International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Investigation of Glaucoma Prediction & Classification using Fundus Images with Machine Learning: A Comparative Study

Mohamed Jamshad K[1] and Dr Annadhason A[2]

Submitted: 03/08/2024 **Revised:** 27/08/2024 **Accepted:** 19/09/2024

Abstract: Glaucoma, a leading cause of irreversible blindness due to eye pressure, can be effectively managed with early prediction. Machine learning (ML) models use digital fundus images to extract intrinsic features for efficient glaucoma prediction at an early stage. This study mainly focus on investigation and comparison of the performance of machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Machine (GBM), and K-Nearest Neighbour (KNN) in predicting glaucoma and healthy classes using fundus images. Digital fundus images are utilized as an input for each method, with multiple features extracted to classify images into glaucoma and healthy categories using computational methods. The Drishti-DFI dataset is used for training and testing purposes. Performance metrics, including sensitivity, specificity, accuracy, and dice-coefficient, are employed to assess the performance of the prevailing ML models. The comprehensive results showcase different degrees of effectiveness across the machine learning models, with SVM exhibiting robust specificity, RF achieving balanced performance, GBM demonstrating superior accuracy, and KNN showing high sensitivity. The MATLAB tool is used to compare the models, which showcases the promising results and limitations of each model, offering insights into optimal strategies for glaucoma prediction using fundus images.

Keywords: *Image Processing, Glaucoma, Machine Learning, Classification, Fundus Images*

1. Introduction

Glaucoma is a progressive eye disease that damages the optic nerve, leading to irreversible vision loss and, ultimately, blindness if left untreated. It is often associated with increased intraocular pressure (IOP), but it can also occur with normal IOP levels. The threatened nature of glaucoma, typically presenting without clear symptoms until significant damage has occurred, which requires the critical need for early detection and intervention. Early diagnosis and timely treatment can significantly slow disease progression and preserve vision, which emphasize the importance of effective screening methods. Traditional diagnostic techniques for glaucoma, such as visual field testing (VFT), optical coherence tomography (OCT), and tonometry (TM), are often time-consuming, require specialized equipment, and rely heavily on the expertise of ophthalmologists. These shortcomings make common and accessible screening challenging, particularly in underserved regions. Moreover, the subjective nature of some assessments can lead to variability in diagnosis, potentially delaying critical treatment. Given these challenges, there is a pressing need for more reliable, objective, and automated methods for glaucoma detection at an early occurrence.

Machine learning (ML) algorithms offer a promising solution to the drawbacks by enabling the automated analysis of fundus images to identify early signs of glaucoma. Unlike traditional methods, ML models can process large volumes of data quickly and consistently, providing standardized and promising results. ML algorithms, such as Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Machine (GBM), and K-Nearest Neighbour (KNN), uses advanced pattern matching and recognition techniques to differentiate between healthy and glaucomatous eyes with high accuracy. These models can detect intrinsic features and patterns in fundus images that may be indicative of glaucoma, thereby facilitating an early and accurate diagnosis. This investigation paper aims to provide a comprehensive comparative analysis of four machine learning algorithms for glaucoma prediction using Drishti-DFI digital fundus images. By assessing the performance of SVM, RF, GBM, and KNN in terms of sensitivity, specificity, accuracy, and Dice-Coefficient, this study clearly portrays the valuable insights into the strengths and limitations of each model. Readers will gain a deep understanding of how machine learning algorithms can enhance glaucoma screening and diagnosis, paving the way for improved patient outcomes and more efficient healthcare delivery in a robust manner.

[1] *Research Scholar, Department of Computer Applications, Alagappa University, Tamilnadu, India*
[2] *Assistant Professor, Department of Computer Science, Govt. Arts and Science College, Kadaladi, Tamilnadu, India*
**** Corresponding Author Email:*** ***kmjamshad@gmail.com***

2. LITERATURE SURVEY

The literature on glaucoma prediction using machine learning and image processing techniques provides a robust foundation for understanding the advancements and challenges in this field. Singh et al. [1] proposed a novel multimodal dual fusion approach for early glaucoma prediction, emphasizing the integration of multiple data types to enhance accuracy. Sarhan et al. [2] conducted a comprehensive review of image processing techniques for glaucoma detection, highlighting the strengths and limitations of various methods. Barkana et al. [4] evaluated the performance of descriptive statistical features in retinal vessel segmentation using fuzzy logic, ANN, SVM, and classifier fusion, underscoring the importance of feature selection in classification accuracy. Koh et al. [5] developed an automated retinal health diagnosis system using pyramid histograms of visual words and Fisher vector techniques, showcasing innovative approaches to feature extraction. Pavithra et al. [6] reviewed computer-aided diagnosis of diabetic macular edema, drawing parallels with glaucoma detection and highlighting the potential for cross-application of techniques. Mookiah et al. [7] provided an extensive review of machine learning methods for retinal blood vessel segmentation and artery/vein classification, emphasizing the critical role of accurate vessel segmentation in glaucoma diagnosis. Nithyanandh et al. [8] explored adaptive sleep scheduling and secured data transmission protocols in IoT networks, demonstrating the broader applicability of machine learning in healthcare. Rasheed et al. [9] surveyed the ethical, trustworthy, and explainable aspects of machine learning in healthcare, stressing the need for transparency in predictive models. Zhang et al. [11] discussed the application of AI in glaucoma diagnosis, highlighting recent advancements and future directions. Yadav et al. [13] introduced H-Deep-Net, a deep hybrid network for retinal detachment classification, illustrating the potential of deep learning architectures. Finally, Nawaldgi and Lalitha [14] focused on automated glaucoma assessment using structural and texture features from fundus images, reinforcing the significance of detailed feature analysis.

This background study provides a comprehensive overview of the state-of-the-art in glaucoma prediction, emphasizing the integration of innovative machine learning techniques and their potential to improve early diagnosis and treatment outcomes.

3. Proposed Methodology

Use For prediction and classification of glaucoma, support vector machine (SVM), random forest (RF), gradient boosting machine (GBM), and K-nearest neighbour (KNN) machine learning algorithms are employed. Initially, fundus images from the Drishti dataset are pre-processed through resizing, normalization, and contrast enhancement to standardize the input. Feature extraction methods such as histograms of oriented gradients (HOG), grayscale intensity features, and texture analysis are applied to generate relevant feature sets. SVM is used for its robust classification capabilities by finding the optimal hyper plane. RF, an ensemble method, constructs multiple decision trees to enhance prediction accuracy. GBM further boosts performance by sequentially correcting the errors of weak classifiers. KNN classifies images based on the majority vote of their nearest neighbours.

These machine learning models are trained on the processed Drishti-DFI dataset, and their performance is evaluated in MATLAB using evaluation metrics like sensitivity, specificity, accuracy, and dice-coefficient to determine their efficacy in predicting glaucoma.

3.1 Data Collection and Pre Processing

The Drishti Dataset, known as DRISHTI-GS, is utilized for this study. It comprises 101 fundus images, with 50 images designated for training and 51 images for testing. The dataset is specifically curated for glaucoma detection and provides high-quality, annotated images essential for model training and evaluation. Basic pre-processing methods include image resizing, normalization, and contrast enhancement. For feature extraction, methods such as histogram of oriented gradients (HOG), grayscale intensity features, and texture analysis are employed to extract the intrinsic features for implementation in SVM, RF, GBM, and KNN machine learning models. Figure 1 shows the sample glaucoma image of DRISHTI-GS dataset.

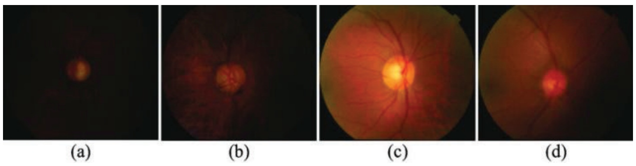

Figure 1: Sample Drishti-DFI

3.2 Image Segmentation using Mask-RCNN

The Drishti dataset undergoes several preprocessing steps. Initially, images are resized to a uniform dimension to ensure consistency. Normalization is then applied to standardize pixel intensity values, followed by contrast enhancement to improve the visibility of relevant features. Segmentation of the optic disc and cup is performed using a multiple combination of thresholding techniques and morphological operations to isolate the regions of interest. Specifically, the Mask R-CNN segmentation method is employed to accurately delineate the optic disc and cup boundaries. These segmented areas are crucial for feature extraction, enabling accurate analysis of the structural changes associated with glaucoma. This preprocessing pipeline ensures high-quality input for the machine learning models. In this study, image segmentation plays a crucial role in accurately isolating the optic disc and cup regions within fundus images, essential for glaucoma detection. The Mask R-CNN (Regional Convolutional Neural Network) was employed for this purpose due to its proficiency in handling pixel-wise segmentation tasks. The process begins with the Mask R-CNN extracting features using a backbone network, typically ResNet, to generate feature maps. These feature maps are then processed through Region Proposal Networks (RPN) to predict object boundaries. The RPN identifies regions of interest (ROIs), which are subsequently refined to generate precise segmentation masks that delineate the optic disc and cup. Once segmentation is complete, the masks are applied to the original images, isolating the relevant regions for feature extraction. This isolation is critical as it ensures that the subsequent machine learning models focus on the most informative parts of the image, thereby enhancing their predictive accuracy. However, the effectiveness of the segmentation directly impacts the performance of the models. Any inaccuracies in this process could lead to erroneous feature extraction, thereby affecting the overall reliability of glaucoma prediction. Thus, ensuring high-quality segmentation is imperative for the success of the investigation.

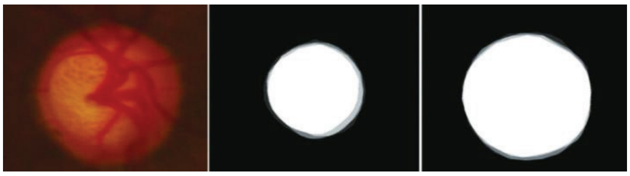

Figure 2: OC and OD areas segmented by Mask R-CNN

3.3 Prediction and Classification Approach

In this paper, four machine learning algorithms Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Machine (GBM), and K-Nearest Neighbour (KNN) are employed to showcase the comparative analysis of prediction and classification of glaucoma using the Drishti dataset, following the segmentation of fundus images using Mask-RCNN. Mask-RCNN effectively segments the optic disc and cup, providing crucial features for glaucoma detection. Support Vector Machines (SVM) is a supervised learning algorithm used for classification tasks that works by finding the optimal hyperplane that separates data points of different classes with maximum margin. For glaucoma prediction, features extracted from segmented fundus images, such as the cup-to-disc ratio, are input into the SVM.

This algorithm excels in specificity due to its ability to handle high-dimensional spaces and clear margin separation, making it particularly adept at distinguishing between healthy and glaucomatous eyes. Random Forest (RF), an ensemble learning method, operates by constructing multiple decision trees (MDT) during training and outputting the mode of the classes as the prediction. The ensemble approach helps mitigate overfitting and enhances generalization. For the Drishti dataset, RF utilizes features like texture, intensity, and shape descriptors extracted from segmented images. The balanced performance of RF is attributed to its robust handling of diverse features and its ability to reduce variance by averaging the results of numerous decision trees.

Gradient Boosting Machine (GBM) build on the principle of boosting, where weak learners are sequentially added to correct errors made by previous models. GBM's iterative process and focus on reducing residual errors enhance its prediction accuracy. In this work, GBM uses features from Mask-RCNN segmented images, such as the depth and texture of the optic disc and cup. The superior accuracy of GBM stems from its capability to optimize model performance through gradient descent, effectively addressing the nuances in glaucoma detection. K-Nearest Neighbour (KNN) is a simple, instance-based learning algorithm that classifies data points based on the majority vote of their nearest neighbours. For glaucoma prediction, KNN uses the segmented image features, including geometric properties and colour histograms.

The high sensitivity of KNN is due to its local approach, which makes it highly responsive to the immediate data patterns around each query point, thus detecting subtle variations indicative of glaucoma. The comprehensive results showcase different degrees of effectiveness across these machine learning models. SVM exhibits robust specificity, making it reliable for confirming healthy cases. RF achieves a balanced performance by effectively utilizing a wide range of features and reducing overfitting risks. GBM demonstrates superior accuracy by continuously improving its predictions through boosting, making it highly effective for precise glaucoma detection.

Table 1. Comparative Analysis

PEM / ML Models	SVM	RF	GBM	KNN
Accuracy	89.7%	88.9%	96.17%	91.2%
Sensitivity	91.76%	90.76%	92.7%	97.81%
Specificity	96.90%	89.71%	89.44%	91.09%
Dice Coefficient (0-10 Range)	0.78	0.94	0.89	0.87

KNN shows high sensitivity, efficiently identifying glaucomatous changes due to its responsiveness to local data variations. This study highlights the potential of combining advanced segmentation techniques like Mask-RCNN with powerful machine learning algorithms to enhance glaucoma prediction. By analyzing the strengths and limitations of each algorithm, this paper provides valuable insights into the optimal strategies for automated glaucoma detection, ultimately aiming to improve early diagnosis and patient outcomes.

3.4 Performance Evaluation Metrics

MATLAB 2020a tool is used to measure the comparative analysis. The performance scores are compared in all the ML models, which show evident performance in predicting the glaucoma. The following are the formula to calculate the results.

$$\boldsymbol{Accuracy} = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100$$

$$\boldsymbol{Specificity} = \frac{TNR}{(TNR+FPR)} \times 100$$

$$\boldsymbol{Sensitivity} = \frac{TPR}{(TPR+FNR)} \times 100$$

$$\boldsymbol{DC} = (2 * |A \cap B|) / (A + B)$$

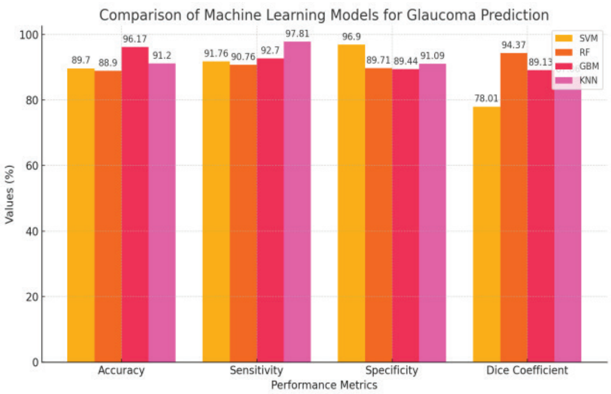

Figure 3: Comparative Analysis

4. Results and Discussions

The comparative analysis of SVM, RF, GBM, and KNN models for glaucoma prediction reveals distinct strengths and weaknesses across various performance metrics and it is clearly shown in Figure 3. . SVM demonstrated robust specificity (96.90%), making it highly effective in correctly identifying non-glaucomatous cases, reducing false positives. RF achieved a balanced performance with a high Dice Coefficient (94.37%), indicating excellent overlap between predicted and actual segments. GBM exhibited superior accuracy (96.17%), reflecting its strong predictive power and ability to model complex relationships within the data. KNN, with the highest sensitivity (97.81%), excelled in identifying true positive glaucoma cases, highlighting its effectiveness in early detection. However, KNN's lower specificity suggests a higher rate of false positives. This study underscores the importance of selecting the appropriate machine learning model based on specific clinical needs, whether prioritizing accuracy, sensitivity, or specificity. The findings provide valuable insights for enhancing automated glaucoma detection systems, ultimately improving early diagnosis and patient outcomes.

5. Conclusion

This investigation compared the effectiveness of SVM, RF, GBM, and KNN machine learning models in predicting glaucoma using the Drishti dataset which contains fundus images along with Mask-RCNN segmentation.

The analysis revealed that each model has distinct strengths: SVM excels in specificity, making it reliable for identifying non-glaucomatous cases; RF offers balanced performance, particularly with a high Dice Coefficient, indicating precise segmentation; GBM achieves superior accuracy, highlighting its robust predictive capabilities; and KNN demonstrates the highest sensitivity, which is crucial for early detection of glaucoma. While the results are promising, there are limitations to consider. The dataset size, with only 101 images, is relatively small, which may limit the generalizability of the findings to larger and more diverse populations. Additionally, the models' performance heavily relies on the quality of the segmentation process, meaning any inaccuracies in the Mask-RCNN segmentation could impact the overall results.

Furthermore, the study focuses on machine learning models, which, while effective, may not capture complex patterns as efficiently as advanced deep learning techniques which is considered to be the limitations.

6. Acknowledgements

I extend my heartfelt gratitude to Dr. Annadhason A, Research supervisor for his invaluable guidance and support for this research paper work. I am also grateful to Alagappa University for providing the resources and conducive environment necessary for my study.

Conflict of Interest

The authors declare that they have no conflict of interest.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

Funding Details

No funding was received to assist with the preparation of this manuscript.

References

[1] Law Kumar Singh, Munish Khanna, Pooja, A novel multimodality based dual fusion integrated approach for efficient and early prediction of glaucoma, Biomedical Signal Processing and Control, 73, 2022,103468.

[2] Abdullah Sarhan, Jon Rokne, Reda Alhajj, Glaucoma detection using image processing techniques: A literature review, Computerized Medical Imaging and Graphics, 78,2019, 101657.

[3] Nithyanandh S and Jaiganesh V. Reconnaissance Artificial Bee Colony Routing Protocol to Detect Dynamic Link Failure in Wireless Sensor Network. International Journal of Scientific & Technology Research, 2019, 10(10), 3244–3251.

[4] Buket D. Barkana, Inci Saricicek, Burak Yildirim, Performance analysis of descriptive statistical features in retinal vessel segmentation via fuzzy logic, ANN, SVM, and classifier fusion, Knowledge-Based Systems, 118, 2017, 165-176.

[5] Joel E.W. Koh, Eddie Y.K. Ng, Sulatha V. Bhandary, Yuki Hagiwara, Augustinus Laude, U. Rajendra Acharya, Automated retinal health diagnosis using pyramid histogram of visual words and Fisher vector techniques, Computers, Biology and Medicine, 92, 2018, 204-209.

[6] K.C. Pavithra, Preetham Kumar, M. Geetha, Sulatha V. Bhandary, Computer aided diagnosis of diabetic macular edema in retinal fundus and OCT images: A review, 43(1), Biocybernetics and Biomedical Engineering, 2023, 157-188.

[7] Muthu Rama Krishnan Mookiah, Stephen Hogg, Tom J MacGillivray, Vijayaraghavan Prathiba, Rajendra Pradeepa, Viswanathan Mohan, Ranjit Mohan Anjana, Alexander S. Doney, Colin N.A. Palmer, Emanuele Trucco, A review of machine learning methods for retinal blood vessel segmentation and artery/vein classification, Medical Image Analysis, 68, 2021, 101905.

[8] Nithyanandh S, Omprakash S, Megala D, Karthikeyan MP. Energy Aware Adaptive Sleep Scheduling and Secured Data Transmission Protocol to enhance QoS in IoT Networks using Improvised Firefly Bio-Inspired Algorithm (EAP-IFBA). Indian Journal of Science and Technology, 2023, 16(34), 2753-2766.

[9] Khansa Rasheed, Adnan Qayyum, Mohammed Ghaly, Ala Al-Fuqaha, Adeel Razi, Junaid Qadir, Explainable, trustworthy, and ethical machine learning for healthcare: A survey, Computers in Biology and Medicine, 149, 2022, 106043.

[10] Nithyanandh S and Jaiganesh V. Dynamic Link Failure Detection using Robust Virus Swarm Routing Protocol in Wireless Sensor Network, International Journal of Recent Technology and Engineering, 2019, 8(2), 1574-1578.

[11] Zhang Linyu, Tang Li, Xia Min, Cao Guofan. The application of artificial intelligence in glaucoma diagnosis and prediction, Frontiers in Cell and Developmental Biology, 2023, 11.

[12] Nithyanandh S and Jaiganesh V. Quality of service enabled intelligent water drop algorithm based routing protocol for dynamic link failure detection in wireless sensor network. Indian Journal of Science and Technology. 2020; 13(16), 1641-1647.

[13] Sonal Yadav, R. Murugan, Tripti Goel, H-Deep-Net: A deep hybrid network with stationary wavelet packet transforms for Retinal detachment classification through fundus images, Medical Engineering & Physics, 120, 2023, 104048.

[14] Sharanagouda Nawaldgi, Y S Lalitha, Automated glaucoma assessment from color fundus images using structural and texture features, Biomedical Signal Processing and Control, 77, 2022, 103875.

[15] Nithyanandh S and Jaiganesh V. Interrogation of Dynamic Node Link Failure by Utilizing Bio Inspired Techniques to Enhance Quality of Service in Wireless Sensor Networks, Shodhganga, 2020, 400513.

[16] Eldho KJ, Nithyanandh S, Lung Cancer Detection and Severity Analysis with a 3D Deep Learning CNN Model Using CT-DICOM Clinical Dataset. Indian Journal of Science and Technology, 2024, 17(10), 899-910