MACHINE LEARNING BASED CLASSIFICATION OF DIABETES MACULAR EDEMA DISEASE OVER RETINAL IMAGES

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Abstract

Patients with diabetes are more likely to experience complications in their eyesight. The retina is damaged in diabetic retinopathy (DR), the macula is damaged in diabetic macular edema (DME), and the optic disk is damaged in severe glaucoma, both of which lead to vision loss. However, early symptoms are scarce because of the gradual course of eye diseases, making diagnosis challenging. This means an early detection and screening procedure needs to be supported by a completely automated system. In this paper, we develop a convolutional neural network (CNN) model, which is used to localisation of the images and then the classification of the localised regions in an image. The study uses Artificial Neural Network for localisation and CNN for classification. The simulation is conducted on different diabetic retinal image datasets that includes ORIGA, MESSIDOR and DR-HAGIS. The simulation is conducted in terms of accuracy, precision, recall and f-measure. The results show that the proposed classification model achieves higher accuracy than the testing results.

Keywords: Diabetic patients, diabetic retinopathy, Machine learning, classification
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1. Introduction

A high blood sugar level is the defining feature of diabetes, setting it apart from other disorders. Diabetic retinopathy (DR) are all conditions that put the eyes and vision at risk in patients with diabetes. DR is an illness that damages the retina and its most common symptoms are impaired vision, floaters, and sudden loss of vision. Hemorrhages, microaneurysms, hard and soft exudates, and other abnormalities [1] have all been related to DR.

Diabetic macular edema, usually known as simply DME, is another eye disorder that can lead to vision loss in people with diabetes. Due to the additional medical difficulties that come from inadequate control of blood sugar, patients with DME have a higher risk of turning blind at any stage of diabetes, albeit this consequence is more likely to occur later in the course of the disease progression. As a result of the accumulation of fluid in that location, diabetic macular edema (DME) can cause the macula, the portion of the retina that is critical for central vision, to expand. If the retina, which contains the macula, receives any form of damage, central vision will be lost. Blurred vision, double vision, floaters in the field of vision, and even blindness can result from diabetic macular edema (DME) if it is not treated [2].

About 80 million people throughout the world are estimated to have glaucoma [3], an eye condition that eventually leads to blindness. All throughout the world, individuals are suffering from glaucoma, which destroys the optic disk (OD) and the optic cup (OC). On the OD, several of the fundamental structural glaucoma tests, such as measuring the size of the disc, calculating the cup-to-disc ratio (CDR), and finding the ratio of neuroretina rim in the inferior, superior, nasal, and temporal quadrants are carried out.

Glaucoma causes damage to the optic nerve as a result of an excessively high intraocular pressure (IOP) in the eye. Damaged nerve fibers can cause a thinning of the retina protective layer, which in turn can hasten degeneration in the inner and outer retina [4]. Optic nerve fibers are damaged by high IOP, and a crater-like hole forms in front of the optic nerve head due to optic degeneration. The outer edge of the disc grows as a result of glaucoma, and the disc itself turns from pink to white as the disease advances.

Ophthalmologists often take a patient medical history, measure intraocular pressure (IOP), and test for visual field loss to diagnose eye illnesses. Ophthalmologists use ophthalmology to visually assess disease by inspecting the optic nerve pigmentation, size, and shape [8]. Segmenting the affected region is helpful for developing a computer-based automatic technique for categorization; it is error-resistant in terms of localization and facilitates more successful complete clinical examinations performed in [5].

The OD eye is typically the first to have a visual evaluation for DR lesions by an ophthalmologist. The disc center drusen diameter (CDR), disc area ratio (DRR), and disc border irregularity are all evaluated in this study. Too few ophthalmologists in practice mean patients often wait much longer than necessary for a diagnosis. Using computer-aided design, researchers are focusing on creating automated glaucoma detection devices (CAD).

The ability to automatically identify eye illnesses has been established through the use of handcrafted features that can distinguish between affected and normal portions of images. However, you shouldn't rely on these features because of issues with colour and size, as well as more intra-class variability and brightness in regions other than OD. Unsatisfactory outcomes from the CAD solution because to inaccuracies in depicting glaucoma, DME, and DR. The detection capabilities of CAD systems can be improved by performing glaucoma classification on a properly segmented glaucoma region, also known as a region of interest (ROI). This is because the afflicted area accurately represents glaucomatous features. Therefore, segmentation is necessary before classification in order to enhance the efficiency of CAD systems.

In this paper, we develop a convolutional neural network (CNN) model, which is used to localisation of the images and then the classification of the localised regions in an image. The study uses Artificial Neural Network for localisation and CNN for classification.

2. Related works

Silve et al. [6] recommended a hybrid feature set that incorporates both textural and structural features of the retina for the purpose of accurately detecting glaucoma. While ML techniques were employed for automated glaucoma identification using OCT, KNN shows its 90% accuracy in findings for early glaucoma detection. Optical coherence tomography has greatly aided in the detection of glaucoma at an early stage (OCT).

Preprocessing was used by the authors of this technique [7] to improve the contrast and reduce the noise in the shots. From the author point of view, the preprocessing procedures make a big difference in how well the complete method works. To use SVM as a classifier, they shot one hundred images of the tCNNing procedure. The next steps after preprocessing were image normalisation and colour conversion. Following that, principal component analysis was used to complete the feature extraction procedure. Images were finally classified as glaucomatous or non-glaucomatous using training and test data with an SVM. The conclusions were derived from the findings of this procedure. The SVM classifier has a 96% accuracy rate, a 100% sensitivity rate, a 92% specificity rate, a 92.59% positive predictive accuracy, and a 100% negative predictive accuracy. In this table, the numbers are all shown as percentages.

Methods for extracting characteristics from the OD region were presented by Akram et al. [8]. Extracted spatial and spectral features are used in the construction of the multivariate model, and LFDA is employed for supervised feature intensification. Since m-medoids recognition is a collection of data, the idea of region of interest (ROI) was incorporated into the evaluation procedure. The authors use MMM to build a sophisticated framework for classifying glaucoma. Several other classifiers, including SVM, GMM, KNN, and Multilayered Perceptron, were used to assess the effectiveness of the proposed approach. Their method exhibited a sensitivity of 92.7%, a specificity of 92.7%, a positive predictive value of 78.1%, and an overall accuracy of 91.7%. Another classifier, GMM, using a Gaussian distribution with 620 degrees of freedom, yielded findings that were very similar to those obtained by LFDA. The fundamental goal of this study is to improve classification accuracy by combining the power of supervised learning with the feature augmentation abilities of LFDA. Also, the recent advancements in the field of computation [9][10] and network bandwidth [11] [12] promotes the new strategies and ideas with high accuracy.

An strategy for extracting properties from the whole image was published by Acharya et al. [9] for the purpose of classifying glaucoma patients. To begin, we used a method called adaptive histogram equalisation to transform the images into grayscale. Then, four filter banks were used to extract textons. The next step entailed putting the incoming textons to work by performing feature extraction using a locally configured pattern. The authors gathered information from all four of the filters they employed before settling on one. For this study [10], the authors collected data on 178 distinct characteristics. Thus, the authors have shifted strategies in the hopes of reducing the total. The committee decided that a sequential floating-forward search (SFFS) would be the most effective method for selecting the characteristics. The authors then used the student t-test to rank the traits and select the ones with a p-value of 0.05 or lower. Each of the five individual classifiers was put through a cross-validation procedure with a 10-fold threshold (discriminate classifier, KNN, decision tree, probabilistic neural network, and support vector machine). The proposed method was 95.7% effective, with a sensitivity of 96.2% and a specificity of 93.7%.

3. Proposed Method

Diabetic eye disease can be diagnosed with the use of fundus images, a process that is educational for the patient and the doctor. The diagnosis and localization of the disease are the most crucial. When performing localization, we employ a convolutional neural network (CNN). For each of the three diseases, we first create CNNotations, and then use BPNN training to extract features from images. This information is passed on to the RoI pooling layer, which in turn feeds the group and bbox regression fully connected layer. As part of the model evaluation, test images are used to pinpoint the affected areas and assign a regression confidence score. The proposed approach is depicted schematically in Figure 1.

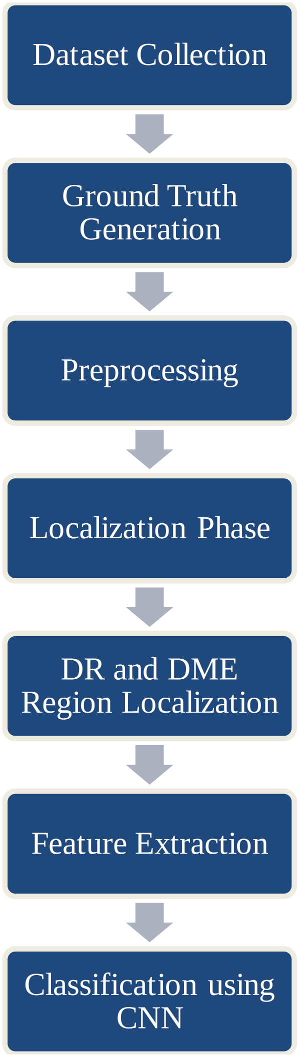

Figure 1: Proposed classification Model

Ground Truth Generation

As part of the training process, images are compared to a ground-truth box to pinpoint the damage. Using the LabelImg application, we can manually create bboxes for each image and also use annotating to automatically annotate the retinal images.

Localization Phase

Localisation is a common theme among the jobs. As a result, all of the tasks can be completed using the same approach.

DR and DME Region Localization

CNN will be posting the images and the places that were suggested. Using max-pooling and convolutional (Conv) layers, our method analyzes the entire image to construct a convolutional feature map. The ROI pooling layer takes as input the Conv feature map and outputs feature vectors of a fixed size. Following its initial processing, the input is sent along to several fully-connected (fc) layers before being split into two separate output layers.

Softmax-probability estimates are calculated over k = 5 area classes in the first layer, and then 4 real-valued values are generated for each of the 5 region classes in the second layer. Each of these values indicates where the bbox falls inside the larger class. Using convolutional neural networks, we have developed a model for multi-class DR object detection (CNN). When a image contains objects from multiple classes, our model can accurately pinpoint their locations.

In order to identify the macula in retinal images, we have trained a convolutional neural network to do so. The macula (center) and the backdrop (margins) are two such locations in this illustration. Both types of areas can be represented by the numbers 0 and 1, respectively. The area within the bbox is the core macular region, whereas the rest of the image is regarded to be background.

The max-pooling and conv layers operate on the entire image to produce the feature map. After the Conv feature map has been sent to a ROI pooling layer, feature vectors of a predetermined length are generated. One layer generates four real-valued numbers for two DME region classes, with each number representing the location of the bbox for one of the DME region classes, and another layer calculates softmax-probability estimates over k = 2 region classes. These predictions are then used as input into a fc layer, which may then split off into a further output layer.

Feature Extraction

Methods for localizing things, such as cars, buildings, and other structures, focus in on the area of interest by utilizing a sliding window. However, the development of DL algorithms like CNN has made the older detection techniques unnecessary. However, since the sliding window method is used for object localisation, the price of such systems is prohibitively high. Contrarily, CNN may train entire network weights by backpropagation and suggests regions via a selective search technique to boost performance. In this paper, we offer a method that uses the lists of images I(x,y) and ROIs (regions of interest) derived from those images as inputs.

In contrast to SPPnet, CNN weights may be trained entirely through backpropagation. Due to the SPP layer inefficiency, RoI derived from a large set of sample images is often inaccurate. Mini-batches are sampled by the stochastic gradient descent (SGD) method during the training of a convolutional neural network (CNN). Mini-batch processing times decrease as N decreases.

Testing through CNN

The localization process is extended by a little bit more than a forward pass after the CNN model has been trained, and object suggestions are then generated. In order to do an evaluation, the framework is given both the image and the potential R objects. Using softmax cross-entropy probabilities, we pinpointed the macula, glaucoma, OD, and OC regions as DR hotspots. Each region is given a Class score and a bbox value. If we want to home in on a certain location, we need to apply the ideas acquired and think about the area where the IoU overlap the most.

4. Results and Discussions

The proposed system is implemented using Matlab R2013a running at 2.53 GHz with 4 GB of random access memory. Matlab r2008a was used for the supervised learning and processing of images.

The study made full use of the information included in the RGB images. In order to facilitate segmentation, the contrast of the blood vessels was increased using image enhancement techniques. The green channel of the RGB colour model provides the most contrast of the three primary colours. The use of the green channel Gabor replies resulted in subpar precision. For this reason, we performed a colour space conversion and settled on the colour channels that, across all colour models, offered the most contrast.

Figure 2: Accuracy

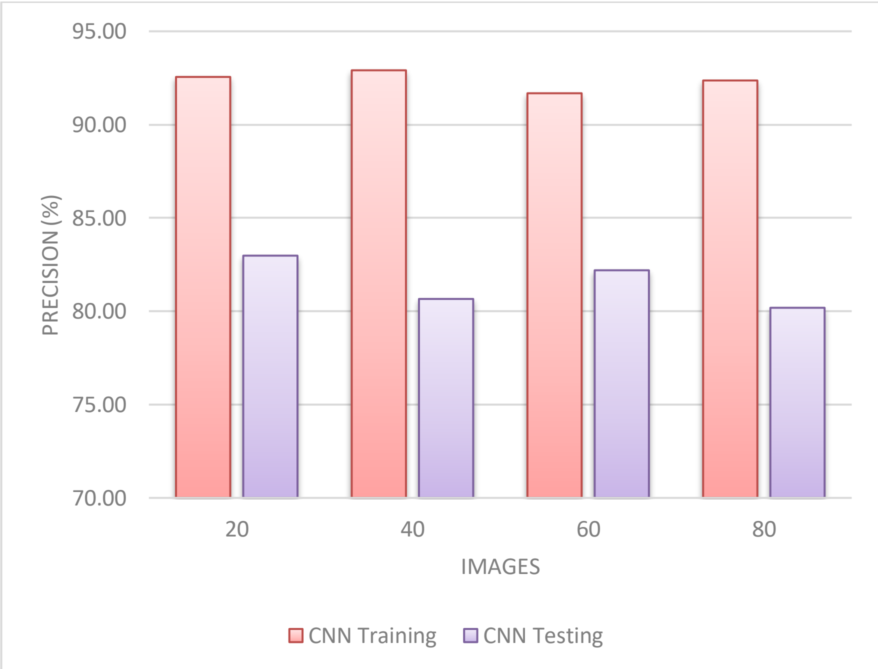

Figure 3: Precision

Figure 4: Recall

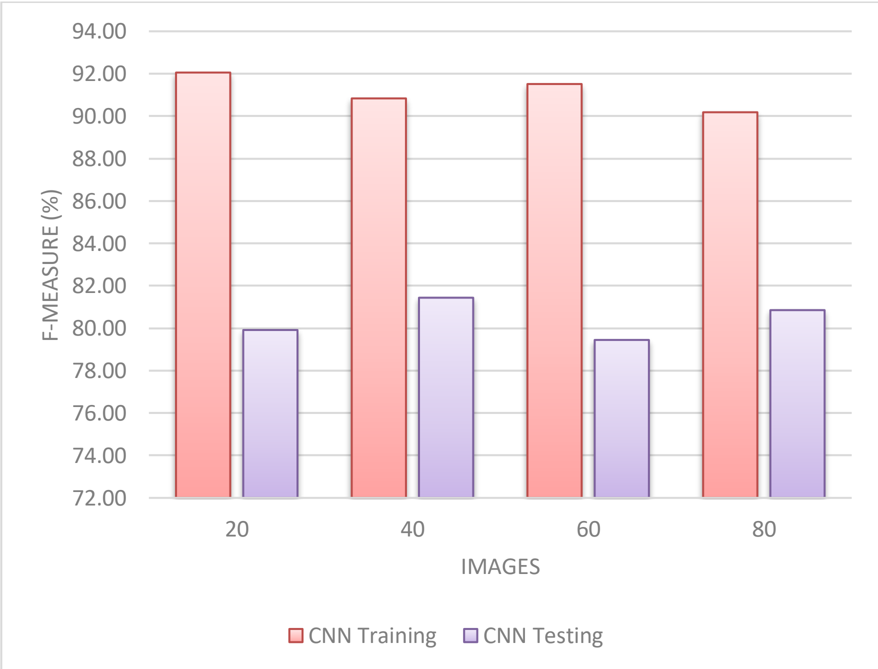

Figure 5: F-Measure

Figure 6: Error Rate

To further improve the contrast in these images, our team used a technique called contrast limited adaptive histogram equalization (CLAHE). CLAHE is distinct from other contrast enhancement methods since it adjusts contrast to minimize the amplification of background noise. After applying contrast enhancement to the images, an early attempt was made to identify vessel and non-vessel pixels using a feature vector with contrast enhanced images. The first attempt was fruitful. This made it crystal clear that additional capability was required.

Since Gabor filtering is the most frequent approach for changing the look of blood vessels, we calculated Gabor responses from the images captured by the four colour channels. The efficiency of the Gabor filter can be drastically altered by changing its parameters. Therefore, we present the values that, after extensive testing, gave rise to the most aesthetically pleasing outcomes. As a result of unwanted noise, which the Gabor detector interpreted as fake blood vessels, the detector results were modified.

The four images that had their contrast raised now have three Gabor replies. The experiments showed that the use of straightforward Gabor responses as the feature vector had no negative impact on segmentation accuracy. The sensitivity, however, was drastically reduced. Experiments were run to see if the green channel inclusion to the 12 Gabor responses improved their accuracy and sensitivity. The final feature vector included a 13-dimensional representation of all the intensities.

Then, during the supervised and unsupervised learning stages, a number of strategies were tested and compared to one another. At initially, we did not combine the clustering and classification steps. When each step was performed independently, the results were more accurate but the sensitivity was poor (about 50% to 60%). Therefore, it was tried again using several distance metrics, with the best results coming from the Manhattan distance. Both high and low cardinality emerge from this method. The low cardinality nodes are linked to the vessel cluster, whereas the high cardinality nodes are linked to the non-vessel cluster.

To improve the efficiency of the classification process, both the clusters are analyzed for further processing. Each of these subsets was then assigned to the appropriate classification. This was found by the CNN training and testing outcomes (Figure 2-6) with those of the subsequent classification. Predictions were made for vessels and non-vessels using distinct classifiers.

5. Conclusions

By comparing the output of the proposed approach to the ground-truth image, we may evaluate how effectively it performs vessel segmentation in fundus images. It was decided that performance indicators like accuracy, sensitivity, specificity, and positive predictive value would be used to assess the quality of the proposed study. There is no denying that the proposed algorithm can hold its own against the state-of-the-art methods. An improvement of just 0.5% in accuracy was shown to be significant in the segmentation of retinal blood vessels in a comprehensive examination of approaches for blood vessel segmentation. This refinement has the potential to aid in the accurate diagnosis of diseases during the analysis phase. In addition, the image contains a very high density of pixels. As a result, an increase of 0.5% means that an even greater number of correctly predicted pixels will be obtained.

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