The Impact Of Neural Network Techniques In The Optimization Of The Image Processing

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Abstract: Image processing is widely utilized recently in many applications of civilian lives and for various purposes. Scholars proposed and suggested various techniques of image processing. One of the main processing techniques is the neural network, which is the state of art in field nowadays. This paper aims to reveal the neural networks techniques in image processing types. Moreover, this paper focuses on the impact of the neural networks in optimizing medical image processing due to importance of medical imaging and the observed trends of utilizing digital medical imaging in the health sectors. In this context, the early diagnosis and detection of the eye has important role in the avoidance of visual impairment, due to the fact that around 45 billion people have visual impairments all over the world according to world health organization. For this reason, the current paper introduce new method based on image processing for vascular segmentation based on morphological active counter, the model input id the fundus images processed using filters techniques, then segmentation carried out based on morphological operations, fuzzy c-means and watershed transform. The output of such segmentation methods were given to the CNN. The optimized feature values are then extracted. The threshold value is set to compare this optimized feature values. From this, the best segmentation methods will be obtained.

Keywords: Neural Network, Image processing, Medical image.

1.1 Introduction

Image processing intervenes in various sectors and applications, and the advancement in the image processing and computer vision influence these sectors and applications;for example the image processing advances the automatic diagnostics of diseases (Ahad, Kobashi, & Tavares, 2018). The image processing includes any forms of signal processing, which its input and output are images or a set of image features or parameters(Raghav & Raheja, 2014). Image processing also defined as wide terms cover any operations of enhancement, correction, analyzing, manipulating or rendering images(White, Pharoah, & Frederiksen, 2004). Stelt defined the image processing as procedures operated on computer devices, which induces changes and variation on saved digital image(Stelt, 2005). The digital images are those images consist of brightness and darkness spots, which constitute of a group of cells located in rows and columns, these cells called "pixels"(Gormez & Yilmaz, 2009). Mathematically, pixels is the amplitude of the image at specific coordinate positions (x,y), determined by the function $f(x, y)$ for each elements in the M×N dimension matrix(Pereira, Morais, & Reis, 2017; Pandele, Budescu, & Covatariu, 2015)

However, the complexity image processing operations increased due to the popularity of digital cameras, multitude photo editing suites, and the growth needs for professional image auditors(Deever, Kumar, & Pillman, 2013). Further, recently the machine vision and image tools and devices has been installed in most daily life equipment such as vehicles for civilian uses, consequently, the size, cost and weight of the image related devices has been reduced gradually(Yang, Prasher, Landry, Ramaswamy, & Dittommaso, 2000).

Accordingly, computational and mathematical methodologies and technologies were adopted for image processing. Artificial neural networks (ANN) are the state of art in the image processing nowadays, that overcome and eliminate the complexity issues faced scholars and technicians by interpreting image precisely and quickly(Yang, Prasher, Landry, Ramaswamy, & Dittommaso, 2000; Vijayan, Vijayan, & Sudhee, 2017). In this paper, attempts to discover the contribution of ANN technology in image processing optimization of the medical images.

1.2 Artificial Neural Network (ANN)

Artificial neural networks simply are group of small processing units known as "neurons". Basically, the ANN works on defining a relation between input and output of the system through defined neurons(Rebizant, Szafran, & Wiszniewski, 2011).ANN inspired by the approach of biological nervous system such as brain, also, ANN stimulates the learning process that people do, mean learning by previous experience (example), as well as, the adjustment to the synaptic connections that exist between the neurons(Charles, et al., 2011).

ANN utilizes the potential powers of the mathematical model for information processing (Sibanda & Pretorius, 2012). Neural networks can be either simple neural network or conventional neural network(Poletaev, Pervunin, & Tokarev, 2016).

1.3.1. Simple Neural Network

Simple neural networks structure embraces various neurons composing layers, where each neurons in the distinct layer interconnected or linked to corresponding neurons in the successive layers that varies in the connectivity coefficients, which reflects the strength of the connections(Charles, et al., 2011). The simplest form of the Ann consists of the input layer projected directly to the output layer neurons but vice versa is not correct. Thus it is called feedforward type, as shown in the figure, where no computational operation occurred on the input layer, only the computational occurred in the output layer that explained name of single –layer model (Haykin, 2009).

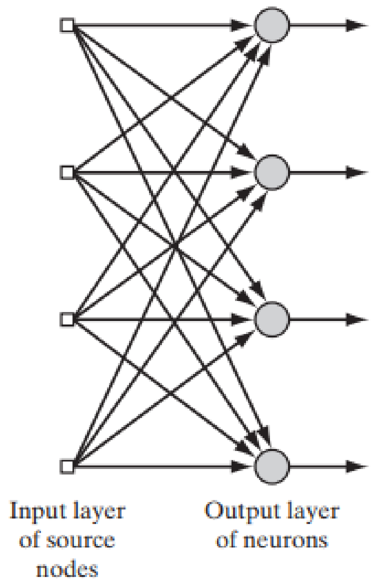

Figure 1. Simple ANN (single layer ANN)**(Haykin, 2009)**

1.3.2. Conventional neural network (CNN)

Deep neural networks are known as Conventional neural networks, which widely used in the recent application and pattern recognitions fields, achieving satisfactory and unprecedented performance(Dai, Tan, & Zhan, 2017)like the brain, the CNN passes information through successive layers of pre-processing, which each specific layer performs distinct operation(Poletaev, Pervunin, & Tokarev, 2016). The CNN is one of the multi-layer feedforward networks, which composed input layer output layer in addition to set of hidden layers, which gain "hidden" name because it be observed directly from neither input layer or output layer(Haykin, 2009). The figure below, illustrates the three layers perception of the multi-layer neural network, where the hidden layer number in the network structure depends on the purpose functionality of the network(Charles, et al., 2011).

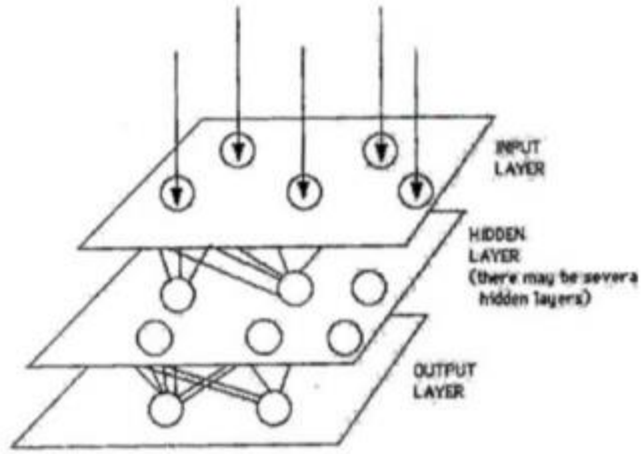

Figure 2. Multi-Layer Neural network (Charles, et al., 2011)

CNNs composed various structural forms of max pooling layers, conventional layer and fully connected layers in addition to the simple form layers, where the connectivity between neurons of successive layers managed by spatial local correlation pattern.conventional layers are the alternative of the max pooling layers, fully connected layer which performed the feature extraction operation for the previous layers(Hu, Huang, Wei, Zhang, & Li, 2015). Conventional neural network architecture is effective due to three main properties(Alaslani & Elrefaei, 2018):

- Local receptive fields: which each neuron input in the current layer is a small part of the prior layer that share same size.

- Weight sharing: weights is parameterization indicators for layers, where each location of the input has the same weights, which used for reducing the complexity and administering the capacity.

- Down sampling operation: which perform nonlinear operation in order to reduce the spatial size of the input (in the current case: image), in same time, minimizing the free parameters number for layers. Down sampling performed in the pooling layer.

Learning is another main concept in CNN that contribute the success of the CNN. The learning either can be supervised or unsupervised(Haykin, 2009). Supervised learning is stimulate the learning with knowledge of input and output examples, which provide the system with the expected and desired response for the training set, and the differences between the expected output and the output in the training stage is called the error. These errors support the iterative step by step enhancement of the system called error back-propagation in order to emulate the optimal and expected response (output). Learning in such based on two forms: forward or backward. In forward pass, the output of network at the end is compared to the desired response, and error is defined for neuron without changing thesynaptic weights. Whilst, in the backward pass the error of the neuron calculated for each layer and propagated back word through network that induceschanging on the synaptic weights(Sathya & Abraham, 2013).

Unsupervised Learning which describes the cases where there is no prior knowledge available, and learning occurred based only on the local information thus it called self-organized form. The network self organizes the data and drives its features. The unsupervised is performed on-line (the training and operation phase are synchronized) contrary to the supervised learning which performed off-line which mean that the learning and operation phase are different and distinct(Charles, et al., 2011).

1.3 ANN in Image Processing

The digital images processing classified in five groups; image restoration, image enhancement, image analysis, image synthesis and image compression. The image restoration is about pre-processing the image to be suitable for viewing which mainly occurred in manufacture side and cannot be manipulated(Gormez & Yilmaz, 2009). Image enhancement is a set of procedure and processing made on image feature to adjust its visual appealing such as reducing the noise, adjust brightness and reducing unsharpness(Singh, Singh, & Kaur, 2013). Image synthesis is about developing high-dimensional display of the specific object in the image that been lost in normal radiographic projection such as light fields or time-varying light fields(Heide, Wetzstein, Raskar, & Heidrich., 2013). Image analysis is about extracting specific information from the image for defined purposes (Wu, Lester, & Cloke, 2006). Image compression that referred to reducing procedure of the data represented the image without impact the quality of the image(Chawla, Beri, & Mudgil, 2014).

(PU & LIN, 2002)proposed a neural network based adaptive interpolation scheme for edge oriented, composed a fuzzy decision system based on human visual system features, mean that the pixel classified either to sensitive class or non-sensitive class based human perception. The learning of the neural network in the model is supervised learning method; the proposed module results compared to the bilinear interpolation model, found that the proposed system over performance the bilinear interpolation in term of smoothness, edge sharpness, and the visual quality. Further, (Bhutada, Anand, & Saxena, 2011) proposed model of image enhancement the computational performance of denoising through utilization adaptive learning step size, which tuned the thresholding parameters. The step size of wavelet transform changed based adaptive thresholding based neural network learning step size. The model proposed for enhancement the edge preservation feature and became free of noise compared to the proposed adaptive thresholding function based on wavelet transform based thresholding neural network (WTTNN) method, introduced by (Nasri & Pour, 2009), which suffer from high sensitivity to noise. Thus the work of Bhutada, Anand, & Saxena based learning neural network enhance the computational performance of the image as well as denoising and edge preservation performance.

In image restoration, neural network used widely in various and different architecture range from relatively straight forward- such as (Greenhil & Davies, 1994) which used a regression feed-forward network to reduce the noise- to complex multilayer model such as (Debakla, Djemal, & Benyettou, 2014). Debakla, Djemal, & Benyettou proposed a multilayer neural network to reduce the total variation due to noise exposure the image.The ideal mainly based on weights in neural network to reduce appropriate functional and get optimal solution, the proposed model exhibited high performance restoring geometric properties such as corners and edges, the result outperformed the Tichonov regularization, ROF proposed by (Rudin, Osher, & Fatemi, 1992) andMultiscale Neural Networksuggested by (Castro, Drummond, & Silva, 2008). The last mentioned model, used the ANN and local spatial information, composed two phase modified Kohonen neural network to clusterize the training data set, then the multilayer neural network used to recover the inverse reconstruction model.

(Ahn & Cho, 2007) combined the two state of art methodologies in denosing technique fields, non-local self-similarity (NSS) prior based methods and convolutional neural network (CNN) based methods, in order to obtain high quality restoration without noise. The proposed combination entitled blockmatching convolutional neural network (BMCNN) method shows better performance compared the existing CNN based method especially in the case of images with regular structure.

Regard the image compression, there are two main paths of related approaches; direct pixel base encoding l decoding using one ANN or the pixel based coding/decoding based on a modular approach. Accordingly, various types of ANN networks trained to perform compression such as Self-organization Map (SOMs), which composed of input and one output layer.(Boopathi & S.Arockiasamy, 2011)usedmodified SOM based vector quantization, where each node in the input linked directly with ine node on output layer via adaptive weight. The adaptive weights induce codebook for vector quantization. The proposed module achieved better PSNR and reduced the mean square error of the image compression techniques compared to standard SOM. Moreover, deep learning one of advanced learning that neural network adopted, such as (Z.Watkins & R.Sayeh, 2016) which utilized the deep learning neural network for both image data compression and correction the noisy channel capability. The model first deploy DNN with Levenberg-Marguardt learning algorithm for compression function; the module represented effective quality restoration image with less computational capacity compared to the DCT Zonal coding, DCT Threshold coding, Set Partitioning in Hierarchical Trees (SPIHT) and Gaussian Pyramid, also the model provides a superior error-correction transmitted binary via Hamming and Repeat-Accumulate coding.

However, the combined approaches considered one of the recent forms of the image compression techniques. The multilayer neural network combined the quick microorganism swarming approach, the simple ANN model combined with Fast Bacterial Swarming Algorithm –FBSA, which enhance the performance and sensitivity. In addition, the adaptive weights in neural network optimized the square measured of FBSA (Chandra & Mishra, 2015).

1.4 ANN in Medical Image processing

Medical Imaging nowadays is essential part in the clinical practices, either for educational purposes or for diagnosing purposes. Consequently, the using of medical images has been gradually increases in last years, for example the computed tomography - CT scan raised from 76% to 90% in 2006(Powell, et al., 2017). Further, the clinical utilization in emergency department of the medical imaging considered superior diagnostic approach and supportive earlier treatment, (Hu, et al., 2016) Found that the utilization of CT scan in the emergency department in Taiwan was increased from 11.10% to 17.70% in the five years period from 2009 to 2013.

The earlier form of medical imaging was acquired via radiological films, compared to the recent imaging that acquired digitally; consequently increasing the utilization trends of medical imagining. Comparing the CT scan of thorax, early cost 25 slices of 10 mm thickness film slices, while now cost 600 Mega byte (MB) to 1 Giga byte (GB).Hence, the health institute has to secure a large datasets and long term preservation, in this context image processing play a facilitating role in reducing medical image size through compression techniques(Liu, Hernandez-Cabronero, Sanchez, Marcellin, & Bilgin, 2017).

Another issue related the medical imaging, is the issue of increasing and improving the quality performance of health analysis based imaging and the automatic diagnosing, which largely advanced the medical healthcare providing for the betterment of civilian life(Ahad, Kobashi, & Tavares, 2018). Various approaches of image processing lay under the umbrella of healthcare advancement.

1.5.1. Detection

(Egmont-Petersen, Schreiner, Tromp, Lehmann, Slaaf, & ARts, 2000)argued the importance of Leukocytes-vessel wall in the human defense system against infections and reacting with inflammatory stimuli. The Leukocytes-vessel wall studied through using intravital video microscopy in environment of vivo animal experiments. Video transformed as sequence of digital image, thus authors proposed a method for detection the Leukocytes in these images using a neural network. The training phases adopted synthesized leukocyte images. Model enables inducing Leukocytes images in various conditions of lighting, shapes and sizes. The model recorded higher performance number compared with normal neural network trained on real image of the Leukocytes.

Another registered utilization of image processing – image analyzing- is defined in the field of cell identification for disease detection purposes as supportive and complement of medical experts advices. (Xu, Papageorgiou, Abidi, Dao, Zhao, & Karniadakis, 2017)conducted the Sickle cell disease (SCD), which classified as hematological disorder that causes blood vessel occlusion, painful episodes, and death. The most distinguished characteristic of the SCD patient is the RBCs properties such as shapes and others bio-mechanical and so forth. Thus, authors proposed high –throughput RBC shape quantification and classification model based on three basic stages. First stage based on RBC extraction automatically in order to investigate the ROI – RBC region. Second phase includes segmentation of the RBC in to unified normal size, and next the third stage of classification RBC based neural network method. Conventional neural network is the NN used for this purpose due to its ability to handle non-linear and complex pattern. Then the shape factors were investigated in order to build general multi-scale shape code. The model achieved 91.01% classification accuracy of RBC and high precision rate.

1.5.2. Object detection

(Xue & Ray, 2018)used the conventional neural network based deep learning in order to automatically detect specific types of cells in the microscopy images. The neural network depends on the encoding of the output pixel space, which referred to the pixel location of cell center. Then the random projection converted the encoding output pixel into fixed dimension vector (decoding the output of the CNN). The proposed method compared with various previous conventional method such as model based CNN proposed by (Malon & Cosatto, 2013)for classification mitotic figures, and (Shadi, Christoph, Felix, Vasileios, Stefanie, & Nassir, 2016) model for annotation biomedical images. In this context, the proposed model outperformance the system and achieved higher F1-score.

In addition, (Shi, 2018) utilized the CNN model for Lung Nodule detection purposes, which used as facilitating to diagnosis lung cancer from the computed tomography - CT scan image. The cancer diagnostic considered a challenge due to the size variation, location variation, shape variation and density of nodules from case to another. The suggested model tested on the Lung Image Database Consortium (LIDC) database.The system achieved 95.8% accuracy rate. In same context,(Khosravan & Bagci, 2018) used the three-dimensional CNN model for Nodule detection in Lung CT scan. The model composed 3D-CNN with dense connection without any prior pre-processing stages. The model tested over publically available 888 CT scans from LUNA challenge dataset achieving high sensitivity reach 97.2% outperforming existence literature.

1.5.3. Diagnostic purposes

Neural network also used for early and fast diagnostic dangers and fatal diseases.(Mehdy, Ng, Shair, Saleh, & Gomes, 2017)revealed that the neural network based medical image processing for early detected the cancer in breast is rarely discussed in the literature, where the automatic detection is requiredin order to upgrade the conventional diagnoses of medical imaging by professional radiologist. There is a need for model that minimizes the time required for diagnosis, and increases the diagnosis accuracy. In this context, the most utilized structure for breast cancer disease is the combined structure of ANN networks.

(Hosseini-Asl, Gimel'farb, & El-Baz, 2016)used the three-dimensional conventional neural networks applied on the ADNI MRI images for early detection of Alzheimer's disease (AD). The conventional neural network depends on the feature of brain structure in the MRI and detecting AD – related features such as ventricles size, hippocampus shape, cortical thickness, and brain volume. The proposed model built over three dimensional conventionalautoencoder, the system evaluated using the ADNI MRI dataset, shown that proposed system outperformance the (Suk & Shen, 2013) proposed system, which based on selected multi-modal feature information with a multi-kernel Support Vector Machine (SVM) learning. The 3D-CNN model accomplish 99.3% compared to

95.9% accuracy in the (Suk & Shen, 2013) system, also the 3D –CNN shown more robustness and confidence of the AD predictions.

Further more, CNN were used for heart disease diagnosis purposes. For example, (Wang & Kong, 2016) using conventional neural network to predict the heart volume based on two-dimensional MRI images, the proposed system depends on the pre-trained VGG and self-trained networks previously introduced in (Simonyan & Zisserman, 2014). The CNN structure composed pre-trained VGG-19, then reshaped 3D, then the self-trained network. The model tested over Continuous Ranked Probability Score –CPRS, evaluating 8 models of structures, where the model embraces of Conv-vgg:15-Convl(fixed)+1-convL(64,4,3)(train)+Fc (128,256,600,1)(train + reg (I2:1 e-1)) layer structures showing higher performance over the rest seven models to detects cardiac end-systolic.

Accordingly, the CNN networks also used for early diagnosis heart diseases utilizing the abnormality of heart sound detection, as shown in the (Humayun, Ghaffarzadegan, Feng, & Hasan, 2018)., who are proposed the CNN structure composed the Finite Impulse Responses (FIR) Bandpass filter, followed by the CNN model utilizing time-convolution (tConv) layers in order to make the FIR filter parameters learnable. The suggested model adopted PhysioNet/CinC 2016 dataset. The prposed combined model achieved 9.54% optimization of the overall accuracy of the FIR filter bank state of art.

1.5 Method

In this model images of retina are processed used of digital image processing tool, where the object are detected then processed,The problem of detecting edges in images can be distinguished as a fuzzy logic problem. The preprocessing technique is realized for removing the noise signal that are existed in the image. Resizing of the image is performed in this step. The filtering technique is then utilized to remove the blur present in the regions of image. By utilizing the canny edge detector, the edges are extracted and detected. In the canny edge detector, the Gaussian filtering is processed automatically. After that the segmentation of the image is achieved with the help of morphological factor, fuzzy c-means and a watershed shed transform techniques. The performance of the systems is estimated for yielding the estimation regarding the accuracy of the detection system. Following is the general flow of the proposed model.

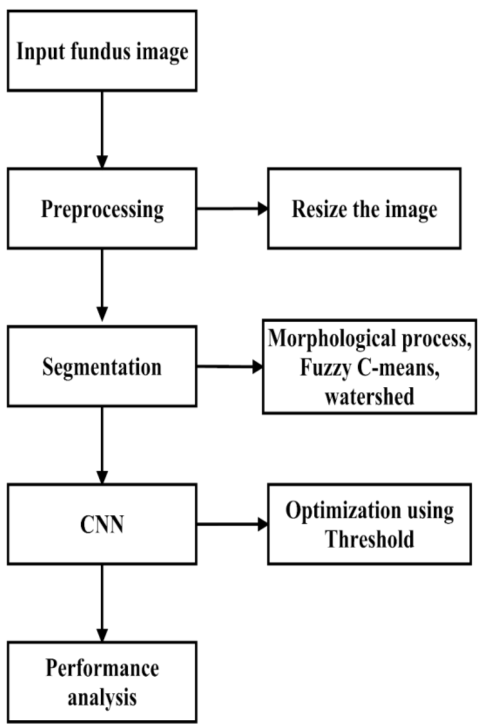

Figure 3.Overall flow of the proposed system

The morphological steps in the segmentation process involves the automatic filtering of the image and then uses a gradient and the intensities of edges for the feature extraction technique. Consequently, in the CNN the optimization methodology was performed with the help of threshold level. A level of threshold is considered for determining the optimization of the image. The images are optimized according to the threshold level. Finally, the performance analysis is made to estimate the optimized values in the image

- Pre-processing stage: the purpose of this stage to remove the excessive noise in the image in order to enhancing the image quality. The main tools used for this purposes are the filers. The Gaussian filter, which is a smoothing filter utilized to enhance the images that are blurred andto eradicate factor and noise, following is describes the Gaussian filter flow.

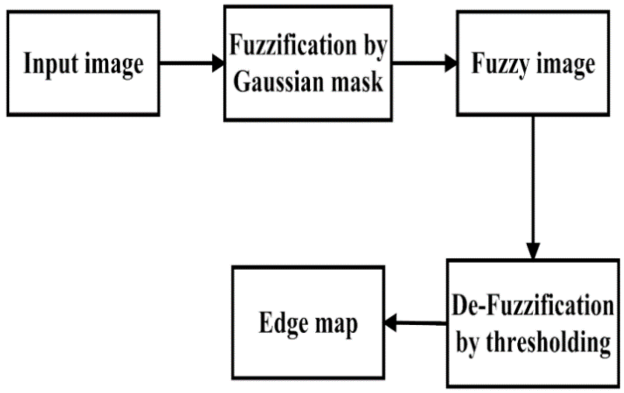

Figure 4. Flow of the Gaussian Filter

- Segmentation Stage: should be made by using a canny edge detector which in turn automatically performs the filtering process, which done by detecting the edges of the image on considering the gradient and intensity level of the edges in the preprocessed image.The idea of Canny filter detection of indicators is cast-off to perceive piecewise direct divisions of blood vessels in these images. To recognize the area of interest for blood vessel organization, it is vital to find the optic disc originally. This procedure of Gaussian filter is accomplished to discover encompassing construction in the blood vessel which is to appearance of irregular indication. Thus,in order to construct a whole retinal image analysis system that will support & recover the broadcast of diabetic retinopathy**.** **Morphological steps,**which used for edge detector purposes,The Canny edge detector is extensively utilized in computer visualization to discover sharp amount variations and to discover objective limits in an image. The Canny edge detector categorizes a pixel as an edge when the gradient level of the pixel is superior to those of pixels at together its edges in the course of extreme intensity alteration. In this paper we will display that significant edges in this way bases some evident limits to be unexploited. We will also display in what way to study the canny edge detector to expand its recognition accurateness.Then edge detection is achieved on the morphologically activated image. Gaussian operator perceives the blood vessels precisely. Then thresholding is achieved on the edge identified image. The blood vessel limits are dispersed to a solitary route size. Formerly the blood vessels are levelled. Smoothing function is cast-off to level the dispersed image for the improvement of blood vessel abstraction. The smoothing is accomplished by means of box technique with window size. **WATERSHED**The Watershed Transform is a single method to segment several images that customs a kind of area emergent technique created on an image gradient. The conception of Watershed Transform is constructed on imagining an image in three extents: two spatial organizes against gray intensities.**Fuzzy C Means based segmentation**utilized to reduce the objective function that fits to the clusters objective function algorithms. When the algorithm is capable of reducing an error function is mostly referred to as C-Means in which the term C denotes the number of clusters or classes. Fuzzy C Meansapproach utilizes a fuzzy membership which allocates a grade of membership for every class.

- CNN Stage: Convolutional Neural Networks are same as that of the ordinary Neural Networks which is made up of neurons that encompasses biases and weights that are learnable. In this network system, each neuron obtains some inputs which helps to perform an operation of dot product and monitors it with an option of non-linearity. The entire network articulates a distinct variable score function from the raw image pixels on one end to the class scores at the other end. three major kinds of layers are utilized to construct an architecture of CNN such as Convolutional Layer, Pooling Layer, Fully-Connected Layer.

1.6 Results

The performance of the system was evaluated using the following parameters such as: sensitivity, specificity, accuracy, precision, recall, Jaccard and dice coefficients. The image applied for analysis shown in appendix.

ROC parameter: The Receiver Operating Characteristics (ROC) is a plot of sensitivity and specificity, which is used to compare the diagnostic tests.Moreover, it is mainly used by the medical researchers, which contains the components like area under curve, specificity at specified sensitivity, and sensitivity at specified specificity.Figure bellow shows the ROC of the implemented method, where the x −axis signifies the 1-specificity, and y −axis indicates the sensitivity. It is fully depends on the values of sensitivity and specificity, so it is highly independent of the occurrence of disease. Then, it helps to identify the required value of sensitivity with the fixed value of specificity.

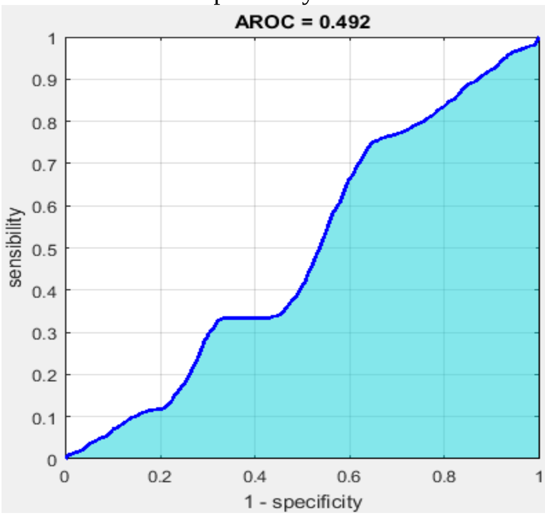

Figure 5. ROC analysis

SENSITIVITY, SPECIFICITY AND ACCURACY

The measures of sensitivity, specificity, and accuracy are extensively applied for evaluating the segmentation techniques. Sensitivity is termed as the proportion of true positives which are accurately classified by a test, and the sum of true positive plus false negative. Likewise, specificity is termed as the number of true negative outcomes that are divided by the sum of the number of true negatives and false positives.

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

$$Accuracy = \frac{TN+TP}{(TN+TP+FN+FP)} \quad (3)$$

The proposed model 's parameters compared to the ANN parameter are shown in table:

Table 1. Accuracy, sensitivity and Specificity of the propsed model

Techniques	Accuracy	sensitivity	specificity
ANN	87	94	80
proposed	89	96	86

PRECISION AND RECALL: Precision and recall are the pixel based measure that utilizes the confusion matrix for analyzing the performance of the optimization techniques. Also, it is the widely used measures in an information retrieval and pattern recognition applications. In which, the precision is calculated by a percentage of true positive pixels which are accurately extracted

$$Precision = TP\,/(TP + FP) \quad (4)$$

The proposed model parameter compared to the ANN parameter are shown in table.

Table 2.Precision and Recall of the proposed model

Techniques	precision	Recall
ANN	83	62
proposed	89	71

JACCARD AND DICE COEFFIICENTS: The Jaccard and dice coefficients are utilized to estimate the similarity between two images, which are widely used on medical image processing applications for estimating the performance of the segmentation mechanisms.

$$Jaccard = \frac{|X \cap Y|}{|X \cup Y|} \quad (5)$$

$$Dice = \frac{2|X \cap Y|}{|X| + |Y|} \quad (6)$$

Table 3. Dice , Kappaand Jaccard Coefficients of the segmentation mechanisms in proposed model

Methods	**Dice**	**Kappa**	**Jaccard**
Morphology	0.92	0.83	0.84
watershed	0.95	0.86	0.86
Fuzzy C	0.98	0.96	0.92

As shown in table above, the performance analysis for the values of dice, kappa, and dice co-efficient for the three methodologies like morphological operations, watershed transform and Fuzzy c-means algorithm. On estimating this three values the optimization values are found and the selection of best optimal algorithm is chosen for the process of segmentation. The morphological operations yields the value of 0.92 for dice co-efficient, 0.83 for kappa co-efficient, and 0.84 for the jaccard co-efficient. Likewise, the watershed algorithm offers a value of 0.95 for the dice co-efficient, 0.86 for the kappa co-efficient, and 0.86 for the jaccard co-efficient. Similarly, the fuzzy c-means clustering is capable yielding the values of 0.98 for the dice co-efficient, 0.96 for the kappa co-efficient, and 0.92 for the jaccard co-efficient. From this analysis it is evident that the fuzzy c-means methods provide a better result on compared to that of the other two morphological and watershed transform. (the output of each segmentation tool shown in figure below).

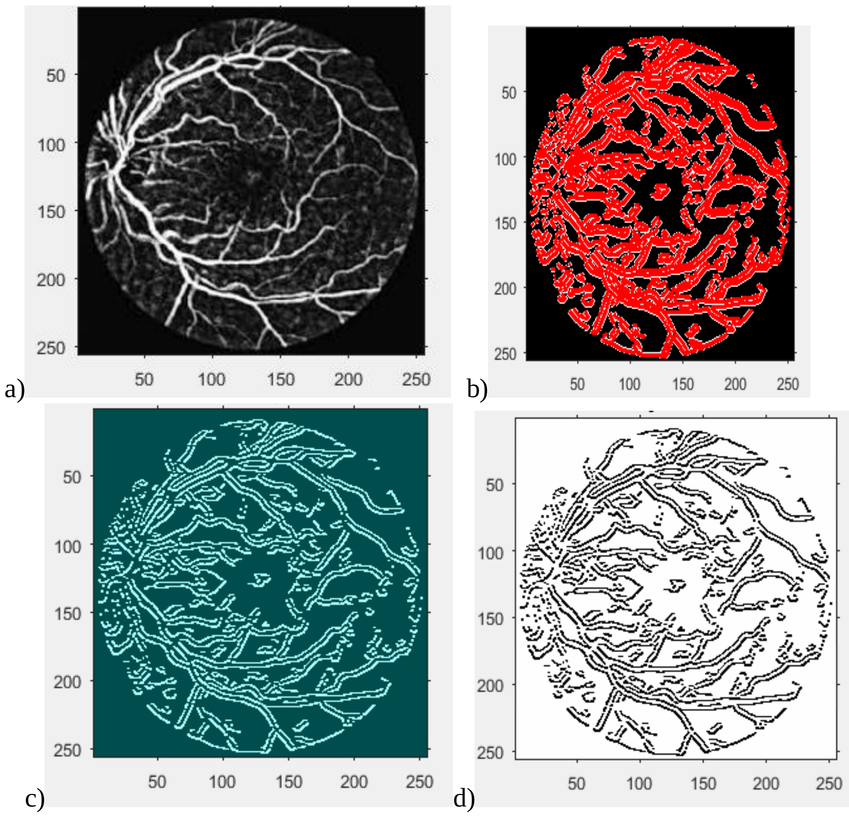

Figure 6.a)the input fundus image from clinical image database. (b) depicts the segmented output using morphological based segmentation technique. c) represents the segmented output using watershed based segmentation approach and (d) gives the segmented output of the Fuzzy C mean based segmentation technique**.**

1.7 Conclusion

The current survey, conduct the optimization of image processing due to utilization in image processing optimization through exploring the previous research and scientific articles that have been published or described the optimization of the image processing. The survey focuses on the optimization of medical images processing due to the significance of such image in the human lives enhancements and maintenance. The survey built based on the purposes for image processing ranges from disease detection, object detection and diagnosis purposes. The survey shown the benefits of such neural networks either by increasing the accuracy and sensitivity rates or optimizing the robustness of the overall system, or support early prediction or diagnosis of specific disease such as cancers or Alzheimer’s disease AD. In the context of health care and detection and diagnosis functions, the current work introduced the morphological active contour for the vascular segmentation in order todiagnose and detect the defects in the eye at the early stages. In this approach, the fundus image is initially taken as an input image which then preprocessed to remove the unwanted noise and to resize the image by utilizing some filtering approaches. Then the preprocessed image is segmented using three different segmentation technique such as morphological based segmentation, watershed based segmentation and fuzzy c means based segmentation. The resulted images that are obtained from these segmentation approaches are then sent into the convolutional neural network for extracting the features. The performance of the proposed methodology is evaluated and compared with the existing techniques. various performance metrics such accuracy, precision, recall, sensitivity and specificity are used for evaluating the performance of the optimization approach and Jaccard, dice and kappa coefficient are used for evaluating the performance of the segmentation approaches. From the results it is concluded that the proposed methodology offers better results. Also the results shows that the fuzzy c mean based segmentation techniques provides better segmentation results

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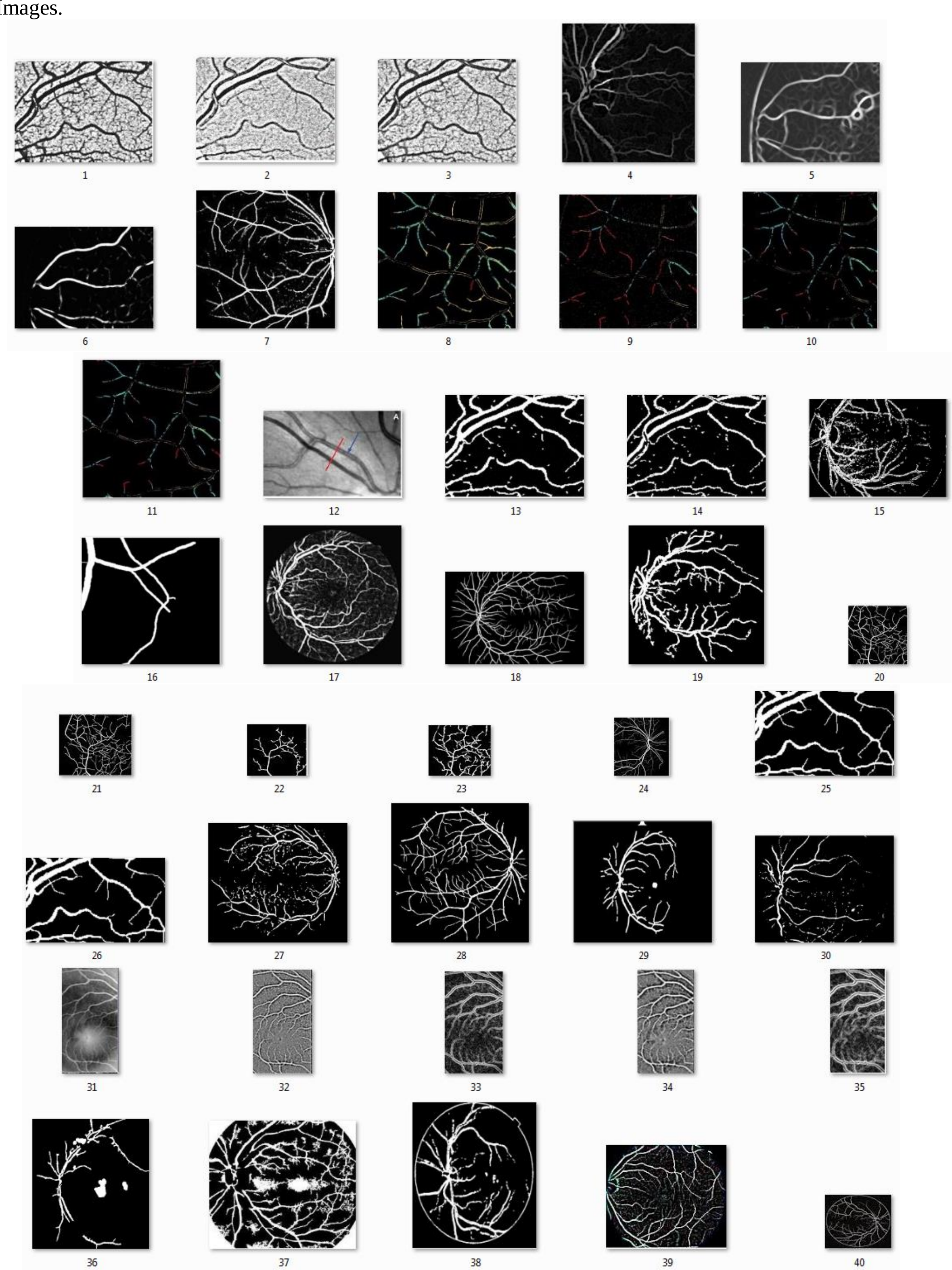
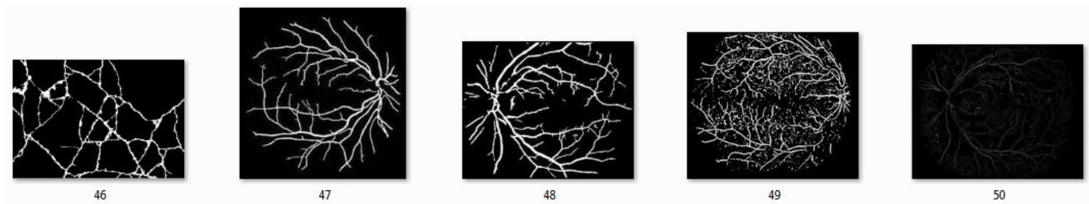
Appendix :
Input Images.

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