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PREDICTION OF HEART DISEASE USING RETINAL IMAGES BY NEURAL NETWORK ALGORITHM

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ABSTRACT

Retina of human eye can provide valuable information about human health using neural network .The state of the retinal vessels has been shown to reflect the health condition of body implement singular spectrum analysis to predict cross section profiles for detecting micro aneryms parts using knn classsifiers to classify the disease .so implement the neural network algorithm to predict the cardiovascular disease.

Keywords: Artificial Intelligence, Cardio Vascular Disease, Deep Learning, Fundus Image.

I. INTRODUCTION

The fundus image is the reflection of the interior surface of the eye, and it is normally recorded by image sensors, usually in three colors. It includes information about the observable biological structures, such as the surface of the retina, retinal vasculature, the macula, and the optic disc. The spectral range of the blue color enhances the visibility of the anterior retinal layers because the blood vessels and posterior retinal pigment layer absorb it. Meanwhile, the green spectrum is reflected by the retinal pigmentation, providing more information from below the retinal surface, and making its filters can improve the retinal layer visualization. The red spectrum is only related to the choroidal layer beneath the pigmented epithelium, and contains content about the choroidal ruptures, choroidal nevi, choroidal melanomas, and pigmentary disturbances. The human eye is an organ that takes in visual information in the form of focused light through light-sensitive tissues. When the light reaches photoreceptors that respond to spectral regions, the sensed information is converted to electrical signals, and they are transmitted via nerve fibers to the visual cortex of the brain. The signals are then interpreted as visual images in the brain.

Retinopathy refers to diseases that cause damage to the ocular structures, leading to vision impairment. The three most common retinopathies that affect people around the world have been introduced, and most studies have focused on these retinopathies. They are diabetic retinopathy (DR), age-related macular degeneration (AMD), and glaucoma. DR is a pathology related to abnormal blood flow, and AMD occurs because of the aging of the tissues in the retinal layers. The basic retinal image processing is shown in fig 1.

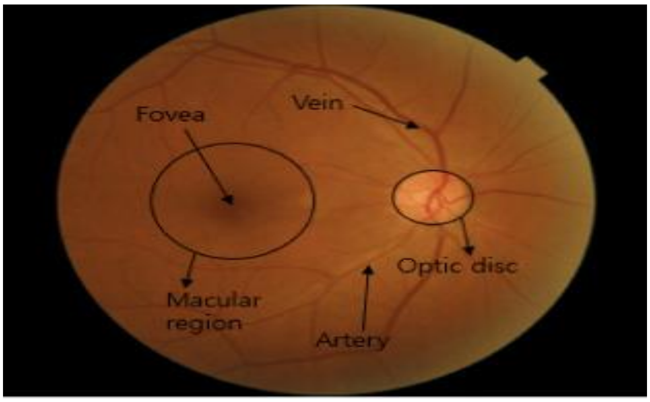

Figure1: Retinal Image Processing

MA: It is the most typical lesion and the first visible sign of DR. It is caused by limited oxygen supply. It appears in the form of small saccular structures represented by round red spots with a diameter of 25 to 100 μm.

Cotton wool spot (soft exudate): It is an acute sign of vascular insufficiency to an area of the retina found in early DR, and it is also called soft exudate. It appears as white patches on the retina, which is a result of damage to the nerve fibers due to the occlusion of small arterioles, and it causes accumulations of axoplasmic material within the nerve fiber layer.

Hemorrhage: Retinal hemorrhage refers to bleeding from the blood vessels in the retina caused by high blood pressure or blockage in arterioles. It ranges from the smallest dot to a massive sub-hyaloid hemorrhage. Depending on the size, location, and shape, it provides clues about underlying systemic disorders such as DR and AMD.

Hard exudate: Hard exudate is caused by increased vascular permeability, leading to the leakage of fluid and lipoprotein into the retina from blood vessels, which are represented as small, sharply demarcated yellow or white, discrete compact groups of patches at the posterior pole.

Neovascularization: When oxygen shortage occurs in the retinal region due to retinal vessel occlusion, the vascular endothelium grows to overcome the lack of oxygen. This new vessel formation can be extended into the vitreous cavity region and leads to vision impairment

II. RELATED WORK

Muhammad mateen, et.al,…[1] covered a detailed survey about the identification of diabetic retinopathy in the light of almost 150 research articles, summarized with the collection of retinal datasets, adoption of different kinds of methodologies to detect the diabetic retinopathy and select the performance evaluation metrics for the representation of their outcomes. Initially, retinal datasets are discussed and then several kinds of approaches have been explained to detect the retinal abnormalities including retinal neovascularization, hemorrhages, micro aneurysm, and exudates. Moreover, the role of evaluation metrics for computer-aided diagnosis (CAD) systems has been briefly discussed. Finally, the authors' observations have been demonstrated in the discussion to highlight the significance of deep learning-based approaches and also provided future directions for scientific researchers against research challenges in the area of diabetic retinopathy.

K. Shankar, et.al,…[2] presented HPTI-v4 model involves the segmentation process by the feature extraction processes based on histogram and Inception v4. For tuning the hyper parameters in Inception v4, the Bayesian optimization technique is involved. Finally, the classification processes are performed by the use of MLP. The experimental outcomes stated that the presented HPTI-v4 model showed extraordinary results with the maximum accuracy, sensitivity, and specificity of 99.49%, 98.83%, and 99.68% respectively. Therefore, the HPTI-v4 model can be employed as an automated diagnostic tool for the classification of DR images. A person affected with diabetes is vulnerable to kidney failure, loss of eyesight, bleeding teeth, lower limb confiscation, nerve failures, and so on. It also leads to a heart attack as well as stroke in diabetic affected individuals. The nephrons present in the kidney are damaged and leads to diabetic neuropathy while neurons present in the brain get damaged, and cause diabetic retinopathy (DR) which results in the retinal infection.

Along He, et.al,…[3] present a novel CABNet that combines CAB and GAB. CABNet can be trained in an end-to-end manner for fine-grained DR grading and learn discriminative features by the attention module. Extensive experiments on three datasets demonstrate that CABNet can achieve superior DR grading performance with different backbone networks, which shows the generality of our method. Our future work is to use generative adversarial networks (GANs) for synthesizing high-quality fundus images with labels. This is critical in the medical field since it is expensive to obtain annotated images. We could thus design a more effective model that can not only provide a grading score, but also indicate the lesion type. The attention blocks can be applied to a wide range of backbone networks and trained efficiently in an end-to-end manner. Comprehensive experiments are conducted on three publicly available datasets, showing that CABNet produces significant performance improvements for existing state-of-the-art deep architectures with few additional parameters and achieves the state-of-the-art results for DR grading.

Harshit kaushik, et.al,…[4] proposed to solve the problem of non-ideal illuminations in the retinal fundus images using the gray world algorithm and to develop an automated DR prediction system. A stack generalization-based ensemble model is prepared using three different CNNs. The performance of image normalization is measured using statistical metrics such as the PSNR and MSE of the original and enhanced images. The stacked ensemble model is an advanced technique of stacking different neural networks whose combined results are produced based on a fusion strategy that combines the best weights of the individual neural networks. Machine learning models are extensively utilized to classify and detect DR in fundus images. However, these techniques require suitable pre-processing and feature extraction methods to improve the results especially when the images are from different sources. DR images are generally taken from different cameras under different lighting conditions and to mitigate these effects we adopted an efficient color constancy technique. Extensive experiments are conducted to evaluate the performance of the proposed model in binary as well as multi-class DR classification tasks. Considering the obtained results using various evaluation metrics, we validate our model, which outperforms state-of-art models in binary and multi-class classification tasks.

Yi Zhou, et.al,…[5] promote research in medical image segmentation, classification, and transfer learning, particularly for the community of diabetic retinopathy diagnosis, in this paper, we proposed a large fine-grained annotated DR dataset, FGADR. Moreover, we conducted extensive experiments to compare different state-of-the-art segmentation models and explore the lesion segmentation task. Joint classification and segmentation methods were demonstrated to have better performance on the DR grading task. We also developed an inductive transfer learning method, DSAA, to exploit our DR dataset for improving ocular multi-disease identification. One-third of people living with diabetes have some degree of diabetic retinopathy, and every person who has diabetes is at risk of developing it. Accurately grading diabetic retinopathy is time-consuming for ophthalmologists and can be a significant challenge for beginner ophthalmology residents. Therefore, developing an automated diagnosis system for diabetic retinopathy has significant potential benefits.

S. Gayathri, et.al,…[6] implemented an approach for classifying DR is proposed in this work by integrating the features extracted using Haralick and ADTCWT. The extracted features using the proposed method made the classification task smoother. For performance analysis, the extracted features are given to four classifiers (SVM, Random Forest, Random Tree, J48) and evaluated the performance. According to the performance analysis, the Random Forest classifier with the proposed feature extraction outperforms all the other classifiers for the MESSIDOR, KAGGLE and DIARETDB0 databases. Thus the average accuracy of the system for binary classification is 99.70% and for multiclass classification is 99.84. The weighted average measures of accuracy, recall, F1 score indicates the efficiency of the classifier. Besides the other classifiers, the weighted average FPR is lower for the Random Forest classifier which shows the marked efficiency of the system. Thus it can be concluded that the proposed method with Random Forest classifier is clinically significant for binary as well as multiclass classification of DR than the existing methods.

Mohammad t. Al-antary, et.al,…[7] presented a novel deep learning model (MSA-Net) is proposed for the classification of the damage caused by DR on retina images. To improve the representation power of the network, the multi-scale attention mechanism on top of the high-level feature representation has been introduced. The multi-scale mechanism consists of the Atrous convolution which processed the input feature with different scales. The attention maps were produced with a series of convolutional layers. The attention maps were employed to focus on more informative parts of the multi-scale representation and suppress the weak ones. Furthermore, the multi-level and multiscale representation layers were included in the network to boost the performance. Training model in form of multitask learning achieved better performance than previous work described in the literature. The experimental results demonstrate the effectiveness and efficiency of the proposed model in diagnosing and classifying the DR disease.

Yi Zhou,et.al,…[8] proposed an effective high-resolution DR image generation model which is conditioned on the grading and lesion information. The synthesized data can be used for data augmentation, particularly for those abnormal images with severe DR levels, to improve the performance of grading models.Thus, large-scale generated data can be used for more meaningful augmentation to train a DR grading and lesion segmentation model. The proposed retina generator is conditioned on the structural and lesion masks, as well as adaptive grading vectors sampled from the latent grading space, which can be adopted to control the synthesized grading severity. Moreover, a multi-scale spatial and channel attention module is devised to improve the generation ability to synthesize small details. Multi-scale discriminators are designed to operate from large to small receptive fields, and joint adversarial losses are adopted to optimize the whole network in an end-to-end manner.

Eman abdelmaksoud, et.al,…[9] developed a novel ML-CAD system that can be applied on varied datasets to diagnose diabetic retinopathy grades. We used nine public benchmark datasets; DRIVE, CHASEDB1, STARE, HRF, IDRiD, DIARETDB1, MESSIDOR, and E-ophtha. At first, the proposed system filters and enhances the

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contrast. Then, it utilizes 11 texture feature descriptors by using GLRLM to determine the normal and DR images. Then, prepares the DR images by postprocessing steps for U-Net model. The U-Net model is trained four times on the four variations (hemorrhages, exudates, Blood Vessels, and microaneurysms). The system extracts 6 features; 2 for BV using GLCM with 11 descriptors and bifurcation point's count, 4 ROIs areas computations. The proposed ML-CAD system visualizes the different pathological changes and diagnoses the DR grades for the ophthalmologists. First, we eliminate noise, enhance quality, and standardize the sizes of the retinal images. Second, we differentiated between the healthy and DR cases by calculating the gray level run length matrix average in four different directions. The system automatically extracts the four changes: exudates, microaneurysms, hemorrhages, and blood vessels by utilizing a deep learning technique (U-Net). Next, we extract six features, which are the gray level co-occurrence matrix, areas of the four segmenting pathology variations, and the bifurcation points count of the blood vessels. Finally, the resulting features were afforded to an ML support vector machine (SVM) based on a classifier chain to differentiate the various DR grades

Teresa araújo, et.al,…[10] proposed a data augmentation scheme to compensate for the lack of PDR cases in DR-labeled datasets. It builds upon a heuristic-based algorithm for the generation of neovessel-like structures which relies on the general knowledge of common location and shape of these structures. The synthesized NVs can be introduced in pre-existent retinal images which can then be used for enlarging the datasets for training deep neural networks. The insertion of the NVs in the retinal images has in account the color coherence with the neighbour vasculature to ensure a realistic insertion. Experiments were performed to assess the influence of this data augmentation scheme in the training of a previous proposed model for DR grading, DR. Graduate. Results have shown that the PDR detection performance has improved, with NVs that were being missed by the model now being highlighted in the explanation maps. However, part of the PDR images is still not detected since they do not present NVs but rather pre-retinal fibrosis or pre-retinal hemorrhages, which were poorly learned by the model. NVs which present an unusual shape or that are too slight are still being missed by the model, likely due to its lack of representation in the generated dataset

III. PROPOSED METHODOLOGIES

Retinal imaging is a recent technological advancement in eye care. It enables optometrist to capture a digital image of the retina, blood vessels and optic nerve located at the back of eyes. This aids in the early detection and management of diseases that can affect both eyes and overall health. Vascular Diseases are often life-critical for individuals, and present a challenging public health problem for society. The drive for better understanding and management of these conditions naturally motivates the need for improved imaging techniques. Eye fundus is the interior surface of the eye, opposite to the lens and includes the retina, optic disc, macula and fovea and posterior pole. The proposed work is shown in fig 2.

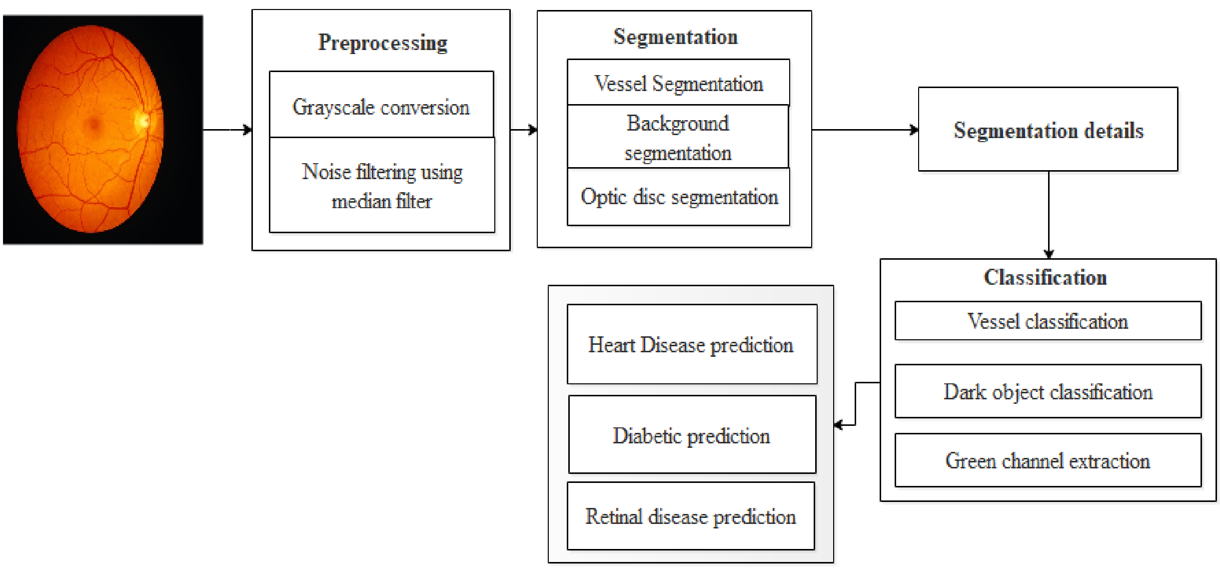

Fig 2: Proposed Framework

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3.1 DATASETS

The DRIVE database has been established to enable comparative studies on segmentation of blood vessels in retinal images. The research community is invited to test their algorithms on this database and share the results with other researchers through this web site. On this page, instructions can be found on downloading the database and uploading results and the results of various methods can be inspected. The data included in this database can be used, free of charge, for research and educational purposes. Copying, redistribution, and any unauthorized commercial use is prohibited. The use of this database is restricted to those individuals or organizations that obtained the database directly from this website. Any researcher reporting results which use this database must acknowledge the DRIVE database.

3.2 PREPROCESSING

Retinal images are acquired with a digital fundus camera which captures the illumination reflected from the retinal surface. The aim of preprocessing is to increase the quality of an image by reducing the amount of noise appearing in the image and highlighting features that are used in image segmentation. Despite controlled conditions, many retinal images suffer from non-uniform illumination given by several factors: the curved surface of the retina, pupil dilation (highly variable among patients), or presence of diseases, among others. The curved retinal surface and the geometrical configuration of the light source and camera, lead to a poorly illuminated peripheral part of the retina with respect to the central part. A large mean filter, large median filter and collectively are used for retinal image have used intensity channel values to detect the dark regions from retinal image personalized medicine. A recent systematic analysis has provided clear evidence supporting relationships between DR and complications of diabetes, including micro- and macro vascular conditions and events. Although many of these associations have been identified in cross-sectional and retrospective studies, several have been confirmed in prospective investigations based on multivariate analyses that controlled for the influence of traditional or other known risk factors. The most relevant risk factors for the development of DR are disease duration, a poor glycemic control (high HbA1c levels), and the presence of hypertension. Other risk factors for DR include higher body mass index, puberty and pregnancy, as well as cataract surgery. There is robust evidence regarding the relationship between blood glucose levels and the development and progression of DR. Diabetic retinopathy (DR) is the most frequent complication of diabetes. The main risk factors are disease duration, a poor glycemic control, and the presence of hypertension. However, there is an important variation in risk which indicates that other factors, such as genetic heritability or glycemic variability, play an important role in accounting for the susceptibility to DR development. Another important concept is that DR is an independent predictor of both microvascular and macro vascular complications. Thus, the presence of DR should be taken into account when evaluating the cardiovascular risk of a diabetic subject. Moreover, the evaluation of retinal neurodegeneration could help to identify those diabetic subjects at risk of cognitive impairment, an emerging complication of the type 2 diabetic population. When evaluating a diabetic subject, the awareness of the presence of DR has also therapeutic implications. In this regard, a worsening of DR could occur after a rapid improvement of blood glucose. In summary, a critical review on the importance of the presence of DR in the general management of subjects with diabetes is provided.

SPREAD SPECTRUM ANALYSIS

Through SSA significantly better data decomposition into subspaces is achieved. After applying SSA, the key characteristics and differences between the candidate profiles of MAs and non-MAs are more significant. The SSA technique briefly described below. SSA generates a trajectory matrix X from the original series x1 by sliding a window of length L. The trajectory matrix is approximated using Singular Value Decomposition. The last step reconstructs the series from the approximated trajectory matrix. The SSA applications include smoothing, filtering, and trend extraction. Two main steps of the basic singular spectrum analysis algorithm include decomposition and reconstruction

Decomposition:

The decomposition consists of embedding operation and singular value

Reconstruction:

Reconstruction In this step, the elementary matrices are firstly divided into a number of groups and summed within each group. Reconstruct the value based on singular spectrum using aggrupation component.

Aggrupation is the function to select which of the principal component that will not be used to reconstruct the series. For reconstruction we consider only part of total matrix.so we want to group the value based on minimum or maximum value of l and k. By using SSA we can decompose the original data into a set of principal components. The aim of this project to obtain the profiles of MA candidates without any noise. the smallest eigenvalues are regarded as noise and the largest eigenvalues belong to the signal subspace

3.3 HEART DISEASE PREDICTION -NEURAL NETWORK ALGORITHM:

Artificial Neural Networks (ANN) can learn and therefore can be trained to recognize patterns, find solutions, forecast future events and classify data. ANN is well documented to be used for traffic related tasks. Neural Networks learning and behavior is dependent on the way its individual computing elements are connected and by the strengths of these connections or weights. These weights can be adjusted automatically by training the network according to a specified learning rule until it performs the desired task correctly. ANN is a supervised learning method i.e. a machine learning algorithm that uses known dataset also known as training dataset. These known parameters help ANN to make predictions. Input data along with their response values are the fundamental components of a training dataset. In order to have higher predictive power and the ability to generalize for several new datasets, the best way is to use larger training datasets. The disease can be classified by using back propagation algorithm. Back propagation is a common method of training artificial neural networks so as to minimize the objective function. It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). The term is an abbreviation for "backward propagation of errors".

Constructing the CNN Model

function INITCNNMODEL (θ, [n1–5])

layerType = [convolution, max-pooling, fully-connected, fully-connected];

layerActivation = [tanh(2), max(),softmax()]

model = new Model();

for i=1 to 4 do

layer = new Layer();

layer.type = layerType[i];

layer.inputSize = ni

layer.neurons = new Neuron [ni+1];

layer.params = θi;

model.addLayer(layer);

end for

return model;

end function

Training the CNN Model

Initialize learning rate α, number of maximum iterationITERmax, minimum error ERRmin, training batches BATCHEStraining, batch size SIZEbatch, and so on;

Compute $n2$, $n3$, $n4$, $k1$, $k2$, according to $n1$ and $n5$;

Generate random weights θ of the CNN;

cnnModel = InitCNNModel(θ, [n1–5]);

iter = 0; err = +inf;

while err >ERRmin and iter<ITERmax do

err = 0;

for bach = 1 to $\text{BATCHES}_{\text{training}}$ do

[$\nabla\theta J(\theta)$, $J(\theta)$] = cnnModel.train (TrainingDatas, TrainingLabels), as (4) and (8); Update θ using (7);

err = err + mean($J(\theta)$);

end for err = err/BATCHEStraining;

iter++;

end while

Save parameters θ of the CNN

IV. PERFORMANCE RESULTS

In this paper, we can survey multiple classification algorithms for disease prediction in retinal images. Retinal images are collected from STARE and Drive Datasets. Different performance measures such as accuracy, sensitivity, specificity, error rate and precision can be derived for analysing the performance of the system.

True positive (TP): number of true positives - perfect positive prediction

False positive (FP): number of false positives - imperfect positive prediction

True negative (TN): number of true negatives - perfect negative prediction

False negative (FN): number of true negatives - imperfect negative prediction

Error rate

Error rate (ERR) is computed as the fraction of total number of imperfect predictions to the total number of test data. The finest possible error rate is 0.0, whereas the very worst is 1.0. Minimization of this error rate will be the prime objective for any classifier.

$$ERR = \frac{FP + FN}{TP + TN + FN + FP}$$

ALGORITHM	ERROR RATE
RANDOM FOREST	0.75
SUPPORT VECTOR MACHINE	0.5
CONVOLUTIONAL NEURAL NETWORK	0.4

Fig 3: Error rate

From the above graph, proposed CNN algorithm provide less error rate than the existing algorithm

Accuracy: Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} x\,100$$

ALGORITHM	ACCURACY
RANDOM FOREST	50%
SUPPORT VECTOR MACHINE	65%
CONVOLUTIONAL NEURAL NETWORK	80%

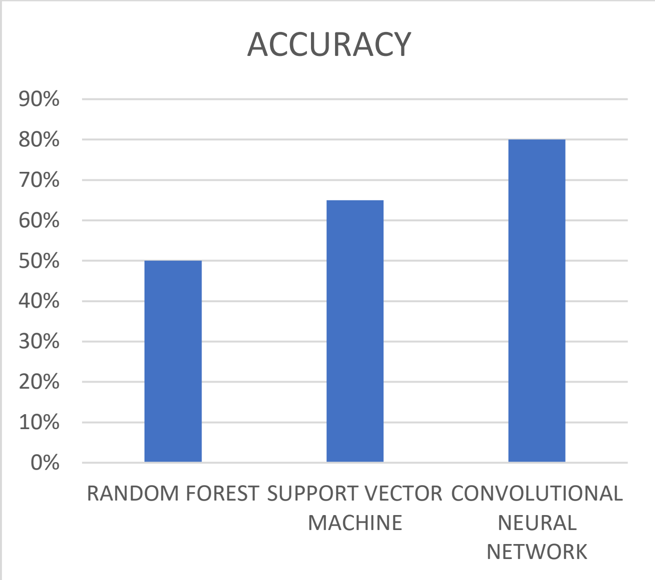

Fig 4: Accuracy chart

From the above graph, proposed CNN algorithm provide high level accuracy rate than the existing algorithm

V. CONCLUSION

We draw the conclusion that our suggested system worked effectively in identifying real vessels accurately and obtaining reliable retinal ophthalmology measurements. On an image-by-image basis, the proposed MA detection obtained good sensitivity and specificity. When this technique is incorporated into a trustworthy automated system for spotting anomalies in digital fundus images, this becomes very significant. The proposed candidate filtering approach can effectively exclude more candidates who are close to the vasculature and drastically lower the amount of non-MA candidates. We utilize a straightforward SSA technique to filter the profiles of MA candidates. And we carry out the vessel segmentation post-processing stage. Tracking all true vessels and locating the ideal woodland are done in this step. By simultaneously identifying the importance of using structural information for A/V categorization, we may overcome incorrect crossover diagnosis. With later vessel segmentation, it is possible to perform more advanced analyses, including measurements of the vessel lengths and diameters, classification of the veins and arteries, and calculation of the arteries-to-veins ratio, as well as a more in-depth examination of the analytical and predictive values of these features on eye disease and other systemic diseases. Also, we contrasted our strategy's introduction with other recently offered ways, and we came to the conclusion that our results were superior. The effectiveness of using structural information for A/V classification is demonstrated by the neural network-based technique with Convolutional neural network, which outperforms the accuracy of the SVM classifier by means of intensity features. Moreover, they enhance precision in retinal illnesses

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