ISRES Publishing

The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 2025

Volume 33, Pages 36-44

IConTech 2025: International Conference on Technology

Enhancing OCTA Image Classification Using Superpixel-Derived Geometric and Texture Features

Stefan Miron
University Dunarea de Jos of Galati

Mihaela Miron
University Dunarea de Jos of Galati

Simona Moldovanu
University Dunarea de Jos of Galati

Marian Barbu
University Dunarea de Jos of Galati

Abstract: Optical Coherence Tomography Angiography (OCTA) is an important imaging technique for diagnosing and monitoring retinal diseases. However, the accurate classification of OCTA images remains challenging due to the complexity of vascular structures and imaging variability. This study introduces a novel approach that enhances OCTA image classification for Diabetic Retinopathy (DR) and Myopia by leveraging superpixel-derived geometric and texture features (Mean Intensity, Area, Perimeter, Compactness, Eccentricity, Contrast and Entropy). The proposed method is evaluated using the FAZID dataset, which contains 304 Superficial Vascular Plexus (SVP) OCTA images classified into Diabetic (107), Myopic (109) and Normal (88) cases. Six machine learning models—Decision Tree, Random Forest, XGBoost, Extra Trees, LightGBM and CatBoost—were tested to assess classification performance. Experimental results indicate that boosting-based classifiers, such as XGBoost, LightGBM and CatBoost, achieved 100% classification performance in terms of accuracy, precision, recall, F1-score and MCC. Among bagging classifiers, Random Forest achieved 95.56% accuracy, 95.67% precision, 95.37% recall, 95.50% F1-score and 93.32% MCC, while Extra Trees obtained 95.84% accuracy, 96.08% precision, 95.58% recall, 95.77% F1-score and 93.76% MCC. Additionally, the Decision Tree classifier achieved 100% accuracy across all metrics. This study highlights the impact of superpixel-based feature representation combined with machine learning techniques, offering a robust solution for automated OCTA image analysis in ophthalmology.

Keywords: Machine learning, Superpixels, Optical coherence tomography angiography

Introduction

Diabetic Retinopathy (DR) and Myopia are two of the most prevalent ocular conditions affecting vision worldwide. DR is a microvascular complication of diabetes that damages the blood vessels in the retina and remains a leading cause of preventable blindness among working-age adults (Cheung et al., 2010; Gandhi et al., 2024). Myopia, on the other hand, is a common refractive error characterized by difficulty seeing distant objects clearly. Its prevalence has increased dramatically in recent decades, particularly in East and Southeast Asia, with global projections suggesting that nearly 50% of the world's population will be myopic by 2050 (Holden et al., 2016).

Optical Coherence Tomography Angiography is an advanced, non-invasive imaging technique in ophthalmology that combines the principles of low-coherence interferometry and motion contrast to produce high-resolution, depth-resolved maps of the retinal and choroidal vasculature (Spaide et al., 2018). This technology allows for detailed visualization of ocular blood flow without the need for dye injection, making it a valuable tool for early detection and monitoring of vascular-related eye diseases. These capabilities make OCTA particularly valuable for detecting and monitoring vascular abnormalities associated with conditions such as diabetic retinopathy, myopic maculopathy and age-related macular degeneration. As technology continues to advance, ongoing improvements in acquisition speed, image quality and the integration of artificial intelligence are set to further enhance the clinical utility and automation of OCTA.

Among the various biomarkers observable through OCTA, the Foveal Avascular Zone (FAZ) is important due to its sensitivity to microvascular changes in retinal disease. The FAZ is a capillary-free region at the center of the macula and its morphology, especially area, perimeter and circularity can reflect the severity of retinal ischemia. In patients with diabetic retinopathy, FAZ enlargement and irregularity have been strongly associated with capillary dropout and visual impairment (Verveka et al., 2015). Similarly, high myopia has been linked to FAZ alterations, often due to retinal thinning and chorioretinal atrophy, which can compromise macular perfusion. OCTA enables precise, layer-specific measurement of the FAZ in both the superficial and deep capillary plexuses, facilitating early diagnosis and longitudinal monitoring of these conditions.

Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL) algorithms, has demonstrated significant potential in enhancing OCTA image classification (Totolici et al., 2024; Wang et al., 2024). The integration of AI in OCTA classification has the potential to identify subtle patterns that may be overlooked by human observers. But despite these advancements, challenges remain. One major concern is the quality and variability of training datasets. OCTA images are sensitive to motion artifacts, segmentation errors and device-specific variations.

In this context, we proposed a ML–based approach for OCTA image classification of DR and Myopia. By fusing superpixel-derived geometric and texture features, we demonstrated that a classification accuracy of 100% can be achieved. The robustness of the proposed approach was validated through the evaluation of six ML algorithms on the FAZID dataset. The paper is organized as follows: The Introduction presents the research context and objectives. The Related Work section reviews relevant literature. The Materials and Methods section details the proposed ML-based framework, including preprocessing steps, the extraction of Superpixel-Derived Geometric and Texture Features and the six machine learning classifiers. The Results and Discussion section presents and analyzes the findings, followed by the Conclusion, which summarizes the key contributions of the study.

Related Work

Machine learning has seen increasing application in ophthalmology, particularly for the analysis of retinal images such as those obtained through OCTA, due to its ability to extract complex patterns and support diagnostic decision-making. Previous research has explored a variety of ML and DL techniques aimed to automate the detection and classification of retinal diseases such as DR, age-related macular degeneration (AMD) and Myopia (Erickson et al., 2017; Meiburger et al., 2021).

For example, Alam et al. (2020) applied transfer learning (TF) using a convolutional neural network (CNN) to classify OCTA images into three categories: healthy, no DR and non-proliferative DR (NPDR). The model achieved an overall accuracy of 87.27%, highlighting the effectiveness of DL, particularly when adapted through TF, in handling complex classification tasks despite limited medical imaging datasets.

Dhodapkar et al. (2022) developed DL-based models to assess the quality of OCTA images, reporting exceptional area under the curve (AUC) values of 0.99 for low-quality and 0.97 for high-quality images. These models significantly outperformed traditional signal strength metrics, demonstrating the potential of ML in improving OCTA image quality control.

Also, the extraction of specific features from OCTA images has proven especially valuable, offering quantitative insights into retinal microvascular health. In this direction, Gao et al. (2023) extracted fractal dimension (FD) and five texture features (contrast, correlation, entropy, energy and homogeneity) from the parafoveal region of OCTA images. Their study demonstrated that these quantitative markers can further facilitate the early detection of DR by capturing the complexity and heterogeneity of the retinal microvasculature.

In addition, Ebrahimi et al. (2023) explored layer fusion strategies in CNN-based classification of OCTA images into control, NoDR and NPDR groups. Among single-layer inputs, the superficial capillary plexus (SCP) produced the best performance, with an accuracy of 87.25%, sensitivity of 78.26% and specificity of 90.10%. However, the intermediate-fusion model achieved the highest overall performance of 92.65% accuracy, 87.01% sensitivity and 94.37% specificity.

Another study, Li et al. (2024) applied ML techniques to classify DR severity by combining clinical data with OCTA features. The study included data from 203 diabetic patients for model development and 169 patients for external validation. Among the models, the RF classifier using both OCTA and clinical data achieved the best performance, with area under the curve (AUC) values of 0.942 for DR, 0.932 for referable DR (RDR) and 0.901 for vision-threatening DR (VTDR) in the internal validation set. In the external validation cohort, the RF model obtained high performance with AUCs of 0.928 (DR), 0.914 (RDR) and 0.884 (VTDR). The most influential predictors included vessel density, retinal thickness, ganglion cell complex thickness as well as body mass index, waist-to-hip ratio and glucose-lowering treatments. These results demonstrates the potential of integrating OCTA features with clinical data for robust and accurate DR screening and staging.

More recently, Thrasher et al. (2025) investigated the use of active learning (AL) techniques to improve retinal disease classification from OCTA images, specifically addressing the limitations posed by insufficient labeled data. Their strategy involved selecting the most informative samples for training a DL model, resulting in more efficient learning and enhanced generalization. The AL approach significantly outperformed traditional methods such as random sampling and class rebalancing, achieving up to a 49% improvement in F1 score. This demonstrates the potential of AL to boost diagnostic accuracy while reducing annotation costs in ophthalmic AI applications.

Finally, Abini et al. (2025) introduced a novel deep learning approach for classifying DR using OCTA images. The model features a custom CNN architecture specifically optimized to capture fine-grained vascular features in OCTA scans, enhancing its ability to detect early microvascular abnormalities associated with DR. The proposed method achieved impressive results, with an accuracy of 97.3%, sensitivity of 96.5%, specificity of 98.1% and an AUC of 0.982, demonstrating both robustness and strong potential for clinical deployment.

These recent innovations, such as texture optimization, layer fusion, clinical feature integration and training efficiency strategies, demonstrate the transformative impact of ML and DL in enhancing the accuracy, performance and clinical relevance of OCTA-based retinal diagnostics.

Materials and Methods

This study is focused on a ML-based framework (Figure 1) for the classification of ischemic alterations such as DR and Myopia within FAZ, using features derived from OCTA images. This represents a pipeline for the classification of OCTA images into three diagnostic categories: Diabetic Retinopathy, Myopia and Normal. First, the OCTA images are loaded and preprocess by cropping and removing text artifacts which are not relevant and can reduce the model accuracy. Next, the Simple Linear Iterative Clustering (SLIC) superpixel segmentation is applied, followed by the extraction of a comprehensive set of superpixel-based features, including mean intensity, geometric descriptors (area, perimeter, compactness, eccentricity) and statistical texture metrics (contrast and entropy). These features quantitatively characterize the structure and complexity of the FAZ and surrounding vasculature. These are further used to evaluate six MLs: tree-based algorithms (Decision Tree - DT, Random Forest - RF and Extra Trees - ET) and gradient boosting methods (XGBoost, LightGBM and CatBoost). From all the evaluated classifiers, DT and gradient boosting algorithms (XGBoost, LightGBM and CatBoost) achieved perfect classification performance, demonstrating their effectiveness in differentiating between the studied pathologies. The proposed framework shows strong potential for the automated, non-invasive evaluation of retinal vascular health, supporting clinical decision-making in the diagnosis and monitoring of ischemic retinal diseases.

Dataset

In this study, we used the FAZID publicly available dataset (Agarwal et al., 2020). The dataset (Figure 2) contains high-resolution en face OCTA images focused on the superficial vascular plexus (SVP). It has 304 retinal scans, grouped into three clinical categories: 107 diabetic, 109 myopic and 88 normal eyes. Each image captures a 6 mm × 6 mm retinal region, standardized to 420 × 420 pixels. Each image is annotated with a disease label and includes a manually segmented FAZ region, serving as ground truth for morphological analysis. The annotations were performed by experienced clinicians following standardized protocols.

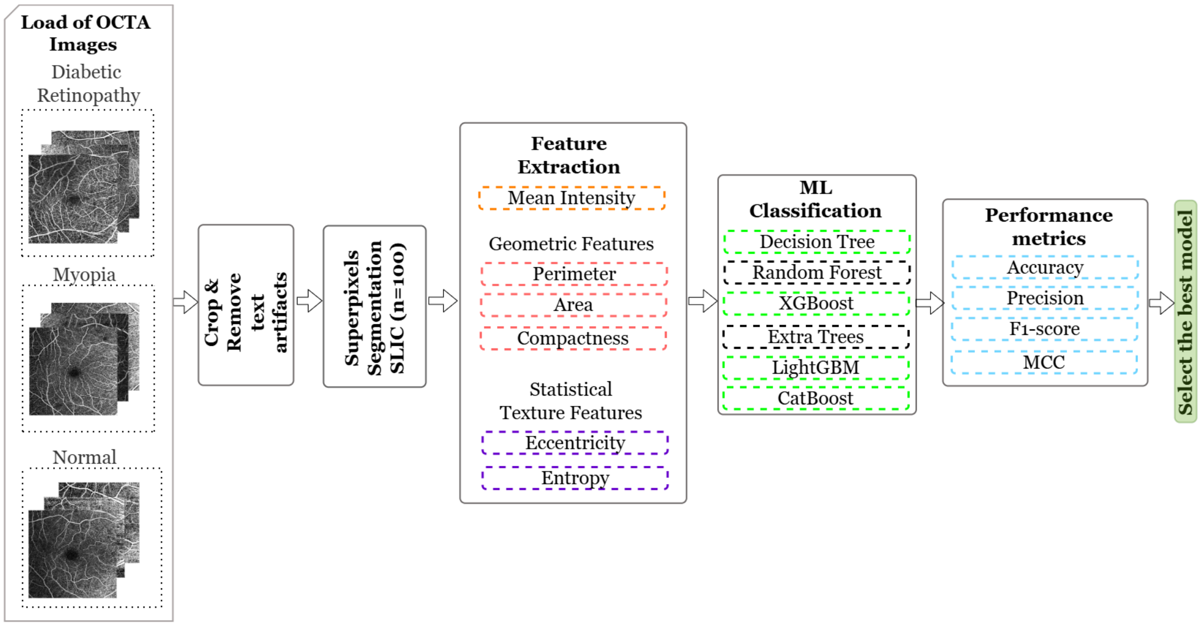

Figure 1. The ML-based framework for superpixel-derived geometric and texture features

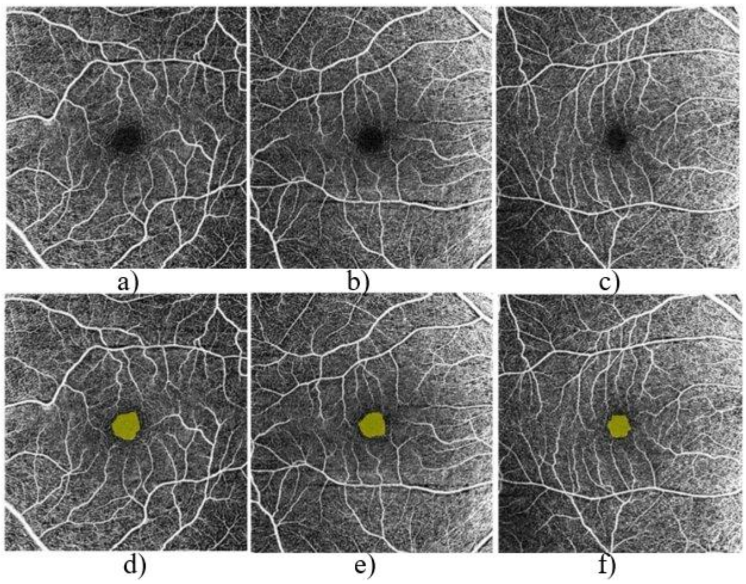

Figure 2. FAZ images: a) Non marked diabetic b) Non marked myopic c) Non marked normal d) Manually marked diabetic e) Manually marked myopic and f) Manually marked normal (Agarwal et al., 2020)

Superpixel-Derived Geometric and Texture Features

To extract regional geometric and texture descriptors from retinal images, superpixel segmentation was performed using the SLIC algorithm (Achanta et al., 2012). The input image was first converted to grayscale to facilitate intensity-based analysis. SLIC segmentation was applied with 100 target superpixels, a compactness value of 20 and a Gaussian smoothing parameter (σ) of 1, generating a spatially coherent and perceptually uniform superpixels.

In Figure 3 is an example of SLIC superpixel segmentation applied to an OCTA image. Red contours indicate the segmented superpixels, highlighting regions of interest (ROIs) used for geometric and texture feature extraction. For each segmented region, a binary mask was generated and analysed using the regionprops function from the Python scikit-image library. The Mean intensity (μ) and the following geometric features were extracted for each superpixel: Area (*A*), Perimeter (*P*), Compactness (*C*) and Eccentricity (*E*) (Gonzales et al., 2018). Also, texture features were quantified using the Gray-Level Co-occurrence Matrix (GLCM) (Haralick et al., 1973). For each superpixel, GLCM was computed at 1 pixel and angle of 0°, from which the following features were generated: Contrast (*c*) and Entropy (*e*). The extracted features were added to a new CSV format dataset.

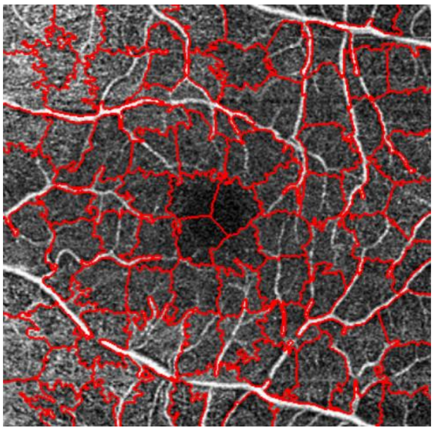

Figure 3. Example of SLIC superpixel segmentation applied to an OCTA image

The mathematical formulas of the features extracted are:

$$\mu = \frac{1}{|R|} \sum_{(x,y)\epsilon R} I(x,y) \tag{1}$$

where $I(x, y)$ is the grayscale intensity at pixel location (x, y) and $|R|$ is the number of pixels in region R.

$$A = |R| \tag{2}$$

where A is the total number of pixels within the superpixel region R.

$$C = \frac{P^2}{4\pi A} \tag{3}$$

where P is the perimeter and A is the area.

$$E = \sqrt{1 - (\frac{b}{a})^2} \tag{4}$$

where a is the length of the semi-major axis of the best-fitting ellipse to the region and b is the length of the semi-minor axis of the ellipse.

$$c = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 P(i,j) \tag{5}$$

where $P(i, j)$ is the probability of two neighboring pixels having gray levels i and j, based on the GLCM; N is the number of gray levels in the image and $(i-j)^2$ gives greater weight to larger intensity differences.

$$e = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j)\, log_2(P(i,j) + \delta) \tag{6}$$

where $P(i, j)$ is the normalized value of the GLCM at row i and column j, representing the probability of pixel intensity pair (i, j); N is the number of gray levels used in the GLCM and δ is a small constant added to avoid computing $log(0)$.

Machine Learning Models

Several ML have been used for classifying the Superpixel-Derived Geometric and Texture Features into Normal, Diabetic and Myopic. For this purpose, six classifiers were selected: Decision Tree, Random Forest, XGBoost, Extra Trees, LightGBM and CatBoost. These were applied because they are well-suited for handling structured data like superpixel-derived features from OCTA images. DT is easy to interpret; RF and ET improve stability and reduce overfitting through ensembling. XGBoost, LightGBM and CatBoost are advanced gradient boosting algorithms known for their high accuracy, speed and ability to capture complex patterns (Erickson et al., 2017).

The dataset of Superpixel-Derived Geometric and Texture Features was split into training and testing sets using an 80/20 stratified split to preserve class distribution. The ML were trained using default or common hyperparameters, such as 100 estimators for ensemble models and a fixed random seed (42) for reproducibility. XGBoost and CatBoost were configured with eval_metric='mlogloss' and iterations=100, respectively, while verbosity was suppressed for CatBoost. Model performance was evaluated using multiple metrics: accuracy, precision, recall, F1-score and MCC (Sokolova et al., 2009; Chicco et al., 2020). Additionally, confusion matrices were computed along with true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN), providing further insight into classification behavior.

The ML-based framework was implemented in Google Colab using the default runtime with Python 3.10.12, ensuring a consistent and reproducible environment. It used Pandas and NumPy for data handling, Matplotlib and Seaborn for visualization and Scikit-learn for the machine learning tasks. Gradient boosting was performed using XGBoost, LightGBM and CatBoost. For image segmentation and feature extraction, the framework applies OpenCV for image processing and skimage for advanced operations, including superpixel segmentation, region analysis, texture feature extraction and image reading.

Results and Discussion

In this section are presented the results obtained with the ML-based framework, which evaluated superpixel-derived geometric and texture features for classifying retinal OCTA images into three categories: Normal (class 0), Diabetic (class 1), and Myopic (class 2). In Tables 1 are presented the performance evaluation of the six MLs (Decision Tree, Random Forest, XGBoost, Extra Trees, LightGBM, and CatBoost) with the superpixel-derived texture and geometric features. The results indicate that XGBoost, LightGBM and CatBoost achieved perfect scores (100%) across all metrics, including accuracy, precision, recall, F1 score and MCC. These models also showed zero false positives (FP) and false negatives (FN). In contrast, Random Forest and Extra Trees models, while still performing well, obtained slightly lower metrics. RF achieved an accuracy of 95.56%, with a relatively higher number of FP (227) and FN (227), influencing its recall (95.37%) and MCC (93.32%). ET performed better than RF, with an accuracy of 95.84% and more balanced precision (96.08%), recall (95.58%), F1-score (95.77%), MCC (93.76%) and with FP and FN of 213.

Table 1. The performance evaluation of MLs on superpixel-derived texture and geometric features

MLs	Acc.	Precision	Recall	F1 score	MCC	TN	FP	FN	TP
Decision Tree	1.0000	1.0000	1.0000	1.0000	1.0000	10242	0	0	5121
Random Forest	0.9556	0.9567	0.9537	0.9550	0.9332	10015	227	227	4894
XGBoost	1.0000	1.0000	1.0000	1.0000	1.0000	10242	0	0	5121
Extra Trees	0.9584	0.9608	0.9558	0.9577	0.9376	10029	213	213	4908
LightGBM	1.0000	1.0000	1.0000	1.0000	1.0000	10242	0	0	5121
CatBoost	1.0000	1.0000	1.0000	1.0000	1.0000	10242	0	0	5121

Figure 4 shows the confusion matrices for the six ML. Each matrix visualizes the number of true versus predicted labels for each class, providing insight into each model's classification accuracy and misclassification patterns. In case of RF, are observed some misclassifications, particularly between class 0 (Normal) and class 1 (Diabetic), and between class 0 and class 2 (Myopic). While overall performance is high, this model occasionally confuses diabetic and myopic cases with normal ones. Also, ET model shows a noticeable number of misclassifications in all three classes. Most errors are in class 0 being confused with class 1 and class 2, and vice versa. These results align with the performance metrics (accuracy, F1-score, MCC), which confirm that boosting algorithms are highly effective for classifying ischemic changes in the FAZ using superpixel-derived texture and geometric features.

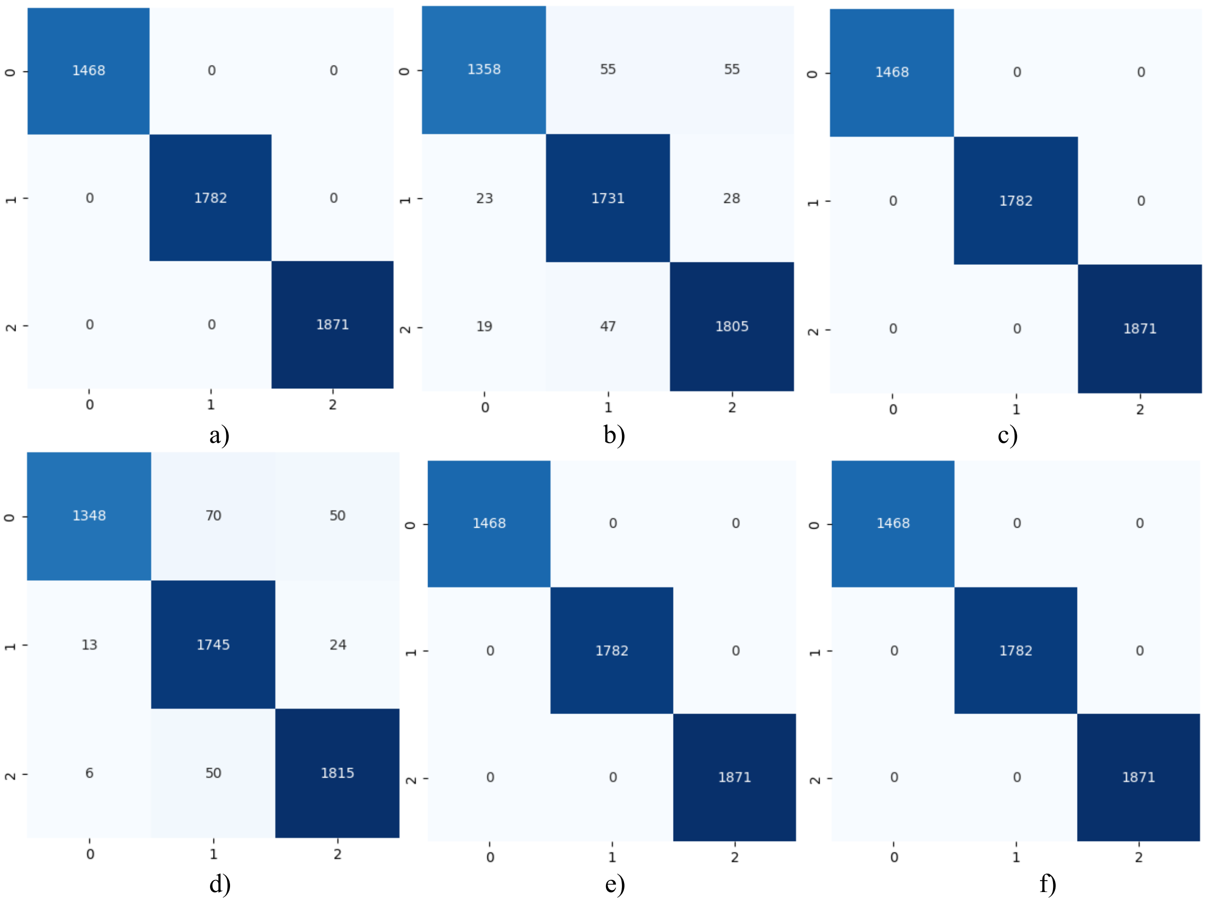

Figure 4. The confusion matrices for the six MLs: (a) DT; (b) RF; (c) XGBoost; (d) ET; (e) LightGBM; and (f) CatBoost.

Conclusion

This study demonstrated the effectiveness of machine learning models in classifying retinal conditions (Normal, Diabetic and Myopic) based on Superpixel-Derived Geometric and Texture Features extracted from OCTA images. A total of six ML classifiers, including DT, RF, ET, XGBoost, LightGBM and CatBoost, were evaluated using stratified training and testing splits. The models were assessed using the performance metrics such as accuracy, precision, recall, F1-score and MCC, providing a comprehensive evaluation of classification performance.

Among the evaluated models, DT, XGBoost, LightGBM and CatBoost achieved high accuracy (100%) and generalization, indicating their suitability for retinal image analysis. The integration of superpixel-based features with robust ML algorithms offers a promising approach for automated retinal disease screening and clinical decision support. Future work may include expanding the dataset, incorporating additional imaging features or biomarkers and exploring deep learning architectures to further enhance diagnostic accuracy and scalability.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

Funding

This study received no external funding.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Technology (www.icontechno.net) held in Trabzon/Türkiye on May 01-04, 2025.

References

Abini, A. M., & Priya, S. S. S. (2025). A novel deep learning approach for diabetic retinopathy classification using optical coherence tomography angiography. *Multimedia Tools and Applications,*1-39.

Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., & Süsstrunk, S. (2012). SLIC superpixels compared to state-of-the-art superpixel methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 34*(11), 2274–2282.

Agarwal, A., Balaji, J. J., Raman, R., & Lakshminarayanan, V. (2020). The foveal avascular zone ımage database (FAZID). *In Applications of Digital Image Processing XLIII* (Vol. 11510, p.1151027). SPIE.

Alam, M., Le, D., Son, T., Lim, J. I., & Yao, X. (2020). AV-Net: Deep learning for fully automated artery-vein classification in optical coherence tomography angiography. *Biomedical Optics Express, 11*(10), 5249–5257.

Cheung, N., Mitchell, P., & Wong, T. Y. (2010). Diabetic retinopathy. *The Lancet, 376*(9735), 124–136.

Chicco, D., & Jurman, G. (2020). The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC Genomics, 21*(1), 6.

Dhodapkar, R. M., Li, E., Nwanyanwu, K., Rezaei, K. A., & Gill, M. K. (2022). Deep learning for quality assessment of optical coherence tomography angiography images. *Scientific Reports, 12*, 13775.

Ebrahimi, B., Le, D., Abtahi, M., Dadzie, A. K., Lim, J. I., Chan, R. V. P., & Yao, X. (2023). Optimizing the OCTA layer fusion option for deep learning classification of diabetic retinopathy. *Biomedical Optics Express, 14*(9), 4713–4724.

Erickson, B. J., Korfiatis, P., Akkus, Z., & Kline, T. L. (2017). Machine learning for medical imaging. *Radiographics, 37*(2), 505–515.

Gandhi, S., Pattathil, N., & Choudhry, N. (2024). OCTA: Essential or gimmick? *Ophthalmology and Therapy, 13*, 2293–2302.

Gao, W., Lin, P., Li, B., Shi, Y., Chen, S., Ruan, Y., Zakharov, V. P., & Bratchenko, I. (2023). Quantitative assessment of textural features in the early detection of diabetic retinopathy with optical coherence tomography angiography. *Photodiagnosis and Photodynamic Therapy, 41*, 103214.

Gonzalez, R. C., & Woods, R. E. (2018). *Digital ımage processing* (4th ed.). Pearson.

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-3*(6), 610–621.

Holden, B. A., Fricke, T. R., Wilson, D. A., Jong, M., Naidoo, K. S., Sankaridurg, P., Wong, T. Y., Naduvilath, T. J., & Resnikoff, S. (2016). Global prevalence of myopia and high myopia and temporal trends from 2000 through 2050. *Ophthalmology, 123*(5), 1036–1042.

Li, X., Wen, X., Shang, X., Liu, J., Zhang, L., Cui, Y., Luo, X., Zhang, G., Xie, J., Huang, T., Chen, Z., Lyu, Z., Wu, X., Lan, Y., & Meng, Q. (2024). Identification of diabetic retinopathy classification using machine learning algorithms on clinical data and optical coherence tomography angiography. *Eye, 38*(14), 2813–2821.

Meiburger, K. M., Salvi, M., Rotunno, G., Drexler, W., & Liu, M. (2021). Automatic segmentation and classification methods using optical coherence tomography angiography (OCTA): A review and handbook. *Applied Sciences*, *11*(20), 9734.

Spaide, R. F., Fujimoto, J. G., Waheed, N. K., Sadda, S. R., & Staurenghi, G. (2018). Optical coherence tomography angiography. *Progress in Retinal and Eye Research, 64*, 1–55.

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information Processing & Management, 45*(4), 427–437.

Thrasher, J., Amireskandari, A., & Gyawali, P. (2025). Enhancing retinal disease classification from OCTA images via active learning techniques. In B. Bhattarai, A. R. Joshi, & R. Garnavi (Eds.), *Data engineering in medical imaging: DEMI 2024* (Lecture Notes in Computer Science, Vol. 15265). Springer.

Totolici, G., Miron, M., & Culea-Florescu, A.-L. (2024). Automatic segmentation and statistical analysis of the foveal avascular zone. *Technologies*, *12*(12), 235.

Veverka, K. K., AbouChehade, J. E., Iezzi, R., Jr., & Pulido, J. S. (2015). Noninvasive grading of radiation retinopathy: The use of optical coherence tomography angiography. *Retina, 35*(11), 2400–2410.

Wang, R. Y., Zhu, S. Y., Hu, X. Y., Sun, L., Zhang, S. C., & Yang, W. H. (2024). Artificial intelligence applications in ophthalmic optical coherence tomography: A 12-year bibliometric analysis. *International Journal of Ophthalmology, 17*(12), 2295–2307.

Author(s) Information

Stefan Miron
University Dunarea de Jos Galati, 47 Domneasca Street, 800008, Romania

Mihaela Miron
University Dunarea de Jos Galati, 47 Domneasca Street, 800008 , Romania
Contact e-mail: *mihaela.miron@ugal.ro*

Simona Moldovanu
University Dunarea de Jos Galati, 47 Domneasca Street, 800008, Romania

Marian Barbu
University Dunarea de Jos Galati, 47 Domneasca Street, 800008, Romania

To cite this article:

Miron, S., Miron, M., Moldovanu, S. & Barbu, M. (2025). Enhancing OCTA image classification using superpixel-derived geometric and texture features. *The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 33,* 36-44.