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***Review Article***

# Diabetic Retinopathy Diagnosis Using Machine Learning Versus Deep Learning

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**Abstract**
Diabetic retinopathy disease affects millions of people around the world. It is considered a complication of diabetic disease and can affect eye vision. Physicians can detect this disease by medical eye examination. Many images need to be processed in order to make the final decision. Fortunately, computer-aided decision support systems can help physicians make accurate decisions with less effort and time. In this study, a review of the current diabetic retinopathy computer-aided systems is introduced. The study includes studies using machine learning or deep learning approaches for diabetic retinopathy detection. This paper compares all those previous studies in terms of the proposed methodology, the used dataset, the acquired results, and the evaluation. The study also compared the current diabetic retinopathy datasets. As a result, we found that the methods that were based on deep learning had the best performance. Besides, the categorical classification of diabetic retinopathy stages was better than doing a binary classification of disease detection. This study helps researchers in their future work to select the best methodologies and datasets.

**Keywords:** Diabetic Retinopathy, Machine Learning, Deep Learning, Blood Vessels, Image Processing, Image Classification.

# Derin Öğrenmeye Karşı Makine Öğrenimi Kullanarak Diyabetik Retinopati Teşhisi

**Öz**

Diyabetik retinopati hastalığı dünya çapında milyonlarca insanı etkilemektedir. Diyabetik hastalığın bir komplikasyonu olarak kabul edilir ve göz görüşünü etkileyebilir. Hekimler bu hastalığı tıbbi göz muayenesi ile tespit edebilirler. Nihai kararı vermek için birçok görüntünün işlenmesi gerekir. Neyse ki, bilgisayar destekli karar destek sistemleri, doktorların daha az çaba ve zaman harcayarak doğru kararlar vermelerine yardımcı olabilir. Bu çalışmada, güncel diyabetik retinopati bilgisayar destekli sistemlerin bir derlemesi sunulmaktadır. Çalışma, diyabetik retinopati tespiti için makine öğrenimi veya derin öğrenme yaklaşımlarının kullanıldığı çalışmaları içermektedir. Bu makale, önerilen metodoloji, kullanılan veri seti, elde edilen sonuçlar ve değerlendirme açısından önceki tüm çalışmaları karşılaştırmaktadır. Çalışma ayrıca mevcut diyabetik retinopati veri setlerini de karşılaştırdı. Sonuç olarak, derin öğrenmeye dayalı yöntemlerin en iyi performansı gösterdiğini gördük. Ayrıca, diyabetik retinopati evrelerinin kategorik sınıflandırması, hastalık tespitinde ikili sınıflandırma yapmaktan daha iyiydi. Bu çalışma, araştırmacıların gelecekteki çalışmalarında en iyi metodolojileri ve veri kümelerini seçmelerine yardımcı olur.

**Anahtar Kelimeler:** Diyabetik Retinopati, Makine Öğrenimi, Derin Öğrenme, Kan Damarları, Görüntü İşleme, Görüntü Sınıflandırma.

# 1. Introduction

Diabetic disease affects not only the retina but also other various tissues like heart and kidneys [1] [2]. According to International diabetes federation [3], diabetes affects more than 537 million people around the world. 90 million diabetic patients have diabetic retinopathy [4]. Diabetic retinopathy (DR), which is a complication of diabetes, affects retina by swelling blood vessels and leaking fluids inside the eye. This complication affects the eye vision and can cause blindness (about 2.6% of blindness cases come from retinopathy disease [5] Diabetic retinopathy is a type of disease in which the diabetes disease affects retina and causes some vision complications (could lead to blindness). Detecting this disease in an early stage helps patients to retrieve their retina's normal condition and avoids blindness [6]. However, detecting diabetic retinopathy via traditional manual methods requires too much time to process the huge amount of data. Besides that, these conventional methods register too many misclassifications [7]. Unlike the manual way, computer-aided decision support tools detect diabetic retinopathy precisely. Almost 75% of diabetic retinopathy diseases come from poor countries [8], which have no sufficient equipment or detection tools. For this reason, the decision-support.systems for detecting diabetic retinopathy have the effect of early detection of diabetic retinopathy. The appearance of lesions in retina image is used to detect diabetic retinopathy. These lesions are hemorrhages (HM), micro-aneurysms (MA), soft nd hard exudates (EX) [9]. The earliest sign of diabetic retinopathy is the MA lesions which appear as red circular points caused by the weakness of the blood vessel's walls. The size of these points is less than 125 μm with sharp borders. According to Arrigo et al. [10], MA has 6 main types which are saccular, focal bulge, fusiform, mixed, pedunculated, and irregular which are shown in Fig.1 [11].

Hard exudates are bright-yellow spots with sharp borders appearing on the retina tissue due to the leakage of plasma. This type of diabetic retinopathy usually appears on the outer layers of the retina. While the soft exudates are white spots caused by the swelling of the nerve fiber. This type of diabetic retinopathy usually appears in an oval shape. Fig.3 shows the Hard and soft EX diabetic retinopathy [13] [14].

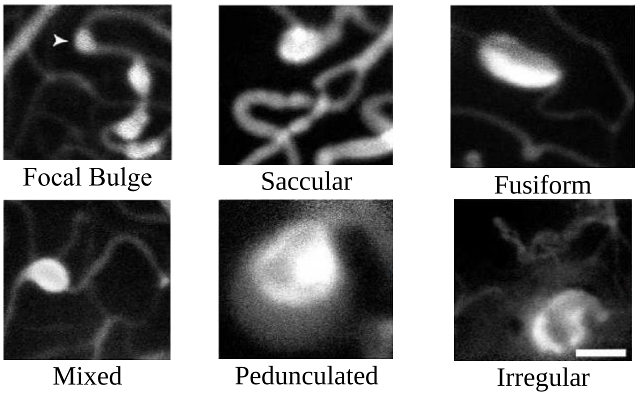


Fig.1. Different types of MA diabetic retinopathy

The second type of diabetic retinopathy is Hemorrhages (HM) which appears as large spots on the retina tissue with size greater than 125 μm with an abnormal margin as shown in Fig.2 [12]

Fig. 2. HM diabetic retinopathy

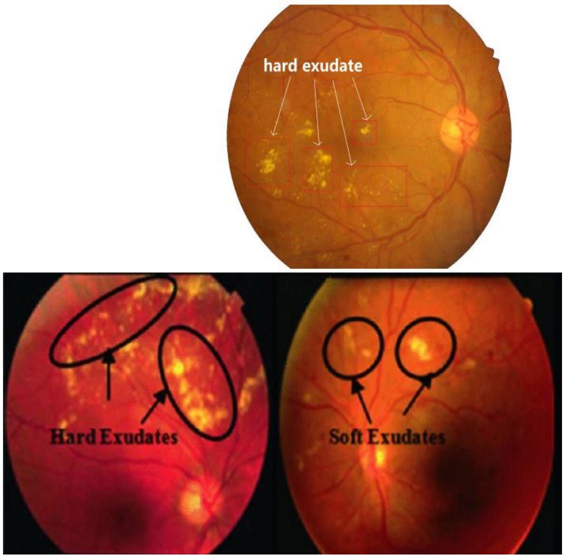


Fig. 3. Soft and Hard exudates diabetic retinopathy

Diabetic retinopathy's four basic types are illustrated in Fig.4 of a sample of the IDRiD dataset [15].

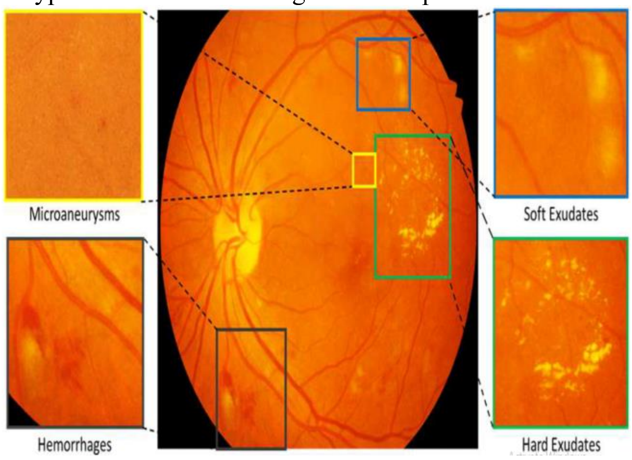


Fig. 4. The main types of diabetic retinopathy

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## 2. Machine Learning methodologies for diabetic retinopathy detection

Many researchers introduced solutions for diabetic retinopathy detection using machine learning algorithms ML. Many ML models were trained and evaluated using many retinal datasets. The main challenge of such ML systems is the low accuracy due to the similarity between diabetic retinopathy diseases, besides the retina image's shape (brightness at the center of the retina and darkness at the borders). Other factors include illumination variations, low contrast, small lesions, and small parts inside retinal images that are not actually lesions [16]. Fig.5 shows the main steps of the ML-based diabetic retinopathy system.

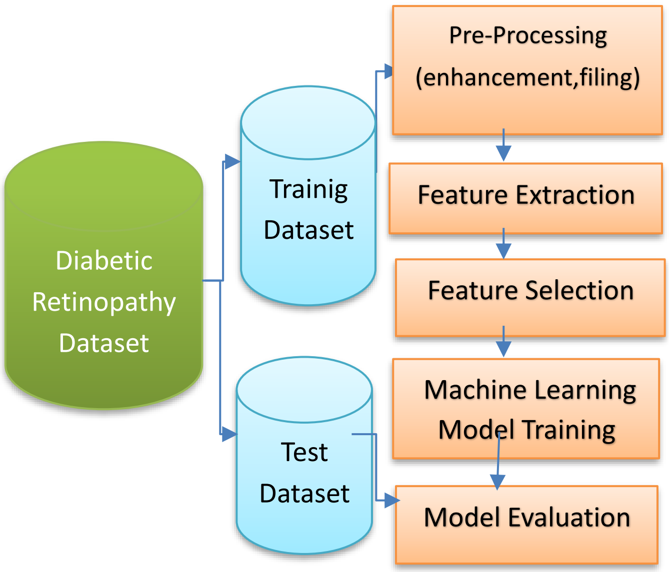


Fig. 5. Common ML steps for diabetic retinopathy detection.

Many ML approaches were used to build a diabetic retinopathy system, including support vector machines (SVM) [17] [18] [19], Decision Trees (DT), Naïve Bayes (NB), Neural Networks (NN), logistic regression (LR), XGBoost model, K-nearest neighbor (K-NN), etc.

**SVM-based DR models**

Bhargavi et al. [17] proposed a diabetic retinopathy system based on the SVM models. They first segmented the retinal images to get the blood vessels by means of the Bilateral filtering and Hessian matrix transform. After that, the foreground bright lesions are extracted. Some statistical and geometrical features were extracted from the segmented images (A total of 20 features were extracted). In the final step, the SVM classifier was trained using the extracted features of segmented retinal images. Their proposed approach was applied to the DIARETDB1 dataset (89 images) and MESSIDOR (1200 images). Their approach achieved 96.66% accuracy. In their study, they used only one type of DR disease.

Using their own collected dataset containing 400 retinal images, Enrique et al. [18] built a diabetic retinopathy detection system based on SVM model. They first isolated the blood vessels, the hard exudates, and the microaneurysms. Then, they extracted the features based on the original, red and green components of the segmented images. The extracted features included the standard deviation, blood vessels density, number of microaneurysms, density of hard exudates, and entropy of green component of the segmented image. The SVM classifier was used for the classification part. They got an accuracy of 92.4%. They detected the presence of diabetic retinopathy without classification of the main types; besides, they used a small dataset.

Chetoui et al. [16] proposed a diabetic retinopathy detection system based on textual features and SVM model. They extracted the Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH) from the segmented retinal images. Those extracted histogram-based features were then used to train an SVM classifier. Results indicated that the LESH features were the best-extracted features with 90.4% accuracy and 0.93 Area Under Curve (AUC). They used 1200 images of MESSIDOR dataset and distinguish between the normal and abnormal conditions without any classification of the other type of retinopathy categories.

Hardes et al. [19] introduced a retinal fundus detection system based on SVM predictors. They used the Gaussian mixture model, K-means algorithm, Principle Component Analysis (PCA), Grey-level co-occurrence matrix (GLCM), and SVM. They achieved an accuracy of 77.3% on the DIARETDB1 dataset. Their approach has no modifications in the ML proposed models and the result accuracy was low.

**Decision Trees**

Aziza et al. [20] suggested using decision trees classifier for the detection of diabetic retinopathy. They used color fundus DRIVE and Messidor datasets. They first segmented the retinal images to get the blood vessels, and then they extracted the geometric features. The Hessian matrix and active contouring algorithms were used for the segmentation of blood vessels. They classified images into DR or No-DR categories. The experiments showed that the accuracy of classification step was 93%.

Early-Stage diabetic retinopathy detection using decision trees models was proposed by Yao et al. [21]. The study included two categories of patients, including 241 patients. The area under the curve (AUC), sensitivity and specificity were used to evaluate the model. Results indicated 0.62, 66% and 76% for AUC, sensitivity and specificity, respectively.

**Random Forests**

Casanova et al. [22] introduced a diabetic retinopathy detection system based on Random Forests (RF) classifier. They used 3443 eye-study images as a retinal dataset. Their approach achieved an accuracy of 90%. They didn't use any segmentation or feature extraction approaches.

Fractal analysis along with the random forest's classifier were used by Alzami et al. [23] for the aim of diabetic retinopathy detection and classification. They used the MESSIDOR dataset and applied a segmentation process on the green component of the retinal images. They also used the morphological Skeltonization process to obtain the vessels. The connected components and closing morphological operations were also used to get the final fundus image. For the feature extraction step, the fractal characteristics were used. The classification step was performed using RF algorithm. Results showed that the accuracy was 80.37%. Their approach distinguished between healthy and diabetic retinopathy patients, but it failed to classify the severity of diabetic retinopathy patients.Hard exudate diabetic retinopathy detection system was proposed by Zaaboub and Douik [24]. They used a dataset of color fundus retinal images and removed the optic disk. Then, they extracted specific parameters of the binary mask of exudate region. Those extracted features were then introduced to the RF classifier which was trained and evaluated. Results indicated that the accuracy of their proposed models was 94.38%.

**Naïve Bayes**

Naïve Bayes classifier was proposed in a study of Kang et al. [25]. They used the statistical feature extraction, including the gray-level co-occurrence matrix, gray-level run-length texture analysis and the statistical texture features. Those features were used to train Naïve Bayes classifier. The trained model was used to classify fundus images of diabetic retinopathy images of China diabetic dataset (consisting of 568 images). The system achieved an accuracy of 93.44%.

In a study by Hadistio et al. [26], diabetic retinopathy detection system was introduced. They used the UCI machine learning diabetic retinopathy dataset (including 1151 data records and 19 attributes). The Stochastic Gradient Descent SGD and Naïve Bayes algorithms were used to classify normal and diabetic retinopathy samples. The obtained accuracy was only 56.74%.

**Mixed Models and ensemble models**

In some studies, researchers used many ML models and compared their performance.

Roychowdhury et al. [27] presented a computer-aided system for detecting diabetic retinopathy using machine learning algorithms. The used ML models were the Gaussian mixture model (GMM), AdaBoost, K-NN, and SVM. The study minimized features using the AdaBoost feature ranking into only 30 features. A two-step hierarchical classification method was suggested in their system. In the first step, they rejected the no lesions parts of the retinal images; while in the second step, they classified the lesions into four main types: hard exudates, cotton spots, and hemorrhages, micro- aneurysms. The experiments were applied on 1200 retinal images of the MESSIDOR dataset. The results showed that the sensitivity was 100% while the specificity was 53.16% and the AUC was 0.9. The main problem of the research was the high false positives.

Reddy et al. [28] proposed an ensemble model for the detection of diabetic retinopathy. They built an ensemble of RF, DT, AdaBoost, K-NN, and Logistic Regression (LR). The normalization step on the used dataset is first applied. Then, the ensemble model was trained. The precision, recall, f1-score, and accuracy of the best model were 78%, 78%, 77% and 77%. The study mentioned that the ensemble model increased the performance by almost 80%. Their study was applied to a textual dataset and the obtained accuracy was low because of using no preprocessing operations. The study also used the binary classification (DR or Not DR classes).

Sidker et al. [29] propose a new ensemble model for diabetic retinopathy based on the gray-level intensity, texture feature extraction, and decision trees. They used the Asia Pacific Tele-Ophthalmology Society 2019 dataset. Their proposed approach consisted of many steps, including preprocessing, textual feature extraction, feature selection, and ensemble learner training. The results indicated an accuracy of 94.2% and an F-measure of 93.51%.

Another diabetic retinopathy detection system based ensemble learning was introduced by [30]. The study focused on microaneurysms eye disease. The ensemble included four classifiers SVM, K-NN, DT, and Naïve Bayes. First, the images were pre-processed. Then, the shape and intensity features were extracted from the pre-processed images. The experiments were applied on the E-ophtha and DIARETDB1 datasets and the obtained AUC score was 0.928 and 0.873 of the used datasets, respectively.

Table 1 includes a comparison between the ML-based diabetic retinopathy and previous systems.

| Researcher | Methods | Dataset | Results | Notes |
|---|---|---|---|---|
| Bhargavi et al. [17], 2016 | SVM, statistical and geometrical features | DIARETDB1 dataset (89 images) and MESSIDOR (1200 images) | Accuracy: 96.66% | Binary classification (DR or Not DR) |
| Enrique et al. [18], 2017 | SVM, Features of the color components | 400 retinal images | Accuracy: 92.4% | Binary classification (DR or Not DR) |
| Hardes et al. [19], 2022 | Gaussian mixture model, K-means, (PCA), (GLCM), and SVM | DIARETDB1 89 images) | Accuracy: 77.3% | No modifications in the ML proposed models (Low accuracy) |
| Aziza et al. [20], 2019 | DT | DRIVE and Messidor datasets | Accuracy: 93% | Binary classification (DR or Not DR) |
| Yao et al. [21], 2022 | DT | 241 cases | AUC: 0.62<br>Sensitivity: 66%<br>Specificity: 76% | Early prediction of diabetic retinopathy |
| Alzami et al. [23], 2019 | RF and Fractal analysis | MESSIDOR dataset | Accuracy 80.37% | Low accuracy<br>Binary classification (DR or Not DR) |
| Zaaboub and Douik [24], 2020 | RF | Not mentioned nor specified | Accuracy 94.38% | Detected only one type of diabetic retinopathy |
| Kang et al. [25], 2020 | Naïve Bayes, statistical feature extraction | China diabetic dataset (568 images) | Accuracy: 93.44% | Low accuracy, they used three categories for classification |
| Hadistio et al. [26], 2022 | Naïve Bayes, SGD | UCI diabetic retinopathy dataset (1151 data records and 19 attributes) | Accuracy: 56.74% | Low accuracy |
| Roychowdhury et al. [27], 2014 | (GMM), AdaBoost, K-NN, and SVM | MESSIDOR (1200 images) | Sensitivity: 100%<br>Specificity: 53.16%<br>AUC: 0.9. | High false positive rate |
| Reddy et al. [28], 2020 | Ensemble learning | UCI diabetic retinopathy dataset (1151 data records and 19 attributes) | Accuracy: 77% | Low accuracy Binary classification (DR or Not DR) |
| Sidker et al. [29], 2021 | Ensemble learning, Textual feature extraction, feature selection | Asia Pacific Tele-Ophthalmology Society 2019 dataset | Accuracy: 94.2%<br>F1-score: 93.51% | Feature selection was applied to minimize computational time |
| Pendekal [30], 2022 | Ensemble learning, | E-ophtha | AUC: 0.928 | The study detected only one type of diseases (Microaneurysms) |

## 3. Deep Learning methodologies for diabetic retinopathy detection

Deep learning (DL) is a new branch of deep learning based on deep neural networks. DL diabetic retinopathy steps are similar to the ML steps with a little bit difference. Figure 6 shows the DL steps of the diabetic retinopathy detection system.

Pratt et al. [31] used the CNN model in order to extract the retinal image features from the diabetic retinopathy Kaggle dataset (80000 images). They used color normalization, data augmentation and L2-regularization in the preprocessing step. For the training step, they used the CNN with Stochastic Gradient Descent optimization. They got 95%, 75% and 30% for specificity, accuracy and sensitivity, respectively. The results indicated too many false negatives.

Soniya et al. [32] introduced CNN single-based and CNN heterogeneous-based diabetic retinopathy systems. The gradient descent and backpropagation algorithms were used for the raining step. Four basic classes were classified (MAs, HEs, hard EXs and soft EXs). The study used 130 images of the DIARETDB0 dataset. They got different accuracies depending on the CNN architecture (95%, 65%, 42.5%, 67.5% and 92.5%).

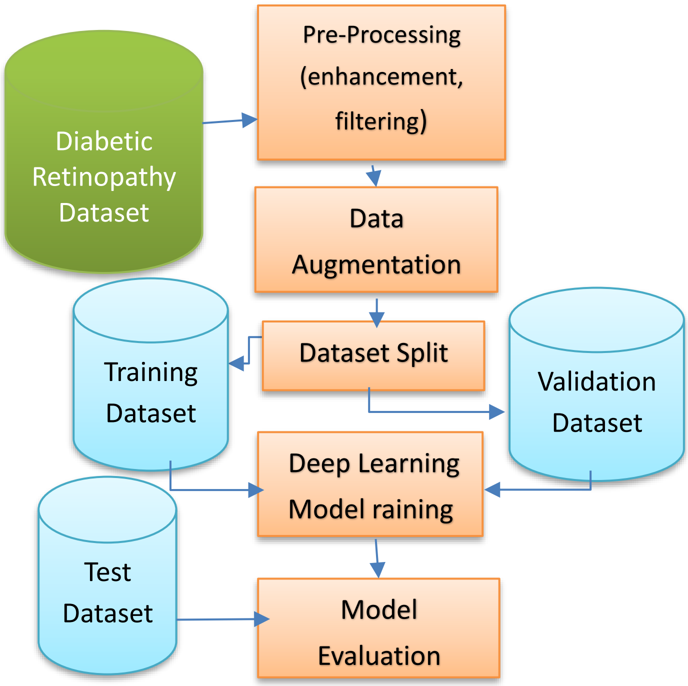


Fig. 6. Common DL steps for diabetic retinopathy detection.

Gargeya and Leng [33] proposed an automated identification system for diabetic retinopathy using deep learning models. The study used the MESSIDOR2 and E-Ophtha datasets. The experiments showed that the designed system achieved 0.94 and 0.95 AUC for the MESSIDOR2 and the E-Ophtha databases, respectively. The sensitivity and specificity values are 93% and 87% for MESSIDOR2 dataset, while the sensitivity and specificity values are 90% and 94% for MESSIDOR2 dataset.

An automated system for diabetic retinopathy detection system was proposed by Lam et al. [34]. They used a Kaggle EyePACS dataset, including 243 retinal images. Many CNN architectures were used with resized retinal images (128*128*3). The used models were: GoogleLeNet-v1, AlexNet, VGG-16, ResNet and Inception-V3. The best-acquired accuracy was 98% for the InceptionV3 model.

Khalifa et al. [35] proposed using many DL models, including AlexNet, ResNet18, SqueezeNet, GoogleNet, VGG16, and VGG19. They used the Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 dataset. The best accuracy was obtained by the AlexNet model with 97.9%, and total average accuracy of 96.3%. They used no ensemble nor fusion approaches.

Nguyen et al. [36] used the transfer learning of VGG16 and VGG19 models for the aim of diabetic retinopathy detection. They used the Kaggle competition dataset 2015, consisting of Serve, Mild, Moderate, Proliferative DR and normal cases. The study applied data augmentation process and achieved an accuracy of 71% and 73% of VGG16 and VGG19, respectively. After modification using sequential dense layers, the performance was improved to 83%.

retinal images were enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE). Then, the efficient model was trained using these images. They got an AUC of 0.94 and 0.93 for MESSIDOR, and IDRiD, respectively.

Thota and Reddy [39] used the VGG-16 model for the diabetic retinopathy detection problem. The transfer learning of VGG-16 pre-trained model was used in order to get the best performance. They used the Kaggle EyePACS dataset and achieved 74%, 80% and 65% for accuracy, sensitivity and specificity, respectively.

Densely CNN (DenseNet-169) was proposed by Mushtaq and Siddiqui [40] for the aim of diabetic retinopathy detection. They classified retinal images into DR, Not-DR, mild, moderate, and Proliferative. The research used two datasets (Diabetic Retinopathy Detection 2015 and Aptos 2019 Blindness datasets). They first apply data preprocessing steps, including cleaning, resizing, and augmentation. Then, the deep learning model was trained using this manipulated data. The achieved accuracy was 90%.

An ensemble of five models from the EfficientNet family was used for DR grading by the authors in [41] by pre-training on ImageNet. These models were also used.

independently for the same, and EfficientNet-B3 performed better than the ensemble model and the other four models.

Parthasharathi et al. [42] proposed an early diabetic detection system based on convolutional neural networks (CNN). They used a Kaggle dataset consisting of 1000 images (300 diabetics and 700 normal). The images were first transformed into HSV format. Then, the extraction of yellow exudate from the color components was performed. The median filtering and feature extraction were then applied. The training process was applied using the "Adam" optimization algorithm. Results showed that the accuracy was 91.5%.

Shaik and Cherukuri [43] introduced a model named "Hinge Attention Network (HA-Net)". They used multiple attention modules for diabetic retinopathy severity grading. VGG-16 model was used to extract the initial spatial representations. The experiments were applied to the IDRid dataset. The obtained accuracy was 66.4%. Oulhadj et al. [44] used four CNN models, including DenseNet-121, Xception, InceptionV3, and ResNet-50. The Retinal images of Kaggle APTOS were registered and diabetic retinopathy was graded using the CNN models. The results showed that the best accuracy was 85.28%. Lahmar and Idri [45] used many DL models for feature extraction (VGG16, VGG19, Inception_V3, DenseNet201, MobileNet_V2, Inception_ResNet_V2 and ResNet50). Four different classifiers (SVM, MLP, DT and KNN) were trained using the extracted features. The performance was performed using accuracy, sensitivity, precision and F1-score. Three different datasets were used (APTOS, Kaggle DR and Messidor-2). The experiments achieved 88.80%, 84.01% and 84.05% of the three used datasets, respectively.Table 2 includes a comparison between the DL-based diabetic retinopathy previous systems.

Table 2. A comparison between the DL-based diabetic retinopathy previous studies.

| Researcher | Methods | Dataset | Results | Notes |
|---|---|---|---|---|
| **Pratt et al. [31]** | CNN with Stochastic Gradient Descent optimization | Diabetic retinopathy Kaggle dataset (80000 images) | Specificity: 95%, Accuracy: 75% Sensitivity: 30% | Too many false negatives. Binary classification (DR or Not DR) |
| **Soniya et al. [32]** | Single and heterogeneous CNN | DIARETDB0 (130 images) | Best accuracy 95% | Low dataset size |
| **Gargeya and Leng [33]**, **2017** | CNN | MESSIDOR2 dataset | AUC: 0.94 Sensitivity: 93% Specificity: 87% | No accuracy measure was computed. |
| | | E-Ophtha dataset | AUC: 0.95 Sensitivity: 90% Specificity: 94% | |
| **Lam et al. [34]** | GoogleLeNet-v1 | Kaggle EyePACS dataset (243 images) | Accuracy: 74% | Binary classification (DR or Not DR) |
| | AlexNet | | Accuracy: 79% | |
| | VGG-16 | | Accuracy: 86% | |
| | ResNet | | Accuracy: 90% | |
| | Inception-V3 | | Accuracy: 95% | |
| **Khalifa et al. [35], 2019** | AlexNet, ResNet18, SqueezeNet, GoogleNet, VGG16, VGG19 | Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 | Best Accuracy 97.9% corresponds with AlexNet | Average Accuracy 96.3% |
| **Nguyen et al. [36], 2020** | CNN, VGG-16 and VGG-19 | Kaggle 2015 competition dataset | Accuracy 82% | No ensemble or fusion were used |

| | | | | |
|---|---|---|---|---|
| **Tymchenko et al. [37], 2020** | Three-head CNN | APTOS 2019 Blindness Detection Dataset (1300 images) | Accuracy 99.3% | Dataset is used to only detect blindness disease |
| **Pour et al. [38], 2020** | EfficientNet B5, CLAHE | MESSIDOR | AUC: 0.94 | Binary classification (DR or Not DR) |
| | | IDRiD | AUC: 0.93 | |
| **Thota and Reddy [39]** | VGG-16 | Kaggle EyePACS | Accuracy: 74% Sensitivity: 80% Specificity: 65% | Low accuracy |
| **Mushtaq and Siddiqui [40], 2021** | DenseNet-169 | Diabetic Retinopathy Detection 2015 and Aptos 2019 Blindness | Accuracy: 90% | No fusion or ensemble was used |
| **Karki and Kulkarni [41], 2021** | EfficientNet | Kaggle APTOS | kappa score of 0.924377 | No well-known evaluation metrics |
| **Parthasharathi et al. [42], 2022** | CNN | Kaggle dataset (1000 images) | Accuracy: 91.5% | Binary classification (DR or Not DR) |
| **Shaik and Cherukuri [43], 2022** | HA-Net, VGG-16 | IDRid dataset | Accuracy: 66.4% | Low accuracy |
| **Oulhadj et al. [44], 2022** | DenseNet, InceptionV3, and ResNet-50 | Kaggle APTOS | Accuracy: 85.28% | Moderate accuracy |
| **Lahmar and Idri [45]** | VGG16, VGG19, Inception_V3, DenseNet201, MobileNet_V2, Inception_ResNet_V2 and ResNet50 | Kaggle APTOS | Accuracy: 88% | Moderate Accuracy |
| | | Kaggle DR | Accuracy: 84.01% | |
| | | Messidor-2 | Accuracy: 84.05% | |
| **Gundluru et al. [46], 2022** | DNN, PCA, Harris Hawks Optimization (HHO) | UCI machine learning Diabetic Retinopathy Debrecen Dataset | Accuracy: 96.7% | limited by the possibility of overfitting |

## Diabetic Retinopathy Dataset

Many publicly available datasets for diabetic retinopathy detection and classification are available for research aims. These datasets help scientists to build diabetic retinopathy detection systems. Researchers usually use these datasets to train, validate and evaluate their systems in order to define the best models and the best hyperparameters for their algorithms [7]. Table 3 includes a comparison between many available DR datasets.

For more detailed information, Fig.7 illustrates the best performance of each diabetic retinopathy dataset. As shown in Fig.7, DIARETDB0 and APTOS have the best accuracy of all datasets.

Table 3. A comparison between many common diabetic retinopathy datasets.

| No. | Dataset | Description | Notes |
|---|---|---|---|
| **1.** | E-ophtha [47] | E-ophtha EX: 47 images with EX and 35 normal images | Binary classification (Existence of EX/MA or normal images) |
| | | E-ophtha MA: 48 images with MA and 233 normal images | |
| **2.** | DIARETDB1 [48] | 89 retina fundus images with 1500 × 1152 dimensions (84 DR images and 5 normal images) | Binary classification (DR or Not-DR (Normal)) |
| **3.** | Kaggle [49] | 88702 images with 5184*3456 dimensions. | Categorical classification (5 classes, including 4 stages of DR and one normal class) |
| **4.** | DRIVE [50] | 40 images of 565 × 584 dimension (7 DR cases and 37 normal cases) | Good for vessel segmentation<br>Not preferable for DR detection |
| **5.** | DDR [51] | 13673 images (757 DR cases) | Binary classification (DR or Not-DR (Normal)) |
| **6.** | DR2 [52] | 435 images of 857*569 dimensions | Referral grading |
| **7.** | Messidor [53] | 1200 images for DR stages | Categorical classification of DR stages |
| **8.** | Messidor-2 [54] | 1748 images for DR stages | Categorical classification of DR stages |
| **9.** | Indian Diabetic Retinopathy Image dataset (IDRiD) [15] | 516 fundus images | Categorical classification of DR stages |
| **10.** | ROC [55] | 100 images of 768*576 to 1389*1393 dimensions | Binary classification (MA or normal cases) |

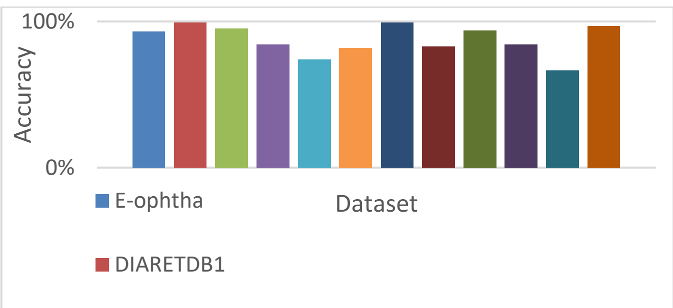


Fig.7. Best performance of diabetic retinopathy detection dataset

# 4. Conclusions

In this research, a statistical and analytical study of the recent methodologies in the field of diabetic retinopathy was presented. The study considered many principles in order to compare the previous studies. The applied machine learning and deep learning diabetic retinopathy methods were analyzed and compared. The comparison was made based on the applied approaches, the utilized datasets, the type of classification (binary or categorical) and the obtained results. The diabetic retinopathy open-source datasets were also listed and compared. The study compared all types of ML and DL, including SVM, LR, RF, DT, K-NN, Naïve Bayes, ensemble models, CNN, AlexNet, GoogleNet, ResNet, Inception, EffiecentNet, etc. The study took into account all possible evaluation metrics, including accuracy, precision, recall and F1-score. The study can be used as a guide for future studies in the field of diabetic retinopathy. However, the main conclusions can be summarized as follows:

1. Some studies used machine learning approaches, while others used deep learning methods.
2. Some studies considered the binary classification problem (DR or Not DR). In contrast, others considered the multi-class classification, using five cases (normal condition and four other stages of DR disease).
3. Some studies detected only one type of DR disease.
4. he most frequently used evaluation metric was accuracy. In some studies, there were other metrics like precision, recall, F1-score, and AUC.
5. While DIARETDB0 and APTOS have the best accuracy of all datasets, IDRiD has the lowest on

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