Hard Exudates Detection for Diabetic Retinopathy Early Diagnosis Using Deep Learning

P. Leela Jancy, A. Lazha, R. Prabha, S. Sridevi, and T. Thenmozhi

Abstract Diabetic retinopathy is the complication of the eye caused due to diabetes mellitus. It is caused due to high glucose level in blood which damages the blood vessels at the back of the eye namely retina. The abnormal blood vessels swell and leak into retina. The microstructures such as microaneurysm, exudates (hard/soft) will occupy the retina area which leads to vision threatening. Nowadays, in medical field, computer-aided systems are performing a promising work in terms of object recognizing, localization, classification, segmentation and analysis of images with the help of deep neural networks. Since diabetic retinopathy is irreversible, detection of early stages of diabetic retinopathy is needed. If it left without proper diagnosis and treatment, it will lead to vision loss. Detection of hard exudates indicates the presence of diabetic retinopathy. The early sign of diabetic retinopathy is the formation of hard exudates in retina. In this method, the main aim is to detect the presence of hard exudates in the retinal image using deep convolution neural network.

Keywords Diabetes mellitus · Classification · Convolution neural networks (CNN) · Diabetic retinopathy (DR) · Hard exudates · Microaneurysm · Deep learning

P. Leela Jancy (✉) · R. Prabha · T. Thenmozhi
Sri SaiRam Institute of Technology, Chennai, TamilNadu, India
e-mail: leela.it@sairamit.edu.in

T. Thenmozhi
e-mail: thenmozhi.eee@sairamit.edu.in

A. Lazha
Sri SaiRam Siddha Medical College & Research Centre, Chennai, TamilNadu, India

S. Sridevi
Vels Institute of Science, Technology & Advanced Studies, Chennai, TamilNadu, India
e-mail: sridevis.se@velsuniv.ac.in

P. Karrupusamy et al. (eds.), *Sustainable Communication Networks and Application*,
Lecture Notes on Data Engineering and Communications Technologies 93,
https://doi.org/10.1007/978-981-16-6605-6_22

1 Introduction

Diabetes mellitus is caused due to the presence of high glucose level in blood. Saeedi et al. [1] estimated that diabetes-affected people as 463 million people which is expected to increase by 578 million by 2030 and by 700 million by 2045 worldwide. Diabetic patient needs to be aware of eye diseases. Diabetic eye diseases are a group of problems that are affecting the eyes of diabetic patients. Diabetic retinopathy is caused due to the presence of high blood sugar in patients with diabetics of type II. This high blood sugar damages the eye (retina). Retina detects the light and sends signal through optic nerves to the brain. Earlier studies focused mainly on fundus images, but early stages of DR seem to be a challenging task.

1.1 Diabetic Retinopathy

Diabetic retinopathy is caused due to the presence of high blood sugar in patients with diabetics of type II. This high blood sugar damages the eye (retina). Retina detects the light and send signal through optic nerves to the brain. In order to prevent the vision loss and to prescribe correct medicine, it is a must to classify the severity level of diabetic retinopathy accurately. If not, it will lead to vision loss which is not reversible. Diabetic retinopathy can be classified into two types namely (i) NPDR—non-proliferative diabetic retinopathy comprises three stages, namely mild, moderate and severe. (ii) PDR—proliferative diabetic retinopathy.

1.1.1 Mild-Level NPDR

The patients with mild NPDR have at the minimum one microaneurysm as in Fig.1. Hence, diabetic patients need routine check-up and precise monitoring because the mild level turns into moderate level within one year.

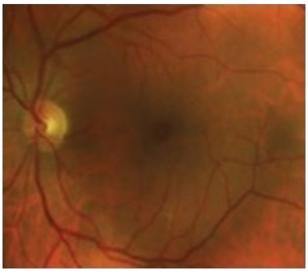

Fig. 1 Mild-level NPDR

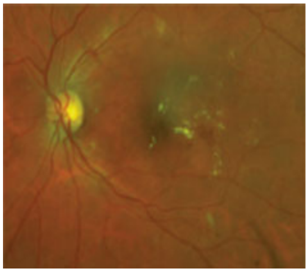

Fig. 2 Moderate-level NPDR

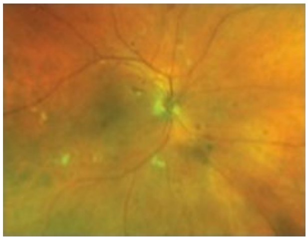

Fig. 3 Severe level NPDR

1.1.2 Moderate-Level NPDR

The patients have microaneurysms in more than one quadrant of retina. Along with/without the following signs—venous beading, hard exudates as in Fig.2.

1.1.3 Severe-Level NPDR

The patient will have more than 20 number of intraretinal bleeding and microaneurysms in each of four quadrants along with venous beading in more than 1 quadrant as in Fig.3.

1.1.4 Proliferative Diabetic Retinopathy

Many numbers of loop of new vessels are located in the optical disk. These vessels will leak which results in retinal edema which also bleeds as in Fig 4.

1.2 Hard Exudates

Small white deposits having sharp edges either yellow in color or whitish in color are called hard exudates. They can be detected at the outer layer of retina. They are formed by the leakage of extracellular lipid that flow from damaged capillaries.

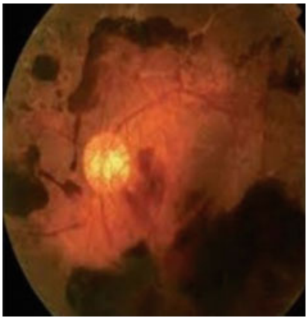

Fig. 4 Proliferative diabetic retinopathy

Accumulation of lipid in/and around retina is diagnosed as hard exudates. Fluids leak from the blood vessels, and it looks as like that of blood plasma in appearance. Hard exudates can be seen initially on the outer plexiform layer of the retina. The main cause of hard exudates is diabetic mellitus. Diabetic retinopathy leads to vision threatening problems and leads to vision loss. Hence, it is the important one to detect the hard exudates which indicates the presence of DR. Their size varies from tiny to larger patches and appears in shapes like rings, stars or plates.

1.3 Convolution Neural Network (CNN)

Convolution neural network (CNN) is a deep learning algorithm mainly used in applications like image processing, segmentation and classification. Manual feature extraction is not needed in convolution neural network. Each layer of CNN extract features using set of filters. The first layer of CNN extracts basic features like horizontal, vertical line from the input image. The second layers extract features like corners, edges from the input image. The hidden layers extract the features and pass the information to the next layer. The last layers of CNN extract the object/patterns from the input image. CNN is useful for detection, segmentation, classification and analysis of medical images. Convolution neural network consists of many layers like convolution layer, pooling layer, drop out layer, regularization layer, flattening layer and fully connected layers. The output from each layer (the activation map) can be input into the next layer. The accuracy of the model is defined as the ratio of total number of images predicted correctly to the total number of images predicted. For classification of images, fully connected network is in the last layer to predict the images either hard exudate image or normal image without hard exudate.

2 Related Works

Earlier works regarding hard exudates were proposed by many researchers. Ladkat et al. [2] proposed a method to differentiate between exudate and non-exudate pixels using intensity level and by tuning matched filters. Palavalasa and Sambaturu [3] proposed a method to detect hard exudates by using two methods, namely background subtraction method and decorrelation stretch-based method. Bharkad [4] proposed a method to detect hard exudates by removing the optical disk so as to avoid wrong classification and features are extracted from green component image. Samah et al. [5] proposed a method to classify three pathologies, namely exudates, hemorrhage, microaneurysm using image enhancement techniques and CNN. Rahi et al. [6] proposed an automatic system for the detection of skin cancer using deep neural networks. Abdar et al. [7] proposed an automatic detection of COVID-19-infected lungs using deep learning-based CNN. Ali and Kumar [8] proposed a model to classify X-ray images using deep CNN to detect pneumonia-affected persons using inception-V3 model. Zhang et al. [9] proposed attention residual learning convolutional neural network (ARL-CNN) to classify skin lesions. Ahmad et al. [10] proposed a method to classify skin diseases using deep CNN by fine-tuning layers of ResNet152 and InceptionResNet-V2 models using triplet loss function. Maya and Adarsh [11] proposed a method to classify the grading of DR severity by removing optical disk, blood vessels and by recognizing hard exudates. Albahar [12] proposed a method using deep CNN to classify the skin lesions. Yu et al. [13] proposed a method that uses four models to classify between normal cell samples and abnormal cells samples. Tiwari et al. [14] proposed the classification of living and non-living images using VGG-16 model. Peng Tang, Qiaokang Liang, Xintong Yan, Shao Xiang and Dan Zhang[15] classified skin lesions using Global-Part CNN. Prabha et al. [16] reviewed machine learning based classification algorithm for medical IOT. Deep learning out performs by extracting the features automatically. No manual interpretation is needed in deep learning algorithms.

3 Materials and Method

Deep learning is one of the promising areas in the field of medical imaging, image segmentation and analysis in research. Deep learning uses convolution neural network to extract patterns or objects from the input image. Convolution neural networks accept input and provide activation map which exhibits the relevant features of the image. The neurons in convolution neural network takes patch pixels as input and multiplies their color values with weights and sum them and executes them with activation function. Deep learning is one of the promising areas in the field of medical imaging, image segmentation and analysis in research.

Deep learning uses convolution neural network to extract patterns or objects from the input image. Convolution neural networks accept input and provide activation map which exhibits the relevant features of the image. The neurons in convolution neural network takes patch pixels as input and multiplies their color values with weights and sum them and executes them with activation function. This implementation method make use of three stages: First stage describes about the dataset used. Second stage describes about methodology. Third stage describes about the image classification using CNN implementation, and the performance of the convolution neural network is evaluated using accuracy.

3.1 Dataset

The images are taken from public database DIARETDB1 which is used as a benchmark for diabetic retinopathy detection from digital images 89 color fundus are there. Samples from DIARETDB1 database is shown in Fig. 5.

The dataset consists of fundus retinal images, ground truth images and fundus mask as in Fig. 6.

The database contains 84 images that shows mild non-proliferative symptoms, and remaining five images do not have any symptoms and they are normal images as in Table 1.

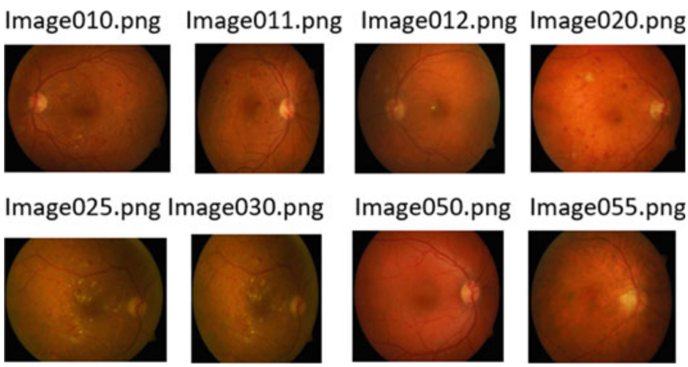

Fig. 5 Sample image of DIARETDB1database

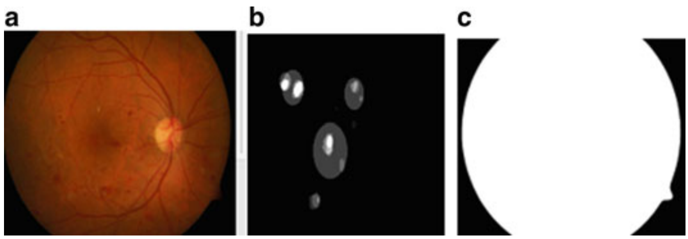

Fig. 6 **a** Original image, **b** hard exudates ground truth image, **c** fundus Mask

Table 1 Dataset details

DR diagnosis	Count	Total
Fundus retinal images with DR symptoms	84	89
Normal/Fundus retinal images without DR symptoms	5	

These color fundus images are also independently marked by four experts. The database consists of color fundus images showing the symptoms that occur for diabetic retinopathy.

3.2 Methodology

The data set itself consists of fundus images and ground truth images with a resolution of 1500 × 1152 pixels. The hard exudates images are identified using ground truth images. Pixels belonging to hard exudates images will have an intensity of 1 and remaining pixels will have an intensity 0. Two folders namely training set with 848 images, and test set with 132 images are created in the working directory. Training set is divided into two classes, namely class 1 (with hard exudate images) and class 0 (normal images) are created and each class consists of 424 images each. Likewise, test set is divided into two classes, namely class 1 (with hard exudate images) and class 0 (normal images) are created each class consists of 66 images each. Initially, input images are preprocessed. Since the dataset is an imbalance dataset (84 with mild DR symptoms and 5 normal images), data augmentation is needed. Data augmentation operations performs normalization, ZCA whitening and operations which resize and reshape the images including shift, rotation, zoom and flipping. The data augmentation creates more images. Data-augmented input images are fed into CNN model. Data augmentation improves the performance of the model.

3.3 CNN Implementation

The model used here is Keras API sequential model. The architecture of our model is shown in Fig. 7. The CNN model consists of six convolution layers. The first convolution layer uses 32 filters followed by 2 layers with 64 filters followed by layer with 128 filters, 256 filters and 512 filters for learning the features. These kernel filters are of 2D and are applied over the images. Rectified linear activation unit (ReLU) is used. ReLU return the input value if it receives a positive input, otherwise it returns zero; it can be written as $f(x) = \text{Max}(0, x)$ where $x > 0$. Pooling layer which performs down sampling follows the convolution layer. Here in this model, max pooling is used. Max pooling layer calculates the largest value of the image patch. Pooling layer summarizes the features of image patches. Convolution

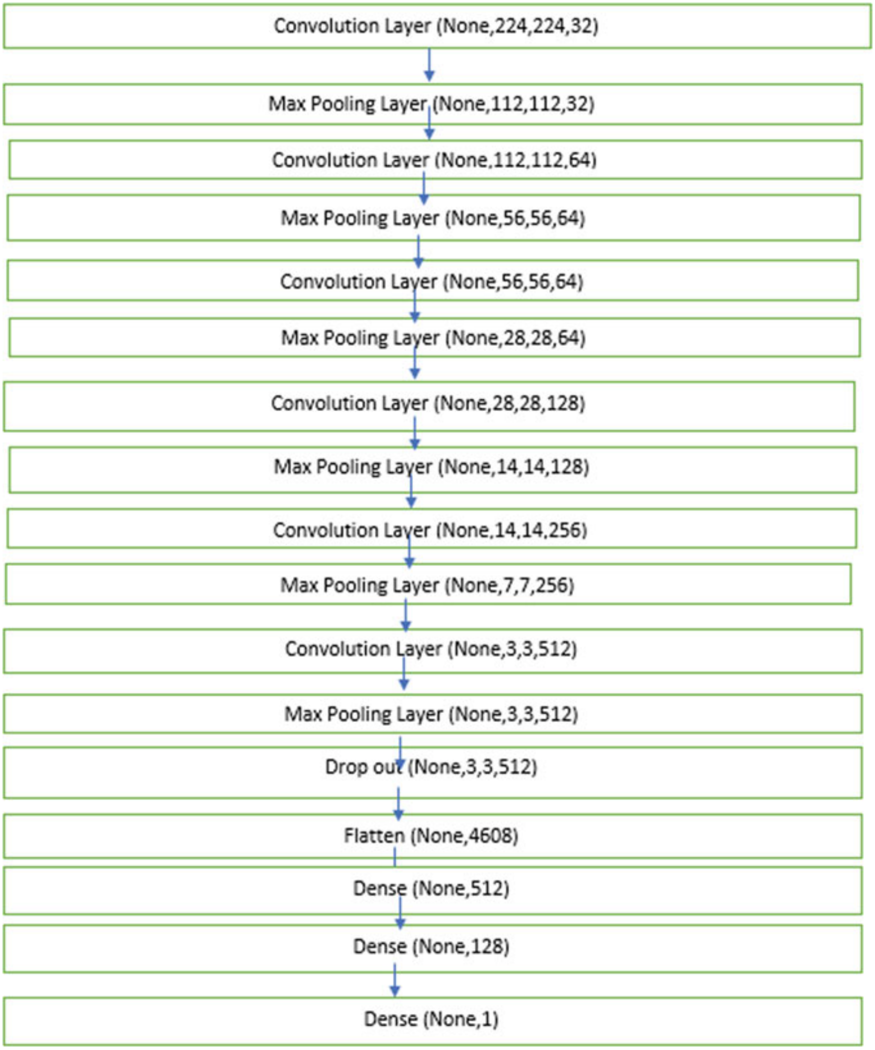

Fig. 7 CNN architecture model for hard exudates detection

and pooling layers learn the features from the input image patches. Drop-out layer is added at the end of the model. Drop-out layer prevent overfitting by removing some neurons in the training stage. Flattening layer converts 2D data into 1D. One-dimensional feature vector from the flattening layer is fed into fully connected layer. In this model, three fully connected layers are used. The sigmoid activation function $F(x) = 1/(1 + \exp(-x))$ is used in the final classification layer (fully connected layer) as in Fig. 7. The sigmoid activation function is used to classify the images into hard exudate image or normal image without hard exudates. The sigmoid activation function is the best option for binary classification. The optimizer used is Adam optimizer with the learning rate of 0.001, and the loss function used in our model is binary cross entropy. It is a stochastic gradient descent method. Regularization and drop-out layers are used mainly added to improve the performance of the model in prediction. Regularization and drop-out layers are added to prevent overfitting.

Once the model is compiled, the model is used for training. Our model summary is shown in Fig. 8. Total trainable parameters are 4,031,105 and non-trainable parameters are 4,031,105.

The model is trained and training accuracy obtained is 99.1%. The test set is fed into the model and the model is evaluated for the performance in term of accuracy,

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_6 (Conv2D)            (None, 224, 224, 32)      896
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 112, 112, 32)      0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 112, 112, 64)      18496
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 56, 56, 64)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 56, 56, 64)        36928
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 28, 28, 64)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 14, 14, 256)       295168
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 7, 7, 256)         0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 7, 7, 512)         1180160
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 3, 3, 512)         0
_________________________________________________________________
dropout_1 (Dropout)          (None, 3, 3, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 4608)              0
_________________________________________________________________
dense_3 (Dense)              (None, 512)               2359808
_________________________________________________________________
dense_4 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 129
=================================================================
Total params: 4,031,105
Trainable params: 4,031,105
Non-trainable params: 0
```

Fig. 8 CNN model summary

i.e., how accurate the model is classifying images into with hard exudates images and without hard exudates images.

3.4 Performance Evaluation of the Classification Model

The performance of the classification model is evaluated using accuracy, specificity and sensitivity. Let True Positive = PosT, True Negative = NegT, False Positive = PosF and False Negative = NegF.

Then

$$\text{Accuracy} = (\text{PosT} + \text{NegT})/(\text{PostT} + \text{NegT} + \text{PosF} + \text{NegF})$$

where PosT defines the number of images correctly classified as images with hard exudates. NegT defines the number of images correctly classified as images with no hard exudates. PosF defines the number of images incorrectly classified as images with hard exudates. NegF defines the number of images incorrectly classified as images with no hard exudates. Accuracy is defined as the ratio of correctly identified images (with hard exudates) and total images. Sensitivity measures the proportion of correctly classified images with hard exudates. Specificity measures the proportion of correctly classified images with no hard exudates.

4 Results and Future Scope

In this paper, the early sign of diabetic retinopathy, i.e., hard exudate is classified using deep CNN. The model starts training the images which are fed to convolution neural network. The model come up with a training accuracy of 99.1% and validation accuracy of 98%. Then, the test images are used for prediction. The model detected the presence of hard exudates with an accuracy of 98.94% for the test images. In future, we have planned to identify hard exudates classification for the early diagnosis of diabetic retinopathy using optical coherence tomography retinal (OCT) modality images. OCT retinal images are of high resolution. Hence, it will be more beneficial if OCT retinal images are explored for the identification of diabetic retinopathy.

References

1. P. Saeedi, I. Petersohn, P. Salpea, B. Malanda, S. Karuranga, N. Unwin, S. Colagiuri, L. Guariguata, A.A. Motala, K. Ogurtsova, J.E. Shaw, D. Bright, R. Williams, On behalf of the IDF Diabetes Atlas Committee, Global and regional diabetes prevalence estimates for 2019 and

projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition (2019)
2. A.S. Ladkat, S.S. Patankar, J.V. Kulkarni, Modified matched filter kernel for classification of hard exudate, in *2016 Internernational Conference on Inventive Computing Technolgy* (IEEE, 2017)
3. K.K. Palavalasa, B. Sambaturu, Automatic diabetic retinopathy detection using digital image processing, in *International Conference on Commnication and Signal Processing* (IEEE, 2018)
4. S. Bharkad, Morphological and neural network based approach for detection of exudates in fundus ımages, in *Proceedings of 2nd International Conference on Computer Methodology and Communication* (2018)
5. A.H.A. Samah, F. Ahmad, M.K. Osman, M. Idris, N.M. Tahir, N.A.A. Aziz, Classification of pathological signs for diabetic retinopathy diagnosis using ımage enhancement technique and convolution neural network, in *9th IEEE International Conference on Control Sysems Computing and Engineering* (2019)
6. M.M.I. Rahi, F.T. Khan, M.T. Mahtab, A.K.M. Amanat Ullah, M.G.R. Alam, M.A. Alam, Detection of skin cancer using deep neural networks, in *IEEE Asia-Pacific Conference on Computer Science and Data Engineering* (2019)
7. A.K. Abdar, S.M. Sadjadi, H. Soltanian-Zadeh, A. Bashirgonbadi, M. Naghibi, Automatic detection of coronavirus (COVID-19) from chest CT images using VGG16-based deep-learning (2020)
8. S.A. Ali, M.S. Kumar, Detecting pneumonia from X-ray images using transfer learning, in *IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation* (2020)
9. J. Zhang, Y. Xie, Y. Xia, C. Shen, Attention residual learning for skin lesion classification. IEEE Trans. Med. Imag. **038**(9), 2092–2103 (2019)
10. B. Ahmad, M. Usama, C.-M. Huang, K. Hwang, M.S. Hossain, G. Muhammad, Discriminative feature learning for skin disease classification using deep convolutional neural network. IEEE Access **008**, 39025–39033 (2020)
11. K.V. Maya, K.S. Adarsh, Detection of retinal lesions based on deep learning for diabetic retinopathy, in *5th International Conference on Electrical Energy Systems* (2019)
12. M.A. Albahar, Skin lesion classification using convolutional neural network with novel regularizer. IEEE Access **007**, 38306–38313 (2019)
13. S. Yu, X. Feng, B. Wang, H. Dun, S. Zhang, Automatic classification of cervical cells using deep learning method. IEEE Access **009**, 32559–32568 (2021)
14. V. Tiwari, C. Pandey, A. Dwivedi, V. Yadav, Image classification using deep neural network, in *2nd International Conference on Advanced in Computing, Communication Control and Network* (2020)
15. P. Tang, Q. Liang, X. Yan, S. Xiang, D. Zhang, GP-CNN-DTEL: Global-part CNN model with data-transformed ensemble learning for skin lesion classification. IEEE J. Bio. med. Health Inform. **024**(10), 2870–2882 (2020)
16. R. Prabha, S. Balakrishnan, S. Deivanayagi, V.K.G. Kalaiselvi, D.P. Rani, G. Aswin, A review of classification algorithms in machine leraning for medical IOT. Int. J. Pharm. Res. **013**(1) (2021). ISSN 0975-2366