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Early Assessment of Diabetic Retinopathy by Detecting Microaneurysm with Deep Neural Network

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Abstract

Objectives: This study aims to detect early signs of diabetic retinopathy, also known as microaneurysm (MA). Early detection of MA can help in diagnosing diabetic retinopathy effectively. **Methods:** To achieve this objective a method is proposed which is based on a deep learning model that incorporates transfer learning. The dataset used in this study is E-Ophtha which consists of 381 high-quality images. The proposed model consists of three steps which are preprocessing, feature extraction and classification. The method uses CLAHE to enhance the details of the fundus image. The feature extraction step and the classification are done using a deep learning algorithm. The proposed method is compared by using parameters such as Recall, Precision, and accuracy. **Findings:** The accuracy achieved by the model is about 98.82%-100%, a recall/sensitivity of 100%, and precision is also 100% which is close to the state of the art. This implies that deep learning methods are a good fit for identifying microaneurysms and ultimately detecting diabetic retinopathy. **Novelty:** Early detection and diagnosis of diabetic retinopathy can be achieved with this approach, and appropriate medication can impede the disease's development.

Keywords: Diabetic Retinopathy; PDR; NPDR; Image Processing; Deep Learning

1 Introduction

A lot of work has been done in the field of diabetic retinopathy for early detection and classification of retinal fundus images. Most focus on detecting and classifying diabetic retinopathy (DR). Microaneurys are the early signs of DR. If they are detected early, they can help diagnose DR. Momeni et al.[1] proposed a method that uses equalisation of images which can cause amplification of noise in the areas with different lighting or textures, and intensity equalisation can cause a visually odd look by removing little details. Wanghu Chen et al.[2] shallow CNN can cause a high computational cost when combining multiscale information. Nahiduzzaman et al.[3] proposed a method based on CNN-SVD. By reducing input features the discriminative power of the classifier would decrease. It could also lead to bias in decision-making. Majumder and Kehtarnavaz [4] suggested a method for DR detection based on Dense Net. It can be computationally costly to train and execute two different models, particularly if the dataset is big or the models are complicated. Abbood et al. [5] present an algorithm for improving the quality of images and classification based on ResNet architecture. The increased depth and complexity of ResNet architectures can result in higher memory consumption during both training and inference. Farag et al. [6] DenseNet-169's computational complexity rises when CBAM is included. Longer training periods and a greater need for computational resources may arise from this. Giroti et al. [7] have randomly resized the images for training which can cause loss of information of important features and can also lead to overfitting. Kapoor et al. [8] used autoencoders. Autoencoders are typically trained in an unsupervised manner. However, this can also be a limitation, as they may not leverage the benefits of labelled data, such as explicit guidance on the task at hand. Joshi et al. [9] their proposed method is based on SHAP which can be computationally expensive, especially for models with a large number of features or complex interactions between features. Kolte et al. [10] have resized the images to 128x128 which can affect the effectiveness of Haralick texture features and Hu moments. Images with low resolution or poor quality may not provide sufficient information for accurate computation of these features, leading to suboptimal results.

2 Methodology

This study seeks to build a classification model to detect Microaneurysms (MA) using retinal fundus images. This study follows these methods, such as feature extraction, classification, and preprocessing. The proposed methodology is shown in the below figure.

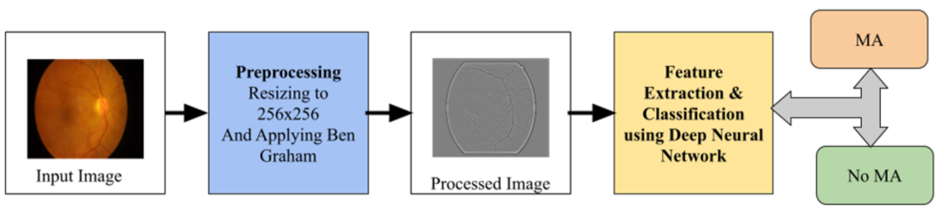

Fig 1. Block diagram of proposed methodology

2.1 Dataset Used

The E-Ophtha [11] dataset was utilised in this investigation. It is made up of 381 pictures. Every image has a resolution of 2544 x 1696 pixels. Healthy and MA are the two groups into which the dataset is divided. The dataset has 233 images of a healthy retina, meaning images with no lesions and 148 images belonging to the class which shows microaneurysms or small haemorrhages. We are utilising a dataset that includes a high-resolution retinal picture captured with several imaging configurations. This dataset may be used to further investigate the course of diabetic retinopathy and to enhance machine learning algorithms for the detection of the condition.

2.2 Preprocessing

It includes the resizing of fundus pictures to a consistent size of 256x256 pixels. There are several benefits of resizing images. Resizing helps the algorithm handle datasets more efficiently as it reduces memory consumption. It also helps in improving the accuracy of the algorithm. After resizing the images are converted into grayscale and an algorithm called Ben Graham [3] is applied to the images to improve their quality. To enhance the details present in the image CLAHE is applied to images.

2.3 Feature Extraction and Classification

Feature extraction and classification are done by using a deep neural network. The proposed method has three convolution layers three max-pooling layers and two dense layers. Hierarchical features are extracted by using the proposed method. At the initial layers features such as edges, textures, gradients etc are extracted. Some mid-level features are also extracted as the model goes deeper which are parts of object textures and patterns. Deeper into the network features such as object parts, and object configurations are extracted. These features are responsible for distinguishing between different classes. For the training of the deep learning model, the processed image dataset is divided into training tests and validation. Layers of Convolution

(Conv2D): A certain number of filters (16 in this example), a kernel size of 3 by 3, and a stride of 1 are defined for each Conv2D layer. ReLU ('relu') is the activation function that is applied following each convolutional operation. This activation function adds non-linearity to the network, enabling it to recognise intricate patterns in the input. Input pictures have three colour channels i.e. RGB and measure 256 by 256 pixels, as indicated by the input shape specification of (256, 256, 3). Layers of MaxPooling (MaxPooling2D): Maxpooling layers serve to control overfitting and lower computational costs by reducing the spatial dimensions of the feature maps generated by convolutional layers. Since no particular pool size or stride is specified in this instance, the spatial dimensions are essentially cut in half. By default, the pool size and stride are set to (2, 2). Flattening layer: To prepare the output for the fully connected layers (Dense layers), the output from the convolutional and pooling layers above is reshaped into a one-dimensional vector by the flattened layers. Fully connected layers, or dense layers: Dense layers are conventional fully connected neural network layers in which all neurons in a layer above are linked to all other neurons in the layer above. There are 256 neurons with ReLU activation in the first dense layer. One neuron with a sigmoid activation function, which is common for binary classification applications, makes up the last dense layer. It provides an output value, ranging from 0 to 1, that indicates the likelihood that the input picture falls into a particular class (e.g., the presence of a specific item in the image). The proposed model is evaluated using gold standards such as precision, recall (sensitivity) and accuracy. The deep classifier archives an accuracy of 98.82%-100% in classifying microaneurysms. Similarly, our study is evaluated on two important evaluation matrices: precision and recall. In the proposed model, recall/sensitivity is computed to 100% and precision is also 100%.

3 Result and Discussion

The Deep Neural Network used in this study performs well in classifying the images. The deep classifier archives an accuracy of 98.82%-100% in classifying microaneurysms. The below figure shows the graph of accuracy.

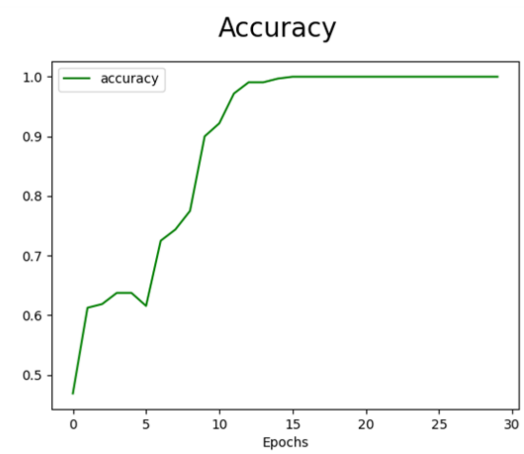

Fig 2. Accuracy of proposed model

Our study is evaluated on two important evaluation matrices: precision and recall. Two significant assessment metrics that are frequently applied in binary classification tasks are Recall and precision.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Precision measures how many of the anticipated favourable instances are truly relevant and focuses on the accuracy of positive forecasts. Recall quantifies the percentage of genuine positive predictions among all real positive examples in the dataset. It is sometimes referred to as a true positive rate or sensitivity.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

The proposed methods attain a recall of 100% and a precision of 100%. The below figure shows the loss during the training of the model.

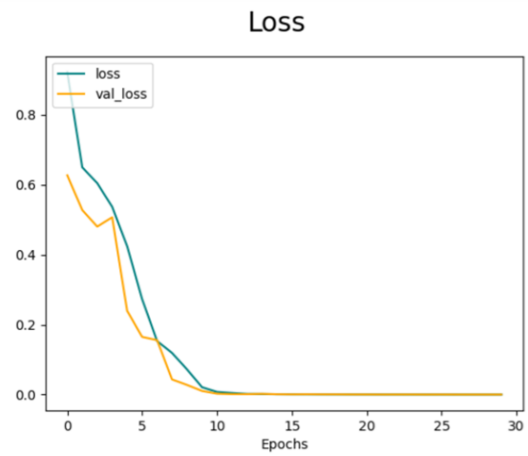

Fig 3. Loss during training

Table 1. Comparison of different methods

Sr No	References No.	Method used	Number of classes	Precision	Accuracy	Recall
1	[2]	Performance-based integration	-	-	0.86	-
2	[3]	Hybrid CNN-SVD	2	99%	99%	100%
3	[6]	Dense Net	2	-	97%	97%
4	[8]	Autoencoder based CNN	2	-	85.33%	-
5	[10]	EfficientNet	5	-	91.8%	90
6	Proposed method	Deep learning	2	100%	100%	100%

The above table shows the comparison between some previously used methods and the proposed method. The proposed method reduces the problem of amplification of noise [1] by utilizing CLAHE as one of the preprocessing steps. By clipping the histogram at a predetermined point, CLAHE restricts the contrast enhancement inside each tile. This keeps noise in low-contrast areas from being overly amplified. The proposed model reduced the computational costs as in [2] as the model uses a moderate number of filters and small filter sizes to reduce model complexity, resulting in lower computational costs during training and inference. Max-pooling layers and flattening reduce spatial information and data complexity. Regularization techniques like dropout prevent overfitting and reduce model complexity. ReLU activation functions are used throughout the model, making it computationally efficient and faster than other methods. This method uses the image size of 256x256 which eliminates the problem of[3]. Larger images provide more visual information, enabling the model to capture finer details and patterns, enhancing its discriminative power and providing more context for predictions. This method also eliminates the problem of computation [4] as smaller image sizes, like 256x256, reduce model parameters and pixel count, resulting in lower computational costs during training and inference. Also, less memory is needed for smaller picture sizes, which facilitates model deployment and training on resource-constrained devices such as embedded systems and mobile phones which solves the issue [5]. Reducing overfitting with smaller photos might be beneficial, particularly when working with smaller datasets. Fewer pixels force the model to concentrate on the most important characteristics, which may improve generalization to previously unobserved data as the problem with [6]. A 256x256 image size is ideal for accurate predictions in tasks like medical imaging or satellite imagery analysis, as it captures the most relevant information that solves the problem [7]. The dataset used is labelled data. Labelled data provides control over annotation quality and accuracy, enabling models to learn from reliable and consistent information, thereby ensuring accurate predictions and solving problems [8]. The problem with [9] can be solved through the use of methods like parameter sharing via convolutional layers, down sampling via max-pooling, flattening to minimize spatial complexity, and computationally efficient activation functions, this approach lowers computing costs. The used dataset E-Optha has images with good quality as compared to other available datasets which solves the problem of extracting features [10].

4 Conclusion

The proposed model follows preprocessing, feature extraction, and classification to provide a comprehensive study for detecting microaneurysms by using retinal fundus images. It utilizes a deep learning model for classifying images into microaneurysm (MA) and No MA. This model attains an accuracy of 98.82%-100%, a recall/sensitivity of 100%, and a precision of 100%. The proposed methods outperform the previous studies with good accuracy and on other gold standard methods. It demonstrates how well the suggested approach can identify and categorise microaneurysms and healthy retina. This method works only as a binary classification which is also its limitation. Future research can expand this approach by detecting more classes of diabetic retinopathy. It has been mentioned that further in-depth research is needed for this.

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