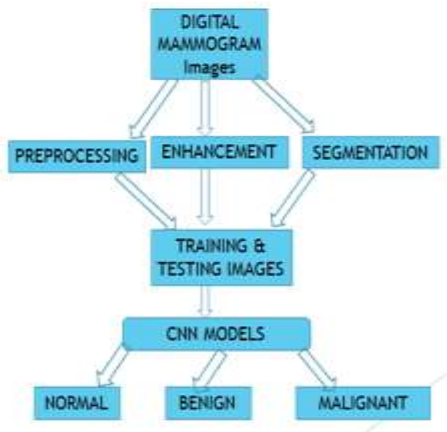

Fig.(C).PictorialrepresentationofModuleDescription

Becausethefragmentationzoneiscriticalforthemammarygland'sabnormaltissuedetectionandfeatureextractionprocesses,itmustbeextremelypreciseandconcentrated.Inthisway,itiscriticaltodividetheimageintoitspartsinordertoextractanROIthatprovidesanaccurateeva

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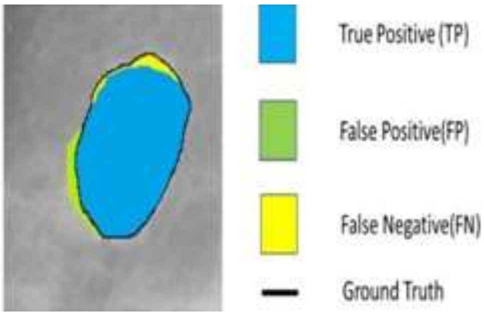
luationofthenormalandabnormalsectionsofthebreast region.Thepicturesegmentationstepincludesthecriticalprocessofseparatingthebreastareafromthebackgroundandmakingplanstoseparatethebosomregionsfromotherobjects.
Followingimagesegmentation,theimageisfedthroughvariousCNNmodels,andtheirlayeredparametersare modified.TheCNNmodelswillexaminethefeaturesof mammographyimagesandextractthem.Thetrainingmammographyimages,forexample,arefedintoaResNet CNNmodel.Afterreceivinginput,thispre-trainedmodelcanextractthefeaturesofanimage.



Asaresult,weusethetransferlearningtechniquetoextractthecharacteristicsfromamammographyimage.
Theimagephaseclassificationisentirelydependenton otherintermediatesteps,suchassegmentingandextractingfeaturesfrommammographyimages.Followingtraining,ourmodelwillbefullyconversantwithphotosand theirvariousclasses.Asaresult,theycanpreciselyclassifythosephotosontheirown.Ifweneedtoimprovetheclassificationaccuracyofthosemodels,wecanincorporateadditionalclassificationmethods,suchasSVM.Becauseweareusingatransferlearningstrategy,wecanchangethecharacteristicsofCNNmodels,specificallythecharacteristicsofeachlayer,togetdifferentresultsforthe CNNmodels.Thenwecanevaluateeachmodel'sperformance,makingiteasiertoconductausefulcomparative study.

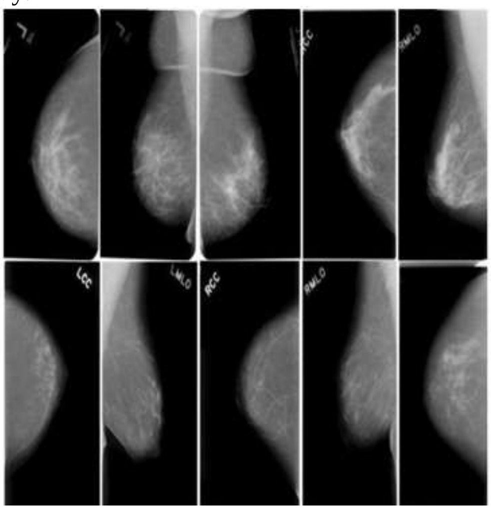


Fig. (D). Scan Images of data set

- **PRE-PROCESING**

ByextractingtheROIs,theimageswerepre-processedandconvertedto299x299images.
Duringthepreprocessingstep,unwantedobjectssuchasannotations,labels,andbackgroundnoisesareremovedfrommammograms.
Preprocessingaidsinthelocalizationofabnormalitydetectionregions.

- **ENHANCEMENT**

Imageenhancementtechniquesareusedtoimprovemammogramqualitybyincreasingcontrastandreadability.
Itimprovesthedetectionofmammographiclesionswithpoorvisibilityandcontrastbythesystem.
Mammogramenhancement'sprimarygoalistoimproveimagequalityonlowcontrastmammograms

- **SEGMENTATION**

Thesegmentedregionisessentialforfeatureextraction anddetectingabnormalbreasttissues,anditmustbefocusedandprecise.

Asaresult,segmentationiscriticalinordertoobtainaROIthatprovidesaprecisemeasurementofabnormaland normalbreastregions.
Beginningwithseparatingthebreastregionfromthebackground,segmentationprogressestoseparatingthebreastregionsfromotherobjects.

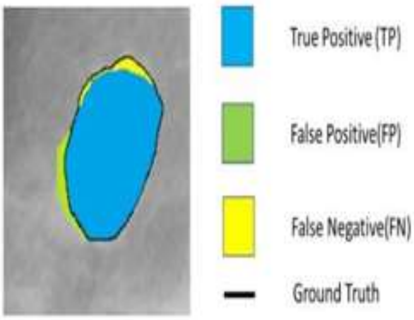


Fig. (E). Segmentation

Despitethepresenceofbreastcancer,afalse-negativemammogramappearsnormal.Overall,screeningmammogramsmissapproximatelyoneoutofevery eightcasesofbreastcancer.Womenwithdensebreasttissuearemorelikelytohavefalse-negativeresults.

4.2. BASICCNNMODELARCHITECTURE

TherehasbeenasignificantincreaseindemandforaskillsetknownasDLinrecentyears.ItisacomponentofMLthatfunctionssimilarlytoourbrain,i.e.,DLaremadeupofneuronsthatfunctionsimilarlytoourbrain,hencethenameneuralnetwork.Theseneuralnetworksteachoursystemstodowhathumansdonaturally.ArtificialNeural

Networks(ANN),RecurrentNeuralNetworks(RNN), Autoencoders,andothermodelsareusedindeeplearning.CNNisamodelthatarosefromthesemodelsandhasmadesignificantcontributionstocomputervisionandimageanalysis.
CNNsareasubsetofDeepNeuralNetworksthatcandetectandclassifyfeaturesinimages;asaresult,CNNsareusedtoanalysesvisualimages.TheseCNNmodelshavenumerousapplications,includingmedicalimageanalysis,imageandvideoanalysis,imageclassification,naturallanguageprocessing(NLP),andcomputervision.The CNNarchitectureissplitintotwoparts.Thefirstisaconvolutiontoolthatwillidentifyandanalysethevariousfeaturesoftheimage.Thisisreferredtoasfeatureextraction. Thesecondlayerisafullyconnectedlayerthatprocesses theconvolutionallayers'output.Theimageclassisthen predictedusingthefeaturesextractedfromtheprevious convolutionallayers.

CNNarchitecturelayers
CNNhasthreedifferenttypesoflayers.Convolutionallayersarethefirst,followedbypoolinglayersandfinally byfullyconnectedlayers.WecanbuildaCNNarchitecture by stacking thesemodels.Inadditionto theselayers,twootherparametersarecritical:dropoutlayersandactivationfunctions.

1. ConvolutionLayer
ConvolutionallayersarethefirstlayersinaCNNmodelthatextractvariousfeaturesfromaninputimage.

Inthiscase,convolutionwasperformedmathematicallybetweentheinputimageandfiltersofsizeMxM. Aslidingfilterovertheinputimageisusedtocalculatethedotproductbetweenthefiltersandtheinputimage.The convolutionoperationisatypeoflinearoperationthatinvolvesmultiplyingtwofunctions toproduceathirdfunctionthatexpresseshowtheshapeofonefunctionismodifiedbytheother.Forexample,multiplyingtwoimagesthatcanberepresentedasmatricesyieldsanoutputthatcanbeusedtoextractfeaturesfromtheimage.
TheinputtoaCNNisatensoroftheform(numberofimages)x(imageheight)x(imagewidth)x(numberofimages)x(numberofimages)x(numberofimages)x(num(inputchannels).Afterpassingthroughaconvolutionallayer,theimageistransformedintoafeaturemap.

2. Pooling
APoolinglayerfollowsaconvolutionallayerinCNN.Thispoolinglayerisusedtoreducethesizeoftheconvolvedfeaturemapinordertoreducecomputationalcosts.We canperformtheseoperationsbyreducingtheconnectionbetweenlayersandoperatingindependentlyoneachfeaturemap.Therearevariouspoolingtechniquesavailablebasedondifferentmethods.Somepoolingtechniques includemaximumpooling,averagepooling,sumpooling,andsoon.TheMaxpoolingtechniqueisnamedaftert he largestelementextractedfromthe featuremap.Theaveragepoolingtechniqueisdefinedascalculatingtheaverageofelementsinapredefinedsizedimagesection.TheSumpoolingtechniqueisusedtocalculatethesumofthepredefinedsizedimagesections.In general,the pooling layerservesasa linkbetweentheconvolutionallayerandtheFClayer.

3. Fullyconnectedlayer
FullyconnectedlayersarethenextlayerofCNN.Itincludesbiasandweightsinadditiontoneurons.Itisusedtoconnectneuronsfromtwodifferentlayers.FClayersareaddedattheendofCNN,infrontoftheoutputlayerandfrom thefinalfewlayers.Thelastlayers'inputimageisflattenedandforwardedto the fullyconnectedlayers.Thisflattenedvectoristhenpassedthroughafewmorefullyconnectedlayers,wheresomemathematicaloperationsareperformed.Theclassificationprocessthenbegins.

- **CLASSIFICATION**

Thefinalstepistodeterminewhetherthelesionunderobservationisnormalorcancerous.Theclassificationstepisheavilyreliantonpreviousintermediatesteps,particularlysegmentationandfeatureextraction.Supportvectormachine(SVM),artificialneuralnetwork(ANN),k-nearestneighbour(KNN),binarydecisiontree,andsimplelogisticclassifierareallexamplesofartificialneural networks.

4. TheDropoutLayer
Whenallofthefeaturesareconnectedtothefullyconnectedlayer,anerrorcalledoverfittingofthetrainingdatasetmayoccur.Overfittingoccurswhenthemodellearnseverysingledetailoftheinput.Assumethatifourmodellearnsthenoiseinourimage,itwillhaveanegativeimpact. Whenweprovidenewinputtothemodel,itwillconsider thenoisepropertiesandproduceanincorrectresult.Adropoutlayerisusedinourmodeltoavoidtheoverfittingproblem.Whiletrainingthemodels,afewneuronsaredroppedfromtheneuralnetworktoperformthisdropoutfunction.Itwillshrinkthemodel'ssize.

5. ActivationFunction
ThesefunctionsareimportantparametersinaCNN.Activationfunctionsareusedtolearnandapproximatecomplexandcontinuousrelationshipsbetweennetworkvariables.Thisactivationfunctionwilldeterminewhichmodelinformationshouldmoveforwardandwhichinformationshouldnotatthenetwork'send.Whenbuildinga CNNmodel,severalactivationfunctionsareused.ActivationfunctionsincludetheReLu,LeakyRelu,Softmax,Sigmoid,tanH,andSoftmaxfunctions.Eachofthesea

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ctivationfunctionshasadistinctpurpose.Forexample,ifweneedtoperformbinaryclassificationinourCNNmodel,weprefersigmoidandsoftmaxfunctions,andsoftmaxisusedformulti-classclassification.

4.3. ARCHITECTURE

Weuseddigitallystoredbreastmammogramimagedatasetsfromthe DigitalDatabaseforScreeningMammographyinfigure(b).(DDSM).Wedividedtheimagesintotrainingandtestingimagedatasetsafterperformingpreprocessingtaskssuchasnoiseremoval,annotationremoval,contraststretch,andadaptivehistogramenhancement.We feedthepreprocessedtrainingdatasetintoCNNmodels suchasResNet,VGG16and19,GoogLeNet,andAlex Net.Aftertrainingthesemodelswithtrainingdata,themodelsexaminethepropertiesofimagesandeffectivelyextractthefeatures.Themodelcanthenbetestedusingthetestimagedataset,andeachmodelcanbecompared.

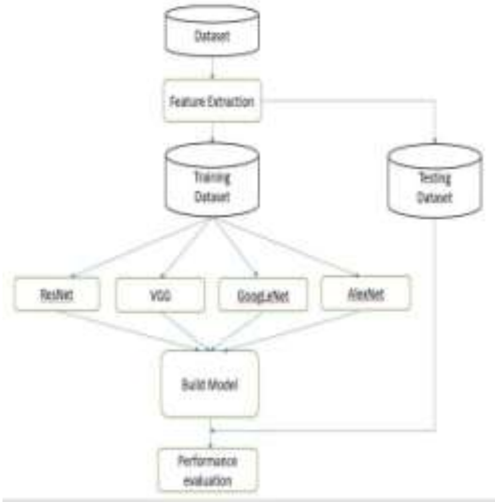

Fig.(F).Architecturediagram

Therearetwotypesofusersinourproject.Thefirstisthedeveloper,whoworksontheentireproject.The developerisinchargeofthepre-processingoperations.Wemustperformpre-processingonourmammogramimagedatasetforthisproject.Imageenhancementandcontraststretchoperationsareexamplesofpre-processingtasks.Followingthesepreprocessingoperations,developersbuildtheCNNmodels.AlexNet,ResNet,VGG-16,GoogLeNet,andacustomisedXceptionmodelareused here.TheseCNNmodelscandetectandclassifyimages, sobyprovidingpre-processedmammogramimages,themodelcanstudytheproperties ofthoseimages.Thedeveloperthenteststhesemodelswithtestingimages,evaluatingeachmodel's performanceandaccuracy.Theuseristhesecond.Users haveaccesstoCNNmodelsaswellastheevaluationsection.Ausercouldbeadoctororaradiographer,forexample.TheseuserscandirectlyaccessthebestCNNmodelaftertakingthemammogramimage.Whenauseruploadsatestingmammogramimagetothemodel,itwillclassifytheimageintooneofthreecategories: normal,malignant,orbenign. Thebenignresultindicatesthatthepatientdoesnothave breastcancerbutisatriskofdevelopingit.WecancureitifIgettherighttreatment.Thenormalcategoryindicatesthatthepatienthas nocancercellsandshouldnotbeconcerned.Canceristhefinalcategory.

4.4. IMPLEMENATATIONANDRESULT

HeretoimplementthisProject,pythoncodeinJupyterNotebookplatformisused.TensorflowKerasandsomebasicpackagesareusedtoperformthisproject. WhencomparedtootherCNNmodels,thecustom-madeXceptionmodelprovideshighertestaccuracy.

S.No:	Model	Test Accuracy
1	Alex Net	82.3%
2	VGG-16	85.5%
3	ResNet	90.2%
4	GoogleNet	82.8%
5	Xception	92.9%

Table2.Test AccuracyTable

Accuracy:-
Theaccuracyofamachinelearningclassificationalgorithmisonewaytodeterminehowfrequentlythealgorithmcorrectlyclassifiesadatapoint.Formula:-

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$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

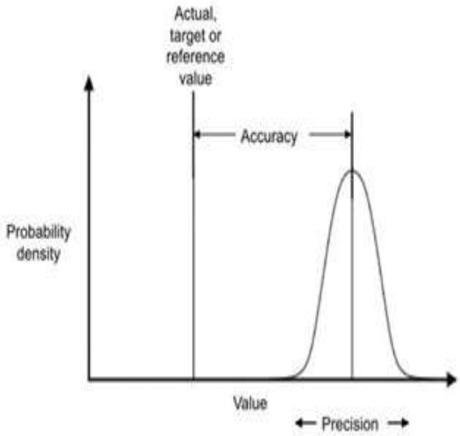

Fig.(G).Accuracy

Thenumberofcorrectlypredicteddatapointsoutofalldatapointsis referredto asaccuracy.Inotherwordsitsiscalculatedeasilybydividingthenumberofcorrectpredictionsbythenumberoftotalpredictions.

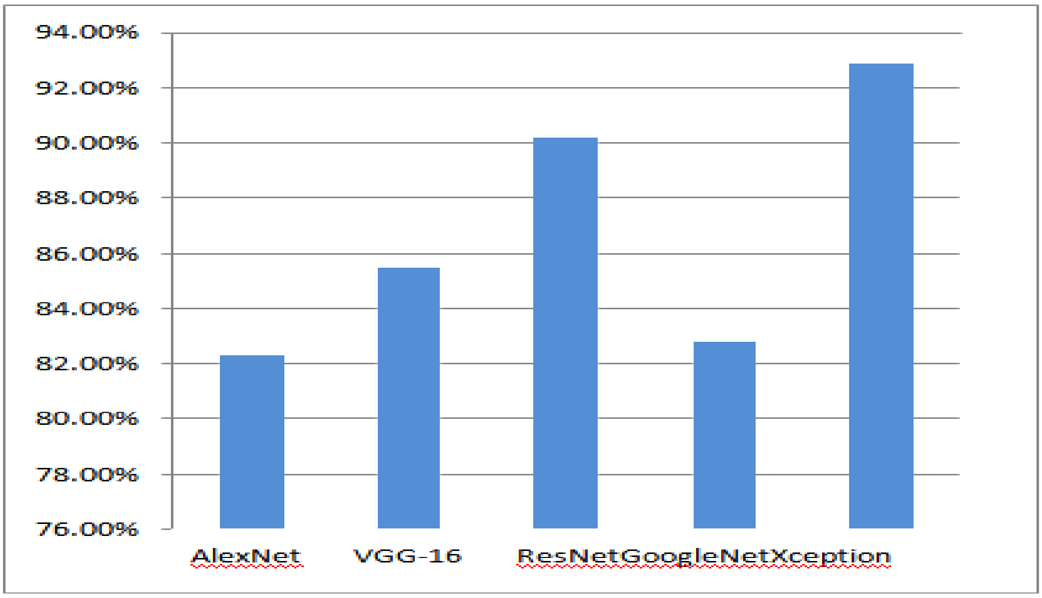

Fig.(H).Graph

Accordingtograph,ourcustomizedXceptionmodelishavinganhigheraccuracyof92.9%.TheAlexNetmodelhasthelowestaccuracyof82.3%.

SL No:	Author	Application	Dataset	Methods	Accuracy
1	FarahnazSadoughi[4]	Diagnosisofbreastcancer	Various medicalimages	ArtificialIntelligence	Ultrasound(95.85%),mammography(93.069%) thermography(100%)
2	SairaCharan[7]	DetectionofBreastCancer	Mammograms-MIASdataset	ConvolutionalNeural Network	65%
3	Dina A. Ragab[8]	Breast cancer detection	Digitaldatabase forscreeningmammography(DDSM)	CNN with Support VectorMachines(SVM)	DCNN=71.01% SVM=87.2%
4	LiShen[11]	Breast cancer detection	DigitalDatabaseforScreening Mammography (CBIS-DDSM)	Deeplearningusingan “end-to-end”training Approach	~90%
5	Naser Safdarian[12]	To Detect and Classification ofBreastCancer	Digitaldatabase for screeningmammography(DDSM)	RBF, PNN, and multi-layerperceptron(MLP),Takagi-Sugeno-Kang(TSK)fuzzyclassification,thebinary statisticclassifier, andKNN clusteringalgorithm	~97%
6	Z.Yan[16]	To Recognize Body Parts	DatasetcontainsCTimageSlicesof12bodyorgans	Two StageConvolutionalNeuralNetwork	~92.23%
7	ChenZhang[15]	Amodelusedtoperformscreeninganddiagnosingofmammograms.	Mammogram imagesfromDDSM	Heretheyusedamulti-view featurefusionNNmodel	94%

8	G.V.Tulder[17]	ToClassifyLungTextureandAirwayDetection	ILD(interstitiallungdiseases)CTscans	ConvolutionalRestrictedBlotzmanMachine	~89%
9	M.Anthimopoulos[18]	ThismodelusedtoLung PatternClassification	ILD(interstitiallungdiseases)CTscans	Used CNNarchitecture	85.5%
10	K. Sirinukunwattana[19]	Detection and Classification ofNuceli	histologyimagesofcolorectaladenocarcinomas	TwoarchitecturesofCNN	~80.2%
11	A.Payan[20]	Prediction ofAlzheimerDisease	MRIImages	CNN with 2DConvolutionsand 3DConvolutions	3D-~89.4% 2D-~85.53%
12	E.Hosseini[21]	Alzheimer DiseaseDiagnosis	MRIImages	DSA-3DCNN	94.8%
13	A.Farooq[22]	ClassificationofAlzheimerDisease	MRIImages	GoogleNet ResNet-18ResNet-152	98.88% 98.01% 98.14%
14	J.Ma[23]	Thismodelusedtoperform ThyroidNoduleDiagnosis	UltrasoundImages	Used a Pre-TrainedCNN	~83%
15	W.Sun[24]	Breast CancerDiagnosis	MammographicImages withROIs	CNNusingsemisupervisedlearning	~82.43%
16	H.Pratt[25]	For Diabetic Retinopathy	KaggleDataset	CNN	75%
17	AyeletAkselrod-Ballin	Predicting BreastCancer	52936imageswerecollectedin 13234womenfromtherangeof2013and2017.	DeepLearning	~91%

Table1: Relativestudytable

V. CONCLUSION

Intoday'sworld,advancedimagepreprocessingisextremelyimportantinavarietyoffieldsofinnovativework. AdvancedImageProcessingisusedtoprocesscomputerizedimagesandextractusefulqualitiesfromthedata,whichcanthenbeusedtomakebasicdecisionswithhighprecision.Theseproceduresarealsobeingusedintheclinicalfield,specificallyinthedetectionofmammaryglandcancer.Breastcancerisoneoftheleadingcausesofdeathamongwomentoday,anditisdifficulttopreventbosomdiseasebecausetheprimarycausesofhiddenbosomcancerremainunknown. However,certaincharacteristicsofbreastcancer,suchasmassesandmicrocalcificationsvisibleinmammogramimages,canbeusedforearlydetectionandarethusextremelybeneficialforladieswhomaybeatriskofmammaryglandcancer.Previously,physicianswouldanalysemammogramimagesanddrawconclusionsbasedonthem,butnow,withthehelpofDeepLearning(DL),wecandeterminewhetheritisbenignormalignantinashortertimeframeandwithgreateraccuracy.Inthisstudy,weusedvariousDeepLearning(DL)architecturemodelstoassesstheirperformanceincancerprediction. Wecreatedacustommodelfromthevariousmodelsusingthe Xceptionmodelarchitecture,andthismodeloutperformstheotherCNNmodelsintermsoftestingaccuracy.Thecustom-madeXceptionmodelgivesbettertestaccuracycomparedtotheotherCNNmodels.ThisXceptionmodelhasatestingaccuracyofapproximately92.9%,whichishigherthanotherCNNmodels.

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