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ANALYSIS OF OPHTHALMIC FEATURES FOR GLAUCOMA DETECTION

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ABSTRACT

The selection of appropriate ophthalmic feature's extraction technique is a crucial pre-requisite for glaucoma detection. There are many features that can be extracted from an image which has been a long-standing problem. This step is essential during the classification process to isolate relevant information from the image. There are various feature extraction techniques to extract the features and feature selection techniques to select best features among them on the basis of the disease type. This paper proposes the best possible subset of various features that are required to be extracted for glaucoma diagnosis using DRISTHI-GS dataset. In the first step, various features like structural features such as cup-to-disc ratio (CDR) and disc damage likelihood scale (DDLS), textural features such as grey level co-occurrence matrix (GLCM) and Grey level run length matrix (GLRM), statistical features such as mean, variance and skewness, wavelet-based features were extracted from retinal images and in the second step RFE method used for the feature selection. Total sixteen features are extracted from the first step and nine features are selected from the Recursive Feature Elimination (RFE) method. Selected nine features are applied on the different classifiers. Performance of the proposed model tested on K-nearest neighbors (KNN), Random Forest (RF), Naïve Bayes (NB) and Support Vector Machine (SVM) classifiers, which provides 98.6% accuracy on RF, 98% accuracy on SVM, 91 % accuracy on KNN and 96% accuracy on NB.

Keywords: Glaucoma, Non-Structural Features, Structural Features, Texture Features, Wavelet Features

1. INTRODUCTION

The optic nerve plays a crucial role in transmitting signals from the eye to the brain. However, sometimes these signals encounter disruptions due to damage in the optic nerve. This damage can lead to problems like visual loss or even complete blindness, and this condition is known as glaucoma, an eye disease. These eye diseases harm the eye's optic nerve and can also lead to either blindness or visual loss. A significant risk factor for glaucoma is high intraocular pressure (IOP), which can harm the optic nerve. If this pressure remains elevated and isn't treated, it can progressively damage the optic nerve, resulting in issues like visual field defects, where your vision becomes patchy or unclear, ultimately leading to blindness [1]. Studies predict a notable rise in individuals affected by age-related eye issues like glaucoma. The number of people dealing with glaucoma is expected to increase by 1.3 times between 2020 (76 million) and 2030 (95.4 million) [2]. Looking ahead to 2040, prevalence studies suggest that approximately 111.8 million people might be grappling with glaucoma [3].

The American Academy of Ophthalmology places significant emphasis on the necessity of regular eye examinations for individuals aged between 40 to 64 at least once in two to four years since glaucoma doesn't have any early symptoms or aches even no abnormality in eyesight [4]. When a patient loses 70% or more of their vision, the condition is considered advanced. Glaucoma is one of the most common causes of blindness which can be prevented with early detection [5]. Traditionally, ophthalmologists diagnose glaucoma manually by analysing retinal images, this procedure demands substantial time, however glaucoma detection using automated approaches takes less time in compare to manual approach. In the manual process an experienced ophthalmologist typically examines the dilated pupil of the eye. Nevertheless, this technique is labor intensive and time-consuming [6]. It takes time and money for experienced clinicians to assess the ONH manually. As a result, screening requires an automated method based on image processing, machine learning, or deep learning [7].

Automated methods of glaucoma detection used the fundus or OCT images for this disease identification [8]. Fundus and OCT images are the retinal images of the eye which contain various features like shape and size of the OC and OD, thickness of the retinal nerve cell etc. Figure 1 shows pipeline to detect the glaucoma using fundus images [9].

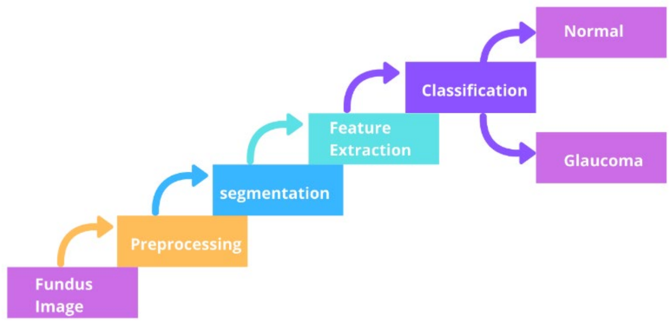

Figure 1 Pipeline to detect the glaucoma

Fundus images captured in first step will undergo in preprocessing step to remove outliers and enhance images quality. This process includes steps such as resizing, cropping, and adjusting contrast to normalize the images for further analysis. Afterward pre-processed images are utilized to extract the region of interest such as OD and OC from the fundus images and to extract the feature using various feature extraction methods. Feature extraction after segmentation bridg the gap between raw images and decision-making models. Feature extraction process extract the related features from the ROI and pass the extracted features to the feature selection algorithms to select the best features which works as the input for the classification approaches of glaucoma detection. This paper focuses on the various techniques used for the feature extraction.

2. FEATURE EXTRACTION TECHNIQUES

Feature extraction is the process of converting raw data into a set of measurable features that can be analysed to support classification or prediction tasks. Glaucoma is the eye disease which can be detected through the different features extracted from the OCT or fundus photographs [10]. This step used to extract the glaucoma specific features like the thickness of the retinal nerve fiber layer, size of OD and OC and vascular changes that may be the causes of glaucoma. This paper proposed a feature extraction framework for the early detection and diagnosis of glaucoma and extract variety of features like structural, textural, statistical and wavelet-based features extracted from retinal images. These techniques help to extract metrics such as CDR, optic disc boundaries, which play crucial role in diagnosis of glaucoma [11] .

In contrast of these manual feature selection method, automatic feature extraction techniques used deep learning models to extract the features from eye images. Deep learning models use multi-layer neural network for extracting features from images. Convolutional Neural Network such as VGGNet and ResNet, are widely used to extract features from the images [12] [13]. Similarly transfer learning use various pretrained models like EfficientNet, InceptionNet, Dense Net etc. used to extract features which can be used to enhance the performance of the model and reduce training time [14]. Object detection model like YOLO models performs feature extraction to detect objects in real-time efficiently [15] , Faster R-CNN is use to detects objects by extracting features with CNN. Segmentation models like U-Net and DeepLabV3 [16] provide further improvements in feature extraction to achieve high precision at the pixel-level for OC and OD boundaries. More recently, attention mechanisms have been widely used, including Squeeze-and-Excitation Networks (SE-Net) and Vision Transformers (ViTs) ACBSS, adaptive cluster-based superpixel segmentation [17] , which aims to make the model more accurate and focus on relevant areas such as the optic nerve head. Together, these advanced techniques not only simplify feature extraction but also help highly accurate and efficient glaucoma detection systems, making them inevitable in modern medical imaging applications. In most of the studies, features used for classification are either very limited [17] [18].

This paper proposes the best possible subset of various features that are required to be extracted for glaucoma diagnosis using DRISTHI-GS dataset and demonstrates the effectiveness of combining multiple feature categories to enhance glaucoma detection and provide deeper insights into retinal changes.

3. PROPOSED METHOD

This section described the methodology to detect the glaucoma on the basis of an extracted feature subset from the fundus image. In the first step, pre-processing is performed to remove outliers, second step is the segmentation of ROI and third step was carried out for the extraction of features such as CDR, DDLS, GLCM, GLRM, HOS, mean, skewness, variance etc. Significant features are selected in the next step using RFE feature selection approach. These selected features are then feed into the different classifiers to diagnose the presence of glaucoma. Our methodology improves predictive capability for diagnosing glaucoma leveraging this enriched feature set, hence this gives a robust base for clinical decision-making.

3.1. DATA COLLECTION AND PREPROCESSING:

The dataset used for this study is the DRISHTHI-GS data set which comprises of 101 images and out of 101, 70 images are glaucomic and 31 are Non glaucomic images and the mask are also provided in the dataset for the corresponding images [19]. These images are pre-processed to enhance visual quality and improve feature extraction process. In the first step, the CLAHE algorithm is employed to prevent excessive contrast enhancement and mitigate the problem of noise over-amplification in AHE. This is achieved by locally limiting contrast enhancement. The second step involves the erosion operation, which reduces the image size by eliminating pixels from both the inner and outer boundaries of regions. In the third step channel separation performed on these images to extract OD and OC on red green and green channel.

Fundus imaging is now considered as an aspect of identifying and monitoring glaucoma. However, analysing these images effectively requires pinpointing the areas of interest, which can be bit complex due to the anatomy and vascular patterns in fundus images. Image segmentation techniques are used to extract the region of interest from these complex images. Segmentation involves separating and outlining structures or areas of focus in an image [20]. Segmentation algorithms play a role in extracting features linked to glaucoma in fundus images, such as the optic OC and OD Feature Extraction and selection.

3.2. FEATURE EXTRACTION

Feature extraction is the crucial step for the process of classification. There are many features that can be extracted from an image to detect the glaucoma. Table 1 contains the extracted features with description.

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S.No.	Features	Type of Feature	Description
1	**CDR**	Structural	Measures the ratio of optic cup diameter to optic disc diameter. A higher CDR indicates a larger optic cup, a key biomarker for glaucoma.
2	**Contrast**	GLCM (Textural)	Reflects the intensity contrast between neighboring pixels. Higher contrast can indicate sharp edges or abnormalities in the optic nerve head.
3	**Correlation**	GLCM (Textural)	Shows the linear dependency between pixel intensities. Changes in correlation values may signal irregular texture patterns in glaucomatous areas.
4	**Energy**	GLCM (Textural)	Represents texture uniformity. Lower energy values suggest complex patterns typical of glaucomatous damage.
5	**Homogeneity**	GLCM (Textural)	Indicates the similarity of adjacent pixel values. Higher homogeneity suggests smoother textures, which 6can be altered in glaucomatous r7egions.
6	**Mean**	Statistical (FoS)	T8he average intensity value of the region. Variations in mean intensity help identify structural changes in the optic cup and disc.

7	**Standard Deviation**	Statistical (FoS)	Measures the spread of intensity values. High standard deviation highlights variability in the optic disc and cup, signaling potential structural issues.
8	**Variance**	Statistical (FoS)	Quantifies overall intensity variation. Higher variance often corresponds to abnormal patterns in the optic nerve region.
9	**Skewness**	Statistical (FoS)	Indicates asymmetry in intensity distribution. Useful for detecting whether intensities are skewed toward abnormal higher or lower values.
10	**Kurtosis**	Statistical (FoS)	Measures "tailedness" of intensity distribution. High kurtosis suggests sharper peaks, which can indicate abnormalities.
11	**Level_1_H_Mean**	Wavelet (Horizontal)	Mean value of horizontal details from the first level of wavelet decomposition. Useful for capturing broad horizontal patterns in the optic nerve region.
12	**Level_1_V_Mean**	Wavelet (Vertical)	Mean value of vertical details from the first level of wavelet decomposition. Highlights vertical structural changes in the optic disc and cup.
13	**Level_1_D_Mean**	Wavelet (Diagonal)	Mean value of diagonal details from the first level of wavelet decomposition. Identifies diagonal patterns linked to glaucomatous changes.
14	**Level_2_H_Mean**	Wavelet (Horizontal)	Horizontal details at the second wavelet decomposition level. Captures finer details for detecting subtle changes in optic cup or disc.
15	**Level_2_V_Mean**	Wavelet (Vertical)	Vertical details at the second wavelet decomposition level. Provides finer analysis of vertical changes in the optic nerve structure.
16	**Level_2_D_Mean**	Wavelet (Diagonal)	Diagonal details at the second wavelet decomposition level. Helps capture complex glaucomatous changes in optic nerve and surrounding regions.

3.3. FEATURE SELECTION

The methods of feature selection involve finding the best possible combinations of feature subsets that can be utilized for disease classification. The wrapper method of RFE is used in this paper for feature selection, aiming to select the most important features of a dataset by recursively removing the least significant features and building the model iteratively. Wrapper selection: This method evaluates a subset of features using an algorithm that applies search strategies forward feature selection, backward feature selection, exhaustive feature selection, or bidirectional search to search in the space for potential feature subsets. This approach selects the nine features out of the extracted sixteen features. Further these selected features are used to classify.

4. RESULTS

In this study, various classifiers are used to detect glaucoma based on the features selected using RFE approach. RFE is a feature selection technique that iteratively removes the least important features according to a predictive model's ranking. The process begins with all features, trains the model, and identifies the features contributing the least to the prediction, which are then removed. This cycle continues until a predetermined number of features remain. RFE enhances model performance by selecting the most relevant features, thereby improving accuracy and reducing complexity. However, it can be computationally intensive and may retain redundant features if they are highly correlated. In this work, classifiers such as RF, SVM, KNN and NB are applied to evaluate the selected features performance in terms of the classification. The classification results show accuracies of 98.6% (RF), 98% (SVM), 91% (KNN), and 96% (NB) as shown in fig.2.

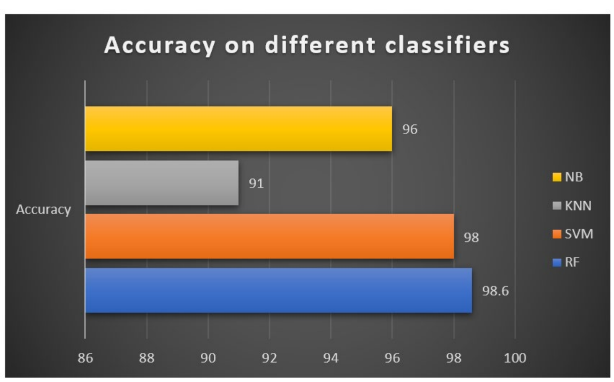

Figure 2 Accuracy of SVM, NB, RF and SVM Classifiers

5. CONCLUSION

This study highlights the importance of selecting appropriate ophthalmic features for effective glaucoma detection using image-based analysis. A comprehensive approach was adopted, starting with the extraction of diverse structural, textural, statistical, and wavelet-based features from retinal fundus images. RFE was employed to identify the most relevant features, refining the feature set from sixteen to nine significant features. These selected features were then evaluated using various classifiers, including RF, SVM, KNN, and NB. The results demonstrated high classification performance, with RF achieving the best accuracy of 98.6%, followed by SVM with 98% accuracy, NB with 96% accuracy, and KNN with 91% accuracy. This robust methodology emphasizes the utility of feature selection in enhancing model efficiency and predictive accuracy. It establishes a reliable framework for automated glaucoma diagnosis, which holds significant promise for early detection and effective clinical decision-making in ophthalmology.

CONFLICT OF INTERESTS

None.

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