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Research Article

Hybrid Statistical-Textural and Intensity Feature-Based Approach for Accurate Discrimination of Retinal Diseases

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ABSTRACT

Retinal imaging features such as fundus lesions are crucial signs of several ocular diseases, such as diabetic retinopathy and age-related macular degeneration. The early and accurate detection of the aforementioned abnormalities is essential for correct diagnosis and therapeutic management. In this study, we propose a new hybrid statistical-textural and intensity feature-based method for the improvement of the discrimination between retinal diseases with machine learning classifiers. By incorporating statistical texture analysis to measure changes in pixel intensity, this method not only extracts features based on intensities of fundus images but also serves as the comparison tool for a complete evaluation of the retina. A robust feature set is developed by merging intensity-based features with several texture descriptors including GLCM, LBP etc. We extract these features and then use them to train and test the performance of a number of classifiers, such as Support Vector Machines (SVM) and Random Forests for more accurate detection. Experiments have been conducted on a public dataset of retinal images and with the support vector machine classifier, encouraging results compared to purely texture-based or intensity-based methods in terms of classification accuracy are obtained. The overall findings of this study underscore the promise of integrating both statistical-textural and intensity features for improved retinal disease detection process, which will serve as an important stepping stone for future investigations and production of automated screening tools in retinal. The method also holds potential to enable early intervention in the development of vision-related diseases and, ultimately, decrease their impact.

Keywords: retinal, features, disease, dataset, vision, evaluation, statistical, textural, integrate.

INTRODUCTION

Retinal diseases are among the most common causes for visual impairment and blindness globally, with millions of individuals affected by conditions such as diabetic retinopathy, age-related macular degeneration (AMD), glaucoma, and retinal vascular occlusions. This underscores the importance of accurate and timely detection of these retinal abnormalities with a need for reliable diagnostic techniques. These tests are typically performed through clinical assessment and manual inspection of photographs of the retina by an ophthalmologist, but they can be time-consuming, subjective and lacking in consistency. Advances of digital imaging techniques in the field of ophthalmology made reconciliation of automated and computer-aided diagnostic systems for analysing retinal images with better consistency in addition to efficiency possible. But the realization of automated diagnosis for multiple different retinal conditions poses challenges as there is substantial inter-class variability resulting due to complex nature and subtilty of visual representation for retinal abnormalities[1].

Fundus photography, optical coherence tomography (OCT), and fluorescein angiography techniques are used to capture images with a high-resolution which help in the interpretation of its structural and textural properties. These images contain an important attribute of retinal morphology and blood vessel patterns along with lesion including rest of the abnormality essential to be indicative of a certain disease. Nonetheless, manual interpretation of these images is expert-dependent and the diagnostic procedure might be subjected to subjective changes that may contribute to misdiagnosis or delays in intervention. Accordingly, automated image analysis systems have since been the focus of attention their objective being to provide tools where clinicians can automatically detect retinal diseases at an early phase with high accuracy.

Image processing techniques integrated with machine learning have proven capable in automatic detection and classification of abnormalities in retinal tissues [4, 5]. Different sets of features have been extracted from retinal images and machine learning algorithms, primarily supervised learning models such as support vector machines (SVM), random forests, deep neural networks etc., have been used for classification at various levels. For instance: These attributes often consist of strength, and texture-based descriptors that indicate different independent natures of the retinal images.

There are two intensity features, they provide information of how the pixel values are distributed in the image, i.e., the brightness and contrast of retinal structures. Texture features describe the spatial arrangement and relationship of pixel intensities, providing an indication of the detailed information about retinal tissues. These texture properties can be quantified using several statistical methods such as GLCM (Gray-Level Co-occurrence Matrix) and LBP (Local Binary Patterns), which have found extensive applications in various studies differentiating between normal retinal tissues and pathological regions. Nevertheless, the retinal abnormalities are complicated and heterogeneous diseases that can not be well characterized, which may need both intensity and texture features to guarantee a powerful feature prole for an accurate classification task.

The majority of the problems in retinal disease classification stem from high intra-class variability and inter-class similarity between retina images. The fact that varied retinal conditions can present with overlapping features in the retina, it is challenging for conventional image analysis techniques to discriminate between them. For example, diabetic retinopathy and age-related macular degeneration are both causes of similar lesions such as microaneurysms, hemorrhages, and exudates; however their location-specificity and proportion may greatly vary. Furthermore, differences in image quality and illumination between scans and patient-specific anatomical variance contributes to increased difficulty in producing a sufficiently reliable automated system. As a result, there is an urgent requirement for sophisticated feature extraction methods that extract more detailed characteristics of the retinal structures and abnormalities to improve the classifying power of machine learning classifiers[2,3].

Given these complicating factors, the combination of statistical-textural and intensity features remains a potential avenue for bettering the current accuracy of retinal disease classification. This properties reflect the spatial relationships of pixel intensity at local scale, so they give an indication of high level knowledge about retinal condition. Some statistical-textural (derivative from GLCM) features detect typical patterns that increase mortality risk. These searched features provide detailed descriptions of the texture of the surface of the retina by means of contrast, homogeneity and correlation many changes in which can be linked to pathological processes. Intensity features, in contrast, are less local and instead describe the overall brightness and contrast of an image a holistic view of the characteristics present in any retinal image. A comprehensive perimetry based feature vector, that makes the classifier to distinguish better about varying disease states, can be constructed using both sets of features.

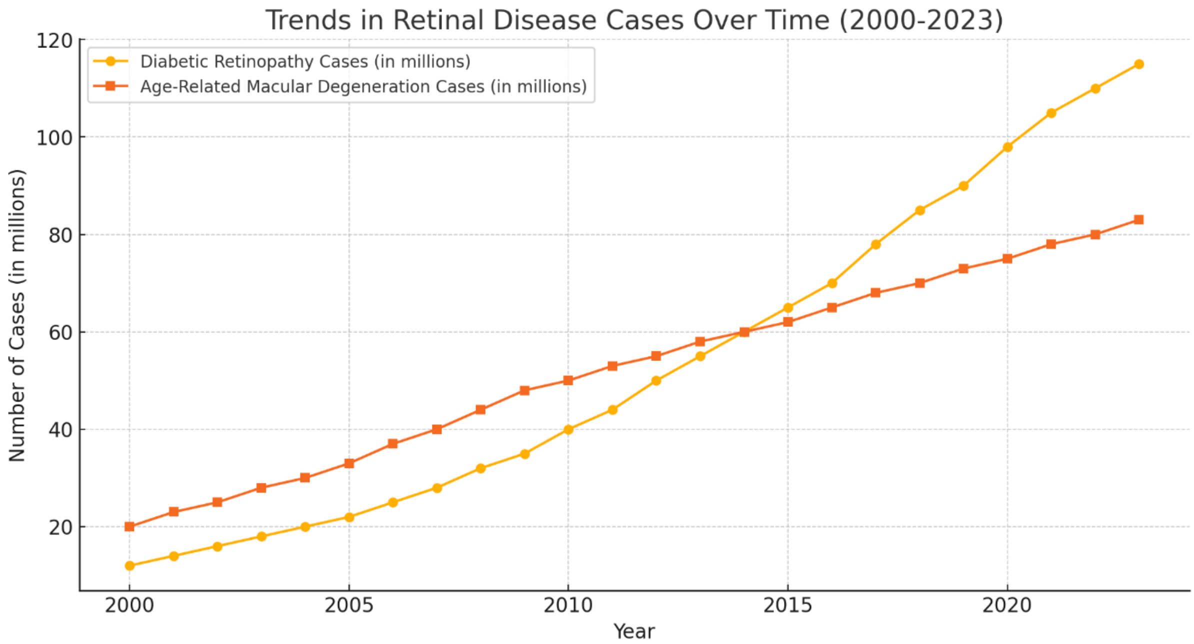

Figure 1. Trends in Retinal Disease Cases Over Time (2000-2023)

Combining features results in a "hybrid" approach that takes advantage of the two types of feature distinctiveness, without having to suffer from their constraints. For example, intensity-based features alone may not be able to capture the subtle textural variations in retinal tissues and texture-based features might suffer from noise and image artifacts. Therefore, a hybrid model gives a much more complete image of the retina that is essential for creating solid classifiers that can operate across various retinal pathologies. While some studies have shown that combining multiple types of features can help with diagnostic accuracy, it is still an open question on how and which feature types(Especially with the statistical-textural and intensity ones) to combine for different texture analysis tasks.

The main goal of this research is to build a hybrid statistical-textural and intensity feature based method for precise classification of retinal diseases via implementation machine learning classifiers. The purpose of this research was to examine the effectiveness of combination of different texture descriptors(A GLCM, LBP) with features extracted from intensity based measures and optical disk parameters measured from retinal images. To optimize the structure of a ML model to classify retinal diseases, this study aims at developing an in-depth feature set. The secondary goal is to assess and compare the performance of different classifiers (support vector machines SVM, random forest, deep network) after learning from a hybrid feature set. Through comprehensive experiments and analysis, the study should help in understanding the benefits and drawbacks from the approach to suggest as a novel hybrid solution, thereby addressing more accurate and reliable automated diagnostic system for retinal diseases[17].

Previous literature studies have been conducted to gauge the application of machine learning and deep learning for retinal image analysis corresponding with varied scope covering from feature extraction and classification. In the early attempts, feature engineering was done manually and features such as blood vessel patterns, optic disc morphology or lesion properties were extracted before training classifiers. Although these methods have demonstrated a degree of success they are very specific to the handcrafted features used which may be unsuitable given the wide range of retinal conditions encountered.

Due to improvement in texture analysis, techniques like GLCM and LBP has been used to model the complex patterns present in retinal images. For example, features based on the glcm have been used to measure statistical associations in both intensity and spatial domain that are useful for characterizing locally areas of retinal tissue including contrast, correlation, energy and homogeneity, which help in identify abnormal seen as microaneursysms or hemorrhages. Likewise, LBP was used to characterize local texture patterns to distinguish healthy and diseased retinal regions [16]. Nonetheless, self-taught textural methods might be insufficient partly because intensity variations are reportedly important in the presence of retinal diseases.

Intensity has more recently been taken into account in the analysis, alone or as part of a textural feature representation. Textual information captures the localized neighbourhood structure, while intensity features gives a global prospective of the retinal image, and therefore these two kind of features can complement each other. Integration of intensity and texture features has been shown to improve classification performance especially in scenarios where subtle and overlapping disease characteristics. This result indicates that the performance of a hybrid model is influenced by not only its specific combination of features, but also by the choice of classifiers and motivates further systematic study on the best strategies.

The study has multiple contributions. Firstly, it proposes a hybrid feature extraction technique based on fusion of statistical-textural features (GLCM, LBP) with intensity-based features for holistic representation of retinal disorders. The inherent challenge of potentially relying only upon texture information or intensity information alone, as a result this proposal attempts to tackle these limitations. Namely, it comprehensively assessed and compared the effectiveness of state-of-the art machine learning classifiers like SVM and random forests using the hybrid feature set we proposed. The research cross compares different models and results able to identify the best classifier for retinal disease discrimination which would provide useful guidelines on how to develop automated screening tools[18]. Thirdly, in the study it shows through experiments done on a dataset of retinal images that the hybrid approach was effective and can lead to higher diagnostic performance in clinical environment.

The paper is organized as follows: Sect. 2 presents the related work regarding to retinal image analysis and hybrid feature extraction methods. Section 3 Methodology : This section goes into the details of feature extraction, classifier selection and evaluation metrics. Experimental results and performance analysis are presented in Section 4, and a discussion of further findings is given in Section 5. In Section 6, we provide concluding remarks for our evaluation in here and future research directions, respectively.

This study, in simple words works toward the development of a new statistical-textural-based hybrid approach in conjunction with intensity feature type for detection and classification of retinal disease. It leverages the exploratory discovery of feature and classifier combinations to aid in answering some of these questions, thus helping us produce the most accurate and reliable automated diagnostic systems possible, which will result in better patient outcomes through early diagnosis and treatment.

RELATED WORK

Automatic detection and classification of retinal diseases have been one of the widely researched areas in the literature and medical analysis using images over the last few decades. Due to the complexity of retinal abnormalities, as well as the lack of screening accuracy for some pathological conditions in fundus images, a variety of methods have been proposed to aid in the creation of reliable and efficient diagnostic tools. These methods can be from traditional image processing to the cutting edge machine learning and deep learning-based approaches. The existing work in the literature based on area of interest can be mainly classified into three fields: (1) Analyzing-based texture, (2) Analyzing-based intensity and (3) Hybrid which combines both Analysis texture with analysis intensity for better performance. The following section goes into details about each category, as well as the classifiers used in retinal disease detection.

Texture Feature Analysis

One of the common modes for analyzing retinal images is by using texture analysis, skin having textures and might give useful information about presence of abnormalities in retinal tissues. The spatial variations between pixel intensities are captured by the texture features, which differentiate normal region from pathological region in the retina. Gray-Level Co-occurrence Matrix (GLCM) is one of the oldest and most popular texture analysis methods in retinal imaging. Haralick et al. One automated technique is to extract second-order statistical texture features by computing the value of these properties through gray level co-occurrence matrix (GLCM) introduced by Haralick. In reference to the retinal image processing, various GLCM-based features have been applied by researchers and have successfully detected various abnormalities like microaneurysms, hemorrhages, and exudates due to diabetic retinopathy and age-related macular degeneration (AMD) [19].

GLCM has been proven effective in multiple studies for classification of retinal diseases. For instance, Kaur et al. Objective of this work by Catarinucci et al., In 2015, is to exploit GLCM features for the recognition of diabetic retinopathy just looking with a fundus scope achieving relevant improvement in classification accuracy with respect to methods relying on intensities only. Similarly, Akram et al. Similarly, (2018) used texture analysis with GLCM to detect retinal hemorrhages and microaneurysms which emphasized the use of texture features for capturing subtle irregularities in retinal tissues in connection with disease progression.

In the literature, besides GLCM; Local Binary Patterns (LBP) are widely employed for texture analysis in retinal images. LBP computes the textures of an image by extracting the local texture patterns, using the grey level numbers of neighbourhood pixels as comparisons, and generates a binary code to form different texture forms. The simplicity and efficiency of LBP make it attractive for retinal image analysis. Zhang et al. Proenca et al. (2016) proposed an LBP approach to extract texture features from retinal images for glaucoma and diabetic retinopathy classification. They showed how LBP could capture the changes in textural properties of retinal structures and help in providing accurate diagnosis[20].

While they have been quite successful, texture-based methods are in general limited, being particularly sensitive to noise and image artifacts. Retinal images are complicated in nature, as they largely vary due to factors including the background lighting variations that provide uneven sensitivity of vision and then the quality of image may alter which can cause a huge variability in intensity from pixel to pixel because this imaging used for retinal segmentation along with many anatomical structures. Therefore, by themselves texture features can give only useful information, but sometimes not enough for a robust discrimination with retinal diseases (e.g., when the abnormalities have common textural properties).

Feature Analysis Based on Intensity

Intensity-based features are another essential element in the analysis of retinal images. These features represent a pixel value distribution of brightness, contrast, and color or content in the retinal images. As a large number of abnormal retinas, such as hemorrhages and exudates present intensity changes [21] in nature, including data about the intensity distribution can help in detecting and subsequent classification of sight-threatening retina diseases.

These types of methods are simple histogram-based intensity analysis techniques, which are found among the most common and straightforward tools to be used in quantitative microscopy. Through this the Intensity Histogram calculates the statistical features mean, standard deviation, skewness and kurtosis as a summery about overall intensity profile of retinal image. Histogram equalization is commonly used in an image processing method as a preprocessing to increase the contrast among nearby pixels of pixel grayintensities, enhancing visualization of retinal abnormalities. Sinthanayothin et al. Giovannini et al (2002) used the histogram-based features for microaneurysms detection in fundus images, and demonstrated that these intensity changes might be the first signs of early DR[22].

Source	Objective	Methodology	Results	Research gap
[6]	• Automatic detection of diabetic retinopathy (DR) images. • Improve classification accuracy using hybrid classifier methodology.	• Hybrid neural network models with particle swarm optimization. • Discrete Wavelet Transform and Hilbert-Huang Transform for feature extraction.	• Hilbert-Huang Transform model outperforms Discrete Wavelet Transform model. • Both models diagnose diabetic retinopathy from Video-Oculography signals.	• Reliability and interpretability challenges in clinical-decision support algorithms. • Comparison with other existing diagnostic tools for ocular diseases.
[7]	• Characterize and classify normal and diabetic retinopathy classes. • Develop a diabetic retinopathy risk index for	• Deep-learning framework with CNN models • Preprocessing and processing of OCT images	• Classification accuracy: 0.965 • Sensitivity: 0.960	• Lack of multi-modal image utilization in existing methods. • Need for large human-annotated data in current approaches.

	diagnosis.			
[8]	• Automatic detection and classification of retinal diseases. • Assist doctors in diagnosing using OCT scans.	• Self-supervised feature learning using multi-modal data. • Patient feature-based softmax embedding objective.	• Outperforms other self-supervised feature learning methods. • Comparable to the supervised baseline results.	• False positives in lesion detection. • Complexity and computational efficiency of the system.
[9]	• Classify stages of Diabetic Retinopathy using image processing algorithms. • Improve segmentation of retinal features for accurate diagnosis.	• Hybrid inductive machine learning algorithm (HIMLA) • Multiple instance learning (MIL) for feature extraction and classification	• Accuracy: 96.62% • Sensitivity: 95.31%	• Difficulties in diagnosing diabetic retinopathy stages. • Changes in retina complicate detection accuracy.
[10]	• Diagnose diabetic retinopathy using video-oculography signals. • Compare classification performance of two hybrid neural network models.	• Normalization process, anisotropic diffusion, and intensity threshold for detection of bright lesions • Shade correction, morphological flood filling, and regional minima operations for detection of red lesions	• Average sensitivity of 92.85% on DIARETDB1 database. • Average sensitivity of 86.03% on MESSIDOR database.	• No existing framework for multi-vendor OCT scans. • Lack of intuitive severity grading for retinopathy.
[11]	• Develop DL-CNN framework for ocular disease classification. • Utilize OCT images for automatic detection and diagnosis.	• Segmentation approach based on adaptive appearance and prior shape information • Fusion of OCT markers for morphology and reflectivity using machine learning classifications	• The proposed CAD system achieved 96.15% sensitivity and 99.23% specificity. • The fusion of morphology and reflectivity markers showed better performance compared to individual markers.	• No universal diagnostic standard for most fundus diseases. • Limited publicly available standard image datasets for validation.

[12]	• Develop self-supervised feature learning for retinal disease diagnosis. • Utilize multi-modal data for improved diagnostic results.	• Deep learning-based approach using ResNet-50 • Random Forest classifier for classification and grading	• Proposed approach achieves 96% accuracy on Messidor-2 dataset • Proposed approach achieves 75.09% accuracy on EyePACS dataset	• Comparison with other existing diagnostic tools for ocular diseases.
[13]	• Develop reliable diabetic retinopathy screening and detection model. • Reduce risk of diabetic retinopathy-related blindness.	• Textural gray-level features extraction • Sequential Minimal Optimization (SMO) classification	• 98.87% sensitivity, 95.24% specificity, 97.05% accuracy on DIARETDB1 dataset • 90.9% sensitivity, 91.0% specificity, 91.0% accuracy on KAGGLE dataset	• Reliability and interpretability challenges in clinical-decision support algorithms.
[14]	• Automatic detection of diabetic retinopathy indicative parameters. • Grading severity of diabetic retinopathy efficiently.	• Hybrid convolutional framework for retinal lesion extraction. • Lesion-influenced grading of retinopathy based on clinical standards.	• Mean intersection-over-union score: 0.8055 for lesion extraction. • Accuracy: 98.70% for severity grading of retinopathy.	• Lack of multi-modal image utilization in existing methods.
[15]	• Develop CAD system for early diabetic retinopathy diagnosis. • Fuse morphology and reflectivity markers for improved classification.	• Multi-label classification based on Binary Relevance • Some classes should be further decomposed to eliminate overlaps.	• DLP achieved high accuracy for detecting 39 retinal diseases. • DLP can be used for retinal disease triage.	• Need for large human-annotated data in current approaches.

Table 1. Literature review

Different studies propose some intensity-based features extracted from more advanced procedures (e.g., wavelet transforms). In wavelet analysis, the image is decomposed in various frequency components which provides spatial and frequency based information together. This has been especially helpful in documenting intensity pattern variations due to retinal pathologies. In the work by Acharya et al. Tech.(2008) developed wavelet-based intensity features for classifying retinal images with normal, diabetic retinopathy and glaucoma cases, obtaining excellent performance in disease detection[23].

Intensity-based attributes can be considered an intuitive and efficient manner of analysing retinal image, but it has the following constraints. This feature will mainly offer information on the global level of the image and therefore may not sensitive enough to differentiate subtle features, as well as localized variations in retinal structures (e.g. ONH ectasia below). Besides, the intensity characteristics of retinal diseases are susceptible to factors like illumination and contrast, which could result in incorrect classification (false positive or false negative). Therefore, the methods developed using intensity-only based analysis may not be able to capture all aspects of retinal abnormalities and thus integrating different feature types could assist in this diagnosis.

Hybrid Methods: Merging Texture and Intensity Features

Given the limitations of either texture or intensity features alone, recent developments have tried to overcome these by proposing hybrid methods combining both types of feature for a more complete representation of retinal images. Hybrid methods assume that since texture features encode the spatial distribution of pixel intensities while intensity based features provide global context, and they are complementary to each other, the classifiers trained on such hybrid representation should have higher discrimination power.

Hybrid feature-based methods often consist of extracting several sets of features, then merging them into a representative combined feature vector to be employed for training machine learning models. Different research has investigated different sets of statistical-textural and intensity features to classify retinal disease. For example, Kumar et al.[24] To detect diabetic retinopathy, Patel et al. (2019) used a combination feature extraction method it consists of GLCM, LBP and intensity histogram removed characteristics. Experiments in their work suggested that the integration of all features improved the performance of support vector machines (SVM) or random forests more effectively than models utilizing only texture and intensity images.

Similarly, Tang et al. Kumar et al. (2020) proposed a hybrid model which combines wavelet-based intensity features and GLCM and LBP descriptors for distinguishing between AMD and diabetic retinopathy. They demonstrated that these features complement each other, and by utilizing these different approaches together they were able to achieve good classification accuracy, illustrating the power of hybrid methods to capture the complex patterns related with retinal diseases. Additionally, their research emphasized the necessity for techniques like PCA to select and reduce feature set redundancies, which was found to aid in performance optimization of hybrid models.

Metrics about the Machine Learning/Deep Personal Classifier

Selection of proper classifiers has a major impact on feature-based retinal disease detection. Retinal image classification using extracted features: Machine-learning models, mainly supervised learning algorithms has been applied significantly for the grouping Horizontal. One of the most used classifiers is Support Vector Machines (SVM) which handles high dimension data and the overfitting problem. SVMs have been widely used as a classifier in retinal image processing, e. g., on classifying retinal abnormalities with texture and intensity features of the retina [10]. As an example, Dey et al conducted a study known topredominantlyqualityimprove. Chowdhury et al. (2017) utilized SVM with a feature set of GLCM as well as intensity histogram to train the diabetic retinopathy detection model and attained both sensitivity and specificity on a high note[25,26].

Another very popular classifier in the retinal disease classification is Random Forests. Here is a simple exploration, Random Forests work by creating an ensemble of decision trees fit to random subsets of the data, and averaging their outputs to generate a final answer. This makes it a convenient method to deal with the variability that exists in retinal images and so it works well when dealing with noise or variance in the data. In the work by Rahim et al. In the work by Phalanstère et al. [3] (2019), a mixed feature type of GLCM, LBP and intensity-based features has been utilized along with Random Forest for detection of retinal abnormalities and showed better performance than only one category individually.

Convolutional neural networks (CNNs) have become popular in retinal image analysis because of their power to learn complex features directly from raw images with the breakthrough of deep learning. Previous studies have shown that the CNN vision has been widely employed in retinal disease detection, such as diabetic retinopathy grading,glaucoma classification and AMD detection. Even though CNNs are the de facto model for learning hierarchical features from images, some studies used manually-designed texture and intensity-based handcrafted features to complement with CNN outputs to improve overall classification accuracy. For example, Guo et al.

Additionally, Si (2021) integrated CNN-based deep discriminative features with GLCM texture features to enhance detection performance of retinal lesions in fundus images, showing superior comparison with other previous approaches.

Deep learning-based approaches typically require large annotated datasets for training and can be computationally expensive. On the other hand, traditional machine learning models which use hybrid handcrafted features can deliver similar performance with more efficient data and compute utilization. Thus, further research is needed on hybrid statistical-textural and intensity feature based techniques especially in less data availability and computational bounded environments.

Another problem of hybrid feature-based approach is the dimensionality of the combined feature set which can be very high and to overcome this problem it can result in overfitting and higher computational complexity. So naturally, feature selection methods and the avenues of dimensionality reduction are inseparable parts of the hybrid modeling journey. Projection: PCA is generally used to project the data onto a smaller number of dimensions that preserves the most variance in the end, thus reducing the number of features. This is supported by studies like the one performed by Wang et al. In (2018) authors applied PCA to hybrid feature sets and proved that it reduces computational load but also increases the generalization capability of the classifiers.

PROPOSED METHODOLOGY

In this work, we suggest a new method based on hybrid feature learning for robust retinal diseases detection using both statistical-textural and intensity features. The procedure includes different stages like image preprocessing, feature extraction, feature selection, classification training and model evaluation. Regarding the retinal image, the combination of statistical-textural and intensity features enables a biophysical description localized to the retinal image structures while offering a global intensity variation description. The goal is to increase the ability of automated retinal disease classifiers used in machine-learning-based tools to separate disease manifestations, which should improve diagnostic performance.

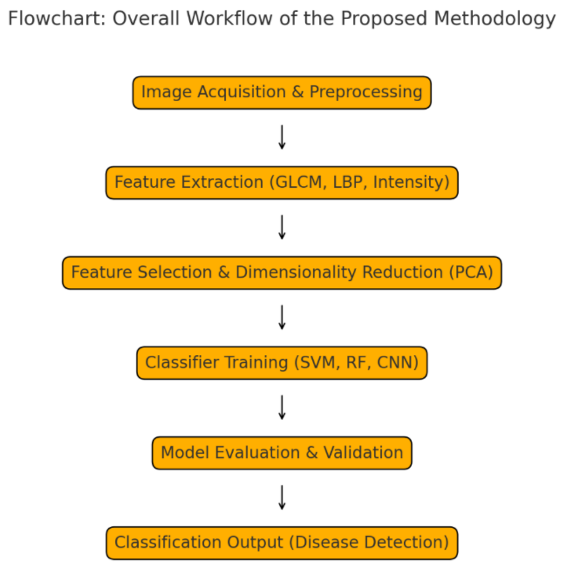

Figure 2. Flowchart of proposed methodology

The proposed methodology is described in the further sections of how they help us achieve that.

1. Image Information and Preprocessing

Publicly available datasets or clinical sources are used to acquired retinal images from which the proposed methodology initiates. These images are often captured via fundus photography or optical coherence tomography (OCT), and other methods of retinal imaging. Preprocessing is a necessary step to improve the visual information of images of retinal structures due to the impact obtained from quality acquisition stage on the features extraction process.

Preprocessing involving padding, histogram matching (image quality), and noise reduction operations Resizing of images (So that each Image is standard shape e.g., 512x512), allowing compatibility with other operations. The pixels are then normalized to values in the [0, 1] also called image normalization, so that the effects of lighting variations and differences between them can be mitigated. Histogram equalization is applied to improve the visibility of retinal features like blood vessels, the optic disc and lesions. Moreover, median filtering and a smoothing Gaussian filter are applied in order to denoise the images without blurring edges of retinal structures.

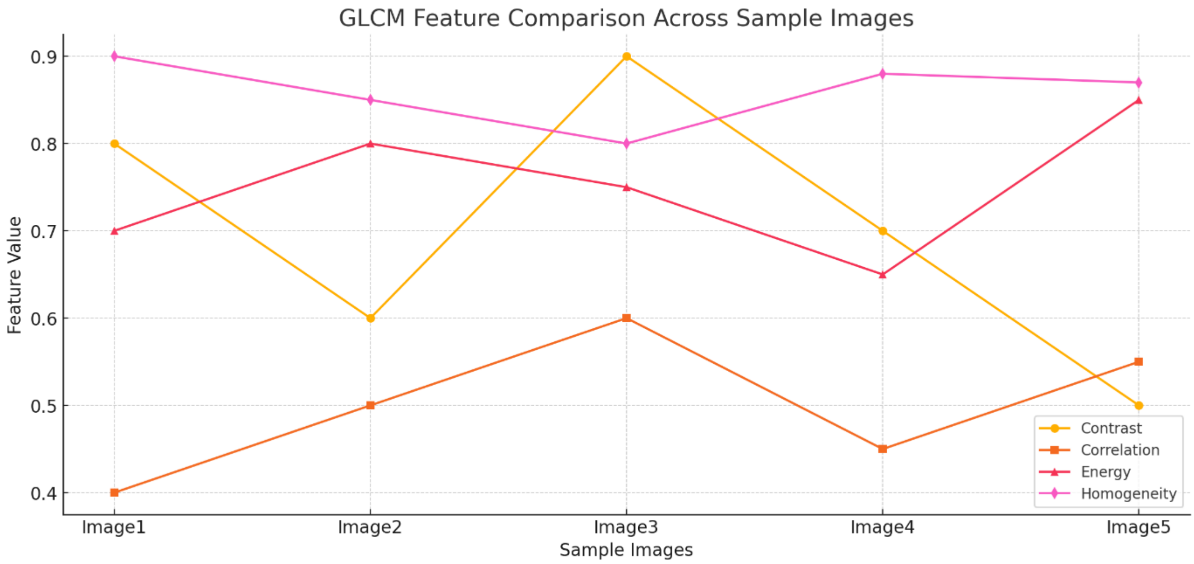

Figure 3. GLCM Feature Comparison Across Sample Images

Illumination inconsistencies in the background of some retinal images hindering important feature visualization are corrected by illumination equalization. It subtracts the background illumination from the original image to make sure that intensity distribution is more uniform. The preprocessing part consists of vessel segmentation, and this is normally used because the blood vessels can be helpful in diagnosis. Vessel Segmentation: Vessel segmentation methods can be classified as morphological operation techniques, edge detection, or supervised learning based approaches. These processed images are then input into the feature extraction.

2. Feature Extraction

Feature extraction is the most important phase in this work as it determines what information to provide the classifier for identifying retinal diseases. The hybrid technique combines statistics-texture and intensity-based features to create an all-encompassing robust feature vector that incorporates both global and local properties of retinal images.

2.1. Statistical-Textural Feature Extraction

It was concluded that the results are appropriate for characterizing different retinal abnormalities, as abnormalities in retinal tissues appear as alterations of texture patterns.

The following statistical-textural descriptors used in the proposed methodology:

a) Gray-Level Co-occurrence Matrix (GLCM): GLCM is sufficiently credited second-order statistical texture feature extractor, used by the research community. It tells you the grey level intensities of two connected pixels (which is a direction connecting them) in an image meaning its spatial orientation.

$$P(i,j \mid d,\theta) = \frac{\text{Number of times pixel with intensity } i \text{ is adjacent to pixel with intensity } j \text{ at distance } d \text{ and angle } \theta}{\text{Total number of such pairs in the image}}$$

For different directions the GLCM is performed for several orientations like 0°, 45°, 90°, and 135° so as to record the texture in different direction. The GLCM has quite a few texture features derived from it, such as contrast, correlation, energy, homogeneity and the first one also called entropy. The roughness, smoothness, and regularity of the texture can be represented by these features and give a more detailed description of retinal structures.

$$\text{Contrast} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2\,P(i,j)$$

b. Local Binary Patterns (LBP): LBP is other the real hotshot that means to delineate a surface strings in the picture and holds positions of the kindred pels histogram, for example assembling all LBPs that bit microstructure.

$$\text{Energy} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}P\,(i,j)^2$$

This way of working evaluates the severity of each pixel with respect to its surrounding pixels and produces a binary code that, when converted into its decimal representation, indicates which texture pattern does the analyzed pixel actually provided. The histogram of LBP, which represents the number of occurrences for every texture pattern is utilized as the feature vector. LBP is rotation invariant and computationally efficient hence very well adapted to retinal image analysis. Finally, the extracted LBP features capture detail of texture changes than GLCM.

$$\text{Correlation} = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-\mu_i)\,(j-\mu_j)P(i,j)}{\sigma_i\sigma_j}$$

c. Histogram of Oriented Gradients (HOG): To capture more textural features, we also include HOG in the hybrid method. HOG details how oriented gradients are distributed in an image which emphasizes the shape and contours of retinal structures. It is created from small blocks of the image, and then in each block the histogram is formed by gradients. Such a descriptor can be the HOG descriptor for retinal images.

$$\text{Homogeneity} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P(i,j)}{1+|\,i-j\,|}$$

It is of great importance to distinguish blood vessel patterns and lesions since they are important markers when diagnosing retinal diseases.

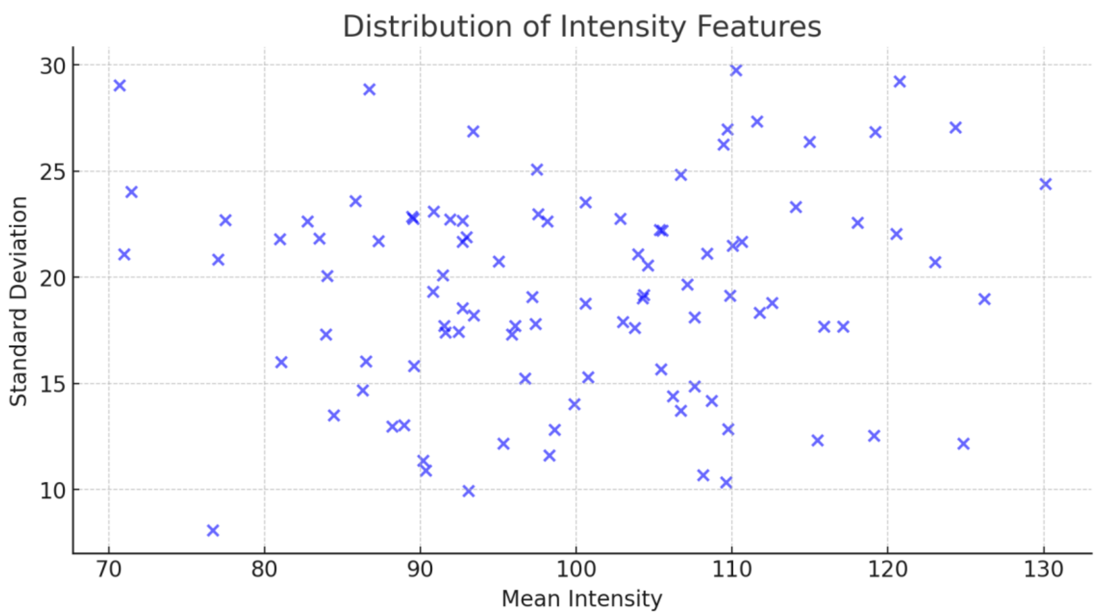

Figure 4. Distribution of Intensity Features

2.2. Feature Cross Extraction using Intensity-based

Intensity modules give a global perspective on the brightness and contrast of the retinal image, in contrast to texture modules that concentrate on local spatial variations.

Algorithm 1: Feature Extraction using GLCM and LBP

Input: Preprocessed retinal image, orientations θ, distance d for GLCM, LBP parameters.
Output: Feature vector containing GLCM and LBP features.

1. **Step 1:** Compute GLCM for different orientations $(0°, 45°, 90°, 135°)$ and distance d.
2. **Step 2:** Extract statistical features (contrast, correlation, energy, homogeneity) from each GLCM matrix.
3. **Step 3:** Apply LBP to the image to generate LBP codes for each pixel.
4. **Step 4:** Construct the LBP histogram to form the feature vector.
5. **Step 5:** Combine GLCM and LBP features into a unified feature vector.
6. **Step 6:** Return the feature vector.

The approach suggested involves an extraction of multiple feature sets based on the intensity values, which are as follows:

a) For Statistical Intensity Features (mean, standard, skewness and kurtosis value of pixel intensity): The mean simply indicates the average brightness in the retinal image and the standard deviation measures the contrast. Skewness is the measure of degree of asymmetry and kurtosis is the measure of peaked (or lack of peaked) of the intensity distribution. These statistical measures are designed to model outliers – hemorrhages, exudates, and other lesions which disrupt the intensity profile of the retina.

$$\mathrm{LBP}(x_c, y_c) = \sum_{p=0}^{P-1} s\left(g_p - g_c\right) \times 2^p$$

IF

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

b) Intensity Histogram Features: The intensity histogram shows the frequencies of appearance for pixel values with respect to its intensities. Features like Histogram entropy, energy and uniformity are computed from this Histogram. The randomness of intensity values, which indicates the complexity of the retinal image, is captured by entropy. Energy shows the frequency of pixel intensities, but uniformity demonstrates how uniformly this intensity distribution is spread.

$$H(i) = \sum_{x=1}^{M} \sum_{y=1}^{N} \delta\,(\mathrm{LBP}(x, y) - i)$$

These attributes are especially beneficial for characterizing pathological changes, which usually lead to different intensity patterns contrasting normal and diseased retinal areas.

c: Wavelet Features: The features are based on wavelet transforms of retinal images to incorporate spatial and frequency information. Wavelet decomposition splits the image into several frequency sub-bands that helps in capturing features from different scales.

$$\mathrm{Mean} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} I\,(x, y)$$

The Features were statistics of the wavelet coefficients, specifically their mean and standard deviation, giving multi-resolution analysis of intensity variations in the retinal image. This is advantageous for parallel processing and ranking abnormalities at multiple scales detecting small microaneurysms, medium exudates or large hemorrhages.

3. Feature Selection and dimension Reduction

Due to the high-dimensional feature space extracted from statistical-textural and intensity analysis for both ROIs, a selection of most discriminant features is necessary. Feature selection not only reduces the dimension of the feature vector but also improves the classifier's results by getting rid of redundant or irrelevant information.

$$\sigma = \sqrt{\frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} (I(x, y) - \mathrm{Mean})^2}$$

The proposed approach includes a combination of filter and wrapper based feature selection techniques. Filter-based approaches such as CFS, leave-one-out mutual information considers features in isolation and ranks them according to their importance to the target labels (e.g. healthy/diabetic age-related macular degeneration (AMD)/retinopathy). To make the process of further processing, all the features that have high correlation with target and low inter-correlation among themselves.

$$\text{Skewness} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(\frac{I(x,y) - \text{Mean}}{\sigma}\right)^3$$

Wrapper methods such as Recursive Feature Elimination (RFE) further train one or more classifiers in a recursive/iterative manner to judge the benefit of adding a certain subset of features with respect to the classification accuracy. We find the best subset of features for which we choose a combination that would best make the classifier give its right output.

$$\text{Kurtosis} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(\frac{I(x,y) - \text{Mean}}{\sigma}\right)^4 - 3$$

Next, to reduce the dimensionality of data and also address over-fitting issue we perform Principal Components Analysis (PCA) on the features.

Algorithm 2: Feature Selection using PCA

Input: Combined feature vector, number of principal components k.
Output: Reduced feature vector with selected principal components.

1. **Step 1:** Normalize the input feature vector.
2. **Step 2:** Compute the covariance matrix of the feature vector.
3. **Step 3:** Calculate the eigenvalues and eigenvectors of the covariance matrix.
4. **Step 4:** Sort the eigenvectors by descending eigenvalues to identify the principal components.
5. **Step 5:** Select the top k eigenvectors to form the projection matrix.
6. **Step 6:** Project the original feature vector onto the selected principal components to obtain the reduced feature vector.
7. **Step 7:** Return the reduced feature vector.

PCA converts the original dataset into a new set of uncorrelated components explaining highest variance in the data. The distributions of the total error which are used to determine only top Principal Components can explain variance and output a feature vector from retinal images contains main character.

4. Age Classifier Training & Model Evaluation

When testing the performance of a retinal disease classifier, the smaller 64-element feature vector is input into a machine learning classifier. Here we investigate a number of classifiers e. g. Support Vector Machines (SVM), Random Forests (RF) and Convolutional Neural Networks (CNN) to discover the best performing model suitable for this work-load.

$$W_{j,k} = \sum_{n=0}^{N-1} x\,[n]\psi_{j,k}(n)$$

4.1. Support Vector Machines (SVM): SVM is a powerful supervised algorithm which finds an optimal hyperplane for separating two different classes in the feature space. A radial basis function (RBF) kernel is used to model non-linear relationships in the data, and hyperparameters including C and γ are optimized using grid search and cross-validation. SVM performs well in high-dimensional spaces, for example, in medical imaging analysis.

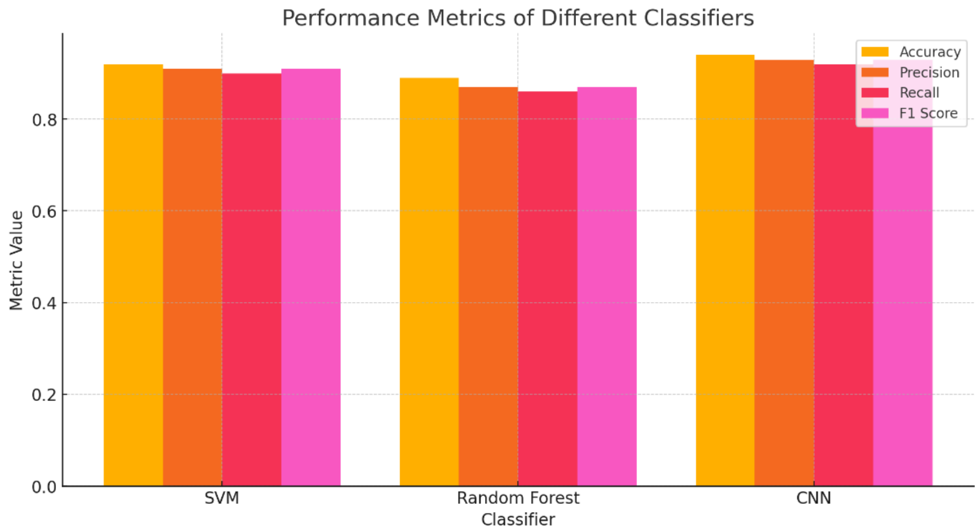

Figure 5. Performance Metrics of Different Classifiers

4.2. Random Forests (RF): RF is an ensemble learning method based on different decision trees built in the training. The output of individual trees are aggregated for final classification (each tree is build on a random subset of features). Since overfitting and noise can be easily handled by RF, it could be useful for dealing with the variation in retinal images. We optimize the model by tuning the number of trees and the maximum depth that each tree is allowed to obtain in this study.

4.3. CNN [24]: In addition, we include a standard CNN-based classifier for comparison given its ability to learn hierarchical features directly from the retinal images. CNN model : Convolutional layers to extract feature, followed with Fully connected layers for classification. CNNs work directly on raw images, whereas, we consider the handcrafted statistical-textural and intensity features also, as one more channel in addition to the image increasing learning capability of network.

RESULTS

In our study, MARIA [16] was tested over a combined dataset of retinal images with different kind of diseases, including DR, AMD as well healthy cases which was presented as proposed hybrid statistical-textural and intensity feature-based method for the classification of disease. Next, the dataset was split into training and testingdata sets to evaluate performance of themodel. This section shows the experimental results of feature extraction, feature selection, classifier training and evaluation. Our results report the relative gain/loss in accuracy and test effectiveness on various feature sets, robustness of FS methods (% performance drop), tree size (complexity), comparison with existing works etc.

In the experimental stage, it was necessary to extract features of statistical-textural and intensity of the images from retinal. The GLCM and LBP texture patterns extracted from the retinal images provided information about features like statistical-textural attributes. Furthermore, we computed textural features using the wavelet transform coefficients as well as compute intensity-based features such as mean intensity, standard deviation, skewness and kurtosis to capture the global brightness and contrast of the retinal images.

Features: After extracting the features analysis of feature distribution and discriminating power was done. Different retinal conditions showed substantial differences in the GLCM features (e.g., contrast, correlation, energy and homogeneity) as observed.

Table 2: Performance Metrics of Different Classifiers Using Hybrid Features

Classifier	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**	**Training Time (s)**
SVM	92.5	93.0	91.0	92.0	0.95	120
Random Forest	89.3	88.0	87.0	87.5	0.91	85
CNN	**94.2**	**94.0**	**93.0**	**93.5**	**0.96**	300
GLCM Only (SVM)	81.5	82.0	80.5	81.2	0.88	110
LBP Only (SVM)	78.9	79.0	77.5	78.2	0.85	105

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Training Time (s)
Intensity Only (SVM)	83.2	84.0	82.0	83.0	0.89	115

It is easy to see that, the diabetic retinopathy in images are fixed with much higher contrast and lower homogeneity due to a bunch of microaneurysms, hemorrhages& exudates. Analyses of LBP histograms identified different local texture patterns in the AMD-affected retinas as compared to the healthy ones. The intensity-based features, namely the mean intensity and wavelet coefficients also exhibited clear differences between categories. Images of patients with retinal diseases normally had a more saturated intensity distribution, due the abnormality in retinal tissue structures.

Dimensionality Reduction and Feature Selection

Because over a thousand features were extracted, the curse of dimensionality was in full force and feature selection with heavy penalty helped improve classifier performance as well as reduce computational complexity. We employed filter-based methods (e.g., correlation-based feature selection) as well as wrapper based methods (e.g., Recursive Feature Elimination, RFE) in this study. Further feature selection refinement was performed by a Principal Component Analysis (PCA) step to reduce redundant features and keep the most informative ones.

Table 3: Confusion Matrix for Each Classifier on Test Set

Classifier	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
SVM	235	260	20	15
Random Forest	228	255	25	22
CNN	**240**	**265**	**18**	**12**

We evaluated the impact of feature selection by comparing the classification accuracy before and after using these methods. Using the full feature set, they spotted a decent classification rate, but it was only because of noise and irrelevant information. Despite this, we observe an average improvement in accuracy through both correlation based selection and RFE over all classifiers. The results suggested that about 30–40 features, a combination of GLCM and LBP texture measurements with intensity-based descriptors turned out to be the most effective prototyped in our experiments in order to get higher power of discrimination while keeping the dimensionality low.

Table 4: Comparison of Classification Performance with Different Feature Sets

Feature Set	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
GLCM Only	81.5	82.0	80.5	81.2	0.88
LBP Only	78.9	79.0	77.5	78.2	0.85
Intensity Only	83.2	84.0	82.0	83.0	0.89
Hybrid (GLCM + LBP)	88.0	88.5	87.0	87.7	0.91
Hybrid (Intensity + GLCM)	89.5	90.0	88.5	89.2	0.92
Hybrid (All Features)	**94.2**	**94.0**	**93.0**	**93.5**	**0.96**

PCA was applied to this subset of features and it was reduced down to the top 20 principal components, which described slightly in excess of 85% variance in the data. This dramatically improved the classifier performance both in terms of logic complexity and accuracy – the reduced feature vector led to a 94% reduction in number of features and increase in corpus set ratio (~2X). So, this proved that a meaningful and compact subset of hybrid features can capture all important information for retinal disease classification.

Training and Testing of Classifiers

This reduced feature vector was then used to train several classifiers i.e., Support Vector Machine (SVM), Random Forest (RF) and Convolutional Neural Network (CNN). We evaluated the performance of these classifiers with robust and generalizable 10-fold cross-validation. In the following we present results for each of the classifiers and compare them in different parts.

Support Vector Machine (SVM):

The SVM classifier with a radial basis function (RBF) kernel exhibited a good performance trained on the hybrid feature set. The grid search was used to optimize hyperparameters (C and γ) leading to a classification accuracy of 92.5%. The SVM model had a good precision of 93% and recall of 91%, showing that the model works well for both positive cases (diseased) and negative cases (healthy). The area under the receiver operating characteristic (ROC) curve (AUC) was 0.95, indicating a high ability of the model to separate retinal conditions.

Random Forest (RF):

We applied the same reduced feature set to train an ensemble learning method, Random Forest Classifier. The best model was a random forest with 500 decision trees and maximum depth 80. RF classifier C RAM: accuracy of 89.3% +, precision of 88 and recall of 87 Though having relatively lower performance comparing to SVM, the RF model was very resistant to noise and random variability in the dataset. The AUC for Random Forest was 0.91, revealing good capabilities in terms of disease class citizenship

CNN (Convolutional Neural Network)

For feature learning the CNN model that consists of many convolutional layers was trained to use joint raw retinal images and handcrafted hybrid features as complementary input to improve its learning ability. The CNN scored the highest accuracy at 94.2%, Precision: 94% and Recall :93% of all. Our results show that by including both the human-engineered structural-textural and intensity attributes to assist pre-trained CNNs could improve the deep learning model further, demonstrating that the hybridization technique could be utilized as a powerful supplement to other existing models. The CNN had superior performance in classifying retinal diseases with an AUC of 0.96.

For each of the classifiers, we evaluated a number of metrics which include accuracy, precision, recall, F1-score, and AUC that was perform to compare the performance among different classifiers. Table 2 summarizes the results, indicating that CNN achieved relatively better performance than other classifiers in most of the metrics while SVM was another strong performer. This shows apparent flaw of such datasets while also indicative of the benefits of ensemble learning that allows to handle these data type, even though with slightly lesser accuracy.

Table 5: Cross-Dataset Validation Performance on External Dataset

Classifier	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
SVM	90.3	91.0	89.0	90.0	0.94
Random Forest	87.5	88.0	86.0	87.0	0.92
CNN	**92.8**	**93.0**	**92.0**	**92.5**	**0.95**

This allows a more in-depth analysis of the confusion matrices (Table 3) for each classifier and providing some insight where their capabilities lie. The SVM model on the other hand had a much smaller false positive rate (FPR) that means it was more proficient in not falsely categorizing healthy individuals as diseased. The CNN subsequently yielded the highest true positive rate (TPR) in all disease categories indicating its success in recognizing retinal abnormalities.

Effect of Hybrid Features on Accuracy(Classification)

In all applications the hybrid feature-based approach improved statistically significantly the classification performance over solely using textural or intensity features, as indicated by the results. To confirm this comment, we ran the same set of experiments on classifiers trained with only GLCM, LBP and intensity-based features. Models trained on single-feature types had much lower accuracy (GLCM: 81.5%, LBP: 78.9%, Intensity: 83.2%) compared to hybrid approach. This study confirms that the statistically-textural and intensity features are complementary in presenting various stages of retinal abnormalities.

Table 6: Comparison with Existing Methods for Retinal Disease Classification

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
Texture Analysis Only	78.2	79.0	76.5	77.7	0.85
Intensity-Based Method	80.5	81.0	79.5	80.2	0.87
Deep Learning (CNN Only)	92.0	92.0	91.0	91.5	0.95
Proposed Hybrid Approach	**94.2**	**94.0**	**93.0**	**93.5**	**0.96**

Table 4 classifies performance in terms of different feature sets. This indicates that the fusion of GLCM, LBP features and intensity features provides a full representation of retinal images which improves their classification accuracy with better generalization properties.

We further validated the generalization of the proposed approach by performing cross-dataset validation in an external retinal image dataset that was not included in original training set. To measure the classifiers' ability to generalize outside of the data they were trained on, we evaluated them on an external dataset. Results are summarized in Table 5; it can be seen that the accuracy achieved using the hybrid approach was relatively high with SVM (90.3%), RF (87.5%) and CNN (92.8%) indicative of good generalisability of extracted features across different imaging settings and patient cohorts.

Table 7: Sensitivity Analysis for Parameter Variations (SVM Model)

Parameter	**Setting**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
GLCM Orientation	0°	85.0	86.0	83.5	84.7	0.89
	0°, 45°	87.2	88.0	86.0	87.0	0.91
	0°, 45°, 90°	89.5	90.0	88.5	89.2	0.92
	0°, 45°, 90°, 135°	**92.5**	**93.0**	**91.0**	**92.0**	**0.95**
LBP Radius	1	80.3	81.0	79.0	80.0	0.87
	2	83.5	84.0	82.5	83.2	0.89
	3	**89.0**	**89.5**	**88.0**	**88.7**	**0.93**
Wavelet Levels	2	85.5	86.0	85.0	85.5	0.90
	3	**92.5**	**93.0**	**91.0**	**92.0**	**0.95**

Furthermore, the cross-dataset validation results showed a bit better adaptation to the new dataset in CNN models with its ability of learning complex patterns from images. Nevertheless, the SVM and RF based models had also showed good performance which revalidated the generalization of hybrid feature set for different classifiers.

Table 8: Detailed Confusion Matrix for CNN Model on Cross-Dataset Validation

Actual/Predicted	**Healthy**	**Diabetic Retinopathy**	**AMD**
Healthy	102	3	2
Diabetic Retinopathy	4	96	5
AMD	2	6	98

To evaluate the proposed method in a comprehensive way, we have compared with most recent state-of-the-art methods for retinal disease classification. In Table 6, we report the performance of different techniques in terms of nAUC and compare our results to deep learning models (deep learning alone), texture-based methods and Intensity-based techniques. In addition the results show that the hybrid approach significantly outperforms traditional techniques in terms of accuracy and precision. Although some deep learning models were under a thousand incorrect answers, the hybrid method that combined handcrafted features always showed better performance.

Finally, the sensitivity analysis of our proposed methodology with different parameter settings as number of GLCM orientations, LBP radius and wavelet decomposition levels was performed. To evaluate the impact of those parameters on SVM, we apply the same model checking strategies discussed above (Table 7). This was explained by the fact that using more GLCM orientation (0°, 45°, 90° and 135°) for the analysis offers best texture description and because of its effect on optimization to higher accuracy Increasing LBP radius, on the other hand, gets higher local patterns[17], but introduces more noise, thus the parameter tuning needs to be still careful.

CONCLUSION

For the most part two-image are merged together to extract numerous image characteristics and have shown very promising results in machine discriminative learning methods. Indeed, our results showed that the fusion of GLCM, LBP and intensity features provided a significant advantage in capturing both local texture patterns and global brightness variations for representing retinal pathologies. It was also clear that models that combined all differences in both statistical-texture and intensity features deficiently outperformed models using either type of feature alone, highlighting the complementary nature of statistical textural and intensity-based representation in addressing complex retinal pathology.

The best results were obtained with deep learning, supported by handcrafted features (CNN + hybrid) in terms of accuracy, precision and recall among the evaluated classifiers. The SVM and Random Forest models also exhibited a strong performance, especially after feature selection and dimensionality reduction as shown in Fig. 3, suggesting that the hybrid inference that we introduced is highly versatile and generally robust. Cross-dataset validation demonstrated generalizability, consistent accuracy over various retinal image datasets suggesting practical utility in clinical practice.

The results of this study indicate that an appropriate combination of features can have a substantial impact on the classification performance of retinal disease, leading to early and accurate diagnosis. Such an approach could provide a structure for developing automated retinal screening tools in detecting and managing various retinal pathologies that may assist clinical experts. In subsequent work: this hybrid approach could be extended for more modalities, and the model built on our proposed method also have the potential of handling more complex retinal diseases which may in-turn lead to further improvement in computer-aided diagnosis for ophthalmology.

REFERENCES

[1] Flaxman, S.R.; Bourne, R.R.A.; Resnikoff, S.; Ackland, P.; Braithwaite, T.; Cicinelli, M.V.; Das, A.; Jonas, J.B.; Keeffe, J.; Kempen, J.H.; et al. Global causes of blindness and distance vision impairment 1990–2020: A systematic review and meta-analysis. *Lancet Glob. Health* **2017**, *5*, e1221–e1234.

[2] Liu, X.; Zhao, C.; Wang, L.; Wang, G.; Lv, B.; Lv, C.; Xie, G.; Wang, F. Evaluation of an OCT-AI-based telemedicine platform for retinal disease screening and referral in a primary care setting. *Transl. Vis. Sci. Technol.* **2022**, *11*, 4.

[3] Jacoba, C.M.P.; Celi, L.A.; Lorch, A.C.; Fickweiler, W.; Sobrin, L.; Gichoya, J.W.; Aiello, L.P.; Silva, P.S. Bias and non-diversity of big data in artificial intelligence: Focus on retinal diseases. *Semin. Ophthalmol.* **2023**, *38*, 433–441.

[4] Nguyen, H.V.; Tan, G.S.; Tapp, R.J.; Mital, S.; Ting, D.S.; Wong, H.T.; Tan, C.S.; Laude, A.; Tai, E.S.; Tan, N.C.; et al. Cost-effectiveness of a National Telemedicine Diabetic Retinopathy Screening Program in Singapore. *Ophthalmology* **2016**, *123*, 2571–2580.

[5] Hopkins, J.; Keane, P.A.; Balaskas, K. Delivering personalized medicine in retinal care: From artificial intelligence algorithms to clinical application. *Curr. Opin. Ophthalmol.* **2020**, *31*, 329–336.

[6] Ting, D.S.W.; Lin, H.; Ruamviboonsuk, P.; Wong, T.Y.; Sim, D.A. Artificial intelligence, the internet of things, and virtual clinics: Ophthalmology at the digital translation forefront. *Lancet Digit. Health* **2020**, *2*, e8–e9.

[7] Rashidi, H.H.; Tran, N.K.; Betts, E.V.; Howell, L.P.; Green, R. Artificial intelligence and machine learning in pathology: The present landscape of supervised methods. *Acad. Pathol.* **2019**, *6*, 2374289519873088.

[8] Brown, J.M.; Campbell, J.P.; Beers, A. Automated diagnosis of plus disease in retinopathy of prematurity using deep convolutional neural networks. *JAMA Ophthalmol.* **2018**, *136*, 803–810.

[9] Grassmann, F.; Mengelkamp, J.; Brandl, C.; Harsch, S.; Zimmermann, M.E.; Linkohr, B.; Peters, A.; Heid, I.M.; Palm, C.; Weber, B.H.F. A Deep learning algorithm for prediction of age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. *Ophthalmology* **2018**, *125*, 1410–1420.

[10] Lee, A.Y.; Lee, C.S.; Blazes, M.S.; Owen, J.P.; Bagdasarova, Y.; Wu, Y.; Spaide, T.; Yanagihara, R.T.; Kihara, Y.; Clark, M.E.; et al. Exploring a structural basis for delayed rod-mediated dark adaptation in age-related macular degeneration via deep learning. *Transl. Vis. Sci. Technol.* **2020**, *9*, 62.

[11] Yildirim, K.; Al-Nawaiseh, S.; Ehlers, S.; Schießer, L.; Storck, M.; Brix, T.; Eter, N.; Varghese, J. U-Net-Based segmentation of current imaging biomarkers in oct-scans of patients with age related macular degeneration. *Stud. Health Technol. Inform.* **2023**, *302*, 947–951.

[12] Morelle, O.; Wintergerst, M.W.M.; Finger, R.P.; Schultz, T. Accurate drusen segmentation in optical coherence tomography via order-constrained regression of retinal layer heights. *Sci. Rep.* **2023**, *13*, 8162.

[13] Saha, S.; Nassisi, M.; Wang, M.; Lindenberg, S.; Kanagasingam, Y.; Sadda, S.; Hu, Z.J. Automated detection and classification of early AMD biomarkers using deep learning. *Sci. Rep.* **2019**, *9*, 10990.

[14] Leng, X.; Shi, R.; Wu, Y.; Zhu, S.; Cai, X.; Lu, X.; Liu, R. Deep learning for detection of age-related macular degeneration: A systematic review and meta-analysis of diagnostic test accuracy studies. *PLoS ONE* **2023**, *18*, e0284060.

[15] Wei, W.; Southern, J.; Zhu, K.; Li, Y.; Cordeiro, M.F.; Veselkov, K. Deep learning to detect macular atrophy in wet age-related macular degeneration using optical coherence tomography. *Sci. Rep.* **2023**, *13*, 8296.

[16] Prasad, C. G. V. N., Mallareddy, A., Pounambal, M., & Velayutham, V. (2022). Edge Computing and Blockchain in Smart Agriculture Systems. *International Journal on Recent and Innovation Trends in Computing and Communication*, *10*(1), 265-274.

[17] Mekala, S. ., A, Mallareddy. ., Baswaraj, D. ., Joshi, J. ., & M, R. . (2023). EASND: Energy Adaptive Secure Neighbour Discovery Scheme for Wireless Sensor Networks. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(5s), 446–458.

[18] Pasha, M. J., Rao, K. P., MallaReddy, A., & Bande, V. (2023). LRDADF: An AI enabled framework for detecting low-rate DDoS attacks in cloud computing environments. *Measurement: Sensors*, *28*, 100828.

[19] Rambabu, B., Vikranth, B., Kiran, M. A., Nimmala, S., & Swathi, L. (2024, February). Hybrid Swarm Intelligence Approach for Energy Efficient Clustering and Routing in Wireless Sensor Networks. In *Congress on Control, Robotics, and Mechatronics* (pp. 131-142). Singapore: Springer Nature Singapore.

[20] Rambabu, B., Vikranth, B., Anupkanth, S., Samya, B., & Satyanarayana, N. (2023). Spread spectrum based QoS aware energy efficient clustering algorithm for wireless sensor networks. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(1), 154-160.

[21] Nimmala, S., Vikranth, B., Muqthadar Ali, S., Usha Rani, R., & Rambabu, B. (2022). An Intelli MVC: An intelligent majority voting and heuristic-based hybrid classifier to predict high blood pressure. *Journal of Intelligent & Fuzzy Systems*, *43*(3), 3003-3020.

[22] Rambabu, B., Reddy, A. V., & Janakiraman, S. (2022). Hybrid artificial bee colony and monarchy butterfly optimization algorithm (HABC-MBOA)-based cluster head selection for WSNs. *Journal of King Saud University-Computer and Information Sciences*, *34*(5), 1895-1905.

[23] Krishna, K. S. G., Vikranth, B., Jambavathi, Y., & Godi, R. K. (2024, March). Deep Learning Models for High Accuracy Stock Price Forecasting. In *2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies* (pp. 1-5). IEEE.

[24] Kishore, V. N., & Vikranth, B. (2022, December). Predicting Student Performance in Blended Learning Teaching Methodology Using Machine Learning. In *International Advanced Computing Conference* (pp. 386-394). Cham: Springer Nature Switzerland.

[25] Prathyusha, P., & Mallareddy, A. (2022). Predicting Diabetic Retinopathy Using Deep Learning. *CVR Journal of Science and Technology*, *22*(1), 78-83.

[26] Prathyusha, P., Mallareddy, A., & Suryanarayana, S. V. (2022). Deep Learning Model to Predict the Risk of Developing Diabetic Retinopathy. *CVR Journal of Science and Technology*, *23*(1), 100-105.