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Identification Of Glaucoma Through Fundus Images Using A deep belief network

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Abstract
Glaucoma is a disease of the retina caused by highintraocular pressure. The intraocular pressure in people withglaucoma can reach 60-70mmHg. This disease is characterizedby an increasing cup to disc ratio size. Glaucoma has threelevels, namely mild with a cup to disc ratio value of 0.3-0.5, moderate with a cup to disc ratio value of 0.5-0.7 and severewith acuptodisc ratio value value above 0.7. For retinalanalysis and calculating the cup to disc ratio value taken from a fundus camera, it must be done by an expert ophthalmologist, but it takes a long time. Therefore, feature detection and automatic cup to disc ratio value calculation are expected to assist doctors in analyzing glaucoma. The data used were132 retinal fundus images consistingof66 mildg laucoma images,26moderateglaucoma images and 40 severe glaucoma images taken from the RIM-ONE dataset(http://medimrg.webs.ull.es).Pre-processing techniques like cropping, resizing, brightness, Median Filter are used for noise removal. Subsequently, feature extraction with the help of GLCM. Consequently, the method used to classify the degree of glaucoma is the Deep Belief Network. The test simulationresults obtained accuracy value of 99% with 99% of precisionand100%of recall.

Keywords: Fundus, Glaucoma, Neural Network, Deep BeliefNetwork,Grey Level ConfusionMatrix.

INTRODUCTION
Glaucoma is a major neurological disease of vision called theoptic nerve. The optic nerve receives nerve impulses that aregenerated by light from the retina and sends them to the brain.Glaucoma is characterized by a special pattern of progressive damage to the optic nerve that generally begins with vague peripheral vision loss. If glaucoma is not diagnosed and treated,glaucomacanprogresstocentralvisionlossandblindness.Glaucoma is the second largest cause of blindness in the world(Bulletin of the World Health Organization) and an estimated 80millionpeoplewilldevelop glaucoma by2021 [1].
Glaucoma is usually, but not always, associated with high pressure in the eye (intraocular pressure). In general, this higheye pressure causes damage to the eye (optic) nerves. In some cases, glaucoma can occurat normal eye pressure which is believed to be caused by poor regulation of blood flow to theopticnerve [2].
Glaucoma has been known for a long time, but not many peopleknow about the dangers of this disease. If it is too late or nottreated properly,glaucoma can cause permanent blindness insufferers. Lack of awareness of the dangers of glaucoma is due to the symptoms of this disease that the glaucoma sufferer cannot feel directly[3].
Research to detect glaucoma has been carried out by several previous researchers, including research conducted by [4] who developed aglaucoma disease identification

system through fundus images using the Back propagation method which has asystemaccuracyrateof98.45%[5]developedasystemtodetectglaucomabycombiningRegionofInterest(ROI)segmentation and automated techniques system by using hemorrhage detection in certain areas of the fundus image with an regression rate of 86.17.57%.Anotherresearchwasconductedby[6]whodevelopedanautomaticglaucomadetection system that was identified by calculating the cup todisc ratio (CDR). They have proven that if the CDR value isbetween 0.0 - 0.3 then the input image is normal. Meanwhile, iftheCDRvalueobtainedisgreaterthan0.3,theimage is identified as glaucoma. This systemhasanF-scoreof96%.Subsequent research conducted by [7] who developed a systemfordetectingglaucomathroughopticaldiscandcupsegmentationusingK-meanclustering.Theaccuracyofthesystemtheydevelopedreached92%.

RELATED RESEARCH

Glaucoma

Glaucoma is a medical term that describes a group of progressive optic neuropathies characterized by degeneration ofretinal ganglion cells and retinal nerve fiber layers and resulting in changes in the opticnerve head[1-3].Impaired vision Glaucoma is usually characterized by damage to the optic nervewhich is usually caused by pressure in the eye. This increased pressure is called intraocular pressure. Intraocular pressure iscaused by excessive eye fluid production or obstruction of the drainage. Glaucoma eye disorder characterized by increased eye pressure, optic nerve papillaatrophy, and shrinking of the field of view[1-3].Nerve damage inglaucoma generally occurs due to increased pressure in the eyeball. The normal eyeball has apressure range between 10 - 20 mmHg while glaucoma sufferershave eye pressure that is more than normal and sometimes it canreach50-60mmHginanacute state.

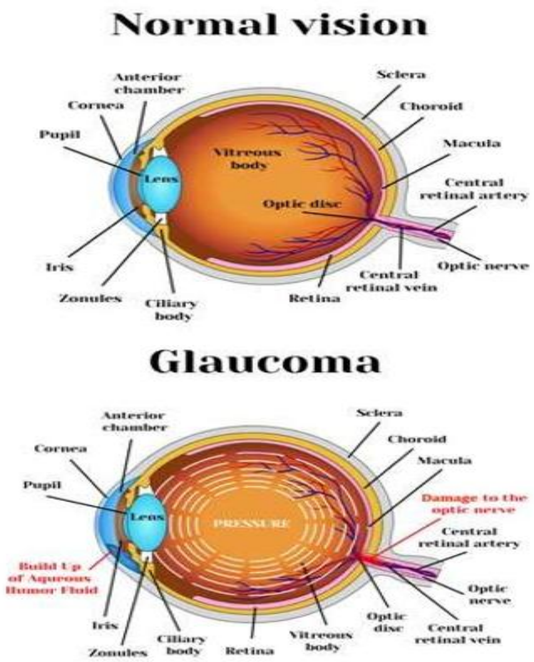

Figure1: Normal Vision and Glaucoma

GLCM

The feature extraction process in this study is carried outusing the Gray Level Co-occurrence Matrix (GLCM) method[16-23]. GLCM is a matrix that represents the spatial distanceand the relationship between two pixels in a grayscale image.GLCM is a matrix of size n × n, where n is the number of graylevels that a grayscale image has. The feature extraction stepsusingthe GLCMmethodareasfollows[4-6].

a. Determinethe workareaofthe matrix.
b. Determine the distance and angle between the reference pixeland neighboring pixels. The distance (d) used is 1 and theangles(θ) usedare 0^{o}, 45^{o},90^{o}, and135^{o}.
c. Calculates the co-occurrence value based on the distance andanglethathasbeendetermined.
d. Adding the co-occurrencematrix with the transpose matrixso thattheco-occurrencematrixissymmetrical.
e. Normalizetheco-occurrencematrixby dividingeachco-occurrence value in the matrix by the sum of all existing co-occurrence values, so that the sum of all values in the matrixis1.
f. Calculating the statistical features of the GLCM based on Haralick features.
   There are 6 characteristics used, namely contrast, homogeneity,energy,entropy, variance, andcorrelation.

$$(i, j) = \frac{(i, j)}{\sum_{i,j=1}^{N} (i, j)} \quad (eq. 1)$$

Contrast is used tomeasure the variation of the pair of graylevels in an image. Contrast is calculated using the formula inequation2.

$$Contrast = \sum_{i,j=0}^{N-1} {}_{(i,j)}(i-j)^2 \quad (eq. 2)$$

Homogeneity is used to measure the homogeneity of images with similar gray levels. Homogeneity is calculated by the formula inequation 3:

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{(i,j)}}{1+(i-j)^2} \quad (eq. 3)$$

Energy is used to measure the homogeneity of animage. Energy is calculated using the formula inequation4:

$$Energy = \sum_{i,j=0} P\,(i-j)^2 \quad (eq. 4)$$

Entropy is used to calculate the level of image irregularity. Entropy is calculated using the formula inequation5:

$$Entropy = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{i,i}(i-\mu_i)^2 \quad (eq. 5)$$

Variance is used to measure the distribution between the meancombination between reference pixels and neighboring pixels. Variance is calculated using the formula inequation6:

$$Variance \models \sigma 2 = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{i,i}(i-\mu_i)^2 \quad (eq. 6)$$

Correlation is used to calculate the association of pixels that have gray level i with pixels that have a gray level j. Correlation is calculated using the formulainequation7:

$$Correlation = \sum_{ij} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma i \sigma j} \quad (eq.7)$$

2.3 Deep Belief Network

Deep Belief Network (DBN) is one of the most popular deep learning models consisting of a number of Restricted Boltzmann Machine (RBM) layers and a Back propagation (BP) layer. RBMis a generative model that can collect structural information in data and can effectively train non-linear data throughu nsupervised training. Each RBM layer extracts input data in abottom-upmannerandtheoutputinformationfromthelastRBM layeris used as input data from the BP neural network.The RBM training process makes it suitable as a DBN module.The objective of DBN is to extract and separate bottom-up input data for each RBM layer ands to reall important information.Themulti-layer RBM layerusestheunsupervisedlearningmethod, while the Backpropagation Neural Network (BNN) usesthe supervised learning method. Each layer of the RBM extractsinput data bottom-up and the output information from the lastlayer of the RBM network is used as input data at the BNN.Because the training carried out by each RBM layer can onlymake the parameters at that layer achieve optimization, we useBNN for top-down tuning of the entire model. Meanwhile, theinformation obtained from the optimization of the RBM networkis used as the BNN data input which solves the problem of theBNN, namely that it is easy to fall into local minimums and hasslow convergence [7-12]. General DBN architecture can be seeninFigure 2.

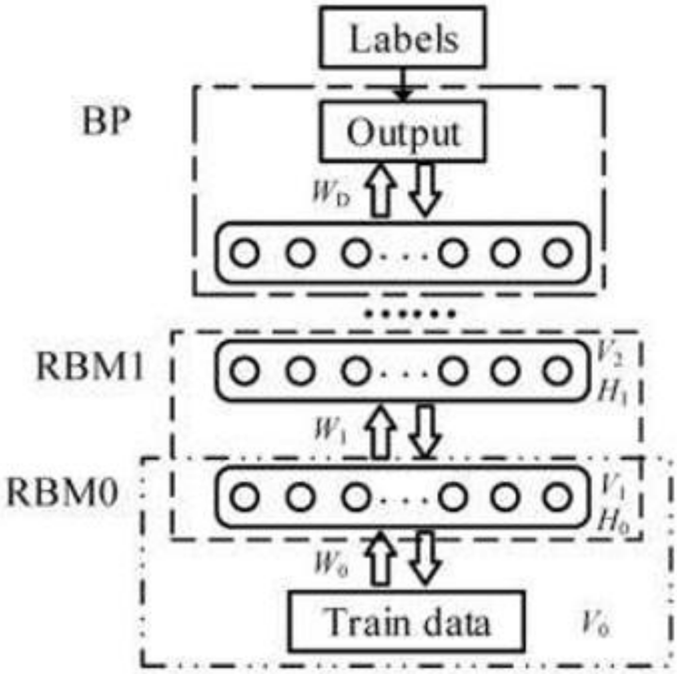

Figure 2: Deep Belief Network

Figure 2 is the overall architecture of a deep neural network thathas an input layer, hidden layer and output layer, but in the firsttraining phase with a deep belief network, in the figure you cansee the training process from the input layer to the hidden layeronly, and then the second phase of training (finetuning) with theentire deep neural network from the input layer to the outputlayer.

Training on Deep Neural Networks

The training process for deep neural networks (DNN) is divided into 2phases. The first phase is to carry out the unsupervised learning process on the generative pre-train algorithm from the deep belief network (DBN) from the lowestlayer to the highest layer, in this phase the weights have beengenerated which will be initialized in the second phase. Then the second phase is fine-tuning the parameters (parameter settings)using supervised learning on the whole DBN to change the weight fromthetoplayerto the bottomlayer [7-12].

1.Training phase - generative pretrain algorithm The firstphase of training is the deep belief network (DBN), namely by conducting restricted boltzman machine (RBM)training. There stricted boltzman machine has two layers, namely the visible layer and the hidden layer, where each visible unit is connectedto each hidden unit, but not connected to itself or between unitson the visible layer and hidden layer. The restricted boltzman machine architecture can be seen in Figure3.

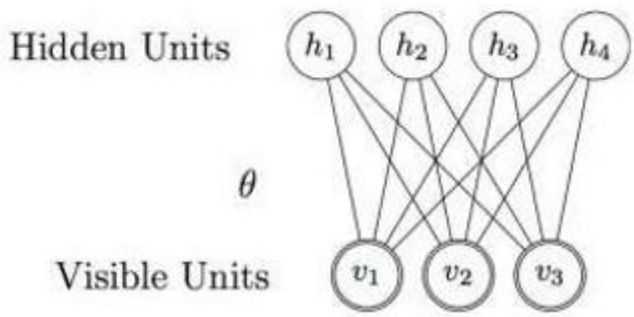

Figure 3: Architecture of the Restricted Boltzman Machine(RBM)

Training restricted boltzman machine(RBM)using Gibbs Sampling requires four stages. In the beginning RBM run thebinary type on its visible layer, so that on its development To receive real value data on the visible layer, a visible unit is required different, namely using the Gaussian Unit or commonlyreferred to as Gaussian Bernoulli RBM.It is assumed that the visible layer in RBMis $v$with layermarkersash^0.

Positive Phase. Update all hidden units in 1 parallel using thefollowing(Positive (Eij)) equation.

$$(H_j = 1|V) = (B_j + \sum W_{ij} V_i) \text{ (eq.8)}$$

Where P is the probability, H hidden units, V visible units, f functions activation, Bbias and Wweights. For Gaussian Bernoulli, then the phase is positive transformed into

$$(H_j = 1|V) = (B_j + \sum_{i=1}^{m} W_{ij} \frac{V_i}{\sigma_i^2}) \text{ (eq.9)}$$

Negative Phase. Reconstructing visible units using techniques similar(Negative (Eij)) asfollows.

$$(V = 1|H) = (C_i + \sum W_{ij} H_j) \text{ (eq.10)}$$

TheNegativePhaseusesGaussianBernoulli,soitbecomes:-

$$(V_i = V|H) = (V|C_i + \sum W_{ij} H_j \sigma^2) \text{ (eq.11)}$$

Where N is the Gaussian probability density function with Mean and Standard deviation, Cbias, andσ standard deviation.

Update the weight of each edge.Update weights usinge quations as follows.

$$Updt\ (W_i) = W_i + L \cdot (Positive\ (E_i) - Negative\ (E_i))\ (eq.12)$$

WhereListheLearningrate:
Repeat the steps until the termination criteria are met.

The Sigmoid Activation Function

Selection of the activation function is very important in a neural network, because it will affect the input data format. The sigmoid activation function is very often used in feed-forward neural networks that require a positive output[7-12]. The equation for the activation function and its derivative functionscan be seen as follows, and a graph of the sigmoid activationfunctioncanbe seeninFigure2.14.

$$\mathrm{f_1(x)} = \frac{1}{1 + \mathrm{e^x}}\ (\mathrm{eq.}\ 2.13)$$

withderivatives

$$\mathrm{f_1(x)} = \mathrm{f_1(x)}(1 - \mathrm{f_1(x)})(\mathrm{eq.}\ 2.14)$$

Soft max Activation Function

The soft max activation function is usually found in the output layer, which generally has more than two output units.The softmax activation function is also usually used in classifications which provide output values ranging between 0 and 1 . The simple equation of the softmax activation function and its derivative function is as follows.

$$f(\mathrm{x}) = \frac{e^{\mathrm{zi}}}{\sum_{k=1}^{k} e^{zi}}\ (eq.\ 15)$$

$$f'(x) = (x)(1 - f(x))\ (eq.16)$$

Parameters in Neural Network Architecture

In a neural network architecture, other parameters are needed besides weight and bias to produce good training. These parameters are the learning rate, momentum, and epoch. Selection of parameters needs to be considered because they can affect the effectiveness of a training.

Learning Rate

Learning rate is the rate of learning. Learning rate has a significant impact on training. The greater the learning rate value, the greater the learning step and the algorithm becomesunstable. The smaller the learning rate, the longer the learningprocess will take to reach local optima. So it is necessary to choose the right value for the learning rate.

Momentum

Momentum is a change in weight based on the gradient direction of the last pattern and the previous pattern. The amount of momentum is between 0 and 1. If the momentum value = 0, then the weight change will only be affected by the gradient. However, if the momentum value = 1, then the weight changewill be the same as the previous weight change. The use ofstandard values of momentum on some problems cannot have a big effect, such as doing a combination with RMSProp.

Epoch

In machine learning, epoch is a series of steps in learning artificial neural networks (ANN). One epoch is defined as oneANN study. Epoch does not mean iteration. Many iterations can occur when one epoch is not over. Therefore, one epoch is defined as one forward and one backward pass for each existing training data. Therefore, learning rate in deep learning architecture Talking about the learning rate, it is related to the gradient descent algorithm. Gradient descent is away to minimize the objective function (θ)parameterized by a parameter model $\theta \in \mathbb{R}d$ by updating the parameters in the reverse direction of the gradient objective function$\nabla\theta J(\theta)$taking into account the previous parameters. However, there are several problems in implementing deep learning and the availability of conventional gradient descent ,namely as follows:

Choosing the right learning rate is not easy.

Scheduling the use of the learning rate in adjusting the learning rate during training.

The speed and performance of conventional gradient descent needs to be improved to support parallel processing in deep learning

Previous Researches

Research to detect glaucoma has been carried out by severalprevious researchers, including research conducted by [13] who developed aglaucom a disease identification system through fundus images using the Back propagation method. This researchwas conducted using 60 images as testing data and 60 images a straining data. However, the scheme is able to classify the glaucoma automatically with a sensitivity and specificity of100% and 80% respectively

The system resulting from this study has an accuracy rate of upto 90%. The researchers [14] developed a system to detect glaucoma by combining the Region of Interest(ROI)segmentation technique and anautomated system usinghemorrhage detection in certain areas of the fundus image. Theimages used are 140 images consisting of 100 normal images, 40images suspected of glaucoma. Of the 100 normal images, 92 ofthem were correctly identified. Meanwhile, of the 40 suspectedglaucoma images, 39 of them were correctly identified using thissystem.The systemaccuracyrate reaches93.57%.

Another research was conducted by[15] who developed an automatic glaucoma detection system that was identified by calculating the cup to disc ratio (CDR). Researchers have proventhat if the CDR value is between 0.0-0.3 then the input image isnormal. Meanwhile, if the CDR value obtained is greater than0.3, the image is identified as glaucoma. The image used in this research is 50 images. From 50 images used, the resulting specificity value is 82% and sensitivity is 82%. And this system has anF-score of96%.

Subsequent research conducted by [16] who developed a system for detecting glaucoma through optical disc and cup segmentation using K-mean clustering. This study used 100 datasets consisting of 73 normal data and 27 glaucoma data. Theaccuracy of the system developed by the researchers reached92%withasensitivityof93%anda specificityof88%.

The next research is the detection of glaucoma using a combination of 2 Texture Feature Extractions, namely the GrayLevel Co-occurrence Matrix (GLCM) and the Markov RandomField (MRF). The data used were 50 data. From the combinationof feature extraction used by the author, the system accuracy rateforglaucoma classification results reaches86%[17].

The research [18] proposes toper form automatic glaucoma recognition using an 18-layer convolutional neural network. Thiswork consists of a standard CNN, with convolution and maximal pooling layers, and a fully connected layer where classification is performed. Initially, 70%of the randomly selected samples are used for training and 30% for testing. 589 images of healthypatients and 837 with glaucoma were used. The process was repeated fifty times with random test and training partitions.
In the research [19] use various architectures such as VGG19,ResNet, Google Net and Denet Disc. The best results obtainedwere obtained using VGG19 with transfer learning, obtaining0.9420 AUC,0.8701 sensitivityand 89.01 specificity.
The research[20]proposes an automatic glauco madetection system using SVM for classification. Combine GIST and PHOGto extract features in images. This technique eliminates the needto segment the image. Instead, it works with a diagnostic systemthat makes use of features like texture and shape to detect the disease. This method gave an accuracy of 83.4% using the basesofDrishti-GS1 and High Resolution Fundus(HRF)data.
Theresearch[21]proposestoimplement2architectures,VGG16 and ResNet, concatenating LSTM blocks. To determinewhich one is the best, they perform several experiments varyingthe number of epochs and the learning rate. 20 epochs and alearning rate of 0.001 are chosen as values to obtain the bestresults. The best results are achieved with the VGG16 network,achievinga sensitivityof95%anda specificityof96%.

PROPOSED ALGORITHM
This section will discuss the steps involved in developing aglaucoma identification application. The steps taken areas follows: the stage of collecting fund us image data consisting of normal images and glaucoma images which will be used a straining data and test data; the prepocessing stage consisting of brightness, median filter, grayscale, and thresholding; the image feature extraction stage uses the Gray Level Co-occurrence Matrix (GLCM); and the image classification stage using the Deep Belief Network. After these steps are carried out, the application can produce output in the form of glaucoma identification results. The stages can be seen in the form of a general architecture in Figure 3.

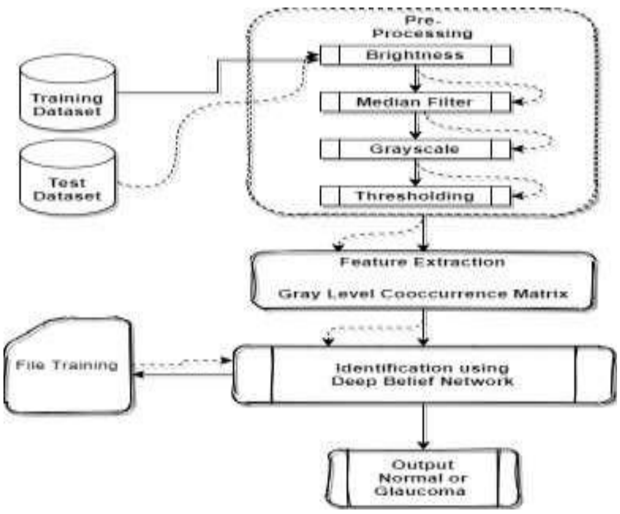

Figure3: Proposed Architecture

Figure3 is an overview of the general architecture of the research classification using deep learning with an adaptive learning rate. The initial process is to collect data related to thedata to be examined, then normalized and transformed thedataso as to produce data that is ready to be tested. Furthermore, thedata is divided into two namely data for training and data fortesting. Classification process using a standard deep neural network on the one hand, and on the other using a deep neuralnetwork with an adaptive learning rate. The training process thedeep neural network has 2 training phases, the first phase isunsupervised learning deep belief network, and the second phase of supervised learning fine-tuning deep neural network.Thefinal result of the classification will be analyzed for each of its performance.

Data Set

The data used in this study are fund us images consisting of normal images and glaucoma images. This data was obtainedfrom the RIM-ONE database (http://medimrg.webs.ull.es). RIM-ONE is are tinal fundus image database developed by 3hospitals, namely Hospital Universitario de Canarias, Hospital Clinico San Carlos, and Hospital Universitario Miguel Servet.The types of images used in this study are normal fundus imagesand glaucoma fundus images. In Figure 4 part (a) is a normal fundus image and in part(b) is a glaucoma a fundus image.

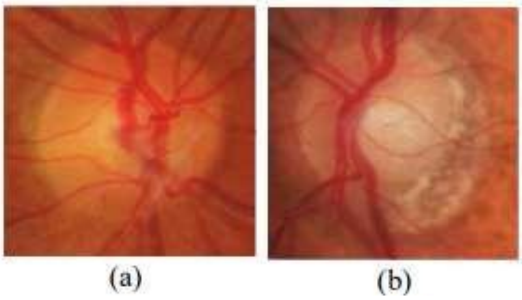

Figure4 (a)Normal Fundus Image(b)Fundus Glaucoma Image

Brightness

Image brightness is the step to adjust the brightness of an image.This stage done to increase the brightness of the image sothatthe optical disc looks even more it is clear where this stage iscarried out so that the image can be more easily processed at thestage next. It can be seen in Figure 5 part (a) is an original imagethathas not been processedand part (b) is the result of the brightness enhancement process carried out on original image.

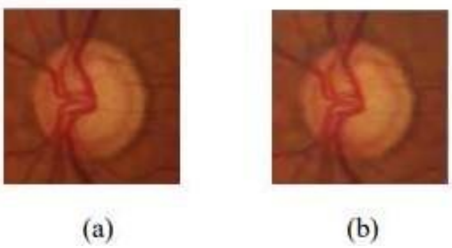

Figure5: (a)Original Image(b)Image Result of Brightness

Median Filter

This stage is done to remove salt & pepper type noise that isoften found in the image. Median filter works by processingevery pixel in the image then replacing each pixel value with thenearest pixel median value. The pattern of the median value ofthe surrounding pixels is called a window. Figure 6 is the image resulting from the median ilter.

Figure 6: Imageof Median Filter Result

Gray scale

Fund us image which is an RGB color image will then be converted into a gray image by utilizing the gray scaling process. In Figure 7,you can see the image of the gray scale process.

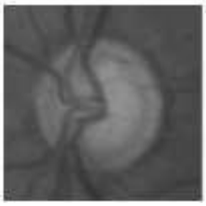

Figure 7:Grayscale Result Image

Thresholding

The thresholding stage is carried out to change the gray image into a binary image is worth 0(black) and 1(white). The image are as that tend to be dark will be changed becomes black(intensity value 0) and an area of the image that tends tobebright is created becomes white (intensity value 1). Figure 8:shows the image of the thresholding result.

Figure8: Thresholding Result Image

Feature Extraction

After going through the preprocessing stage, the next step is the extraction stage feature (feature extraction). The feature extraction method used in this study is the Gray Level Co-occurrence Matrix (GLCM). Here are the steps feature extraction using GLCM.

1. Forming a framework matrix using the degree of gray value (graylevel) image. The gray level value used is256.
2. Determine the direction and distance between one pixel andthe surrounding pixels. Distance used is 1 and the directionused is0^{o} , 45^{o} , 90^{o}, and135^{o}.
3. Calculating the co-occurrence value based on the predetermined direction and distance.
4. Adding the co-occurrence matrix with the transpose matrix so that the matrixco-

insurance to be symmetrical.

5. Normalize the co-occurrence matrix that is in symmetrical form with how to divide the co-occurrence value in the matrix by the total number of values the existingco-occurrence values, so that the sum of all the values is1.
6. Calculate the value of the features of the GLCM. There are 6 features used, namely contrast, homogeneity, energy, entropy,variance, and correlation.

Proposed Algorithm

The next step after getting the GLCM feature value is image identification using the Deep Belief Network (DBN) method.The initial stage carried out in the image identification process isthe training dataset training process. In this study, researchers used 80 input data to be trained. The Restricted Boltzmann Machine (RBM) algorithm is also used during the training process. The parameters used in the DBN method are:

1. Determine the number of visible nodes. In this study, there are 3 nodes taken from the characteristics of glaucoma images, name lyoptical disc,opticcup, and vessels retinal blood.
2. Determine the number of hidden nodes. In this study there are2-nodes determined because the results were normal and glaucoma.
3. Determine the value of the learning rate. The value specifiedis0.1.
4. Determine the momentum value.The value specifiedis0.5.
5. Determine the unsupervised depoch value.
6. Determine the supervise depoch value.

Determining the Network Architecture

Before data processing, it is necessary to determine the network architecture, such as determining the number of layers used, the number of neurons in each layer used, the activation function used, and other parameter values.

Input layer Based on the attributes to be used, there are contrast, homogeneity, energy, variance and correlations like attributes that will be used as neuron input.

Hidden layer/dense layer In a neural network, it is generally not more than 2 layers, but in deep learning it is possible to have more than two hidden layers. However two layers can also be used for simple datasets. There are three rules in choosing the number of neurons in each hidden layer

1. The number of neurons between the input and output sizes ofneurons
2. The number of neurons is 2/3 of the input neurons plus theoutputofthe neurons
3. The number of neurons is less than 2 times the input ofneurons From the above criteria, this study will use 2 hiddenlayerswith9neuronsoneachlayer.

Output layer Generally, the number of neurons in theoutput layer depends on the classification problem. This studyincludes a multi-class classification, which will classify threetypes of mangrove sprouts, so that the number of neurons in theoutputlayeris3.

Activation function The activation function commonlyused in classification on neural networks with a value between0-1 is the sigmoid activation function, but the sigmoid activationfunction is generally used for binary classification. This study uses amulti-class classification which has 3neurons in the output layer. The softmax activation function can be used inmulti-class classification which has an output of more than 2neurons, this activation function is generally used at the outputlayer in a neural network.So this research uses the sigmoid activation function in the hidden layer, and the soft max activation function in the out putlayer.

Parameters Parameters such as weights and bias used are random, and the learning rate use dis0.1.Other parameters in this study such as momentum are not used, this is based on theuse of standard values of momentum on several problems thatcannot have a major effect, such as doing a combination with softmax. Architectural specifications to be built is depicted below.

Steps for Training using DBN

The deep belief network (DBN) that has been trained in the firstphase of training will be transformed into a deep neural network(DNN) by adding a discriminative layer y at the top layer of theRBM, then changing the connection within the DBN (from twodirectionstoonedirection)becomesfeed-forward.Theparameters that have been previously estimated by DBN can beused directly as DNN parameters, or can also be improved, for example by applying the back propagation algorithm. The flow of the back propagation algorithm is as follows:

Using the same number of neurons and structures as the DBNthat was pre-trained using the Contrastive Divergence algorithm in the first training phase.

1. Change the direction of the weight which was originally two-way or not directional to one direction like the Multi-layerPerceptron
2. Set weight for each weight and bias is the final weight in theDBNContrastive Divergenceprocessabove.

Feed Forward

Each hidden unit**(□□)** receives asignal from each input unit **(□□)**with the following equation.

□_□□□=□□□+∑n□□□

Use the activation function to calculate the output signal:

□□=□(□_□□□)

And send the signal to all the upper layer units(output units).

This step is done as many as the number of hidden layers.

Calculate all network outputs in the output layer(□□,□ **=1,2,...,**□)

□_□□□=□□0+∑p □□□

Use the activation function to calculate the outputsignal:

□□=□(□_□□□)

- **BackPropagation**

1. Calculate the output unit factor based on the error in each unit output(□□,□**=1,2,...,**□)

□□=□□-□□□'(□_□□□)

δisaunitoferrorthatwillbeusedinchangingthecluster weightatunderneath(step7)

Then calculate the weight correction(which will be used later forfix□□□)withan accelerationrate□

□□□□=□.□□.□□

Then also calculate the correction bias(which will later be used forfixthevaluew_{k0})

Δ□□0=□□k

Calculate the hidden unit factor based on the error in each unit hidden(□□,□**=1,2,...,**□**)**□_□□□**=**∑p

RESULTS AND SIMULATION

Data Implementation

This study uses a dataset in the form of digital images derivedfrom retinal photographs. The dataset obtained is sourced froman online data science and artificial intelligence platform calledRIM-ONEdataset(http://medimrg.webs.ull.es)howeverthesame data is also available on kaggle.com.From these data, theclassification can be divided into 2 categories of eye blindness,namelynormalorglaucoma

Pre-processing

To start there search, pre-processing was carried out which consisted of several stages. Pre-processing is done to convertdigital raw intodigital images that are idealfor the trainingprocess. The first thing to do is to make sure the datasetused asa label for the type of blindness that each eyehas and can beused for the training process. The data that has been preparedmust bevisualized toshow the eye andthe type of label asshownbelow.

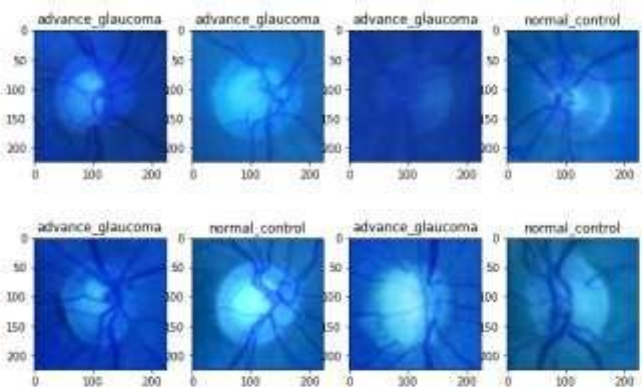

Figure 9: Fundus Images(Dataset)

From the results of the visualization above, it can be ascertainedthat the data used already has alabel and is a dataset that is inaccordance with the needs of this study. Then the thing that mustbe done is pre-processing so that the dataset becomes an ideal data set so that there are no obstacles in the training process.

Brightness

This stage increases the brightness of the images othat the optical disc looks even more it is clear where this stage is carried out so that the image can be more easily processed at the stage next.

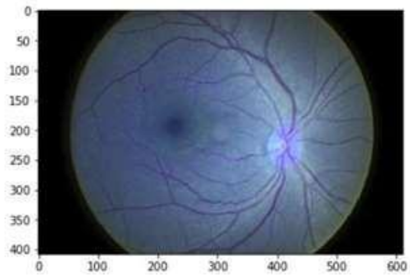

Figure10: Brightened Retina Image

Median Filter

Median filter function store move noise in the image. Noise removal is carried out in order to produce better quality images

The filter used with 2Dimages asunder:

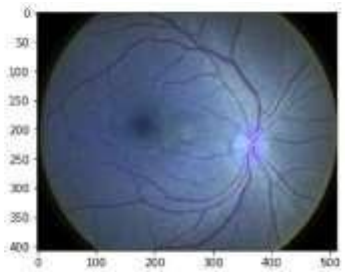

Figure11:Filtered Retina Image

Grayscale

Grayscale means a process to turn an eye digital image into amonochromatic digital image. In this study, the purpose of carrying out the gray scale process is to ensure that the eye anomaly that has been described as a parameter can be seen when the training process is inprogress. At this stage the grayscale process is carried out using the gaussian blur method. The Gaussian method is combined with the image blending process. The image blending formula used is as follows.

$$g(x) = (1 - \alpha)\ .f_0(x) + \alpha f_1(x)$$

The image blending process with the Gaussian blur method allows for several variations. Variation is carried out at α using avalue between 0 and 1. The process of changes can produce different transformations depending on the type of requirement.

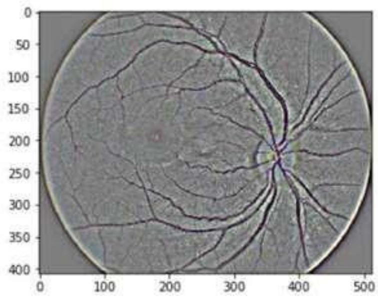

Figure12: Retina Image Converted to Grayscale

GLCM

The extraction of second-order statistical features is carried outwith a co-occurrence matrix,which is an intermediate matrixthat represents the adjacency relationship between pixels in animagein various orientations andspatialdistances .Theco-occurrence matrix is a matrix of size L x L (L represents thenumber of gray levels) with the elementP (x_1, x_2) which is ajoint probability distribution of a pair of points with a gray level$x_1$located at coordinates (j, k)where $x_2$is located at coordinates(m, n). The coordinates of the pair of points are r with the angleθ. The second level histogram P (x_1, x_2) is calculated with thefollowingapproximationresults.

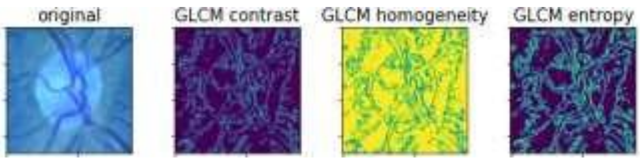

Figure13: Feature Extraction using GLCM

SystemTesting using DBN

System testing is carried out to determine the ability of the system that is built to identify fund us images. The system's ability to identify fund us images depends on the training process using the Deep Belief Network because the training process produces the final weights that will be used in the testing phase.Previously, 66 glaucoma images and 66 normal images weretested with different epoch parameters. The graph of the systemaccuracyvalueaftertesting40imageswithdifferentepochparameterscanbeseeninFigure4.6.Fromtestscarriedoutusing different epoch parameter values as under with accuracy of98.00%.

Confusion Matrix

Based on the system evaluation score using confusion matrix, the system is considered quite effective in identifying glaucoma through fund us images using the method that has been applied to the system. The system achieves a precision in advance glaucoma the precision score of 99%, recall of 100%, and the f1 score of 99% where as in normal control or glaucoma the precision score of 100%, recall of 98%, and the f1 score of 99%and the overall system accuracy score of99.0%.

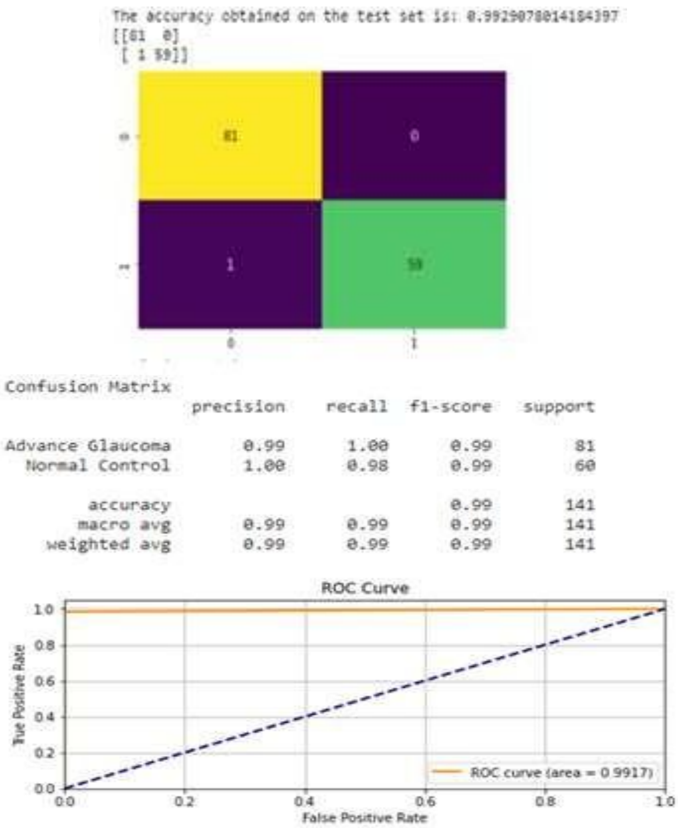

Figure14: Result Illustration using Confusion Matrix and ROC

Based on the results of the experiment from this study, it can be concluded that the use of the Deep Belief Network architectural model results in a maximum and linear change in process. The results of research using Deep Belief Network produce a more rational accuracy when compared to other Neural Architectural mode ls as student in literature with several iterations of almost 99% of accuracy. Therefore, this scheme can act as defacto standard for Glaucoma Detection.

CONCLUSION AND FUTURESCOPE

Conclusion

The conclusions that can be drawn from the results of testing the identification of glaucoma through fundus images using the Deep Belief Network are as follows:

1. The Deep Belief Network method is able to identify glaucomathrough fundus imageswell. The results of the identificationprocess of glaucoma through fundus images with anadvanceglaucoma the precision score of 99%, recall of 100%, and the f1score of 99% where as in normal control orglaucoma the precision score of 100%, recall of 98%, and the f1 score of 99%and the overall systemaccuracyscore of99.0%.
2. The selection of DBN parameter values has an influence onthe accuracy results. The parameters used are supervised epoch100.

The difference in the values used for the parameters also affects the duration of the training. The higher the epoch value,thelongerthe trainingdatawillbe..

FutureWork

The suggestions that can be given by the author regarding thisresearchfor further developmentareasfollows:

1. Using other neural network methods to compare with the classification results obtained from the Deep Belief Network method.

Inculcate the layers which can reduce the training time with same level of accuracy.

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