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DME-Deep: A Computerize Tool for Detection of Diabetic Macular Edema Grading Based on Multilayer Deep Learning and Transfer Learning

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ABSTRACT

Diabetic macular edema (DME) is a common disease of diabetic retinopathy (DR). Due to the infection of DME disease, many patients' vision is lost. To cure DME eye disease, early detection and treatment are very important and vital steps. To automatically diagnosis DEM disease, several studies were developed by detection of the macula center which is dependent on optic disc (OD) location. In this paper, a novel features pre-training based model was proposed based on dense convolutional neural network (DCNN) to diagnose DME related disease. As a result, a computerize tool "DME-Deep" for detection of DME-based grading system was implemented through a new dense deep learning model and feature's transfer learning approaches. This DCNN model was developed by adding new five convolutional and one dropout layers to the network. The DME-Deep system was tested on three different datasets, which obtained from online sources. To train the DCNN model for features learning, the 1650 retinal fundus images were utilized from the Hamilton HEI-MED, ISBI 2018 IDRiD and MESSIDOR datasets. On datasets, the DME-Deep achieved 91.2% of accuracy, 87.5% of sensitivity and 94.4% of specificity. Compare to obtain hand-crafted features, the automatic feature' learning it provided favorable results. Hence, the experimental results also indicate that this DME-Deep system can automatically assist ophthalmologists in finding DEM eye-related disease.

Keywords: Diabetic retinopathy, Retinal fundus image, Diabetic macular edema, Deep learning, Convolutional neural network, Transfer learning

INTRODUCTION

Diabetic retinopathy (DR) is a common eye disease and then eventually leads to vision loss. Diabetic macular edema (DME) of DR usually appears as exudates closed to the macula [1]. As a result, the DME of DR caused the central vision loss of many patients. In practice, the DME is categorized as the thickness of macula, hard exudates (HEs) and Hemorrhage (HA) DR-related lesions. Clinically, the severity of DME of DR is largely divided into two main classes such as clinical and non-clinical macular edema. A visual example of DME of DR is represented in Figure 1. As shown in this figure, DR-related lesions can be used in many automatic systems to identify DME disease. Compare to clinical DME, non-clinical DME is the mild-class of maculopathy in which the distance between the lesions and the center of the macula is higher than one optic disc diameter. In the past systems, many authors claimed that the hard exudates (HEs) are having the main clinical features for non-clinical DME. Whereas in the case of clinical DME, it is the type of maculopathy in which hemorrhage (HMs) and hard exudates (HEs) occurred within a distance of less than one optic disc (OD) diameter from the center of macula [2]. It is believed that if DME eye-related disease is detected at an early stage then the treatment may recover the visual vision-loss.

Several retinal fundus cameras were utilized to screen the process of DME disease. There were different imaging modalities were used to capture this disease such as fundus photography, fluorescein angiography (FA) and optical coherence tomography (OCT) [3]. When study past automatic DME systems, the authors developed many computer-aided diagnosis (CADs) systems to grade the DME by using digital image processing and machine learning techniques. Those complex image processing algorithms were used for exudate, fovea detection and segmentation using retinal fundus images. To detect and grade the severity of DME disease, many state-of-the-art DME methods were based on either detection of the location and segmentation of exudate and the macula [4-7] or the extraction of texture and image-based features [8-10].

Over the past few years, the authors were focused on image processing and machine learning algorithms. Those methods were applied to the OCT image [11] or color fundus image to develop an automatic solution to identify retina based on segmentation [12]. However, the segmentation of these DR-related lesions is difficult because of the complexity of domain-expert knowledge. Apart from those segmentation techniques, few papers have focused on machine learning techniques to identify DME eye disease from retinal fundus images. Those machine-learning-based methods are very useful to even identify DME and age-related macular degeneration [13-16] another eye disease. As a result, the primarily focus of this article is to use the latest machine learning techniques to automatically identify DME eye-related disease. It was also noticed that if segmentation techniques were deployed to detect DME disease then it has many limitations [17-20] in a real-time application.

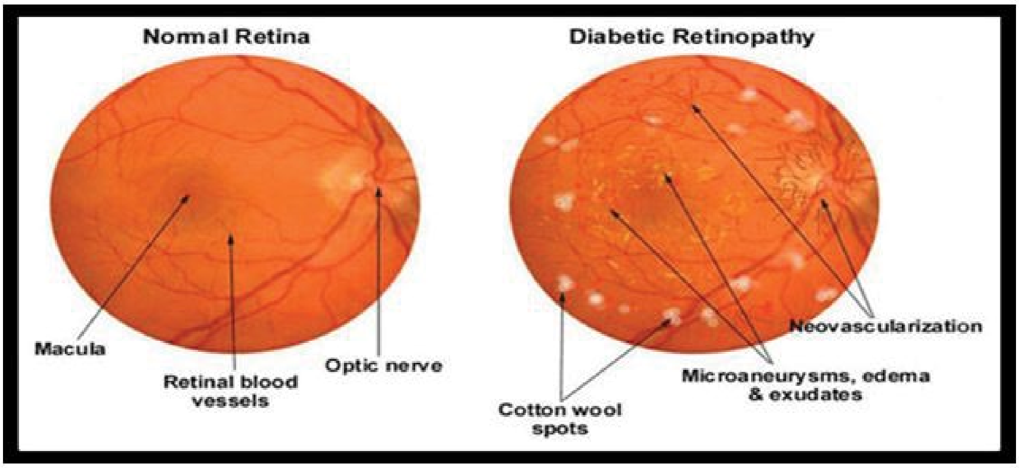

Figure 1 A visual example of DR-related lesions presented in retinal fundus images

In this paper, an alternative fully-automatic computer-aided diagnosis (CADx) system is proposed to detect retinal DME eye-related disease from color fundus images through advanced deep-learning algorithms. Currently, a few studies proposed that utilized deep-learning based multi-layer architectures to identify DME disease [17]. Compare to hand-crafted features, the deep-learning based models are best to detect DME eye-related disease having capability to automatically extract features. This proposed system identifies DME disease without an expert intervention. Section 2 introduces state-of-the-art latest deep-learning and conventional machine-learning based methods. Afterwards, the section 3 demonstrates the background of the proposed model. Then section 4 represents the dataset acquisition and development steps. The results analysis by accuracy, sensitivity and specificity through 10-fold cross validation were presented in section 5. Finally, the outline of conclusions and future directions are described in section 6.

Literature Review

An automatic grading system of diabetic macular edema (DME) was developed to assist ophthalmologists in clinical practice [4]. In that study, the authors integrated two convolutional neural networks (CNN) based attention modules to diagnose DME eye-related disease. The authors utilized two public benchmark datasets such as ISBI 2018 IDRiD and Messidor datasets to evaluate this technique. On these datasets, the authors report based results compare to others. Whereas Acharya, et al. [5], detected DME-eye disease through hybrid features based on Radon transforms (RT), discrete wavelets transform (DWT) and discrete cosine transform (DCT) methods. Those features were then fed into locality sensitive discriminant analysis (LSDA) classifier. On average, the authors reported the classification accuracy of 100% and 97.01% on two different datasets such as on private and another MESSIDOR, respectively. The authors claimed that the hybrid features were obtained higher accuracy compared to another method for detecting DME-eye disease.

Liu, et al. [6], analyzed the importance of fundus vascular-tree by predicting the retinopathy grade and risk of macular edema base on fundus images. The authors used many neural networks (NN) based on machine learning models to detect DEM disease. The authors achieved 96.8% classification accuracy to detect DME disease on fundus images. Finally, they claimed that the vascular features are very important in the diagnosis of eye-related disease. The authors utilized an advanced deep-learning-based model such as a convolutional neural network (CNN) to detect DME [7]. They presented that a new feature-learning approach was developed to detect the severity of DME using color fundus images. Without any user intervention, the authors extract features from retinograph images using the CNN model. They trained the CNN model on 1200 DME images obtained from the MESSIDOR dataset. On average, the results showed an accuracy of 88.8%, sensitivity of 74.7% and specificity of 96.5%. In the end, the authors conclude that the obtained results are favorable compared to time-consuming hand-crafted features. However, the authors trained and tested the CNN model on a limited dataset. As a result, the classification accuracy is not up-to-the-mark.

The authors used knowledge of hard exudates and maculae DR-related lesions to diagnosis DME eye-related disease [8]. The authors used a segmentation-based approach to extract hard exudates along with foveae from retinal-fundus images. They extracted hybrid features and utilized the support vector machine (SVM) to classify clinical and non-clinical DME disease. To test the performance of this model, the authors used both public and private datasets. On average, the authors showed 96.1% detection accuracy on these datasets. Moreover, the authors developed a SVM based method to segment hard exudates (HEs) from fundus images to diagnose DME eye-related disease [10]. In that study, the authors used morphological features to detect macula. The authors used DIARETDB1 and MESSIDOR datasets to test and evaluate the proposed technique. On average, the authors achieved 92.11% on DIARETDB1 and 90% accuracy in the case of MESSIDOR datasets. The authors claimed that this system can be used to detect the severity-level of DME in most cost-effective in a real-time environment. The DME disease was detected through the segmentation of hard exudates and detection of macula location concerning the OD region [14]. The possible exudate regions are segmented using a vector quantization technique and formulated using a set of feature vectors. Afterward, the authors used semi-supervised learning with a graph-based classifier to identify DME eye-related disease. On average, the organizers obtained 97.5% classification accuracy.

The DME disease was detected by Moura, et al. [9] by using Optical Coherence Tomography (OCT) images compare to fundus images. They used a deep-features learning approach to detect DME based on the CNN model. They used the pre-trained CNN model to identify distinct features. The authors achieved high accuracy and optimize features to detect DME eye-related disease through this pre-trained CNN model compare to manually extract hand-crafted features. Similarly Chan, et al. [11], pre-trained CNN model for classification of DME eye-related disease on OCT images. With the pre-trained model, the authors used principal component analysis (PCA) and bag-of-words (BoW) to reduce features. On the 8-fold cross-validation test, the authors reported an accuracy of 96.88% on the SERI dataset.

A pre-trained GoogleNet based CNN model was used by Karri, et al. [12] to diagnosis DME disease based on OCT images. Compare to the classical learning approach, the authors used the fine-tune pre-train CNN model. The authors demonstrated that the models trained on non-medical images can be fine-tuned for classifying OCT images with limited training data. Also, Kaymak, et al. [13], used OCT images to diagnose DME eye-related disease using features transfer learning approach. The CNN models were pre-trained and features extracted based on this pre-trained model. As a result, the automatic feature learning is getting higher accuracy to compare to traditionally hand-crafted features.

A pre-processing step on color fundus images and hierarchical ensemble CNN (HE-CNN) model was developed by Singh, et al. [15] to detect DME eye-related disease. To preprocess images, the authors used a morphological opening and Gaussian kernel to solve the class imbalance problem. On IDRiD and Messidor datasets, the authors achieved an accuracy of 96.12%, Sensitivity of 96.32% and Specificity of 95.84% (Table 1). The authors concluded that these obtained results provided the best DME screening in the domain of biomedical image processing. Mo, et al. [16], detect DME disease through a deep convolutional residual neural network (CRNN) model. The authors used the CRNN model to avoid any pre- and or post-processing steps on retinograph images. The authors also used a segmentation-based approach to detect centered-region and that information was later on fed into the CRNN model to the classification of DME disease. On HEI-MED and e-ophtha EX datasets, the authors achieved significant results for the detection of DME disease.

In another study, the authors' used features transfer learning approach to detect DME hat most common cause of vision loss [18]. The authors used OCT image technology and different features selection techniques applied to deep features. On 400 different patients, the authors reported an accuracy of 97.50%, using only 14.65% of the deep features in the classification. The authors used candidate regions to segment DME and then used CNN based deep-learning approach to classify those areas [19]. In contrast with this approach, a transfer-learning based technique was utilized by Safwan, et al. [20] to detect DME eye-related disease. The authors observed that the CNN model is dependent on the architecture of the network, training data and pre-processing steps. As a result, they used a transfer learning approach to solve the problem of huge data availability. On the IDRiD-2018 dataset, the authors reported high accuracy to detect DME related eye disease. Varadarajan, et al. [21] in his study also suggested using train a deep-learning model to predict DEM disease.

Another research study by Kori, et al. [22], the authors used an ensemble of CNN models to detect DME eye-related disease. The authors used a supervised approach by using a features-transfer learning approach in that study. They used a large pre-trained general dataset and then later one fine-tuned using retinal fundus images. They claimed that this step may be able to solve the problem of the limited data for the training task. For grading DME eye-related disease, the authors achieved 95.45% classification accuracy on n=44 subjects.

Table 1 State-of-the-art automatic systems for identify the diabetic macular edema (DME) eye-related disease

Cited	Methodology	Datasets	Results	Limitations
[4]	Convolutional neural network (CNN) based attention model to detect DME eye disease.	ISBI 2018 IDRiD and MESSIDOR datasets	NA	No comparisons and real-time applicability is limited
[5]	Hybrid features extracted through Radon transforms (RT), discrete wavelets transform (DWT) and discrete cosine transforms (DCT) methods. Those features fed into on locality sensitive discriminant analysis (LSDA) classifier.	Private and MESSIDOR	97.01	Domain-expert knowledge and limited applicability
[6]	Many neural network (NNs) models are used to detect vascular-tree for predicting DME.	Private	96.80%	Domain-expert knowledge and limited applicability
[7]	Features-learning thorough deep-learning based pretrained CNN model to identify DME.	MESSIDOR	88.80%	Trained on limited dataset
[8]	Hybrid features from foveae and hard exudates and classify through SVM.	Public and private	96.10%	Domain-expert knowledge and traditional-machine learning algorithm
[9]	Pre-trained CNN model to extract optimize features.	NA	NA	Tested on limited dataset
[11]	Pre-trained CNN model with principal component analysis (PCA) and bag-of-words (BoW) to reduce features	SERI dataset	96.88%	Tested and trained on limited dataset. Domain-expert knowledge is required.
[14]	The exudate and OD regions are segmented and those features fed into a semi-supervised learning with graph based classifier.	NA	97.50%	Domain-expert knowledge
[15]	A pre-processing step on color fundus images and hierarchical ensemble CNN (HE-CNN) model	IDRiD and Messidor	96.12%	Domain-expert knowledge

BACKGROUND

Literature review on detection of DME eye-related disease suggested that many authors [4-6] utilized to contrast and illumination adjustment steps as a pre-processing step to enhance the retinal fundus images. Followed by the pre-processing step, the authors removed blood vessels and then the location of the macula is detected through segmentation or machine-learning approaches. In the latest trend, the authors used the pre-training model through the CNN model to automatically [7-15] learn features without pre-processing steps. It was further noticed that the performance of the automated grading system for DME is highly dependent on the extracted features. Those features are not always representing distinct features for classification DME eye-related disease. If traditional machine learning approaches were used then the features extraction step is a time-consuming process to get hand-crafted features. Later on, the authors used a pre-training step through the CNN model to automatically learn features from retinal images.

This feature transfer step is more adapted to a generalized and automatic feature extraction method. Moreover, it provided the best classification results compare to other methods. In general, the features transfer step is provided the best solution to counter these problems (Figure 2).

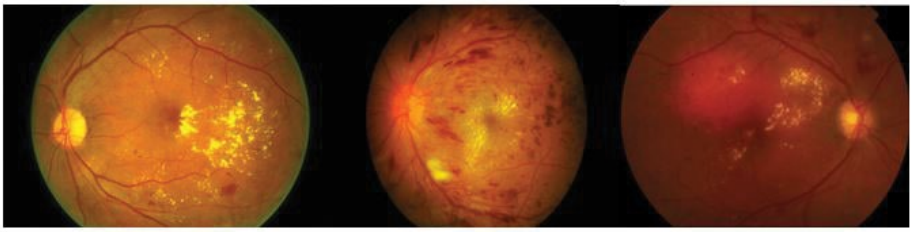

Figure 2 An example of dataset of utilized retinal fundus images having diabetic macular edema

To solve the above-mentioned problems, an automatic feature learning scheme was developed in this paper to grade the severity of DME eye-related disease. In this paper, a convolutional neural network (CNN) multi-layer architecture was used to automatically extract features from retinal fundus images without any pre-processing or segmentation steps. After extracted these optimize features, the classification decision is provided based on features fed into a fully-connected classification layer. To build this pre-train CNN model, the five convolutional, max-pooling, dropout and fully connected layers were successfully added to the network. Especially in the case of five convolutional layers, there are five different sequences of filters were used to perform a two-dimensional (2D) convolution with the input image. The output of this layer is called the feature map. The max-pooling layer is a subsampling layer where the feature map is down-sampled. The inclusion of a dropout layer is a regularization technique that is essential for reducing over-fitting. The fully connected layer is the final layer on CNN where each neuron is completely connected to the other neurons. The proposed system therefore represents a promising solution to address the above-mentioned concerns of traditional systems since it does not depend on any kind of segmentation or handcrafted features.

RESEARCH METHODOLOGY

Acquisition of Dataset

To develop and train the DME-Deep system, there are three online resources utilized in this paper. Those data sources were acquired from different places such as (1) Hamilton eye institute macular edema (HEI-MED), (2) ISBI 2018 IDRiD and (3) MESSIDOR datasets. These datasets were mostly utilized in the past to measure the performance of the proposed system for detecting DME eye-related disease from retinal fundus images. The retinograph images were having different sizes and all those images were resized to (800×600) pixels resolution and remove the background frame. From these three data sources, there are various images but only those retinograph images selected that were having DME eye-related disease. On the total, there are 1650 digital retinograph selected for testing and training the proposed DME-Deep system. An example of DME eye-related disease is visually represented in Figure 3.

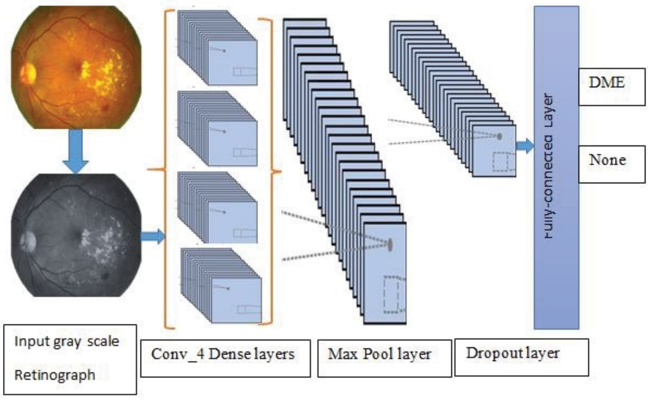

Figure 3 A systematic diagram of the proposed DME-Deep system to detect clinical and non-clinical diabetic macular edema on retinal fundus images

Pre-train Dense CNN model

The systematic flow diagram of the proposed dense convolutional neural network (DCNN) is visually represented in Figure 3. Five CNN architectures were implemented and trained with one of four different convolutional filters image sizes (64 × 64), (128 × 128), (256 × 256) and (512 × 512) pixels. For faster computational, these four kernels of different sizes were utilized in this paper for training purposes as well. The weights of the networks were fully-trained on the smaller images to initialize the networks and later one trained on the larger retinograph images. This helps to speed up the process of training without resorting to resizing images below a level where key features may not be detectable for the final classification.

Compare to Karri, et al. [12] study, the DCNN model was trained from the scratch by using region-of-interest (ROI) of diabetic macula edema (DME) region of size (256 × 256) pixels. In this paper, a pre-trained CNN model was followed based on the authors [4] who integrated two convolutional neural networks (CNN) based attention modules to diagnose DME eye-related disease. To make a difference from the attention-based CNN model, five-convolutional, dropout and pooling layers were added to the model as shown in Figure 3. To develop this dense CNN pre-trained model, the first and last layers are fully-connected layer. The final DCNN model is developed by combining five-connected layers that are trained on different sizes of ROI DME retinal fundus images. In the DCNN model, the different sizes of convolutional filters (5 × 5) and (3 × 3) were used. Each multi-layer convolutional layer (CNN-L) is preceded by a rectified linear unit (ReLU) of 0.01 step value. Based on different windows sizes, two max-pooling layers with the size of 3 × 3 provided 1024 active neurons. After that, the dropout layer is added between last and fully-connected layers to avoid over-fitting. In this study, the dataset is randomly divided into 30% training and 70% testing into three different datasets.

To further optimize and avoid over-fitting of features, each network was passed through a single epoch through the training dataset. During each training step, each ROI image of DME images is randomly selected. To get a more uniform distribution of classes, the detection performance of the DEM class is increased through the uneven distribution of the dataset used in this paper. Moreover, the stochastic gradient descent (SGD) technique was utilized to train the CNN layers. Based on total 150 epochs iteration, the first, second and third network is fully trained. To predict clinical DMS or non-clinical DMS, the loss function and mean square error were utilized with a constant threshold value. This threshold value is 1.5 fixed by doing repeatedly experiments on the selected dataset. Based on these values, the accurate results are predicted with a weight decay factor of 0.005 value is used. Whereas in this paper, the convolutional layers and a dropout rate of 0.5 are used between fully connected layers.

After this DCNN model was trained on this selected dataset then the input retinograph image was used to test the performance of the proposed DME-Deep system. To measure those results, the sensitivity (SE), specificity (SP) and accuracy (ACC) statistical values are used in this paper. To find the sensitivity (SE), it is defined as the percentage of retinograph images that are correctly classified as having DME out of the true total number of images with DME. Furthermore, specificity (SP) is defined as the percentage of images that are correctly classified as not having DME out of the true total number of images without DME. Accuracy is the percentage of images that are correctly classified.

EXPERIMENTAL RESULTS

To perform experiments on the proposed DME-Deep system, all the modules were implemented in Python® open-source tool and tested on a Core i7-56680 CPU having 16 GB of RAM and running windows 10 professional 64-bit. To measure the performance of the DEM-Deep system, a statistical analysis was performed by analyzing sensitivity, specificity and accuracy metrics. In this paper, a comparison to the state-of-the-art system was also performed. For comparison purposes, XMeng-CANet [4] system was utilized. The reason is that the XMeng-CANet [4] system is almost having the same datasets for training and the same deep-learning model. For evaluation of these two models, three data sources were acquired from different places such as (1) Hamilton eye institute macular edema (HEI-MED), (2) ISBI 2018 IDRiD and (3) MESSIDOR datasets. These datasets were mostly used in the past system to test and train the deep-learning models.

In this paper, all 1650 retinograph images were resized to (800 × 600) pixels resolutions and the background frame was fully removed. On average, the computational time was 0.25 seconds on 1650 retinograph images. The training of dense CNN model (DCNN) took almost 62.45 seconds per set of two class categories classification problems. In this classification task, the clinical and non-clinical categories related to DME disease were identified. This training time does not cost too much computational time because later on only input image will be classified by spending only 0.15 seconds.

Table 2 Comparison results of proposed DEM-Deep an automatic system for identifying the diabetic macular edema (DME) eye-related disease

No.	Methods	Accuracy	Sensitivity	Specificity
1	XMeng-CANet HEI-MED, ISBI-2018 and Messidor 1 datasets	86.45%	81.30%	88.62%
2	Proposed DME-Deep using pre-train CNN on datasets HEI-MED, ISBI-2018 and Messidor	91.20%	87.50%	94.40%

To develop and train the DME-Deep system, there are three online resources utilized in this paper. Those data sources were acquired from different places such as (1) Hamilton eye institute macular edema (HEI-MED), (2) ISBI 2018 IDRiD and (3) MESSIDOR datasets. This proposed DME-Deep system was evaluated on 30% of 1650 retinograph (495 images). The experimental results were mentioned in Table 2. From this table, the proposed DME-Deep system achieved higher results such as 91.2% accuracy, 87.5% of sensitivity and 94.5% of specificity. In this paper, the comparisons of the DME-Deep system were performed with XMeng-CANet [4] system on the same dataset. On average, the XMeng-CANet [4] system achieved lower results than the DME-Deep system with 86.45% of accuracy, 81.30% of sensitivity and 88.62% of specificity on 1650 retinograph images.

DISCUSSION

Detection of diabetic macular edema (DME) is a time-consuming task for clinical experts. Therefore, several computerize diagnostic systems (CADs) were developed in the past to recognize the severity of DME eye-related disease. The detection of DME is not a simple task as the macula has appeared near the center of the retina, and it has small in the center known as the fovea. In practice, the fovea is responsible for the object's sharpness as well as color vision. When there is DME disease then it might be damaged the macula, resulting in blurred vision [3,4] or later on eventually it leads to even blindness. As a result, many clinical experts are diagnosing DME disease with diabetes confirming vision loss [5]. It is, therefore, a very important step for clinical experts to measure macular edema [6-8] for patients with DME eye-related disease.

In particular, the CADx systems are nowadays developed to assist ophthalmologists by using digital image processing and machine-learning techniques [9-15]. Those CADx systems were very common to provide health-care support to many patients as well as medical doctors. Pre-processing and post-processing steps were used in many automatic CADx systems for recognition of DME disease. Moreover, they used a segmentation step as well to detect macula and OD-region from retinal fundus images. Therefore, the accuracy of those CADx systems was depended on the segmentation results. Later on, many authors utilized deep-learning-based algorithms to automatically extract features without having domain-expert knowledge about image processing techniques.

It was further noticed that the performance of the automated grading system for DME is highly dependent on the extracted features. Those features are not always representing distinct features for classification DME eye-related disease. If traditional machine learning approaches were used then the features extraction step is a time-consuming process to get hand-crafted features. Later on, the authors used a pre-training step through CNN [7,9,11] model to automatically learn features from retinal images. This feature transfer step is more adapted to a generalized and automatic feature extraction method. Moreover, it provided the best classification results compare to other methods. In general, the features transfer step is provided the best solution to counter these problems.

To solve the above-mentioned problems, an automatic feature learning scheme was developed in this paper to grade the severity of DME eye-related disease. In this paper, a convolutional neural network (CNN) multi-layer architecture was used to automatically extract features from retinal fundus images without any pre-processing or segmentation steps. This developed system is known as DME-Deep. After extracted these optimize features, the classification decision is provided based on features fed into a fully-connected classification layer. To build this pre-train CNN model, the five convolutional, max-pooling, dropout and fully connected layers were utilized. Especially in the case of five convolutional layers, there are five different sequences of filters were used to perform a two-dimensional (2D) convolution with the input image. The output of this layer is called the feature map. The max-pooling layer is a subsampling layer where the feature map is down-sampled. The inclusion of a dropout layer is a regularization technique that is essential for reducing over-fitting. The fully connected layer is the final layer in CNN where each neuron is completely connected to the other neurons. The proposed system therefore represents a promising solution to address the above-mentioned concerns of traditional systems since it does not depend on any kind of segmentation or handcrafted features.

CONCLUSION

It was concluded from the literature that traditional methods were based on the position of hard exudates (HEs) and the center of the macula to detect the severity level of DME eye-related disease. However, the extraction of those features required extensive domain-expert knowledge and the accuracy depends on the segmentation of macula. As a result, those systems were failed to accurately detect DME disease. Later on, many researchers suggested detecting DME disease through a pre-trained CNN model. Therefore in this paper, a novel features pre-training based model was proposed based on dense convolutional neural network (DCNN) to diagnose DME related disease. As a result, a computerize tool "DME-Deep" for detection of DME-based grading system was implemented through a dense deep learning model and feature's transfer learning approaches. The DME-Deep system was tested on three different datasets, which obtained from online sources. To train a DCNN model for features learning, the 1650 retinal fundus images were utilized. On two other datasets, the DME-Deep achieved 91.2% of accuracy, 87.5% of sensitivity and 94.4% of specificity. Compare to obtain hand-crafted features, the automatic feature' learning is provided favorable results. Hence, the experimental results also indicate that this DME-Deep system can automatically assist ophthalmologists in finding DEM eye-related disease. In the future, a mobile application will be developed to help clinical experts for detecting the severity level of DME disease.

DECLARATIONS

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Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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