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DIABETIC RETINOPATHY DIAGNOSIS USING KERNEL FUZZY C MEANS WITH CONVOLUTIONAL NEURAL NETWORK BASED RESIDUAL MODEL

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ABSTRACT. Presently, Internet of Things (IoT) becomes popular owing to diverse its application scenarios like transports, building, healthcare, etc. This study introduces an efficient IoT based diabetic retinopathy (DR) diagnosis model using Kernel Fuzzy C Means Segmentation and Residual Network. The proposed model involves a sequence of processes namely image acquisition, pre-processing, segmentation, feature extraction and classification. At the initial stage, retinal fundus image acquisition takes place which captures the retina image of the patient using head mounted camera. Next, kernel fuzzy c-means (KFCM) based segmentation process is applied to identify the diseased area. Then, the features are extracted using convolutional neural network (CNN) based residual network (ResNet) model. Finally, softmax function is employed to carry out the classification task. The validation of the presented model takes place using Kaggle DR dataset and the experimental results verified the superior performance of the presented model. The obtained results indicated that the KFCM-CNNR model has resulted to a maximum accuracy of 96.89%, sensitivity of 93.12% and specificity of 98.16%.

1. INTRODUCTION

In recent times, diabetic retinopathy (DR) is considered to be the major reason for vision loss in today's world. There are numerous causes for blindness,

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but DR plays a major role for loss of eye sight. The main problem of DR is that, it is incurable at earlier phase, thus primary analysis is highly significant. Therefore, it is referred as a standard complexity in medical system because of massive patients and minimum amount of medical facilities and experts. As a result, it led to deploy automatic diagnosing method which is highly helpful for DR analysis. Various studies were performed by many developers on the basis of hand-based features that have been resulted with a maximum efficiency while analyzing DR regions in retinal fundus images. Hand-based features are mostly applied with conventional Machine-Learning (ML) models for the purpose of DR analysis. Diverse research has been reviewed the conventional approaches [1]. For instance, [2] classified DR analysis using the applied models like mathematical morphology, retinal lesion tracking, thresholding and deformable schemes, clustering-relied techniques, matched filtering as well as hybrid methodologies. When preparing the manuscript you should take care for the following: In recent times, DR has become a frequent infection among the diabetes affected peoples and the loss of eye sight can be eliminated by earlier prediction of DR. If the disease is analyzed, patient should undergo regular check-up for all 6 months so that the health condition is under a specific control [3]. An effective approach for detecting and classifying the fundus images would be useful for the ophthalmologist in preventing the blindness problem. Developers have established many number of models regarding images to which has to be précised in diagnosing DR. The default formation of human eye is developed with optic disc (OD) and optic nerves. Prediction and categorization of DR is performed by image segmentation which divides images into portions from fundus image for examining the existence of haemorrhages, lesions, micro aneurysms, exudates, and so on. The developers in [4, 5] have categorized DR images according to the existence of micro aneurysms (MA). Features such as circularity and region of MA are assumed in feature extraction process. Datasets such as DRIVE, ROC, and DIARETDB1 have been applied in these studies. A methods developed by the authors have offered optimal sensitivity and specificity.

2. The Proposed KFCM-CNNR Model

The working process of KFCM-CNNR model is explained here. Initially, the head mounted camera captures the retina image of the patient. Next, KFCM based segmentation process is applied to identify the diseased area. Then, the features are extracted using CNNR model. Finally, softmax function is employed to carry out the classification task.

2.1. **KFCM based Segmentation.** Once the images are captured and preprocessed, KFCM based segmentation process takes place. The FCM technique has normalized the clustering method of objective function to fuzzy clustering on the basis of portioning fuzzy sets. To enhance the model, the given objective function could be applied as:

$$J_2(u,\ v) = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^2(d_{ik})^2,$$

where $c$refers the count of clusters, d_{ik}denotes the distance, Nshows the count of pixels from gray image, u_{ik}implies the membership degree of k-th pixel present in i-th cluster which meets the condition $\sum_{i=1}^{c} u_{ik}= 1,\ \forall u_{ik} \in [0, 1]$.
An extensively applied classical FCM approach is defined as clustering model. The objective function is reduced iteratively to accomplish best image segmentation. The objective function of conventional FCM approach is depicted as:

$$J_m = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^m \left\| x_k - v_i \right\|^2,$$

where $\{x_k,\ k = 1, 2,\ \cdots,\ N\}$ defines a data set of pixels from a gray image, $\{v_i,\ i = 1, 2,\ \ldots, c\}$ represents the collection of cluster centers, m implies index of fuzzy weight. Novel measures of membership degree u_{ik} and new cluster centers v_i are determined under the application:

$$u_{ik} = \frac{(||x_k - v_i||^2)^{-1/(m-1)}}{\sum_{j=1}^{c}(||x_k - v_j||^2)^{-1/(m-1)}},\ v_i = \frac{\sum_{\mathrm{k=1}}^{\mathrm{N}} u_{ik}^m x_k}{\sum_{k=1}^{N} u_{ik}^m}.$$

Hence, the model is a local-search approach which depends upon gradient descent (GD) and contains a higher dependence from initial conditions. The models which depend upon kernel functions that are efficiently used for pattern analysis function optimization, and so on. The feature space of a kernel function is demonstrated in the following:

$$K\,(x,\ y) = \langle\Phi\,(x)\,,\ \Phi\,(y)\rangle\,,$$

where $\langle , \rangle$ refers the internal product. A condition which satisfies the Mercer theorem could be selected as a kernel function. Here, Gaussian kernel function is applied:

$$K\left(x,y\right) = \exp\left(-\|x-y\|^2/\sigma^2\right) \ ,$$

where σ denotes the features of kernel function. The objective function for KFCM segmentation can be described in the following:

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m ||\Phi(x_k) - \Phi(v_i)||^2, \tag{2.1}$$

where Φ implies the non-linear mapping function from a low-dimensional to high-dimensional feature space. $||\Phi(x_k) - \Phi(v_i)||^2$ in Eq. (2.1) is depicted as:

$$||\Phi(x_k) - \Phi(v_i)||^2 - = K(x_k,\ x_k) + K(v_i,\ v_i) - 2K(x_k,\ v_i). \tag{2.2}$$

Based on the Eq. (2.2), objective function Eq. (2.1) is represented by:

$$J_m = 2 \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m (1 - K(x_k,\ v_i)) \ .$$

The membership-degree u_{ik} as well as cluster centers v_i could be attained in the followig:

$$u_{ik} = \frac{\left(1 - K(x_k, v_i)\right)^{-1/(m-1)}}{\sum_{j=1}^{c} \left(1 - K(x_k, v_j)\right)^{-1/(m-1)}}, \qquad v_i = \frac{\sum_{\mathrm{k}=1}^{\mathrm{N}} u_{ik}^m K(x_k,\ v_i) x_k}{\sum_{k=1}^{N} u_{ik}^m K(x_k, v_i)} \ .$$

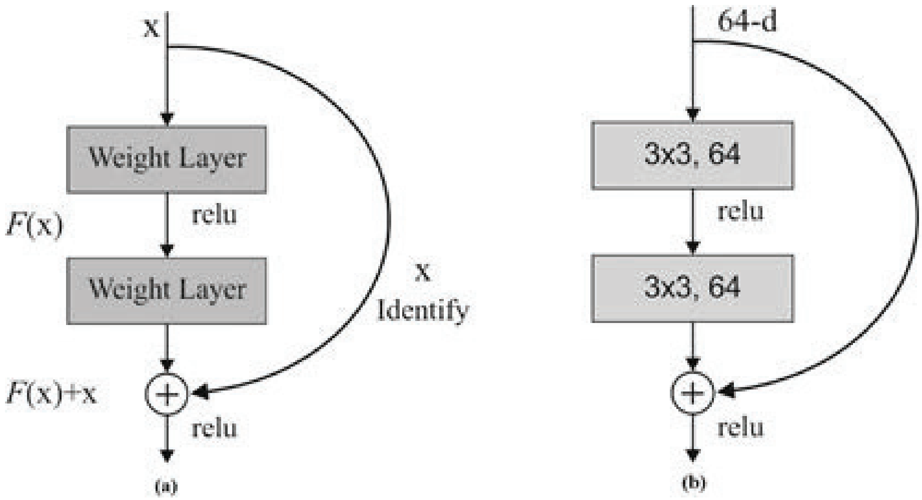
The efficiency of KFCM approach for clinical image segmentation is optimal when compared to classical FCM model.

2.2. **ResNet50 based Feature Extraction.** The CNN is defined as a kind of feed-forward artificial neural network (FF-ANN) that is evolved by arranging animal visual cortex. It is composed of wider applications in image and video analysis, recommender systems as well as natural language computation.CNN is often developed by 2 major portions namely, convolutional layers and pooling layers. Initially, convolutional layer is defined as major building block of a CNN that provides feature maps by processing a dot product from local region in input feature maps as well as a filter. ResNet employs residual block for resolving the degradation as well as GD issues present in general CNNs. The remaining block is not based on network depth, and enhances the function of a network. ResNet networks have provided better results in ImageNet classification process.

Also, residual block in ResNet executes the residual by enclosing input of residual block as well as result of residual block. The function of residual block is given in the following:

$$y = F(x, W) + x,$$

where x refers the input of residual block; W implies the weight of residual block; y signifies the result of residual block. The infrastructure of a block is projected in Fig 1. ResNet network is composed of various residual blocks where convolution kernel size of convolution layer is varied. The traditional architecture of ResNet contains RetNet18, RestNe50, and ResNet101. In this study, ResNet50 is employed as a feature extractor.



(A) Residual block (B) 2-Layer Deep

FIGURE 1. Blocks in ResNet

Features obtained by ResNet residual network have been fixed in FC layer for image classification. The softmax function is applied for classification purpose.

2.3. **Softmax based Classification.** Finally, it is connected with a softmax layer that detects various classes by processing the possibility of belonging to all categories. Eventually, the features will rasterize into x, with a column feature vector:

$$p(y = j \mid x, \theta) = \frac{e^{\theta_j^T x}}{\sum_{j=1}^{k} e^{\theta_j^T x}},$$

where target is composed of k classes, and θ_j^T refers the weight vector.

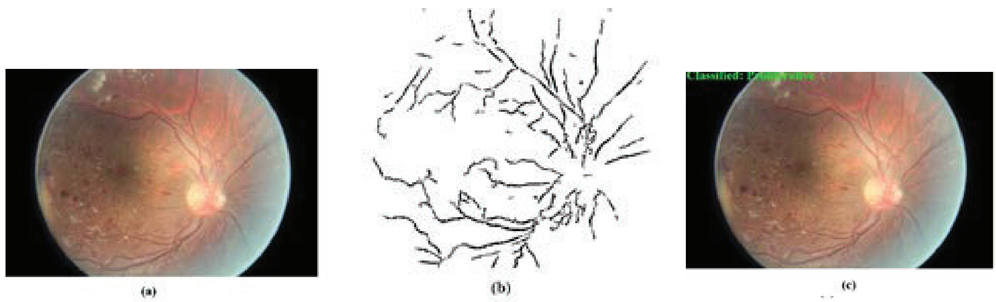
3. Performance Validation

The evaluation of the KFCM-CNNR model takes place in the diagnosis performance of DR using Kaggle DR dataset [6]. The dataset holds images under 5 classes, ranging from class 0-4. The class 0 includes 25810 images, 2443 images under class 1, 5291 images under class 3 and 708 images under class 4. The information about the dataset is provided in Table 1.

Table 1. Dataset Description

Class Name	DR Grades	Number of Images
Class 0	Normal	25810
Class 1	Mild	2443
Class 2	Moderate	5291
Class 3	Severe	873
Class 4	Proliferative	708

3.1. **Results analysis.** The visualization results of the KFCM-CNNR model has been assessed in a comprehensive way. Fig 2. shows the sample DR image with its segmented and classified versions. The images portrayed that the input image is classified into class 4 proliferative. Fig 3 demonstrates the DR diagnosis



(A) Original Image (B) Segmented Image (C) Classified Image

Figure 2. Output Image

results analysis of the KFCM-CNNR model over existing methods with respect to accuracy. The figure portrayed that the AlexNet model is appeared as a worse classifier, which has reached to a minimal accuracy of 89.75 %. On continuing with, the ResNet model has managed to exhibit slightly better outcome by

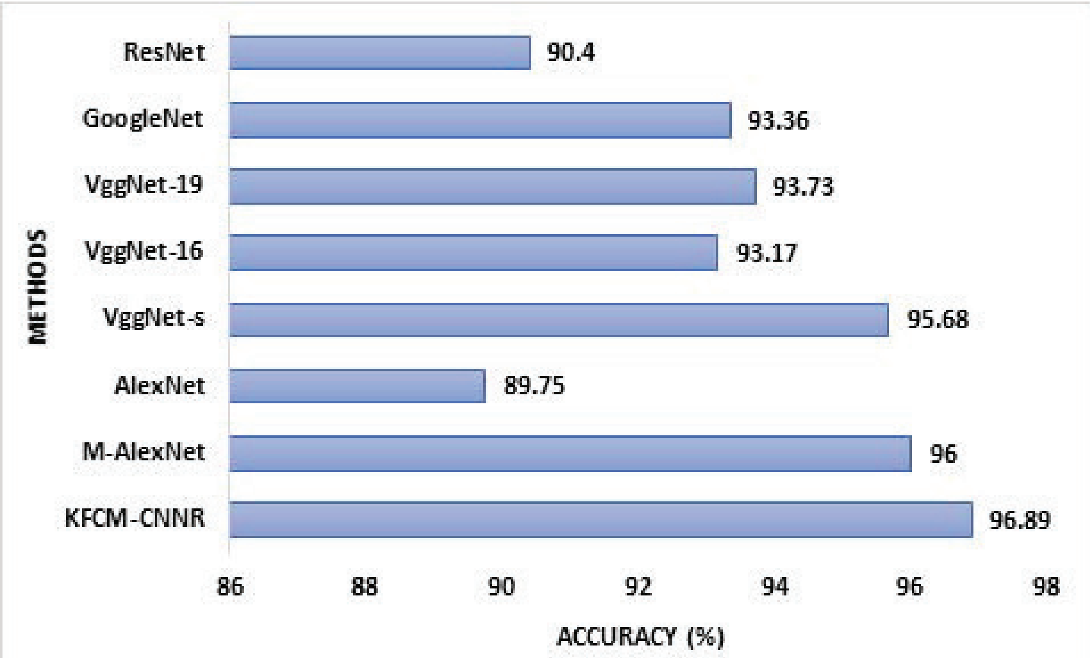


FIGURE 3. Accuracy analysis of KFCM-CNNR model on DR

attaining an accuracy of 90.4%. Along with that, the VGGNet-16 model has showcased moderate results by obtaining an accuracy of 93.17%. Besides, it is apparent that the GoogleNet and VGGNet-19 models have ended up to a certainly higher and closer accuracy values of 93.36% and 93.73% respectively. Furthermore, it is obviously indicated that the VGGNet-s model has obtained an accuracy of 95.68%. Simultaneously, the M-AlexNet model is found to be a competitor to the KFCM-CNNR model and has attained a high accuracy of 96%. But the projected KFCM-CNNR model is an effective DR classifier, which has obtained to a highest classification accuracy of 96.89%. Fig 4 shows the DR diagnosis results analysis of the KFCM-CNNR method interms of sensitivity. The figure exhibited that the GoogleNet approach is appeared as a worst classifier that has reached to a least sensitivity of 77.66%. B At the same time, the VGGNet-s model has showcased moderate outcomes by obtaining a sensitivity of 86.47%. Also, it is apparent that the ResNet and VGGNet-19 methods have ended up to a certainly higher and nearer sensitivity values of 88.78 % and 89.31% correspondingly. In addition, it is noticeably indicated that the VGGNet-16 model has attained a sensitivity of 90.78%. Concurrently, the M-AlexNet

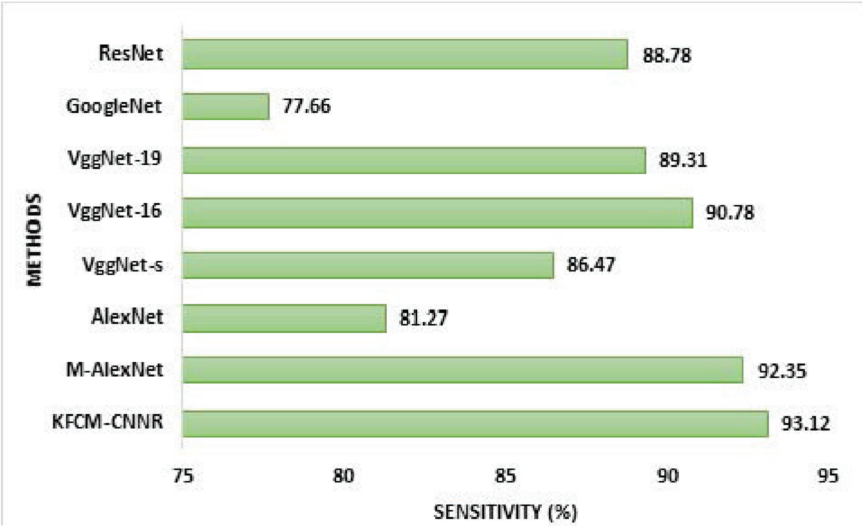


FIGURE 4. Sensitivity analysis of KFCM-CNNR model on DR

model is found to be a competitor to the KFCM-CNNR model and has obtained a high sensitivity of 92.35%. However the proposed KFCM-CNNR method is an efficient DR classifier that has reached to a highest classification sensitivity of 93.12%. Fig 5 illustrates the DR diagnosis results analysis of the KFCM-CNNR approach with respect to specificity. The figure demonstrated that the GoogleNet method is appeared as a worst classifier that has reached to a minimum specificity of 93.45 %. In line with, the AlexNet method has managed to perform slightly optimal result by obtaining a specificity of 94.07%. Along with that, the VGGNet-16 model has shown moderate results by attaining a specificity of 94.32%. Furthermore, it is obviously indicated that the VGGNet-s model has obtained a specificity of 97.43%. At the same time, the M-AlexNet approach is establishing to be a competitor to the KFCM-CNNR method and has achieving a high specificity of 97.45%. Although, the presented KFCM-CNNR method is an efficient DR classifier that has reached to a highest classification specificity of 98.16%.

4. CONCLUSION

This paper has developed a novel IoT based DR diagnosis using KFCM-CNNR model. The proposed model involves a sequence of processes namely image

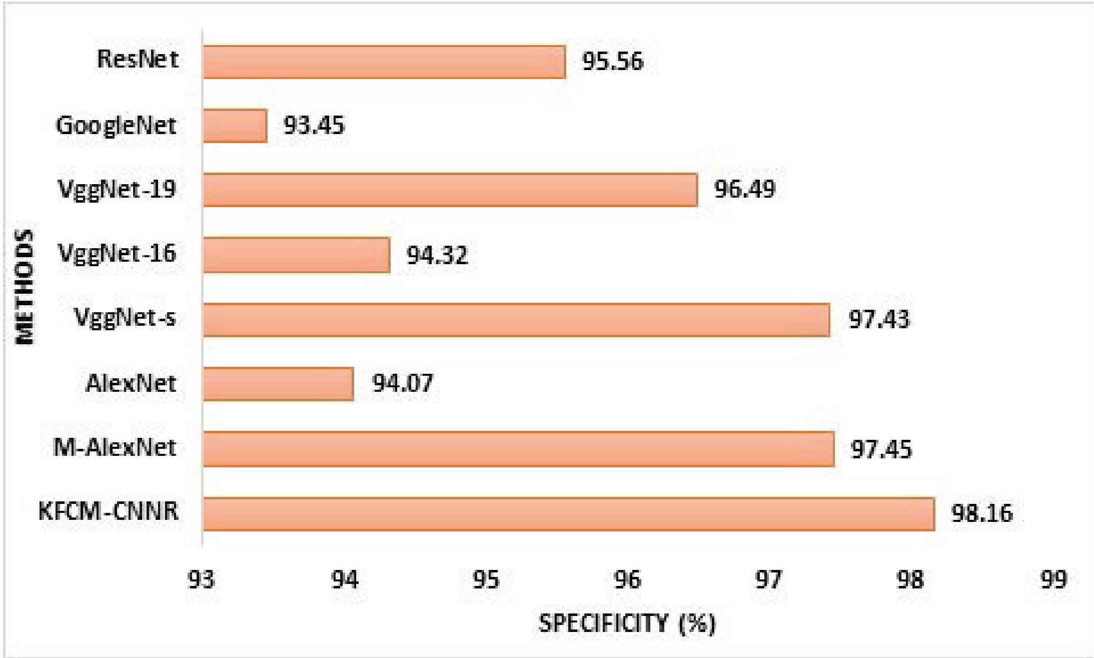


FIGURE 5. Specificity analysis of KFCM-CNNR model on DR

acquisition, pre-processing, KFCM based segmentation, CNNR model based feature extraction and softmax based classification. At the earlier stage, the head mounted camera captures the retina image of the patient. Next, KFCM based segmentation process is applied to identify the diseased area. Then, the features are extracted using CNNR model. Finally, softmax function is employed to carry out the classification task. The validation of the presented model takes place using Kaggle DR dataset and the experimental outcomes verified the superior performance of the presented method. The obtained results indicated that the KFCM-CNNR model has resulted to a maximum accuracy of 96.89%, sensitivity of 93.12% and specificity of 98.16%.

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