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Performance Analysis of Convolutional Neural Network for Retinal Image Classification

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Abstract--- *The performance of convolutional neural network(CNN) has been evaluated and discussed in this paper by comparing the other existing classification techniques. Most of the state-of-the-art classification techniques are trying to detect the abnormal retinal images from the color retinal images. The existing classification techniques misclassify the abnormal retinal image as normal retinal image and it will be required for the diagnosis purpose. In order to overcome the limitations of misclassification, the enhanced convolutional neural network(CNN) is proposed and analyzed to detect the affected retinal images from the color retinal images. The performance of existing classification techniques and proposed classification technique is evaluated and compared for detecting the abnormal images in color retinal images. The proposed CNN provides best result by comparing the experimental results of all the algorithms and it is suitable for detecting the abnormal images in the retinal images.*

Keywords--- *Retinal Images, Classification, Fuzzy Set, Diabetic Retinopathy (DR), Convolutional Neural Network (CNN).*

I. INTRODUCTION

The medical images are mostly useful to identify various kinds of diseases and also helpful in finding the severity levels of diseases .In medical imaging and analysis, the retinal imaging has rapidly grown in the field of ophthalmology. It primarily focuses on automatic detection of diabetic retinopathy (DR) disease from fundus retinal images. The retinal image data is produced by imaging modalities. The main challenge of this field is how to extract the image features and classify the extracted result to identify which parts of retinal image are affected by diabetic retinopathy(DR) disease from the image classification result[18].There are three main stages of Medical Image classification include (1) preprocessing (2) feature extraction and (3) classification [11]. The first stage pre processing [19] is required to remove the noise from the input image and also to increase the reliability of an image. The feature extraction is needed to extract interest part from the retinal image for classification. The main focus of classification [17] is to map the input data become the output variables to represent one specific class(normal image or abnormal image).

Classification is a big challenge for analyzing the medical images. The main aim objective of classification is not only to reach high accuracy and also to find the infected parts of the human body by the disease [20]. The classification is needed to develop an automatic diagnosis system for better clinical care. Caner Mercan et al.[1] developed classifier to compute multi-classlocalization and the classification within whole slide images were selected to include the full range of challenging the diagnostic categories. Hind Oulhajet al.[2] proposed a novel method for characterizing the bone texture to increase the classification performance. Fengying Xieet al.[3]

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developed a novel method to classify the melanocytic tumors as benign or malignant by analyzing the digital dermoscopy images. The proposed algorithm has three steps. In first step, self-generating neural network (SGNN) is implemented to extract the lesions. In second step, features such as tumor color, texture and border are extracted and in third step lesion objects are classified using neural network ensemble mode classifier. Alan Joseph Bekkeret al. [21] applied a multi-view-classifier to classify benign category and malignant category from the breast micro calcifications clustered image. The proposed method was computed on a large variety number of different cases from a digital standard database for screening the mammography. Jean-Paul Charbonnieet al. [12] proposed a method for automatic classification of pulmonary arteries and veins in CT (computed tomography) images. The proposed method takes local informations to separate the segmented vessels, and global information to classify the artery-vein in CT images. Lama Seoudet al. [13] described a method for detection of both microa-neurysms and hemorrhages in color fundus images. It uses Dynamic Shape Features for computer-aided screening and grading of diabetic retinopathy.

In this work, few classification techniques have been implemented to classify the retinal images and improve the accuracy of classification. The performances of all classification techniques have been compared in term of the accuracy, sensitivity and specificity. The study of the proposed system is organized as follows: Section 2 elaborates the classification techniques which include the classifier to classify the retinal images. Section 3 describes proposed classification method for DR screening system. Section 4 estimates the statistical parameters for measuring the performance of classifiers. Section 5 compares the performance of various classifiers and the work is concluded in Section 6.

II. CLASSIFICATION TECHNIQUES

Classification techniques are used to classify the data into different classes based on some constrains. Many classification techniques are developed for increasing the performance of the classifier. In this section few classification techniques have been analyzed to improve the accuracy of classification.

2.1 Neural Network Classifier (NN)

A neural network is a biologically inspired classification technique. It consists of three layers. There are input layers, middle layers and output layers. Each layer contains the number of neuron-like processing units and every processing unit in layer is connected with all processing units in previous layer. Anirban Santara et al. [4] proposed deep learning architecture which extracts feature such as band specific spectral-spatial features and it performs land cover classification using neural network classifier. Fengying Xie et al. [3]developed a novel method to classify the melanocytic tumors as benign or malignant by analyzing the digital dermoscopy images. It follows three steps:

In first step, self-generating neural network (SGNN) are used to extract lesions, In second step, border, texture and features are extracted and finally lesion objects are classified using a neural network classifier ensemble model. Rudolf Resselet al. [14] developed a classification algorithm and it is based on Terra SAR-X Scan SAR data. The texture features (gray-level co-occurrence matrix) are extracted from the input image and the extracted data are given as input to an artificial neural network for each pixel classification.

2.2 Support Vector Machine (SVM)

SVM is a classifier which is defined by a separating hyper plane. A hyper plane separates between a set of objects having different class memberships. It was used to evaluate the data for classification. Gabriele Cavallaro et al. [15]developed support vector machine methods to classify the remotely sensed images. Haoyang Yu Cavallaro et al. [5] introduced new spectral-spatial classification method for hyperspectral images. A subspace-based support vector machine (SVMsub) is used to obtain the classification maps with multiscale inputs and classification result is achieved. Li Xieet al. [6] proposed a novel method which is based on discrete space model (DSM) and support vector machines (SVMs) to classify the hyperspectral image (HSI).The proposed method is evaluated and it is applied to each real HSI for classification. It provides the best accuracy of classification for the SVM.

2.3 Recurrent Neural Network Classifier (RNN)

Recurrent Neural Network Classifier is a type of artificial neural network which involves directed cycles in memory. It consists of neuron-like nodes and each node has a directed connection with every other node. Emmanuel Maggioriet al. [7] introduced a generic iterative enhancement process derived from partial differential equations. It can express as a recurrent neural network (RNN). It improves the quality of satellite image classification maps. Lichao Mouet al. [8] proposed a novel RNN model which can evaluate hyperspectral pixels and each pixel is considered as sequential data. It defines the information categories through network reasoning. Dino Iencoet al. [9]developed a model for land cover classification by using multi temporal spatial data and it is derived from a time series of satellite images.

2.4 Texture Classification

The texture classification involves two phases. The first phase is learning phase and the second phase is recognition phase. In learning phase, it constructs model for the texture content of each texture in training data. In recognition phase, the textural features of the sample are compared with training image. Rouzbeh Maani et al. [16] developed a method for robust volumetric texture classification and also proposed 2D and 3D gradient calculation methods. The gradient information is extracted on the XYZ orthogonal planes at each voxel using the proposed 2D method and it forms a local coordinate system. The proposed 3D gradient calculator is used to define volumetric texture features. Jinwang Fenget al. [10] proposed a structural difference histogram representation. It is implemented by fusing the refined LBP, segmented structure pattern and the neighbor difference pattern for texture classification.

III. PROPOSED CLASSIFICATION METHOD FOR DR SCREENING SYSTEM

In this work, the convolutional neural network has been proposed with fuzzy logic module for improving the accuracy of detecting Diabetic Retinopathy screening system.

3.1 Pre Processing

A preprocessing technique consists of three steps. The first step of preprocessing is to remove the vessel central light. The reflection from the interface between the blood column and vessel wall forms the light reflex of the retinal vessel. In order to remove this brighter strip, the morphological opening is applied to filter the green plane of the retinal image as shown in Fig.1.The second pre processing step is to perform the Background Homogenization shown in Fig.2. Due to non uniform illumination, the fundus images contain background intensity variation. A 3x3 mean filter is used to smooth occasional salt-and-pepper noise and the noise smoothing is determined by convolving the resultant image with a Gaussian kernel of dimensions. The shade-correction algorithm is proposed to reduce background intensity variations.

Figure 1: Input image and Green channel

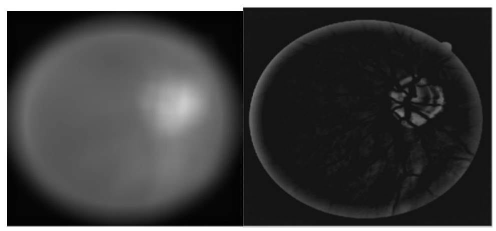

Figure 2: Background image and Homogenized retinal image

The final step of preprocessing is to enhance the vessel parts in retinal images. It generates a new vessel-enhanced image by evaluating the complemsentary image of the homogenized image. It is shown in Fig.3 which is more suitable for further feature extraction. The vessel extraction and optic disc detection are necessary for detecting diabetic retinopathy disease. An improved saliency based method is proposed for vessel extraction and optical disk detection. The Salient' regions of a medical image contains meaningful information for diagnostic purposes. The saliency of a given pixel is computed as follows.

$$\mathrm{C} = D[\left(\frac{1}{N1}\sum_{p=1}^{N1} Vp\right), \left(\frac{1}{N2}\sum_{q=1}^{N2} Vq\right) \qquad (1)$$

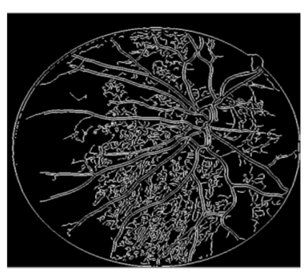

Figure 3: Vessel enhanced retinal image

3.2 Convolutional Neural Network Design

A CNN (convolutional neural network) is a specific type of artificial neural network. It uses machine learning unit algorithm for analyzing the retinal images. It consists of input layer, various hidden layers and an output layer. In this work, The CNN architecture contains five convolutional layers, rectified linear units (ReLUs), spatial max-pooling, fully connected layer and soft-max. The convolutional layers are used to compute features from retinal images. It uses 32 small size filters of size 3×3and 2×2 size of max-pooling for each convolutional layer.

It performs max-pooling operations to summarize the feature responses and it is useful for learning the features which are spatially invariant with respect to the object's location. The outputs of the convolutional layers are given as input to fully connected layer followed by soft-max layer for classification. For a given input retinal image, it outputs a score ranging between 0 and 1, which indicates the probability of the pixel to belong to the positive class. The Fully connected layer consists of 1024 nodes. The architecture of convolutional neural network is shown in Fig.4.

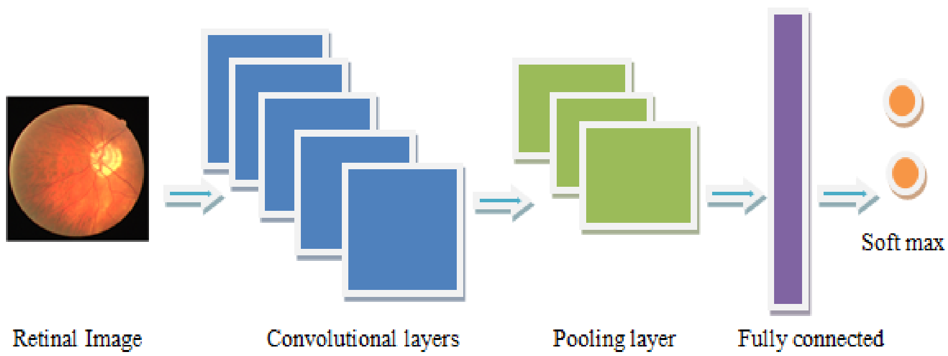

Figure 4: Architecture of the convolutional neural network

3.3 Fuzzy Model of Convolutional Neural Network

The fuzzy logic module has been introduced into the CNN (convolutional neural network) system for improving the performance of image classification. The fuzzy logic describes with truth values between 0 and 1 and these values are considered as intensity of truth. The fuzzy logic module is used to adjust the values of convolutional neural network output layer for producing better accuracy rate of detection system. This system improves the accuracy rate of retinal image classification and also improves the performance of the diabetic retinopathy detection system

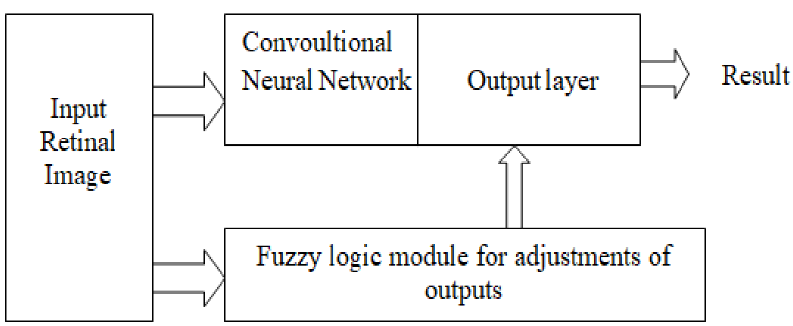

Figure 5: Architecture of the system testing scheme

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IV. ESTIMATION OF STATISTICAL PARAMETERS

The performance comparison of classification techniques under the study has been carried out based on the statistical parameters Sensitivity (SE), Specificity (SP) and Accuracy (ACC). There are four parameters which are used to measure the statistical parameters. True Positive(TP), False Positive(FP), True Negative (TN) and False Negative(FN). The proposed classifier classifies the retinal images into two classes (DR image, Non-DR image)

4.1. Parameters

(i) True Positive(TP) : True positives are the cases when the actual value of the data was one and the predicted value is also one. TP is measured by correctly classified DR images.

(ii) True Negative (TN): True negatives are the cases when the actual value of the data was zero and the predicted value is also zero. TN is measured by correctly classified Non-DR images

(iii) False Positive (FP): False positives are the cases when the actual value of the data was zero and the predicted value is one. FP is measured by the number of Non-DR images are classified wrongly as DR images.

(iv) False Negative (FN): False negatives are the cases when the actual value of the data was one and the predicted value is zero. FN is measured by the number of DR images are classified wrongly as Non-DR images

4.2 Sensitivity

The sensitivity determines the proportion of positives which are correctly classified by classifier. It measures how likely the test is positive who someone has a diabetic retinopathy disease.

$$\text{Sensitivity}= \frac{TP}{TP+FN} \quad (2)$$

4.3 Specificity

The specificity determines the proportion of negatives which are correctly classified by classifier. It measure show likely the test is someone doesn't have the diabetic retinopathy disease.

$$\text{Specificity}= \frac{TN}{TN+FP} \quad (3)$$

4.4 Accuracy

Accuracy is a key measurement to classify the diabetic retinopathy patients and non-diabetic retinopathy patients from the database.

$$\text{Accuracy}= \frac{TN+TP}{TN+FP+FN+FP} \quad (4)$$

V. RESULTS AND DISCUSSION

5.1 Datasets

In this work, the STARE and DRIVE datasets are used to evaluate and analyze the performance of Diabetic Retinopathy (DR) screening system. The STARE and DRIVE datasets are publically available databases for retinal images. The STARE(Structured Analysis of Retina) dataset consists of 20 retinal fundus images and ground truth images. The images of STARE dataset are captured by TopconTRV-50 fundus camera with 35 degree field of view.

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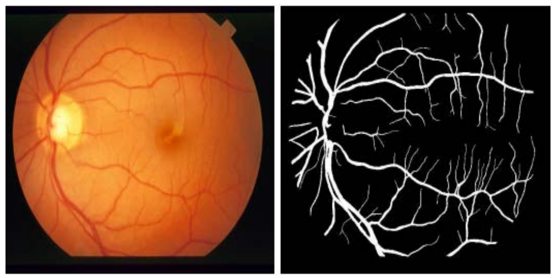
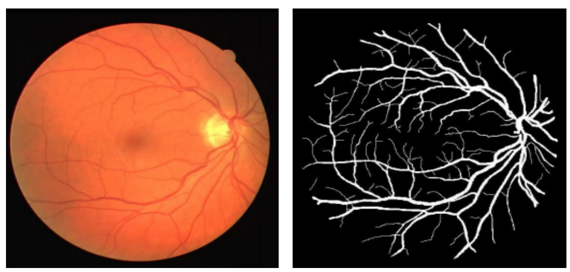
Each retinal image was available with size 768 × 584 in the digital form with 24 bits per pixel resolution. The example image of STARE dataset is shown in Fig. 6.

The second dataset is Digital Retinal Images for Vessel Extraction (DRIVE) dataset. It contains40 colour fundus photographs with their ground truth images. The images of DRIVE dataset are captured by Cannon CR5 nonmydriatic 3CCD camera with a 45^{O}field of view. The retinal images of DRIVE dataset is shown in Fig. 7. Each retinal image was available with size 605 × 700 in the digital form with 24 bits per pixel resolution.



(a) (b)

Figure 6: STARE dataset (a) Retinal image (b) Ground truth vessel segmentation



(a) (b)

Figure 7: DRIVE dataset (a) Retinal image (b) Ground truth vessel segmentation

5.2 Experimental Results

The proposed classification technique has been evaluated on two retinal imaging datasets STARE and DRIVE. In this work, the process of classification has been carried out for the retinal images using the existing and proposed classification techniques. The proposed CNN is trained with training set and tested using test set images for the performance analysis of proposed technique. The performances of the classification techniques are evaluated using statistical measurements such as sensitivity, specificity and accuracy. The performance of proposed technique is compared with the state-of-the-classifiers as given in Tables 1, 2 respectively.

The statistical measurements of various classification techniques for the retinal images from STARE dataset are analyzed and compared as given in Table I. The proposed technique detects and identifies the abnormal retinal images at an average sensitivity rate of 94.5% and specificity rate of 92.5% and accuracy rate of 93.6%, respectively, in STARE dataset.

Table I: Performance comparisons on STARE dataset

Classification Techniques	**Sensitivity (SE)**	**Specificity (SP)**	**Accuracy (ACC)**
Neural Network Classifier	86.2	84.3	85.6
Support Vector Machine	90.7	91.5	91.1
Recurrent Neural Network	91.6	90.7	91.3
Texture Classification	92.1	90.7	91.6
Proposed Classification technique (Fuzzy model of CNN)	94.5	92.5	93.6

The Table II compares the statistical measurements of classification techniques for the retinal images from DRIVE dataset. The accuracy of various classification techniques are evaluated and analyzed. The proposed technique identifies the abnormal retinal images at an average sensitivity rate of 95.6% and specificity rate of 93.6% and accuracy rate of 94.6%, respectively, in DRIVE dataset.

Table II: Performance comparisons on DRIVE dataset

Classification Techniques	**Sensitivity (SE)**	**Specificity (SP)**	**Accuracy (ACC)**
Neural Network Classifier	88.2	86.3	87.5
Support Vector Machine	91.6	90.3	92.4
Recurrent Neural Network	93.5	91.5	92.5
Texture Classification	92.5	91.6	90.7
Proposed Classification technique (Fuzzy model of CNN)	95.6	93.6	94.6

From the results it is found that the fuzzy model of CNN gives better performance than other classifiers in terms of sensitivity, specificity and accuracy.

VI. CONCLUSION

The classification technique is essential for DR diagnosis and severity classifications in retinal images. In this paper, various existing classification techniques and proposed fuzzy model of CNN technique were applied on the retinal images from STARE and DRIVE datasets. The classification techniques have been analyzed for detecting abnormalities in retinal images and the performance of the classification techniques has been evaluated by using three statistical measurements such as Specificity (SP), Sensitivity (SE) and Accuracy (ACC). The proposed CNN achieves better results in terms of SP, SE and ACC measures. The proposed technique produced the average classification accuracy of 94.6% in DRIVE dataset and 93.6% in STARE dataset, respectively. From the experimental results and performance analysis, it is observed that the proposed fuzzy model of CNN correctly identifies the abnormal retinal images with better accuracy rate and also it reduces misclassification for diabetic retinopathy diagnosis purpose.

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