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Automated Detection and Classification of Diabetic Retinopathy and Diabetic Macular Edema in Retinal Fundus Images Using Deep Learning Approach

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Abstract. Diabetics Retinopathy(DR) and Diabetics Macular Edema(DME) are the main eye diseases that should be identified earlier for preventing loss of vision. The proposed work mainly addresses these kinds of defects with different levels of classification using Convolution Neural Network (CNN). Many researchers proved that CNN achieves better performance for computer vision-based images and the CNN, recently has a wider scope in the medical field. Our proposed model consists of a convolution layer, pooling layer, and dense layer and classifies these DR and DME diseases with better accuracy.

Keywords: Deep learning, retinal images, CNN, diabetic retinopathy, diabetic Macular Edema

1 Introduction

In recent days many people affected by eye-related issues due to diabetics. There are two main eye diseases is Diabetic Retinopathy (DR) and another one is Diabetes Macular Edema (DME). These two will cause permanent vision to lose. The severity of this condition may lead to blind loss and some eye-related symptoms [3]. Diabetic retinopathy diseases are classified into 5 classes based on the severity nature. The five classes are mild, moderate, severe, proliferate, and normal retinal images. Next, the DME is related to age-related macular degeneration. It will lead to side effects such as Choroidal neovascularization, subretinal fluid, DME with thickening of intra retinal fluid, Multiple Drusen, and absence of retinal fluid[1]. In recent years, many researchers have worked together in the field of Diabetic related to eye deceases in recognition and classification. Hence deep learning has made solutions to all these sorts of problems. In deep learning, a convolution neural network (CNN), a kind of neural network, is found with common applications for analyzing visual images[16-21]. In the proposed system, a CNN-based model is proposed to classify the type and severity of the images in the dataset.

II. Literature Review

The paper[l], reflects and reviews the worldwide effect of diabetic retinopathy and its recent changes in the evaluation and treatment of the affected patients. With the concurrent introduction of intraocular VEGF-inhibitor therapy, which can prevent vision loss and induce visual improvement, the treatment of diabetic macular edema and diabetic retinopathy has changed dramatically form better, and the evolution of effective treatment should continue for years to come.

In the paper [2], Diabetic Retinopathy stage classification was done using CNN. Five different categories of Diabetic retinopathy (DR) images were discussed according to the experiment of ophthalmologists. They have applied InceptionNetV3 model of CNN and achieved accuracy is 65.23%.

In paper [3], they have proposed a CNN-based model for diabetic retinopathy for automatic detection of the disease. They have been tested by using MRSSIDOR and IDRiD datasets. Their CNN model has resulted in maximum accuracy of 90.89%.

In paper [4], the authors developed a DL algorithm for the automatic diagnosis of Diabetic Retinopathy(DR). They mainly dealt with the laterality of the eyes. They have considered a dataset with 53000 images and used 35000 images for training. They have achieved the results like sensitivity with 80.28% and specificity with 92.29% and accuracy with 93.28%.

In the paper [5], the authors have done diabetic retinopathy identification using weighted CNN. This CNN reduces averaging operation and also convergence rate of training is very fast. This model achieves 94.23% accuracy, 90.94% sensitivity, and 95.74% as specificity.

In paper [6], the authors have developed a joint DME segmentation and characterization using OCT Images. In that work, various steps were evaluated with a 262 OCT image dataset. They have done manual labeling provided by the clinicians and their system while applying segmentation yielded an accuracy of 87.68%, 74.75%, and 89.13% for SRD, CME, and DRT edemas, respectively.

The authors [7] suggested a machine learning algorithm for the automatic prediction of visual outcomes for the patients with Diabetic Macu1ar Edema. Using these data, ANNs regression calculation is optimized. The various input parameters considered are sex, age, diabetes type or condition, systemic diseases, eye status, and treatment time tables.

In paper [8], a CNN for automatic classification was proposed for normal and DME volumes in OCT eye images. Their model called OCT-NET is based on CNN for the categorization of OCT volumes. They have used a leave-one-out cross-validation strategy and obtained an accuracy of 93.75%.

In paper [9], Diabetic Macular Edema (DME) detection with transfer learning for Optical Coherence Tomography (OCT) images was proposed which is a robust diagnosis model. They used a dataset that has 38,057 OCT images with four classes. They have taken 37,457 images were for training and 600 images for validation. Their model reached 97.7%, 97% , and 97.02% for sensitivity, specificity, and precision respectively with the testing dataset.

In paper [10], the author proposed a model for DME detection using transfer learning for SD-OCT images. They have applied Block-Matching and 3-Dimension (BM3D) filtering for removing the noise from the images. They have used the AlexNet model for extracting features and further applied the Support Vector Machine (SVM) for classification. They have produced 96% accuracy by the denoised and cropped images.

The authors [11] suggested and validated a deep-learning method for predicting diabetic retinopathy with 28,899 images. They have increased the training process with multitask learning. Their models reduced the costs while upgrading vision-related outcomes.

In the paper [12], the authors have suggested a CNN-based model for the automatic diagnosis of diabetic retinopathy. In their model, they have used 35,000 retinal images for training and got the results of sensitivity as 80.28%, specificity as 92.29%, and accuracy as 93.28% with 8,816 images in the validation set.

The authors [13] proposed a deep neural network model with Grey Wolf Optimization (GWO) technique to classify DR and compared their model with the Naive Bayes Classifier, SVM, Decision Tree, and XGBoost machine learning algorithms. The authors proved that their model produced good performance compared with other algorithms.

The authors [14] have developed novel DME detection structures in that they have combined features extracted from the three pre-trained CNN networks: VGGNet, AlexNet, and GoogleNet and the feature space reduction is done with component analysis[23-25]. The Optical Coherence Tomography datasets are used in their work and produced an accuracy of 93.75%.In paper [15], the authors have calculated entropy for the green component of fundus photography images. They have applied unsharp masking (UM) for preprocessing to improve performance.

The organization of the rest of the paper is as follows: section III discusses the proposed system architecture, sections IV describes the dataset, section V discusses the performance of the proposed system for different parameters and section VI offers the conclusion and future work.

III. Fundus Image Classification

The Convolution Neural Network (CNN) is the recent form of ANN which is mostly used for image classification when compared with conventional machine learning algorithms. It consists of many layers which are referred to as convolution, pooling, flattening, and fully connected. The convolution layer layers mainly perform convolution operation in CNN that extracts the high-level features and these extracted features are stored in a feature map. There are many convolution layers are used in each CNN-based model which is used to understand different features in the input image. The feature maps derived from the convolution layer are next given to the pooling layer where its size is reduced in the spatial dimension. The two types of pooling operations commonly applied are Max pooling and Average pooling. The average pooling most considers the mean or average presence of a feature whereas the max-pooling considers the most active existence of a feature. The output of the pooling layer is next performed with a flattening operation where the 2D image is converted into a one-dimensional vector which is given to the final layer, the fully connected layer. This final layer also referred to as the dense layer, is trained with extracted features and then performs the classification operation.

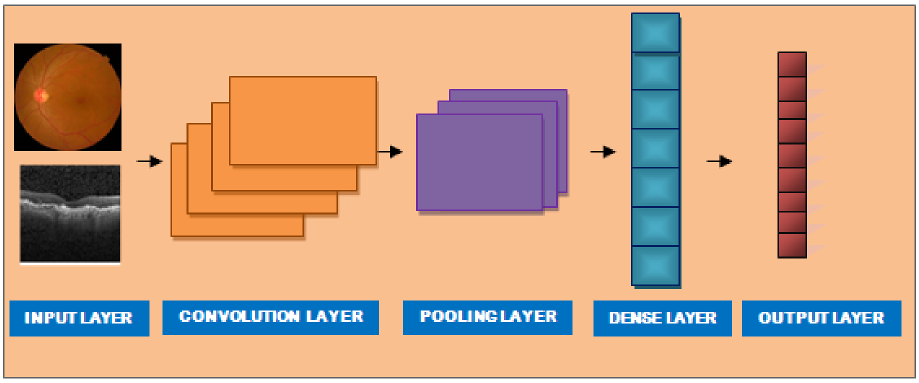

Fig.1. Proposed CNN architecture

The proposed CNN model is made with 4 convolution layers, 3 pooling(max) layers, and 7 dense(fully connected) layers. APTOS 2019 dataset is used for DR diseases and OCT Images dataset is used for DME diseases. The images for the DR disease are in RGB format whereas the images for the DME disease in grayscale format. All diverse images are resized into 100x100 dimensions. The ReLU activation function is used at each layer except the last one and the softmax function with 9 neurons is used in the last layer for differentiation of 9 different classes. Figure 1 gives the overall structure of the proposed CNN model.

Initially, all the images in the dataset are converted into 100x100 dimensions which are fed as input to the CNN model. The python code snippet for the definition of the proposed model is given in Table 1. The description of each layer is defined as follows: The size of each input image is 100 x 100 which is in RGB format. The number of filters used in the first convolution layer is 128, each with size 3x3. The parameters that are trained in the first layer are 3 x 3 x 3 x 32 + 32 bias = 896. The first layer produced an output image of size 98 x 98 x 32 as there are 32 filters; each creates 98 x 98 size image. Next, the image is given to the pooling (max) layer. The size of the filters in the pooling layer is 2 x 2 and the number of filters is 32 which are used with stride=1. Now, the output image size is reduced to 49 x 49 x 32. The resultant images are given to the next convolutional layer. The number and size of the filters in the second convolution layer are 64 and 3 x 3 respectively. The dimension of the images derived from this second convolution layer is 47 x 47. Next, it is given to the MaxPooling layer which has a filter size of 2 × 2 and a stride of 1. Now, the image size is reduced to 23 x 23. In the third convolutional layer, 128 filters with 3 x 3 size

Table 1. Proposed system model definition

```
model = models.Sequential()

model.add(layers.Conv2D(32,(3,3),activation='relu',input_shape=(100,100,3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3)))
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model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3)))
model.add(layers.Flatten())
model.add(layers.Dense(2048, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(1024, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(9,activation='softmax'))
```

are used. The output of this third convolution layer is 21 x 21 x128. The third convolution layer is followed by a max-pooling layer having 2 x 2 filter size and stride=1. This max-pooling layer produces an output of 10 x 10 x 128. Finally, in the last convolutional layer(fourth layer), 128 filters with 3 x 3 size are used and it produced an output of 8 x 8 x 128. When this output is flattened, the image size is reduced to 8192x1. Then, it is given to the fully connected (dense) neural network. There are a total of 7 dense layers in the NN. The number of neurons at each layer is 2048, 1024, 512, 256, 128, 64, and 9. Since there are 9 classes of images to be trained, the last layer (output) contains 9 neurons and softmax activation.

IV. Dataset Description

The proposed work classifies two types of images (DR and DME). For Diabetic Retinopathy, APTOS 2019 dataset has been used. The APTOS 2019 consists of 3658 images with 5 different classes based on severity which are No DR(normal),

Table2. DR and DME dataset

S. No	Classes	No. of Samples	Type of disease
1.	No DR	1804	Diabetic Retinopathy(DR)
2.	Mild DR	370	
3.	Moderate DR	997	

4.	Severe DR	193	
5.	Proliferate DR	294	
6.	CNV	264	Diabetic Macular Edema(DME)
7.	DME	254	
8.	DRUSEN	364	
9.	Normal	253	

mild, moderate, severe, and proliferate. For Diabetic Macular Edema, the OCT image dataset is used. The OCT Images consists of 32107 images and has 4 different classes namely, CNV, DME, DRUSEN, and Normal. The number of images in DR and DME is not equal. To avoid overfitting, from the DME dataset, a portion of images from each class is considered. The images belong to each class in the data set are given in Table 2 and the sample images are also shown in Figure 2.

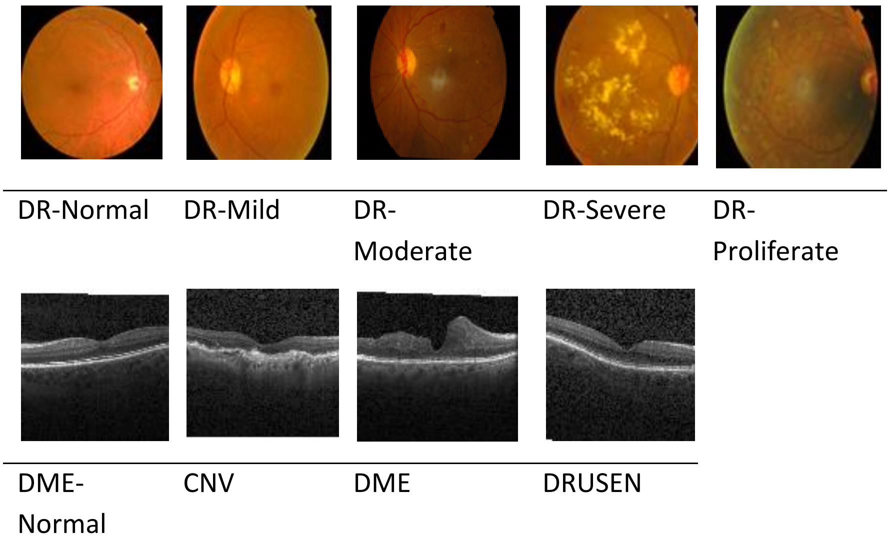

Fig.2. Sample images from each class

Accuracy is one of the metrics considered for evaluation. Accuracy is defined as how many predictions that a model correctly able to identify without any flaws. It is calculated as the ratio of true predictions with the total number of predictions that are made and it is given in equation 1:

$$\text{Accuracy} = \frac{(\text{True Postive(TP)}+\text{True Negative(TN)})}{(\text{True Positive (TP)}+\text{True Negative(TN)}+\text{False Positive(FP)} +\text{False Negative(FN)})} \quad (1)$$

The accuracy is measured by varying the Batch size and the epoch by fixing the learning rate as 0.001 and the obtained results are given in Tables 3 and 4. The results are plotted in Figures 3 and 4. Batch size is referred to as the number of samples considered for an iteration during the training process. Epoch is referred to as the number of times the model undergoes the training process. When analyzing with different epoch and batch size, the proposed system gives better accuracy with batch size 64 and for epoch 15.

Table 3. Results obtained for epoch =10

Batch size	Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
16	90.3	4.97	87.12	12.88
32	92.2	7.8	91.63	8.37
64	94.75	10.39	92.23	8.77

Table 4. Results obtained for epoch =15

Batch size	Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
16	93.35	3.49	93.25	6.75
32	93.35	3.49	93.25	6.75
64	97.19	5.79	95.32	4.68

VI. Conclusion

The proposed work achieves retinal fundus image classification with CNN. The deep learning models were built using neural networks. The proposed approach uses different CNN layers outputs along with fully connected layers for creating a model to classify retinal images. In the proposed work, max pooling is applied to resize the image. The maximum accuracy obtained in classifying diabetic macular edema and diabetic retinopathy is 95% with 15 epochs and for batch size 64. The proposed work is further enhanced by applying denoising techniques. It can be further analyzed with existing models like AlexNet, VGGNet, etc.

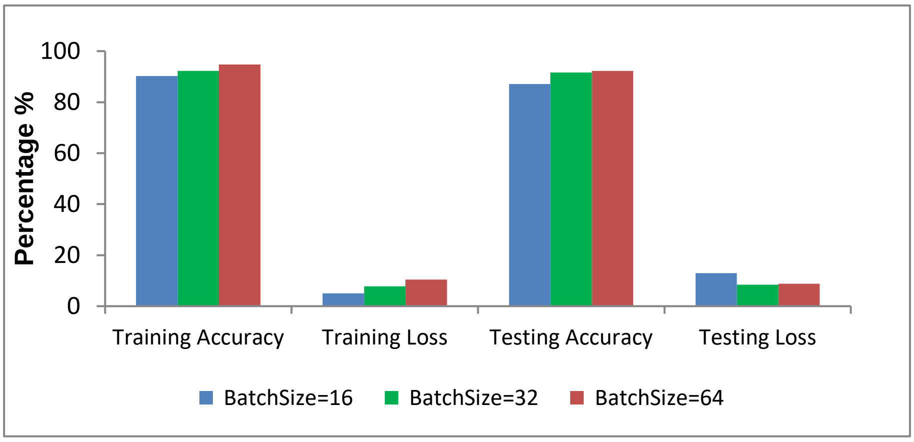

Fig.3. Results in percentage for epoch=10

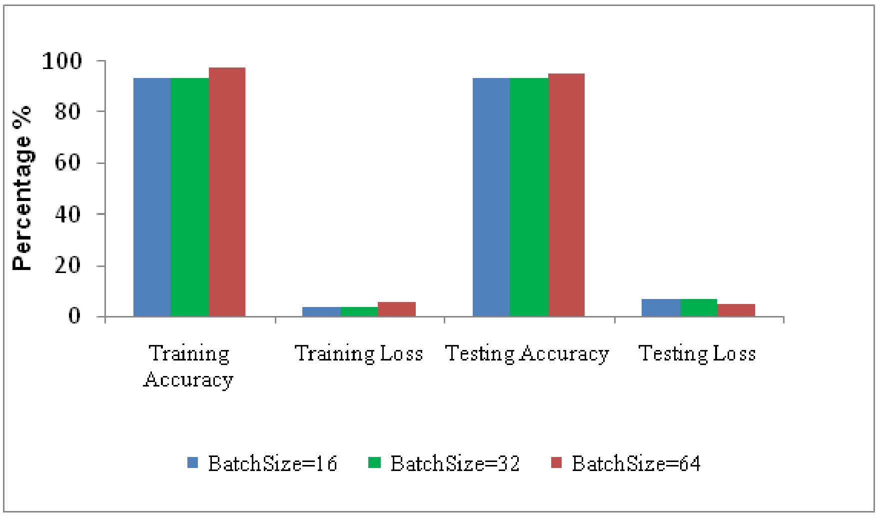

Fig.4. Results in percentage for epoch=15

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