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Pretrained Models and the Role of Feature Selection: An Artificial Intelligence-Based Approach in the Diagnosis of Diabetic Retinopathy

Mehmet Kaan KAYA[1], Burak TAŞCI[2*]
[1] Ophthalmology Clinic, Universal Göz Hospital, Elazig 23040, Turkey
[2] Vocational School of Technical Sciences, Firat University, Elazig 23119, Turkey
[1] opht1980@gmail.com, [2*] btasci@firat.edu.tr

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Abstract: Diabetic retinopathy is a significant complication occurring in the retina of the eye as a result of prolonged diabetes. When not detected early, this condition can lead to vision loss. Advanced image processing techniques and artificial intelligence algorithms have enhanced the possibilities of early diagnosis and treatment. This article discusses current advancements in artificial intelligence-based diabetic retinopathy detection and explores future possibilities in this field. In the experimental studies of the article, the Kaggle Aptos 2019 dataset was utilized. This dataset comprises 5 classes and a total of 3662 images. The class distribution is as follows: No DR (No Diabetic Retinopathy): 1805, Mild: 370, Moderate: 999, Severe: 193, Proliferative DR: 295. The study consists of four fundamental stages. These stages are (1) Feature extraction from VGG16 and VGG19 pretrained models, (2) Feature selection using NCA, Relieff, and Chi2, (3) Classification with Support Vector Machine classifier, (4) Iterative Majority Voting. Using the proposed method, a high accuracy of 99.18% is achieved. Furthermore, sensitivity of 100% for the No DR class, sensitivity of 100% for the Moderate class, sensitivity of 98.80% for the Severe class, and an F1-Score of 99.89% for the No DR class are obtained. This study demonstrates the effective utilization of machine learning methods in diabetic retinopathy diagnosis. The experimental results underscore the significant contributions of diabetic retinopathy patients' diagnosis and treatment processes.

Key words: VGG16, VGG19, Neighborhood Component Analysis, Relieff, Chi2.

Ön Eğitimli Modeller ve Özellik Seçiminin Rolü: Diyabetik Retinopati Tanısında Yapay Zeka Tabanlı Yaklaşım

Öz: Diyabetik retinopati, uzun süreli diyabet hastalığının bir sonucu olarak gözün retinasında meydana gelen ciddi bir komplikasyondur. Erken teşhis edilmediğinde görme kaybına neden olabilen bu durum, gelişmiş görüntü işleme teknikleri ve yapay zeka algoritmalarının kullanımıyla erken teşhis ve tedavi imkanlarını artırmıştır. Bu makalede, yapay zeka tabanlı diyabetik retinopati tespiti alanındaki güncel gelişmeler ve geleceğe yönelik ihtimaller ele alınmıştır. Makalemizin deneysel çalışmalarında, Kaggle Aptos 2019 veri seti kullanılmıştır. Bu verisetinde 5 sınıf bulunmaktadır ve toplamda 3662 görüntü içerir. Sınıf dağılımı şu şekildedir: DR (Diyabet Retinopatisi) yok: 1805, Hafif: 370, Orta: 999, Şiddetli: 193, Proliferatif DR: 295. Çalışma dört temel yapıdan oluşur. Bu aşamalar (1) VGG16 ve VGG19 ön eğitimli modellerinden özellik çıkarma, (2) Nca, relieff ve chi2 ile özellik seçimi,(3) destek vektör makinesi sınıflandırıcı ile Sınıflandırma,(4) yinelemeli çoğunluk oylama'dır. Önerilen yöntem kullanılarak %99.18'lik yüksek bir doğruluk elde edilmiştir. Ayrıca, Dr yok sınıfı için %100 hassasiyet, Orta sınıfı için %100 duyarlılık, Şiddetli sınıfı için %98.80 duyarlılık ve Dr yok sınıfı için %99.89 F1-Skoru elde edilmiştir. Bu çalışma, diyabetik retinopati tanısında makine öğrenimi yöntemlerinin kullanılmasının etkili bir yaklaşım olduğunu göstermektedir. Deney sonuçları, diyabetik retinopati hastalarının tanı ve tedavi süreçlerine önemli katkılar sağladığını ortaya koymaktadır.

Anahtar kelimeler: VGG16,VGG19, Komşuluk bileşenleri analizi, Relieff,Chi2.

1. Introduction

Diabetes is a chronic condition characterized by long-term elevated blood sugar levels due to insufficient or ineffective insulin in the body. This condition leads to disruptions in carbohydrate, protein, and fat metabolism, as well as changes in capillary membranes and progressive atherosclerosis [1]. As of 2019, the global number of individuals with diabetes was estimated at 463 million, projected to rise to 578 million by 2030 [2]. One of the most prevalent microvascular complications of diabetes is called diabetic retinopathy (DR). DR arises due to damage in the blood vessels of the retinal layer. It is considered one of the leading causes of vision loss worldwide [3]. While DR is generally observed in approximately 30% of diabetic individuals, its prevalence increases within the population as diabetes duration lengthens [4], thus elevating the risk of vision impairment. Early diagnosis is crucial to slow down DR progression and prevent vision loss. Consequently, diabetic patients are recommended

* Corresponding author: btasci@firat.edu.tr. ORCID Number of authors: [1] 0000-0002-3027-9159, [2] 0000-0002-4490-0946

to undergo regular retina screenings under the supervision of eye doctors. However, these screenings can be time-consuming and require expertise. To address this challenge and support healthcare professionals, the utilization of rapid and reliable computer-aided automated screening systems is increasingly growing [5].

Artificial Intelligence (AI) is a field of computer science where machines mimic human cognitive processes. It finds extensive applications in the field of health and medicine. AI has been employed in the medical domain since the early 1950s, aiming to enhance diagnostic accuracy through computer-assisted algorithms [6]. Presently, rapid technological advancements in the healthcare sector offer substantial potential for early disease diagnosis and treatment. In this context, the early detection and effective management of chronic conditions like diabetic retinopathy hold paramount importance. Diabetic retinopathy is a severe complication occurring in the retinas of diabetes patients, potentially leading to vision loss. Moreover, due to its suitability for processing complex images, AI has been applied in image-based medical fields such as radiology and ophthalmology [7, 8]. These systems swiftly scan the retinas of diabetic patients, assisting physicians in early problem detection. Therefore, the use of automated screening systems has become an inevitable necessity in contemporary healthcare.

The contributions of the proposed Diabetic Retinopathy detection method based on VGG16, VGG19, and feature selection are provided below. To achieve overall performance, 10-fold cross-validation and extension validation are employed. An SVM classifier was chosen to demonstrate the general success of the proposed VGG16, VGG19, and feature selection-based method. The proposed approach utilizing VGG16, VGG19, and feature selection achieved an exceptional classification rate %99.18 for Diabetic Retinopathy detection using OCT images.

In order to generalize performance and attain a robust model, it is essential to test the model with various datasets. In the future, we are considering exploring the possibility of utilizing the proposed model, using OCT images, to detect different types of diseases. Furthermore, the model we have developed can also serve as a learning model for solving other computer vision problems.

The literature contains numerous studies conducted using deep learning and machine learning techniques [9-11].

Math and Fatima (2021) [12] proposed a segmentation-based approach utilizing deep learning to detect and classify DR and its lesions. Initially, preprocessing was applied to fundus images and factors like normalization. Preprocessed images were employed for image segmentation, adapting a pretrained Convolutional Neural Network (CNN) for obtaining lesion segmentation at the level of DR. Subsequently, all segmentation levels were integrated for fundus image classification. An end-to-end segmentation-based learning approach was used to better identify irregular diabetic retinopathy lesions. The evaluation results of the proposed model yielded values of 96.3% AUC, 96.37% sensitivity, and 96.37% specificity. Mahmoud et al. (2021)[13], proposed a hybrid inductive machine learning-based approach for automated DR diagnosis. The model evaluates color fundus images through four stages: preprocessing, segmentation, feature extraction, and classification. The preprocessing step normalizes retina images to enhance image quality, while the segmentation step involves encoding and decomposition of images. In the feature extraction and classification stages, a multi-instance learning technique was employed. According to experimental results, the suggested hybrid model achieved accuracy of 96.62%, sensitivity of 95.31%, and specificity of 96.88%. Ali et al. (2020) [14], developed an image processing and machine learning-based method for DR diagnosis. The model utilized a total of 2500 retinal images for each DR class. Four different features, including histogram, wavelet transform, co-occurrence matrix, and run-length matrix, were extracted from the images. A hybrid dataset was created using data augmentation to enhance classification accuracy. By applying four different feature selection techniques on 245 hybrid features per image, 13 optimized features were selected. With the proposed model, sequential minimal optimization, logistic regression, Canonical Correlation Analysis (CCA), logistic model tree, and simple logistic machine learning classifiers achieved accuracy of 98.53%, 99%, 99.66%, 99.73%, and 99.73%, respectively. Yıldırım et al. [15], conducted DR detection using a dataset comprised of 1365 fundus fluorescein angiography images. In their study, they proposed the utilization of the MobileNetv2 model in conjunction with a nested patch-based image classification approach. Through this methodology, they achieved a classification accuracy of 87.40% on the collected dataset. Kobat et al.[16] proposed a method based on horizontal and vertical patch segmentation for DR classification. With their suggested approach, they achieved accuracy values of 94.06% and 91.55% for three-class classification, respectively. Tang and et al.[17] attempted to automatically detect epiretinal membrane regions using OCT images. They achieved an accuracy of 95.65% at the image level. Pramil et al.[18] classified OCT images of 90 cases of geographic atrophy, 32 cases of intermediate age-related macular degeneration, and 16 healthy controls. They employed a five-fold cross-validation method and data augmentation techniques. Their proposed method demonstrated high repeatability for geographic atrophy area measurements with ICC values of 0.99 and 0.94, along with expansion rates of the geographic atrophy area.

1.1. Motivation

The utilization of technologies such as Artificial Intelligence (AI) and Deep Learning (DL) has sparked a significant revolution in the medical field, particularly in areas like image analysis, pattern recognition, and data mining. In the realm of image-based diagnostics, AI methods hold the potential to mitigate errors made by medical doctors and accelerate the diagnostic process with heightened precision. The incorporation of AI-based techniques in the diagnosis of diabetic retinopathy can enhance patients' quality of life and provide healthcare professionals with a more effective roadmap. The fundamental motivation of this article is to underscore the potential and advantages of AI in diabetic retinopathy diagnosis. The primary focus of this research is to propose a hybrid deep learning model utilizing pretrained VGG16 [19] and VGG19 [19] architectures, thereby highlighting the application of AI in diabetic retinopathy diagnosis.

2. Material and method

2.1. Dataset

In this study, the publicly available APTOS 2019 blindness detection dataset (APTOS 2019) related to the diabetic retinopathy classification competition organized by the Asia Pacific Tele-Ophthalmology Society (APTOS) was employed [20]. The dataset comprises a total of 3662 retinal fundus images collected from multiple clinics using fundus photography by technicians from the Aravind Eye Hospital in India. The image resolutions range from 474 × 358 pixels to 3388 × 2588 pixels, and all files are in .png format. Each image has been graded by expert individuals on a scale from 0 to 4 for the detection of diabetic retinopathy. The severity of the disease increases from 0 to 4. The criteria are as follows: criterion 0 for non-DR images, criterion 1 for images with mild NPDR, criterion 2 for images with moderate NPDR, criterion 3 for images with severe NPDR, and criterion 4 for images with PDR. The number of images in each class is presented in Table 1. Sample images from the dataset are provided in Figure 1.

Table 1. Distribution of disease severity levels in the fundus image dataset.

Criterion	DR Condition	Number of Images
0	No DR	1805
1	Mild	370
2	Moderate	999
3	Severe	193
4	Proliferative DR	295

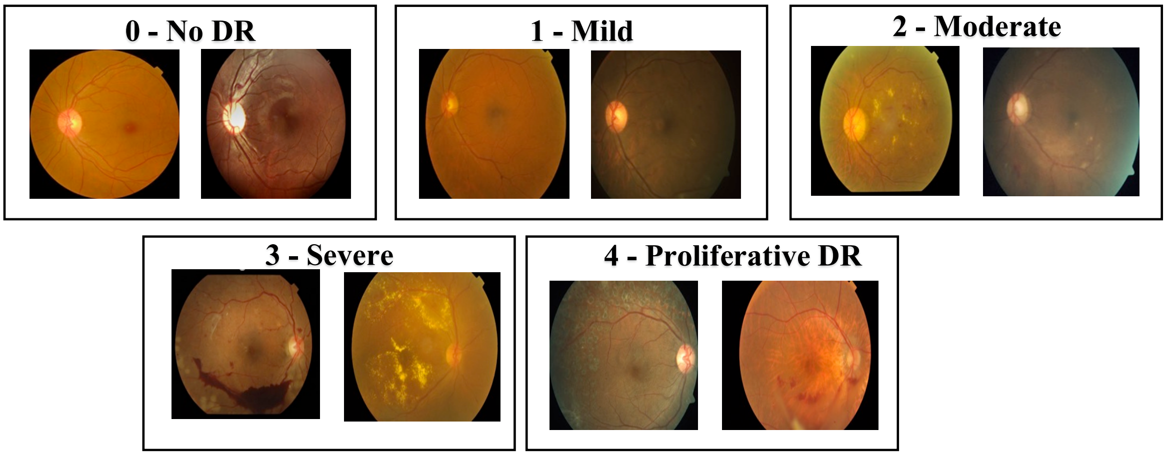

Figure 1. Sample images in APTOS dataset classes.

2.2. The Proposed Model

In this study, DR was classified using the pretrained VGG16 and VGG19 models. The study consists of four stages: (1) Feature extraction, (2) Feature selection, (3) Classification, and (4) Iterative Majority Voting. The proposed method's schematic is illustrated in Figure 2. In the initial stage of feature vector extraction, the fc8 and drop7 layers of the VGG16 and VGG19 pretrained models were utilized (F1: fc8, F2: drop7, F3: fc8, F4: drop7). Subsequently, the extracted feature vectors were selected using the NCA, Relieff, and Chi2 feature selection algorithms. The resulting feature vectors were then classified using an SVM classifier, yielding 12 prediction vectors (P1, P2... P12) after classification. The final outcome was obtained by applying the Iterative Majority Voting algorithm to the obtained prediction vectors. The block diagram of the proposed method is depicted in Figure 2.

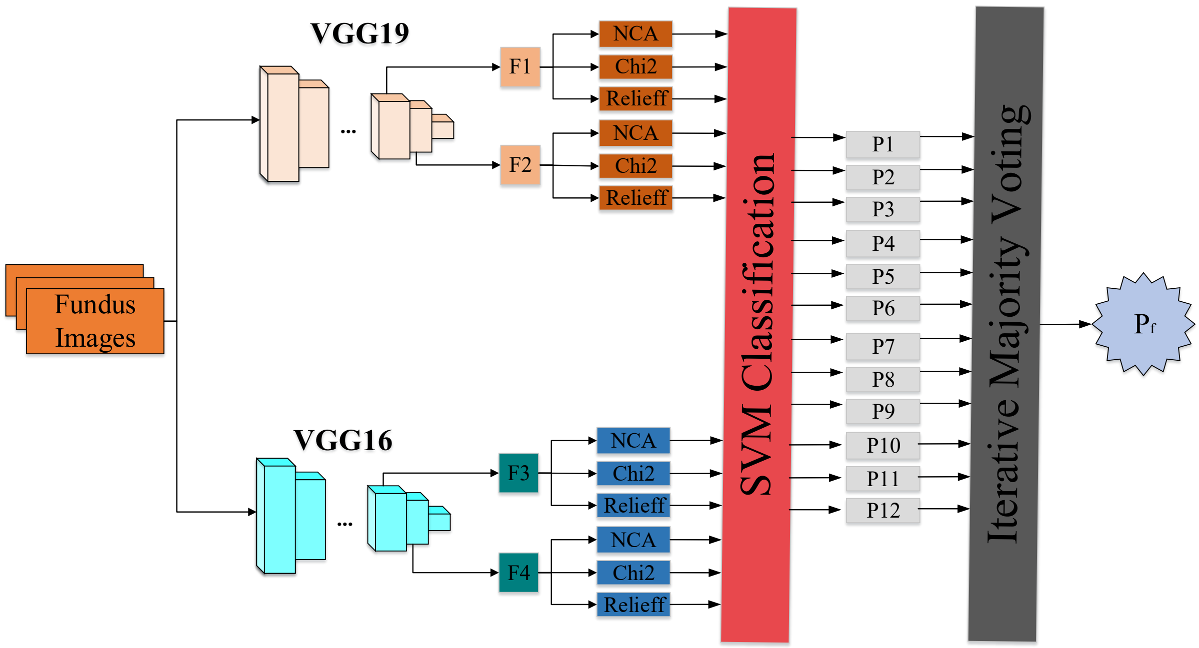

Figure 2. Block diagram of the proposed method

VGGNet: VGGNet, developed by the Visual Geometry Group (VGG) at the University of Oxford, secured the first place in ILSVRC 2014. VGGNet has two widely used variations, namely VGG16 and VGG19, containing 16 and 19 layers, respectively. VGGNet is composed of a stack of 3x3 filters, utilizing 3x3 filters instead of larger ones significantly reduces the number of parameters. In some configurations, 1x1 convolution filters are used with a fixed convolution stride of 1 pixel to ensure a linear transformation of input channels. Padding may be required to maintain resolution after performing convolution operations. VGG16 is a deep learning algorithm consisting of 13 convolutional and 3 fully connected layers. The input layer of the network requires images of dimensions 224 x 224 x 3. The architecture comprises a total of 41 layers, including pooling, fully connected, ReLU, dropout, and classification layers. This deep learning algorithm achieved an accuracy rate of 89% on the ImageNet database [19, 21].

NCA (Neighborhood Component Analysis) [22],: NCA is a feature selection algorithm used in classification problems. Its objective is to enhance the similarity among data points and improve classification performance. NCA calculates a weight matrix for each data point and determines the importance order of features using this matrix. This ensures that more important features contribute more to the classification performance.

Relief[23],: Relief is an algorithm employed in classification and feature selection problems. Essentially, it computes the proximity of data points to their labels and uses this information to determine the importance order of features. Relief assesses the contribution of features to classification performance and selects the most relevant ones. Additionally, the Relief algorithm performs well on datasets with class imbalance.

Chi2 (Chi-square) [24],: Chi2 is a feature selection algorithm utilized in classification problems. It measures the relationship between features and the target variable using the Chi-square statistical test. The Chi2 test evaluates whether features are independent of the target variable and tests the hypothesis of independence. As a result, it filters out features with weak associations to the target variable and enhances classification performance.

Support Vector Machine (SVM)[25]: SVM is a powerful machine learning algorithm commonly used for data classification and regression problems. Its primary goal is to find a hyperplane or surface that separates data points into two or more classes. The core idea of SVM is to divide data points with the largest margin between classes, aiming to maximize the distance between data points of different classes using a hyperplane or surface.

Iterative Majority Voting[26]: Iterative Majority Voting is a classification method utilized in machine learning and data mining. This technique brings together multiple classifiers to achieve more accurate results. The method employs multiple classifiers to classify each instance in a dataset. These classifiers evaluate data instances in different ways and merge their results through a common voting process. The voting process assigns an instance to a class based on the majority decision made by the classifiers.

3. Experimental results

To obtain the experimental results in this study, Matlab 2023 environment was utilized. The experimental outcomes were obtained using a computer equipped with an Intel Core i9 processor, 128GB RAM, and an NVIDIA graphics card. The study comprises four fundamental stages: (1) Feature extraction, (2) Feature selection, (3) Classification, and (4) Iterative Majority Voting.

The 12 feature vectors' accuracy results, obtained through 10-fold cross-validation and SVM, are presented in Table 2.

Table 2. Classifier results for the 12 feature vectors

No	Generation method				Accuracy
1	VGG16	fc8	NCA	SVM	96,23%
2		fc8	Chi2	SVM	97,68%
3		fc8	Relieff	SVM	96,26%
4		drop7	NCA	SVM	95,25%
5		drop7	Chi2	SVM	97,27%
6		drop7	Relieff	SVM	95,39%
7	VGG19	fc8	NCA	SVM	96,72%
8		fc8	Chi2	SVM	98,06%
9		fc8	Relieff	SVM	96,37%
10		drop7	NCA	SVM	95,90%
11		drop7	Chi2	SVM	97,30%
12		drop7	Relieff	SVM	95,17%

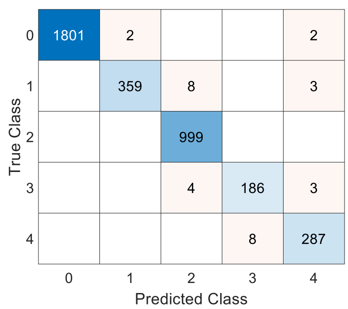

Figure 3. Confusion matrice

The confusion matrix obtained with the proposed method and the APTOS dataset is illustrated in Figure 3. The metrics calculated from the confusion matrix are presented in Table 3.

Table 3. Results of the proposed model.

Classes		Accuracy	Precision	Recall	Sensitivity	F1-score
Proposed Model	No DR	99.18%	**100,00%**	99,78%	98,73%	**99,89%**
	Mild		99,45%	97,03%	86,49%	98,22%
	Moderate		98,81%	**100,00%**	**98,80%**	99,40%
	Severe		95,88%	96,37%	75,13%	96,12%
	Proliferative DR		97,29%	97,29%	85,08%	97,29%

Based on the results presented in Table 3, the model's ability to recognize five distinct retinal conditions has been examined. The condition of 'No DR,' indicating the absence of Diabetic Retinopathy, stands out as the most successful classification with the highest accuracy, sensitivity, recall, and F1-score. However, there are fluctuations in sensitivity and recall values for other retinal conditions. Particularly, the 'Mild DR' and 'Severe DR' conditions highlight some classification challenges. These results underscore the model's potential to exhibit varying levels of performance for different retinal conditions. This research contributes to our understanding of the strengths and limitations of AI-based classification models in the field of medical imaging.

4. Discussion

In this article, the proposed SVM classifier and the selected CNN-based deep features have been compared with existing systems in the literature, and the results are presented in Table 4

Table 4. Results of studies using the same dataset.

Study	Model	Split:ratio	Dataset	Accuracy (%)
Gangvar et al.[27]	CNN, Inception-ResNet-v2	75:25	APTOS 2019	82.18
Kassani et al.[28]	Xception	70:20:10	APTOS 2019	83.09
Alyoubi et al.[29]	CNN512 and YOLOv3	80:20	APTOS 2019	89.00
Proposed Model	VGG16,VGG19,NCA,Relieff,Chi2,IHMV	10 Fold Cv	APTOS 2019	99.18

Despite using pretrained models and CNN architectures, researchers [27-29] who employed the same dataset in Table 3 achieved lower classification performance compared to our proposed model. With this method, a classification accuracy of 99.18% was achieved.

Our artificial intelligence system aims to complement the practical experience of medical experts, which is its primary purpose. The fundamental objective here is for the recommendations provided by artificial intelligence not to replace the competence and expertise of medical professionals but to play a complementary role. In complex cases, artificial intelligence can assist in delivering more precise and reliable outcomes based on the information gathered from medical professionals.

5. Conclusions

Despite the limitations of traditional diagnostic methods, it is believed that artificial intelligence can support early disease diagnosis using big data analysis, deep learning algorithms, and image processing techniques. Additionally, it has the potential to ease the need for regular patient examinations and monitoring, thus alleviating the burden on healthcare systems. In this study, the proposed method was established using the APTOS 2019 dataset available on the Kaggle platform, consisting of 3662 images. In our suggested model, features were extracted using the drop7 and fc8 layers of pretrained VGG16 and VGG19 models. Extracted features were selected using NCA, Relief, and Chi2. Subsequently, by applying the IHMV algorithm, an accuracy of 99.18% was achieved. In future research, there are plans to explore high-performance network architectures by employing larger datasets with a greater number of images and classes.

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