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A Novel IoT based Wavelet and PCA Approach for Improved Glaucoma Classification Using Retinal Images

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Abstract

The proposed research implements a new 3D-block-based alpha-rooting enhancement method, which uses PCA classification for detecting glaucoma. The use of Euclidean distance in current image enhancement methods tends to lose important structural details that result in incorrect classification outcomes. The proposed method executes block-matching and grouping operations to locate equivalent 3D patterns before using adaptive alpha-rooting adjustment, which automatically controls contrast throughout optic disc and optic cup regions. Following enhancement processing an additional polishing stage optimizes these results for classification purposes. The classification of enhanced images takes place using PCA and its wavelet variants to extract important retinal features. The proposed system utilizes both ACRIMA dataset and real-world hospital images to show better classification achievements than CLAHE-based enhancement while validating its effectiveness. The experimental outcome demonstrated both high accuracy and reduced time consumption when using biorthogonal DWT with (2D) ²-PCA for classification. The proposed method offers a time-effective hardware-oriented solution for automatic glaucoma detection by combining conventional statistical techniques with deep learning-based classification approaches. The method provides clinical facilities with a dependable standard for glaucoma identification and diagnosis improvement. The Proposed 3D block-based adaptive alpha rooting method achieves a total accuracy level of 95.1%. The U-net model achieves 91.0% accuracy while CNN reaches 90.3% and RF delivers 87.1%. At the same time, SVM provides 86.3% accuracy while PCA returns 85.2% and DWT reaches 84.2% and KNN establishes 81.2% accuracy.

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1. Introduction

MIP stands as a signal processing method, which uses captured images from human body organs turned from human body organs. Medical facilities frequently use different sources to obtain these input images. Medical imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasound, and Photoacoustic Tomography (PAT). The primary benefit of this method includes examination of human organs through non-invasive procedures. Identification of pathologies. MRI imaging requires magnetic fields together

with radio waves as essential components for operation. CT imaging makes use of X-rays together with cross-sectional computer images. In ultrasound, the usage of high-frequency sound waves constitutes the imaging method. The combination of ultra-medical practitioners uses optical and acoustic signal pulses for performing PAT imaging. In very recent years, a variety Researchers have developed different varieties (2D or 3D) of multidimensional images, which monitor human bodily structures Gan structures in various aspects. Research shows that medical professionals encounter multiple problems with their work. Doctors lack the capability to detect all medical image abnormalities automatically and appropriately categorize them properly. Several limits exist which cause specialists to misinterpret images visually. Interpretation, weariness, and distraction. Researchers' col Doctors teamed up with clinicians to introduce computers in medical image analysis activities Automatic interpretation of images led to high-speed optimal performance achievements. Later, the combined work of researchers together with clinicians resulted in the introduction of CAD [1-2]. The system provides support to medical professionals for examining medical images to determine their pathology outcomes. A CAD-based image diagnosis is dependent on existing tools for image acquisition as well as computer vision methodologies. and computer vision approaches. The process uses software applications operating from computers as its main component. The results enable operators to track down the target lesions inside the input image. In the past two decades, the various medical fields now enormously value CAD applications in their processes. Breast cancer treatment commonly uses Mammography as a diagnostic instrument. Identification in its early stages.

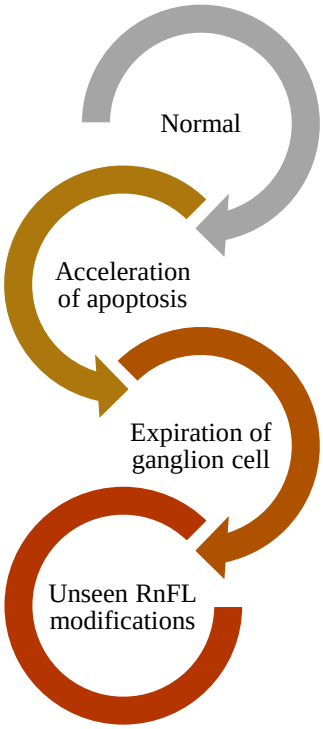

Figure 1. Progressive Deterioration of Retina Ganglion cells as well as neural fibres Levels

The medical illustration depicts the stepwise deterioration of retinal nerve fiber layers (RnFL) and ganglion cells, which occurs during glaucoma disease [3]. The diagram at its top features a gray circular arrow pointing to "Normal" that shows an undamaged eye entering the sequence. The arrow turns yellow during the lower stage along with the label "Acceleration of apoptosis" which indicates the beginning of cellular death. Apoptosis represents a natural cellular death process that becomes pathological when ganglion cells start deteriorating faster than normal.

The existence of an orange arrow within the diagram suggests "Expiration of ganglion cell" that shows how affected cells reach a state where they stop working and cause vision loss [4]. The last stage shows unseen RnFL modifications in deep red-brown coloration because they represent structural changes that remain undetectable until vision deterioration becomes more noticeable. Careful early diagnosis and prompt treatment become essential for protecting retinal ganglion cells because this degenerative process progresses in stages before complete damage occurs.

1.1 Human eye and its Anatomy

Various destructive diseases exist that create vision problems worse than those associated with unintended vision reduction do. By unintended vision loss. Glaucoma stands as the main source of vision disability throughout various nations but its early-stage assessment remains challenging. Early stages. A systematic and detailed examination of the human retina and its related Ophthalmologists need to perform diagnostic examinations of retinal structures to detect glaucoma correctly. Medical imaging plays a critical role in this scenario [5]. Medical imaging techniques offer the key benefit of allowing non-invasive assessments for viewing inside human body organs. Lows non-invasive clinical examination of human internal organs for their functional status. Several methods for specific image acquisition of human organs have been developed through numerous years of research. Recommended. Medical image experts use their specialized knowledge to create a general understanding of the medical data available.

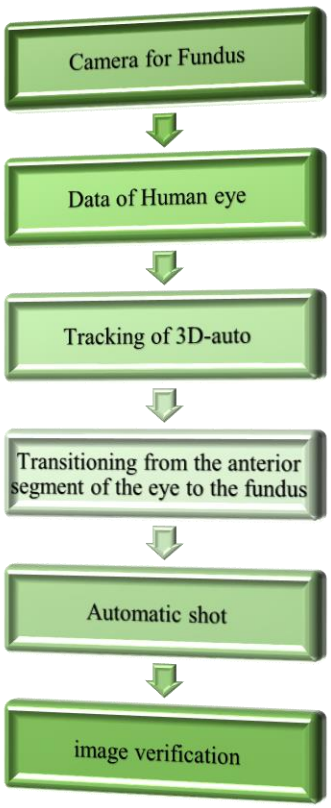

Figure 2. Imaging of the retina with a fundus camera

Before moving on to clinical treatment, one must first identify the condition based on medical imaging results. In Ophthalmology, the medical field adopts fundus cameras referred to as retinal cameras for their ability to create effective retinal images. As shown in Fig 2. When performing fundus imaging medical equipment captures both the internal eye muscles and their parts. The fundus camera succeeds in making complete photographs of the primary eye parts along with the internal structures. This retinal camera includes a low-power microscope designed exclusively for precise observation of eye internal organs such as Optic Disc (OD), fovea, retinal vessels and macula. Ophthalmologists conduct retinal structure evaluations based on fundus image examinations. For identification of glaucoma development signs. A deep and detailed retinal image Eye screenings identify glaucoma at its beginning before it causes unrepairable damage to retinal structures. Structural retinal damage. The medical screening procedure including complete involvement needs all medical professionals and their collaboration. Experts in ophthalmology are required for all steps in this process because their involvement makes it into a manual evaluation [6]. However, retinal image the process of manual interpretation faces hindrances because physicians experience fatigue while looking at images and these images also have distracting features and overlapping structures and variation in visual perception abilities. Several factors affect visual perception and retinal structure overlapping and distraction from images while performing retinal image screening. Eye examination of patients

demonstrates a continuous increase in numbers because of different underlying factors. The increasing number of patients requires medical examination because of aging populations together with those with diabetes and nutritional deficiency. Manual screening of retinal images the process of screening retinal images on a big scale that matches clinical needs proves difficult to achieve. This leads to Error-prone diagnosis together with insufficient time leads to poor screening quality in medical examinations.

These obstacles become manageable through an approach, which enables the processing of large-scale qualitative examinations. Medical imaging automation methods were developed for physicians to utilize in eye fundus image clinical assessments through various automated methods [7]. The application of CAD enables medical professionals to seek duplicate evaluations through "second opinion" usage. Over the past two decades, various retinal imagining and analysis CAD systems have become available during the past two decades. The CAD approach starts by bringing scientific data from standard retinal images of healthy and glaucomatous patients to work from. Image quality enhancement. The designing of a computer-based image interpretation procedure. It requires a suitable assessment of robustness through targeted tests with retinal data. Professionals performing clinical trials conducted tests to validate the system. For the most part CAD approaches can be grouped as Computer-Aided Detection (CADe) and Computer-Aided Diagnosis (CADx).

The CADe uses the computer system to identify abnormal retinas. The CADx system when combined with structural changes functions to analyse glaucoma suspect cases through proper diagnosis. Proper analysis. A CAD mechanism operates as a scanner to perform deep scanning procedures. The method analyses the retinal images to detect existing anomalies through interpretation of texture patterns according to predefined procedures. The test outcomes enable ophthalmologists to gain a proper medical approach receives its beginning from clear understanding of patient eye health status. Treatment. Integration of CAD-based glaucoma screening with a decision-making. The entire approach benefits from this robust system to accommodate higher demand requirements. Demand for glaucoma screening. The decision system combines the results obtained from the CAD process. Using its experience base the method analyses retinal images through CAD before making judgment about whether the image shows normal or glaucoma characteristics. The system identifies the image type as normal or glaucoma-moderated case type. Medical professionals use detailed retinal diagnostics to confirm diagnoses after CAD-based glaucoma screening. The qualitative screening the qualitative screening ability depends on how well the designed CAD procedure works while expert collaboration from software and medical domains is essential. Medical professionals along with software experts need to collaborate for successful completion of this project.

CAD-based approaches deliver glaucoma detection performance results through accuracy measurements together with sensitivity specifications and specificity determinations and accompanying true/false positive and negative values. Negative rates. The main purpose of retinal image screening with CAD software is to establish whether a image is healthy or not [8]. The usage of CAD technology for glaucoma screening greatly helps reduce the workload of ophthalmologists. Through automated screening, the ophthalmologists successfully fulfil the screening requirements on larger patient groups. A greater scale. This research sought to create a CAD platform for glaucoma screening application several innovative image enhancement methods together with proper image pattern detection systems aim to classify images into glaucoma or non-glaucoma groups.

The techniques detect specific images patterns before sorting images into glaucoma or non-glaucoma categories. High decision-support. Our daily functions obtain illumination through the human organic eye. The structure of the human eye remains normal with its high sensitivity. The absence of sight creates major difficulties for living as a human being. Task. Human eyes take the form of a sphere measuring approximately 40 mm in size. Diameter. Human eyes contain three main identifiable sections. The external part of the eye includes sclera with cornea. The cornea is composed of sensory nerves and has 10.5 mmand11.5mmaverageverticalandhorizontal diameters [9]. The pre-pupillary section from the cornea provides the main refractive function and exists within this part. in the cornea's centre. The intermediate region contains three components, which include the choroid together with the ciliary body and the iris. The iris. Light reaches the retina through the pupil that the iris regulates for access. The lens operates through commands from the ciliary body that also generates aqueous fluid. Produced. Multiple tissues in the eye receive nourishment as well as oxygen supply from the vascular layer choroid. Retinal layers. Cells within the neurons create the inner area along with the retina. The inner retinal tissues constitute the inner area of the human eye. The OC. initiates retina embryo development.

The optic vesicles inward fold into the eye cavity to create the neural part of the retina. Retina. The tissue surrounding the retina belongs to the pigment epithelium cell type. Photoreceptors are the major the photoreceptor neurons utilize their cells to detect and transform incoming light signals. Rods and cones are two photoreceptor classes. Rods act as the responsible element to produce electrical signals from first light input. The entering light produces signals in rods and cones act as detectors of colour information. The pupil allows visible light wavelengths between 400 and 700 nanometres to pass through as electrical information. Signals. The brain receives visual data from optic nerve transmission of these signals for interpretation. Scenes. The cornea conducts optical wave refraction to centre the light beams upon the pupil [10]. The sclera protects the eye from hazards. The

angle of the light entering the pupil makes another refractive journey through the lens. The image turns upside down, as it reaches the surface of the retina. Photoreceptors operate within the retina layer. One of the multiple layers comprising the retina converts the incoming light waves into electrical signals for use by the brain. The brain interprets the incoming signals for creating pictures from two-dimensional views of three-dimensional objects.

1.2 Retinal Imaging

The process of retinal imaging depends on the reflection of light from eye retinal tissues. The 3D structure of the eye retina enables the generation of a 2D retinal image. In the final image, each pixel brightness indicates the amount of light reflection that occurred during imaging. During fundus imaging procedures, the acquired features originate from the retina since these features represent essential information for interpreting eye health status. Interpretation of the eye's health status. Anatomically, the word fundus refers to the structure of the organ from the other side of its opening. Consequently, fundus imaging the internal region of the human eye becomes visible through fundus imaging since it integrates the retina and blood vessels as well as the OD and fovea and macula. Fovea and macula.

The eye has essential vision component parts, which consist of responsible for the essential vision operations: ONH serves as both optic nerve head and it receives the name OD. Through the OD, the optic nerve contacts the retina. The receptor cells completely lack from the OD region where the view remains obstructed. View is obstructed. An average normal OD shape appears as either an oval or a circle and measures 2 millimetres in size. Diameter of 2 mm. A high number of blood vessels form this region. The Retina contains various strata that together generate the pigment epithelium. Among all retinal layers, the epithelium stands out as the major structure. The photoreceptors function as the main receptors in this structure. The light energy directs photoreceptors to produce brain-interpretable electric signals. One photoreceptor known as cones maintain daylight vision together with second photoreceptors, which support night-time vision. Rods are responsible for detecting blue-green light [11]. The visual details of Macula combined with Fovea are managed by the macula, which acts as a vision magnification component. The retinal centre holds both macula and fovea very close to each other. A small trench inside the retina Clear vision happens because the fovea exists within the eye. Blood vessels contain two main types with arteries transporting oxygen-rich nutrients to the eye and veins transporting waste blood towards lungs and heart for refreshment.

1.3 Glaucoma and its Risk Factors

A group of eye disorders known as glaucoma constitutes a pathological condition, which has Intraocular Pressure (IOP) as its common factor. A multi-aspect aetiology with IOP as a common characteristic. The deterioration of vision progresses gradually from peripheral to central views because of glaucoma. Proper and early diagnosis of glaucoma prevents the development of permanent blindness because timely treatment is absent. Blindness. Time-related glaucoma development can be measured through IOP evaluation. Ciliary body organs generate the ciliary body aqueous humour before they transfer it into the space between lens and iris.

2. Related Work

These methods determine pixel intensity relationships in retinal images to achieve analysis. This method determines contrast patterns and luminosity modifications. The highlight boarders of retinal structures including OD and OC usually receive contrast correction treatment from most texture improvement methods. OD, OC, and blood vessels. The techniques strive to enhance the visual output while implementing improvement procedures across the board. These techniques help to normalize the improper blur while also compensating for missing contrast. Several histograms-based techniques, such as HE, CLAHE, and Several authors have published weighted AGC along with CLAHE and HE as corrective methods. These techniques improve the User-visible image contrast enhancement arrives from the spread of most occurring pixel intensities through pixel intensity range stretch [12]. The stretch technique applies adaptation through distinct areas of the image. Area-wise (local) image intensity histograms together with mechanisms to limit contrast-spreading serve as methods to improve image quality .pixels' neighbourhood intensity information. In the case of RGB colour space, these both the red and blue and green colour channels receive treatment simultaneously. These HE-based techniques function underground on the value and luminance channels after converting RGB retinal pictures into the Hue-Saturation-Value or Hue-Saturation-Lightness format. RGB images need transformation before they can be processed through either Hue-Saturation-Value or Hue-Saturation-Lightness colour space. The retinal images undergo background illumination removal through a specific process image pixel intensity from the average intensity. The in-depth analysis becomes possible due to this technique foreground retinal structures. Morphological operations such as dilation and erosion.

The technique has additional applications, which enhance edges of retinal structures and segment blood vessels and remove them from the images. The technique enables segmentation and removal of blood vessels and fills small isolated regions throughout the image. Every pixel in the image receives an $n \times n$ structuring element-based

convolution operation. The top hat Tran's transformation serves as the main morphological image enhancement operation. This operation extracts brighter parts from darker background areas during the process. However, the major common disadvantage of texture enhancement techniques is the improvement of both the components of interest along with unwanted noise elements. When performing the enhancement, the system simultaneously strengthens both the original retinal image and its background noise elements.

Variations of filtering methods exist to reduce the noisy elements present in retinal images. Different noise suppression methods have appeared in existing literature. Image pixel values get replaced using pixel replacement technology within the basic method. Each pixel is replaced by the statistical measure from its surrounding values [13]. The smoothing approach introduced itself as a solution to standardize irregular minor pixel intensity fluctuations intensities. This method uses neighbouring pixel values to modify original pixel data in order to minimize the edge blurring. Images with impulse noise can be successfully processed through median filtering functions. The algorithm removes all outliers throughout the image at the same time it maintains image sharpness. The filtering method of media enables the removal of salt-and-pepper noise. Along with noise reduction, the process of enhancing image contrast involves an application of Gaussian filtering techniques. A fixed-size Sliding-window operates within guided filters to change centre pixel values with the mean values obtained from neighbouring pixels. The sliding window contain all pixel values, which collectively produce their mean intensity value.

The system moves its sliding window beginning at its top left corner. The filtering window moves from the upper left to the lower right area of the image display. Adaptive filters such as Wiener. The filter algorithm modifies its processing procedure by considering the specific variation in its operating area. In the case of high variance, adaptive filters perform minor smoothing. The most appropriate application of adaptive filters exists in pre-conditioned scenarios. The filter preserves important details in retinal structures as it eliminates noise. Retinal images can be transformed the technique of DWT enables transformation of images from one domain into a different domain. The image coefficients produced from transformation can be employed during the denoising procedure. The selection of threshold value depends on a specific approach in this methodology. The threshold determination depends on the pixel intensity level. The universal threshold together with other detection methods authors approach as well as adaptive threshold by IAWDMBNC method and energy-based threshold by IWST investigator approach are among the various thresholds employed. The research incorporated threshold methods from IWST approach as reported in literature. Using the noise-cancellation operation through windowed shrinkage methods starts after threshold values have been computed. The algorithm applies windowing-based shrinkage operations to all pixels in the image for removing noise components.

Table 1: A brief overview of ML techniques

Techniques of ML	Advantages	Disadvantages
Support Vector Machine (SVM) [14]	SVM employs linear combinations for inputs to achieve minimum generalisation error.	When trained with mixed-type input data, SVMs are sluggish and ineffective.
K-Nearest Neighbour (KNN) [15]	In spite of its sensitivity to anomalies, the KNN learning procedure is inexpensive.	As dataset sizes grow, KNN's efficiency becomes less predictable and costly.
Decision Trees (DT) [16]	DT is resilient in the face of value shortages and does well with bigger datasets.	Over-fitting occurs when using DT on variables with linear pairs and tensor products.
Random Forest (RF) [17]	RF training is incredibly efficient and produces outcomes that are more trustworthy.	Compared to other ML techniques, the output prediction speed is comparatively sluggish.
Linear Regression (LR) [18]	When fitting examples, LR is easy to use and works best with linearly separable data.	Both underfitting and outliers are common problems with complicated data when using LR.
Logistic Regression (LoR) [19]	It can be quickly adjusted to accommodate different types of input.	Neither continuous factors nor values that are lacking are well suited to it.
Naïve Bayes (NB) [20]	It works well with smaller datasets and is easy to use.	NB treats all the traits similarly since it considered them independently.
K-means [21]	It is capable of handling greater sets of input data effectively.	In addition to being sensitive to noisy input, it often stalls at a local optimal.

Scientists have invested major research efforts into developing machine learning with high-resolution image processing for glaucoma diagnostic purposes. Researchers have investigated multiple ways to improve images from the retina and extract relevant features along with creating efficient models for early glaucoma diagnosis. Improved glaucoma classification results from the evolution of computer-aided diagnosis systems because of their incorporation of advanced enhancement techniques and feature extraction models and machine learning algorithms.

- Authors investigated retinal image enhancement through wavelet transform-based methods, which managed to improve contrast while maintaining structural preservation details.
- During their research, investigation scientists created a wavelet decomposition strategy that improved detection of optic cup and optic disc boundaries while producing images appropriate for subsequent classification.
- The study's findings corroborated previous findings that wavelet-based augmentation approaches significantly improved classification accuracy by making retinal features more visible.
- Scientists performed another investigation where they introduced image denoising and enhancement methodology utilizing adaptive histogram equalization to prove the significance of image pre-processing for enhancing glaucoma classification outcomes.
- The authors proposed that properly designed enhancement methods minimize noise and illumination artefacts in fundus images, which benefits medical image classification.

Principal component analysis (PCA) was studied as a dimensionality reduction technique for glaucoma classification by researchers [22]. The investigator demonstrated the beneficial relationship between PCA reductions of features in retinal images to boost processing efficiency without negatively affecting diagnostic accuracy. Researched studies showed that using PCA with discrete wavelet transform (DWT) provided an additional enhancement to feature discrimination through multi-resolution analysis. Retinal image representation becomes both compact and informative when PCA works alongside DWT thus enabling better glaucoma classification outcomes according to the authors' research.

- Research investigated different distance algorithms for retinal image similarity assessment to determine their effects on imaging treatment along with diagnostic classification methods.
- Statistical evidence from the observer revealed that Euclidean distance as a popular measurement tool proves inadequate when measuring similar blocks since it remains sensitive to image intensity changes and abnormal data points.
- The research merged cosine similarity with Minkowski distance to enhance image similarity detection thus establishing that union strategies produce stronger group stability and robustness during image organization.
- Application of improved metric calculation methods results in enhanced image recognition and upgrading processes according to the study findings.
- The researchers investigated adaptive alpha rooting as a technique for medical image contrast enhancement.
- The researcher implemented an adjustable alpha-rooting technique, which adapts the alpha parameter for retaining medical image structural integrity while improving visual contrast.
- Alpha-rooting applications at regional blocks produce superior optic disc border protection compared to using it on full images.
- The research showed that by uniting alpha-rooting methods with adaptive thresholding procedures medical staff could stop their work from damaging retinal structures throughout the process of contrast enhancement.

Researchers conducted additional investigations to study how feature selection stands in glaucoma classification because choosing the right discriminating features remains vital for machine learning model performance. The research used principal component analysis together with linear discriminant analysis and independent component analysis to determine glaucoma-related features for classification purposes [23-25]. The outcome showed how several employed feature selection methods enhance diagnostic precision because they detect diverse aspects in retinal visual elements. The researcher noted that using combined feature selection methods would enhance both efficiency and accuracy in the classification process.

Deep learning models were studied regarding glaucoma detection effectiveness through the testing of convolutional neural networks (CNNs) against traditional machine learning classifiers [26-28]. Through tests, the researcher proved that Convolutional Neural Networks produce superior outcomes than traditional classifiers when it comes to detection accuracy alongside robustness and scalability measures.

- This research analysed deep learning difficulties, which include the necessity of significant annotated databases together with growing computations together with the possibility of overfitting the system.
- The author argued that the application of wavelet-based feature extraction with principal component analysis to CNNs would enhance deep learning model generalization without requiring extensive data sets.
- The research examined glaucoma detection through machine learning model integration with DWT.

- The research established an approach that used DWT decomposition of retinal images to separate their elements into multiple frequency bands for extracting spatial and frequency domain characteristics.
- The research showed that wavelet decomposition applied before classification enhances accuracy since it produces better-detailed images of retinal structures.
- Among multiple wavelet families studied by the author including Haar, Daubechies, and biorthogonal wavelets, the selected wavelets proved effective in glaucoma classification because they maintain the high-resolution features of retinal images most accurately.

Different glaucoma detection classification methods constitute a major area of scientific research because they determine diagnostic outcome effectiveness. Researchers investigated glaucoma classification effectiveness using four algorithms including SVM, DT, KNN and artificial neural networks (ANN) [29]. The observation during research indicated that SVM provides superior accuracy in glaucoma diagnosis via its successful processing of high-dimensional data and complex decision boundary detection [30-33]. Results found by the study show that deep learning architectures within neural networks might outperform conventional classifiers with adequately extensive datasets for training. The investigation supported a model, which integrates different classifiers because it delivers superior performance levels within practical use.

3. Objective of the research work

- This investigation goal is to create a new glaucoma classification technique, which optimizes the quality of retinal images with simultaneous improvements to classification precision. Standard practices using Euclidean distance methods for image enhancement achieve poor results since they destroy structural information that affects classification outcomes.
- The main research goal combines PCA and its variants with DWT to extract important retinal image features while enhancing classification results. The research considers both 2D-PCA and $(2D)^2$-PCA variant techniques for PCA to achieve dimension reduction of retinal images which maintains their essential patterns.
- This investigation establishes a computer-efficient and hardware-compatible glaucoma detection system, which unites conventional statistical methods with deep learning-based classification approaches.

4. Motivation for the research work

- This research stems from an urgent requirement to identify glaucoma early and with precision since glaucoma currently stands among the main causes of permanent blindness worldwide.
- Current image improvement solutions prove ineffective when processing illuminance variations and noise and contrast changes in retinal images. This research establishes a new 3D-block-based alpha-rooting enhancement system that automatically adjusts image contrast without altering either optic disc or optical cup regions.
- Hospital clinics operating without sufficient medical data or advanced computing systems find deep learning technologies too complex to implement. The research emerges from a requirement to discover an efficient hardware-compliant model that matches deep learning performance levels without its elaborate structure.

5. Experimental set up

Data acquisition precedes the research method's steps, which include pre-processing and feature extraction, classification, and performance evaluation tasks. The research uses both ACRIMA dataset images and genuine hospital fundus images during evaluation to provide a full analysis of the proposed methodology. The input retinal images utilize adaptive alpha-rooting enhancement that groups image blocks when applying 3D-block-based retinal image pre-processing by using cosine similarity and Minkowski distance as their novelty screening method. The enhancement method automatically adjusts contrast patterns throughout an image while upholding the edges of OD and OC structures thus maintaining critical retinal elements needed for correct classification.

Evaluates both computational efficiency and classification accuracy in the proposed framework.

6. Dataset used

The performed research utilizes both ACRIMA dataset and authentic hospital fundus images. ACRIMA represents one of the prominently available retinal image datasets that contains glaucomatous and non-glaucomatous fundus images to perform glaucoma classification. These glaucoma images include multiple illumination conditions and retinal features alongside contrast variations so they work effectively to test proposed method robustness. The data undergoes preliminary processing which both increases image quality and harvests essential features needed for classification.

7. The Projected method

The developed algorithm for retinal image enhancement and classification commences with a collection of fundus images that maintain vital visual retina data in fig 3. Many different sources including research institutions and

medical databases and ophthalmology clinics contribute retinal image data offering a range of scans between normal and abnormal conditions. The assessment of different eye conditions including diabetic retinopathy requires fundus images in order to make proper medical diagnoses.

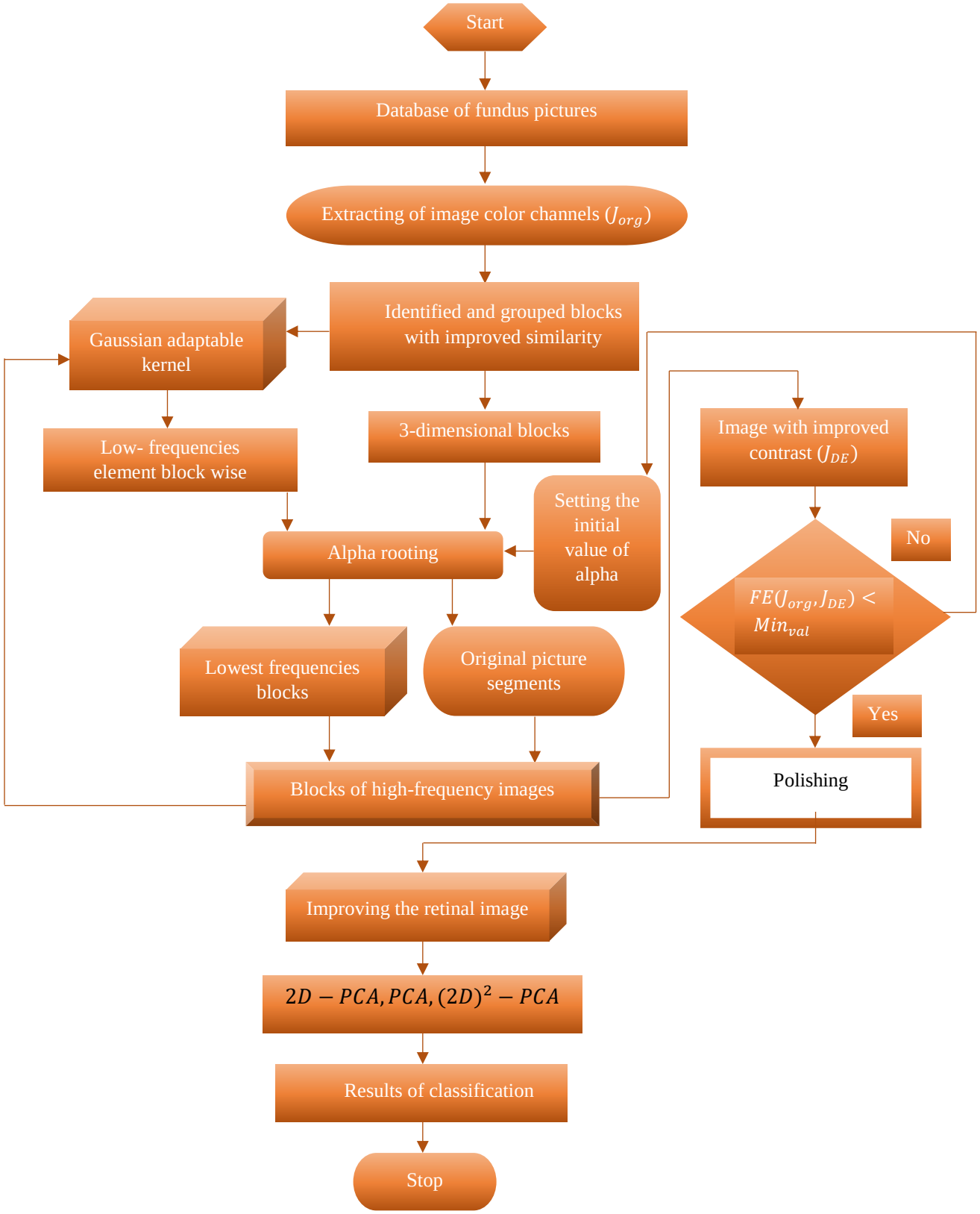

Figure 3. Flow diagram of the suggested procedure

The images present difficulties for feature extraction because they contain weak contrast, irregular patterns of illumination and abundant noise throughout the visual field. Image Color Channels extraction (J_{org}) stands as the first stage of the proposed approach because it divides image spectral components to isolate different retinal structures. Fundus images are collected through color imaging technology, which enables separate analysis of red green and blue channels. The green channel serves best for extracting blood vessels because it creates the clearest contrast between vessels and other retinal structures yet the red channel better reveals deeper retinal structures. The process selectively divides the channels for analysis and ensures detail preservation without including distractive noise that would disrupt forthcoming processing operations.

$$CR = R_N D \quad (1)$$

$$B = (D_i) = 1,2,\ldots,M \quad (2)$$

$$QNE(j) = \frac{G_{req}(j)}{\sum G_{req}} \quad (3)$$

$$V_{RFG}(K) = \frac{r\sum_{l=1}^{r} RFG_l\,(K)}{1+r\prod_{l=1}^{r} RFG_l\,(K)} \quad (4)$$

$$Q = SU_D \quad (5)$$

$$\bar{S} = \frac{1}{N}\sum_{j=1}^{N} S_j \quad (6)$$

CR denotes the Block Similarities Score. R_N = A similarity metric derived from Minkowski distance. D denotes the cosine similarity metric. D_i = Distinct elements of the block, M = Total count of components, $QNE(j)$ = Possibility masses functional at intensity j. $G_{req}(j)$ = Needed histogram's values at intensities j, $\sum G_{req}$ = Total of all histogram values. $V_{RFG}(K)$ = Modified CDF at intensity K, r = Scales element. $RFG_l\,(K)$ = Cumulative Distribution Function for the k-th picture intensity. Q represents the projected data within the PCA space. S = Raw retinal image information. U_D = Matrix for the key component modification. S = Average of the dataset, N = Total count of photos inside the dataset. S_j = Individualised retinal image.

The method continues its process by finding and organizing blocks, which present enhanced similarity between them. Medical image processing relies on image segmentation because this technique enables researchers to separate key features including the optic disc and both macula and blood vessels. The method takes this step to combine pixels that match each other in terms of intensity together with pixels sharing same visual features or colors. The segmentation process enables the method to process different image areas specifically while ensuring that blood vessels remain separate from nearby background areas. The refined blocks arise from applying a Gaussian adaptable kernel to the output.

$$D = \sum_{j=1}^{N}(B_S)\,(B_S)^V \quad (7)$$

$$D = \frac{1}{N}\sum_{J=1}^{N}\left(S_J - \bar{S}\right) \quad (8)$$

$$Q = SU_D U_D' \quad (9)$$

$$E_{Train} = SU_D \quad (10)$$

$$E_{Test} = S_{Test}U_D \quad (11)$$

$$e(E_{Test}) = ||\ E_{Train} - E_{Test}\ ||^2 \quad (12)$$

$$J(m,n,s) = \sum_{M_q=1}^{M_q}\sum_{M_q=1}^{M_q}\sum_{M_s=1}^{M_s} J(m,n,s) \quad (13)$$

$$F = e\left(iE(w_1)\right) \quad (14)$$

$$J_{DF} = MIN_{value} \quad (15)$$

$$V_{JMV}(j) = \left(MAX_j - 1\right)\cdot V_{DEG}(K) \quad (16)$$

C represents the covariance matrices. B_S = Mean-adjusted the retinal image information $(B_S)^V$ represents the transformation of mean-adjusted data. S = Average of training pictures, U_D'= Secondary projections matrices. E_{Train}= Features vectors for the training dataset. E_{Test} = Features vectors for the testing dataset. S_{Test} = Test retina image information, $e(E_{Test})$ = The separation among training and test vectors of features $||\cdot||$ 2 represents the Euclidean distance metric. $J(m,n,s)$ = The degree of effort at pixel coordinates (m,n,s), M_q, M_q, M_s= Block size factors. e(·) = Alpha-rooting operation, j = Imaginary unit, $E(w_1)$ = the Fourier coefficient value at w_1, J_{DF}

= Contrast-enhanced picture. MIN_{value} = Minimal entropy differential limit. $V_{JMV}(j)$ = Intensity transforming function, MAX_j = maximal picture intensity.

Image processing relies on Gaussian filtering because it delivers smoothing effects that protect edge definitions. The technique allows noise reduction as it preserves vital features like blood vessel edges. Gaussian kernels display adaptive properties that let them optimize structure enhancement based on retinal region characteristics.

The system extracts block-wise low-frequency components as its next step. The enhancement of unique image elements in processing relies on analysing frequencies through domain examination. The generalized picture elements make up the low-frequency part while small-scale components comprise the high-frequency elements. The method separates low-frequency components for processing to maintain the image structure while avoiding unwanted distortion of fine image elements. The process then continues with alpha rooting as a contrast-enhancing mathematical technique for transformation. Alpha-rooting technology adjusts pixel intensity values through a specific exponential formula, which depends on the value of alpha parameter. The enhancement process requires setting the initial alpha value for obtaining the best possible contrast results. Fundus images benefit highly from this step since they commonly face contrast problems due to irregular lighting and pigment variation. Gaining enhanced contrast visibility helps medical professionals had better inspect reticular structures, which leads to improved abnormality detection.

$$J_{JNQ} = J_{DF} \quad (17)$$

$$\sum_{e=1}^{e} \lambda_j \, Q_j \quad (18)$$

$$D_{row} = \frac{1}{N} \sum_{l=1}^{N} \sum_{j=1}^{n} S_j \quad (19)$$

$$D_{col} = \frac{1}{N} \sum_{l=1}^{N} \sum_{i=1}^{m} S_i \quad (20)$$

$$\mathrm{C} = \mathrm{argmin} e(E_{Test}) \quad (21)$$

$$G_{req} = JNH_G + VMJ_G \quad (22)$$

J_{JNQ} = Enhanced image subsequent to interpreting, λj = eigenvalues, Q_j = Principal components scalar. D_{row} = The covariance matrices pertaining to rows, n = the quantity of rows in the picture, D_{col} = The covariance matrices for columns, m = The quantity of columns in the picture. C = Estimated category (glaucoma or non-glaucoma), argmin = Segmentation that uses the required distance. G_{req} = Histogram requisite for improvement, JNH_G = Histogram of contrast-enhanced picture, VMJ_G = Uniform histograms, references

After alpha-rooting completion, the method creates a separation of minimal frequency blocks thus removing background noise while maintaining important retinal characteristics. The reference material stays intact as part of the original picture segments to enable further processing. The two-stage processing design lets healthcare professionals achieve better noise reduction together with the protection of essential image characteristics. The method proceeds toward reassembling high-frequency image blocks because these components play a crucial role in identifying microaneurysms together with haemorrhages and exudates that appear in diseased retinas.

Algorithm 1: Enhancing of Retinal Images using a Novel 3D-Alpha Rooting Method

Request: Individualized retinal pictures from the dataset.
Guarantee: An enhanced retinal image IIMP

1. Identify analogous segments of the retinal vision and aggregate them to create three-dimensional blocks.
• Systematically divide the input picture into m × m blocks by taking into account the neighborhood of size n.
• Assess the degree of similarity among each S_Block and J_Block with the suggested block similarities metric.
• Arrange the most analogous N − 1 blocks atop the respective S_Block to create m×m×N image 3D blocks.
Modification of 3D blocks in the alpha-rooting sector.
• Estimation of low-frequency signals in 3D picture blocks via an adaptable 2D Gaussian kernel.
• Implement a novel alpha rooting methodology through the adaptive modification of the α value.
• Enhancing contrast produced a better picture by eliminating low-frequency features.
3. Adjustment of picture over-enhancement by DEG transformations (VDEG) for the creation of enhanced images.

High-frequency components establish borders and textures that are essential for proper identification of objects. The algorithm restores and amplifies these components after processing to maintain all subtle characteristics in the input data. The retinal image enhancement process advances to total image quality improvement after performing high-frequency detail enhancement. Dimensionality reduction techniques allow practitioners to utilize Principal Component Analysis (PCA) for their operations. PCA stands as a commonly recognized statistical tool because it reduces high-dimensional data into a lower-dimensional space while holding onto the most vital information. The proposed method utilizes various PCA techniques that involve 2D-PCA together with PCA and (2D) 2 2 -PCA. The methods decrease the complexity of operations but maintain fundamental image characteristics. Traditional PCA analyses images through vectorized formats yet this approach normally results in the loss of spatial image characteristics. Two-dimensional principal component analysis and (2D) 2 2 principal component analysis preserve image matrix structure for direct computation so they better extract spatial information from the data. Dimensionality reduction methods optimize the retinal images specifically for classification purposes without eliminating crucial diagnostic information. The system checks the enhanced image (J_{DE}) against a specified threshold at this evaluation period. The method evaluates enhancement effectiveness by using the function $FE(J_{org}, J_{DE})$ to produce an output. The image enhancement process continues until the system identifies that the minimum threshold (Min val) is not met. At this point additional image processing will start to increase image contrast and clarity. The classification phase follows only when the image enhancement meets the established minimum threshold. The classification procedure plays an essential role since it decides if the retinal picture shows healthy or sick features.

$$M = F * [|E(w_1, w_2, w_3)|]^{\propto} \quad (22)$$

where α is a number within the interval (0,1), $|E(w_1, w_2, w_3)|$ denotes the currently present magnitude element, and F is specified as an integral of $||E(w_1, w_2, w_3)|$, β, and η.

$$F = e(|E(w_1, w_2, w_3)|, \beta, \eta = abs\left(\beta - \frac{\beta}{(|E(w_1, w_2, w_3)|^{\eta}}\right) \quad (23)$$

We achieved optimal enhancing outcomes by modifying the values of β within the interval (0.6, 1.0) and η within the interval (0.1, 0.5), where abs denote the absolute value. VMJ_G denotes the statistical analysis of contrast-enhanced images (JDF) and the uniform histograms, They have defined an instance of the needed histogram (G_{reg}) to align JNH_G closely with VMJ_G.

$$G_{reg} = \phi(JNH_G) + (1 - \phi)VMJ_G, 0 < \phi < 1 \quad (24)$$

The application of machine learning along with deep learning models determines classification tasks in medical imaging systems. The enhanced images produce attributes, which feed into classifiers that consist of Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), and other progressive classification systems. Modalities process the retinal structures to detect specific patterns that indicate diseases like diabetic retinopathy at glaucoma at age-related macular degeneration.

Algorithm 2: Glaucoma Detection using 2D-PCA

Request: Expanded data sets for training and testing in DWT representations.
Guarantee: Verify the categorization outcome of glaucoma.

1. Compute the 2D Discrete Wavelet Transform coefficients matrices (m×n) of the input tests and training retinal datasets as 2D vector forms. This is the source vector set (J1, J2, ..., JQ) in two dimensions and the evaluation vectors set (I1, I2, ..., IQ) in two dimensions.
2. Calculate the mean $\bar{S}$ of the simulated dataset. (Refer to Equation 6).
3. Eliminate the mean value from each of the vectors in the initial training and testing data sets, resulting in the modified sets.
4. Acquire the matrix of covariant C of a training dataset by focusing just on each row of data pertaining to the retinal picture (refer to Equation 8).
   Construct a transformed matrix VC by using the eigenvectors associated with the d greatest eigenvalues derived from the eigen decomposed of matrices C.
5. Acquire retinal image features vectors E_Train and E_Test of dimensions [e × e] × Q and [e × e] × P, respectively (refer equation 12).
6. Categories each retina imaging vectors in the one being tested set as glaucoma or non-glaucoma based on its adjacent neighbors in the training set.

The diagnostic result from classification identifies the disease category the image belongs to or determines it lies within normal parameters. The obtained result gets stored for medical professionals to analyse ahead. Through image enhancement and feature extraction enhancement that occurs systematically the proposed method delivers dependable automation for diagnosing retinal diseases. The systematic enhancement process combined with noise reduction and frequency domain processing and contrast improvement and dimensionality reduction and classification produces a valuable medical imaging tool for retinal images.

$$I_{org} = e(R, G, B) \quad (25)$$

$$I_s(m,n) = \sum_{j=-l}^{l} \sum_{i=-l}^{l} H(j,i)\, I_{org}\,(m-j, n-i) \quad (26)$$

$$I_{enh}(m,n) = I_s(m,n)^{\propto} \quad (27)$$

$$I_{low} = E^{-1}[G_{low}(r,s) E\big(I_{enh}(m,n)\big)] \quad (28)$$

$$I_{PCA} = Z^V\, I_{enh} \quad (29)$$

$$D = \arg\max_j Q(x = j|\ I_{PCA}) \quad (30)$$

I_{org} → The initial picture obtained using the fundus imaging database, R, G, B → The image's red, green, and blue colour pathways, $e(R, G, B)$ → An operation which analyses and retrieves the requisite colour elements. $I_s(m,n)$→ The smoothed picture subsequent to the application of the Gaussian filter, $I_{org}\ (m,n)$ → The original picture pixel located at locations (m,n), $H(j,i)$ → The Gaussian kernel utilised for noise reduction. l → The kernel's windows size, $I_{enh}(m,n)$ → The contrast-enhanced picture, $I_s(m,n)$ → The picture subsequent to Gaussian softening, α → The alpha-rooting variable that regulates the level of improvements, I diminishes The frequencies low element of the picture, $E\big(I_{enh}(m,n)\big)$ → The Fourier transformation of the augmented picture, $G_{low}(r,s)$→ The low-pass filtering is utilised in the rate area; E^{-1} denotes the inverse of the Fourier transform for conversion back to the spatial realm. I_{PCA} represents the image with fewer dimensions following PCA application, while W signifies the main portion of the change's matrices. I_{enh} indicates the contrast-enhanced picture, and C denotes the class that is anticipated (e.g., typical or disease-affected retinal). $Q(x = j|\ I_{PCA})$ refers to the chances that the pictures is related to class j, based on the features extracted via PCA. The coefficient argmax chooses the class alongside the greatest probability.

An effective process of fundus image evaluation offers clear benefits to ophthalmologists through early disease discovery which facilitates prompt interventions for better patient results. The proposed method integrates seamlessly into telemedicine systems to conduct distant diagnoses of retinal diseases through removing limitations that arise from distant medical facilities in underserved areas. The proposed system can become even more efficient and precise through the addition of deep learning for end-to-end image processing of retinal diseases. The method establishes a complete framework to upgrade retinal images while performing classification tasks that builds advanced diagnostic systems for ophthalmology practice.

8. Results

Our research focuses on the systematic improvement of fundus images prior to glaucoma categorization. The suggested 3D block-based adaptable alpha rooting approach has demonstrated its superiority compared to HE or CLAHE enhancing methods. The final photos exhibit a harmonious combination of color and structural information. Glaucoma categorization is performed on the improved pictures utilizing combinations of PCA and DWT. Our method's effectiveness is comparable to that of glaucoma categorization with CNN. Empirical evidence indicates that the biorthogonal DWT combined with (2D)2-PCA is the ideal approach for glaucoma categorization. This PCA-based technique for classification relies solely on the most prominent principal component for patterns the extraction procedure, potentially resulting in a loss of textural features in certain instances.

8.1 Accuracy: This is the proportion of accurately identified occurrences (including both true positives and true negatives) relative to the total number of occurrences. Increased accuracy signifies improved results.

8.2 Sensitivity: This evaluates the model's capacity to accurately detect positive cases. It is especially advantageous when negative results are more harmful.

8.3 Specificity: The evaluation analyses the model's accuracy in spotting negative situations. When the potential for false positives is high, this becomes more crucial.

8.4 Precision: Estimates that turn out to be correct are quantified by precision. For positive forecasts in particular, it reveals what percentage were right. An indication of few false positives is a high level of accuracy.

8.5 F1-Score: This strikes an even balance between the two extremes of accuracy and memory, like a harmonic mean. It really shines in situations when the separation of classes is not uniform.

8.6 Processing Time (s): This refers to the duration required for the algorithm to analyse and provide predictions based on the input data, quantified in seconds. Reduced processing time is advantageous for expedited decision-making.

8.7 Execution Time (s): The algorithm's execution time, in seconds, is the sum of all the time it spends training or testing. This consist of not just the processing time of the design but also any associated expenses. It is more efficient to have a lower execution time.

8.8 AUC (Area Under the ROC Curve): At different threshold values, it measures the efficacy of categorization issues. It shows how likely it is that the algorithms will give more weight to a positive instance than a negative one, based on a random selection. An improved efficiency of the model is indicated by a higher AUC.

Table 2: Contrasting Models Using Their Sensitivity and Accuracy

Models	Accuracy (%)	Sensitivity (%)
CNN	90.3	88.2
SVM	86.3	83.1
KNN	81.2	79.0
RF	87.1	85.3
PCA	85.2	82.6
DWT	84.2	80.1
U-net	91.0	90.2
Proposed 3D block-based adaptive alpha rooting method	95.1	93.8

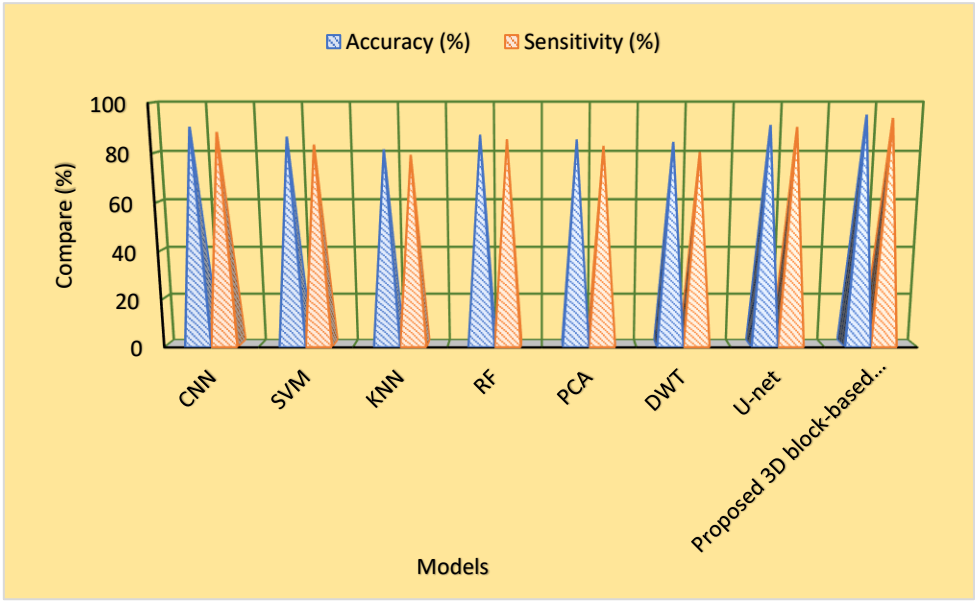

Figure 4. Testing Different Models Using Accuracy and Sensitivity

The two vital metrics Accuracy and Sensitivity provide the basis for evaluating the different machine learning models in the table. A Proposed 3D block-based adaptive alpha rooting method succeeds in outperforming other models while achieving maximum Accuracy at 95.1% and maximum Sensitivity at 93.8%. U-net delivers an accuracy result of 91.0% and sensitivity measurement of 90.2%. The CNN model displays effective performance through Accuracy of 90.3% along with Sensitivity of 88.2%. Models like SVM (86.3% Accuracy, 83.1%

Sensitivity) and RF (87.1% Accuracy, 85.3% Sensitivity) exhibit moderate results. The KNN model demonstrates the lowest performance compared to other models because it achieves 81.2% Accuracy alongside a Sensitivity of 79.0%. The Performance scores from PCA and DWT fall behind other methods because their Accuracy reaches 85.2% and Sensitivity reaches 82.6% and 84.2% and 80.1%, respectively.

Table 3: Examining Different Models Using Specificity and F1-Score

Models	Specificity (%)	F1-Score (%)
CNN	89.4	89.6
SVM	84.5	85.3
KNN	80.4	82.3
RF	86.3	86.8
PCA	83.2	84.5
DWT	82.1	82.2
U-net	90.3	90.5
Proposed 3D block-based adaptive alpha rooting method	94.5	95.7

The performance assessment table presents Specificity and F1-Score values from different models for evaluation. The Proposed 3D block-based adaptive alpha rooting method achieves the highest Specificity at 94.5% as well as the best F1-Score of 95.7% because of its superior overall performance. Both the U-net exhibits promising metrics as it attains Specificity of 90.3% and F1-Score of 90.5%. CNN proves to be the second-best model according to Specificity at 89.4% while achieving 89.6% F1-Score. The RF model demonstrates a good performance level through 86.3% Specificity and 86.8% F1-Score measurement results. SVM along with PCA demonstrate average performance levels with F1-Score at 85.3% and Specificity at 84.5% respectively. However, DWT, KNN show substantial variation in output ratings with Specificity at 82.1% and F1-Score at 82.2% alongside Specificity at 80.4% and F1-Score at 82.3%.

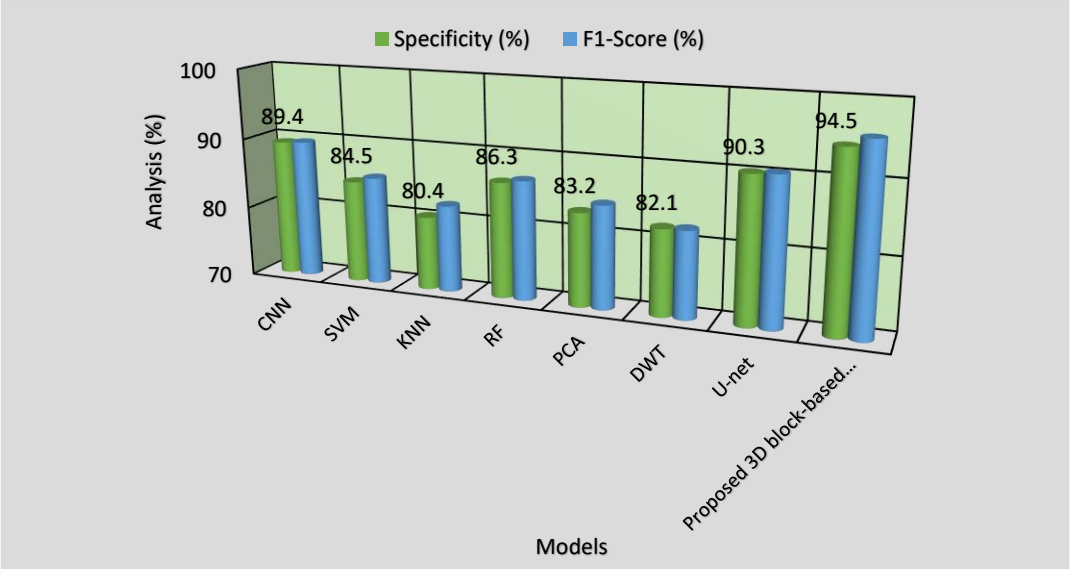

Figure 5. Comparing of Models according to Specificity and F1-Score

Table 4: Evaluating the Suggested DDCNN-F against Current Models Using F1-Score and AUC

Models	AUC	Precision
CNN	0.92	0.89
SVM	0.88	0.85
KNN	0.86	0.80
RF	0.90	0.87
PCA	0.89	0.84
DWT	0.87	0.83
U-net	0.93	0.90
Proposed 3D block-based adaptive alpha rooting method	0.97	0.95

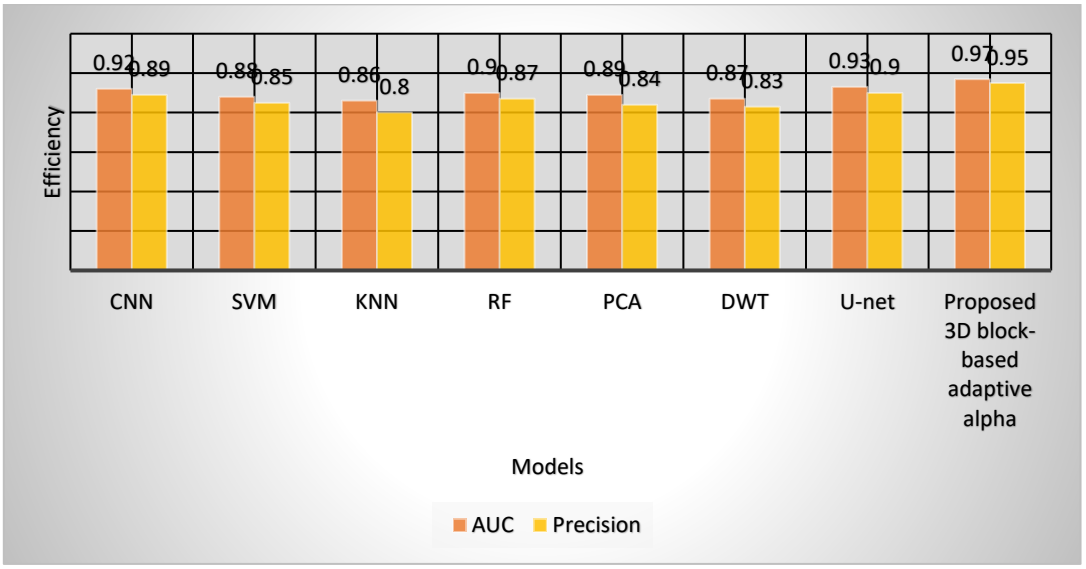

Figure 6. Analysis of the Suggested DDCNN-F's Effectiveness in Relation to Current Models Using F1-Score and AUC

The different models perform according to AUC (Area Under the Curve) and Precision metrics as presented in the table. A Proposed 3D block-based adaptive alpha rooting method stands out best since it achieves top marks for both AUC at 0.97 and Precision at 0.95. The results from U-net match the values of 0.93 AUC and 0.90 Precision yet CNN achieves similar outcomes at 0.92 AUC and 0.89 Precision. The analysis of the RF model reveals a solid performance through its AUC measurement of 0.90 and Precision measurement of 0.87. PCA shows equivalent outcome to DWT since their AUC values match at 0.89 and their precision levels match at 0.84 while precision stands at 0.83. The performance metrics of SVM (AUC: 0.88, Precision: 0.85) along with KNN (AUC: 0.86, Precision: 0.80) score the lowest in both evaluation measures.

Table 5: Comparing of Models via Processing and Execution Time

Models	Processing Time (s)	Execution Time (s)
CNN	4.8	6.4
SVM	4.5	5.8
KNN	3.9	5.2
RF	4.6	5.9

PCA	3.8	4.9
DWT	3.5	4.7
U-net	4.2	6.0
Proposed 3D block-based adaptive alpha rooting method	3.1	3.9

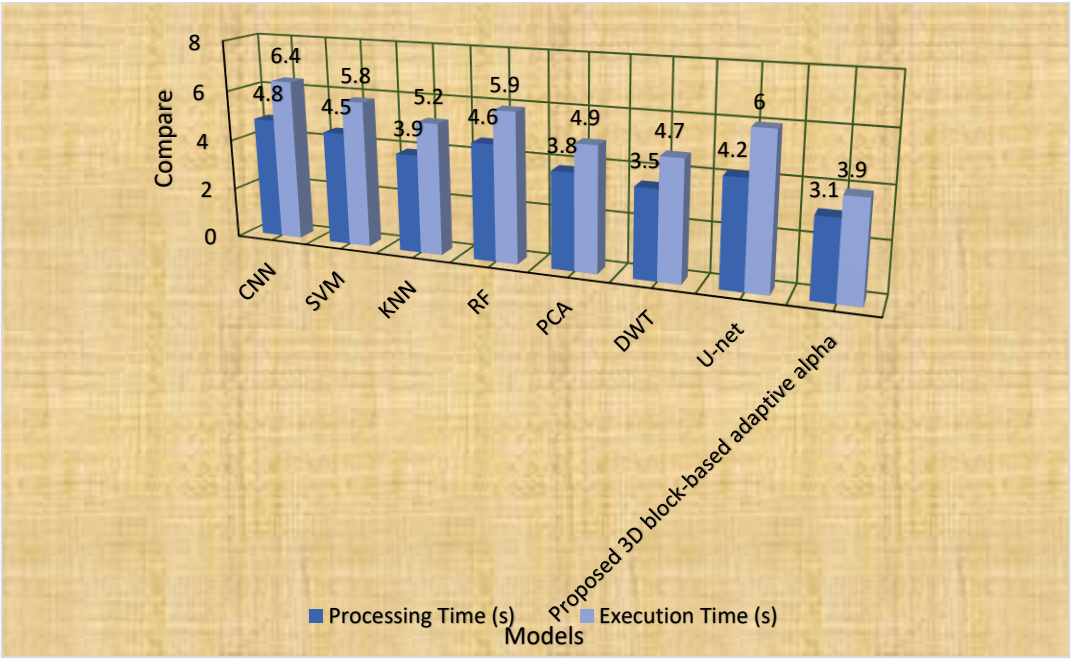

Figure 7. Evaluation of Models Using Processing Time and Execution Time

Processing Time and Execution Time serve as the basis for the model comparison in the provided table. The Proposed 3D block-based adaptive alpha rooting method delivers the best performance through its lowest Processing Time (3.1 seconds) and Execution Time (3.9 seconds) which indicates high efficiency. This DWT model attains Processing Time results of 3.5 seconds together with Execution Time results of 4.7 seconds. The Processing Time of PCA amounts to 3.8 seconds and its Execution Time reaches 4.9 seconds. The Processing Time for KNN amounts to 3.9 seconds while its Execution Time reaches 5.2 seconds. SVM requires 4.5 seconds for Processing and 5.8 seconds for Execution. The RF model completes its Processing Time in 4.6 seconds before finishing its Execution Time at 5.9 seconds. The Processing Time for CNN model lasts 4.8 seconds before reaching an Execution Time of 6.4 seconds yet U-net leads with 4.2 seconds of Processing Time followed by 6.0 seconds of Execution Time making it slower than other models.

9. Conclusion

A new adaptive alpha-rooting 3D-block system serves as a retinal image enhancement method that also performs glaucoma detection through classification. Many enhancement techniques at present generate misclassification through their inability to keep optic disc and optic cup structures intact. This method solves the block identification and enhancement problems through a new similarity computation model, which unites Minkowski distance with cosine similarity measures. This approach rapidly alters contrast without influencing important retinal structural aspects, leading to improved picture clarity and superior classification results. The research incorporates transform-based analysis with principal component analysis variants to obtain features. Biorthogonal wavelet transform integrated with two-directional principal component analysis reaches its highest accuracy level during experimental testing on public databases, which include hospital-acquired fundus images. The method utilizes efficient computation that produces results better than traditional statistics yet reaches equivalent outcomes to deep learning methods. This proposed detection approach resolves the distance between traditional image processing and deep learning techniques by supplying a budget-friendly solution with hardware-friendly components and accurate glaucoma diagnosis. Researchers have developed dependable computer-aided diagnosis systems through

this study, which presents an applicable clinical solution. The proposed method should adapt for future work by applying it to multiple retinal imaging modalities alongside techniques designed to enhance classification precision in real clinical situations.

Future Work

The suggested approach can be expanded to multi-modal retinal imaging in the future by including other imaging modalities to improve diagnosing precision, for example, OCT and fluorescein or angiogram. To make it more resilient, we may optimize the categorizing architecture even further by employing deep learning and statistics hybrid models, as well as sophisticated method for selecting features. Improvements in computing effectiveness by real-time processing methods make the system well suited for use in healthcare settings. Another way to make the algorithm more applicable in real-world situations is to add retinal pictures from a wider range of demography to the dataset. The categorization findings may be made more interpretable by looking into the incorporation of explainable AI approaches, which can help eye specialists make better clinical judgments.

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