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Classification of Fundus Images with Pre-Trained Model Using Principal Component Analysis and Support Vector Deviation

Manaaf Abdullredha Yassen[1], Dhurgham Hassan Mahlool[2], Zainab Abed Abdulla[3]

[1]AL-Qadisiyah University, College of Arts, college of engineering
[2]Ministry Of Agriculture, college of engineering
[3]AL-Qadisiyah University, college of engineering

ABSTRACT:

A new field of study that uses imaging technologies to diagnose diseases is called automated analysis of medical images. Diabetic patients are identified with diabetic retinopathy (DR), a retinal condition. Fundus images taken from suspicious individuals are often used to classify diabetic retinopathy using deep neural networks (DNNs). Through the use of a Gaussian mixture model, and (VGGNet) visual geometry group network, also using singular value decomposition (SVD), in addition, principle component analysis (PCA), Softmax for region segmentation, high dimensional feature extraction, feature selection, and fundus image classification, respectively, the proposed DR classification system achieves a symmetrically optimized solution. 32,228 images from the website KAGGLE dataset were used in the experiments. In terms of classification accuracy and computational time, the suggested VGG-19 DNN-depending DR model fared better than AlexNet and spatial invariant feature transform (SIFT). The classification accuracies of 93.33%, 98.22%, 97.98%, and 98% for FC7-PCA, FC7-SVD, FC8-PCA, and FC8-SVD, respectively, were obtained by using PCA as well as SVD feature selection using fully connected (FC) layers.

KEYWORDS: VGG-19; SVD; deep convolutional neural network; DNN; diabetic retinopathy; fundus images; PCA; DR.

Introduction

Advancements in science and technology are leading to more secure, comfortable, and livable human healthcare. Automated diagnosis systems, offer services that make life easier for people [1]. Automated diagnosis systems are essential for the early detection of severe illnesses. Globally, diabetic retinopathy (DR) is a dangerous and common condition. According to a recent World Health Organization (WHO) estimate, diabetes is expected to rank seventh globally in terms of disease-related mortality by 2030. It is extremely difficult to save the lives of diabetic people in this situation. One common condition that affects people with diabetes is diabetic retinopathy as a result of damage in the eyes caused by diabetic retinopathy, irreversible blindness eventually results [2].

As illustrated in Figure 1, these lesions include irregular retinal blood vessels, microaneurysms, also cotton wool patches, additional exudates, and hemorrhages.

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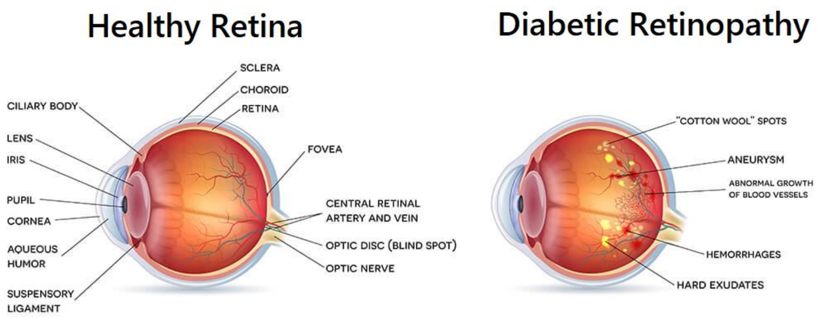

Figure 1. A healthy retina and retinopathy caused by diabetes.

Diabetic retinopathy can be categorized into five stages based on the disease severity scale, non-DR, mild severe, moderate severe, severe, and proliferative DR [3]. Numerous researchers have contributed significantly to the field by introducing various techniques, designs, models, and frameworks, as well as by identifying lesions in the early stages of DR. A technique for identifying exudates and spots on cotton wool presented by researchers [4]. Moreover, the Proposers [3] detected microaneurysms in color retinal fundus images using deep neural networks. A brand-new method for identifying sudden hemorrhages was presented by Researchers [5]. Furthermore, by employing several kernel approaches to identify hemorrhages and microaneurysms, prepared by researchers [6]. obtained noteworthy experimental results.

However, determining the degree of DR severity is also a crucial step in the healing process for an afflicted eye. Using random forests, presented researcher. [6] created a computer-aided approach for classifying fundus images [7]. the proposers supported the use of DCNN for the identification of diabetic retinopathy based on deep learning techniques [8]. Using more than 126 thousand DR images, Gulshan et al. [9] suggested categorizing the fundus images into non-DR and moderate-severe with the assistance of 54 American ophthalmologists and other medical researchers. Moreover, the fundus pictures were categorized as non-DR, mild DR, and severe DR [10]. The researchers suggested a reliable method for categorizing the degrees of DR severity, which was then compared to the severity scale's criteria [11]. To identify the DR disease early on. Developed a machine learning bagging ensemble classifier (ML-BEC) [12]. There are two stages to the ML-BEC method. The initial stage entails the identification of noteworthy characteristics from the retinal fundus pictures. In the second step, an ensemble classifier based on machine learning is used for the features that were derived from retinal fundus images. An ensemble CNN-based method for bioimage categorization was presented by researchers. [13]. the research proposed The new method improved the performance of medical picture analysis and classification by combining multiple CNNs[14] The researchers proposed creating a deep visual feature-based automatic computer-aided diagnosis system that can classify DR severity levels without the need for preprocessing. Deep learning algorithms are used in a multilayer semi-supervised approach to generate deep visual features (DVFs). [15] used deep learning and domain expertise to create an Innovative approach to the detection of red lesions. Using this method, the retinal fundus images were classified according to a severity scale using the random forest classifier. [16] presented a method for utilizing convolutional neural networks to identify exudates in color retinal fundus images. inserted a regression activation map (RAM) after the pooling layer of the convolutional neural networks as part of a deep learning technique to comprehend the diagnosis of diabetic retinopathy [17]. RAM's purpose is to locate the fundus image's interesting areas and determine the region of interest based on severity degree. An evaluation method was presented by the researchers [18] to examine the outcomes of retinal fundus images produced by applying various architectures, models, and frameworks. A novel deep features learning method based on CNNs and employing fully linked layers was described [19]. the proposers suggested in this method, the normal, drusen, as well as exudates, were classified using a nonlinear classifier. A novel method for classifying the image quality (IQS) of the retinal fundus [20]. This method of executing the computer algorithms was based on the human visual model.

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To feed the support vector machine (SVM) classifier with supervised and unsupervised features, respectively, the suggested technique used convolutional neural networks (CNNs) and saliency maps. Using a structured analysis retinal database (SARD), prepared by researchers. [21] used a multi-categorical deep learning method to identify many lesions when retinal fundus images were available. Classifying retinal fundus images is a common practice in diabetic retinopathy research that makes extensive use of deep learning. Based on the International Clinical Diabetic Retinopathy Disease Severity Scale, numerous writers in this field have discovered various methods to cluster the retinal pictures [1].

To identify micro-aneurysms, blood vessels, as well as hard exudates, it's presented by researchers. [22] presented multiple segmentation methods. The "Haar wavelet transform" principal component analysis (PCA) feature extraction method was used in this research. For two-class classification, the researchers propose backpropagation in neural networks.[23] Their study utilized a multilayer perception-based deep neural network. An automated computer-aided identification method based on optic disk segmentation was created using the graph cuts technique [24], for micro aneurysm recognition and DR picture classification, presented by the researchers [25] employed optic disk identification and exudate feature extraction. In their study, [26] utilized the genetic algorithm to detect exudates in DR pictures. Similarly, red lesions, including exudates, were localized by researchers. [27] by utilizing the intersection of abnormal thickness in retinal blood vessels. Diabetic retinopathy has also made use of fuzzy and k-means clustering methods [28]. An automated approach for diabetic retinopathy [29] the researcher utilizes to measure the severity of pictures of the retinal fundus and to detect abnormalities. The method developed. [30] for identifying microaneurysms and hemorrhages relies on shape features. We used the JSEG method to identify micro aneurysms and exudates in DR pictures [31]. To diagnose retinal fundus images early, Quellec et al. [32] suggested a pixel-based ConvNets DNN method. The ConvNets method categorizes retinal fundus images according to their severity using a softmax classifier.

[33] To detect blood vessels and hemorrhages, the researchers suggested a method based on texture analysis. A two-stage DCNN-based automated DR analysis method for red lesion localization and detection in retinal fundus images was created by researchers. [34] The automated approach went a step further by categorizing the retinal fundus images according to their severity.

The researchers utilize it to automatically detect DR in color retinal fundus pictures. [35] put out a method. The retinal fundus images were categorized into three groups: normal, mild severe, and moderate severe. To segment the retinal blood vessels from the input fundus images, a Gaussian filtering model was employed. The researchers Utilized 25 _ 25 picture patches taken from retinal fundus pictures. [36] assessed the capacity to detect microaneurysms. Three different types of neural networks—NN, RF, and SVM—were employed to categorize DR into five distinct severity levels. To lower the dimensionality, we used PCA and RFFI, or random forest feature importance.

A computer vision system was developed by researchers. [37] using both handcrafted and non-handcrafted features. Three methods were used for the non-manufactured features: PCA, convolutional neural networks (CNNs), and compact binary descriptors (CBDs). In contrast, the features that were hand-crafted utilized various algorithms such as local phase quantization rotated local binary patterns, finished local binary patterns, and others. Excellent picture classification results were obtained when the suggested method was applied to many datasets.

[38] Here, the researchers studied previous work on automated computer-assisted diagnosis methods and came up with a new way to identify glaucoma automatically by building on the current methodology. To evaluate Google Inception v3 with human ophthalmologists, researchers implemented an evaluation strategy for retinal fundus picture detection [39]. To determine the severity degrees of DR, the researchers used modified versions of current de-noising methods [40]. Using the convolutional neural network (CNN) classifier, the updated work successfully classified input datasets about retinal fundus images. To classify diabetic retinopathy exudates, hemorrhages, and

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microaneurysms, created by researchers. [10] built a convolutional neural network (CNN) architecture that could detect these intricate features.

An innovative concept for an automated diabetic retinopathy screening system that can detect microaneurysms at an early stage was developed by researchers. [41]. The automatic DR screening system was built using the fuzzy histogram method, which was employed for feature extraction and retinal fundus picture preprocessing. Automatically categorizing retinal fundus images according to severity levels[28] created a unique computer-aided diagnostic approach for the early detection of aberrant retinal blood vessels. To reduce dimensionality, Mansour used principal component analysis (PCA), and to extract features, he used AlexNet DNN architecture. Using this current feature extraction method as a foundation, the suggested method enhances it to achieve higher classification accuracy. What follows is an outline of the remaining content of the article. Section 2 explains the proposed procedure, and Section 3 discusses and presents the experimental results. Lastly, Section 4 concludes the findings.

Proposed Method

The suggested method successfully constructed a reliable automated diabetic retinopathy categorization system. Segments in fundus images could be created by the suggested system based on severity grades and diseases. By breaking down the suggested strategy into sequential parts, the system was properly implemented to reach the DR severity. This allowed for a better understanding and execution of the procedures.

2.1. Data Gathering

Gaining relevant data is an essential first step in conducting experiments with the suggested system.
For the experiments, a website KAGGLE competition dataset was utilized within the framework of diabetic retinopathy [42]. A wide variety of fundus cameras have contributed high-resolution images to the standard KAGGLE. The KAGGLE database contains 32,228 fundus images, each annotated with the corresponding eye. Fundus pictures from the KAGGLE RD dataset follow a normal distribution, as shown in Table 1.

Table1. dataset from the KAGGLE website

Class	Diabetic Retinopathy Classification	Diabetic Retinopathy Images
0	Non-DR	23190
1	Mild severe	2443
2	Moderate severe	5002
3	Severe	885
4	Proliferative DR	708

Various fundus cameras, each with its own unique set of settings and quality standards, were used to collect the images. A small percentage of the images were found to contain dots, circles, triangles, or squares, but the majority were regarded as normal. Some images can flip in these settings. Additionally, blurry, out-of-focus, under-exposed, or over-exposed images might be characterized as noisy. In such a scenario, there must be a way to anticipate the DR images even when noisy data is present.

2.2. Data Preprocessing

Optimal diabetic or non-diabetic retinopathy attainment is a critical part of the preprocessing step. Micro aneurysms (MAs), exudates, and hemorrhages are among the numerous illnesses that can be found in diabetic retinopathy. Finding and differentiating between real DR lesions or characteristics from the noisy data requires preprocessing. Consequently, the raw pavement digital photos have to undergo a preprocessing treatment before feature extraction. The primary goal of preprocessing in the proposed CADS is to detect microaneurysms (MAs) in the blood arteries. To provide improved

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contrast, algorithmic approaches like the grayscale conversion method are executed throughout the preprocessing phase. Estimating the image and then subtracting it from the existing image is done using the shade correction method. The following step involves using GMM for vessel segmentation. Figure 2 illustrates the fundus images that were utilized to extract the backdrop retrieved visual information from the colorful image.

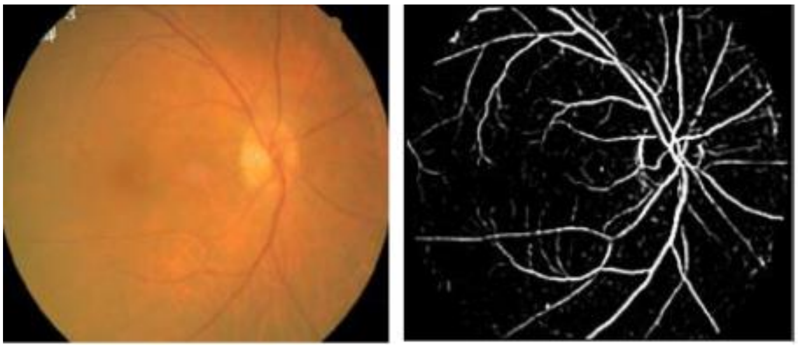

Figure 2. Colored retinal fundus image and background

The image with the highest level of discrimination is in the background. The adaptive learning rate (ALR) did an excellent job in the ROI of obtaining the most discriminating information. Micro aneurysms in DR were located using a robust method based on ensemble clustering by the researchers [43].

2.3. Region of Interest Detection

Blood vessel extraction was executed with the association of ROI localization before the feature extraction was used. At this stage, the ROI in the DR pictures was extracted using blood vessel segmentation. Many methods, including neural networks, fuzzy models, edge-based segmentation, and ROI-based segmentation, can be used for this purpose. This work describes the application of a Gaussian mixture approach for vascular segmentation. The background subtraction strategy was obtained by using Gaussian sorting, as described by the researchers. [44]. An adaptive learning rate (ALR)-based Gaussian mixture model (GMM) was suggested as part of the hybrid strategy to improve region detection outcomes in the proposed technique.

This approach suggested a parametric idea to get the difference and enable the quasi-linear adaptation to remove such restrictions. Figure 3 provides a comprehensive overview of the method used to detect and segment retinal blood vessels. To begin, the DR dataset is used as an input for picture data segmentation and detection. It is retrieved from the KAGGLE repository. Part 2 explains how to use the sub-process to understand GMM-based blood vessel segmentation and detection. The connected components analysis (CCA) method is used to evaluate the size, location, and region of diabetic retinopathy characteristics, such as hemorrhages, hard exudates, as well as MAs, following the vascular segmentation procedure. When comparing abnormalities to normal retinal characteristics, CCA can help distinguish between them based on size, shape, and distance. Once the CCA was finished, the ROI of the blood vessels could be found, and we could go on to the feature extraction utilizing VGG-19.

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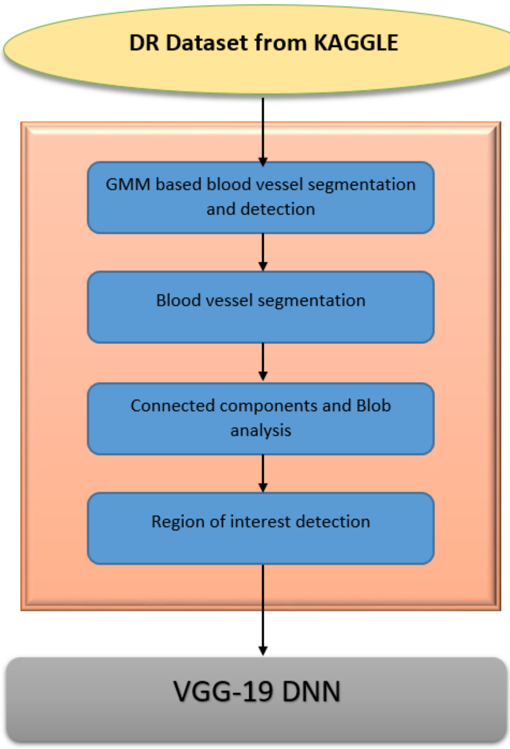

Figure3. Segmentation and identification of retinal blood vessels

2.4. Feature Extraction

The convolutional neural networks (CNNs) create a fresh representation of the input picture with each layer by gradually extracting relevant data. To extract useful information from fundus images, the suggested method used VGG-19. The visualization reveals the representation's categorized image format.

Pixel area, perimeter, minor axis in length. major axis length and circularity are all important features that should be considered during the extraction process to obtain a robust diabetic retinopathy system (DRS). These features aid in the identification of blood vessels, exudates, hemorrhages, optical distance, and microaneurysm areas. One multi-layered deep neural network is the visual geometry group network or VGGNet. The VGGNet uses the ImageNet dataset and is based on the CNN model. The simplicity of VGG-19, which uses three stacked 3 _ 3 convolutional layers to scale with depth, makes it a powerful tool. To decrease the volume size, VGG-19 made use of max pooling layers as a handler.

There were 4096 neurons in two FC layers. The input data for the VGGNet DNN was the vessel-segmented images, as seen in Figure 4. In the training phase, features were extracted using convolutional layers, and dimensionality reduction was achieved through the use of max pooling layers associated with some of those convolutional layers. The input pictures were feature extracted using 64 kernels with a 3 _ 3 filter size in the first convolutional layer. The feature vector was prepared using fully connected layers. To improve classification results, the obtained feature vector was subsequently processed using principal component analysis (PCA) and support vector descent (SVD) to reduce dimensionality and pick features from picture data. Significant effort is required to use PCA and SVD to minimize the data's high dimensionality. PCA and SVD outperform other reduction approaches in terms of utility due to their numerical stability and speed. In the testing phase, the DR pictures were classified using the softmax activation technique, and a 10-fold cross-validation was done. The suggested VGG-19-based system was tested against SIFT and AlexNet, two alternative feature extraction architectures, to see how it performed. One CNN architecture that uses multiple layers for feature extraction is AlextNet. In the realm of computer vision, the scale-invariant feature

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transform (SIFT) was first presented by the researchers [28]. as a conventional feature extraction method for detecting the input image's local features.

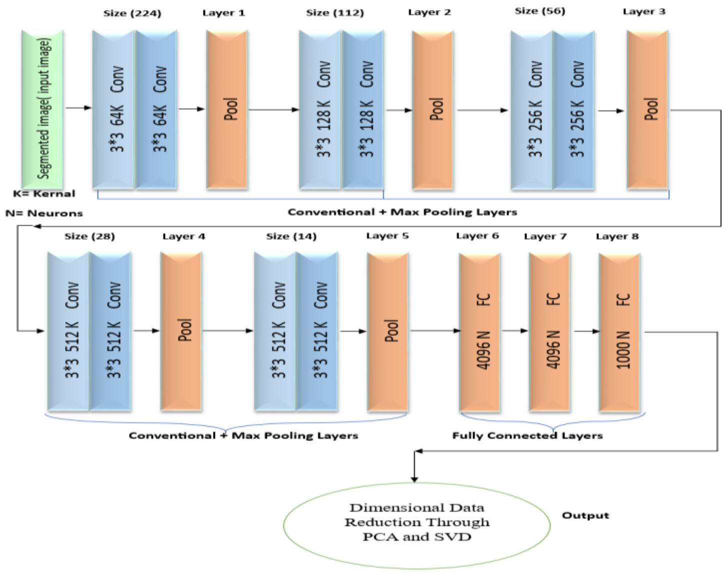

Figure 4. Representation of the VGGNet on Retinal fundus image

2.5. Data Reduction

Feature selection is the subsequent stage in picture analysis following feature extraction from VGGNet. Minimizing the number of dimensions in the imaging data is the goal of feature selection. Data reduction was accomplished using the PCA and SVD techniques in the proposed technique. Using principal component analysis (PCA) reduces the dimensionality of image data by focusing on its most salient aspects. One other difficulty with DR fundus image extraction is differentiating between the extracted features and the most expressive features (MEF). The principal component analysis (PCA) strategy aims to discern between them by transforming the feature components into new feature vectors. Conversely, SVD is employed to reduce dimensionality based on dependability. A primary goal of SVD is to drastically cut down on calculations in the intricate network and the number of parameters. As with the DNN's overfitting problem, VGGNet uses max pooling to minimize dimensionality based on the maximum value. Two fully connected layers, FC7 and FC8, are used to extract characteristics of the DR-ROI based on the VGGNet, as shown in Figure 5, which represents the algorithmic framework of the retinal fundus image classification process.

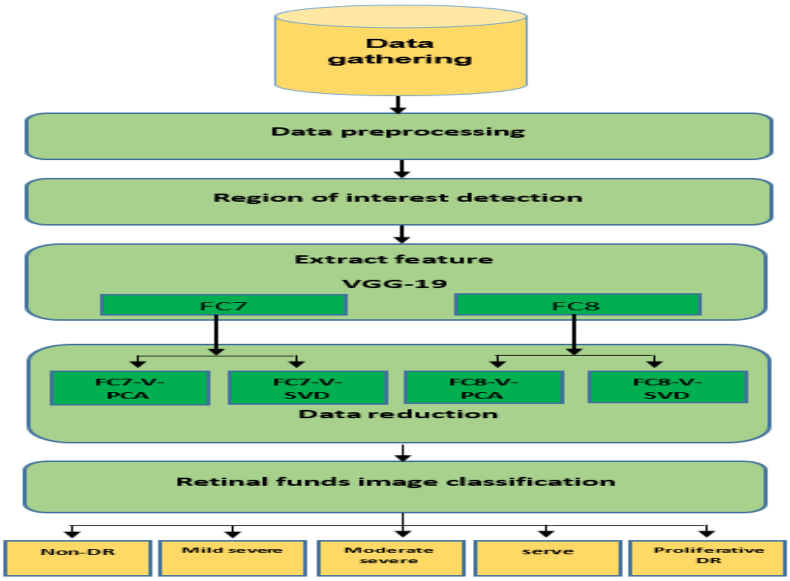

Figure 5. Diagram of the suggested method.

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2.5.1. Principle Component Analysis

To decrease computing time and storage requirements, the dimensionality reduction procedure is crucial. An essential function of principal component analysis is the accurate reduction of dimensional complexity. Performing principal component analysis (PCA) allows one to extract useful feature vectors from a high-dimensional feature space and store them in a lower-dimensional one. Important fundus imaging characteristics in diabetic retinopathy are often interdependent. A feature's most expressive features are those that are linked with one another. Using principal component analysis (PCA) to re-align the features vector with the new, uniquely treated feature elements is the best way to address this issue. To accomplish accurate and rapid feature computation, principal component analysis (PCA) played a crucial role in minimizing feature vectors with similar elements and moving them to the most significant vectors.

2.5.2. Singular Value Decomposition

As an orthogonal matrix decomposition method, SVD is dependable and strong. SVD finds extensive application in image analysis for the resolution of issues about least squares, pseudo-inverse matrix computing, and multivariate experiments. Collaborative filtering, metric learning, manifold learning, and dimensionality reduction are all applications of SVD-based algorithms in machine learning.

The use of parallel processing to deploy systems and execute large-scale datasets in seconds rather than days is typically not possible with complicated data. Here, SVD is the way to go for rapidly computing dimensionality reduction on massive datasets. In particular, SVD outperformed other methods in terms of classification accuracy while using optimal computational time for fundus image classification.

2.6. Retinal Fundus Image Classification

The fundus images were classified using the attributes of the photos using the softmax classifier in this study. A softmax algorithm was taught to display the categorization as a binary value in the proposed method. The features extracted from the data reduction were used as a basis for the softmax-based classification. Fundus pictures were re-trained using the suggested classification to place them into one of five predefined categories: non-DR, mild severe, moderate-severe, severe, or PDR.

Discussion of Experiment Findings

Here we detail the experimental findings of the suggested method. An experimental evaluation of the proposed DR system was conducted on KAGGLE datasets.

A total of 32,228 fundus images taken under varying lighting conditions are included in the KAGGLE datasets.

Fundus images are categorized into five kinds in the standard KAGGLE dataset: non-DR, mild severe, moderately severe, severe, and PDR. The percentages of each group are reported in Table 1. To start, fundus images were downsized to 224 by 224 pixels for better computational efficiency. After that, microaneurysm segmentation was carried out after the preprocessing procedure for improved outcomes. The noteworthy outcomes were achieved by employing general-purpose units (GPUs) to get a versatile VGGNet implementation. We applied PCA and SVD algorithms to the suggested method to find the best result. As can be shown in Table 2, the outcomes were superior to those of the more conventional approaches, such as AlexNet and SIFT.

The results outperformed those of AlexNet and SIFT, and they were produced using VGGNet's fully connected layers FC7 and FC8. In comparison to the more conventional methods, this demonstrated that the VGG-19 DNN model achieved superior classification accuracy. When PCA and SVD were used together, the features that were part of the suggested method worked better. After correctly selecting the important feature vectors, SVD retrieved the discriminatory features. As shown in Figure 6, the accuracy of classification is graphically represented.

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Table 2. Diabetic retinopathy findings compared using AlexNet, VGGNet, and SIFT.

Method	Proposer	ACC%
VGG	FC7-V-PCA	93.33
	FC7-V-SVD	98.22
	FC8-V-PCA	97.98
	FC8-V-SVD	98
AlexNet	FC6-A-PCA	91.15
	FC6-A-SVD	97.83
	FC7-A-PCA	96.36
	FC7-A-SVD	97.33
SIFT	S-PCA	91.03
	S-LDA	94.4

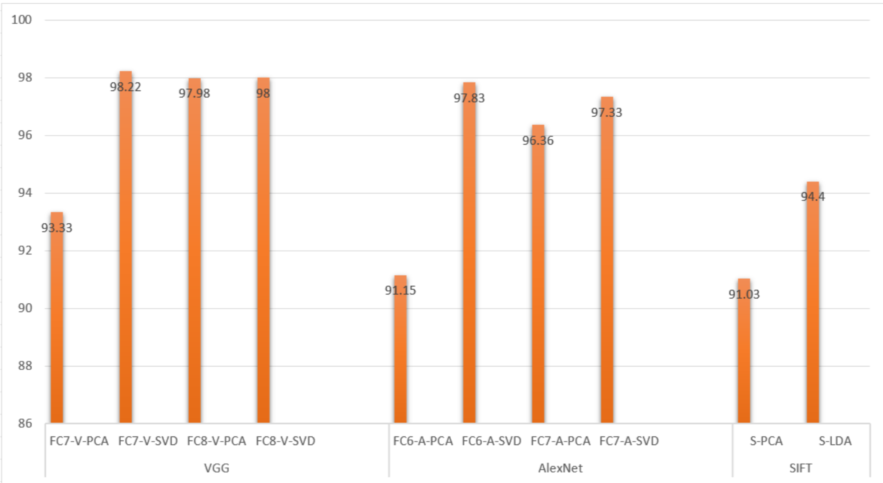

Figure 6. Accuracy for diabetic retinopathy classification.

There was a tenfold cross-validation procedure used for training and validating the model, as stated in Section 2.4.1. We utilized employing the tools of Keras 4.3.0, TensorFlow 2.7.0, and Python 3.8.8. This computer has 16 GB of RAM, a graphics processing unit (GPU), and a ten-generation Intel Core i7 processor. While Alex Net required 190 minutes to process all 32,228 photos, Python completed the task in 105 minutes, which is longer than SIFT but shorter than AlexNet. With a reduced classification accuracy, SIFT's computing time was recorded at 95 minutes. Table 3 displays the comparative performance results of several methodologies employed for DR fundus picture classification, allowing for a better evaluation of the accuracy of the categorization in the images.

Table 3. Comparison of classification findings

Methods with features	Accuracy classification
SVM + NN	89.60
GLCM + SVM	82.00
FCM+NN	93.00
HEDFD	94.60
DWT+PCA	95.00
FC7-V-PCA	93.33
FC7-V-SVD	98.22
FC8-V-PCA	97.98
FC8-V-SVD	98

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Conclusions

The prevalence of diabetes has been rising at an alarming rate in recent years. This has led to diabetic retinopathy (DR) being a major concern. To address this issue, a deep neural network has been utilized to detect symptoms at the early stages of DR, which is crucial. In the proposed DR classification system, features of retinal fundus images were extracted using VGGNet, while the dimensionality of the large-scale retinal fundus images was reduced using PCA and SVD. PCA and SVD were more effective in their roles to speed up and improve the reliability of the data reduction process. Using GMM with an adaptive learning model based on vessel segmentation allowed us to detect the region of interest. The VGGNet is a more robust and in-depth design for ImageNet technology, which is why we chose it over the VGG-19. Through principal component analysis (PCA) and structural vector decomposition (SVD) feature selection, the suggested VGGNet DNN-based DR model outperformed the AlexNet and SIFT models, achieving 93.33%, 98.22% for FC7 and 97.98%,98% for FC8 classification accuracy, respectively.

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