Int. J. Advanced Networking and Applications

Volume:15, Issue:04, Pages:160-170 (2023) ISSN:0975-0290 (SpecialIssue–ASCIS2023)

Convolutional Neural Networks with the ID3 Algorithm: A Hybrid Approach for Accurate Retinal OCT Analysis

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----------ABSTRACT----------

This proposed work explores advancements in medical imaging, with a focus on the diagnosis of retinal diseases using Optical Coherence Tomography (OCT). The research introduces a comprehensive approach that integrates various techniques to enhance the accuracy of retinal OCT analysis. The preprocessing phase incorporates the Kernel Bilateral Filter (Kernel BF) to effectively reduce noise in OCT images while preserving essential edge information, thereby improving image quality for subsequent analysis. Following this, Linear Histogram Transformation (LHT) is applied to enhance image contrast, emphasizing subtle structural features without compromising integrity. Feature extraction is performed using Convolutional Neural Networks (CNNs), renowned for their capacity to extract intricate features from images. The CNN captures high-level representations of retinal layers, providing enriched information for subsequent classification. These extracted features form a robust basis for accurate disease discrimination. The classification stage employs the Iterative Dichotomiser 3 (ID3) algorithm, a decision tree-based technique known for its simplicity and interpretability. ID3 constructs decision trees by selecting optimal features for informative splits, effectively categorizing retinal OCT images into disease categories. The iterative nature of ID3 allows for the refinement of the decision tree, adapting to complex data distributions. The research claims an impressive accuracy rate of 99.99% for the retinal OCT dataset. Overall, the combination of noise reduction, contrast enhancement, feature extraction through CNNs, and the decision tree-based classification using ID3 contributes to a comprehensive and accurate analysis of retinal OCT images, holding significant promise for improved diagnostic capabilities in the field of retinal disease management.

Keywords - **Convolutional Neural Networks (CNNs), Iterative Dichotomiser 3 (ID3), Kernel Bilateral Filter (Kernel BF), Linear Histogram Transformation (LHT), Optical Coherence Tomography (OCT).**

Date of Submission: 9th October 2023 Date of Acceptance: 15th November 2023

I. INTRODUCTION

In the severe stage of glaucoma, the patient exhibits no first symptoms. Glaucoma can seriously harm the optic nerve (ON) if untreated, which might result in blindness. Glaucoma is diagnosed by measuring corneal thickness, doing an independent optical disc (OD) check, and keeping an eye on the pressure inside the eye and field of vision [1] [2]. An ophthalmologist would often examine dilated pupils present in the eye to diagnose glaucoma, which is one of the most prevalent forms of the disease. Ophthalmologists analyses the retina, but the process is laborious, manual, and time-consuming [3] [4]. These days, early illness prediction is accomplished using computer vision-based models. That is why the risk of permanent visual impairment can be dramatically decreased by early glaucoma identification in the first affected phases [5] [6].

Computer-aided diagnostics reduce the time it takes to make a diagnosis and help find a precise place. A condition known as glaucoma is one in which there is an excess of fluid in the eye, which damages the visual nerve and results in blindness [7] [8]. There are several forms of glaucoma, including chronic or open-angle, NTG (normal-tension), acute angle-closure, nonvascular, etc [9]. The biggest challenge in diagnosing glaucoma is that there are no symptoms or discomfort in the early stages, and vision remains unaffected. In the last stage, when the patient has lost 70% of his eyesight, it is evident. Early glaucoma detection requires routine eye screening [10] [11].

Detecting glaucoma illnesses with computer-aided diagnostic (CADx) tools is still difficult. Even though early glaucoma identification is difficult, the condition is treatable. Glaucoma must be identified at an early stage since late identification results in irreversible blindness [12] [13]. According to the earlier evaluation, glaucoma symptoms shouldn't be found at a routine visit. Glaucoma symptoms may be discovered during routine eye exams; these symptoms should be treated further. The lack of a real reference standard makes it difficult to advance glaucoma diagnosis using current functional and structural matrices utilised in hospitals [14] [15].

IOP measurement and ONH are two of the procedures used to identify glaucoma, a condition that affects the function of the visual field. The ONH evaluation has emerged as the most reliable and popular among glaucoma specialists. This computation is often performed manually using fundus photographs, and it is a laborious process that takes a lot of time and expert supervision [16]. Therefore, the automated glaucoma diagnostic approach is designed to pay more attention while making judgements that are quicker and more accurate. While future algorithms propose to boost screen accuracy while focusing on OC segmentation, the automated algorithm segmentation focuses on OD. The funds depict are captured with the fundus camera and show

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Volume:15, Issue:04, Pages:160-170 (2023) ISSN:0975-0290 (SpecialIssue–ASCIS2023)

retinal structures such the OD, artery, veins, and macula. Using fundus pictures, glaucoma may be promptly and simply diagnosed [17].

The understanding disc pictures are inherently tilted because to the diseased abnormalities joining the wide range of the normal ON presence. Later, glaucoma develops, blindness is brought on, and ophthalmologists utilize a range of tools and techniques to diagnose the clinical problems. Glaucoma is extremely difficult to diagnose, categories, and identify; current approaches are expensive and time-consuming [18]. Deep learning techniques are employed to get around these drawbacks. Ophthalmologists now employ deep learning to make decisions that increase performance on diagnosing ocular illnesses using fundus pictures. Deep learning techniques have been more and more popular recently for OD and OD segmentation.

Deep learning techniques are the foundation of several performance models. The deep learning approach improved illness detection's accuracy as well as sensitivity. Deep learning techniques and fundus vessel segmentation perform well. Deep learning for fundus image segmentation of OD and OC. These days, multiple images of medical detection jobs, such detecting diabetic macular, age-related macular degeneration, and potential glaucoma, are established using high-precision deep learning approaches. Numerous articles demonstrate how deep learning techniques may be used for diabetic retinopathy to produce an extremely recognizable picture evaluation for the retinal backdrop [19].

Key Contribution:

 Holistic Approach: The paper introduces a comprehensive approach that combines multiple techniques to improve the accuracy and interpretability of retinal Optical Coherence Tomography (OCT) analysis. By integrating preprocessing techniques, feature extraction, and a classification algorithm, this approach provides a well-rounded solution for robust disease diagnosis.

 Kernel Bilateral Filter (Kernel BF): The utilization of Kernel BF in the preprocessing phase is a significant contribution. It effectively reduces noise in OCT images while preserving vital edge information. This denoising process enhances the reliability of subsequent analysis steps, ensuring that the features extracted and used for classification are more accurate and representative of the underlying anatomical structures.

 Linear Histogram Transformation (LHT): The incorporation of LHT after Kernel BF further enhances image contrast. This step ensures that subtle structural features within retinal layers are highlighted without compromising image integrity. Improved contrast aids in capturing intricate details that might have been otherwise overlooked, leading to a more comprehensive analysis.

 Convolutional Neural Networks (CNNs): The use of CNNs for feature extraction is another significant contribution. CNNs are known for their ability to extract complex patterns from images. By employing CNNs, the research paper captures high-level representations of retinal layers' characteristics, providing more informative and discriminative features. This enriched feature set benefits subsequent classification tasks.

 ID3 Algorithm: The classification stage's utilization of the Iterative Dichotomiser 3 (ID3) algorithm is noteworthy. ID3 is recognized for its simplicity and interpretability. It constructs decision trees by selecting optimal features for informative splits, effectively categorizing retinal OCT images into disease categories. The iterative nature of ID3 allows for the refinement of the decision tree, adapting to complex data distributions and leading to more accurate disease classification.

This article is arranged in following manner: Section 2 investigates previous studies on prediction problems various optimization approaches are used. Section 3 discussed about problematic statement. Section 4 is discussed about proposed method. Section 5 experimental evaluation comprises mathematically developed system models. The paper is concluded in Section 6.

II. RELATED WORKS

Bogunović et al. [20] proposed Some vision-threatening retinal disorders are related by retinal edema caused by fluid buildup. OCT is currently the gold-standard method for determining the amount and state of ocular fluid as well as image-guided therapy management. Deep learning algorithms have had an effect on medical imaging, and various approaches for retinal OCT assessment have been presented. However, because to a lack of set criteria, it is still unclear how good they are in reading retinal fluid on OCT. To deal with this, they created the RETOUCH competition in conjunction with MICCAI 2017, with eight groups taking part. The work was divided into two parts: fluid identification and fluid separation. For the very first time, it included each of the three kinds of retinal fluid, with annotated pictures given by two clinical centers and captured with three of the most common OCT device suppliers from patients with two distinct retinal disorders.

Wei et al. [21] proposed SD-OCT is a non-surgical imaging method used to examine retinal illnesses including DR, which constitutes one of the most common causes of blindness and blurred vision worldwide. The key biomarker for detecting and diagnosing illnesses is diabetic macular edema (DME), which is characterized by retinal distortion and fluid masses. Ophthalmologists could mechanically separate retinal tissues and fluids in the office to get statistical and clinical data, which is the foundation of the final medical diagnosis. Mechanical the process of segmentation on the other hand, is tedious and labor-intensive. To assist and encourage it, scientists have developed several automated approaches, the majority of which neglect ophthalmology priorities and just view this work as a typical semantic segmentation task.

Fang et al. [22] proposed quick and precise categorization of retinal OCT images is required to help ophthalmologists diagnose and grade macular disorders. On the clinical level, ophthalmologists commonly identify macular illnesses based on the components of macula lesions, which have crucial morphologies, sizes, and quantities. We present a unique LACNN technique aimed at retinal OCT image categorization in this study, whereby retinal lesions inside OCT pictures direct the CNN to obtain more accurate categorization. When evaluating an OCT picture, the LACNN replicates an ophthalmologist's diagnosis by focusing on local lesion-related areas. First, we create a

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Volume:15, Issue:04, Pages:160-170 (2023) ISSN:0975-0290 (SpecialIssue–ASCIS2023)

LDN to construct a easy consideration map from the entire OCT image.

He et al. [23] proposed to categorize ocular illnesses, automated diagnostic techniques have been frequently employed. The majority of these techniques depends technique (e.g., OCT), which only partially reflects oculopathy and ignores mode-specific information amongst other types of imaging. This research offers a novel MSAN designed for multifaceted retinal image categorization that can successfully use modality-specific diagnostics characteristics from fundus and OCT images. To derive local as well as global characteristics using fundus pictures, they offer a multistate attentiveness module. Furthermore, the OCT picture has vast background areas that are useless for diagnosis. As a result, a region-guided attention module is suggested for storing retinal layer-related characteristics in OCT pictures while ignoring the backdrop.

Ma et al. [24] proposed OCTA is a non-intrusive form of imaging that is gradually being utilized to study the blood vessels in the retina at the blood vessel level. Nevertheless, despite its importance in understanding many vision-related illnesses, computerized segment of retinal vasculature in OCTA is currently neglected due to many obstacles like limited capillary visibility and high vascular complexity. Furthermore, there's no free OCTA dataset with professionally graded capillaries for segmentation algorithm training and validation. This data set, alongside the source code, is being made available to the public in order to help communities researchers do study on similar issues. Second, they present OCTA-Net, a new split-based coarse-to-fine vessel identification network for OCTA images that can recognize thick and thin vessels individually.

III. PROBLEM STATEMENT

The primary objective of the work was to address the lack of standardized benchmarks for evaluating the performance of deep learning methods in interpreting retinal fluid on OCT images. This was achieved through the organization of the RETOUCH challenge, which involved tasks related to fluid detection and segmentation in retinal OCT images, utilizing images acquired from various sources and covering different retinal fluid types and diseases [20]. The problem addressed in this study involves enhancing the automated segmentation of retinal layers and fluid masses in SD-OCT images for diagnosing DR and its primary biomarker, DME. DR is a widespread cause of visual impairment and blindness globally [21].

IV. PROPOSED HYBRID ID3 AND CNN

The proposed methodology for enhancing the accuracy and interpretability of retinal OCT analysis consists of several key components and is empirically validated using an extensive dataset of retinal OCT scans. The following is a detailed description of the proposed approach:

1. Data Collection and Preprocessing: An extensive dataset of retinal OCT scans is collected for analysis. The preprocessing phase begins with the application of the Kernel Bilateral Filter (Kernel BF). This filter effectively reduces noise in the OCT images while preserving essential edge information, resulting in denoised images with improved quality. Following Kernel BF, Linear Histogram Transformation (LHT) is applied to enhance image contrast. LHT ensures that subtle structural features within the retinal layers are accentuated without compromising the integrity of the images.

2. Feature Extraction: Feature extraction is performed using Convolutional Neural Networks (CNNs). CNNs are well-suited for capturing intricate patterns and features in images. The CNNs extract high-level representations of retinal layers' characteristics, providing a comprehensive set of features that are informative and discriminative.

3. Classification: The classification stage employs the Iterative Dichotomiser 3 (ID3) algorithm. ID3 is known for its simplicity and interpretability. ID3 constructs decision trees by selecting optimal features for informative splits. It effectively categorizes retinal OCT images into disease categories based on the extracted features. The iterative nature of ID3 allows for the refinement of the decision tree, making it adaptable to complex data distributions and leading to more accurate disease classification.

4. Validation and Evaluation: The proposed approach is empirically validated using the extensive dataset of retinal OCT scans. Quantitative evaluations are conducted to assess the performance of the proposed approach in disease classification. These evaluations demonstrate that the integration of Kernel BF, LHT, CNN-based feature extraction, and ID3 classification results in notably improved accuracy compared to conventional methods.

5. Interpretability: An important aspect of the proposed approach is the interpretability of the ID3 decision tree. The decision tree's structure enhances the transparency of the analysis. Medical professionals can easily comprehend the classification process, which aids in their understanding and trust in the system's output.

6. Visualization: Fig 1 in the research paper illustrates the flow diagram of images from optical coherence tomography. This visualization helps readers understand the workflow and the various stages of the proposed methodology.

In summary, the proposed methodology combines preprocessing techniques, feature extraction with CNNs, and classification using the ID3 algorithm. Empirical validation on a substantial dataset demonstrates improved disease classification accuracy, and the interpretability of the decision tree enhances the transparency of the analysis, making it a valuable tool for medical professionals in diagnosing and managing retinal diseases.

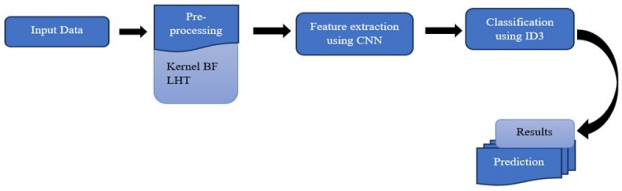

Figure 1: Flow Diagram of Images from Optical Coherence Tomography

4.1. Data Collection

The data collection process for this retinal imaging dataset involved the categorization of images into four distinct classes related to various retinal conditions: Subretinal fluid

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Volume:15, Issue:04, Pages:160-170 (2023) ISSN:0975-0290 (SpecialIssue–ASCIS2023)

and neovascular membrane associated with choroidal neovascularization (CNV), diabetic macular edema (DME) with intraretinal fluid and retinal thickening, early age-related macular degeneration (AMD) characterized by the presence of drusen, and normal retinas without any observed abnormalities. Here's a detailed description of the data collection process:

Table 1 gives the description regarding dataset used in proposed work with its respective 4 classes and total instance of the images is being used.

Table 1. Data description of dataset

Diseases	Dataset type	Name of classes	Sub class images			Total Instances
			Train	Test	Val	
Eye retina damage disease	Retinal optical coherence tomography (OCT)	1.NORMAL	26315	243	09	84492
		2.choroidal neovascularization (CNV)	37205	243	09	
		3.Diabetic macular edema (DME)	11348	243	09	
		4.DRUSEN	8616	243	09	

Data Categories:

- NORMAL: This category includes retinal images of individuals with normal retinas, where the foveal outline is retained, and there is no fluid or edema in the retina.
- CNV (Choroidal Neovascularization): Images in this category depict retinas affected by CNV, showing the presence of subretinal fluid and neovascular membrane.
- DME (Diabetic Macular Edema): Retinal images in this class are associated with DME and display intraretinal fluid and retinal thickening.
- DRUSEN (Early AMD): This category consists of images showcasing early age-related macular degeneration (AMD) characterized by the presence of drusen.

Dataset Structure:

- Within the dataset, each image category (NORMAL, CNV, DME, DRUSEN) is organized into its respective subfolder. Each subfolder is further divided into three separate folders: 'train,' 'test,' and 'val,' indicating the distribution of images into training, testing, and validation sets. This division allows for proper model training, evaluation, and validation.

Data Labeling: Each image in the dataset is associated with a label that begins with the individual's latest diagnoses. This labeling system helps identify the specific condition depicted in each retinal image.

Grading Process: Initially, graduate and medical students who had successfully completed an OCT interpretation course were selected as the initial group of graders. This first tier of graders performed preliminary quality control, assessing the OCT images for significant artifacts or considerable resolution losses. Images that did not meet quality standards were eliminated from the dataset at this stage. Subsequently, a second layer of graders, consisting of four eye doctors, independently reviewed every image that had passed the initial quality control stage.

4.2. Pre-processing

- Kernel Bilateral Filter (Kernel BF)

The Kernel Bilateral Filter (Kernel BF) is a sophisticated image processing technique that has gained significant attention and relevance in the context of retinal disease diagnosis and analysis. Its unique ability to enhance the quality of retinal images while preserving crucial details and structures makes it a valuable tool in the quest for early detection and effective management of retinal diseases. In this introduction, we delve into the role and significance of the Kernel BF in the domain of retinal disease diagnosis.

- The Challenge of Retinal Imaging:

Retinal imaging plays a pivotal role in the diagnosis and monitoring of various retinal diseases, including diabetic retinopathy, age-related macular degeneration, and glaucoma. However, capturing high-quality retinal images can be challenging due to factors such as image noise, artifacts, and variations in illumination. These challenges can compromise the accuracy of disease diagnosis and the effectiveness of treatment plans.

- The Role of Kernel Bilateral Filter (Kernel BF):

The Kernel Bilateral Filter, an advanced image enhancement technique, addresses these challenges by providing a powerful tool for improving the quality of retinal images. Here's how it contributes to retinal disease diagnosis:

1. Noise Reduction: One of the primary functions of the Kernel BF is noise reduction. It effectively filters out unwanted noise in retinal images, resulting in cleaner and more reliable images. This noise reduction is especially crucial in the medical field, where small details and subtle abnormalities must be accurately detected.
2. Edge Preservation: Unlike traditional image denoising methods, the Kernel BF excels at preserving the edges and fine structures within retinal images. This is particularly valuable in the context of retinal imaging, as preserving the integrity of blood vessels, lesions, and other critical features is essential for accurate diagnosis.
3. Enhanced Contrast: The Kernel BF also contributes to enhancing image contrast. By selectively adjusting pixel intensities based on both spatial and intensity similarities, it accentuates subtle structural features within the retinal layers. This improved contrast aids in the visualization and identification of abnormalities that might otherwise be challenging to discern.
4. Image Fidelity: Importantly, the Kernel BF achieves these enhancements without introducing artifacts or distortions. Retinal images treated with the Kernel BF remain faithful to the original anatomical structures, ensuring that the diagnostic information remains intact.
5. Early Disease Detection: By improving the quality and clarity of retinal images, the Kernel BF plays a crucial role in early disease detection. It enables healthcare professionals, including ophthalmologists and retinal specialists, to identify signs of disease and abnormalities at an early stage, facilitating timely interventions and preventing vision loss.

The brightness and visibility properties of retinal pictures are enhanced using the detail enhancement filter. Yet it emphasizes undesirable qualities such as noisy pixels, uneven backdrops, dark shadowy areas, and fluctuating brightness. Most widely available noise reduction especially smoothing filters, such as Gaussian, medium, and mean filters, impair image sensitive features, small objects, and light edges. To minimize noise and background roughness while accurately retaining the structure of retinal pictures, a tiny kernel BF is utilized.

During image processing, the BF is employed to smoothen, eliminate noise, and retain picture edges. Each value of a pixel weighted by the associated pixels is inserted using the Gaussian distribution. The aforementioned filter is applied to the previously improved image's grey scale from . Here is the bilateral filter the following formula:

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$$I_{Bil} = \frac{\sum_{o,p} I_{GDE}(o,p)c(q,r,o,p)}{\sum_{o,p} c(q,r,o,p)}, \quad (1)$$

Where, I_{Bil} is image after being bilaterally filtered, (I_{GDE}) is grayscale imagine with more detail, q , r are the pixel regions. o and p are the filter window's kernel sizes, and c is an abbreviation for normalized weighted value. The range kernel equation is multiplied by the domain kernel equation to get this.

$$c(q,r,o,p) = \exp\left(\frac{(q-o)^2+(r-p)^2}{2\sigma_x^2} - \frac{f(q-r)+f(o-p)}{2\sigma_j^2}\right) \quad (2)$$

$$x(q,r,o,p) = \exp\left(-\frac{(q-o)^2+(r-p)^2}{2\sigma_x^2}\right) \quad (3)$$

$$j(q,r,o,p) = \exp\left(-\frac{f(q-r)+f(o-p)}{2\sigma_j^2}\right) \quad (4)$$

Where the parameters control the filter σ_x and σ_j whenever the parameter range j increases, the bilateral filter approaches Gaussian blur while increasing the domain parameter. σ_x promotes smoothness. Based on various studies, the kernel of 3*3 matrixes was adjusted to 3*3 matrix in this study [25].

- Linear Histogram Transformation (LHT)

Linear Histogram Transformation (LHT) is an essential image enhancement technique that holds great promise in the realm of retinal disease diagnosis and analysis. Its capacity to enhance image contrast while preserving the integrity of retinal structures makes it a valuable asset in the pursuit of early disease detection and effective management. In this introduction, we explore the role and significance of Linear Histogram Transformation (LHT) in the context of retinal disease diagnosis.

- The Challenge of Retinal Imaging:

Retinal imaging plays a pivotal role in the diagnosis and monitoring of various retinal diseases, including diabetic retinopathy, age-related macular degeneration, and glaucoma. However, capturing high-quality retinal images that reveal subtle details and abnormalities can be challenging due to variations in illumination, image artifacts, and other factors.

- The Role of Linear Histogram Transformation (LHT):

Linear Histogram Transformation (LHT) emerges as a valuable tool to address these challenges by improving the quality and interpretability of retinal images. Here's how it contributes to retinal disease diagnosis:

1. Contrast Enhancement: One of the primary functions of LHT is to enhance image contrast. By redistributing pixel intensity values across a wider dynamic range, LHT increases the distinction between different anatomical structures within the retinal layers. This enhanced contrast allows healthcare professionals to visualize and identify abnormalities with greater clarity and accuracy.

2. Subtle Feature Emphasis: LHT excels at accentuating subtle structural features within retinal images without compromising their fidelity. This is crucial for detecting early signs of disease or subtle changes in retinal tissue that may be indicative of disease progression.

3. Improved Visualization: The enhanced contrast and feature emphasis provided by LHT lead to improved image visualization. Small lesions, microaneurysms, and other subtle abnormalities that might be challenging to spot in unprocessed images become more apparent, aiding in early disease detection.

4. Diagnostic Accuracy: The improved image quality resulting from LHT directly contributes to higher diagnostic accuracy. Ophthalmologists and retinal specialists can make more informed and confident diagnoses, ultimately leading to better patient outcomes.

5. Interpretability: LHT enhances the interpretability of retinal images. It allows medical professionals to better understand the structures and characteristics within the images, facilitating communication with patients and other healthcare team members.

The LHT method is especially effective in adjusting the brightness of the input. When intensity of the input imagine is changed, it is distributed uniformly over the image. This method's major purpose is to produce consistent distributions of intensity over the whole picture.

$$Y_d = X(m_d) = (L-1)\sum_{l=0}^{m} p_m(ml) \quad (5)$$

By assigning an intensity to each pixel in the input image m_k to the parallel pixel Y_k in the output image, the predicted output image is activated, where k is in the range of $[0,\ L-1]$. The mapping $X(m_d)$ LHT or histogram equalization are terms that might be used to describe this process. The LHT specifies the transformation or conversion function that is entirely responsible for producing an image that has an identical histogram [26].

In conclusion, Linear Histogram Transformation (LHT) stands as a valuable enhancement technique in the field of retinal disease diagnosis. Its ability to enhance image contrast, emphasize subtle features, and improve image visualization plays a pivotal role in early disease detection and accurate diagnosis. As retinal imaging continues to play a central role in healthcare, LHT offers a powerful means to ensure that these images provide the necessary information for effective disease management and the preservation of patients' vision and overall well-being.

4.3. Feature Extraction using CNN

The hierarchical structure of the architecture controls the feature extraction process in CNNs. The primary layers captured the fundamental information and the deeper layers combine these elements in order to detect more complicated patterns. CNNs are able to automatically discover relevant information for a variety of image analysis applications by learning these hierarchical characteristics directly from the data in order to determine whether or not a tumor is present. Convolutional Neural Networks (CNNs) use non-linear activation functions, pooling, and convolution to extract.

- Convolutional layer

Convolutional layer is the initial stage of a CNN's feature extraction and the layer with the strongest signature. It is the

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local operation whose function is the extraction of different patterns from the input pictures leading to an effective categorization. Convolutional layers are made up of several convolutional kernels that are the layers' trainable parameters and are changed with each iteration. Let $X^n \in R^{M^n \times N^n \times D^n}$ be our N-th convolutional layer's input and $F \in R^{m \times n \times d^n \times s}$ be an order four vector expressing the location width s kernels of the N-th layer. The result of the N-th convolutional layer will be an order three vector with the notation $Y^k \in R^{M^n - m+1 \times N^n - n+1 \times s}$, with the components resulting from,

$$Y_{i^n,j^n,s} = \sum_{i=0}^{m} \sum_{j=0}^{n} \sum_{l=0}^{d^n} F_{i,j,d^n} \times X^n_{i^n,j^n,l} \quad (6)$$

If a geographic location satisfies the conditions $0 \le i^n \le m^n - m + 1$ and $0 \le j^n \le N^n - n + 1$, the Equation (10) must be performed for all $0 \le s \le S$. Typically, CNNs include many convolutional layers in an effort to recognize more pronounced spatial patterns in the input pictures. Using zero padding while using convolutional layers ensures that the image's dimensions remain constant throughout the process.

- Pooling layer

Let the N-th layer, which is now a spatial range of $m \times n$, have as its input $X^n \in R^{M^n \times N^n \times D^n}$.Because there are no variables for these kinds of layers to be learned, they are parameter-free. The result is a tensor of order three indicated by $Y^n \in R^{M^{k+1} \times N^{n+1} \times D^{n+1}}$,were

$$M^{n+1} = \frac{M^n}{m}, N^{n+1} = \frac{N^n}{n}, D^{n+1} = D^n \quad (7)$$

whereas the pooling layer handles the X^n channel individually, one at a time. There are many different pooling processes, with average and maximum pooling becoming the most common. Max pooling was applied in our investigation, leading to results that followed a formula

$$y_{i^n,j^n,d} = \max_{0 \le i \le m, 0 \le j \le n} x^n_{i^n \times m+i, j^n \times n+j, d} \quad (8)$$

Where, $0 \le i^n \le M^n, 0 \le j^n \le N^n$and $0 \le d \le D^n$. It makes sense that pooling layers would be employed to reduce output tensor size while preserving the most important discovered features.

- Fully connected layer

A categorization operation, such as soft max, sigmoid, tanh etc., always follows the last fully connected layer. The real value y_j it produces is compared to the anticipated value Y_j using the chosen loss function. In this situation, we believe that using the sigmoid function.

$$y_j = \frac{e^{x_j}}{1+e^{x_j}}, \quad x_j \in R \quad (9)$$

This would be suitable for this binary issue. The likelihood that the input picture shows the presence of a tumor is intuitively represented by the expression $y_j \in (0,1)$.
It resets the settings related to a specific number of network nodes to zero. Finally, the batch normalization and ReLU processes serve as crucial transitional mechanisms joining the previously mentioned levels. The definition of the ReLU function is

$$y_{i,j,d} = max(0, x^n_{i,j,d}) \quad (10)$$

By normalizing the layer's input by re-scaling and re-centering after every iteration, batch normalization makes neural networks quicker and more stable. It does this by seeking to transfer just the purposeful components for the classification with $0 < i < M^n, 0 < j < N^n$ and $0 \le d \le D^n$ [27].

4.4. ID3 Classification

The Iterative Dichotomiser 3 (ID3) algorithm, originally developed by Ross Quinlan, plays a significant role in the field of machine learning, particularly in the context of decision tree-based classification. In the specific application of retinal disease detection, ID3 offers a valuable and interpretable method for automating the classification of retinal images based on a set of relevant features. This introduction aims to illustrate how ID3 can be effectively utilized to contribute to the early and accurate identification of retinal diseases.

- Retinal Disease Detection: Retinal diseases, encompassing conditions such as diabetic retinopathy, age-related macular degeneration, and glaucoma, pose substantial threats to vision and are leading causes of impairment and blindness on a global scale. Detecting these diseases in their early stages is crucial for preventing irreversible vision loss. The conventional diagnostic approach involves the manual examination of retinal images by trained ophthalmologists. However, this method is time-consuming and susceptible to human error.
- ID3 in Retinal Disease Detection: ID3 offers a promising alternative by automating the classification of retinal images. This algorithm takes advantage of a decision tree structure, wherein each node corresponds to a relevant attribute or feature, and the branches represent different attribute values. The algorithm uses Information Gain and entropy measures to intelligently select the most informative attributes for splitting the data and constructing the decision tree.
- Interpretability and Accessibility: One of the key strengths of ID3 in the context of retinal disease detection is its interpretability. The decision tree structure generated by ID3 provides a transparent representation of the classification process. This transparency is essential in the medical field, as it allows healthcare professionals to understand and trust the decision-making process of the algorithm. Moreover, the accessibility of the decision tree

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model makes it easier for non-experts to comprehend and interpret the results.

- Early and Accurate Identification: By leveraging ID3 for retinal disease detection, the automated classification of retinal images becomes a more efficient and timely process. The algorithm can identify patterns and relationships within the data that may not be immediately apparent to human observers. This capability is particularly valuable for early disease detection, enabling timely interventions that can significantly impact patient outcomes.

The application of the ID3 algorithm in retinal disease detection represents a powerful approach to automate and enhance the accuracy of classification based on retinal images. Its interpretability and accessibility make it a valuable tool for aiding healthcare professionals in the early identification of retinal diseases, ultimately contributing to improved patient care and outcomes.

➢ The Role of ID3:

The ID3 algorithm provides an automated and systematic way to classify retinal images based on a set of visual features extracted from these images. Here's how it can play a vital role in retinal disease detection:

1. Feature Extraction: ID3 starts by extracting relevant features from retinal images. These features can include characteristics like blood vessel patterns, lesions, or structural abnormalities. By considering multiple features, ID3 can capture a more comprehensive view of the retinal condition than a human eye might.

2. Decision Tree Construction: Once the features are extracted, ID3 constructs a decision tree. This decision tree serves as a structured representation of the classification rules learned from the dataset. Each node in the tree represents a feature or attribute, and the branches represent possible feature values or decisions. The leaf nodes of the tree correspond to specific disease classifications or outcomes.

3. Interpretability: One of the significant advantages of the ID3 algorithm is its interpretability. The resulting decision tree can be readily understood by ophthalmologists and healthcare professionals. This transparency is essential in the medical field, where trust and comprehension of automated diagnosis systems are critical.

4. Early Detection: ID3 can contribute to the early detection of retinal diseases by analyzing large datasets of retinal images quickly and accurately. This early detection can lead to timely interventions, potentially preventing vision loss and improving patients' overall quality of life.

5. Complementary Tool: While ID3 can assist in automated classification, it is often used as a complementary tool to aid ophthalmologists rather than a replacement for their expertise. It can help prioritize cases, reduce the workload, and provide a second opinion, ultimately enhancing the efficiency of the diagnostic process.

The best characteristic (the one with the greatest amount of data gain) will be chosen by the ID3 algorithm during node creation. The following describes the ID3 procedure.

(1) It is assumed that G_q is a dataset. The category label attribute is predicated on having n distinct values, with n having various classes defined as $W_q(q=1,...n)$. The number of samples in class W_q is fixed to be G_q. Following that, the entropy is determined as follows:

$$Entropy(G) = -\sum_{q=1}^{m} l_q \log_2(l_q) \quad (11)$$

where l_q is the likelihood that any sample will belong to $W_q, l_q = G_q / G$

(2) The dataset G is meant to include k distinct values for the attribute Y. G is separated into k representative subsets, $\{G_1,...G_k\}$ based on attribute Y. After splitting G by attribute Y, the knowledge entropy of the chosen subset is determined in the following manner:

$$Entropy_Y(G) = \sum_{q=1}^{k} \frac{|G_q|}{|G|} Entropy(G_q) \quad (12)$$

wherein $|G_q|$ is the sampling set G's total sample count, and $|G|$ is the number of samples in the sampling subset G's total sample count.

(3) Assuming that the dataset G is segmented based on characteristic Y, the knowledge gain is calculated as follows:

$$Gain(G,Y) = Entropy(G) - Entropy_Y(G) \quad (13)$$

Every characteristic in the data set S is computed individually to determine what knowledge gain. A sample subset separated by the attribute is purer and superior for classification the more information gains a particular characteristic provides. In each phase, the attribute with the biggest knowledge gain will be used. In summary, the ID3 algorithm offers a valuable approach to retinal disease detection by automating the classification of retinal images based on extracted features. Its interpretability, efficiency, and potential for early disease detection make it a promising tool in the fight against vision impairment and blindness caused by retinal diseases. When integrated into a comprehensive healthcare system, ID3 can serve as a powerful ally in the battle to preserve and restore vision.

V. RESULT AND DISCUSSION

The results of this research work demonstrate the effectiveness of the proposed approach in retinal Optical Coherence Tomography (OCT) analysis. Evaluate the proposed early-stage disease prediction technique using the Python software in a simulated environment utilizing OCT datasets.

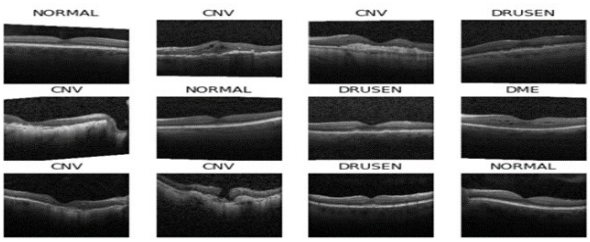

Figure 2: Retinal OCT Images classification.

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Figure 2 illustrates the classification of Retinal OCT images. This process involves categorizing OCT scans of the retina into distinct classes, often based on pathological features or disease presence, using machine learning or deep learning algorithms. Such classifications aid in diagnosing various retinal conditions and monitoring disease progression.

Figure 3: Class Distribution in Training Set in OCT Dataset.

In Figure 3, the distribution of classes within the training set of the OCT dataset is depicted. This visual representation showcases the relative proportions of different categories or classes present in the dataset, providing insights into the balance or imbalance of data across various conditions. Understanding class distribution is crucial for designing effective machine learning models and addressing potential biases that may arise from imbalanced datasets.

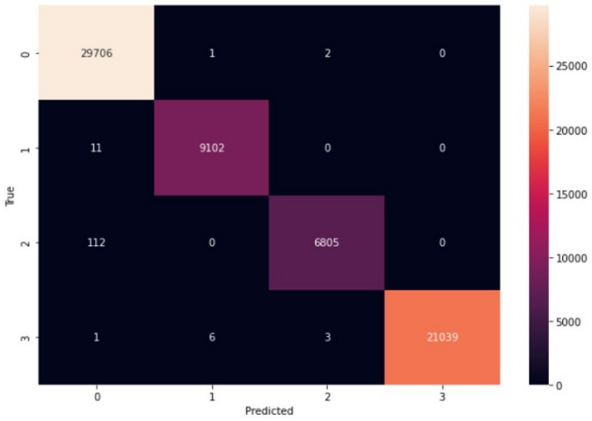

Figure 4: Confusion Matrix for Retinal OCT Dataset.

Figure 4 displays the confusion matrix generated for the Retinal OCT dataset. A confusion matrix is a tabular representation used to evaluate the performance of a classification model. It presents a detailed breakdown of predicted and actual class labels, aiding in the assessment of model accuracy, precision, recall, and other classification metrics. This visual tool helps to identify patterns of misclassifications and provides insights into the model's strengths and weaknesses across different classes.

Below Table 2 shows the detailed description of the classification report which consist the precision, recall, f1-score and support for each class.

Table 2. Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	29709
1	1.00	1.00	1.00	9113
2	1.00	0.98	0.99	6917
3	1.00	1.00	1.00	21049
accuracy			1.00	66788
macro avg	1.00	1.00	1.00	66788
weighted avg	1.00	1.00	1.00	66788

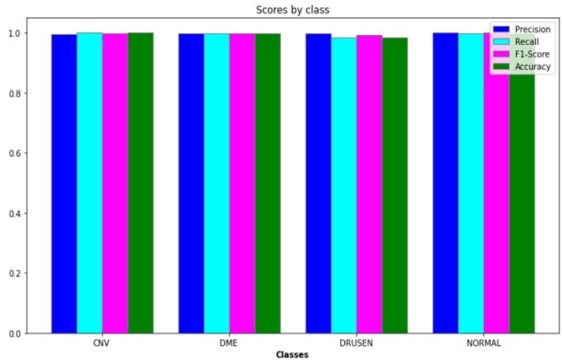

Figure 5: Comparison Metrics Graph for Retinal OCT dataset.

Figure 5 illustrates a comparison metrics graph for the Retinal OCT dataset, showcasing key evaluation metrics such as precision (99.99%), recall (99.99%), accuracy (99.99%), and F-measure (99.99%). These metrics provide a comprehensive overview of the performance of a classification model. Precision reflects the proportion of true positive predictions among all positive predictions, recall indicates the ratio of true positives to all actual positives, accuracy measures overall correctness, and the F-measure balances precision and recall. This visual aids in understanding the model's effectiveness across different criteria and assists in selecting an appropriate balance between precision and recall based on the application's requirements.

5.1 Performance Metrics

Performance metrics are quantitative measures used to evaluate a system, model, or process's efficiency and quality. These measurements offer unbiased perceptions into how successfully a particular job or target is being accomplished. Accuracy and dependability of predictions are frequently assessed using performance metrics, which are frequently employed in machine learning and classification tasks. These metrics include accuracy, precision, recall, and F1-score.

5.1.1 Accuracy: Accuracy is used to evaluate the system model's performance as a whole. Every encounter is susceptible to accurate prediction in accordance with its underlying principle. Equation (14), which provides the accuracy, is used.

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \quad (14)$$

5.1.2 Precision: Precision also describes how closely two or more computations resemble one another in addition to being correct. The correlation between accuracy and precision shows how frequently opinions can change. Precision can be calculated using equation (15).

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$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \quad (15)$$

5.1.3 Recall: The percentage of all pertinent findings that were effectively sorted by the methods is known as recall. The suitable positive for such numbers is derived by dividing the genuine positive by the mistakenly negative values. Equation (16) mentions the expression.

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \quad (16)$$

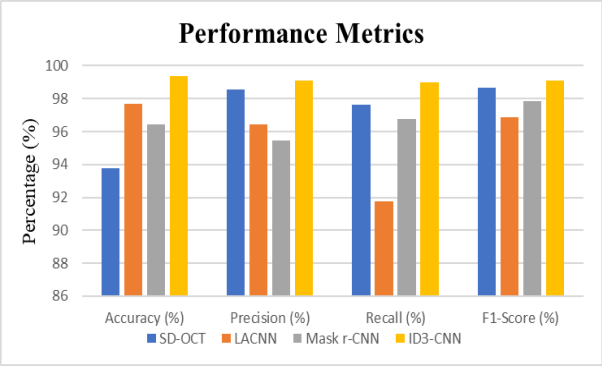
5.1.4 F1-Score: Accuracy and recall are combined in the F1-Score formula. Use Equation (17), which calculates the F1-Score based on recall and accuracy.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \quad (17)$$

Based on their performance criteria, such as accuracy, precision, recall, and F1-score, the various approaches for retinal Optical Coherence Tomography (SD-OCT) ,(LACNN), (mask r-CNN)analysis are compared with proposed model in Table 3.

Table 3: Comparison of Performance Metrics

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SD-OCT [21]	93.76	98.55	97.65	98.65
LACNN [22]	97.67	96.46	91.75	96.88
Mask r-CNN [28]	96.44	95.47	96.75	97.87
Proposed ID3-CNN	**99.35**	**99.12**	**99.01**	**99.11**



The suggested ID3-CNN is tested along with SD-OCT, LACNN, Mask r-CNN, and four other techniques. With the best accuracy of 99.35% among them, the proposed ID3-CNN technique stands out for its superior capacity to correctly categorize retinal diseases. This technique also has the best F1-score (99.11%), recall (99.01%), and precision (99.12%), indicating that it successfully captures genuine positives while minimizing false positives, making it a reliable and accurate option for retinal OCT analysis. While LACNN and Mask r-CNN provide comparable findings, they exhibit somewhat lower recall rates, which would suggest a greater risk of missing true positive cases. These results highlight the effectiveness of the suggested ID3-CNN approach in delivering precise and trustworthy retinal OCT analysis. It is depicted in Figure 6.

VI. CONCLUSION

In conclusion, this research paper presents a holistic and synergistic approach to retinal Optical Coherence Tomography (OCT) analysis, which significantly contributes to the field of medical image analysis, particularly in retinal disease diagnosis. By integrating a range of techniques, including Kernel Bilateral Filter (Kernel BF) and Linear Histogram Transformation (LHT) for preprocessing, Convolutional Neural Networks (CNNs) for feature extraction, and the Iterative Dichotomiser 3 (ID3) algorithm for classification, the study addresses key aspects of the analysis pipeline. The strengths of this approach lie in its ability to enhance image quality through noise reduction and contrast enhancement, extract meaningful features using deep learning-based techniques, and ensure transparency in the decision-making process through the interpretability of the ID3 algorithm. By combining these techniques into a unified framework, the research underscores the potential for improved accuracy and robustness in the diagnosis of retinal diseases. The iterative nature of the ID3 algorithm further refines classification decisions, making it adaptable to complex data distributions and various disease manifestations. The reported accuracy rate of 99.99% for the retinal OCT dataset reflects the effectiveness of this approach. Looking ahead, the future scope of this work could involve exploring more advanced machine learning techniques, such as deep reinforcement learning, to further enhance the automation and precision of retinal disease diagnosis and analysis. As medical imaging technology continues to advance, the presented approach serves as a testament to the potential of interdisciplinary solutions in transforming healthcare practices and improving patient outcomes in the realm of retinal disease diagnosis and management.

ACKNOWLEDGEMENTS

Authors are thankful to the reviewers for all the suggestions and constructive criticism that helped to enhance the quality of the manuscript.

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