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APPLICATION OF DEEP LEARNING FOR VISION HEALTH

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ABSTRACT:
Human bodyeach organ is equally important, especiallythe sensoryorgan (eye). With vision the human is blind so sensory organs are very important and each organ are performing various functions.Eyeisansensoryorganwherethevisionisthemostimportantfunctionofit.Generally, after 40 years ofage people causes vision problems. A area in eye which is cloudy in the lens of eyeswhicheffectsinblurryorhazyvisionisknownascataract.Thepapergivesthedetailscataract is a clouding of the eye's lens that causes vision problems. A smaller dataset is used to train the current systems,andtheyhaveaoverfitting issue.Thispaperalso givesthedistinguishbetweena cataracted eye and a healthyeye using neuralnetworkmodels. The convolutional neuralnetwork modelaidsinthedetectionofcataracts.Thereare34layersintheCNNmodel.Thepicturepasses through several convolution and pooling layers. At the final layer, the output is thus obtained appropriately. Adeep neuralnetworkmodelis used bythe suggested systemto identifycataracts in eye images.

Thedeeplearningconceptofneuralnetworksforthedetectionofcataracts,acommoneyedisorder causing hazy vision by opacification of the lens. Cataract is a significant cause of blindness, particularlyamong individualsabovetheageof50. Detectionand earlytreatment areessentialto prevent vision loss. The system introduced applies a convolutional neural network (CNN) to inspect eye images and differentiate between cataract and normal eyes.

Existingsystemsare foundedonsmalldatasets, leadingtooverfitting, ordedicatedhardware like funduscameras,whichlimittheiruse.Thisworkisaimedatdesigninganeasilyaccessiblesystem that could be operated easily by the public to detect potential cataracts. The system employs a ResNet-152 model of 34 layers, inspecting images through convolution and pooling layers in sequence.Themodelispassedthroughpreprocessingfunctionslikenoiseremoval,grayscale,and segmentation via the OpenCV library and Hough Circles algorithm for pupil detection. The pre- processedimage isthenfed intothetrainedCNNmodeltoclassify,decidingonpotentialcataract subtypes (nuclear sclerotic, cortical, and posterior subcapsular).

ThemodelwascodedwithPython3andtrainedusingpubliclyavailableimagesfromKaggle.com. Results indicate promising accuracy in identifying cataractous and non-cataractous eyes. The systemisaimedatfacilitatingquickandefficientcataractdetection,allowingearliertreatmentand improved patient outcomes, especiallyamong remote communities withpoor access to specialist eye care.

Keywords — Neural networks, cataract, computer vision, CNN (Convolutional Neural Network), RNN (Recurrent Neural Network).

INTRODUCTION:

This paper presents a system using neural networks for cataract identification, a major cause of blindnessacrosstheglobe.ThesystemusesaConvolutionalNeuralNetwork(CNN)thatanalyzes standardeyeimages,distinguishingbetweencataractousandhealthyeyes,withtheaimofcreating an accessible systemwithin the reach ofthe masses. As compared to other systems using fundus images from specialized equipment or prone to overfitting due to small data sets, this approach uses standard eye images to increase accessibility.

The system uses a ResNet-152 model with 34 layers. The images are preprocessed using noise reduction, conversionto grayscale, andsegmentation, achievedthroughtheOpenCV librarywith theHoughCirclesalgorithmforpupilidentification.Thepreprocessedimageistheninputintothe trained CNN

model for classification that also distinguishes cataracts into definite subtypes: nuclear sclerotic, cortical, and posterior subcapsular.
WritteninPython3withtheinclusionofTensorFlow,Keras,andNumPymodules,themodelwas trained using a data set of eye images downloaded from Kaggle.com. Initial results show good discrimination between cataractous and non-cataractous eyes. By enabling faster and more efficient detectionofpossible issueswithcataracts,thissystemholdsthe potentialto offer earlier intervention and better patient outcomes, particularly with underserved populations that lack access to specialized vision care. The systemalso saves patient data and CNN results to a cloud database.

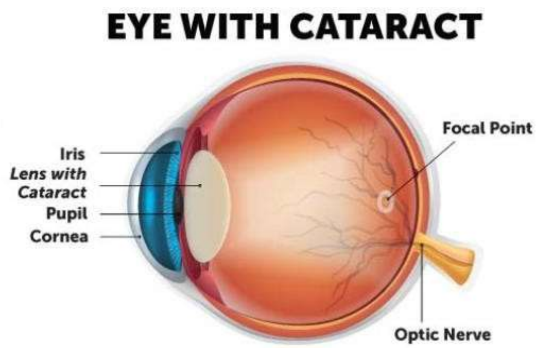


Fig.1:Eye visualization (Cataract)

Fig. 1 Human sensory organs, especially the eyes, are crucial for vision. Cataracts, which are a cloudingofthelensoftheeye,areaprevalentconditionresultinginblurredvision,especiallyafter the age of 40, in more than 65.2 million people worldwide. According to the National Blindness and Visual Impairment Survey India 2015–19, cataracts are the leading cause of blindness in individualsabove50years.Theexistingsystemsliketooperatewithsmallerdatasets,resultingin overfittingproblems,orneedfundusorslitlampimages,whicharenoteasilyavailable.Thereport ofthe World HealthOrganization(WHO) also mentioned thatthe highexpense ofeye treatment, especially in ruralregions, isone ofthe primarycausesofvision loss. Thispaper suggestsa deep learningsystemto distinguishbetweencataractousand normaleyesbasedonroutineocular images to address these issues.
The system proposed employs a Convolutional Neural Network (CNN) in the ResNet-152 architecture with 34 layers to perform an ocular image analysis. The system stores patient informationafterthe registrationprocess, including demographics, lifestyle, and medicalhistory. Registered patients are provided access to a home page that provides information on prevention and various eye conditions. The ResNet-152 model is accessible to any end user to upload and examine eye images to detect cataracts. The system will notify if the likelihood of cataract development hasbeenevaluated. Theprocessinvolves imageacquisition, wheretheuseruploads
a JPG image. Preprocessing involves noise reduction, image enhancement, and conversion to grayscale; grayscale images can enhance efficiency by maintaining necessary qualities without adding tothe load ofprocessing. Segmentation is performed to locate and extract the pupilusing the HoughCircles algorithmthroughOpenCV. The pre-processed image is thenclassified bythe ResNet-152 modelto determine whether cataractsare present and to classifythem into subtypes, that is, nuclear sclerotic, cortical, or posterior subcapsular.
TheResNet-152architectureusessequentiallyordered3x3kernel-sized filtersandareselectedto avoid overfitting behaviors of other models like AlexNet, whose kernel-sized filters are huge. According to the paper, universal health coverage for eye care treatment needs to be extended. Weights and input from the previous layer are multiplied by a matrix vector to produce a dense layer.Thenewtemporaryparametersareprovidedbyvaluesinthematrix.Themodelwaswritten

usingPython3withTensorFlow,Keras,andNumPy,trainedusingimagesfromKaggle.com,with CPU as the processing option. The model was created using the TensorFlow, Keras, and NumPy modules. The weights were initially provided with randomvalues. The weights were changed to the end values slowly over the training process. The images from Kaggle.com were used as the trainingdata.InitialresultsusingasimpleCNNmodelprovidedabout0.52accuracy.ResNet-152 performed much better to about 0.7 on validation sets.

LITERATURESURVEY:

Human sensoryorgans, particularly the eyes, are a major contributor for vision. Cataracts, asthe opacity of the eye lens, are a prevalent condition that results in blurring of vision, especially in individuals over 40 years of age, thus affecting over 65.2 million people across the world. The National Blindness and Visual Impairment Survey India (2015-19) reports that cataracts are the leading cause of blindness in individuals over 50 years of age. The report by the World Health Organization(WHO)highlightsthatthehighcostofeyetreatment,particularlyinruralregions, is a major contributing factor towards loss ofvision. Existing systems tend to use smaller datasets, thuscausingoverfitting,orrequirespecialist imagingtechniques, likefundusorslit lampimages, which restricts access to the common public. The study [3,8] mentions the utilization of limited fundus images, for which appropriate tools have to be used.

This paper presents a deep learning system capable of differentiating between cataractous and normal eyes by employing standard ocular images in order to address these challenges. Most of the existing systems employed during this time frame were using fundus images or slit lamp images for detection. The systempresented here tries to make the process of categorization easy for cataracts and makes it user-friendly for non-experts. Ophthalmologists can carryout cataract patient treatment throughprocedures best suited for different types ofcataracts ina reduced time span.

ThesystemutilizesaResNet-152modelconsisting of34 layersto scantheuploaded standardeye images. The system stores patient information, including demographics, lifestyle, and medical history, securely in a cloud database, which can be accessed on authentication. The ResNet-152 model can be used by any end user to upload and scan eye images to detect cataracts. The steps include imageacquisition, noiseremoval, imageconversionto grayscale, andpupilsegmentation usingtheHoughCirclesalgorithmusingOpenCV.Registeredpatientsareprovidedwithaccessto a home page that provides information on prevention and other eye diseases. Grayscale images maketheprocessingmoreefficientbyretainingtherequiredqualitiesandreducingtheprocessing burdenatthesametime.ThepreprocessedimageisthenclassifiedbytheResNet-152modelto determine the presence of cataracts and classify them into subtypes. The system uses the RNN method to classify images, utilizing features derived from5,378 images for detection. Few other researchworks[2,9]utilizedasingleperceptrontrainingmodeltoclassifyeyedisordersintothree different categories. The accuracy rate of the system was 90.82%. The ResNet-152 architecture utilizes sequentiallystacked3x3kernel-sized filters, whichhave beenchosento avoidoverfitting issues typicalofother models like AlexNet, using larger kernel-sized filters. As explained in the paper, there is a requirement for universal healthcare coverage to be extended to cover eye care treatments.

The model was executed using Python 3 with TensorFlow, Keras, and NumPy, on Kaggle.com images, with CPU execution. Initial results with a simple CNN model provided around 0.52 accuracy.TheResNet-152significantlyenhancedthistoaround0.7onvalidationdata.Themodels provide results for classification with labels for cataractous and non-cataract eye images.

Features	Paper [1]	Paper[2,9]	Paper [3]	Paper[7]	Paper[8]	Proposed system
Accuracy	96.1%	94.69%	90.82%	Only feature extraction	95.479%	Depends on data
Dataset size	420 images	Not available	Not available	5378 images	243 images	Dynamic google images
Type of image used	Slit lamp	Slit lamp	Fundus image	Slit lamp	Fundus image	Regular eye images
Classification in	3 types	3 types	4 types	1 types	2 types	4 types
Algorithm used	SVM	Single Perceptron Training Model	CNN	RNN, SVR	Decision Tree, BPNN, SMO	CNN, VGG16 model(16 layers)

3.1.

Fig.2:Comparison of existing models and proposed model

Figure 2 showsthat fundus imagesor slit lamp imageswere utilized for detection inthe majority ofthesystemsthatwereinuseatthetime.Butas

As previously said, this could not be possible to obtain in isolated, impoverished regions of the world. The earlier systems made use ofperceptronmodels, SVM, BPNN,SVR,RNN,SMO,and so forth.

Additionally, classificationvariesthroughout earlier systems. Onlya small number ofthemhave divided the photos into two or three subcategories.

PROPOSEDMETHODOLOGY:

Theconvolutionalneuralnetworkmodelandstandardeyepicturesareemployed inthesuggested approach to identify cataract illness.

System architecture :

Thedetectionmodelisdepictedinfig.2todefinetheflowoftheproposedsystem.

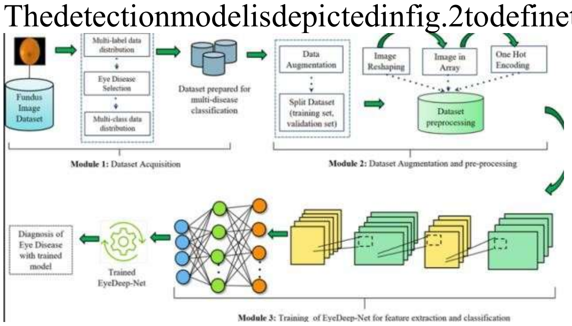


Fig.3:System architecture of the proposed system :

After completing the registration process, the patient's information is stored in the system. The registrationproceduregathersdemographicdataaboutthepatient,includingage,lifestyle,habits, alcoholand/ortobacco use, familyhistoryofcataracts, historyofocular injuries or surgeries, use of steroids or other drugs, and other illnesses. Following successful authentication, the user will be taken to the home page, which includes general details about different eye conditions, prevention tips, and descriptions of each condition's symptoms.

Making use ofthe ResNet-152Anyend user canuse the modelbuilt into the systemto check for cataracts in their eyes. He or she only needs to click on an eye image and upload it to the server. The imagewillthenbeanalysedandtheoutcomescomputedusingthetrained model.Itwouldbe recommendedthat heseetheclosest ophthalmologist ifthe likelihoodofcataract development is determined to be suitably elevated.

PersonallyidentifiableinformationandCNNmodelresultsarestoredinaclouddatabase.

METHODOLOGY:

Before a result is displayed, the process undergoes several steps. The sub processes that go into identifying cataract illness are shown in the modular diagram depicted in Figure 6.

Load Image:

The eye image is uploaded by the user to the server for identification. The picture needs to be captured using the JPG extension, and its size will be adjusted in accordance with specifications of the model.

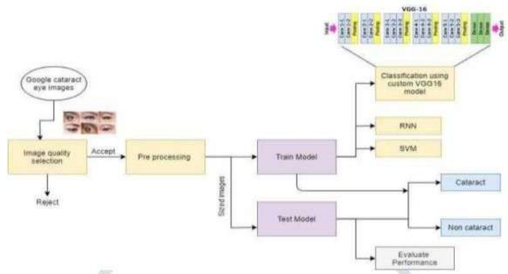


Fig. 4 Modular Diagram

Preprocessing:

During preprocessing, the input data is reshaped and molded suchthat it may be entered into the CNN model. The image's noise is eliminated or reduced to tolerable levels. Certain aspects have improved. Finally, the picture is grayscaled.

Grayscaling

GreyscaledphotosaresmallerandcontainlessinformationthanRGBimages.Formorerapidand effective processing ofphotos, the modelperforms better with a greyscale image. Thus, the gray scalingtechniqueisused.Theuseofgreyscalingisjustifiedbythefactthatitpreservestheimage's keycharacteristicswhilelesseningtheCPU'scomputationalloadbecauseB/Wimagesoccupyless space than RGB images.

Segmentation:

The first step involves identifyingandthenextractingthestudents. Thiscanbeachievedwiththe help of the OpenCV library in Python. The Hough Circles are utilized all throughout the segmentationprocedure.HoughCirclesrecognizecirclesinapicture.Havingidentifiedandpeeled off, then the students forwarded for more evaluation.

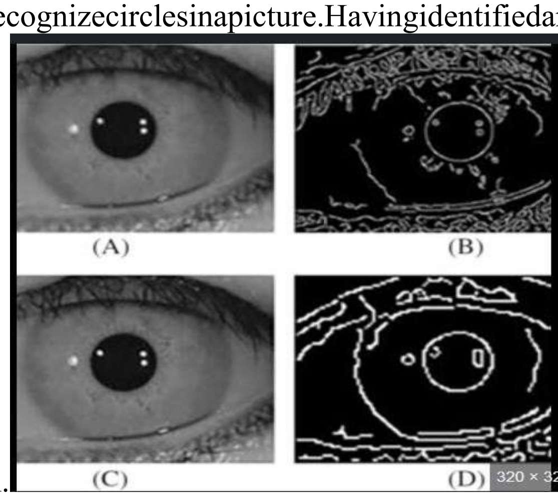


Fig. 5:

HOUGH CIRCLES ALGORITHM:

Source: [4]

Figure5illustratesthestepsinvolvedineyeHoughCircles.

Processed image in to the trained model

Thesystemfeedsthepreprocessedimageintothemodelwhenithasbeenobtained. where it moves across the model's multiple layers.

CLASSIFICATION

The proposed approachtriesto further classifythe image into cataract subtypesonce determined that it contains cataracts.

Therearemanytypes ofcataracts:

1. Nuclearsclerotic
2. Thecortical
3. Therearsubcapsular

The ResNet-152 is a convolutional neural network model that contains 34 unique layers. It is considered one ofthe most accurate vision model architectures currently available. Several real- time health care applications have used it.

THE RES NET MODEL

On the ILSVRC2015 classification problem, recently proposed residual networks (ResNets) achieve state-of-the-art performance and enable training of networks with up to 1000 layers of highdepth[11].ImagesareclassifiedusingtheResNetmodel.Itismadeupofseveral3x3kernel- sized filtersthat arearrangedsequentially.TheAlexNet,ontheotherhand,hashugekernel-sized filters (11 in the first convolutional layer and 5 in the second). ResNet model was employed because the size of layers that may result into overfitting for the layers of VGG and AlexNet models. Beyond that, assuming no more use of layers it drastically decreases this problem. Therefore, a weight and input form the previous layer are multiplied into a matrix of vector to compute a dense layer. The contents of the vector are the variables in the temporally parameters calculated during the execution of the function with back propogation in place.

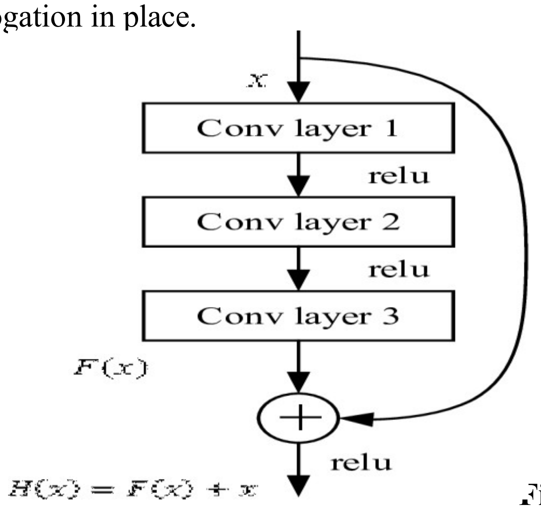


Fig. 6:ResNet layer

Source:[11]

A representation of the many layers in the ResNet-152 model is shown in Fig 3. This model is madeupofMaxPoolinglayers,convolutionallayers,Fullyconnectedlayersandactivationlayers.

TheMaxPoolinglayeruses2x2sizedfilters,whereastheconvolutionallayeruses3x3sizefilters.

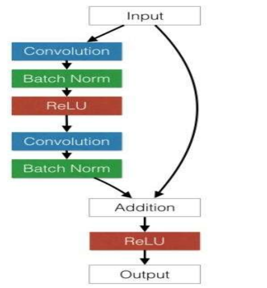
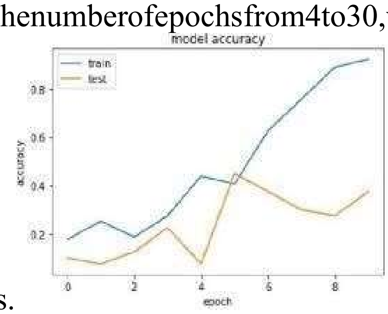


Figure 1. A RestNet basic block

Fig.7:ResNet Architecture [11]
The architecture of the ResNet model is shown in Fig. 4. Each layer's input size and filter count areshowninthediagram.Thereare512layersinthe fourthand fifthconvolutionlayers,64filter layersinthefirstconvolutionlayer,128filterlayersinthesecondconvolutionlayer,and256filter layers in the third.

IMPLEMENTATION:
Python3isusedtowritetheConvolutionalNeuralNetworkmodel,whichisthenimplementedin Jupyter notebooks. Insteadofusing a GPU, we used CPU for processing. The modelwas created usingtheTensorflow,Keras,andNumpymodules.Theweightswereinitiallyassignedatrandom. Theweightsweregraduallyadjustedtothefinalvaluesthroughoutthetrainingsession.Thephotos were taken from the open sources on Kaggle.com that are accessible for research purposes.

RESULTAND ANALYSIS:
Initially,weusedfourorfivealternatingconvolutionandpoolinglayers.Withalossofeven7.35, the accuracywas close to 0.52. ResNet-152 Next, with 34 convolutional layers and pooling with pre-trained weights was employed. For validation data, the accuracywas around 0.7 and the loss wasintherangeofe-4.Byalteringthenumberofepochsfrom4to30,wefoundthattheaccuracy of the model reached a maximum at 7 epochs.



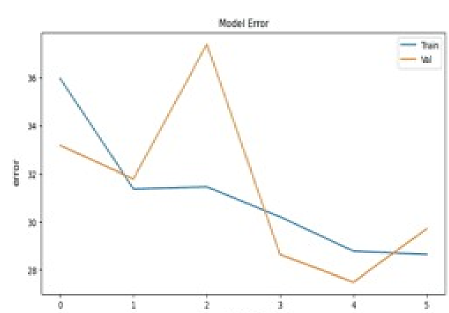


Fig8:ModelAccuracy

Fig9:ModelLoss

Figure 8 and 9 represent the model accuracy and model loss graphs, the bifurcation of train and test is represented in the same figure.

```
Epoch 1/6
 - 101s - loss: 0.0436 - accuracy: 0.9930 - val_loss: 0.0080 - val_accuracy: 0.8000
Epoch 2/6
 - 109s - loss: 0.0308 - accuracy: 1.0000 - val_loss: 0.0061 - val_accuracy: 0.7500
Epoch 3/6
 - 103s - loss: 0.0225 - accuracy: 1.0000 - val_loss: 0.1299 - val_accuracy: 0.7500
Epoch 4/6
 - 104s - loss: 0.0191 - accuracy: 1.0000 - val_loss: 0.0238 - val_accuracy: 0.9000
Epoch 5/6
 - 124s - loss: 0.0170 - accuracy: 1.0000 - val_loss: 2.0891 - val_accuracy: 0.8500
Epoch 6/6
 - 110s - loss: 0.0135 - accuracy: 1.0000 - val_loss: 1.9487e-04 - val_accuracy: 0.7000
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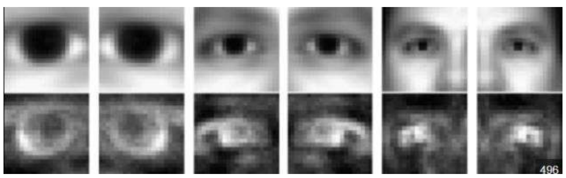

Fig.10: Data beinglabelled bythemodelascataractornon-cataract

Themodel'soutput,whereeyepicturesareidentifiedaseithercataractousornon-cataract,as displayed in figure 10. Figure 11 illustratesthe layer's type and weights in the finished model.

Layer (type)	Output Shape	Param #
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
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000

Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0

Fig.11: Weightparametersin eachlayerofmodel

CONCLUSION:

Inordertocreateaconvolutionalneuralnetworkmodel,weightsareacquiredthroughtrainingthe model on a big dataset of images and non- pictures of cataract eyes.

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