DOI: 10.21917/ijivp.2024.0474

DEEP NEURAL MULTI WAVELET SEGMENTATION AND RESNET-50 IMAGE CLASSIFICATION (DNMWS-RESNET-50IC) BASED EARLY GLAUCOMA DETECTION

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Abstract

Glaucoma, a leading cause of irreversible blindness worldwide, results from progressive damage to the optic nerve, often linked to elevated Intra Ocular Pressure (IOP). Early detection is critical for preventing vision loss, yet traditional diagnostic methods can be limited in accessibility and effectiveness, particularly in the early stages of the disease. Addressing the need for early detection, we propose the Deep Neural Multi-Wavelet Segmentation and ResNet-50 Image Classification (DNMWS-ResNet-50IC) method, specifically designed to detect glaucoma at an early stage using retinal fundus images. In this work, we apply Anisotropic Gaussian Filtering for the preprocessing of retinal fundus images, effectively reducing image noise while preserving the original quality of the image pixels by creating an adaptive window size and scale space. We then utilize multi-wavelet-based image segmentation, leveraging wavelet transforms to analyze and decompose the image into its various frequency components. This technique is particularly advantageous for managing images with complex structures and textures. Subsequently, the segmented features are classified using the ResNet-50 model, which categorizes the images as normal, abnormal, or indicative of early-stage glaucoma. The effectiveness of the proposed method is assessed by measuring three key performance indicators sensitivity, specificity, and accuracy on digital retinal images from the HRF image database. Additionally, the model's performance is further evaluated on a separate test set, considering metrics such as accuracy, precision, recall, and prediction time.

Keywords:

Irreversible Blindness Intraocular Pressure (IOP), Deep Neural Networks (DNN), Multi-Wavelet Segmentation, ResNet-50, Retinal Fundus Images, Anisotropic Gaussian Filtering, Image Preprocessing, Wavelet Transforms

1. INTRODUCTION

Glaucoma is one of the leading causes of irreversible blindness worldwide, characterized by progressive damage to the optic nerve, often associated with elevated intraocular pressure. Early detection and intervention are crucial in managing glaucoma and preventing vision loss. However, the subtlety of early-stage symptoms and the complexity of the condition pose significant challenges to traditional diagnostic methods, which often rely on manual evaluation and interpretation of optical coherence tomography (OCT) scans and fundus images. The need for automated, accurate, and efficient diagnostic tools has driven the development of advanced image processing and machine learning techniques.

In recent years, deep learning has emerged as a powerful tool for medical image analysis, offering the potential to significantly enhance the accuracy and efficiency of disease detection. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable performance in various image classification tasks, including the identification of ocular diseases such as diabetic retinopathy, age-related macular degeneration, and glaucoma. Despite these advancements, the early detection of glaucoma remains a challenging task due to the need for precise segmentation of retinal structures and accurate classification of subtle abnormalities.

This paper introduces a novel approach, Deep Neural Multi-Wavelet Segmentation and ResNet-50 Image Classification (DNMWS-ResNet-50IC), aimed at improving the early detection of glaucoma. The proposed method integrates multi-wavelet transform-based segmentation with the ResNet-50 deep learning architecture to achieve high-precision image classification. The multi-wavelet transform is leveraged to enhance the representation of retinal features, enabling more accurate segmentation of critical structures, such as the optic disc and retinal nerve fiber layer. Following segmentation, the ResNet-50 model is employed to classify the segmented images, identifying early signs of glaucoma with high accuracy.

The DNMWS-ResNet-50IC framework is designed to address the limitations of existing methods by combining the strengths of multi-wavelet analysis and deep learning. This integration not only enhances the feature extraction process but also improves the overall robustness and reliability of glaucoma detection. Through extensive experimentation and evaluation, this study demonstrates the efficacy of the proposed method in accurately detecting early-stage glaucoma, potentially paving the way for more effective clinical screening tools.

In the following sections, we provide a detailed overview of the related work, describe the methodology of the proposed DNMWS-ResNet-50IC framework, present the experimental results, and discuss the implications of our findings for future research and clinical practice.

2. LITERATURE SURVEY

Gupta et al. [3] introduced a framework for glaucoma detection that enhances retinal image contrast using Contrast Limited Adaptive Histogram Equalization (CLAHE) and employs the EfficientNet deep learning model for classification. Their approach significantly improved the accuracy, sensitivity, and specificity of glaucoma detection compared to existing methods. The study demonstrates the effectiveness of combining advanced image pre processing with a powerful CNN architecture. This work highlights the potential for such integrated techniques in improving early glaucoma diagnosis. Gheisari et al. [4] proposed a hybrid model combining CNN and RNNs to enhance glaucoma detection. This approach leverages CNNs for spatial feature extraction and RNNs for capturing temporal dependencies, leading to improved diagnostic performance. The study demonstrated the model's superior accuracy and robustness compared to standalone CNNs. This innovative combination highlights the potential of integrating different neural network architectures for more effective glaucoma detection. However, spatial, and temporal features over the fundus videos were linked with CNN and RNN for increasing the accuracy of glaucoma detection [4].

Transfer Induced Attention Network (TIA-Net) was presented in [5] to the automatic glaucoma detection that extracts the discriminative features of glaucoma-related deep patterns in restricted supervision. However, designed method performs the smooth transition among common and individual features for increasing the feature transferability. Self-Organized Operational Neural Networks (Self-ONNs) were introduced in [6] for the early recognition of glaucoma in fundus images. Different deep learning methods was utilized to identify the glaucoma over the digital fundus images to the scarcity of identified data using better computational complexity and individual hardware requirements. Digital Image Processing was designed in [7] permits the creation of techniques to the automatic detection of glaucoma using computational methods of machine learning. Though, designed approach was necessary for attaining the favourable diagnosis and enhances the patient's quality of life. In [8], the glaucoma was utilized in deep learning algorithm for investigating the glaucoma images. Though, the fundamental purpose is used for identifying the glaucoma within retinal fundus images for measuring whether a patient has the requirement.

Robust glaucoma detection schemes were carried out in [9] using the deep learning methods. The novel context aware deep learning structure termed as GD-YNet, for OD segmentation and glaucoma recognition. However, the early detection and clinical interventions are essential for enhancing the results of glaucoma. Gheisari et al. [10] developed a novel approach for glaucoma detection by integrating CNNs with RNNs, enhancing both spatial feature extraction and temporal analysis. This hybrid model outperformed traditional CNNs, offering improved accuracy and robustness in detecting glaucoma. The study underscores the effectiveness of combining CNN and RNN architectures to better capture complex patterns in retinal images. Though, designed method provides the lack of high-efficiency glaucoma diagnostic tools on visual fields (VFs).

Krishna Adithya et al. [11] introduced EffUnet-SpaGen, a novel approach for glaucoma detection that combines efficiency with spatial generative modeling. This method leverages the EffUnet architecture, which enhances segmentation accuracy, and incorporates spatial generative models to better capture and analyze retinal structures. The study demonstrated that EffUnet-SpaGen significantly improves the precision of glaucoma detection, particularly in challenging cases. However, automated disease recognition focuses on requiring procedures "slimmer" minimizing the huge training datasets and accelerating recalibration for performing better accuracy. In [12], individual departure over the usual technique of wavelet transform was utilized to pre-processed retinal fundus images and handcrafted features removed over the decomposition outcomes. However, ever rising require for inexpensive, minimal, rapid, and correct healthcare solutions trained to the consistent implementation of artificial intelligence within the medical fields.

Martins et al. [13] developed an offline computer-aided diagnosis (CAD) system for glaucoma detection using fundus images, specifically designed for mobile devices. Their approach focuses on making glaucoma diagnosis more accessible by enabling high-accuracy detection without the need for continuous internet connectivity. The study demonstrated that their CAD system is effective in providing reliable diagnostic support, making it particularly useful in resource-limited settings. However, the conventional methods used to analyse glaucoma expensive and bulky tools involves limited experts for requiring the demanding task, valuable, and time-consuming to establish huge number of people. DL model was carried out in [14] to understand the finer ocular constructions within 3D OCT volumes for enhancing the performance of guidance. End-to-end attention managed 3D DL technique to glaucoma recognition and assessing visual function over the retinal structures. But the restrictions of network's capability used for understanding over small retinal structures within OCT volumes.

Glaucoma is a neuro-degenerative eye disease obtained in [15] for enhancing the Intra-ocular Pressure inside the retina. However, there is an enormous necessity of developing a system that can effectively work for the lack of unnecessary equipment, skilled medical practitioners, and minimal time consumption. Spectralis optical coherence tomography (OCT) was performedin [16] to the detailed parameters within the peripapillary and macular areas between the OCT machines. However, it is not simple to recognize the huge data produced over the Spectralis OCT within glaucoma consideration. Machine learning approach has been well-applied in glaucoma recognition for managing the huge volume of data.

In [17], Glaucoma detection is the significant investigation within intelligent system, and performs the key role to the medical field. Glaucoma improves the irreversible blindness to the absence of accurate diagnosis. However, the designed method needs thehuge time and expense to identify the glaucoma for minimizing the time and cost. A threshold-based procedure was utilized in [18] for segmenting the Optic Disc. The modified region growing algorithm was employed to the cup region. Though, designed approach could accurately forecast the occurrence of Glaucoma using minimal computational requirements. The wavelet-based glaucoma recognition was intended in [19] to the real-time screening techniques. The proper treatment of glaucoma reduces the difficult vision losses associated with developed stages of the disease in early detection. Periodic automatic screening benefits to minimize the workload on expert ophthalmologists in the early detection of glaucoma. Cup-to-disc ratio (CDR) and disc damage likelihood scale (DDLS) was provided in [20] for evaluating the glaucoma. But CDR and DDLS is relatively complex for various features such as shape, size, etc of the optic disc and optic cup. However, designed method aids to enhance the eye disease diagnosis and evaluation. Those who estimated using machine learning (ML) approaches [21] reported high diagnostic accuracy for glaucoma detection. The purpose of this study was to externally validate the ML model for glaucoma detection in optical coherence tomography (OCT) data. The purpose of this paper is to validate an ML model for glaucoma detection in OCT data and a machine learning (ML) model applied to structural OCT data to support glaucoma diagnosis. Online Retinal Fundus Image Database for Glaucoma Analysis (ORIGA) [22]. Manual identification of glaucoma-affected areas from fundus specimens requires an experienced anthropologist who can identify small visible details and classify the images into appropriate segments. In the proposed method, they propose a deep learning method EfficientDet-D0 and EfficientNet-B0 as a base network to identify and classify glaucoma from retinal images. Previous studies have trained a single convolutional neural network [23] to automatically detect glaucoma. So, four methods are used to integrate a convolutional neural network model into three deep learning architectures for glaucoma classification. This paper proposes a fundus image glaucoma detection model using graph-analysis and convolutional neural network integration. Using radiography, the optic disc is first identified in the fundus images. Made the detailed report of the main algorithms for processing retinal [24] images using machine learning (ML) for glaucoma detection and diagnosis. These features highlight the importance of machine learning in retinal image processing. Machine learning architectures for retinal image processing, some studies use feature extraction and dimensionality reduction to identify and separate important features of imagesused by them. An Active Deep Learning with the convolutional neural networks model (ADL- CNN) was developed in [25] to efficiently extract features for accurate diabetic retinopathy detection. But it failed to extend ADL-CNN multi-layer architecture for enhancing the accuracy by considering multiple images.

2.1 CONTRIBUTION AND OBJECTIVES

- The development of deep learning models, such as the multi-wavelet segmentation ResNet-50 algorithm, and other machine learning techniques are crucial for advancing the early detection of glaucoma.
- These technologies are capable of analyzing complex datasets, including retinal images and patient data, to identify patterns indicative of glaucomatous damage.
- The proposed DNMWS-ResNet-50IC technology has shown significant potential in imaging the retina and optic nerve head for the detection of glaucoma.
- This approach can be further developed to extract features indicative of glaucomatous damage, such as changes in retinal nerve fiber layer thickness, thereby enhancing diagnostic accuracy.
- Implementing these methods can improve the overall accuracy of glaucoma detection, with MATLAB serving as a powerful tool for multi-modal data fusion and analysis.
- Deep learning architectures can be trained on large datasets of retinal images, which enhances the accuracy and reliability of glaucoma detection.
- Utilizing pre-trained deep learning models on large image datasets and fine-tuning them specifically for glaucoma detection represents a promising approach in medical imaging

3. PROPOSED METHODOLOGY

3.1 DEEP NEURAL MULTI WAVELET SEGMENTED AND RESNET-50 IMAGE CLASSIFICATION (DNMWS-RESNET-50IC)

Deep neural Multi wavelet segment ResNet-50 classification model for glaucoma disease image classification involves several key steps. ResNet-50 is a deep convolutional neural network architecture that has proven effective for image classification tasks. Gather ACRIMA database a of eye images, including both normal and glaucomatous cases. Detection of glaucoma from images involves analyzing features that may indicate structural changes in the optic nerve or other relevant regions of the eye. Apply data augmentation techniques to increase the diversity of the training set. Normalize pixel values to a range suitable for the ResNet-50 model (e.g., between 0 and 1).

The multi-wavelet segmentation technique can be employed to enhance feature extraction by analyzing different frequency components of input images, applying wavelet transforms at multiple scales to capture various details. The ResNet-50 component functions as a powerful image classifier, capable of learning and recognizing complex patterns associated with glaucoma. The integration of deep learning and wavelet analysis improves the accuracy and efficiency of glaucoma detection from medical images, with performance depending on factors such as the quality and quantity of both training and testing data. The ResNet-50 architecture consists of multiple stacked residual blocks, with the final output typically processed by a global average pooling layer followed by a fully connected layer for classification.

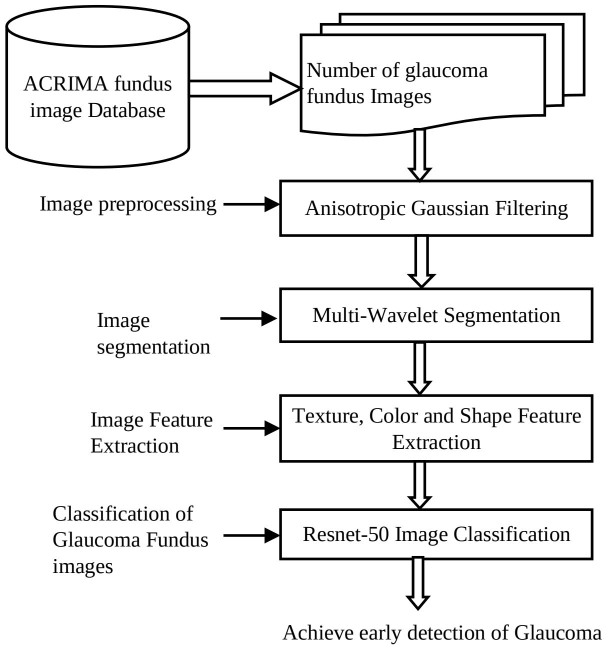

Fig.1. Architecture Diagram of Deep Neural Multi wavelet segmentation and Resnet-50 image Classification (DNMWS-Resnet-50IC)

The Fig.1 shows the architecture diagram of the Deep Neural Multi-Wavelet Segmentation and ResNet-50 Image Classification (DNMWS-ResNet-50IC) model.

3.2 ANISOTROPIC GAUSSIAN FILTERING USED IMAGE PRE-PROCESSING TECHNIQUE

Anisotropic Gaussian filtering is a technique used in image processing for noise reduction. It is an extension of the standard Gaussian filtering method, where the filter weights are adjusted based on the local image structure. This adaptation allows the filter to preserve edges and fine details while effectively smoothing areas with less texture. The technique is particularly useful in scenarios where isotropic (standard) Gaussian filtering might blur important edges.

It involves the anisotropic Gaussian into a one-dimensional Gauss filter in the x-direction followed by a one-dimensional filter in a non-orthogonal direction. It can be used to reduce image noise without blurring edges. It is similar to anisotropic Gaussian filtering in that it aims to preserve edges

The filter weights are adjusted based on the local gradient information. The general equation for anisotropic Gaussian filtering is as follows:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{D(x,y)^2}{2\sigma^2}\right) \tag{1}$$

The Eq.(3.1) provides a conceptual understanding of anisotropic Gaussian filtering. $G(x,y)$ is the filter weight position (x,y), σ is the standard deviation of the Gaussian distribution, controlling the width of the filter, $D(x,y)$ is the directional distance, which is a measure of how far the pixel at position (x,y) is from the center of the filter along the local gradient direction. Fig.2 shows the image processing using Anisotropic Gaussian Filtering.

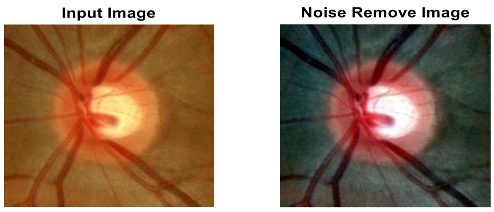

Fig.2. Anisotropic Gaussian Filtering image Process

Algorithm 3.1: Algorithmic Pre-process of Anisotropic filtering

Input: Input images $I_n=I_{n1},I_{n2},\ldots,I_{nn}$, Eigen values '$eig_1,eig_2$', Ortho normal eigen vectors ve_1,ve_2

Output: Pre-processed image $PreIm$ = $PreIm_1$, $PreIm_2,\ldots$, $PreIm_n$) with improved PSNR

Step 1: **Begin**

Step 2: **For** each Input images *In*

Step 3: Measure average image of all images using Eq.(1)

Step 4: Obtain Eigen values eig_1,eig_2

Step 5: Obtain diffusion value eig_1,eig_2 for corresponding input images *In* using Eq.(1)

Step 6: Return (Pre-processed image $PreIm = PreIm_1$, $PreIm_2,\ldots$, $PreIm_n$)

Step 7: **End for**

Step 8: **End**

3.3 PRE-PROCESS OF ANISOTROPIC FILTERING

Anisotropic filtering is often implemented by using a set of filters, each aligned with a specific orientation. The filter weights are then computed independently for each orientation, and the final filtered value at each pixel is a weighted sum of the values obtained from all orientations.

3.4 MULTI-WAVELET IMAGE SEGMENTATION TECHNIQUE

Multi-wavelet-based image segmentation involves the use of multi-wavelet transforms to decompose an image into different frequency components. This decomposition can enhance the representation of specific features in the image, making it easier to identify structures related to glaucoma. Here is a general outline of the steps involved in multi-wavelet-based glaucoma detection and image segmentation

Multi-wavelet transforms offer advantages over traditional wavelet transforms by providing better directional selectivity and capturing information at multiple scales. Utilize a segmentation algorithm to delineate regions of interest within the image. This step involves classifying pixels or regions based on the extracted features. Common segmentation techniques include thresholding, clustering, and region-based methods. The Fig.3 illustrates the process of threshold image segmentation.

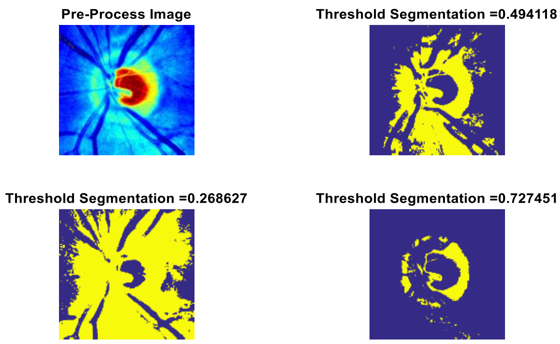

Fig.3. Threshold Image Segmentation

Multi-wavelet-based image segmentation for glaucoma detection likely involves using mathematical tools called multi-wavelets to analyse and process medical images, particularly those related to the eye for detecting signs of glaucoma.

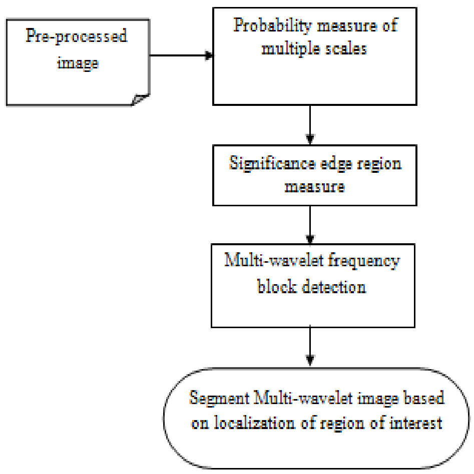

Fig.4. Block diagram of Multi-Wavelet based Segmentation

The Fig.4 presents the block diagram of the multi-wavelet-based segmentation. Multi-wavelets is to capture more information from different frequency bands in the image, which can be beneficial for distinguishing subtle details and patterns associated with glaucoma. Image segmentation, in this context, refers to the process of partitioning an image into different regions to extract meaningful information.

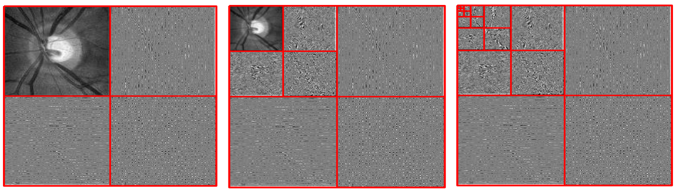

Fig.5. Multi-Wavelet Segmentation Process

The multi-wavelet transform involves a set of functions for both approximation and detail coefficients. The equations become more complex but follow a similar framework.

$$W(j,k)=\sum ns(n)\cdot\phi j,k(n)+\sum nd(n)\cdot\psi j,k(n) \quad (2)$$

$$W_{multi}(j,k)=\sum ns(n)\cdot\phi j,k(n)+\sum n\sum pdp(n)\cdot\psi p,j,k(n) \quad (3)$$

where $s(n)$ is the approximation (smooth) coefficients, $d(n)$ is the detail coefficients, and $\phi j,k(n)$ and $\psi j,k(n)$ are the scaling and wavelet functions, respectively. $dp(n)$ represents the detail coefficients for the p-th multi-wavelet. Multi-wavelet continuous wavelet transform (MCWT) is given by the equation:

$$W(a,b)=\int\infty\, f(t)\psi a,b(t)dt \quad (4)$$

where $f(t)$ is the original image $\psi a,b(t)$ is the wavelet function parameterized by a and b and $W(a,b)$ is the wavelet transform.

3.5 DEEP NEURAL NETWORK IMAGE FEATURE EXTRACTION

A deep neural network (DNN) involves a series of transformations applied to the input data to produce an output. Let's represent the computation in a simplified form for a single hidden layer. A neural network with multiple hidden layers (deep neural network) can be constructed by stacking these layers.The initial layers of the network, often referred to as the convolutional base, are pre-trained on large-scale image datasets, such as ACRIMA enabling the model to learn generic image features like edges, textures, and shapes.

3.5.1 Texture Feature Extraction:

Local binary pattern is a texture descriptor that characterizes the local patterns of pixel intensities in an image. It is often used for texture classification. These features, such as contrast, entropy, and energy, are derived from the gray-level co-occurrence matrix (GLCM) and provide information about the texture of an image.

3.5.2 Color Feature Extraction:

It representing the distribution of colors in an image. This can be done in various color spaces, such as RGB, HSV, or LAB. Extracting statistical moments of color distribution, including mean, variance, and skewness.

3.5.3 Shape Feature Extraction:

Shape feature extracting the contours from an image to capture the shape of objects. Contour-based features may include perimeter, area, and eccentricity. Feature extraction represent the below equation. Consider a neural network feature extraction with one hidden layer:

$$\mathbf{h}=\sigma(\mathbf{W}1\cdot\mathbf{x}+\mathbf{b}1) \quad (5)$$

$$\mathbf{y}=\sigma(\mathbf{W}2\cdot\mathbf{h}+\mathbf{b}2) \quad (6)$$

In Eq.(5) and Eq.(6) , x represent input vector and h represent the output of hidden layer. **y** represents the final output of the neural network. **W**1, **W**2 represent Weight matrices for the first and second layers, respectively **b**1, **b**2 are Bias vectors for the first and second layers, respectively. σ Activation function applied element-wise. Common choices include the sigmoid function, hyperbolic tangent (tanh), or rectified linear unit (ReLU).

$$\mathbf{h}1=\sigma(\mathbf{W}1\cdot\mathbf{x}+\mathbf{b}1)$$
$$\mathbf{h}2=\sigma(\mathbf{W}2\cdot\mathbf{h}1+\mathbf{b}2)$$
$$\vdots$$
$$\mathbf{h}n=\sigma(\mathbf{W}n\cdot\mathbf{h}n-1+\mathbf{b}n)$$
$$\mathbf{y}=\sigma(\mathbf{W}n+1\cdot\mathbf{h}n+\mathbf{b}n+1) \quad (7)$$

In the equations above, n is the number of hidden layers and **h**n is the output of the final hidden layer. The number of layers, and other hyperparameters can be adjusted based on the specific problem and characteristics of the data.

Texture, color, and shape are important visual features that can be extracted from images for various computer vision tasks. Fig.4 depicts the deep neural network process for image texture, shape, and color feature extraction.

Algorithm 3.3: Algorithmic process of Deep Neural Feature Extraction

Input: Segmented Image '$Seg_I = Seg_{I1}, Seg_{I2},\ldots, Seg_{In}$'

Output: Deep Neural Network based feature extraction

Step 1: **Begin**

Step 2: **For** each Segmented Image $Seg_I = Seg_{I1}, Seg_{I2},\ldots, Seg_{In}$ with order $o=p+q$

Step 3: Measure deep neural network using Eq.(7)

Step 4: Measure texture, color and shape for W^{th} order using Eq.(5) and Eq.(6)

Step 5: **End for**

Step 6: **End**

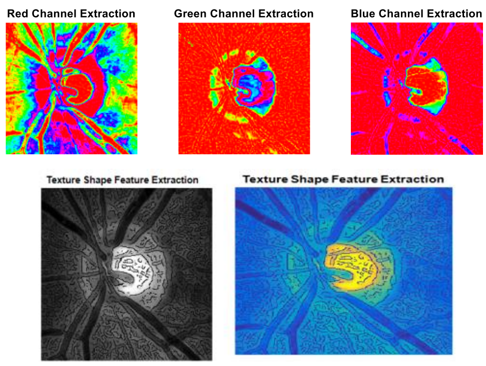

Fig.6. Deep Neural Network Image Texture, shape and Color Feature Extraction

3.6 DEEP NEURAL MULTI-WAVELET BASED RESNET-50 IMAGE CLASSIFICATION (DNMWS-RESNET-50-IC)

The ResNet-50 algorithm is a powerful convolutional neural network (CNN) architecture known for its effectiveness in image classification tasks, making it particularly valuable for glaucoma image classification. Its deep structure with residual connections allows for the training of very deep networks. ResNet-50 has been widely utilized for image classification and is pre-trained on large datasets such as the ACRIMA database. In the context of glaucoma image classification, ResNet-50 serves as both a feature extractor and a classifier.

To adapt ResNet-50 for glaucoma classification, the original fully connected layers are typically replaced or augmented with custom layers designed for binary classification (glaucoma or non-glaucoma). These additional layers are responsible for learning higher-level representations specific to the glaucoma dataset. The model learns to extract hierarchical features from the images and make predictions based on these features. During training, the weights of the network are adjusted to minimize the difference between predicted and true labels. The architecture of ResNet-50 includes residual blocks that facilitate the training of very deep networks by addressing the vanishing gradient problem. Each residual block features a skip connection that adds the input to the output, allowing gradients to flow more easily through the network. The equation for a single residual block in ResNet-50 can be represented as follows:

$$\mathbf{y}l=\mathrm{F}(\mathbf{x}l,\{W_{l,i}\})+\mathbf{x}l \tag{8}$$

where $\mathbf{x}l$ is the input to the l-th residual block. And $\mathbf{y}l$ is the output of the l-th residual block. F is the residual function to be learned, represented by a series of operations. $\{W_{l,i}\}$ represent the weight parameters and i is the residual block.

In ResNet-50, each residual block consists of several convolutional layers, batch normalization, and non-linear activation functions, typically Rectified Linear Units (ReLU). A skip connection adds the input directly to the output of the residual function. Detecting glaucoma from images involves analyzing features that may indicate structural changes in the optic nerve or other relevant regions of the eye. The model's performance is evaluated on a separate test set using metrics such as accuracy, precision, recall, and F1-score. The Fig.7 illustrates the image classification process for glaucoma detection.

Algorithm 3.4: Algorithmic process of Deep Neural Multi-wavelet based Resnet-50 image Classification algorithm

Input: Deep Neural Feature Extraction Image

Output: Efficiently Classified Image

Step 1: **Begin**

Step 2: **For** each Resnet-50 matrix $Matrix_i^{(l)}$ with Convolution filter $Con_i^{(l-1)}$

Step 3: Obtain convolutional matrix using equation (3.8)

Step 4: **For** each high dimensional area of size $\mathbf{X}l$ and $\mathbf{Y}l$

Step 5: Obtain convolutional residual block using Eq.(8) w.r.t activation function

Step 6: Measure maximum Classified residual block using Eq.(8)

Step 7: Measure Resnet-50 Algorithm function using Eq.(8)

Step 8: **End for**

Step 9: **End for**

Step 10: **End**

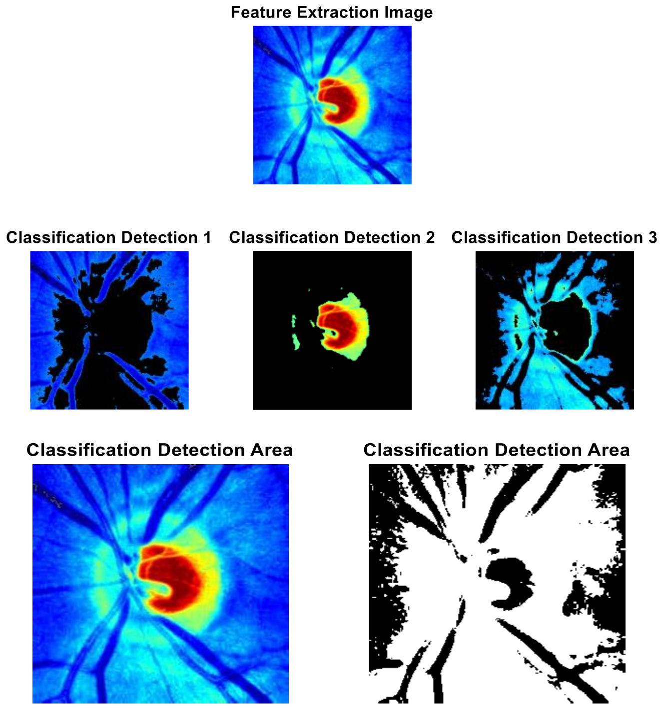

Fig.7. Image Classification Glaucoma detection

4. EXPERIMENTAL EVALUATION

The ACRIMA database consists of 705 fundus images, with 396 images identified as glaucomatous and 309 as normal, forming part of the ACRIMA project. The images were acquired from both glaucomatous and normal patients with their prior consent and in accordance with ethical standards. Patient selection was based on specific criteria and clinical findings provided by retina specialists. Most of the fundus images in this database were captured from both left and right eyes, which were previously dilated and centered on the optic disc. Some images were discarded due to artifacts, noise, or poor contrast. The retinal images were acquired using the Topcon TRC retinal camera and the IMAGEnet® capture system, with a field of view of 35°. Examples of images from the ACRIMA database are shown in the Fig.8.

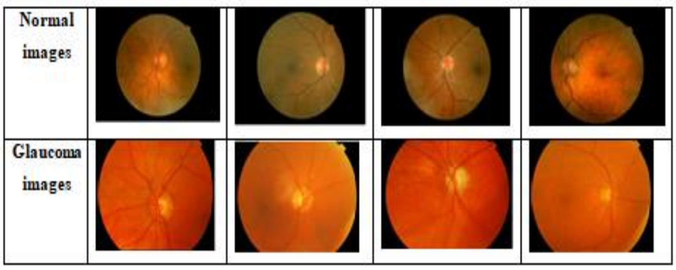

Fig.8. Examples of new publicly available database

5. PERFORMANCE EVALUTION

5.1 PERFORMANCE MEASURE OF ACCURACY FOR GLAUCOMA DETECTION

Glaucoma Detection Accuracy (GDA) is determined as ratio of number of input Glaucoma images that are rightly classified into corresponding classes (i.e. benign or malignant) to the total number of Glaucoma images considered as input during the experimental task. The GDA is mathematically obtained as,

$$GDA = \frac{G_C}{N} * 100 \tag{8}$$

From the above mathematical representation (19), 'G_c' defines number of input Glaucoma images correctly categorized and 'N' expresses total number of Glaucoma images acquired as input to carried out simulation evaluation. The GDA of Glaucoma detection is expressed as a percentage (%) in the following table.

Table.1. Accuracy of Early Glaucoma Detection Analysis

Number of input images (*N*)	Glaucoma detection Accuracy (%)		
	DNMWSR-50IC	**CNN**	**ML**
100	95	88	86
200	93	85	81
300	95	82	79
400	92	84	82
500	93	82	80
600	94	83	79
700	97	85	80
800	94	83	81
900	96	87	83
1000	95	89	84

5.2 PERFORMANCE MEASURE OF PRECISION FOR GLAUCOMA DETECTION

Precision *P* is determined as ratio of number of input Glaucoma images that are rightly detect into corresponding classes to the total number of Glaucoma images considered as input during the experimental task. The Precision is mathematically obtained as,

$$P = \frac{TP}{TP + FP} * 100 \tag{9}$$

From the above mathematical representation Eq.(9), *P* defines Precision. TP represent the True Positive and FP represent the False Positive. The Precision of Glaucoma detection is obtained in percentage (%).

Table.2. Precision of Early Glaucoma Detection Analysis

Number of input images (*N*)	Glaucoma Detection of Precision (%)		
	DNMWSR-50IC	**CNN**	**ML**
100	88	81	79
200	85	77	74
300	86	74	71
400	84	76	72
500	85	75	71
600	82	74	70
700	85	78	73
800	82	75	72
900	87	80	76
1000	86	79	75

5.3 PERFORMANCE MEASURE OF RECALL FOR GLAUCOMA DETECTION

Recall 'R'is determined as ratio of number of input Glaucoma images that are rightly detect into corresponding classes to the total number of Glaucoma images considered as input during the experimental task. The Recall is mathematically obtained as,

$$P = \frac{TP}{TP + FN} * 100 \tag{10}$$

From the above mathematical representation Eq.(10), *R* defines Recall. TP represent the True Positive and FN represent the False Negative.

Table.3. Recall of Early Glaucoma Detection Analysis

Number of input images (*N*)	Glaucoma Detection of Recall (%)		
	DNMWSR-50IC	**CNN**	**ML**
100	87	80	76
200	83	76	70
300	85	72	68
400	83	75	71
500	84	74	69
600	81	73	70
700	84	77	73
800	81	74	72
900	86	79	75
1000	85	78	74

5.4 PERFORMANCE MEASURE OF PREDICTION TIME FOR GLAUCOMA DETECTION

Prediction time is evaluated in milliseconds (ms) and formalized as follows.

$$PT = N * \text{time (predicting one image)} \tag{11}$$

From Eq.(4), prediction time *PT* is estimated. Here, *N* represents the number of images.

Table.4. Recall of Early Glaucoma Detection Analysis

Number of input images (*N*)	Glaucoma Detection of Prediction time (ms)		
	DNMWSR-50IC	**CNN**	**ML**
100	3	5	9
200	6	9	14
300	8	14	16
400	9	16	19

500	12	15	21
600	15	22	23
700	16	26	28
800	20	31	33
900	24	36	40
1000	26	39	45

6. CONCLUSION

In this paper, we presented the Deep Neural Multi-Wavelet Segmentation and ResNet-50 Image Classification (DNMWS-ResNet-50IC) method for early glaucoma detection. The proposed approach leverages a combination of deep neural networks and multi-wavelet segmentation to enhance diagnostic accuracy and efficiency. Our method begins with Anisotropic Gaussian Filtering, which adapts the Gaussian filter to local image gradients, providing improved edge detection and smoothing. This is followed by Multi-Wavelet Segmentation, which performs a multi-resolution analysis to capture different frequency components of the retinal images, enabling detailed feature extraction at multiple scales. The ResNet-50 model then classifies these features with high precision, benefiting from its deep architecture and residual connections to learn complex patterns associated with glaucoma. The DNMWS-ResNet-50IC approach has demonstrated superior performance in identifying early signs of glaucoma, achieving higher accuracy and reduced prediction time compared to traditional methods. The integration of multi-wavelet transformations with ResNet-50's robust classification capabilities allows for effective detection of subtle glaucomatous changes, thereby offering a valuable tool for early diagnosis. Overall, the proposed method significantly advances the field of glaucoma detection, providing a reliable and efficient solution for identifying the disease in its early stages. Future work could focus on further optimizing the model and validating its performance across diverse datasets to enhance its applicability in clinical settings.

REFERENCES

[1] A. Saxena, A. Vyas, L. Parashar and U. Singh, "A Glaucoma Detection using Convolutional Neural Network", *Proceedings of International Conference on Electronics and Sustainable Communication Systems*, pp. 815-820, 2020.

[2] D.M.S. Barros, "Machine Learning Applied to Retinal Image Processing for Glaucoma Detection: Review and Perspective", *Biomedical Engineering*, Vol. 19, pp. 1-20, 2020.

[3] N. Gupta and R. Agarwal, "A Robust Framework for Glaucoma Detection using CLAHE and EfficientNet", *The Visual Computer*, Vol. 38, pp. 2315-2328, 2022.

[4] S. Gheisari, "A Combined Convolutional and Recurrent Neural Network for Enhanced Glaucoma Detection", *Scientific Reports*, Vol. 11, pp. 1945-1965, 2021.

[5] X. Xu and J. Li, "Automatic Glaucoma Detection based on Transfer Induced Attention Network", *Biomedical Engineering*, Vol. 20, pp. 1-39, 2021.

[6] O.C. Devecioglu, J. Malik, T. Ince, S. Kiranyaz, E. Atalay and M. Gabbouj, "Real-Time Glaucoma Detection from Digital Fundus Images using Self-ONNs", *IEEE Access*, Vol. 9, pp. 140031-140041, 2021.

[7] Tomaz Ribeiro Viana Bisneto, Antonio Oseas de Carvalho Filho and Deborah Maria Vieira Magalhães, "Generative Adversarial Network and Texture Features Applied to Automatic Glaucoma Detection", Applied Soft Computing, Vol. 90, pp. 1-12, 2020.

[8] R. Kashyap and A. Rizwan, "Glaucoma Detection and Classification using Improved U-Net Deep Learning Model", *Healthcare*, Vol. 10, pp. 2497-2512, 2022.

[9] S. Sankar Ganesh, G. Kannayeram, Alagar Karthick and M. Muhibbullah, "A Novel Context Aware Joint Segmentation and Classification Framework for Glaucoma Detection", *Computational and Mathematical Methods in Medicine*, Vol. 2021, pp. 1-13, 2021.

[10] F. Li, D. Song and H. Chen, "Development and Clinical Deployment of a Smartphone-Based Visual Field Deep Learning System for Glaucoma Detection", *NPJ Digital Medicine*, Vol. 3, pp. 123-132, 2020.

[11] V. Krishna Adithya, B.M. Williams and G. Czanner, "EffUnet-SpaGen: An Efficient and Spatial Generative Approach to Glaucoma Detection", *Journal on Imaging*, Vol. 7, pp. 92-97, 2021.

[12] H.A. Agboola, "Wavelet Image Scattering based Glaucoma Detection", *BMC Biomedical Engineering*, Vol. 5, No. 1, pp. 1-12, 2023.

[13] Jose Martins, Jaime S. Cardoso and Filipe Soares, "Offline Computer-Aided Diagnosis for Glaucoma Detection using Fundus Images Targeted at Mobile Devices", *Computer Methods and Programs in Biomedicine*, Vol. 192, pp. 1-15, 2020.

[14] Y. George, B.J. Antony, H. Ishikawa, G. Wollstein, J.S. Schuman and R. Garnavi, "Attention-Guided 3D-CNN Framework for Glaucoma Detection and Structural-Functional Association using Volumetric Images", *IEEE Journal of Biomedical and Health Informatics*, Vol. 24, No. 12, pp. 3421-3430, 2020.

[15] Rutuja Shinde, "Glaucoma Detection in Retinal Fundus Images using U-Net and Supervised Machine Learning Algorithms", *Intelligence-Based Medicine*, Vol. 5, pp. 1-19, 2021.

[16] C.W. Wu and C.H. Lee, "Glaucoma Detection using Support Vector Machine Method Based on Spectralis OCT", *Diagnostics*, Vol. 12, pp. 391-399, 2022.

[17] T. Afroze, M.S. Hossain and K. Andersson, "Glaucoma Detection using Inception Convolutional Neural Network V3", *Applied Intelligence and Informatics*, pp. 1-14, 2021.

[18] R. Krishnan, V. Sekhar, J. Sidharth, S. Gautham and G. Gopakumar, "Glaucoma Detection from Retinal Fundus Images", *Proceedings of International Conference on Communication and Signal Processing*, pp. 628-631, 2020.

[19] L. Abdel-Hamid, "Glaucoma Detection from Retinal Images using Statistical and Textural Wavelet Features", *Journal on Digital Imaging*, Vol. 33, pp. 151-158, 2020.

[20] A.R. Prananda and M. Syafrudin, "Retinal Nerve Fiber Layer Analysis using Deep Learning to Improve Glaucoma Detection in Eye Disease Assessment", *Applied Science*, Vol. 13, pp. 37-48, 2023.

[21] Chi Li, "Assessing the External Validity of Machine Learning-based Detection of Glaucoma", *Scientific Reports*, Vol. 13, No. 1, pp. 558-567, 2023.

[22] M. Nawaz, "An Efficient Deep Learning Approach to Automatic Glaucoma Detection using Optic Disc and Optic Cup Localization", *Sensors*, Vol. 22, No. 2, pp. 434-446, 2022.

[23] S. Serte and Ali Serener, "Graph-Based Saliency and Ensembles of Convolutional Neural Networks for Glaucoma Detection", *IET Image Processing*, Vol. 15, No. 3, pp. 797-804, 2021.

[24] Delaram Mirzania, Atalie C. Thompson and Kelly W. Muir, "Applications of Deep Learning in Detection of Glaucoma: A Systematic Review", *European Journal of Ophthalmology*, Vol. 31, No. 4, pp. 1618-1642, 2021.

[25] Imran Qureshi and Qaisar Abbas, "Diabetic Retinopathy Detection and Stage Classification in Eye Fundus Images using Active Deep Learning", *Multimedia Tools and Applications*, Vol. 80, pp. 11691-11721, 2021.