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DIAGNOSIS AND CLASSIFICATION OF DIABETIC RETINOPATHY WITH YOLOv8-BASED DEEP LEARNING MODEL

YOLOv8 TABANLI DERİN ÖĞRENME MODELİ İLE DİYABETİK RETİNOPATİ TEŞHİSİ VE SINIFLANDIRMASI

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ABSTRACT

Diabetic retinopathy is a complication of diabetes that affects the eyes. High blood sugar levels damage the vessels of the retina, damaging the light-sensing cells in the eye, and can cause vision loss and, in severe cases, blindness. Deep learning models are powerful tools that can process and learn large data sets, and if used in the diagnosis of diabetes and diabetic retinopathy, they can benefit the early diagnosis of the disease. Deep learning enables early and high-accuracy detection of diabetic retinopathy symptoms with high sensitivity and specificity, as well as minimizing errors made by experts. In this study, we aimed to detect and classify diabetic retinopathy using the YOLOv8 (You Only Look Once) model, one of the CNN (convolutional neural network) architectures. The experimental studies were conducted with two different CPUs and two different GPUs. As a result of the experimental studies, the highest accuracy value was obtained as 84.91% with GPU1, and the average accuracy across the four different methods (CPU1, CPU2, GPU1, GPU2) was 83.82%.

Keywords: Diabetic retinopathy, deep learning, Yolov8, CNN

ÖZET

Diyabetik retinopati, diyabetin gözlere etki eden bir komplikasyonudur. Yüksek kan şekeri düzeyleri, retinanın damarlarına zarar vererek gözdeki ışığı algılayan hücrelere zarar vermekte ve görme kaybına, ciddi durumlarda ise körlüğe neden olabilmektedir. Derin öğrenme modelleri, büyük veri setlerini işleme ve öğrenme kapasitesine sahip güçlü araçlardır ve diyabet ile diyabetik retinopati teşhisinde de kullanılması durumunda hastalığın erken teşhisine fayda sağlayabilecektir. Derin öğrenme, yüksek hassasiyet ve spesifiklik ile diyabetik retinopati belirtilerinin erken ve yüksek doğrulukla tespit edilmesini ve bunun yanı sıra uzmanlar tarafından yapılan hataların minimize edilmesine olanak sağlar. Gerçekleştirdiğimiz bu çalışmada da CNN mimarilerinden biri olan YOLOv8 modeli kullanılarak diyabetik retinopati hastalığının tespiti ve sınıflandırılması amaçlanmıştır. Çalışmamızda 2 farklı CPU ve 2 farklı GPU ile deneysel çalışmalar yapılmıştır. Yapılan deneysel çalışmalar sonucunda en yüksek doğruluk değeri GPU1 ile %84.91 olarak elde edilmiş ve dört farklı yöntemin (CPU1, CPU2, GPU1, GPU2) ortalama doğruluk değeri de %83.82 olarak elde edilmiştir.

Anahtar Kelimeler: Diyabetik retinopati, derin öğrenme, Yolov8, CNN

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INTRODUCTION

Diabetes, which is an increasing health problem worldwide, causes various complications in the body by causing a series of metabolic disorders (Association, 2022). One of these complications is diabetic retinopathy. Diabetic retinopathy is a disease that occurs in the eyes of diabetic patients and can progress over time. This condition can cause vision loss as a result of damage to the blood vessels on the retina (Yau et al., 2012). Diabetic retinopathy occurs when long-term high blood sugar levels damage retinal tissue. At the beginning of the disease, symptoms are usually mild and may not be noticed by the patient. However, as it progresses, it can cause serious problems such as leaks in blood vessels, edema, and even new vessel formation. This condition may progress to permanent vision loss for the patient. Early diagnosis and effective treatment are critical to minimize the effects of diabetic retinopathy and prevent vision loss (Wong et al., 2018).

The relationship between diabetes and the retina is based on a complex interaction. Diabetes triggers diabetic retinopathy through its direct effects on the retina when blood sugar levels are persistently high (Fong et al., 2003). Diabetic retinopathy is a dangerous disease that affects the light-sensing cells and blood vessels at the back of the retina. High blood sugar levels damage the blood vessels in the retinas, which can lead to dilation, leakage, and even bleeding. Edema may occur in the retina tissue, which may affect visual functions (Vujosevic et al., 2020). In the long term, diabetic retinopathy can lead to serious vision loss. Therefore, diabetic individuals need to have regular eye examinations and keep their blood sugar levels under control. Early diagnosis and treatment is a critical process in preventing or delaying vision loss (Ansari et al., 2022). Additionally, in the management of diabetic retinopathy, it is necessary to regulate blood sugar levels as well as blood pressure and lipid levels.

It is a known fact that computer-aided diagnosis and support systems provide very successful results in detecting health-related problems. There are many studies in the literature that detect diabetic retinopathy. The first of these studies is the study conducted by Deperlıoğlu and Köse (Deperlıoğlu and Köse, 2018). In this study, a method developed for the diagnosis of diabetic retinopathy from retinal fundus images is discussed. In the study, a method including HSV (hue, saturation, brightness) color space, V rotation algorithm, and histogram equalization techniques was used to improve retinal fundus images. The results obtained from the evaluation performed on a total of 400 retinal fundus images are quite impressive. As a result of the study, the accuracy rate was determined as 97%, sensitivity 96.67%, specificity 93.33%, precision 97.78%, recall rate 93.33%, and F-score 93.33%. Çavli and M. Toğaçar (Çavli and Toğaçar, 2023) proposed a hybrid artificial intelligence model for the early diagnosis of retinopathy disease. As a result of experimental analyses, 100% overall accuracy was achieved with the proposed approach. Özçelik and Altan (Özçelik and Altan, 2021) devised a deep-learning model utilizing fundus images for the early detection and treatment of DR. The constructed model comprises two stages. Initially, two-dimensional signal processing techniques were employed on the fundus images to mitigate overfitting. Subsequently, a classification model was established utilizing Convolutional Neural Network and transfer learning methods, both being deep learning techniques. The proposed model achieved a classification performance of 97.8%. Özçelik, Y.B. and Altan, A. (Özçelik and Altan, 2023) present an artificial intelligence (AI)-based model that could use fundus images to determine the phase of DR disease. The proposed model consists of four stages, excluding the preprocessing stage. In the preprocessing stage, fractal analysis is performed to reveal the presence of chaos in the dataset consisting of 12,500 color fundus images. In the first stage, two-dimensional stationary wavelet transform (2D-SWT) is applied to the dataset consisting of color fundus images to prevent information loss in the images and to reveal their characteristic features. In the second stage, 96 features are extracted by applying statistical and entropy-based feature functions to approximate, horizontal, vertical, and diagonal matrices of 2D-SWT. In the third stage, the features that keep the classifier performance high are selected by a chaotic-based wrapper approach consisting of the k-nearest neighbor (kNN) and chaotic particle swarm optimization algorithms (CPSO) to cope with both chaoticity and computational complexity in the fundus images. At the last stage, an AI-based classification model is created with the recurrent neural network-long short-term memory (RNN-LSTM) architecture by selecting the lowest number of feature sets that can keep the classification performance high. Vipparthi et al, (Vipparthi et al., 2022) can assist ophthalmologists in clinical diagnosis and detection and classification of diabetic retinopathy. There are three phases in this diabetic retinopathy detection and classification technique enhancement Feature Extraction and Retinopathy Detection and Classification. Feature extraction involves blood vessel extraction and exudate extraction. The first two phases assist the ophthalmologists by providing clear images of the retina and blood vessels and exudates extracted images. In this work, from the presented retinal fundus pictures, the Res-Block model is used to classify and diagnose diabetic retinopathy. Fang and Qiao (Fang and Qiao, 2022), propose a novel DAG network model for the classification of diabetic retinopathy based on multi-feature fusion of fundus images. Firstly, under the advice of the doctor, three indicative features of diabetic retinopathy are extracted using different algorithms: retinal hemorrhagic plaque, fundus neovascularization, and retinal varices. Then three features are sent to a classification model based on a novel DAG network for realizing multi-feature fusion and feature learning. Finally, the optimized classification model is used to recognize and classify diabetic retinopathy. DIARETDB1 dataset and real hospital data from Dalian NO.3 People's Hospital are used to evaluate the performance of the proposed method. For the DIARETDB1 dataset and real hospital data, the accuracy can reach 98.7% and 98.5%, respectively. Arslan Tuncer, Çinar and Fırat, (Arslan Tuncer, Çinar and Fırat, 2021) propose system is a CNN-SVM (Convolutional Neural Networks – Support Vector Machine) model and doesn't require any additional extraction of features or noise filtering on OCT images. A total of 968 OCT images are classified in pre-trained CNN methods with Alexnet, Resnet18, and Googlenet. Accuracy is achieved with the highest Googlenet 97.4%. To examine the performance of the proposed CAD system, the CNN-SVM method achieves 98.96% with the highest accuracy hybrid Alexnet-SVM model, which is implemented with Alexnet-SVM, Resnet18-SVM and Googlenet-SVM models. Shaukat et al(Shaukat et al, 2023), Several current approaches of preprocessing, segmentation, feature extraction/selection, and classification are discussed for the detection of DR lesions. also includes a detailed description of DR datasets that are accessible by the researcher for the identification of DR lesions. The existing methods' limitations and challenges are also addressed, which will assist invoice researchers in starting their work in this domain. Dulkadir and Gültekin, (Dulkadir and Gültekin 2023) used three different convolutional neural network models (YOLOv5, YOLOv8) for the autonomous classification of banana ripeness levels for use in multiple autonomous robotic harvesting systems. The models were trained on a 6-class banana ripeness level dataset and the test results were compared using commonly used performance metrics. Ağca and Takci (Kemal and Takci, 2022) introduced a hybrid approach combining ESA and machine learning for the identification and classification of DR. The transfer learning model adopts ESA architecture, employing ResNET-50 as an automatic feature extractor. Machine learning algorithms, including K-Nearest Neighbor Algorithm, Random Forest Algorithm, and Extra Trees Algorithm, function as classifiers. The classification process yielded an accuracy of 93% and an F1 score of 93%. Fang et al. (Fang et al., 2022) developed DeepDR, a deep learning system that enables the detection of diabetic retinopathy from early stages to late stages. DeepDR was trained for real-time image quality assessment, lesion detection, and grading using 466,247 fundus images of 121,342 diabetic patients. The success rates for grading diabetic retinopathy as mild, moderate, severe, and proliferative were 0.943, 0.955, 0.960, and 0.972, respectively. In this study, a computer-aided system that enables the diagnosis and classification of Diabetic retinopathy was proposed using the YOLOv8 model, one of the CNN architectures. YOLOv8 is extremely fast and accurate in real-time object detection. This allows fundus images to be scanned and abnormalities detected instantly. It is relatively easy to use and implement. It can be easily customized to suit different datasets and tasks. It is supported by an active research community. This means that the model is constantly being improved and updated. In the study, 3600 diabetic retinopathy images were used for 5 different disease levels ("Mild", "Moderate", "No_DR", "Proliferate_DR" and "Severe"). The training was done with the CPU and lasted 35 minutes. The overall accuracy value of the model was measured as 93%. In the study, the performances of image processing and different deep learning methods were comparatively analyzed in the diagnosis of diabetic retinopathy. We worked on a scattered and small data set with a short training time. The dataset used was readily available and no pre-processing was applied. No parameters were changed except dropout. All of them were left as default. By working on fungal images, it is aimed that Yolov8 can be used in different areas.

In the continuing parts of the study, the second section includes materials and methods, the third section includes experimental results, the fourth section includes discussion, and the last section includes results.

MATERIAL AND METHOD

In the study, Diabetic Retinopathy Detection (Dugas et al., 2015) in the Kaggle dataset is used. The data set consisting of fundus images consists of a total of 3600 retina images. The resolution of the retina images in .png format in the dataset is 224 × 224 pixels. There are 270 "Mild", 690 "Moderate", 1212 "No_DR", 219 "Proliferate_DR" and 137 "Severe" retina images for training. For verification, there are 100 retinal images belonging to the "Mild", 303 "Moderate", 537 "No_DR", 76 "Proliferate_DR" and 56 "Severe" classes. When the data set is examined, the imbalance in the number of images belonging to the classes draws attention.

Retinal images of the "No_DR, Mild, Moderate, Severe, and Proliferate_DR" classes in the fundus data set used in the study are shown in Figure 4.

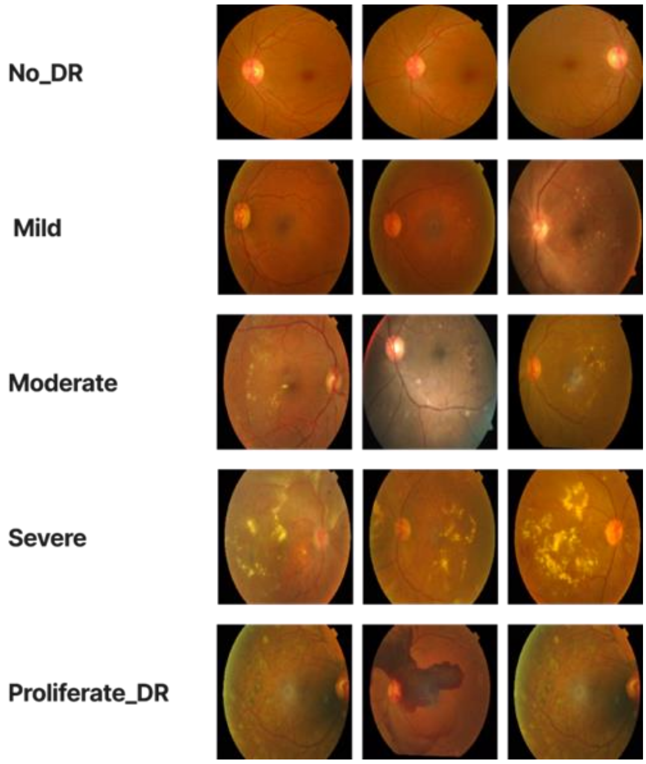

Figure 1. Retinal Images from Different Classes in the Data Set (Dugas et al., 2015)

Figure 1 shows the flow chart of the model developed with the data set consisting of fundus images for the diagnosis of DR disease and classification of its stages. To classify DR disease, the model was trained with the YOLOv8 algorithm, one of the CNN architectures. 70% of the data set consisting of fundus images is reserved for training the model, and the remaining 30% of the data set is used to test the validity of the model. The performance of the model is measured by classification performance metrics such as accuracy, precision, recall, and F1-score.

Ultralytics YOLOv8 is a model that builds on the success of previous YOLO versions and introduces new features and improvements to further increase performance and flexibility. It is shown in Figure 2.

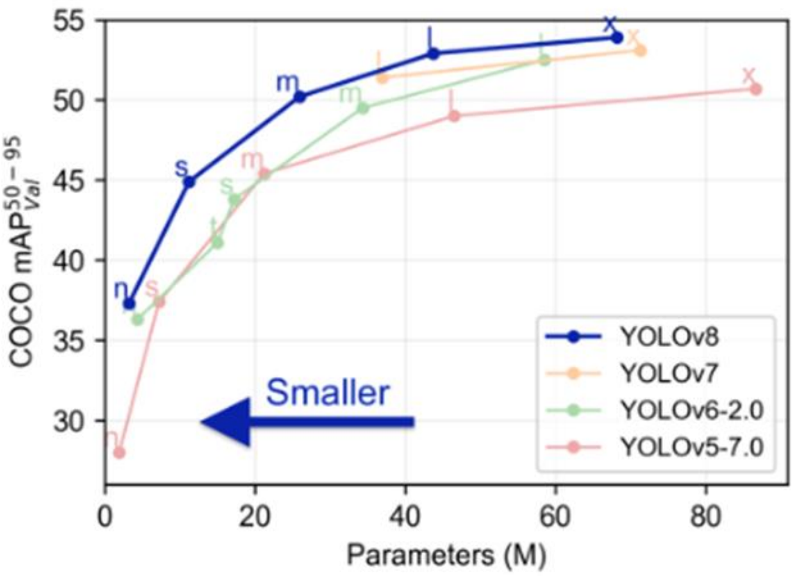

Figure 2. Comparison of Yolo Models

The basic underpinnings of the model build on the successes of previous YOLO versions. However, thanks to the innovations brought by YOLOv8, a higher level of performance and greater flexibility in the field of object detection has been achieved. Newly added features and improvements have enabled the model to be used effectively in various tasks. YOLOv8's focus on speed, accuracy, and ease of use has contributed to making this model preferable for a wide range of applications. These features enable it to be used successfully in several applications including object detection and tracking, sample segmentation, image classification and pose estimation tasks (Ultralytics et al., 2024). The architecture of the model is shown in Figure 3.

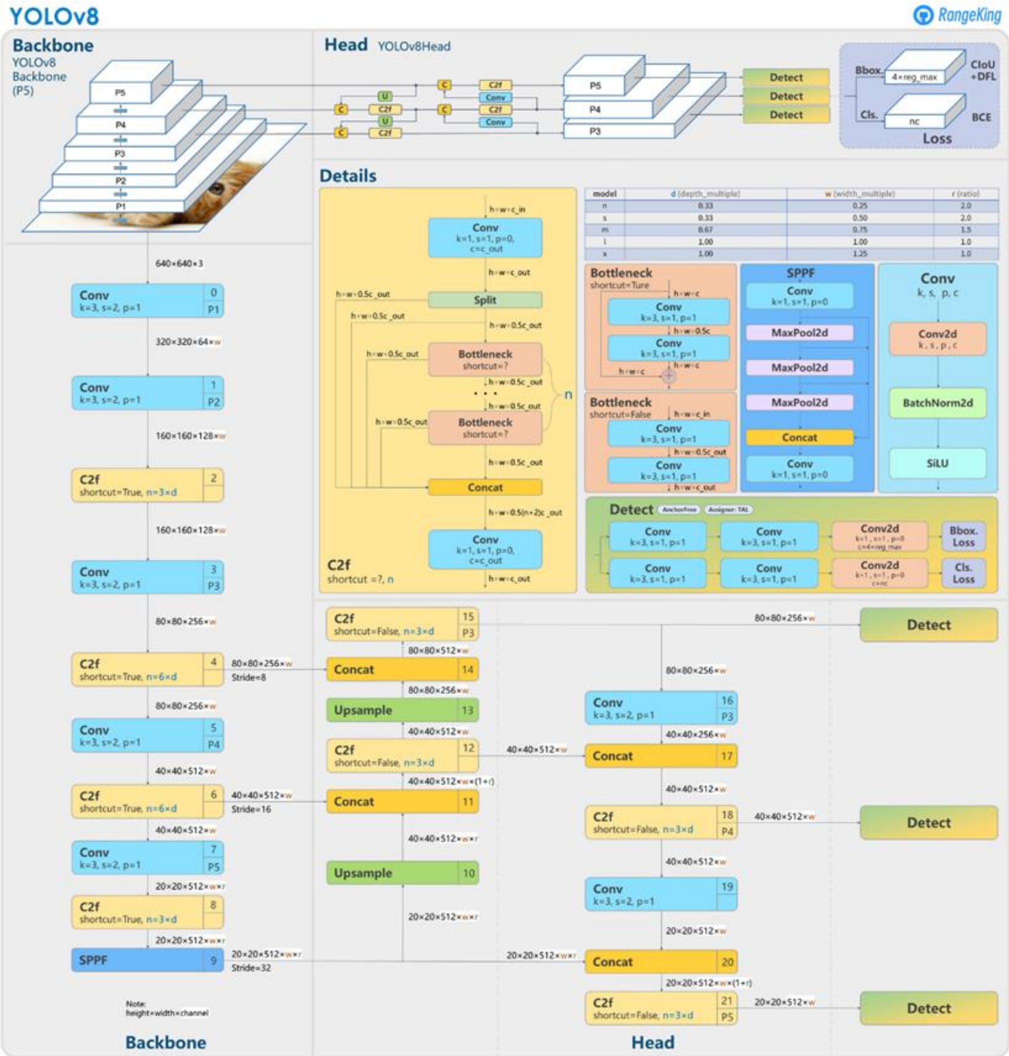

Figure 3. YoloV8 Architecture (King et al., 2024)

The model used consists of 10 layers. It has 1444693 parameters and is shown in Figure 3. It works with 224x224 images. Adam was preferred as the optimizer. To prevent overlearning, dropout was used, and its value was chosen as 0.2. Training with CPU Training lasted 50 epochs, 35 minutes. Those with GPU lasted 50 epochs, 5 minutes.

EXPERIMENTAL RESULTS

The confusion matrix is an important tool for calculating various evaluation metrics and understanding the performance of the model. The confusion matrix consists of four key terms detailing the relationship between true and predicted classes: True Positive (TP) represents cases where the model correctly predicts the positive class. That is, the actual value is positive (1), and the estimated value is positive (1). True Negative (TN) represents cases where the model correctly predicts the negative class. That is, the actual value is negative (0), and the estimated value is also negative (0). False Positives (FP) represent situations that the model predicts as positive but are negative. That is, the actual value is negative (0), but the estimated value is positive (1). False negatives (FN) represent situations that the model predicts as negative but are positive. That is, the actual value is positive (1), but the estimated value is negative (0).

Table 1. Model Parameters

Parameters	Module	Arguments
464	Convolution layer	[3, 16, 3, 2]
4672	Convolution layer	[16, 32, 3, 2]
7360	Fully Connected Layer	[32, 32, 1, True]
18560	Convolution layer	[32, 64, 3, 2]
49664	Fully Connected Layer	[64, 64, 2, True]
73984	Convolution layer	[64, 128, 3, 2]
197632	Fully Connected Layer	[128, 128, 2, True]
295424	Convolution layer	[128, 256, 3, 2]
460288	Fully Connected Layer	[256, 256, 1, True]
336645	Classification Layer	[256, 5]

Model performance is typically assessed using classification performance metrics, which include accuracy, precision, recall, and F1-score. Accuracy measures how often the classifier correctly predicts the outcome. Precision represents the proportion of correctly predicted positive samples out of all samples predicted as positive. Recall, also known as sensitivity, indicates the proportion of true positive samples that are correctly identified by the classifier. The F1-score is a harmonic mean of precision and recall, providing a single score that balances both metrics, giving an overall measure of a model's performance in classification tasks.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - Score = \frac{2\ x\ Rec\ x\ Prec}{Rec+Prec} \tag{4}$$

Performance evaluation was made using these metrics specified in our study. The performance results obtained are given in the table below.

Table 2. Performance Results

Class	Precision	Recall	F1 Score	
Mild	0.63	0.44	0.52	
Moderate	0.72	0.86	0.78	CPU 1
No_DR	0.96	0.98	0.97	
Proliferate_DR	0.70	0.58	0.63	
Severe	0.50	0.23	0.32	
Accuracy		0.83		
Mild	0.62	0.45	0.52	
Moderate	0.72	0.86	0.78	CPU 2
No_DR	0.96	0.98	0.97	
Proliferate_DR	0.75	0.57	0.65	
Severe	0.48	0.22	0.30	
Accuracy		0.83		
Mild	0.61	0.53	0.56	
Moderate	0.76	0.87	0.81	GPU 1
No_DR	0.96	0.98	0.97	
Proliferate_DR	0.71	0.56	0.63	
Severe	0.60	0.32	0.41	
Accuracy		0.8491		
Mild	0.62	0.63	0.62	
Moderate	0.76	0.83	0.79	GPU 2
No_DR	0.96	0.98	0.97	
Proliferate_DR	0.70	0.52	0.60	
Severe	0.51	0.32	0.39	
Accuracy		0.8436		

The confusion matrix used to show the classification performance of the best model is given in Figure 4 below. The least errors were encountered especially in the No_DR and Moderate classes. The most errors belong to the Severe class. Mild class is confused with Moderate class.

Yolov8 - GPU(1)

OUTPUT \ TARGET	mild	Moderate	No_DR	Proliferate_DR	Severe	SUM
mild	53 4.82%	21 1.91%	8 0.73%	4 0.36%	0 0.00%	86 61.63% 38.37%
Moderate	30 2.73%	264 24.00%	1 0.09%	23 2.09%	28 2.55%	346 76.30% 23.70%
No_DR	14 1.27%	7 0.64%	556 50.55%	1 0.09%	0 0.00%	578 96.19% 3.81%
Proliferate_DR	2 0.18%	5 0.45%	0 0.00%	43 3.91%	10 0.91%	60 71.67% 28.33%
Severe	1 0.09%	6 0.55%	0 0.00%	5 0.45%	18 1.64%	30 60.00% 40.00%
SUM	100 53.00% 47.00%	303 87.13% 12.87%	565 98.41% 1.59%	76 56.58% 43.42%	56 32.14% 67.86%	934 / 1100 84.91% 15.09%

Figure 4. Confusion Matrices

To evaluate whether the training process has been successful or not, training and validation loss graphs are shown in Figure 11. The loss graph shows the learning ability of the model during the training process. The decrease in training loss over time indicates that the model has learned the data better and its generalization ability has increased. The decreasing loss trend observed during deep learning model training indicates that the model's performance improves over time and becomes a more reliable predictor. This trend reflects the increasing ability of the model to learn from data and its ability to predict desired outcomes more accurately. Therefore, considering the decreasing loss trend during deep learning model training provides an important indicator to evaluate and improve the performance of the model.

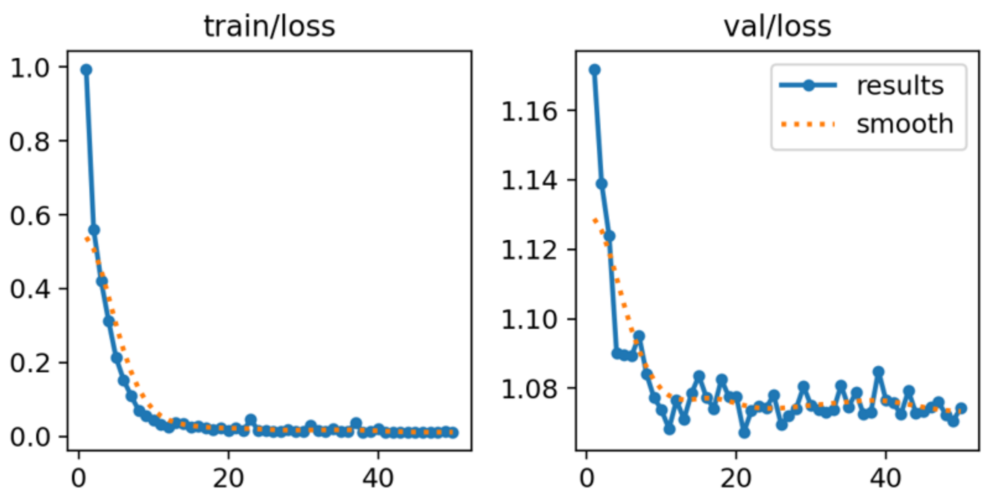

Figure 5. Train and Validation Graphic

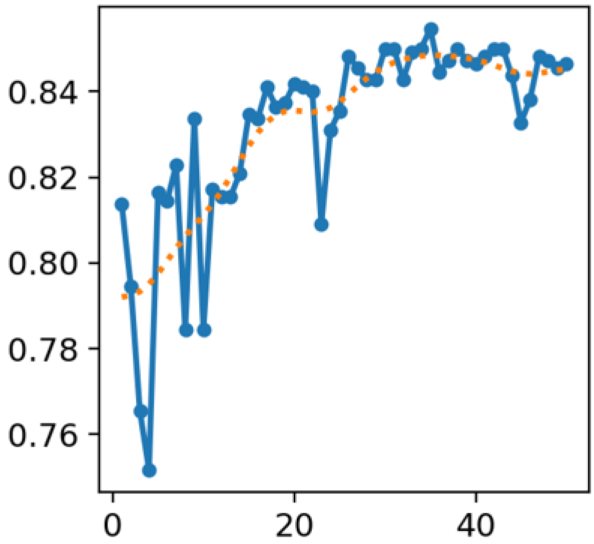

Figure 6. Accuracy Graphic

To evaluate the classification accuracy of the best model, the accuracy graph is presented in Figure 6. The Accuracy chart shows the percentage of correct predictions the model has. A high level of accuracy values throughout the training process indicates that the model has learned successfully and can generalize to new data.

DISCUSSION

In this study, no pre-processing, data augmentation, or data inequality removal process was applied to the data set before training. Training time was performed on CPU (12th Gen Intel Core (TM) i5-12400F) with 35 minutes and 50 epochs. The model was trained using a total of 3600 images. The F1 Score of the No_DR class exceeded 97%. For example, in the study of Özçelik and Altan (Özçelik and Altan, 2021), it was observed that the F1 Score remained around 88% in some models. At the same time, the accuracy of the model is 93%. This value is between 86% and 93% in the study of Ağca and Takci (Kemal and Takci, 2022) study. Compared to other studies, promising results were obtained regarding the diagnosis and classification of Yolov8 Diabetic Retinopathy.

Table 3. Comparison of Studies

Study	Dataset Size	Preprocessing	Accuracy (%)
(Deperlıoğlu and Köse, 2018)	400	Yes	97
(Çavlia nd Toğaçar, 2023)	2111	Yes	100
(Özçelik and Altan, 2021)	3662	Yes	97
(Kemal and Takci, 2022)	3662	No	93
(Dai et al., 2021)	466,247	Yes	97
(Dulkadir and Gültekin 2023)(Yolo)	18257	Yes	80
This Study	3600	No	84

CONCLUSION

In this study, a computer-aided system that allows early diagnosis and classification of diabetic retinopathy disease is proposed using a deep learning architecture. In the study, a fundus dataset consisting of retinal images was used for early diagnosis and treatment of DR disease by classifying it as "Mild, Moderate, No_DR, Proliferate_DR, Severe" and a model was created using YOLOv8, one of the CNN architectures. Accuracy values were measured as 83%, 83%, 84.91% and 84.36% respectively. Despite the dispersed data set and short training time, high accuracy in the images and especially a high F1-score in the No_DR class were achieved. It has been understood that YoloV8 can be used for classification problems. With a larger and more balanced data set, the overall values of the model can be increased. To improve the model's accuracy and other evaluation metrics, the model can be improved by making fine calculations of the model parameters.

REFERENCES

Ansari, P., Tabasumma, N., Snigdha, N. N., Siam, N. H., Panduru, R. V., Azam, S., Hannan, J., & Abdel-Wahab, Y. H. (2022). Diabetic retinopathy: an overview on mechanisms, pathophysiology, and pharmacotherapy. *Diabetology*, *3*(1), 159-175.

Arslan Tuncer, Seda & Çinar, Ahmet & Fırat, Murat. (2021). Hybrid CNN Based Computer-Aided Diagnosis System for Choroidal Neovascularization, Diabetic Macular Edema, Drusen Disease Detection from OCT Images. Traitement du Signal. 38. 673-679. 10.18280/ts.380314.

Association, A. D. (2022). Standards of medical care in diabetes—2022 abridged for primary care providers. *Clinical Diabetes*, *40*(1), 10-38.

Çavli, A., & Toğaçar, M. (2023). Yapay Zekâ Yaklaşımlarını Kullanarak Retinopati Hastalığının Tespiti. *Mühendislik Bilimleri ve Araştırmaları Dergisi*, *5*(1), 88-97.

Dai, L., Wu, L., Li, H., Cai, C., Wu, Q., Kong, H., Liu, R., Wang, X., Hou, X., & Liu, Y. (2021). A deep learning system for detecting diabetic retinopathy across the disease spectrum. *Nature communications*, *12*(1), 3242.

Deperlıoğlu, Ö., & Köse, U. (2018). Diagnosis of diabetic retinopathy by using image processing and convolutional neural network. 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT),

Dugas, E., Jared, J., & Cukierski, W(2015). Diabetic retinopathy detection. *URL https://kaggle. com/competitions/diabetic-retinopathy-detection*, *7*.

Dulkadir, S., & Gültekin, G. K. (2023). Tarımsal Otomasyon Sistemleri için Muz Olgunluk Seviyelerinin Derin Öğrenme Yöntemleri İle Sınıflandırılması. EMO Bilimsel Dergi, 13(3), 27-34.

Lingling Fang, Huan Qiao(2022),Diabetic retinopathy classification using a novel DAG network based on multi-feature of fundus images,Biomedical Signal Processing and Control,Volume 77, 2022, 103810, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2022.103810.

Fong, D. S., Aiello, L., Gardner, T. W., King, G. L., Blankenship, G., Cavallerano, J. D., Ferris III, F. L., Klein, R., & Association, A. D. (2003). Diabetic retinopathy. *Diabetes care*, *26*(suppl_1), s99-s102.

Kemal, A., & Takci, H. (2022). Hibrit Bir Model Oluşturarak Diyabetik Retinopati Sınıflandırılması. *Avrupa Bilim ve Teknoloji Dergisi*(36), 227-236.

King, R. Retrieved 01.01.2024 from https://github.com/open-mmlab/mmyolo

Özçelik, Y. B., & Altan, A. (2021). Diyabetik retinopati teşhisi için fundus görüntülerinin derin öğrenme tabanlı sınıflandırılması. *Avrupa Bilim ve Teknoloji Dergisi*(29), 156-167.

Özçelik YB, Altan A(2023). Overcoming Nonlinear Dynamics in Diabetic Retinopathy Classification: A Robust AI-Based Model with Chaotic Swarm Intelligence Optimization and Recurrent Long Short-Term Memory. *Fractal and Fractional*.; 7(8):598. https://doi.org/10.3390/fractalfract7080598

Ultralytics. *Ultralytics Documentation.* . Retrieved 01.02.2024 from https://docs.ultralytics.com/

Vujosevic, S., Aldington, S. J., Silva, P., Hernández, C., Scanlon, P., Peto, T., & Simó, R. (2020). Screening for diabetic retinopathy: new perspectives and challenges. *The Lancet Diabetes & Endocrinology*, *8*(4), 337-347.

V. Vipparthi, D. R. Rao, S. Mullu and V. Patlolla(*2022*). "Diabetic Retinopathy Classification using Deep Learning Techniques," *3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Coimbatore, India, 2022, pp. 840-846, doi: 10.1109/ICESC54411.2022.9885687.

Wong, T. Y., Sun, J., Kawasaki, R., Ruamviboonsuk, P., Gupta, N., Lansingh, V. C., Maia, M., Mathenge, W., Moreker, S., & Muqit, M. M. (2018). Guidelines on diabetic eye care: the international council of ophthalmology recommendations for screening, follow-up, referral, and treatment based on resource settings. *Ophthalmology*, *125*(10), 1608-1622.

Yau, J. W., Rogers, S. L., Kawasaki, R., Lamoureux, E. L., Kowalski, J. W., Bek, T., Chen, S.-J., Dekker, J. M., Fletcher, A., & Grauslund, J. (2012). Global prevalence and major risk factors of diabetic retinopathy. *Diabetes care*, *35*(3), 556-564.