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Deep Learning Based Models for Detection of Diabetic Retinopathy

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Abstract: Diabetic retinopathy (DR) is an important disease that occurs because of damage to the retinal blood vessels in the human eye due to diabetes and causes blindness. If diagnosed correctly, the treatments to be applied increase the possibility of preventing vision loss or blindness. This study aims to present an evaluation of deep learning methods to detect diabetic retinopathy from retinal images. In this direction, the VGG16 model was considered, and two different versions of this model were obtained by making improvements. Besides, a model has been proposed, the first layers are dense, the next layers have decreasing convolution, and have fewer layers. According to the results, the VGG16 model, which reached 75.48% accuracy, reached 76.57% accuracy due to the dropout layer added to the classification layers, and 77.11% accuracy due to the dropout layer added to all blocks. The highest accuracy was obtained in the proposed model with 81.74%.

Keywords: artificial intelligence; deep learning; detection; diabetic retinopathy

1 INTRODUCTION

Diabetic retinopathy (DR) is a diabetic disease in which the retinal blood vessels of the human eye are damaged, causing blindness [1]. Diabetic retinopathy, the most common diabetic eye disease in the world, is the leading cause of blindness [2]. Defining the DR stage, which is considered one of the most dangerous complications of diabetes, is a complex task and needs to be interpreted by experts. If left untreated, it can cause permanent blindness [3]. Assessment of the severity and extent of retinopathy is currently performed by medical professionals based on fundus retinal images of the patient's eyes [4].

Diabetes is a serious and long-term condition that has a major impact on the lives of people around the world. The prevalence of diabetes, which was estimated to be 463 million people in 2019, is estimated to increase to 578 million in 2030 and to 700 million in 2045 [5]. DR is a preventable eye disease, and its early symptoms can be detected by the specialist either by visual observation of the retina or by automatic examination mode. DR affects the person's vision, if not detected and treated, it may not be noticed until the disease progresses and can lead to blindness [6]. The best treatment options that should be applied to patients differ according to the stages of the disease. For patients without DR or mild DR, only regular screening is required, while for patients with moderate or worse DR, treatment options range from diffuse laser therapy to vitrectomy. Therefore, it is important to degree DR severity in the first degree to provide patients with appropriate treatment [7]. Early detection of DR formation can be very helpful for clinical treatment. Although several different feature extraction approaches have been proposed for this, the classification task for retinal images does not yet provide adequate assistance to clinical treatments. Recently, deep convolutional neural networks have shown superior performance in image classification compared to previous handcrafted feature-based image classification methods [8].

The term deep learning or deep neural network refers to multi-layer Artificial Neural Networks (ANN). This term has been recognized as one of the most powerful tools in the last few decades and has become very popular in the literature as it can handle large amounts of data. The interest in having deeper hidden layers has recently begun to surpass classical method performance in different fields. One of the most popular deep neural networks is Convolutional Neural Network (CNN) [9]. Deep learning allows computational models consisting of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have significantly improved cutting-edge technology in many fields such as speech recognition, visual object recognition, object detection, drug discovery, and genomics. Deep learning explores complexity in large datasets by using the backpropagation algorithm to specify how a machine should change its internal parameters used to calculate the representation in each layer from the representation in the previous layer. While deep convolutional networks have revolutionized the processing of images, videos, speech, and audio, recursive networks have shed light on sequential data such as text and speech [10].

Supervised techniques, in which training data are used to develop a system, have become increasingly popular in medical image analysis. Applications of deep learning to medical image analysis have been increasing rapidly in recent years. Although it has been applied in many areas, it is still not fully represented in the most important areas such as retinal image [11]. Automatic grading of diabetic retinopathy has potential benefits such as increasing efficiency, reproducibility, and coverage of screening programs, reducing barriers to access, and improving patient outcomes by providing early detection and treatment [12]. Automated techniques to be applied for the diagnosis of diabetic retinopathy are very important to solve these problems. In general, deep learning achieves high validation accuracies for binary classification, while multistage classification results are less impressive, especially for early-stage disease [13]. Deep learning, a new branch of machine learning technology under the broad term artificial intelligence, has significant potential for healthcare. It allows us to determine which patients are most likely to have a certain disease among those with certain disorders, which patients should be treated more severely, and the most appropriate specific treatments to be applied to patients [14].

Due to uncontrolled blood sugar levels in diabetics, there is a lack of blood flow and oxygen in the retina. If not detected early, when the tension in the blood vessels increases, it can cause fluid leakage in the blood vessels and loss of proper vision in the eye [15]. Patients who are usually asymptotic in their early stages show different symptoms because of disease progression. Symptoms can include blurred vision, blind spots, distorted central vision, large floaters, and sometimes sudden vision loss. Therefore, it is important to accurately detect the disease in its early stages and determine at what stage it is to reduce the complications of the disease and the possibility of vision loss [16]. Although there are enough treatment procedures to cope with DR disease that occurs in people with diabetes for a long time, neglect, and failure of early diagnosis cause people's eyesight. Recent advances in digital image processing and machine learning are used in the detection of DR [17]. Computer-aided diagnostic systems significantly reduce the burden on ophthalmologists [18].

Diabetic retinopathy due to diabetes is an eye disease that can damage blood vessels and lead to blindness. Physicians have a great job because it is a difficult, laborious, and demanding task to detect this disease. Every day, as in many other fields, pre-diagnosis systems are developed to help physicians to detect the symptoms of the disease in this field. For this purpose, in this study, the VGG16 model, which is one of the deep learning methods, and two different modified versions of this model were used, and a new model was proposed, to detect diabetic retinopathy. A new dataset, Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 Blindness Detection dataset, published in mid-2019, was used to test the performance of the models. The current work aims to contribute to the increasing knowledge about the use of deep learning methods in diabetic retinopathy by characterizing the detection performance of diabetic retinopathy, which can cause blindness, with deep learning methods.

The remainder of the study is structured as follows. In Section 2, relevant studies are given. In Section 3, the materials and methods used in deep learning are explained. In Section 4, the experimental results are discussed, and in Section 5, the results of the study are presented.

2 RELATED WORKS

In studies carried out by increasing data on the APTOS 2019 Blindness Detection dataset or approaching it with different classification and different image sizing:

Khalifa et al. (2019) conducted training by applying the data augmentation technique in the APTOS 2019 Blindness Detection dataset with AlexNet, Res-Net18, SqueezeNet, GoogleNet, VGG16, and VGG19 deep transfer models. The highest performance was achieved with the AlexNet model, which has the least number of layers among the models used in the study, at a rate of 97.9%. In another study using the data augmentation technique, Chaturvedi et al. (2020) [19] made changes to the pre-trained DenseNet121 network and trained on the APTOS 2019 Blindness Detection dataset and obtained 96.51% accuracy.

Tymchenko et al. (2020) proposed a deep learning-based method for detecting DR from human retinal images with a multi-stage transfer learning approach. EfficientNet-B4, EfficientNet-B5, and SE-ResNeXt50 convolutional neural network models achieved 99% success in binary classification results with DR/no DR. Similarly, Narayanan et al. (2019) [20] examined the results provided by deep neural networks for the detection of two-class DR as well as different diseases. In their studies with GoogleNet and ResNet models, they reached 97.3% and 96.2% binary classification accuracy, respectively. Chetoui and Akhloufi (2020) proposed a deep learning architecture based on EfficientNet convolutional neural network to detect DR. As a result of the tests, they applied for the detection of transferable DR and sight-threatening DR on the APTOS 2019 Blindness Detection dataset, they achieved a classification rate of 96.60% and 99.80%, respectively.

Kassani et al. (2019) [21] presented a new feature extraction method for the diagnosis of DR disease, based on deep layer clustering, which combines multilevel features from different convolution layers of a modified Xception architecture. They evaluated the performance of their proposed approach with four deep feature extractors, including Inception V3, MobileNet, ResNet50, and the original Xception architecture. As a result of the experiments, they carried out on the images they sized as 600x600 pixels, different from the ones in our study, they determined that the model they proposed achieved higher success than the other models they used in their studies. They revealed that the modified Xception deep feature extractor improves DR classification with a classification accuracy of 79.59% versus 83.09% compared to the original Xception architecture.

Like our study, in studies that preprocess the APTOS 2019 Blindness Detection dataset and classify the dataset in the same way:

Dekhil et al. (2019) [22] presented a convolutional neural network-based computer-assisted diagnostic tool to classify diabetic retinopathy into one of five stages. They have reached a test accuracy of 77% with the alternative solution they offer so that ophthalmologists can automatically detect the disease. Bodapati et al. (2020) [23] blended by extracting features from retinal images with pre-trained VGG16-fc1, VGG16-fc2, and Xception models to detect DR. They conducted two studies by considering the dataset with both two classes and five classes. They achieved 80.96% success with the DNN model they trained to detect one of the five classes using representative blended features. Zhuang and Ettehadi (2020) [24] developed solutions for the DR classification problem. They used transfer learning to retrain the last modified layer of a very deep neural network, such as Efficientnet-B3 to improve the generalization of less frequent class's ability of their shallow neural network model. As a result of their training, they achieved the best test accuracy of 77.87%.

Dondeti et al. (2020) [25] created a NASNet model to automatically predict the severity level of DR based on retinal images of diabetics. Focusing on extracting suitable features from retinal images, they stated that performance improves when projecting into t-SNE (T-distributed stochastic neighbor embedding) space to obtain lower-dimensional representations from the deep features extracted from the NASNet model. In their experiments on the APTOS 2019 Blindness Detection dataset, they emphasized that the proposed model became more powerful with the robustness of the SVM (Support Vector Machine) models. They observed that deep features transformed using T-SNE provided more distinctive representations of retinal images and helped to achieve 77.90% accuracy.

3 EXPERIMENTAL METHOD

3.1 Dataset

In this study, Asia Pacific Tele-Ophthalmology Society (APTOS) Blindness Detection dataset published in mid-2019 was used. The dataset containing 3662 images consists of 5 classes No DR, Mild DR, Moderate DR, Severe DR, and Proliferate DR. There are 1805 images in the No DR class, 370 in the Mild DR class, 999 in the Moderate DR class, 193 in the Severe DR class, and 295 in the Proliferate DR class [26].

Each image in the dataset consisting of five classes was labeled and grouped under the class it belongs to, and then converted to 224×224 pixel dimensions and grey format. In Fig. 1, sample images of each class in the APTOS 2019 Blindness Detection dataset are given.

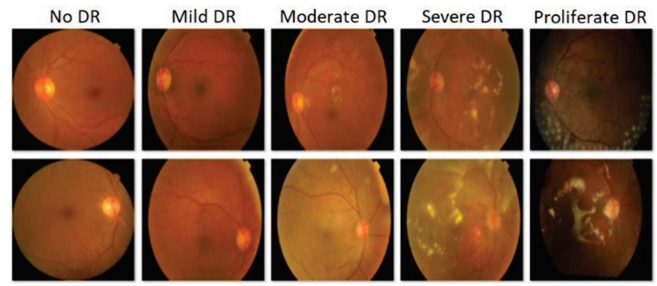


Figure 1 Example images of each class in the APTOS 2019 Blindness Detection dataset

3.2 Convolutional Neural Network (CNN) Model

Convolutional Neural Networks (CNNs), a branch of deep learning, have an impressive track record for applications in image analysis and interpretation, including medical imaging [27]. Among the deep learning algorithms, especially convolutional networks have quickly become a preferred methodology for analysing medical images [11].

With the convolutional neural network method, which provides good success in deep learning, feature extraction and classification can be done well. There are many successful models such as AlexNet [28], VGGNet [29], GoogLeNet [30], and ResNet [31] developed using convolutional neural networks. The VGG16 model is one of these models.

Table 1 Model architectures

<table>
<tr><th>VGG16 - Original</th><th>VGG16 - Modified Version 1</th><th>VGG16 - Modified Version 2</th><th>Proposed Model</th></tr>
<tr><td colspan="4">Input (224 × 224 × 1)</td></tr>
<tr><td>Conv1 (3×3) – 64
Conv2 (3×3) – 64
MaxPool1 (2×2)</td><td>Conv1 (3×3) – 64
Conv2 (3×3) – 64
MaxPool1 (2×2)</td><td>Conv1 (3×3) – 64
Conv2 (3×3) – 64
MaxPool1 – (2×2)
Dropout – 0.5</td><td>Conv1 (3×3) – 32
Conv2 (3×3) – 32
Conv3 (5×5) – 32
Conv4 (7×7) – 32
AvgPool1 (5×5)
Dropout – 0.5</td></tr>
<tr><td>Conv3 (3×3) – 128
Conv4 (3×3) – 128
MaxPool2 (2×2)</td><td>Conv3 (3×3) – 128
Conv4 (3×3) – 128
MaxPool2 (2×2)</td><td>Conv3 (3×3) – 128
Conv4 (3×3) – 128
MaxPool2 (2×2)
Dropout – 0.5</td><td>Conv5 (5x5) – 64
Conv6 (7x7) – 64
AvgPool2 (5x5)
Dropout – 0.5</td></tr>
<tr><td>Conv5 (3×3) – 256
Conv6 (3×3) – 256
Conv7 (3×3) – 256
MaxPool3 (2×2)</td><td>Conv5 (3×3) – 256
Conv6 (3×3) – 256
Conv7 (3×3) – 256
MaxPool3 (2×2)</td><td>Conv5 (3×3) – 256
Conv6 (3×3) – 256
Conv7 (3×3) – 256
MaxPool3 (2×2)
Dropout – 0.5</td><td rowspan="3">Conv7 (7×7) – 128
AvgPool3 (5×5)
Dropout – 0.5</td></tr>
<tr><td>Conv8 (3×3) – 512
Conv9 (3×3) – 512
Conv10 (3×3) – 512
MaxPool4 (2×2)</td><td>Conv8 (3×3) – 512
Conv9 (3×3) – 512
Conv10 (3×3) – 512
MaxPool4 (2×2)</td><td>Conv8 (3×3) – 512
Conv9 (3×3) – 512
Conv10 (3×3) – 512
MaxPool4 (2×2)
Dropout – 0.5</td></tr>
<tr><td>Conv11 (3×3) – 512
Conv12 (3×3) – 512
Conv13 (3×3) – 512
MaxPool5 (2×2)</td><td>Conv11 (3×3) – 512
Conv12 (3×3) – 512
Conv13 (3×3) – 512
MaxPool5 (2×2)</td><td>Conv11 (3×3) – 512
Conv12 (3×3) – 512
Conv13 (3×3) – 512
MaxPool5 (2×2)
Dropout – 0.5</td></tr>
<tr><td>Flatten – 25088</td><td>Flatten – 25088</td><td>Flatten – 25088</td><td>Flatten – 128</td></tr>
<tr><td>FC1 – 4096</td><td>FC1 – 4096
Dropout – 0.5</td><td>FC1 – 4096
Dropout – 0.5</td><td rowspan="2">FC1 – 32
Dropout – 0.5</td></tr>
<tr><td>FC2 – 4096</td><td>FC2 – 4096
Dropout – 0.5</td><td>FC2 – 4096
Dropout – 0.5</td></tr>
<tr><td colspan="4">Output-5 (Softmax)</td></tr>
<tr><td colspan="3">134.279.877 params</td><td>743.269 params</td></tr>
</table>

The VGG16 model has an architecture consisting of 13 convolutional and 3 fully connected layers. The model has a total of 41 layers with Maxpooling, Fullconnected, ReLu, Dropout, and Softmax layers [29]. In our study, two different modified versions of the VGG16 model with the original were used and a new model was proposed. In Tab. 1, VGG16 original, VGG16 modified the first version, VGG16 modified the second version, and proposed model architectures are given. In Fig. 2, the block diagram of the proposed research is shown.

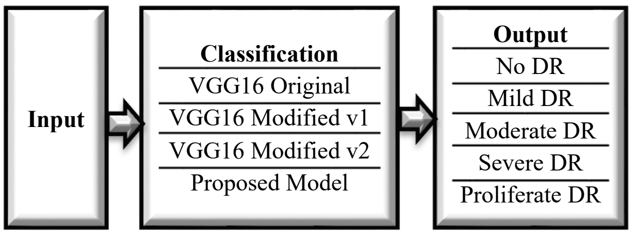


Figure 2 Block diagram of the proposed research

In Tab. 1, VGG16 modified version 1 was created by adding 0.5 dropout to the classification layers and VGG16 modified version 2 architectures were created by adding 0.5 dropout to all blocks of the VGG16 original architecture. In addition, a new model is proposed. Contrary to the VGG16 model, the proposed model is both a smaller model and has a denser convolution layer in the first layers and a decreasing convolution layer structure in the next layers. The proposed model contains fewer layers and fewer parameters than the VGG16 model. Besides, while maximum pooling is used in VGG16 architecture, average pooling is used in the proposed model. All models used in the study have a softmax layer with 5 classes in the output layer.

4 RESULTS AND DISCUSSION

Applied experiments for the detection of diabetic retinopathy with the models discussed in the study. It was made using the Python language with Jupyter Notebook in Google Colaboratory (CoLab).

The dataset is divided into three as 80% training, 10% validation, and 10% testing. There are 2928 images in the training set and 367 images in each of the validation and test sets. The parameters used during the training of VGG16 original, VGG16 modified version 1, VGG16 modified version 2 and the proposed model are given in Tab. 2.

Table 2 Model training parameters

Parameter	Value
Epoch	150
Mini Batch Size	16
Dropout	0,5
Activation Function	ReLu
Optimization Algorithm	Adamax

The training of the 4 models used in the study was repeated 5 times and the best accuracy and loss graph obtained for each model because of the training is given in Fig. 3. When the figure is examined, it is seen that the training of the VGG16 original, VGG16 modified version 1 and VGG16 modified version 2 models are close to each other, and these three models initially started learning with a 49% training and validation rate. It is seen that learning takes place by reaching a rate of just over 70% of training and validation success until the first 30 iterations, and they reach a validation success of 70%-76% until 150 iterations. Like each other, these three models started training with a validation loss rate of 1,300 and showed a decrease in the loss rate in the first 30 iterations, and an increase in the loss rate because of the non-learning after 30 iterations. It is seen that the proposed model in the figure starts learning with 49% training and 65% validation rate, training and validation continues successfully until the 100th iteration, and learning continues after the 100th iteration, reaching 81.74% success accuracy because of 150 iterations. It is understood that learning takes place at every stage of the training of the proposed model. In addition, it is seen that the model, which started training with a validation loss rate of 1.018, reached a validation loss rate of 0.658 at the end of 150 iterations.

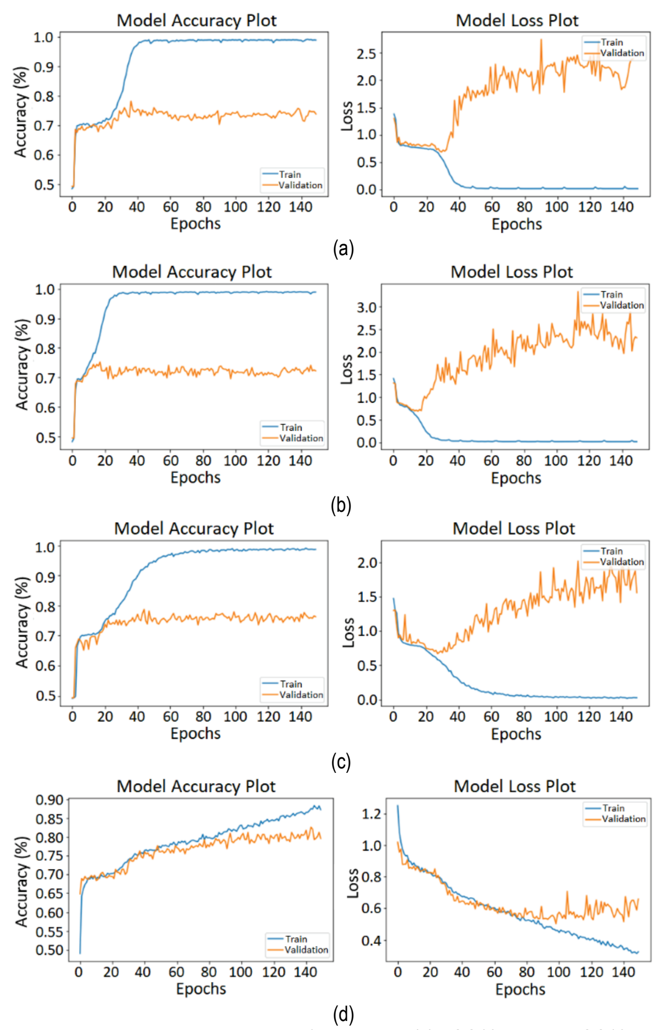


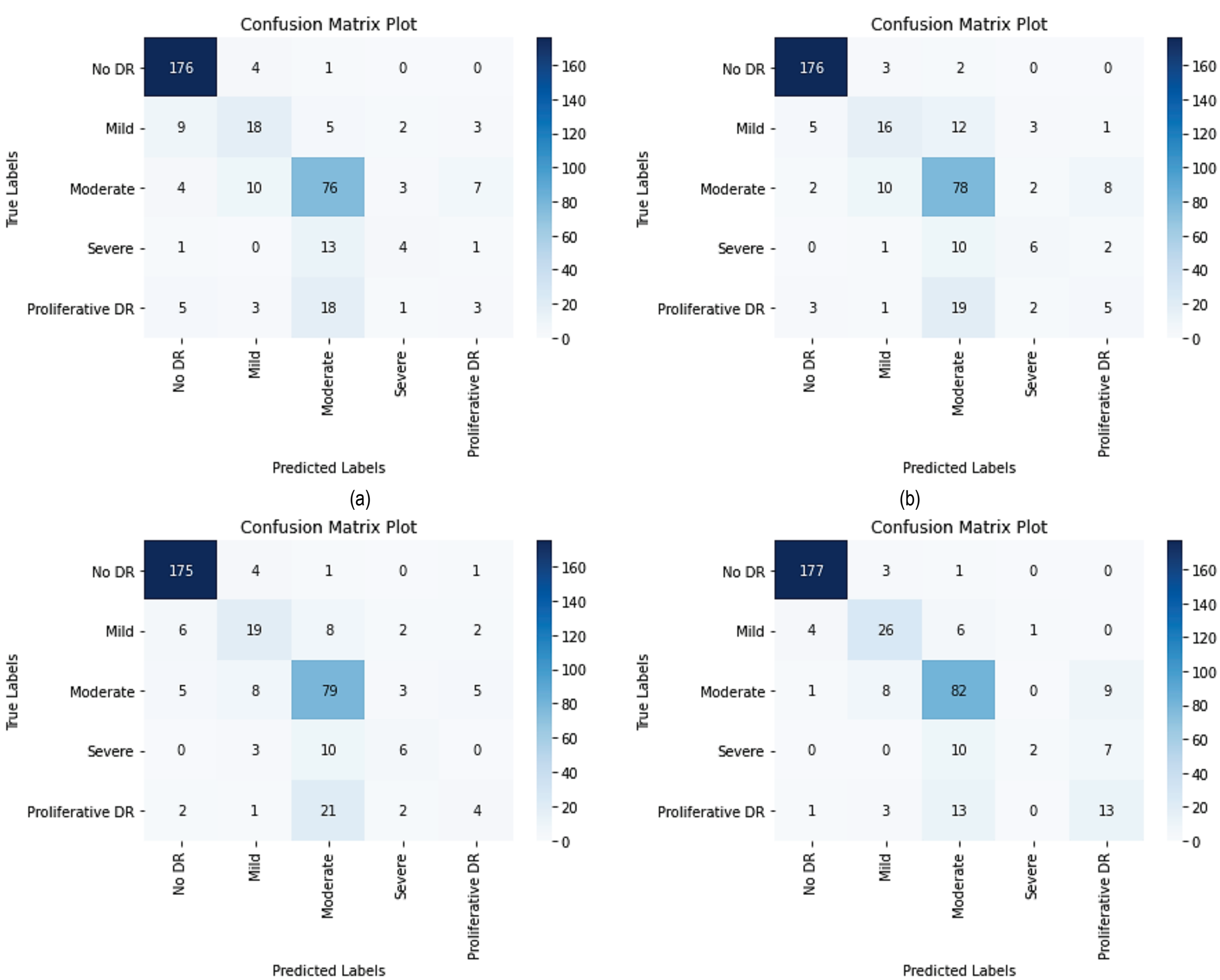
Figure 3 Accuracy and loss plots of the models: (a) VGG16 original, VGG16 modified version 1, (c) VGG16 modified version 2, (d) proposed model

Table 3 Accuracy and loss rate

Model	Accuracy (%)			Loss		
	Training	Validation	Test	Training	Validation	Test
VGG16 Original	98,91	73,84	75,48	0,012	2,465	2,696
VGG16 Modified Version 1	98,98	72,21	76,57	0,012	2,309	2,210
VGG16 Modified Version 2	98,67	76,29	77,11	0,026	1,558	1,793
Proposed Model	87,19	79,56	81,74	0,325	0,658	0,724

The results of the accuracy and loss rates obtained because of training the four models are given in Tab. 3. When the table is examined, it is seen that the success accuracy of the VGG16 original model is 75.47%, the VGG16 modified version 1 model which is obtained as a result of adding a 0.5 dropout layer to the classification layers of the VGG16 model is 76.57% and the VGG16 modified version 2 model which is obtained as a result of adding 0.5 dropout layer to all blocks of the VGG16 model is 77.11% on 367 images in the test dataset that are not included in the training. In parallel with the increase in test performance, the loss rates obtained in the test dataset have also decreased. The increase in the accuracy rate and the decrease in the loss rate is because of the dropout layer. In addition, it is seen that the proposed model has a 0.5 dropout layer in all blocks and has more convolution in the first blocks and less convolution in the next blocks, reaching a high accuracy of 81.74%. In the proposed model, unlike the VGG16 model, the use of more convolutions in the first blocks significantly increased the learning success in this dataset consisting of few and disproportionate data.

The confusion matrix obtained from the test dataset consists of a total of 367 images created by taking 181, 37, 100, 19, and 30 images from the No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR classes respectively, is given in Fig. 4. When the figure is examined, it is seen that the highest performance in all four models is in the No DR and Moderate DR classes respectively, the lowest performance is in the Proliferative DR class in the VGG models used in the study and in the Severe DR class in the proposed model. It is noteworthy that in all four models, Severe DR and Proliferative DR classes are confused at most with the class Moderate DR images. Example images where Severe DR and Proliferative DR classes are confused with Moderate DR classes are given in Fig. 5. The fact that there are few images in the Severe DR class is seen as one of the obvious reasons for this situation.



(a) (b) (c) (d)

Figure 4 Confusion matrix of the models: (a) VGG16 original, VGG16 modified version 1, (c) VGG16 modified version 2, (d) proposed model

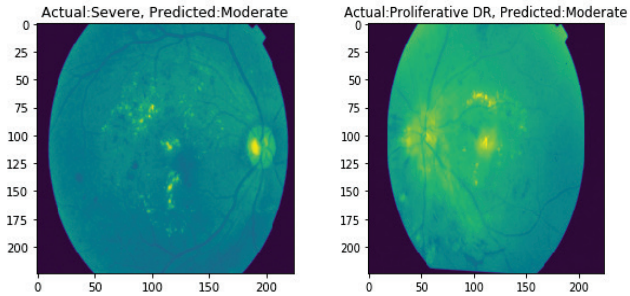


Figure 5 Example images where the Severe DR and Proliferative DR classes are confused with the Moderate DR class

It would be beneficial to apply the proposed method, which is used in the detection of diabetic retinopathy with successful results, in areas such as Covid-19 detection and diagnosis [32, 33], fault diagnosis of electric impact drills [34], thermographic fault diagnosis of the shaft of a BLDC (Brushless Direct Current Electric) engine [35], and detection and classification of weapon types [36].

5 CONCLUSIONS

In this study, diabetic retinopathy disease was determined besides two different versions of the VGG16 model modified with the original, by making a new model proposed. To reveal the effect of the dropout layer, an alternative model was created by first adding the dropout layer to the classification layers of the original VGG16 model, and then another alternative model was created by adding the dropout layer at the end of all blocks of the VGG16 model. APTOS 2019 Blindness Detection dataset consisting of 5 classes and 3662 images was used to test the performance of the four models obtained with the proposed model.

According to the test results, the success rates of the VGG16 original, VGG16 modified version 1, VGG16 modified version 2, and the proposed model was 75.48%, 76.57%, 77.11%, and 81.74% respectively. An increase in test performance was observed with the effect of the dropout layer added to the VGG16 models. The highest classification success was achieved with the proposed model with an accuracy rate of 81.74%. This performance of the proposed model which is created with fewer layers is achieved by applying dense convolution in the first blocks and diluted convolution in the next blocks.

It has been observed that deep learning methods which provide successful results in the classification of images give good results in classifying diabetic retinopathy by being developed according to the dataset and the amount of data. As a result of our research, no study with better results than this study was found in the classification of diabetic retinopathy on this dataset. In cases where the number of data is low and disproportionate in the classes in the dataset, when classifying with deep learning, it is important to achieve higher performance by using models with denser first layers and decreasing convolution layers in the next layers. As a result, the proposed method will increase the diagnostic performance of specialists in the detection of diabetic retinopathy, which occurs due to diabetes and can cause blindness. This study, which is thought to guide studies on similar datasets, is thought to be used on datasets with similar structures in different fields in future studies. In addition, our future studies will focus on the recognition of "No DR" images for diabetic retinopathy disease using different deep learning approaches.

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