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Glaucoma Detection using Hybrid SVM+ANN Classification

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ABSTRACT: Glaucomaisaneurologicaldisease and one of the mostwell-knowncausesofvisionloss, according to the abstract. Be causenervedegenerationisanirreversible process, early detection of the conditionisessential to preventing permanent visual loss. Glaucoma is mostly caused by elevated intraocular pressure, and if it is not identified and treated promptly, it can damage vision. Glaucoma is a vision condition that gradually become sworse over time and affects theeye's optic nerve. It results from pressure accumulation inside the eye. Glaucoma frequently runs in families and may not manifest itself since later in life. One of the most crucial and difficult parts is the identification of glaucoma to us progression. Inthisstudy, we presented aunique hybrid algorithm for glaucoma diagnos is. In this study, we provide anovelhybrid approach for classification utilising Artificial Neural Networks (ANN) and supported vector machines (SVM). For segmentation, we used HMM with Cuckoo search optimization (CSO), and for classification, we employe dahybrid of SVM and ANN. When compared to other approaches already in use, the results demonstrate strong performance.

Keyword: [Glaucoma Detection, Artificial Neural Network (ANN), Supportvectormachine (SVM), Cuckoosearch optimization (CSO), HMM.]

1. INTRODUCTION

Glaucomaisavarietyofprogressivedisordersinwhichtheeye's in traocularpressure (IOP)rises, narrowing the opening that the optic nerve enters the eye. The pressure being applied to the optic nerve is increased by this narrowing of the aperture. The optic nerves are damaged as a result of this pressure.

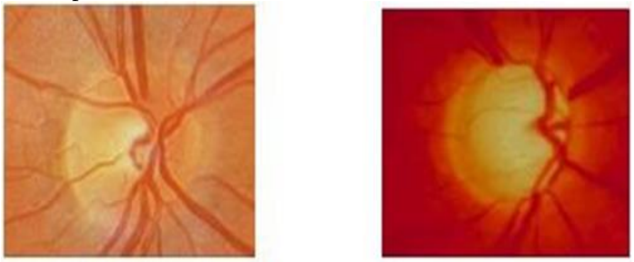

Figure1 (a) Normalopticnerve (b) Glaucomaaffectedopticnerve

Due to the high eye pressure brought on by an unbalance in the formation and outflow of the aqueous humour of the eye, glaucoma causes harm to the optic nerve of the eye. If neglected, the problem worsens over time and finally results in total blindness. Glaucoma cannot be cured, although visual loss can be avoided with medicine. Aqueous humour normally exits the eye through the trabecular meshwork. However, the aqueous humour will increase if this pathway is closed. The increase in this liquid will result in an increase in pressure and the loss of ganglion cells. Patientswithg laucomagradually losetheireyesightbecausetheganglioncellsdonotrenew. By 2020, glaucoma cases will have increased by more than 30%, according to research. It is currently the second most common cause of blindness globally. Glaucoma is one of the main worldwide causes of visual impairment, according to the World Health Organization [2].

The name "glaucoma" is derivedfromanancient Gree kphrasethatmeans" clouded orblue green hue, "ostensiblydescribingsomeonewhohasadilatedcorneaorisd evelopingrapidlyalens, both of whichmightbeimpactedby chronic (long-term) riseinintraocularpressure in theeye. Agroup of illnessesknownasglaucomacausedamageto the opticnerve, whichresultsinpermanentvisual loss. The vast majority of the time, this injury is brought on by an enormous rise in intraocular pressure. The posteriorchamber, which is the area between both the irisandthelens, is where the eye produces aqueous hum our, a vitreous fluid that drains via the trabecular mesh network. The rates of drainage and secretion are equal in a healthy eye. Glaucoma develops when a drainage canal is partially or entirely clogged, causing an increase in intraocular pressure and harm to the optic nerve, which is responsible for sending signals to the brain where sensory data may be processed. Untreated injury might result in complete blindness. As a result, glaucoma must be detected early [3].

The mostintricate, fragile, and delicateorgans in the humanbody are the eyes, through which we observe the outside world. They are in charge of providing our brain with 45% of all the information. The word "glaucoma "referstoaseries of eyeillnesses that eventuallycauseb lindness byirreparably harming the opticnerve, which is the nervethats endsvisualsignals to the brain [4]. The refore, the reisarequirementforacomputer-aideddiagnostic

(CAD) solution [3] forglaucoma that can assist ophthalmologists in quickly and thoroughly analysing medical pictures. Pre- processing, segmentation, and categorization of medical pictures are all included in the CAD system's glaucoma diagnosis capabilities. Pre-processing is the first stage in the process of preparing an image for subsequent analysis using various filters, morphological procedures, etc. byremovingsomenoiseandoutliers from the input picture. Inorder to extract the desired area of interest (ROI), whichismoresignificantthanotherpartsandmakesiteasiertoassesstheanomaly, the input picture is further segmented into numerous regions. The classification process, which determines whether a picture is "normal" or "abnormal," is the last step. The categorization function of CAD systems employing machine learning techniques in retinal pictures is the focus of this work [5].

Byeliminatingsomeclutterandoutliers from the input image, pre-processing is the in itial step in the process of prepping an image for lateranalysisusingdifferentfilters, morphologicalprocesses, etc. The incoming picture is then divided into several regions in order to identify the desired interest area (ROI), that is more important than other areas and facilitates the evaluation of the anomaly. The next phase is categorization, which decides whether an image is "normal" or "abnormal. "This work [5] focuseson the classification function of Digital systems using machine learningapproachesinretinalimagery. The Optic Nerve Head featureextractionmethodologyaids inautomateddetectionandisanon-invasivemethod. Changesintextureandintensitycanbeused to distinguish between glaucoma and normal images. When structural alterations take place in a sick picture, the texturing is a structure of that image that alters. To accurately comprehend the illness s and the sort of structuralalterations, several text urecharacteristicsmayberetrieved from a picture [7].

2. LITERATURESURVEY

A innovative, automated, appearance-based glaucomaclassification method thatdoes notrely on segmentation-based measures was created by Rudiger Bock et al. We may use our wholly data- driven approach in extensive screening exams. It uses a typical two-stage classification pipeline for patternrecognition. Inordertocaptureglaucomatousstructures, varioustypesofimage-based characteristics were examinedandmerged. In the preprocessing stage, somedisease-independent variablessuchilluminationinhomogeneities, sizevariations, and vesselarchitecture are removed. Physiciansmaygetnewknowledgeabout and abetterunderstandingofglaucoma from the "vessel free" pictures and intermediate findings of the procedures. On a data set made up of 200 genuine photographsofhealthyandvasodilatoreyes, ouralgorithmhasan 86% successrate. Thesystem's effectiveness in identifying glaucomatous retina fundus pictures is on par with that of human medical specialists.

Ahmed El-Rafei and others [9] Analysis of the visual system's white matter fibres using DTI has recentlybeenusedtotheglaucomacondition.Theprovidedapproachisthefirstcategorisationfor diagnosing glaucoma based upon DTI and ocular radiation analysis. The suggested visual pathway-based method is a fresh viewpoint in glaucoma classification, in contrast to the typical oculardetection systems that relyoneyeimagingtechniques.

Themethodhasgoodidentification rates for distinguishingbetweenentities ofglaucoma as wellas healthyparticipants fromvarious categories of glaucoma sufferers. Additionally, it performs better than several of the most advanced retina-based cataract detection algorithms and yields fair categorization rates. In line with other research, our study highlights the DTI-derived measures' sensitivity to glaucoma and advises integrating them into the glaucoma exam flow. Glaucoma is a challenging systemic condition. Therefore, acomprehensiveinvestigation of the visual system may help with glaucoma diagnosis and prognosis. Giventhedevelopmentsinneuroscienceandretinaimaging,thismaybe accomplished by combining the information from several visual system regions.

Zhuo Zhang and others, [10] In clinical practise, the diagnosis of glaucoma is based on a number of variables, including the patient's medical history, an examination of the eyes, and an ophthalmoscopy examination of the opticnerve'shead. Forcomputer-aideddiagnosis, combining several data sources can improve the simulation of clinical decision-making in the actual world. Theblackboxnatureofreinforcementmethodsisoneofitsdrawbacks.WithmRMR,itispossible to train a simpler module and, more crucially, to offer a clear list of characteristics to clinicians. This makesitmucheasy to explaintodoctorswhattheclassifierlearnedfromofthedataandhow the expert knowledge came from.Additionally, the mass screening procedure for glaucoma early detection may be guided by the characteristics derived, requiring less data to be gathered. The suggested framework may be used to treat various eye conditions including retinopathy and cataract.

Using an SVM-based learning algorithm, N. Anantrasirichai et al. [11] describe an automatic texture classification for the identification of glaucoma. The inner retina's thickness and texture aretakenintoaccount.Theclassificationaccuracycanbeincreasedbyupto4%byutilisingtexture characteristics as opposed to just layer thickness, according to the results. This might also be evidence that the speckle, which humans interpret as texture, contains information that can be utilisedtounderst and howglaucomaaffectsretinaltissue. Futureresearchwillexaminethetexture of more retinal layers, and early glaucoma diagnosis will incorporate data from visual fields.

TangilaSabaand others [12] Oneof theneurodegeneration, glaucomais thoughtto beoneof the most commonly understood causes of vision loss. Since nerve degeneration is an irreversible process, it is essential to diagnose the condition early in order to prevent a permanent loss of eyesight. The articleincludesaschematicoftheglaucomadisease,including itstypes, symptoms, risks, treatments, and suggested image-handling methods for analysis. Various symptomatic approaches have been examined and dissected. Benefits and drawbacks of each approach have beendiscussedindetailbyhighlighting the circumstancesinwhichoneapproachissuperiorthan the other. Clinical diagnosis is necessary for the condition known as glaucoma. There is no accepted method for gauging glaucoma progression. Due to the lack of an ultimate calculation in ourcurrentstructuralmethodologies,itisdifficulttobepositiveregardingtherelativespecificities and sensitivities. In contrast to the subjective and rudimentary methods used in the past, developments in structure and function assessment methods provide greater aim precision and precision for the identification and diagnosis of diseases.

P.V. Rao et al. The cup over disc ratio is utilised to segment the glaucoma section of the glaucomatous picture, and wavelet sub bands are then applied to the segmented image to extract theenergylevels.TheenergylevelsoftheDaubechies(Db4),Symlets(sym4),andCurveletfilters (bio3.7, bio4.2, and bio4.7) are clearly different from those of the conventional retinal picture. Normaldataisusedtotrain the ANN algorithmsArtificialNeural network (annandMLP-BP.

With a classification accuracy of 89.6%, Bayes classifies the photographs in the database. The database's photos are accurately classified with 97.6% accuracy using the MLP-BP ANN algorithm. Comparing the suggested approach to current glaucoma classification systems, the proposed system displays more accuracy. This technology is affordable and simple to use in hospitals. This approach lessens the pressure on doctors and eliminates human mistake.

Gayathri.R. and others [15] The energy levels retrieved from the glaucomatous picture utilising thewaveletsubbandsDaubechies(Db4),Symlets(sym4),and curveletfiltering(bi03.7,bi04.2& bi04.7) clearly show a difference in the energies levels compared to those of the normal retina image. The Naive Bayes and MLP-BP ANN algorithms classify input pictures as normal or abnormalbytakingextractedenergylevelsintoconsiderationafterbeingtrainedonnormalretinal images. With an accuracy of 89.6%, Naïve Bayesian classifies the photos in the database. Classification accuracy for the database's photos by the MLP-BP ANN method is 97.6%. Comparing the suggested approach to current glaucoma classification systems, the proposed systemdisplaysmore accuracy. Thistechnologyisaffordableandsimple touseinhospitals. This approach lessens the pressure on doctors and eliminates human mistake. Future upgrades to the device might use artificial intelligence to categories other eye problems.

SumaiyPathan and others [16] Strong segmentation of OD was made possible by the use of the circle finding technique and decision tree classifier. The suggested OC segmentation approach seekstoimprovetheOCregionbyintroducinganewchannelsincethereislessvariationbetween the OD and OC pixels. The threshold value determined by the segmentation algorithms may be applied to a variety of datasets because it is not specific to any one dataset. Statistical aspects of colour and texture are combined with domain knowledge of glaucoma, such as CDR and NRR area.SVM, ANN, and an ensemble of AdaBoost classifiers are employed for classification, and dynamic selection techniques have been devised to discriminate between normal and glaucomatous fundus pictures. Additionally, an ensemble of AdaBoost classifiers using dynamic selection techniques, SVM, and ANN is tested usingten-fold cross validation. On a hospital data of 300 photos and the publicly accessible Drishti dataset, the suggested approach is tested. The method's effectiveness is demonstrated by the numerical parameters. When mass screening for glaucomaisbeingdone, thesuggestedapproachcanbeemployedasacomponentoftheglaucoma detection system.

Aneffective network form yopiascreeningthatbuildson DENet[14]hasalreadybeensuggested by S. Phasuk et al. The network consists of two segmentation networks for segmenting the optic discandtheopticcupaswellasfourclassificationnetworks,includingthefinalclassification.The experimentalfindingdemonstratesthat,withanAUCof0.94,thesuggestedsolutionoutperforms the original DENet on publicly available datasets such as ORIGA-650 [18], RIM-ONE R3 [19], and DRISHTI-GS [5].

A method for glaucoma disease detection has been put into place, according to A. Soltani et al. [18].Ifthisdangerousillnessisnotdiscoveredintime, blindnessmayresult. Asaresult, we created a brand-new automated diagnostic system that is based on several image-processing algorithms that can extract the crucial information needed to identify this pathology. In order to givethemedicalpersonnelapreciseand trustworthy diagnosis,thisprogrammealsoincorporates adecisionsupportsystemcreatedusingtwodistinctartificialintelligencetechniques,probabilistic reasoning and artificial neural networks.

Summary:

Artificialintelligencecanbeincludedintothesystemtocategoriseo the reyedis orders. In order to beutilisedfortelemedicine, itmay alsobebuiltto automaticallycreateareport with allthepatient's data.

Somearemade tocreatereportsontheirown,completewith patientdata,sotheymay beutilised in telemedicine.

By including additional examples in both the training database and the validation database, we may continue to enhance the performance of the proposed system. In fact, if indeed the data of both the learning instances is modified, the neural net will generalise more well.

3. PROPOSEDMETHOD

This study suggests a model that uses a variety of extracting features and SVM + ANN Hybrid classifier approaches to diagnose glaucoma in fundus image pictures. The retinal fundus pictures were used as the source for further processing, which performed a detailed analysis of the those image sutilising 20 characteristics [15]. Results of the aboveglaucomaidentification for each data set, namelyretinaphotographs, may be both normal and glaucoma-infected. The proposedmethod is broken down into many phases, as seen in Fig. 2: input information, processing, extraction of features, dimension reduction, and classification.

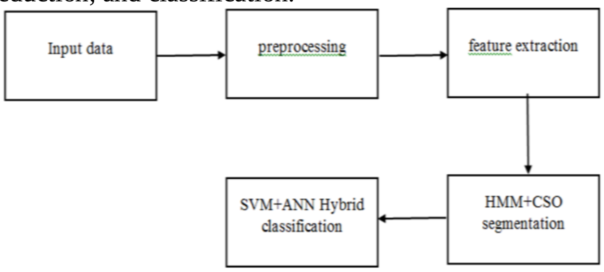

Figure 2. Block Diagram

Dataset

ORIGA-650 [18]: 650 fundus photographs taken from 482 healthy eyes and 168 glaucomatous eyes. Optic disc plus cup mask manual ground truths were also supplied. The ophthalmologists personally annotated every retinal image and optic cup mask.

RIM-ONE Version3 [19]:ThethirdRIMONEreleaseincludes85healthyeyes, 74 glaucomatous eyes, and 159 stereoscopic retinal fundus pictures. Two 2D retinal fundus photos taken from slightlydifferentperspectivesareputsidebyside to createastereoretinalfundusimage. Only the first (left) stereo retinal fundus picture from each set of stereo retinal fundus photos was used in thisstudy.Ophthalmologyspecialistshavesplitthemechanicaltruedataoftheeyeimageandcup. Alsofromdifferentsourcestotally10000imageswerecollectedamongthose7000wereglaucoma affected image and 3000 normal images. The proposed model is trained with 7000 images where 2250 normalimageand 4750 glaucomaaffected images and testing performed with 3000 images (2250 abnormal and 750 normal images)

FeatureExtraction

The glaucoma condition alters the structure of a picture, causing texture and intensity shifts. Because of this, glaucoma picture features are different from those of a normal image. These characteristics are retrieved and categorised as abnormal or ill. In the suggested technique, the Markov Random Domain and Grey Level Word co - occurrence Matrix are recovered.

Markov Random Field Least Estimates

Avisualmodelmadeup of stochastic process with Markov-like features is call eda Markov Field (MRF). The MRF model's primary goal is to accurately determine the distribution of picture intensity. The modelisadaptableandstochastictodiscoverthe textureoftheimageandanalyseit. The proximity of pixels is a key factor in determining the image's intensity and pixel position.

Theintensitiesofthepictureandsignificantimagepropertieslikelabels,textures,andimageedges may be used to calculate the Markov Random Field. In essence, it is an undirected graph.

The intensitiesofapicturearereregardedasrandomvariables. Thevaluesaretheintensitiesofboth the spatial neighbourhoods. A pixel array with an intensity value between 0-255 makes up the input picture. Using the Cartesian coordinates on the grid as, and the M*M lattice, P(Ys |allYr,r s)= P (Ys |Yr,whereriss'sneighbour)

The Hidden Markov Field is mostly utilised in the photo editing industry for tasks like texture analysis and picture segmentation. The suggested solution makes use of the Gaussian Markov Random (GMRF).

		7	6	7		
	5	4	3	4	5	
7	4	2	1	2	4	7
6	3	1	X	1	3	6
7	4	2	1	2	4	7
	5	4	3	4	5	
		7	6	7		

Figure 3. GMRFModelOrganization

The centre pixel of the GMRF model, shown in Figure 3, is referred to as X, and its surrounding pixels are identified by numbers. The neighborhood's rank is indicated by the numbers. The suggested solution takes into account the fourth order neigh bourhood.

Gray Level Covariance Matrix

To determine how frequently pixel pairings with specific values appear in a picture, the GLCM texture feature is represented in the matrix. It describes the connection between the intensities of individual pixels inside the specified neighbourhood. This approach is excellent for obtaining texture properties of an image since the matrices produced are big.

The many qualities of an image, such as contrast, correlation, energy, and homogeneity, are retrieved once the GLCM has been obtained. Contrast is employed to quantify variations, and correlations calculate the likelihood that a specific pair of pixels will appear. Homogeneity and energy both gauge how evenly the components are spread across the matrix.

4. SEGMENTATION

a) Combined HMM and CSO

In simpler Markov models, the soleparameters are the probability of state change; in contrast, the standing in the HMM is notreadilyob servable, buttheoutputbecomesobviousinaccordance with the state. A probability distribution across potential output tokens exists for each state. As a result, the tokens offered by the HMM offer certain details about just the status sequence, commonly referred to as the model theory. The model is additionally known as an HMM since these variables are exactly understood. The detection of temporal patterns such speech, handwriting, gestures, voice components, incidentalmusic, partialdiscards, and bioinformaticsis one of the main applications of HMM [20].

Cuckoo search optimization (CSO), a biologically inspired optimization approach developed by Yang and Deb, is based on the brood parasites of avian cuckoos. Typically, cuckoos don't build nests; instead, the ylayher eggs in the nests of certainhostbirds. The hostbirdwilleitherrebuild its nest or discard its eggs if it realises the chicks are not its own. A nest egg is regarded as a solution, while a cuckoo egg is regarded as a brand-new solution [22].Here, the optimal wavelet transformscalarvaluesarefoundusingthecuckoosearchopti mizationtechnique.Usingtrialsand errors values, a range of scalars is generated. Each solution is seen as a nest in CSO. 50 chicks within the range were created your application. Based on the Levystruggle, acuckoochoosesat randomanesttobuildanestinwhichtodepositeggs.Followingt heevaluationofthenest'sfitness via nest selection, cuckoo changes the rank of the nests based on fitness value [23].

Only each state and its ac companying seen object are necessary for HMM to function: In addition to getting a link with specific words, the sequence la belling also has relationships with other elements including the observed length, word context, and others. We are improving the HMM with Chopper search optimization to fix its shortcomings. Continuous non-linear optimization yields superior results for this optimizer.

Algorithm1.CombinedHMM andCSO Algorithm

1. IM iisamultidirectionalsub-image of Ib ,there forefirstcalculateIMi=HMM (lb).
2. InitializetheHMM parameterusing the firstequationand (2)
3. Thereare3columnsintheimagematrixIMi.
4. Repeatsteps1-3foreachcolumninthepicturematrix.
5. AdjustHMMparametersusingEquations(3)and(4)
6. Ifthereis avessel discontinuity,
7. ThepixelstateispredictedbyHMM.
8. Thefinalimageis IMF.
9. Randomlyinitialiseacolonyofnnest
10. whilenotmeetingthehaltingcriteriondo
11. UseLevyflightstopickarandomcuckooXi.
12. Pick anestXjat random.
13. IfF(Xi)issuperiortoF(Xj),then
14. Changejtothenew answer.
15. end
16. Use Levy flights to buildnewnests inplaceofsomeoftheinferiorones.
17. End

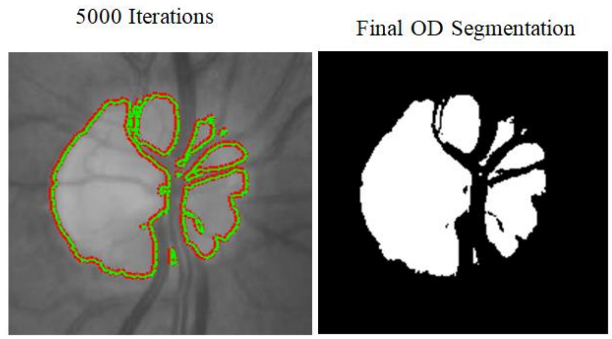

Figure 4. Potential segmented picture

SVM Classification

SVM is amachine learning approach used for supervisedclassification of binaryclasses. It makes an effort to linearly distinguish between two classes by fitting a hyper - plane through feature space. In actuality, the majority of information in the field cannot be separated linearly. If we employ the kernel functions, their separation will be most effective. The feature points can be mapped to higher dimensions using the kernel function. We have employed kernel functions with cubic, exponential, linear, and radial basis functions in this study [2].

Data must often be divided between training and testing groups when performing a classification job. Each instance in the training sethasa number of characteristicstoge the r with a goalvalue (the class labels) (i.e. the features or observed variables). We have employed a supervised learning approach called the vector support machine (SVM) classifier to distinguish between normal and glaucoma-affected ocular fund i. The objective of SVM is to develop a system (based on training data) that can predict the key parameters of the testing data given just the properties of test data [4].

Thetaskofimplyingafunctionfromlabelledtrainingdataisref erredtoassupervisedlearning.A collectionoftrainingexamplesmakeupthetrainingdata.Each examplepairinsupervised learning

H as the intended output value and the in put objects. An inferred function is created by as upervised algorithm for learning using the trainingexamplesandmay beused to mapping examples [1]. To identify between glaucoma-affectedandhealthyocularfundi, we employedasupervisedlearning approach known as the support vector machines (SVM) classifier. The objective of SVM is to predict the test data's target values simply based on its features. The changed input image matrix from the previous PCA and processing steps serve as the test data.

Data must often be trained and tested sets when performing a classification job. The training set has one target value per instance. We have employed a supervised learning approach called the relevance vector model (SVM) classifier to distinguish between normal and glaucoma-affected ocular fundi. The objective of SVM is to predict the target outcomes of the tests data given just the test data features (trainingdata). Test data arechange dinputimagematricesfromtheprevious phases' preprocessing and PCA procedures.

SVM is a helpful machine learning method for the classification process of discrete classes. To make an organizer choice between two classes, the approach fits a hyperplane over the feature space. It is actually impossible to linearlysegregatetheoverwhelmingmajority of data thatexists. The best way to separate them is through kernel functions. Use the kernel [10] to map facial landmarks to higher dimensions.

The generalversion of the SVM's decisionfunction,u(x),isas follows:

$$u(x) = \sum_{i} Naiyik(x, xi) + b \qquad (5)$$

The SVM develops the kernel, which is represented by the notation (x, xi), while a biding by the constraints aiyi=0 and 0=ai=A. The user-determined punishment time In a supported vector machine, the parameter A controlsgeneralisation performance. Only a small portion of s would be non-zero after the training. The classification SVM's structure is shown in Figure 5. The generalisation performance of optical character recognition, facial recognition, and text classification using SVMs has all been good. Additionally, it has been used to examine data on expression of genes, DNA, and proteins.

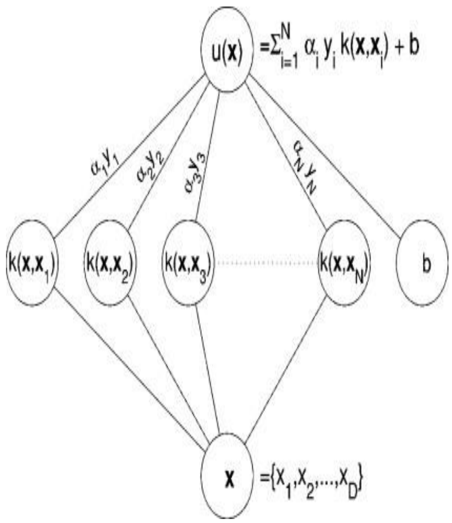

Figure 5. Are presentation of the SVM's classification architecture [13].

ANN

The back propagation algorithm was employed in this investigation. It is the training algorithm in neurons that is most frequently employed. To reduce the error function between the target output value and the network output value, gradient descent is used [18].

Three layers make up the suggested network: the input layer, which has five inputs and a biased, the hidden layer, which has ten neuron and a bias, and the final output layer, which has just one neuron. In Fig. 5, a feed for word network is depicted.

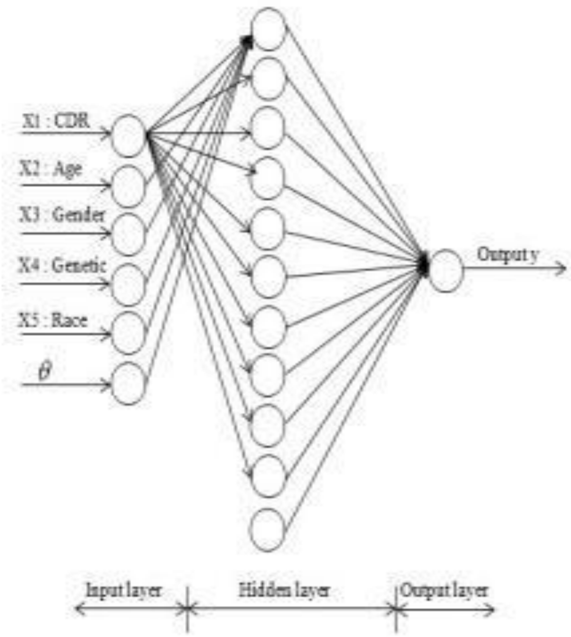

Figure 6.ThesuggestedANN'sstructure

The biases and weights are adjusted in this backward phase in accordance with the error slope vector. During the forward computing stage, an input pattern is applied, and the result is a network output vector. To direct the network's output toward the anticipated desired value, a targeted killingst is given to it [14]. Calculate the standard errors and gradientas follows, starting the with output layer and working your way back towards to the input layer:

$$w_{ij}^{l}(L+1) = w^{l}(L)_{ij} + \Delta w^{l}(L)_{ij} \qquad (3)$$

Wij (l) (L) is the current synapse weight where l=1,2...L(l)and j=0,1...L(l-1) are in the equation.

The revisedsynaptic weights designated Wij (l) (L+1), will be applied in the following geed-forward iteration. In neural network training, the term "period" refers to athoroughrunthrougheach of the training examples. We demonstrate the whole cycle of this phrase. The neural network's weights may bead justed on ceat the conclusion of the periodoraftereachsequence is given to the network.

Combined Hybrid SVM+ ANN Algorithm

SVM divides the pictures in the information source into a subspace using an ideal linear hyperplane. Maximizing the margin between two sets results in the ideal hyperplane. The final hyperplane is the reforedependen ton the boundarytrainingpatterns known as b as is functions. The back propagation technique was used as the ANN in this in vestigation. It is the learning algorithm in deep learning that is most frequently employed. To reduce the error function between the target output value and the network output value, gradient descent is used. To improve classification for glaucoma detection, we adopt a combined hybrid SVM+ANN algorithm.

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Algorithm2. HybridSVM+ANNAlgorithm
1. Addingdatatothe load
2. Establishcategoriestodividethedatasamplesintoglaucomaandnon-glaucomatous categories.
3. Select thetrainingandtestsetsof photos.
4. Gettingtheclassifierready.
5. DescribethehyperplaneH usedasthedecisionsurface.
6. Usinginputfeaturexiandvectorxforani-thfeatureinsidethefeaturespace,K(x,xi) denotes the internal vectors product of feature axes in the feature space.
7. Formachinelearning,thekernelfunctionischosenasapolynomialsinceitisnecessaryto satisfy Mercer's theorem.
8. ThedefinitionofthenonlinearSVMclassifierfunctionisf(x)=wTx+b.
9. ThedefinitionoftheasymmetricSVM classifieris f(x)=wT(x)+b.
10. Setthesynapticweightsinthenetworktoextremelylowrandomvalues.
11. Introducethelearningdatabase(input,output).
12. Distributetheinputsignalthroughoutthenetworkandcomputetheoutputafter that.
13. Dothetotalmeansquare calculation.
14. Theejlerrorwordreferstoajth neuroninthelthlayer.
15. ForL=1
16. Inwhichejl=(u-xjl)
17. Ifl=1,2,3,…L-1
18. Consequently,e jl=wij(l+1)s j(l+1)
19. $Thederivative of the activation function is sj(l+1)$.
20. Wij(l)(L+1) represents the new connection weights to be applied in the following feed- forward iteration.
21. Theneuralnetwork'sweightsmaybeadjustedfirstatthe conclusion ofthe period orafter any pattern is given to the network.

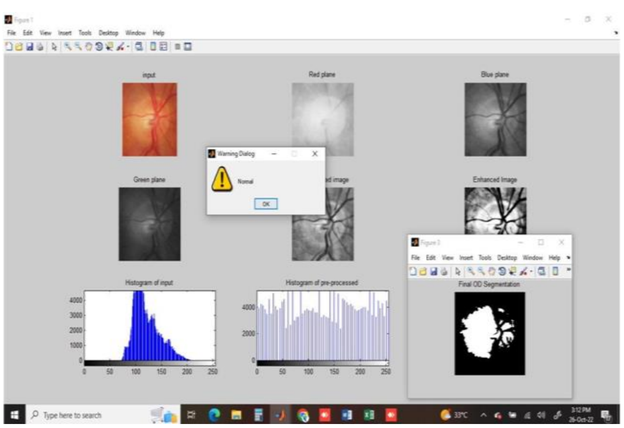

Figure7.Classificationofeyeimageresulting Normal

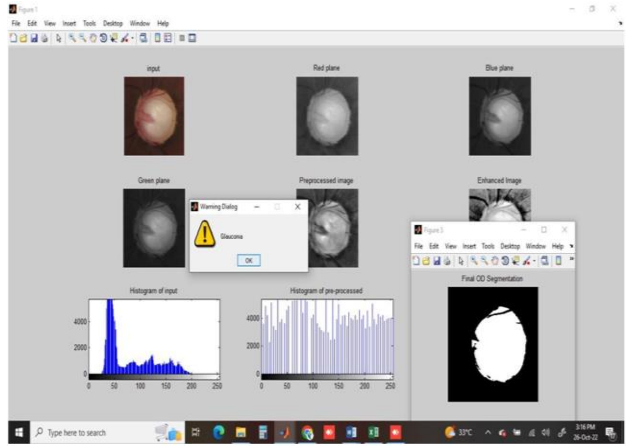

Figure 8.Classification of eyeimageresultingAbnormal-Glaucomaaffected

iv) Results:

Performance evaluation standards Utilizing the three fundamental performance requirements of specific, precision, and sensitivity, the effectiveness of the proposed technique was evaluated. Performance indicators include the following, as examples:

Metrics	TP	FN	TN	FP
Dataset	2724	26	732	18

Table 1.Confusion matrixresultingfromproposedmethod

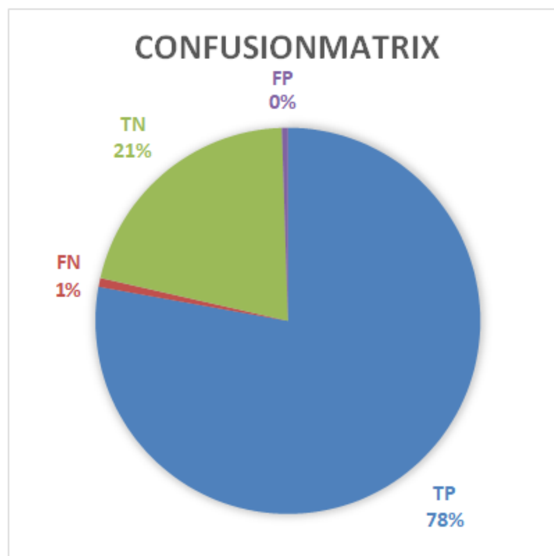

Figure 9.Piechart displaying confusion matrix parameters.

Specificity: A recognised TNR. It calculates the proportion of properly detected healthy test images. Here is the calculation:

$$SPE\ (\%) = TN/(TN + FP)x\ 100(4)$$

Sensitivity:ItisTPR.Itisdefined astheproportion ofglaucomatestimagesthatwere appropriately identified as having the condition. The equation reads as follows:

$$\mathrm{SEN}(\%) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}\chi 100 \qquad (5)$$

Accuracy:Itistheproportionofalltestimagesthatproperlyrecognised glaucomaandhealthy subjects. The equation reads as follows:

$$\mathrm{ACC}\ (\%) = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}\chi 100 \qquad (6)$$

Table 2.Validation Parameter

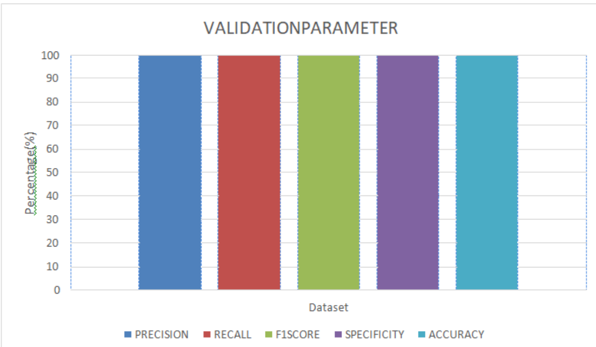

Figure 9. Bar chart displaying Validation parameters of proposed method.

TP, TN, FP, and FN areas follows:

Imagesclassifiedasglaucomaonesarethoseparticularimages .TP: True Positive. Images that fit into this category are those that are TN: True Negative, Healthy.
False Positive (FP), Imagesthathavebeenclassified asglaucomaphotographsarereallyhealthy images.
Photosofcataractsarerecordedasbeinginexcellenthealth, thereforetheresultisafalse negative.

Methods	Accuracy	Specificity	Sensitivity
VGG-19	92	86.5	93.5
CNN	87	84.5	90.5
LS-SVM	88.33	90	85
HMM-CSA-SVM	95	95	95
Proposed	98.34	96.53	98.84

Table 3. Comparison Accuracy, Specificity and Sensitivity among different algorithms

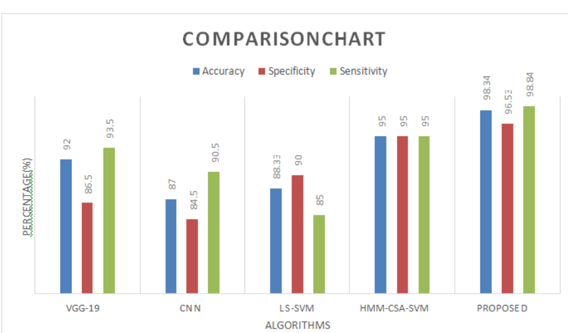

Figure10.Comparison Accuracy, Specificity and Sensitivity among different algorithms

From Figure 9 and 10 it is proved that the proposed algorithm performs well on all required aspects with high TP, TN and low FP, FN. Also validation parameters like precision, recall, sensitivity, specificity and accuracy of proposed methodology is high and all values are above 98% which proves the system is good. Finally in figure10, Accuracy, Specificity and sensitivity of proposed system compared with state-of-art methods and proved the

	PRECISION	RECALL	F1SCORE	SPECIFICITY	ACCURACY
Dataset	99.05	98.84	98.94	96.53	98.34

proposed methodology has better performance comparing to others.

CONCLUSION

In this study, we presented a unique hybrid algorithm for glaucoma diagnosis. In this study, we provideanovelhybridapproachforclassificationutilising Artificial Neural Networks(ANN)and supported vector machines (SVM). For segmentation, we used HMM with Cuckoo search optimization (CSO), and for classification, we employed a hybrid of SVM and ANN. When compared to other approaches already in use, the results demonstrate strong performance.

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