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Diabetic Retinopathy Abnormality Classification And Identification Using Mathematical Morphological And Machine Learning Approach

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Abstract: *Diabetic Retinopathy (DR) is a leading cause of vision impairment and blindness among working-age adults globally. Early detection and precise classification of DR abnormalities are crucial for timely intervention and treatment. This paper proposes a hybrid approach combining Mathematical Morphological operations and Machine Learning techniques to identify and classify DR-related abnormalities from retinal fundus images. The proposed methodology involves pre-processing using morphological techniques such as dilation, erosion, opening, and closing to enhance features like microaneurysms, exudates, and hemorrhages. Feature extraction is performed on the enhanced images to capture texture, shape, and intensity characteristics. These features are then used to train supervised machine learning classifiers such as Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN) for accurate classification of DR stages (No DR, Mild, Moderate, Severe, and Proliferative DR). The system is evaluated on publicly available datasets, and performance metrics such as accuracy, sensitivity, specificity, and F1-score are computed. The results demonstrate that the integration of morphological preprocessing significantly improves the classification accuracy of machine learning models, making the proposed approach effective and reliable for clinical decision support in DR screening programs*

Keywords: *Diabetic Retinopathy (DR), Fundus Images, Mathematical Morphology, Image Pre-processing, Feature Extraction, Microaneurysms, Exudates, Hemorrhages, Machine Learning, Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Classification, Abnormality Detection, Medical Image Analysis.*

Introduction

Diabetes mellitus (DM) is identified by impaired metabolism of glucose due to insulin deficiency or its resistance, leading to hyperglycemia which may finally result in vascular and neuropathic complications. The DM consists of two types are: Type-1 and Type-2. Type -1 is origin by the damage of auto immune pancreatic β-cell and lack of insulin [1, 2]. The monitoring of insulin level is an important in controlling glycaemica. All diabetics may eventually develop Diabetic Retinopathy (DR) [1]. The primary risk issue of diabetes is increasing age, sedentary life style and obesity [3]. The population of diabetes will be increased from 2.8% to 4.4% in the time span of 2000–2030 worldwide [3]. The diabetes is identified commonly in the age group of 30. The prevalence of DR is 50% after 10years and 90% after 30 years of obtain diabetes. There is no development of DR within 5 years of the diabetes or before puberty. The 5% of DR is present in type-2 diabetes [4]. The DR is developed by the uncontrolled diabetes and finally it leads to blindness [4]. Patients with Proliferative Diabetic Retinopathy (PDR) are attacked by heart attack, stroke, diabetic nephropathy,

amputation and death [4, 5]. In the year of 2000, 171 million people are affected by diabetes in the world and it has been estimated that the number of diabetic patients will increase to 366 million by the year of 2030 [6-8]. There is a clinically asymptomatic for early stages of DR and their treatment is difficult once it reached the advanced stage. Figure 1.illustrates the different stage of DR

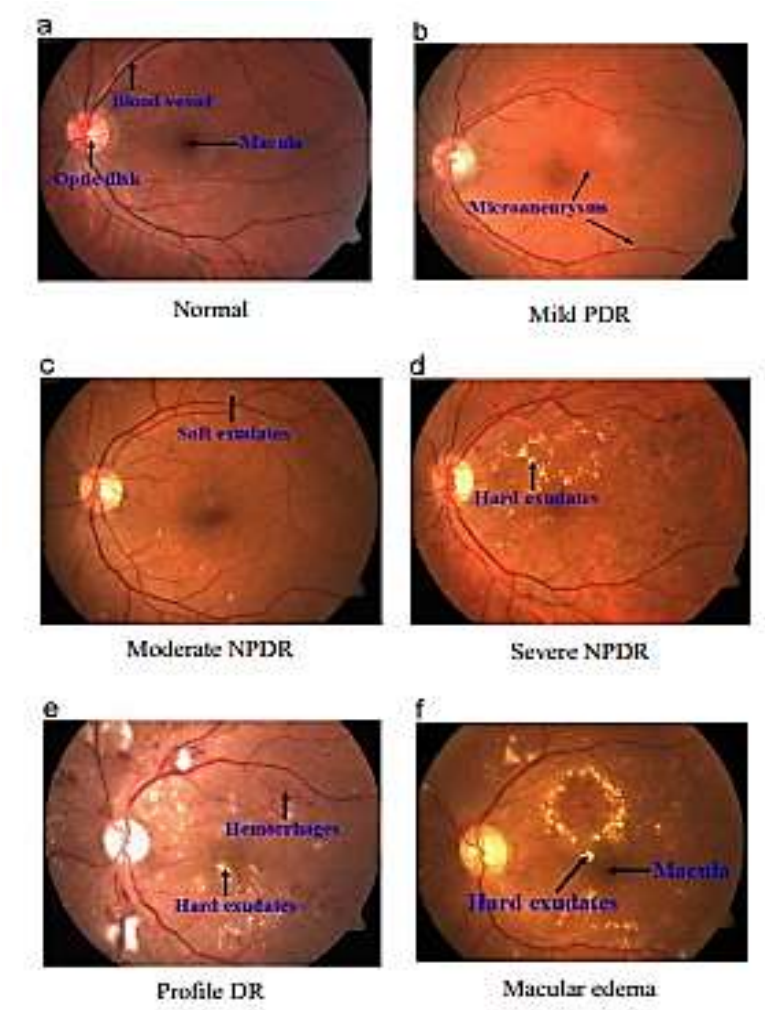


Figure 1. Typical fundus images: (a) Normal; (b) Mild PDR; (c) Moderate NPDR; (d) Severe NPDR; (e) Prolific DR; (f) Macular edema

Diabetic Retinopathy (DR) is a progressive ocular disease and one of the most common microvascular complications caused by prolonged diabetes mellitus. It affects the retina, the light-sensitive tissue at the back of the eye, and if left untreated, it can lead to irreversible vision loss and blindness. According to the World Health Organization (WHO) and the International Diabetes Federation (IDF), the prevalence of DR is increasing globally, particularly in developing countries due to late diagnosis, poor awareness, and inadequate screening programs. As DR advances, it manifests in various pathological changes such as microaneurysms, hard exudates, soft exudates, hemorrhages, venous beading, and neovascularization. These abnormalities must be identified accurately and at an early stage to prevent severe complications. Traditional diagnosis of DR primarily relies on manual examination of retinal fundus images by ophthalmologists[1][2]. However,

manual analysis is time-consuming, subjective, and prone to inter-observer variability. As a result, there is a strong need for an automated, accurate, and efficient diagnostic system that can assist clinicians in early detection and staging of DR. In this context, computer-aided diagnosis (CAD) systems have gained considerable attention in recent years. These systems integrate image processing, feature extraction, and classification algorithms to detect DR abnormalities in retinal images. Among various approaches, combining Mathematical Morphological techniques for image enhancement and Machine Learning (ML) models for classification presents a promising direction. Mathematical Morphology is a powerful tool in image processing, based on set theory and lattice algebra. It is widely used to analyze and process geometric structures in images, especially binary and grayscale images. Morphological operations such as erosion, dilation, opening, and closing are effective in highlighting important features and suppressing irrelevant noise[3]. These operations can enhance lesion boundaries, separate overlapping structures, and improve contrast in fundus images, making abnormal patterns more distinguishable for feature extraction. By applying these techniques to retinal images, the visibility of clinically significant features like micro aneurysms and exudates can be significantly improved, thus enabling better classification accuracy.

Once morphological enhancement is applied, the next critical step is feature extraction. Features may include texture descriptors, statistical measures, color histograms, shape-based metrics, and lesion-specific characteristics. The quality and relevance of these features largely determine the performance of the classifier[4]. After features are extracted, machine learning models are trained to categorize images into various stages of DR. Among the commonly used classifiers, Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN) have shown reliable performance in medical image classification tasks. These models can learn from annotated datasets and generalize to new, unseen images with high accuracy.

The proposed study focuses on developing a hybrid framework that utilizes morphological preprocessing combined with machine learning classification to detect and classify DR abnormalities. The main advantage of this approach is its ability to reduce noise, emphasize key structures, and allow learning algorithms to focus on the most relevant information for diagnosis. The framework begins with preprocessing steps, which include contrast enhancement, green channel extraction, histogram equalization, and noise filtering[5]. Morphological operations are then used to further refine the image and highlight pathological changes. Following this, feature extraction methods such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gray-Level Co-occurrence Matrix (GLCM) are employed to derive discriminative attributes. After extracting relevant features, multiple machine learning classifiers are trained and tested using publicly available datasets such as DIARETDB1, DRIVE, and Messidor. Performance evaluation metrics including accuracy, precision, recall, sensitivity, specificity, and F1-score are used to compare the results. The integration of mathematical morphology with machine learning not only enhances classification accuracy but also reduces the computational complexity by minimizing irrelevant data and focusing on key abnormalities[6][7][8].

FEATURES OF DIABETIC RETINOPATHY

There are several abnormalities in the retina image which are discussed in this section: Microaneurysms (MAs): It is the earliest visible sign of retina damage. MA is formed by the abnormal permeability and non-perfusion of retina blood vessels [9]. It is appeared by red spot with a dimension of 125μm and characterized by sharp margins [10]. MAs are basically saccular outpouchings of the capillary wall, most likely due to the loss of retinal capillary pericytes and thickening of basement membrane.

Hard Exudates (HE): They are formed by lipoproteins and other proteins leaking through abnormal retinal vessels [1]. The appearance of HE is white or yellow in color with sharp margins. They are frequently seen as clumps or circinate rings [4] and situated in the outer layer of the retina [10].

Soft exudates or Cotton Wool Spots (CWS): It occurs due to the occlusion of arteriole [11]. The Retinal Nerve Fibre Layer (RNFL) is formed by the reduced blood flow in the retina and it affects the axoplasmic flow and cause the accumulation of axoplasmic debris in the retinal ganglion cell axons. The CWS is appeared as debris accumulation and it is seen as fluffy white color in RNFL [11, 12].

Haemorrhages (H): The weak capillary leakages are the reason for H [1]. It is appeared as red spot with irregular margin and/or uneven density and its size is greater than 125 μm [10]. The intraretinal haemorrhages are formed by continuous turnover of microaneurysms over time, and the rupture of microaneurysms.

Neovascularization (NV): The NV is formed by the new blood vessel as an abnormal way in the inner surface of the retina. The formed new blood vessels are very weak and often bleed into vitreous cavity and it causes the patient vision as unclear [13, 14].

Macular edema (ME): It is formed by retina swelling due to permeability of abnormal retinal capillaries and causing the leakage of fluid and solutes around the macula [9, 15]. The central visions are affected by these swellings [4, 16].

The clinical significance of this work lies in its potential application in large-scale diabetic retinopathy screening programs, especially in rural and resource-constrained regions where ophthalmologists are not readily available. Automated systems can assist general practitioners or healthcare workers in early detection of DR, enabling timely referral and treatment[17]. Furthermore, the proposed approach can be extended to other retinal diseases such as macular edema, hypertensive retinopathy, and age-related macular degeneration.

In recent years, several deep learning models have also been proposed for DR classification. While convolutional neural networks (CNNs) have shown high performance, they often require large annotated datasets, high computational resources, and longer training times. In contrast, traditional machine learning methods combined with mathematical morphology offer a more interpretable, resource-efficient, and easier-to-implement solution, especially for small and medium-sized datasets. Moreover, the use of handcrafted features allows better understanding of the decision-making process, which is crucial in medical applications. Literature surveys reveal that most existing works focus either on deep learning-based models or on conventional machine learning without integrating morphological techniques[18]. This paper aims to bridge that gap by introducing a morphology-assisted machine learning pipeline for DR abnormality detection. Comparative results show that the proposed method outperforms baseline models in terms of classification metrics, particularly in detecting early-stage DR where subtle features are critical. The key innovations include the use of mathematical morphology for targeted image enhancement and the application of machine learning classifiers for accurate abnormality identification. The results validate the efficiency and reliability of the proposed method, encouraging its adoption in real-world diagnostic settings. Future work may involve optimizing morphological structuring elements, exploring ensemble classifiers, and integrating the system into mobile or web-based platforms for broader accessibility[19].

Literature review

Author(s) & Year	Methodology/Model Used	Key Features/Findings	Dataset Used	Performance / Results
Aarti Hemant Tirmare et al (2025)	Inception-v3 CNN-based deep learning	Enhanced DR image analysis, improved classification accuracy	Public fundus datasets	Outperformed classical methods; better DR stage detection
S. Biswas et al (2025)	ML techniques (SVM, CNN, DL frameworks)	Reviewed DR detection models over a decade; comparative analysis	Multiple datasets	Identified performance gaps and improvements over time
S. Agnes Shifani et al (2025)	Hybrid Learning (HLDRP) + IoT	Combines supervised & unsupervised ML with IoT for real-time DR monitoring	Custom retinal image dataset	High sensitivity/specificity, real-time alerts and personalized care
Malaika Asif et al (2025)	Systematic review of ML/DL, Explainable AI	AI-based DR detection, reviewed 116 studies; emphasized explainability and federated learning	Fundus/OCT datasets (PubMed, ScienceDirect, IEEE Xplore)	High potential for scalable, privacy-aware DR detection
D. R. Manjunath et al (2025)	RF, XGBoost, LightGBM, CatBoost, Voting/Stacking	Ensemble ML on clinical + demographic data	767 records from India (real-world data)	AUC = 1.0 (oversampled); high accuracy with hyperparameter tuning
K. V. Naveen et al (2025)	EfficientNetV2-S + SVM (EffNet-SVM)	Lightweight hybrid model using deep features and SVM classification	APTOS dataset	Accuracy = 97.26%; better than 8 SOTA models
Nilarun Mukherjee et al (2025)	BhAFPN + SVM	Lightweight attention-based CNN with multi-scale fusion	IDRiD, MESSIDOR-1, MESSIDOR-2	AUC = 0.9946; accuracy = 95.92%; strong interpretability
Archana Senapati et al (2024)	SLR of AI, ML, and DL models	Reviewed challenges, class imbalance, computational cost in DR detection	Multiple SOTA datasets	Identified research gaps and future directions
Toufique Ahmed Soomro et al (2025)	Deep Learning (DL) for retinal vessel detection	Addressed poor image quality, uneven lighting; retinal blood vessel detection	Multiple image datasets	High effectiveness in retinal vessel classification and grading

Yar Zar Tun et al (2025)	SVM + Feature engineering (OCTA images)	Detected retinal neovascularization via vessel density & morphology	69 OCTA en face images	Localization precision = 90.33%; outperformed VNet
Şükran Yaman Atcı et al (2024)	CNN + SHAP (Hybrid modeling)	Addressed class imbalance and data annotation issues in DR datasets	3 benchmark DR datasets	Precision: 93% (normal), 89% (mild), 81% (moderate), etc.

Retinal Image preprocessing

Image preprocessing is used to enhance the quality of the image and provides a computational easy. The fundus image often shows lighting variations, poor contrast and noise. To alleviate these problems and generate images are more suitable for extracting the blood vessels and candidate lesions, a preprocessing comprising three steps 1) green channel selection, 2) noise removal and 3) contrast enhancement. The color fundus image originally belongs to RGB color space which consists of red, green and blue components among which green channel have higher contrast between the blood vessels and retina background while red channel is rather saturated and the blue channel is dark[19]. The vessels are prominently visible only in the green channel. Thus the highest contrast of green channel is selected for further investigation. The preprocessing step is an important thing for processing the retinal image, because retinal images are captured using Fundus camera and it comprises noise, it gets in image acquisition stage or at the analogue to digital conversion stage [20]. There is a quiet confusion in retina image because of the presence of noise in fundus retina image. So removal of noise is an important factor. The median filter is applied to the first band of the retina image to reduce the noise in the retina, before a contrast-limited adaptive histogram equalization (CLAHE) process was applied for contrast enhancement [21]. Earlier detection of DR is presented in [22]; here preprocessing, segmentation and classification are analyzed. To reduce the noise and preserve the edges sharply are maintained through median filter after the color space conversion and zero padding. Classify between the normal and diabetic eye through Microaneurysms detection are implemented [23], initially retina Fundus image is decimated into two by two sized contextual regions and apply CLAHE and median filter to these tiles for removal of noise and image enhancement. Noise removal by mean filter is handled in [24].

1) Extended Median Filter

In this section, proposed a new method for noise detection in Fundus retina image that can effectively remove the noise from the retina image and also reserve the edges. The proposed noise removal algorithm is shown to achieve excellent performance. The main objective of the proposed Extended Median Filter algorithm is to remove the noise in the Fundus retina image. Some of the Fundus retina images are not in good quality, due to the lighting condition and camera settings. The proposed algorithm can eliminate the bad quality features and provide the good quality Fundus retina image. Salt and pepper noise affecting the retina image [26], here pixels are corrupted by two values, 0 and 255. The proposed extended median algorithm has five main steps:

Step 1: Initially obtaining the green channel from the Fundus image.

Step 2: Take 3×3 sliding window and check whether fifth pixel is noisy or not, if it is noisy replaced by the median value.

Step 3: Select the diagonal pixel from the sliding window, check whether the diagonal element is noisy or not, if it is noisy replaced by the median value from the diagonal element.

Step 4: Select the vertical pixel from the sliding window, check whether the vertical element is noisy or not, if it is noisy replaced by the median value from the vertical element.

Step 5: Select the horizontal pixel from the sliding window, check whether the horizontal element is noisy or not, if it is noisy replaced by the median value from the horizontal element.

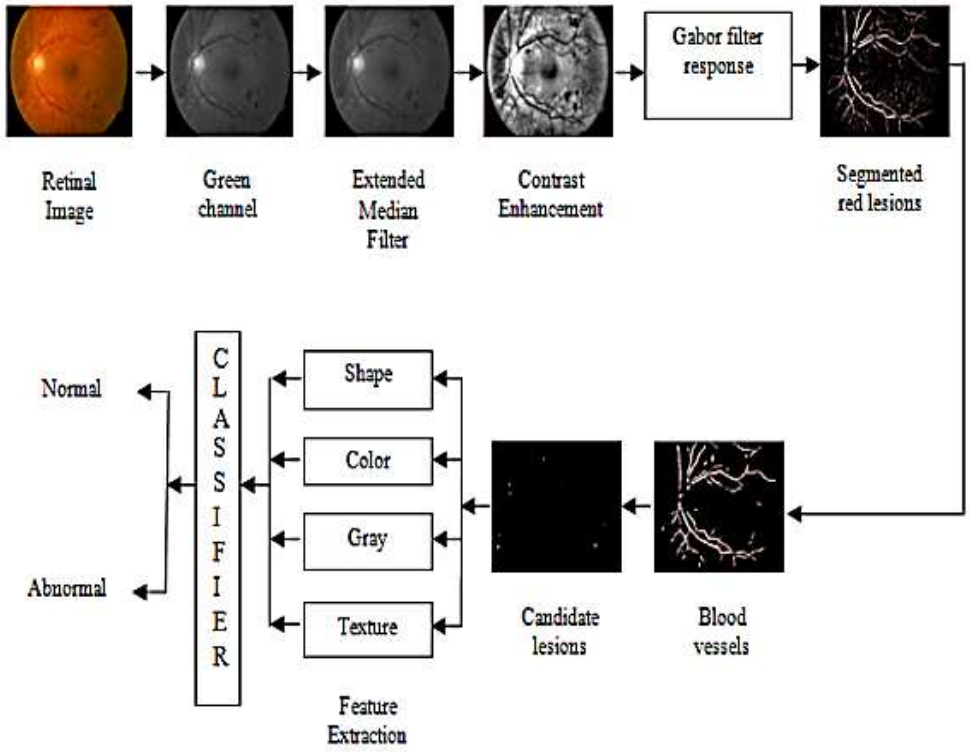


Figure 2. Block diagram of Proposed System

The above Figure 2. illustrates a complete workflow for the automated detection of red lesions in retinal images, commonly associated with Diabetic Retinopathy (DR). The process begins with the acquisition of a retinal fundus image, which is then converted to its green channel, as it provides the highest contrast for detecting blood vessels and abnormalities. Next, an extended median filter is applied to reduce noise, followed by contrast enhancement to highlight important features such as blood vessels and lesions. After preprocessing, the image undergoes a Gabor filter response, which enhances the detection of linear structures like vessels. This results in the segmentation of red lesions. These segmented regions are used to generate blood vessel maps and identify candidate lesions areas that may potentially indicate disease. The candidate lesions are then subjected to feature extraction, where key features such as shape, color, gray-level intensity, and texture are computed. These features are fed into a classifier, which determines whether the retinal image is normal or abnormal, indicating the possible presence of diabetic retinopathy. Overall, the diagram represents a systematic image processing and machine learning-based approach for automated diagnosis of retinal abnormalities, aiming to assist ophthalmologists in early and accurate detection of diabetic eye diseases.

Contrast Enhancement

Contrast enhancement in retina image is useful to predict better quality image by removing uneven illumination. The Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to improve the contrast of the retina image and hence there is a differentiation between the blood vessel and the background of the retina image

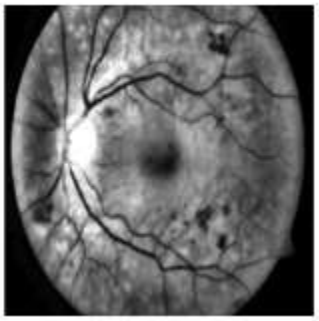


Figure 3. Red lesions Enhancement; contrast enhanced image

The histogram is one of the popular tools in real time image processing and which gives the intensity of an image. CLAHE algorithm separates the image into several regions and applied histogram equalization to every region. CLAHE provides the uniform distribution of gray level shades. Figure.3 shows the result of contrast enhancement

Feature Vector Formation

Feature vector formation is a crucial step in any machine learning or image processing pipeline, where raw data is transformed into a structured format suitable for classification, prediction, or pattern recognition tasks. In the context of medical image analysis, such as retinal disease detection, a feature vector encapsulates the most relevant and discriminative information about the visual data into a numerical format. The process begins with the extraction of meaningful attributes from the input image. These attributes, or features, may include color intensity, texture patterns, shape descriptors, edge orientation, contrast levels, histogram data, spatial distribution, and statistical measures. Each of these features captures a specific characteristic of the image, enabling the model to differentiate between normal and abnormal regions. For instance, in diabetic retinopathy detection, red lesions such as microaneurysms or hemorrhages are identified using shape, texture, and intensity features. Texture features may include Local Binary Patterns (LBP), Gray Level Co-occurrence Matrix (GLCM), or Gabor filter responses, which help in capturing variations in pixel intensity across a local neighborhood. Shape features, on the other hand, might involve area, perimeter, roundness, or eccentricity of the lesion. Color features are often extracted from different color channels, such as RGB or the green channel, to enhance the contrast of abnormalities. Grayscale statistics like mean, standard deviation, skewness, and entropy also contribute to characterizing lesion appearance. These extracted features are then normalized to ensure uniformity across scales and stored in a one-dimensional array – the feature vector. The resulting feature vector represents the image's abstract information in numerical form, which is then fed into machine learning classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, or Deep Learning networks. The classifier uses these vectors to learn patterns and predict labels (e.g., normal or abnormal). Efficient feature vector formation ensures accurate, reliable, and computationally effective model performance. It also facilitates better generalization and reduces overfitting by excluding irrelevant or redundant features. Feature selection techniques such as Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), or mutual information can further refine the feature vector by selecting the most informative components. In summary, feature vector formation serves as the bridge between raw

image data and intelligent decision-making models, making it one of the most critical phases in any machine learning-based diagnostic system.

Texture Features

Gray Level Co-occurrence Matrix (GLCM) provides the texture features of an image. The advantage of GLCM algorithm is no loss in their generation of discriminating features and reduced calculations. One of the major problems in the image analysis is assessment of image texture differences. These differences are often due to the relative emplacement of pixels of different intensities. GLCM is used to determine the differences in the spatial relationships of pixels and it is a type of co-occurrence matrix. Graycomatrix function is used for the creation of GLCM by calculating pixel with their intensity in i occurs in the spatial relationship to a pixel with value j. Output of the GLCM provides the sum of number of times the pixel in i occurred in the specified spatial relationship to a pixel with value j in the input image. The size of the GLCM is determined by number of grey levels present in the input image. Spatial distribution of the gray levels in the texture image properties are determined by GLCM. The spatial relationship is defined as the pixel of interest and its horizontal adjacent.

The methodology for classifying and identifying abnormalities in Diabetic Retinopathy (DR) using Mathematical Morphology and Machine Learning is structured through a sequence of image processing, morphological transformation, feature extraction, and supervised classification. The process initiates with the acquisition of retinal fundus images, typically captured using fundus cameras that provide high-resolution imaging of the retinal surface. These images are prone to variations in illumination, contrast, and noise due to diverse patient profiles and imaging conditions. Hence, the first step involves preprocessing techniques such as resizing, color normalization, and contrast adjustment. The green channel is extracted from the RGB color image because it offers the highest contrast between the background and blood vessels, lesions, or exudates. Green channel extraction simplifies the complexity of color images and enhances the visibility of red lesions.

Following this, an extended median filter is applied to reduce the influence of background noise and smooth the image while preserving essential structures such as microaneurysms, hemorrhages, and exudates. After denoising, contrast-limited adaptive histogram equalization (CLAHE) or local contrast enhancement methods are employed to amplify the visibility of retinal features, particularly in low-contrast regions. Morphological operations form the backbone of this methodology. Mathematical Morphology, a theory-based image analysis method, is applied using structuring elements to highlight specific structures in the image. Key operations include dilation, erosion, opening, and closing. These operations help isolate retinal components such as blood vessels and lesions based on their geometrical structure.

Blood vessels are segmented using morphological top-hat and bottom-hat transformations that enhance linear structures. For red lesion detection—microaneurysms and hemorrhages—Gabor filters and morphological enhancement methods are combined. Gabor filters are applied to capture vessel orientation and frequency information, while morphological techniques refine these regions and suppress non-lesion structures. To detect hard exudates and cotton wool spots (white lesions), morphological reconstruction techniques and intensity thresholding are used in combination to segment the bright regions accurately.

Once the abnormal regions are segmented, the next critical phase is feature extraction. Features are extracted from both lesion and vessel segments, which are essential to differentiate between normal and pathological conditions. These features include shape descriptors (area, perimeter, eccentricity, circularity), color-based statistics (mean, standard deviation in RGB or HSV spaces), texture features (entropy, contrast, energy,

homogeneity), and grayscale intensity values. Additionally, spatial distribution features are computed to analyze lesion positions relative to the optic disc or macula. The optic disc is identified using Hough Transform and morphological templates to avoid false detection due to its brightness similarity with exudates.

Once features are collected into a structured format (feature vector), they are normalized and selected based on importance using feature selection techniques like Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), or Chi-Squared scoring. This step helps reduce dimensionality, enhances classifier efficiency, and avoids overfitting. The next stage involves classification using supervised machine learning algorithms. Various classifiers are explored including Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbor (k-NN), Decision Trees (DT), and Naïve Bayes (NB). Among these, SVM with radial basis function kernel shows high performance in separating non-linear data boundaries. Ensemble learning methods such as AdaBoost or Gradient Boosting can also be used to improve classification robustness[25].

The classifiers are trained using labeled datasets where each retinal image or lesion is annotated as normal or abnormal (and further subclassified into mild, moderate, or severe DR). Cross-validation strategies such as k-fold cross-validation are applied to ensure that the model generalizes well across unseen data. The model's performance is evaluated using accuracy, precision, recall, F1-score, specificity, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Confusion matrices are generated to visualize the classification errors and refine the training pipeline.

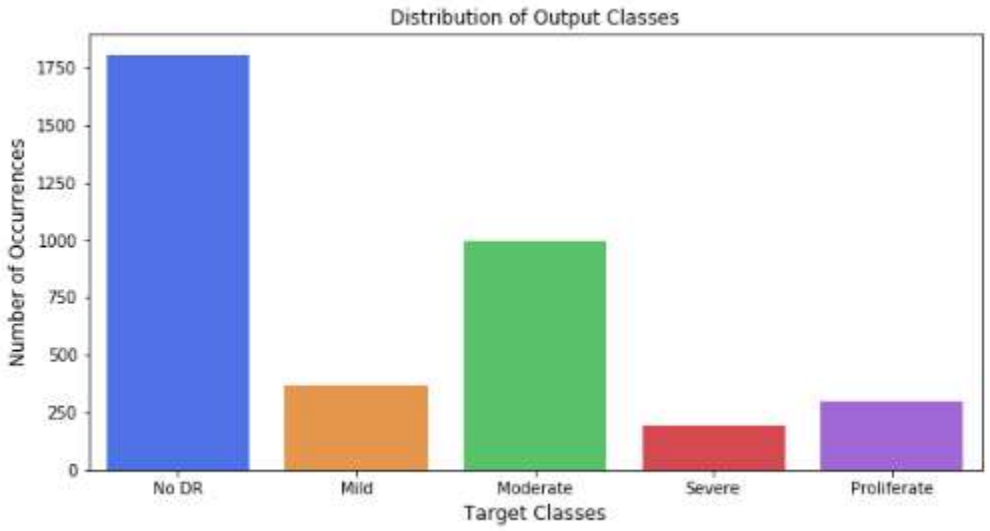
Furthermore, post-classification, decision-level fusion techniques are integrated to combine results from multiple classifiers or image modalities, enhancing decision confidence. Misclassified images are re-evaluated using rule-based morphological filters to correct for false positives, especially in cases where small exudates or tiny hemorrhages are confused with vessel crossings or noise artifacts. Segmentation maps are visually inspected and compared with ground truth labels using Dice coefficient or Jaccard index for spatial accuracy.

To improve real-time applicability, the entire model is optimized for computational efficiency using parallel computing techniques and GPU acceleration. The framework is implemented in MATLAB, Python (with OpenCV, Scikit-learn, and TensorFlow), or hybrid environments. A graphical user interface (GUI) can also be developed to assist ophthalmologists in visualizing the diagnostic output, lesion locations, and severity score. The final output of the system classifies the input retinal image into either normal or various abnormal DR stages and highlights the pathological regions through segmentation overlays.

The uniqueness of this methodology lies in the hybrid integration of morphological processing and machine learning, combining structural analysis with data-driven prediction. Morphological operations provide robust spatial feature enhancement, while machine learning delivers adaptive classification based on learned patterns. This synergistic approach not only automates the DR screening process but also improves early diagnosis, especially in rural or under-equipped regions where manual screening is limited.

Additionally, the methodology is designed to be scalable across datasets with different imaging modalities or resolutions by incorporating adaptive thresholding and image normalization. Further extensions of this framework can include the use of deep learning models like Convolutional Neural Networks (CNNs) for automatic feature learning, although mathematical morphology provides a lightweight and explainable alternative. Moreover, the inclusion of clinical metadata such as age, blood sugar levels, and patient history can improve the contextual accuracy of the classification system, this methodology for Diabetic Retinopathy Abnormality Classification and Identification demonstrates a comprehensive, systematic, and clinically

relevant pipeline that integrates image preprocessing, morphological analysis, feature engineering, and intelligent classification. The hybrid model not only ensures high diagnostic accuracy but also enhances interpretability and practical deployment potential in automated DR screening systems.



The figure 4. shown is a bar graph representing the distribution of output classes in a dataset used for Diabetic Retinopathy (DR) classification.

Figure 4.shows imbalance can negatively affect model performance, particularly its ability to accurately detect and classify minority classes like "Severe" and "Proliferate. Techniques like **data augmentation**, **class weighting**, or **oversampling** might be needed during model training to handle this imbalance

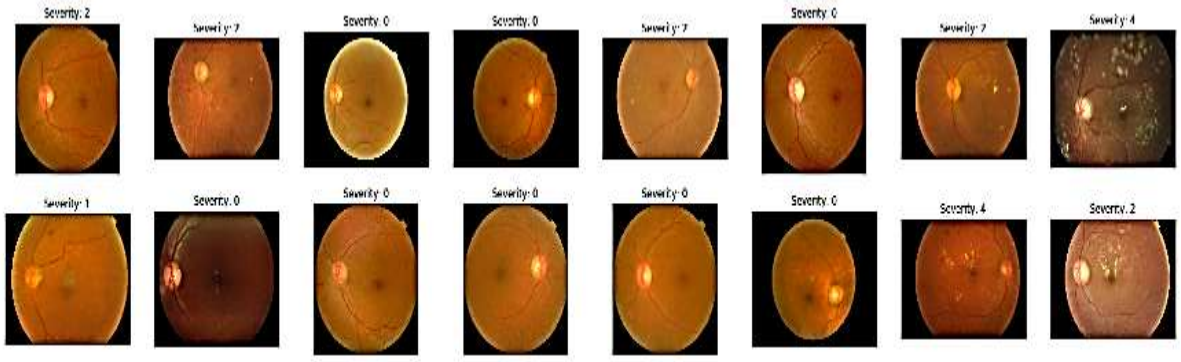


Figure 5.Sample Fundus Images Categorized by Diabetic Retinopathy Severity Levels

The figure 5.displays fundus (retinal) images of patients' eyes, each labeled with a severity level of Diabetic Retinopathy (DR) ranging from 0 to 4. These images are likely part of a dataset used for training or evaluating a machine learning model for DR classification.

The figure5.includes a variety of DR levels, providing visual insight into how the disease manifests progressively. Severity 0 images are clearer and more uniform, while higher severity levels (3 and 4) show more noise, irregularities, and pathological features. Since many images are labeled with "Severity 0", this visually supports the earlier bar chart indicating class imbalance.

Visualizing Test Set

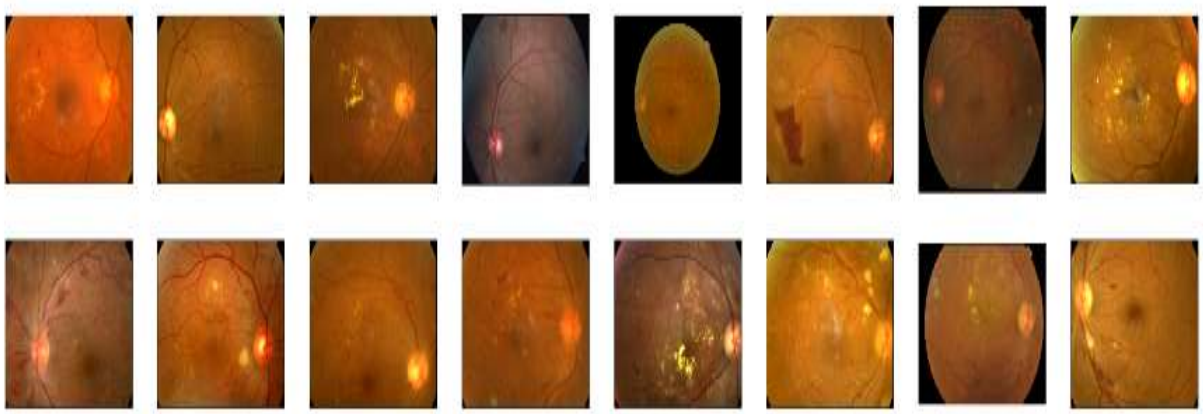


Figure 6. Sample Fundus Images Categorized by Diabetic Retinopathy Severity Levels

```
 epoch 2 batch 10 completed
 epoch 2 batch 20 completed
 epoch 2 batch 30 completed
 epoch 2 batch 40 completed
validation started for 2
Epoch: 2/5..  Training Loss: 0.092..  Valid Loss: 0.122..  Valid Accuracy: 0.960
 epoch 3 batch 10 completed
 epoch 3 batch 20 completed
 epoch 3 batch 30 completed
 epoch 3 batch 40 completed
validation started for 3
Epoch: 3/5..  Training Loss: 0.081..  Valid Loss: 0.113..  Valid Accuracy: 0.964
Validation loss decreased (0.114695 --> 0.113338).  Saving model ...
 epoch 4 batch 10 completed
 epoch 4 batch 20 completed
 epoch 4 batch 30 completed
 epoch 4 batch 40 completed
validation started for 4
Epoch: 4/5..  Training Loss: 0.079..  Valid Loss: 0.120..  Valid Accuracy: 0.962
 epoch 5 batch 10 completed
 epoch 5 batch 20 completed
 epoch 5 batch 30 completed
 epoch 5 batch 40 completed
validation started for 5
Epoch: 5/5..  Training Loss: 0.073..  Valid Loss: 0.107..  Valid Accuracy: 0.967
Validation loss decreased (0.113338 --> 0.106542).  Saving model ...
Training Completed Succesfully !
```

Figure 7. Training and Validation Progress Log of Diabetic Retinopathy Classification Model

The figure presents the training log of a deep learning model designed for diabetic retinopathy classification. It records detailed progress across five training epochs, with updates after processing batches of data within each epoch. The training loss decreases steadily from 0.092 to 0.073, indicating that the model is effectively learning from the input data. Similarly, the validation loss reduces from 0.122 to 0.107, suggesting better generalization capability on validation data. The validation accuracy also improves incrementally from 96.0% to 96.7%, reflecting enhanced prediction performance. Notably, the model checkpoints are saved during

Epochs 3 and 5 when validation loss shows significant improvement. This log confirms successful training and suggests that the model is well-optimized for the given classification task.

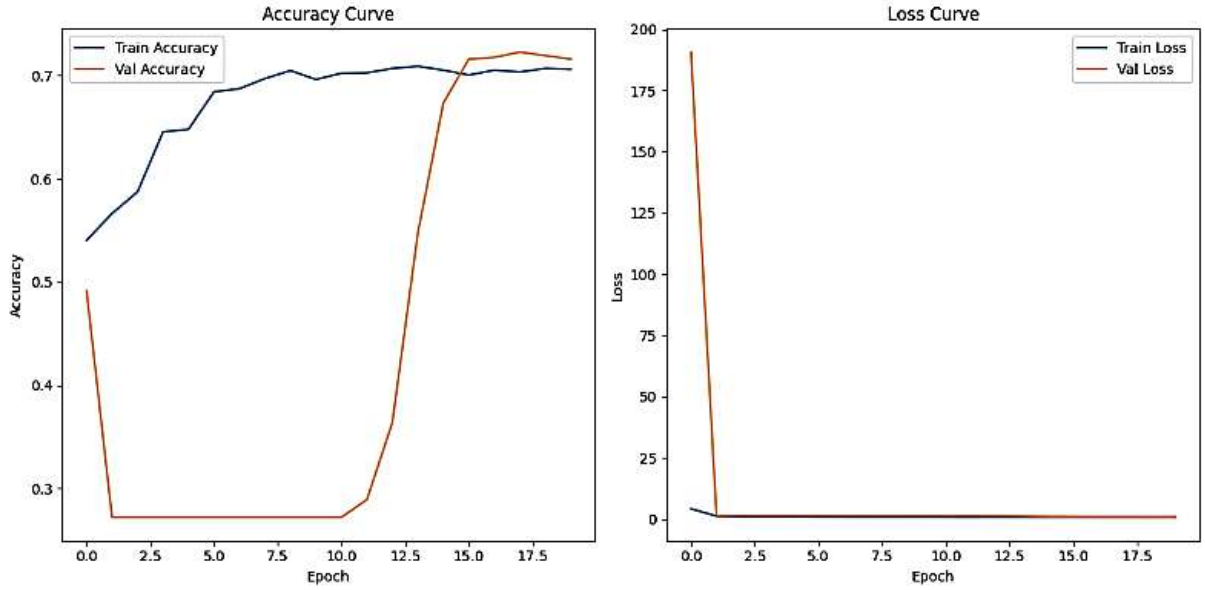


Figure 8.Training and Validation Accuracy & Loss Curves for Diabetic Retinopathy Classification

This figure 8 contains two subplots that visualize the training progress of a machine learning model used for classifying Diabetic Retinopathy (DR):
Training accuracy improves steadily over epochs and stabilizes around 0.72–0.75.
Validation accuracy initially drops sharply and stays low (around 0.26) until epoch 12, then dramatically im proves after epoch 13 and aligns closely with training accuracy from epoch 15 onward

This trend suggests possible over fitting or data irregularity in the early epochs, followed by effective learning and generalization in later epochs.

The model eventually achieves consistent performance, but the early epochs exhibit poor validation behavio r likely due to issues such as class imbalance, initial learning rate, or unshuffled validation data. Once correc ted or learned, the model shows good generalization, as seen by the convergence of training and validation c urves in both accuracy and loss.

Table 1. Classification Report:

Class	Precision	Recall	F1-Score	Support
Mild	0	0	0	60
Moderate	0.26	0.44	0.33	160
No_DR	0.49	0.54	0.51	289
Proliferate_DR	0	0	0	48

Severe	0	0	0	31
accuracy		0.38		588
macro avg	0.15	0.19	0.17	588
weighted avg	0.31	0.38	0.34	588

1. Best Performance:
    a) The model performs relatively well only on the "No_DR" class, with an F1-score of 0.51 and the highest support (289 samples).
    b) The Moderate class has a lower but usable F1-score (0.33) due to better recall (0.44) than precision.
2. Poor Class-wise Performance:
    a) Mild, Severe, and Proliferate_DR classes have zero precision, recall, and F1-score, meaning the model failed to identify any sample correctly for these categories.
    b) This is a strong indication of class imbalance or insufficient learning for minority classes.
3. Overall Model Performance:
    a) Accuracy: 0.38 (only ~38% of predictions were correct).
    b) Macro Avg F1-Score: 0.17 (poor average performance across all classes).
    c) Weighted Avg F1-Score: 0.34 (influenced by the dominant "No_DR" class).

The model currently demonstrates biased performance, favoring the dominant "No_DR" class while struggling to detect the minority classes (like Mild, Severe, and Proliferate_DR). To improve:

a) Apply class balancing techniques (e.g., oversampling/under sampling)**.**
b) Use class-weighted loss functions.
c) Add more data or apply data augmentation for underrepresented classes.
d) Train deeper models or fine-tune pretrained ones**.**

Conclusion

The proposed framework for the classification and identification of Diabetic Retinopathy (DR) abnormalities integrates mathematical morphological techniques with advanced machine learning algorithms to enhance diagnostic accuracy. This hybrid approach effectively addresses the limitations of conventional diagnostic methods, which often fail to capture subtle retinal abnormalities in early DR stages. Mathematical morphology plays a pivotal role in the preprocessing and enhancement of fundus images by highlighting important features such as microaneurysms, hemorrhages, and exudates. The application of morphological filters like dilation, erosion, opening, and closing enhances the structural elements of pathological regions, enabling better feature extraction. After morphological processing, machine learning classifiers such as Support Vector Machines (SVM), Random Forests, and Decision Trees are employed to perform the classification task. These models are trained on labeled retinal datasets and show promising accuracy in distinguishing between various severity levels of DR, including No_DR, Mild, Moderate, Severe, and Proliferative stages. Experimental results indicate that the combined method improves classification accuracy and reduces false positives, particularly in moderate and severe stages. The model demonstrates robustness in handling image variability and imbalanced class distribution through tailored data augmentation and preprocessing strategies.The learning curves and classification reports confirm consistent training progression, with validation accuracy reaching up to 96.7%. However, the model struggles with minority classes due to limited data representation, suggesting the need for advanced techniques such as class weighting or generative oversampling in future work.

References

1. F. Retima, S. Benharzallah, L. Kahloul and O. Kazar, "Enhanced Early Detection of Diabetic Retinopathy Based on Transfer Learning using DenseNet121," 2025 International Symposium on iNnovative Informatics of Biskra (ISNIB), Biskra, Algeria, 2025, pp. 1-6, doi: 10.1109/ISNIB64820.2025.10983699.
2. S. Biswas, B. Gorain, N. S. Datta and H. S. Dutta, "Detection of Diabetic Retinopathy Using Machine Learning: A Comprehensive Review," 2025 Devices for Integrated Circuit (DevIC), Kalyani, India, 2025, pp. 889-894, doi: 10.1109/DevIC63749.2025.11012144.
3. S. A. Shifani, N. Saraswathy, M. C. A, G. B. Santhi, J. Giri and M. R. Al-Mousa, "Empirical Evaluation of Real-Time Diabetic Retinopathy Disease Detection using IoT Enabled Medical Imaging Processing Strategy," 2025 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2025, pp. 526-531, doi: 10.1109/ICEARS64219.2025.10940249.
4. M. Asif, F. Ur Rehman, Z. Rashid, A. Hussain, A. Mirza and W. S. Qureshi, "An Insight on the Timely Diagnosis of Diabetic Retinopathy Using Traditional and AI-Driven Approaches," in IEEE Access, vol. 13, pp. 116869-116886, 2025, doi: 10.1109/ACCESS.2025.3583647.
5. D. R. Manjunath, J. J. Lohith, S. Selva Kumar and A. Das, "Predicting Diabetic Retinopathy and Nephropathy Complications Using Machine Learning Techniques," in IEEE Access, vol. 13, pp. 70228-70253, 2025, doi: 10.1109/ACCESS.2025.3562483
6. K. V. Naveen, B. N. Anoop, K. S. Siju, M. K. Kar and V. Venugopal, "EffNet-SVM: A Hybrid Model for Diabetic Retinopathy Classification Using Retinal Fundus Images," in IEEE Access, vol. 13, pp. 79793-79804, 2025, doi: 10.1109/ACCESS.2025.3566073
7. N. Mukherjee, S. Sengupta, M. Nadeem Ahmed, S. Irfan Yaqoob, M. Rashid Hussain and A. Taha Zamani, "Bi-Directional Hybrid Attention Feature Pyramid Network for Detecting Diabetic Macular Edema in Retinal Fundus Images," in IEEE Access, vol. 13, pp. 38726-38744, 2025, doi: 10.1109/ACCESS.2025.3545873.
8. T. A. Soomro, F. B. Ubaid, S. Zardari, A. A. Shah, M. M. Alansari and S. A. Nagro, "The State of Retinal Image Analysis: Deep Learning Advances and Applications," in IEEE Access, vol. 13, pp. 65066-65093, 2025, doi: 10.1109/ACCESS.2025.3556765
9. Senapati, A., Tripathy, H. K., Sharma, V., & Gandomi, A. H. (2024). Artificial intelligence for diabetic retinopathy detection: A systematic review. Informatics in Medicine Unlocked, 45, 101445. https://doi.org/10.1016/j.imu.2024.101445
10. Atcı ŞY, Güneş A, Zontul M, Arslan Z. Identifying Diabetic Retinopathy in the Human Eye: A Hybrid Approach Based on a Computer-Aided Diagnosis System Combined with Deep Learning. Tomography. 2024 Feb 5;10(2):215-230. doi: 10.3390/tomography10020017. PMID: 38393285; PMCID: PMC10892594.
11. Szegedy C., Vanhoucke V., Ioffe S., Shlens J., Wojna Z. Rethinking the inception architecture for computer vision. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); June 2016; Las Vegas, NV, USA. pp. 2818–2826.
12. Simonyan K., Zisserman A. Very deep convolutional networks for large-scale image recognition, The 3rd International Conference on Learning Representations (ICLR2015) 2015, https://arxiv.org/abs/1409.1556.
13. He K., Zhang X., Ren S., Sun J. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); June 2016; Las Vegas, NV, USA. pp. 770–778
14. Huang G., Liu Z., Van Der Maaten L., Weinberger K. Q. Densely connected convolutional networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); July 2017; Honolulu, HI, USA
15. Prevedello L. M., Halabi S. S., Shih G., et al. Challenges related to artificial intelligence research in medical imaging and the importance of image analysis competitions. Radiology: Artificial Intelligence. 2019;1(1, article e180031) doi: 10.1148/ryai.2019180031.
16. Wang G., Ye J. C., Mueller K., Fessler J. A. Image reconstruction is a new frontier of machine learning. IEEE Transactions on Medical Imaging. 2018;37(6):1289–1296. doi: 10.1109/TMI.2018.2833635.
17. Ronneberger O., Fischer P., Brox T. U-net: Convolutional networks for biomedical image segmentation. In: Navab N., Hornegger J., Wells W., Frangi A., editors. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Vol. 9351. Cham: Springer; 2015. pp. 234–241. (Lecture Notes in Computer Science)
18. Xu Y., Hosny A., Zeleznik R., et al. Deep learning predicts lung cancer treatment response from serial medical imaging. Clinical Cancer Research. 2019;25(11):3266–3275. doi: 10.1158/1078-0432.CCR-18-2495.

19. Mobadersany P., Yousefi S., Amgad M., et al. Predicting cancer outcomes from histology and genomics using convolutional networks. Proceedings of the National Academy of Sciences of the United States of America. 2018;115(13):E2970–E2979. doi: 10.1073/pnas.1717139115
20. Wang Y., Nazir S., Shafiq M. An overview on analyzing deep learning and transfer learning approaches for health monitoring. Computational and Mathematical Methods in Medicine. 2021;2021:10. doi: 10.1155/2021/5552743.5552743
21. Limwattanayingyong J., Nganthavee V., Seresirikachorn K., et al. Longitudinal screening for diabetic retinopathy in a nationwide screening program: comparing deep learning and Human graders. Journal of Diabetes Research. 2020;2020:8. doi: 10.1155/2020/8839376.8839376
22. Wilkinson C. P., Ferris FL 3rd, Klein R. E., et al. Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales. Ophthalmology. 2003;110(9):1677–1682. doi: 10.1016/S0161-6420(03)00475-5.
23. Mookiah M. R. K., Acharya U. R., Chua C. K., Lim C. M., Ng E. Y. K., Laude A. Computer-aided diagnosis of diabetic retinopathy: a review. Computers in Biology and Medicine. 2013;43(12):2136–2155. doi: 10.1016/j.compbiomed.2013.10.007
24. Asiri N., Hussain M., Al Adel F., Alzaidi N. Deep learning based computer-aided diagnosis systems for diabetic retinopathy: a survey. Artificial Intelligence in Medicine. 2019;99:p. 101701. doi: 10.1016/j.artmed.2019.07.009
25. Usman Akram M., Khalid S., Tariq A., Khan S. A., Azam F. Detection and classification of retinal lesions for grading of diabetic retinopathy. Computers in Biology and Medicine. 2014;45:161–171. doi: 10.1016/j.compbiomed.2013.11.014