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Retinal Image Analysis for Diabetic Retinopathy Detection

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Abstract: Diabetic Retinopathy (DR) is a severe ocular complication resulting from diabetes, characterized by damage to the retinal blood vessels. This condition can occur in individuals with either type 1 or type 2 diabetes and is exacerbated by prolonged hyperglycemia. As the retinal vessels deteriorate, they may become blocked or leak, leading to compromised blood supply, loss of vision, and, in some cases, irreversible damage due to the formation of scar tissue. The conventional approach to examining fundus images for DR diagnosis is often cumbersome and time-consuming, requiring significant manual analysis to detect subtle differences in retinal morphology. In this study, we propose a Customized Convolutional Neural Network (CCNN) as an advanced deep learning technique for the automated detection of Diabetic Retinopathy. Our methodology follows a structured workflow encompassing essential phases such as input data retrieval, data preprocessing, segmentation, feature extraction, model creation, training, testing, and interpretation of results. By employing this systematic approach, we aim to enhance the efficiency and accuracy of DR detection, ultimately contributing to improved patient outcomes.The performance evaluation is conducted using the MESSIDOR dataset, which includes 560 images for training and 163 images for testing. Our proposed model achieved a notable test accuracy of 97.24%, indicating a significant improvement over existing algorithms in terms of detection accuracy. The experimental results underline the potential of deep learning models in revolutionizing the traditional diagnostic process, allowing for faster and more reliable assessments of Diabetic Retinopathy.Through this research, we not only highlight the importance of leveraging advanced machine learning techniques in medical diagnostics but also provide insights into the potential future applications of such technologies in broader healthcare settings. By reducing the reliance on manual examination methods, our CCNN approach presents a viable solution to the pressing challenges posed by Diabetic Retinopathy diagnosis and management.

Keywords: Automated Detection, Convolutional Neural Network, Deep Learning, Diabetic Retinopathy, Feature Extraction, Image Segmentation, MESSIDOR Dataset, Machine Learning.

Introduction

Diabetes Mellitus (DM) is a group of medical conditions in which the human body ends up with high blood sugar. There can be various causes of high blood sugar, for example, deficiency in insulin production or lack of cell response towards insulin [1]. The World Health Organization (WHO) predicted an increase in DM in the near future DR is one complication that occurs because of diabetes. It mostly remains undetected until the later stages of the disease. Hence, its early detection is necessary to prevent vision loss [2]. The increased sugar content affects the vessels inside the retinal tissues. Fundoscopy is a medical imaging technique used to capture the internal structure of the retina [The fundus images captured through this technique reveal different retinal structures of the eye. The grading of DR images by an ophthalmologist is a long process that requires meticulous examination. The different abnormalities caused by DR in the eye include red lesions such as Microaneurysm (MA) and intra-retinal hemorrhages. Besides these, white lesions that appear in the eye because of DR include exudates (EX) and cotton-wool spots. A Microaneurysm (MA) is a tiny aneurysm or swelling on the side of a blood vessel [3]. These small aneurysms can weaken the capillary walls, which can rupture and leak blood from the blood vessel. The leaked blood because of a Microaneurysm causes hemorrhages around the blood vessels inside the retina. The cause of vessel damage in the retina is not only limited to diabetes. An excess of reactive oxygen species during active retinal usage and obstructive sleep apnea syndrome can also cause various retinal disorders [4]. The abnormalities caused by DR also surface in other molecular and genetic analyses of the retina. These retinal pathologies cause the alteration of specific pathways such as inflammation and vascular alterations. There are many traditional image processing and machine learning (ML) techniques that are proposed in the literature for isolating these lesions [5]. Support Vector Machines (SVM) are an important technique that helps in the fast and accurate separation of different classes by transforming the input features into hyperplanes using kernel functions [6].

Recently, the image processing field has been aided by Convolutional Neural Networks (CNN) [7]. An end-to-end system requiring minimal preprocessing results from the integration of the various image features and classifiers in CNN. Multiple layers and their depth can greatly affect the enhancement of Feature extraction. It was found that deep learning networks (DL) maximize the performance. However, increasing the depth of the network can introduce various problems such as vanishing gradients and degradation, resulting in high training errors. Different architectures were proposed in the literature to optimize these networks for image classification [8].

Methodology

Diabetes-based eye diseases detection from fundus images is considered a two-way method. The first is the detection and localization of disease, and the second step is the segmentation of localized regions using the FKM clustering. In the localization step, we utilize the FRCNN method. We develop the annotations for three diseases and passes to the FRCNN training which extracts the features from images and passes to the RoI pooling layer as an input of the group and bbox regression fully connected layer. The model is evaluated by using the test images to localize the affected portions with a score of regression confidence. At the last, FKM clustering is applied for the segmentation, which is considered as a robust method, especially for image segmentation. Figure shows the framework of the proposed method.

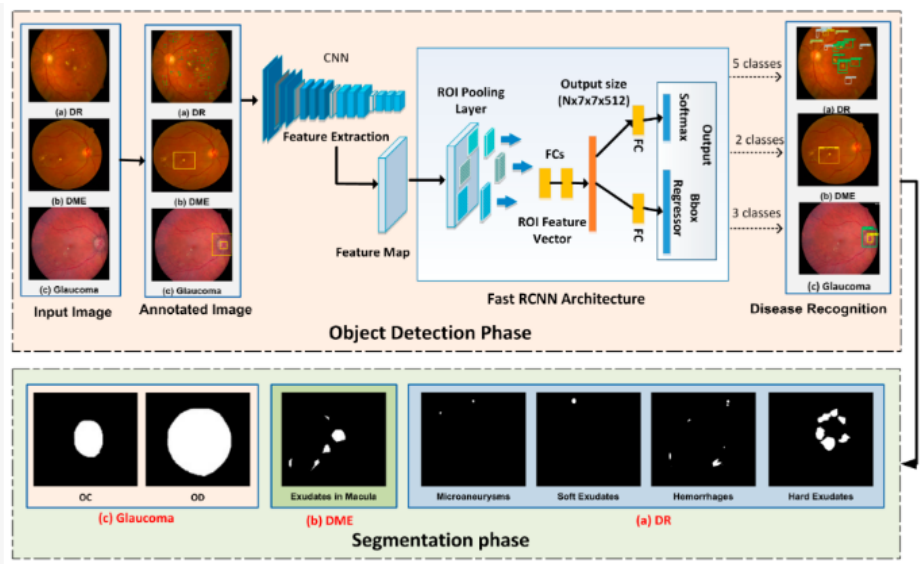

Figure: Framework of the proposed method.

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Ground Truth Generation

The ground-truth bbox against each image is required to identify the affected region for the training process. The LabelImg tool is used to annotate the retinal images and manually create a bboxes for each image. fig shows an example of an original image and the corresponding ground truth image. The annotations are saved in .xml files which includes the class of object and their bbox values i.e., xmin, ymin, xmax, ymax, width and height. Xml file is created against each image and these files are used to create the csv file, train. Record file is created from csv file which is later used in the training process.

Classification of Fundus Images

Machine learning algorithms classify images based on the features that are extracted from them. The main idea of image classification is the grouping of images with similar features. Linear or nonlinear combined image features are used in the classification process.

Support Vector Machine (SVM) An SVM is among the traditional classifiers and supervised machine learning algorithms The way that an SVM works is that it classifies the data input by forming a hyperplane in a higher dimension space. The process allows for applying a Kernel function to transform the input into hyperplanes, thus dividing the data into separate classes. SVM utilizes structural error minimization in the classification process and works to maximize the margins between the hyperplane classes. The different Kernel functions utilized by SVM include sigmoid function, hyperbolic tangent kernel, polynomial kernel, isotropic Gaussian kernel, etc.

Random Forest (RF): RF is another traditional classifier among the ensemble-based classifiers that work by combining different algorithms for the classification process Initially, randomly generated decision trees are formed together like a forest. The training set data are used to train all these trees. Another randomness with RF is that the data used for training are generated randomly. Bagging is a process within RF that prevents overfitting. Test features extracted after the initial creation of the forest are used in the final prediction of every output of the individual decision trees. The final vote of the decision tree is taken as the f inal output. After training, any new data are presented to the RF with the maximum vote used to determine the final output.

Radial Basis Function (RBF): Radial Basis Function (RBF) is another classifier that measures the similarity between the input data and training sample to determine the class

A radial basis kernel is used to transform the n-dimensional input to a higher m-dimension. It is capable of generating a polynomial of infinite power allowing for the non-linear classification of the input data.

Naïve Bayes (NB): NBisyet another traditional classifier that is based on the probabilistic statistics model of the Bayes theorem The assumption that strong independence exists between the features of the images gives this classier the name of naïve. In the original Bayes classifier, the conditional probability of whether data belongs to a particular class is calculated through the conditional and unconditional probabilities of the same data belonging to each class within the dataset. The complexity of NB is finding the class within the data that has the same number of attributes with strong dependence.

Results and Discussions

In binary classification, the data no longer suffer from the imbalance issue after combining stage 1–4 images into a single class, i.e., DR. For multiclass classification, we reduce the number of classes from five to three, i.e., NDR (stage 0), MDR (stage 1–2), and PDR (stage 3–4). We determine the smallest number of images in three classes and perform a randomized selection of the same number of images from the other classes. Using this method, we obtain the lowest number of images in the combination of stage 3–4 labeled class (PDR), i.e., 488. Hence, 488 images are randomly selected from each of the

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remaining classes, i.e., NDR and MDR. These images are passed on to the CNN models to extract the feature vectors. The batch size is set to 32. The feature vectors from the individual models are combined to form the hybrid feature vector, which is passed on to different classifiers. For additional comparison, the individual transfer learning models that use only the Google Net or ResNet-18 feature vector of 1000 features are also passed on to the classifiers. The hardware used in this work contains an AMD Ryzen 2700× processor with 32 GB of RAM. The Graphics Processing Unit (GPU) installed in the system is an NVIDIA GeForce RTX 2080 with 8 GB memory. MATLAB was used for extracting the features of the pre-trained Google Net and ResNet-18 architectures based on APTOS image data. Different classifiers are used in MATLAB for binary and multiclass classification of input images.

The evaluation metrics which are used for assessing the performance of the system are accuracy, precision, recall, and f-measure. Accuracy represents the fraction of total predictions that are correctly classified. The precision determines what fraction of predictions classified as positive in a certain class are actually correct. Recall determines which fraction of actual correct labels in the data were predicted correctly by the classifier. F-measure provides the harmonic mean of recall and precision.

Table: Experimental results of different classifiers for multi class classification using hybrid features

Classifier	Metrics	NDR	MDR	PDR	Weighted Average
RF	Accuracy	96.66	76.58	83.96	85.64
	Precision	92.40	84.00	79.70	85.60
	Recall	96.70	76.60	84.00	85.60
	F-Measure	94.50	80.10	81.80	85.50
SVM	Accuracy	96.66	81.64	90.07	89.29
	Precision	96.70	87.80	83.10	89.40
	Recall	96.70	81.60	90.10	89.30
	F-Measure	96.70	84.60	84.60	89.30
RBF	Accuracy	98.66	62.65	82.44	80.86
	Precision	93.70	81.10	67.90	81.50
	Recall	98.70	62.70	82.40	80.90
	F-Measure	96.10	70.70	74.50	80.50
NB	Accuracy	94.00	74.68	71.75	80.41
	Precision	89.80	74.70	75.80	80.20
	Recall	94.00	74.70	71.80	80.40
	F-Measure	91.90	74.70	73.70	80.30

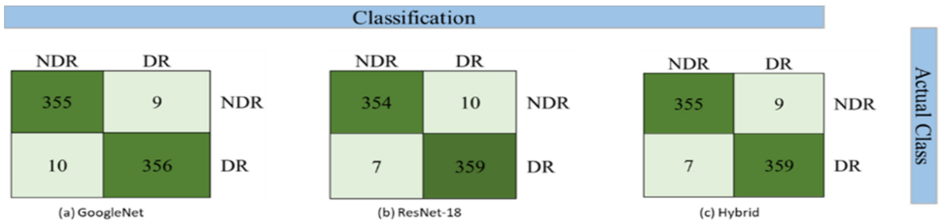

Figure: Confusion matrix for binary classification using SVM classifier

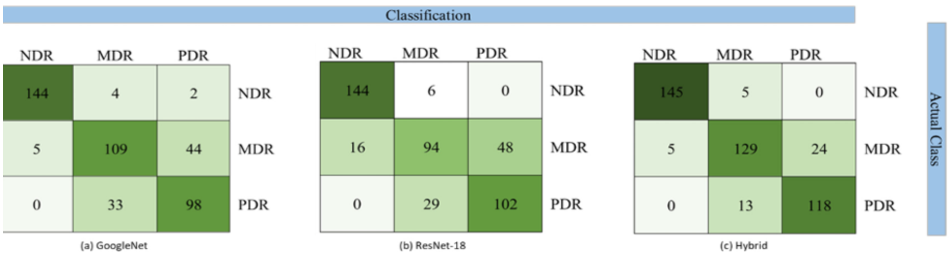

Figure: Confusion matrix for multi class classification using SVM classifier

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Conclusions

This research work provides a hybrid approach for early Diabetic Retinopathy detection using transfer learning to extract fundus image features from ResNet-18 and Google Net models. These features are input to different classifiers which perform binary and multiclass classification of DR images from the APTOS dataset. In multiclass classification, the combination of features extracted from Google Net and ResNet-18 help improve the MDR and PDR class metrics that increase the overall performance of the system. The proposed classification technique can assist ophthalmologists in the early detection of Diabetic Retinopathy. The results also indicate that using CNN for feature extraction followed by other machine learning classifiers besides ANN can provide fast and highly accurate results. The hybrid model using the SVM classifier achieves the highest average accuracy of 97.80% for binary classification and 89.29% for multiclass classification. The results outperform recent similar approaches to binary and multiclass DR detection. Future work will continue in the line of detection and diagnosis of Diabetic Retinopathy using various machine learning algorithms and using deep learning algorithms. Enhancements can be carried out to improve the results such as data augmentation and applying different preprocessing techniques to remove different artifacts and noise from the input images.

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