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A novel eye disease segmentation and classification model using advanced deep learning network

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ABSTRACT

An effective deep learning model is recommended for detecting glaucoma. Here, the detection process contains three phases: image collection, segmentation, and detection. At first, the required images are collected from benchmark sources. Further, the collected images undergo optic cup and disc segmentation. Here, the segmentation is performed by Trans-MobileUnet with Novel Loss function (TMUnet-NL). The segmented image with minimal loss is given as input to the Attention-based Dilated Hybrid Network (ADHNet) for detection. It is a powerful solution for eye disease classification by combining the strengths of Dilated and attention-based VGG16 and DTCN models. In this ADHNet, the features from cup, disc, and raw images are extracted by Visual Geometry Group (VGG16) network. The features from the cup, disc, and whole images are fused and it is given to the Deep Temporal Convolution Network (DTCN) for Glaucoma detection. While compared with classical techniques, the recommended method shows an accuracy rate of 94%. In earlier stage, the accurate treatment of the eye disease can take some precautions from the sight loss. The significance of eye disease primarily lies in early detection to enhance the treatment outcomes and offer more reliable solutions in eye health management. By adopting the deep learning model, the segmentation and classification of eye diseases have the ability to make a better decision-making process from the clinical experts. Regular eye examination is conducted by clinical experts to improve eyesight to enhance the quality of day-to-day life.

1. Introduction

Glaucoma stands as a prominent cause of irreversible blindness globally; damage to the retinal ganglion cells as the underlying cause of permanent vision loss [1]. This eye condition manifests as optic neuropathy, primarily impacting the retinal structure, particularly within the Optic Nerve Head (ONH) region. Among its variations, Open-Angle Glaucoma (OAG) emerges as the most prevalent form [2]. OAG develops gradually, characterized by the gradual blockage of the drainage system. This obstruction results in the enlargement of the optic cup area with elevated intraocular pressure. In contrast, Angle-Closure Glaucoma (ACG) manifests as another subtype, stemming from blockages in the drainage canals. This variant leads to sudden and rapid surge in intraocular pressure. Glaucoma has been recognized by the World Health Organization (WHO) as the second most prevalent cause of vision impairment and blindness worldwide. Although glaucoma can affect individuals of any age, it becomes more prevalent among the elderly population. Notably, among those who aged 60 and above, glaucoma ranks as a primary contributor to blindness [3]. The gradual progression of the disease often means that individuals remain unaware of diminishing vision until the condition has reached an advanced stage [4].

The realm of glaucoma diagnosis is experiencing a shift towards employing medical image analysis techniques, supplanting more traditional testing methodologies. In these instances, a multitude of aspects

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within the retinal structure necessitate scrutiny, including the ONH, the cup, atrophy, and the layer of retinal nerve fiber. Within fundus images, the ONH emerges as a prominent and circular region, housing a smaller inner area known as the cup. Encircling the ONH, atrophy presents as a crescent-shaped zone [5]. The retinal nerve fiber layer, marked by its white striated patterns, lies exterior to the ONH. To decipher the requisite features for glaucoma diagnosis through computer vision, two primary techniques find application: segmentation and feature extraction [6]. Numerous established methods involve localization and segmentation techniques, including active contours and thresholding. Inclusive of these, other methodologies like fuzzy c-means have been developed [7]. These techniques often encounter challenges in accurately classifying the ONH region. Consequently, to address such limitations, morphological operations are typically implemented. Concurrently, various strategies for extracting textural features from the ONH have emerged with its significance in glaucoma detection [8].

A multitude of studies have showcased the capacity of image processing algorithms to autonomously detect hemorrhages, microaneurysms, cotton wool spots, and hard exudates [9]. Yet, the task of identifying neovascularization remains relatively nascent. The intricacy of distinguishing between regular blood vessels and newly formed vessels impedes progress, further compounded by the scarcity of labeled neovascularization images available for research. Angiography-based techniques have the potential for comprehensive retinal imaging, albeit at the cost of invasiveness, rendering them less suitable for early-stage or routine diagnoses [10]. Consequently, a deep learning approach for neovascularization detection has gained traction, with transfer learning serving as a foundation. Commonly, a hybrid network combining ResNet18 and GoogLeNet is favored [11]. The efficacy of this combined network is measured against its constituent pre-trained networks, including GoogleLeNet, AlexNet, ResNet50, and ResNet18 [12]. Moreover, the assessment of transfer learning outcomes gauges the efficiency in neovascularization detection. Notably, findings suggest that the network featuring the ResNet18 and GoogLeNet fusion excels in detecting neovascularization, surpassing the performance of other pre-trained networks through transfer learning [13].

1.1. Research questions of the study

The following research questions of eye disease segmentation and classification are further illustrated below.

RQ1. Is the effective classification done in this research work? What techniques have been adopted?

RQ2. How can we adopt a better segmentation framework for eye disease with sufficient training data?

RQ3. How the accuracy gets improved by the developed model for eye disease segmentation and classification model?

The advanced glaucoma detection model contributed significant importance mentioned below:

- To develop a novel deep learning model that detects the eye disorder even before any noticeable symptoms become visible to the naked eye. This system used advanced models to analyze images of the eye and identify patterns associated with various diseases, allowing for early detection and treatment. By catching eye disorders in early stages, patients can receive prompt medical intervention and prevent further damage to their vision. Ultimately, this classification system aims to improve patient outcomes and reduce the prevalence of vision loss due to undiagnosed eye conditions.
- To design a TMUnet-NL to perform accurate segmentation of optic cup and disc. Here, the transformer layer is included to provide a better vector representation. This innovative approach combines advanced technology with medical expertise to create a powerful tool for diagnosing eye conditions. The use of a transformer layer in the network enhances the accuracy of the segmentation process, allowing for precise identification of the optic cup and disc. By accurately detecting and classifying eye disorders, medical professionals can intervene early and effectively improves patient care and minimizes the vision loss on individuals and society as a whole.
- To design the ADHNet for eye disease classification, by using the combination of feature extraction capabilities of VGG16 with the classification expertise of DTCN, ADHNet effectively leverages the strengths of both architectures to achieve accurate and reliable predictions in the realm of eye disease classification from medical images. By incorporating attention mechanisms and dilated convolutions into the network, ADHNet can focus on important regions of the input image while capturing contextual information at different scales. This results in improved performance in distinguishing between different types of eye diseases and making more precise predictions.
- To assess and quantify the performance improvement achieved by the developed deep learning model in comparison to traditional techniques. This could involve diverse measures as sensitivity, specificity, and overall accuracy. This quantitative analysis can provide significant outcomes into the potential benefits of incorporating deep learning technology into the field of ophthalmology.

The section labels for the following content are suitable. Section 2 delves into the research examination of various eye disease classification methods. An intelligent framework of eye disease classification using an attention-based hybrid technique is covered in Section 3. Section IV provides optic cup and disc segmentation using transformer-aided MobileUnet and its novel loss function. Section V describes the attention-based dilated hybrid network for classifying eye disease. The execution and results of the empirical analysis are elaborated in Section VI, while the outcomes of the intended task are outlined in Section VII.

2. Existing works

2.1. Related works

2.1.1. Research based on deep learning techniques

In 2020, Masot *et al.* [14] have implemented a diagnostic instrument designed to aid in the identification of glaucoma using fundus images of the eye. Initial subsystem has employed a blend of segmentation and machine learning techniques to identify optic cup and disc. This component was then merged, and their physical and positional attributes were extracted. Next, the transfer learning methods were utilized on a pre-trained Convolutional Neural Network (CNN). This second subsystem focused on detecting glaucoma by comprehensively analyzing the entire fundus image of the eye. The outcome from both subsystems was synergistically amalgamated to effectively identify instances of glaucoma and enhance the overall detection process.

In 2022, Shyamalee *et al.* [15] have developed the CNN model to classify the glaucoma subjects using the fundus image. The comparative analysis has been suggested with different configurations with CNN architectures that have been validated using the ACRIMA fundus dataset to achieve maximum accuracy. In 2022, Islam *et al.* [16] have developed an innovative approach to automatically classify glaucoma. The process began with the creation of a novel, proprietary dataset consisting of 634 color fundus images. The consideration of deep learning models such as MobileNet, EfficientNet, DenseNet, and GoogLeNet were employed to discern the presence of glaucoma in fundus images. In order to enhance accuracy, a distinct dataset was generated by employing a U-net technique to meticulously segment the blood vessels from retinal fundus images. However, the high resolution images were utilized in the UNet model.

In 2021, Kaushik *et al.* [17] have initiated an innovative approach known as the stacked generalization of CNN. This approach entailed integrating the weights of three distinct custom CNN models into a single *meta*-learner classifier. This *meta*-learner harnessed the optimal weights from the sub-neural networks, resulting in robust prediction outcomes and enhanced evaluation metrics. After thorough evaluation, the proposed stacked model showcased enhanced performance in the image processing schema and the stacked deep learning technique led to significant enhancements in diagnostic accuracy and reliability. In 2023, Shamsan *et al.* [18] have employed hybrid approaches that combine processes such as feature extraction and unification for classifying a dataset on eye diseases. Three approaches were taken: first, after decreasing high-dimensional and recurrent features employing Principal Component Analysis (PCA), an Artificial Neural Network (ANN) with MobileNet and DenseNet121 techniques independently was employed; second, fused characteristics from both algorithms were employed before and following reducing characteristics; and third combined with handmade characteristics. AUC of 99.23 %, precision, precision, specificity, and sensitivity values of 98.45 %, 98.45 %, and 98.75 % were all attained by the ANN.

In 2023, Topaloglu and Ismail [19] have developed a new technique for diabetic retinopathy disease utilizing deep learning-based Convolutional Artificial Neural Networks (CANN). The proposed method was effective, which has resized accessible data with total amount of pixels before generating an average information pool. The mathematical framework combined every data by the total amount of components and epoch-time eight tendons. The case study employed both the VGG19 image classification approach and an algorithm. The simulation obtained 87 % train precision, 88 % test accuracy, 93 % precision, and 83 % recall.

In 2022, Tang *et al.* [20] have introduced a neovascularization detection method utilizing transfer learning. The approach involved leveraging the capabilities of four pre-trained CNN models: GoogLeNet, AlexNet, ResNet50, and ResNet18. Furthermore, an enhanced network was introduced by combining GoogLeNet and ResNet18 architectures. Through rigorous examination of 1174 retinal image patches, the proposed network demonstrated remarkable effectiveness.

In 2017, Ting *et al.* [21] have implemented a method to train and validate a Deep Learning System (DLS) designed to identify cases of referable DR, vision-threatening diabetic retinopathy, and associated eye conditions. The training and validation process utilized retinal images in an ongoing nationwide DR screening initiative in Singapore. The method's efficacy was further confirmed through external validation across ten additional multiethnic datasets from various countries. This comprehensive methodology not only demonstrated the effectiveness of the DLS in detecting DR across diverse datasets but also offered valuable insights into its potential applications within different screening models.

2.1.2. Existing pre-processing techniques for eye disease classification

In 2021, Aruandzeb *et al.* [22] have suggested Modified Particle Swarm Optimization (MPSO) to fine-tune the parameters of Contrast Limited Adaptive Histogram Equalization (CLAHE). The primary emphasis was placed for optimizing contextual regions and clip limit within the CLAHE process. By employing this approach, the MPSO-optimized CLAHE method demonstrated enhanced image quality, as evidenced by standard evaluation metrics. Notably, these improvements were most pronounced when utilized in conjunction with deep learning models. The outcomes obtained through this strategy highlighted a substantial and beneficial influence in medical imaging tasks of this nature. In 2020, Zhang *et al.* [23] have developed a groundbreaking automated method known as the Hyper Parameter Tuning Inception-v4 (HPTI-v4) model, meticulously crafted for the precise detection and classification of Diabetic Retinopathy (DR) using color fundus images. Pre-processing model has the ability to improve image contrast by adopting the CLAHE model. Afterward, the preprocessed images undergo segmentation via a histogram algorithm. Following segmentation, the HPTI-v4 model comes into action, extracting crucial features. These extracted features were fed into a Multilayer Perceptron (MLP) for classification purposes.

2.1.3. Machine learning technique for eye disease classification

In 2018, Poplin *et al.* [24] have developed an innovative machine-learning technique, capable of autonomously extracting novel insights from images. By utilizing models trained on a comprehensive dataset comprising 284,335 patients, the method was subsequently validated on two separate datasets, one containing 12,026 patients and the other 999 patients, respectively. This approach unveiled previously undetected cardiovascular risk factors present within retinal images. The models put forth in this study harnessed distinct anatomical features within retinal images to generate each prediction. These features included elements like the optic disc or blood vessels, offering promising avenues for future exploration and research. In essence, this groundbreaking technique showcased the potential of machine learning to uncover hidden cardiovascular insights from retinal fundus images, expanding the scope of knowledge attainable through this visual medical data.

2.1.4. Clinical in-sights of eye disease classification

In 2024, Vyas et al. [25] have suggested a popular clinical test for diagnosing Dry Eye Disease (DED), which was the Tear Film Breakup Time (TFBT) test, yet it was labor-intensive, personal, and time-consuming. The extent of DED could not be determined by current computer-assisted detection approaches. This research proposed a unique TFBT-based DED detection method that used TFBT to reliably identify the severity of DED, detect whether it was present or absent from TFBT footage, and classify it as normal, mild, or extreme. The method has 83 % classification accuracy, a 90 % agreement with ophthalmology views, and 90 % detection accuracy for DED in TFBT movie intensity grading. In 2022, Shyamalee et al. [26] have implemented a strategy of a combination model to segment and classify the retinal fundus image in glaucoma detection. To enhance the image quality, diverse pre-processing techniques were adopted to achieve accuracy. Also, the data augmentation technique has been eradicated by considering the data augmentation techniques. The RIM-ONE dataset was taken for the implementation to achieve better accuracy rate of the model.

2.1.5. UNet-based Techniques for segmenting fundus images

In 2022, Shyamalee *et al.* [27] have implemented a novel attention U-Net model along with three CNN architectures like Inception-v3, Visual Geometry Group 19 (VGG19), and Residual Neural Network 50 (ResNet50) for accurately segmenting the fundus image. To reduce overfitting issues, the data augmentation technique has been adopted to achieve high accuracy. Overall, the empirical outcome of the model has attained 99.53 % using RIM-ONE dataset.

2.1.6. Inception techniques for image segmentation

In 2023, Faizal *et al.* [28] have suggested a method for automating the identification of cataract illness focused on normal visual wavelength images and medically obtained anterior segmental images. The technique was optimized using Inception-v3 and adaptive thresholding to provide immediate and precise outcomes. Images in visible wavelengths were used to train the model, while anterior segment eye pictures collected through medical means were used to validate it. The model design and suggested image pre-processing method provide a classification precision of almost 95 %. Nuclear glaucoma cortical glaucoma or a hybrid comprising both kinds of cataracts could all be identified by the technique.

2.2. Research Gaps and challenges

The vision function is carried out by the eye and it is considered as the most important organ of the human. Vision loss has occurred to be result of several eye diseases. Several techniques have been developed for eye disease classification. However, they are not suitable for identifying glaucoma disease, or diabetic retinopathy disease. Moreover, the symptoms of the eye disease are not identified by the existing

Table 1
Strength and weakness of traditional eye disease classification models.

Author [citation]	Methodology	Strength	Weakness	Advantages of the developed model
Islam *et al.* [16]	EfficientNet	• It is used for the glaucoma classification process. • It is used to dissect the blood vessels from the retinal images.	• It requires more amounts of computation possessions so it takes more cost for the classification process. • It is only suitable for the fixed-size input.	• The effective classification performance is done by attaining the essential features to enhance the performance. While focusing better data quality and addressing data imbalance issues, the developed model could effectively resolve this drawback to enhance classification performance.
Masot *et al.* [14]	pre-trained CNN	• It detects glaucoma in the eye fund images so the damage in the optic nerves is highly prevented. • It is used to extract the physical and the positional features from the images.	• It is only suitable for the particular format of images. • It gives poor reliability and sensitivity.	• By implementing the novel deep learning model, the sensitivity of the model increases to strengthen the reliability of the model in the eye disease classification model.
Zhang *et al.* [23]	HPTI-v4, MLP	• It is employed to extract features from segmented images. • It is utilized for the comprehensive classification of diseases.	• It does not automatically classify the diabetic retinopathy images. • It does not identify the rise in the glucose level of the human body.	• It is efficient to classify the eye disease by introducing the novel deep learning model as ADHNet.
Tang *et al.* [20]	AlexNet, CNN	• It is used to analyze the patches of the retinal images. • It is used for neovascularization detection with higher accuracy.	• It is not fit for retrieving the complex features from the images. • It is not a deep model it performs slowly as compared to the other techniques.	• The adoption of the deep learning model facilitates to boost-up the training process compared to other neural networks. Also, the convergence of the model shows higher performance.
Kaushik *et al.* [17]	CNN	• It is used for the luminosity normalization process to get more accurate results. • It gives accurate prediction results by combining the weight values so it solves the non ideal illumination issues in the images.	• It gives high generalization errors during the prediction process. • It is not suitable for the diverse quantities of images.	• The generalization error of the model is reduced by validating the data with large data to enhance the performance of the eye disease classification model. In order to express better quality outcomes, the images are collected from standard datasets to enrich the performance in the developed model.
Aruandzeb *et al.* [22]	CLAHE	• It optimizes the clip limit and the contextual regions of the images to find the eye disease effectively. • It is used to augment the green strait of the retinal fund images.	• It is not suitable to neglect the noise amplification so the results are affected by this process.	• To eradicate noise in the images, the research work adopts an advanced segmentation technique in order to improve the image quality. Within the specified region, the noise can be removed using the segmentation technique.
Ting *et al.* [21]	DLS	• It is used to identify the Diabetic Retinopathy and other eye-related disease. • It attains high specificity and specificity during the prediction process.	• It does not give accurate vision outcomes.	• The developed model focuses on identifying the complex patterns to enhance the accuracy in classification performance. This accurate analysis helps to significantly improve the treatment and vision loss.
Poplin *et al.* [24]	Neural network	• It is used for identifying the cardiovascular risk identification process. • It is used for analyzing the features and color of the images to get an effective outcome.	• It is only suitable for developing the attention heat maps so it gives poor results.	• By employing standard deep learning techniques in this research work, the model's generalizability could be performed within the unseen data which helps to enhance the result outcomes in the developed model. Based on this context, the clinicians provide appropriate treatment for the individuals.

techniques. Table 1 presents the features and challenges associated with the current eye disease classification methods.

- Existing eye disease classification models have limited generalization capability, where models struggle to perform well on unseen data or different populations. This gap is effectively addressed by leveraging deep learning techniques. Deep learning models shows great impact in learning complex patterns and features from data, enabling them to generalize better to new and diverse datasets.
- Existing eye disease classification models have the issue of inadequate localization of abnormalities within eye images. This gap can be effectively addressed by enhancing the segmentation process. This process can accurately identify and segment specific abnormalities in the eye images, leading to more precise disease diagnosis and classification.
- Existing eye disease classification models lack model fusion, where models do not effectively combine multiple modalities or architectures to leverage complementary information for more accurate disease classification. On the other hand, the research work adopts the hybrid models that integrate features from different sources. Hybrid models can effectively bridge the gap in existing models by leveraging diverse information sources to improve overall performance of eye disease classification systems.
- Existing eye disease classification models has the ability to classify certain rare or complex eye conditions due to insufficient information. This gap is addressed by incorporating dilation in the classification models. By utilizing dilation in image preprocessing, classification models can potentially improve their performance in distinguishing subtle differences in eye diseases, leading to more precise diagnoses and treatment recommendations.
- Existing eye disease classification models provide a limited focus on capturing important relationships and features within the eye images. This gap can be effectively solved by considering attention mechanisms into the models. Incorporating attention mechanisms helps the model to process dynamically focus on relevant parts of the input data, emphasizing important features while suppressing irrelevant ones.

To tackle the existing challenges, in this work, we developed a novel eye disease classification with advanced model.

3. An intelligent framework of eye disease classification by attention-based hybrid learning model

3.1. Collection of retinal images

The eye disease dataset is a reputable and standardized data

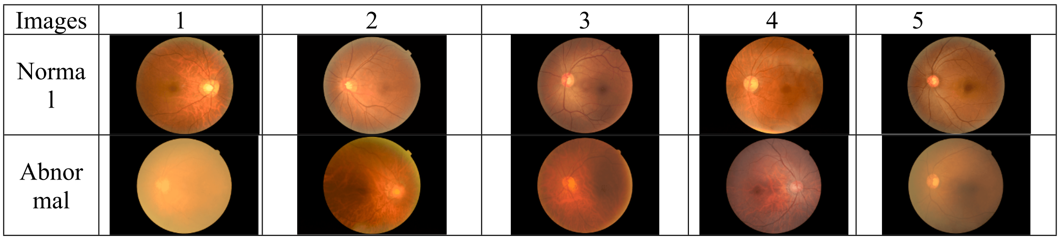

Fig. 1. Sample images for eye disease classification system.

Table 2
OD-OC ratio for each image.

Images description	Accuracy (%)
Image-1	91.03
Image-2	92.93
Image-3	92.02
Image-4	93.50
Image-5	92.83

Table 3
Description of parameters and network complexity.

Parameters	Range
Activation	Relu
Input shape	(224, 224, 3)
Kernel size	(3, 3)
Loss	Categorical_crossentropy
Optimizer	Adam
Complexity of the network	$O = Max_{Itera} + N_{POP} + Ch_{length} + 1$ Here, the term Max_{Itera},N_{POP} and Ch_{length} are the maximum iteration, number of population, and chromosome length.

repository. A concise overview of the collected dataset is provided below.

Dataset 1 (Glaucoma Detection dataset): The information collected from the link is given as "https://www.kaggle.com/datasets/sshikamaru/glaucoma-detection?select = glaucoma.csv access date: 04–08-2023". These datasets commonly encompass a diverse assortment of images or OCT scans depicting various aspects of the eye, encompassing both typical and glaucomatous conditions. These datasets often come with accompanying annotations or labels that provide information regarding the existence or degree of glaucoma within the depicted cases. The dataset comprises several classes like ACRIMA, Fundus, and ORIGA. For each class, the total count of images includes 705, 630, and 650. The image size is taken as 512 × 512. From the total data, the training and testing data is considered as 75 % and 25 %.

From the above-mentioned dataset, the collected images are represented as Im_e^{inp}, here $e = 1, 2, \cdots, E$, the quantity of gathered images is represented as E. Fig. 1 shows the sample images for the eye disease classification system and the OD-OC ratio for each image is given in Table 2.

3.2. Trainable parameters

The description of the parameters employed in the developed model is given in Table 3.

3.3. Proposed methodology of eye disease classification

Recently, the emergence of artificial intelligence and medical imaging has ushered in a new era of healthcare, particularly in the field of ophthalmology. Automated systems for classifying eye diseases based on medical images have garnered significant attention for their potential to revolutionize early detection and diagnosis. These systems utilize advanced algorithms to analyze images of the eye, ranging from retinal scans to OCT data, to identify various ocular conditions. This technological innovation presents a host of advantages that promise to enhance patient care and streamline medical processes. However, alongside these benefits, there are also limitations like automated systems cannot consider broader patient context, such as medical history and symptoms, which play a crucial role in accurate diagnosis. This limitation could potentially lead to misdiagnose or overlooking important factors. Automated systems cannot often consider broader patient context, such as medical history and symptoms, which play a crucial role in accurate diagnosis. The proposed method is used to address these mistakes and helped to improve the classification method. Fig. 2 depicts the view of a novel deep learning-based eye disease classification model.

Our primary goal is to detect Glaucoma even before any noticeable symptoms as visible to the naked eye, ultimately enhancing early intervention and patient outcomes. The recommended system consists of several phases for diagnosing Glaucoma and classifying eye diseases using medical images. In this initial phase, the system gathers relevant images from online sources. The optic cup and disc are located at the back of the eye, and they are the entry points for the optic nerve. In Glaucoma, damage to these structures is often one of the earliest signs of the disease. Accurate segmentation is a crucial step in diagnosing Glaucoma. The system employs the TMUnet model for image segmentation tasks. It is to be enhanced with a novel loss function, likely tailored to enhance accuracy of the segmentation results. With the extracted features, the system proceeds to classify eye diseases. The designed model, called ADHNet, appears to be a fusion of VGG16 and DTCN, combining the feature extraction capabilities of VGG16 with the classification expertise of DTCN. The ADHNet model leverages the advantages of VGG16 and DTCN to achieve accurate and reliable predictions in the realm of eye disease classification from medical images. It's capable of classifying the segmented images into various eye disease categories, including Glaucoma.

4. Optic cup and disc segmentation using transformer-aided MobileUnet and its novel loss function

4.1. Basic model of MobileUnet

MobileUNet [29] is a CNN architecture specifically crafted for semantic segmentation tasks, with a particular focus on applications within the realm of computer vision. The deep explanation of MobileUnet is elaborated below.

Mobilenet: MobileNet [30] is designed to create lightweight and efficient CNN suitable for mobile and embedded devices.

Depthwise Convolution: In a depthwise convolution, each input channel is convolved separately with a set of corresponding filters. This means that if an input has C channels, there will be C individual filters, each operating on a single channel.

Pointwise Convolution: Pointwise convolution, also known as 1x1 convolutions, involves applying a 1x1 filter to each of the channels independently. The primary purpose of this step is to linearly combine the outputs of the depthwise convolutions. The number of 1x1 filters

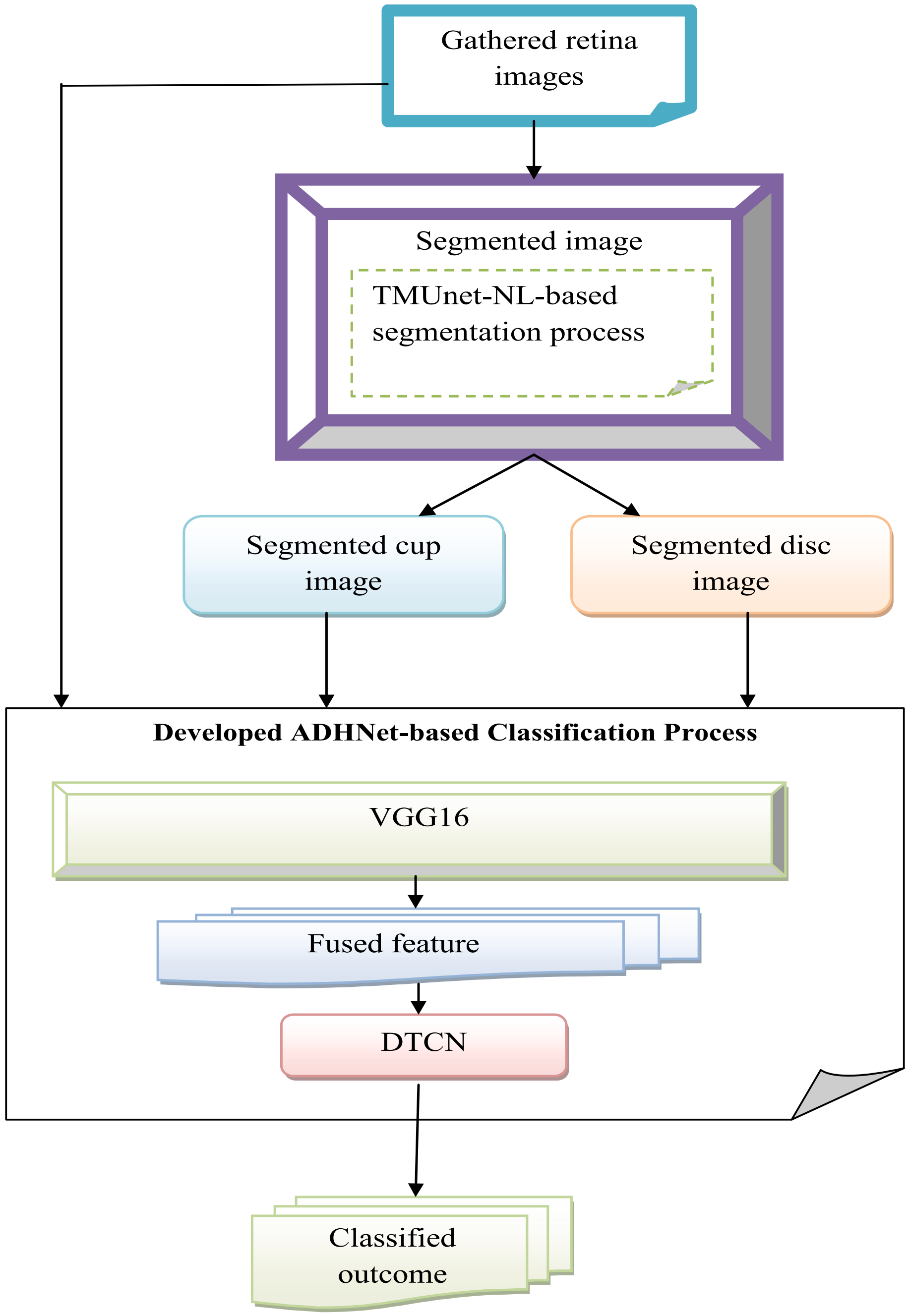

Fig. 2. A view of novel deep learning-based eye disease classification model.

used here to control with the final number of output channels.

The depthwise convolution step produces multiple intermediate feature maps, and the pointwise convolution combines these intermediate maps by linearly combining them through the 1x1 convolution operation.

This design philosophy allows MobileNet to significantly reduce the number of computations and parameters, making it well-suited for resource-constrained environments without sacrificing too much in terms of performance. It's worth noting that while MobileNet is effective in many scenarios, there might be trade-offs in terms of accuracy compared to larger and more complex models.

Unet: The U-Net [31] architecture is a popular CNN architecture designed for semantic segmentation tasks. The approach involves reshaping feature maps to match the desired image dimensions. Achieved by employing convolutional and deconvolutional techniques, this process revitalizes the feature stage. The architectural layout incorporates two main ways: the developing path and the expansive path, in which it is composed of three layers of blocks. Within the developing path, every layer is succeeded by a 2x2 max pooling operation. The convolutional process entails the concatenation of two upsampling layers with two merging layers. The final output layer, responsible for generating pixel-by-pixel value scores, adopts a 1x1 convolutional layer activated by the sigmoid function.

The block layers are configured with filter counts of 112, 224, and 448, respectively. On the expansive path, the filter counts are adjusted to 224, 122, and 122. Notably, the architecture draws inspiration from the original UNet architecture, while integrating novel CNN dropout techniques exclusively within the expansive path. The proposed system replaces the traditional convolutional layers in the UNet architecture with MobileNet-based layers to make the network more efficient while still

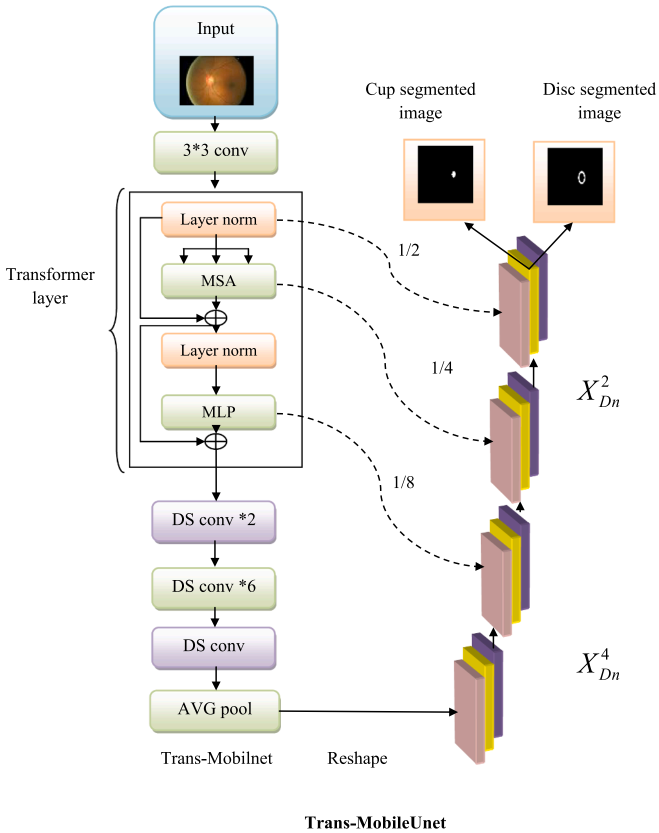

Fig. 3. A view of Trans- MobileUnet for segmentation.

maintaining the semantic segmentation capabilities of UNet.

4.2. Tmunet for segmentation

TMUnet architecture combines the efficiency of MobileNet, the contextual understanding of transformers, and the segmentation capabilities of U-Net to create a powerful model for accurate and contextually informed pixel-wise classification in images. The collected image Im_e^{inp} is the input to MobileUNet, which is given in section IV.A, and the Transformer is explained below.

The key concept of the transformer [32] architecture is self-attention, which enables capturing long-range dependencies between elements in a sequence. In the context of image processing, transformers can be used to process and understand images by treating them as sequences of patches or tokens.

The Transformers model is designed to tackle supervised learning tasks. Tokenization is a crucial technique employed in this context, involving the conversion of input data into a set of 2D patches, which are essentially segments the image that have been partitioned. Each patch's size is represented by the symbol p, and P signifies the total count of patches in the image. The following step involves patch embedding. In this process, each vectorized patch y is transformed using a learnable linear projection that maps it to a D-dimensional embedding space. Eq. (1) captures the positional information associated with this operation..

$$Em(y) = W_{patch}.y + E_{pos} \tag{1}$$

Here the term $Em(y)$ stands for the embedding of the patch y, the variable W_{patch} represents the learnable weight matrix that performs the projection of the patch. Also E_{pos} denotes the positional embedding associated with the patch, incorporating information about its location.

The Transformers decoder comprise of Multihead Self-Attention (MSA) and Multi-Layer Perceptron (MLP). This configuration leads to the formulation of Eq. (2) and Eq. (3), which describes the output of a single layer.

Eq. (2) captures the outcome of a MSA layer operation, where MSA_{in} represents the MSA process applied to the input. The symbol $\oplus$ denotes the concatenation operation.

$$MSA_{out} = MSA_{in} \oplus L_{in} \tag{2}$$

Eq. (3) formulates the result of the MLP operation within a layer. The symbol $\otimes$ represents element-wise multiplication.

$$MLA_{out} = MLP(MSA_{out}) \otimes MSA_{out} \tag{3}$$

These equations encapsulate the transformation and information flow within a single layer of the Transformer decoder, involving MSA and MLP components. Finally, obtained the cup and disc segmented image, which is represented as Cup_e^{seg} and Dis_e^{seg}. Eye disease segmentation using TMUnet has numerous advantages to provide accurate detection and segmentation of eye diseases. This advanced algorithm combines the power of transfer learning and mobile-friendly architecture to enhance the segmentation performance of various eye conditions, providing significant benefits in clinical settings. One key advantage of TMUnet is its high accuracy in segmenting eye diseases from medical images. The algorithm leverages transfer learning, which allows it to adapt pre-trained models to new datasets with limited annotated data. This capability significantly improves the segmentation accuracy of eye diseases, such as diabetic retinopathy or glaucoma, by learning from diverse and extensive datasets. As a result, healthcare professionals can rely on TMUnet to provide precise and reliable segmentation results, aiding in early diagnosis and treatment planning. Moreover, TMUnet offers real-time processing capabilities, making it suitable for applications requiring quick and efficient analysis of eye images. The mobile-friendly architecture of TMUnet ensures that the algorithm can run efficiently on resource-constrained devices, such as smartphones or tablets. This advantage enables healthcare providers to perform on-the-spot analysis of eye diseases, facilitating timely decision-making and patient care. The ability to process images rapidly without compromising accuracy is a significant benefit of TMUnet in clinical practice. Additionally, TMUnet enhances the scalability and accessibility of eye disease segmentation in healthcare systems. The algorithm's efficient architecture allows for seamless integration into existing medical imaging systems, enabling healthcare facilities to adopt advanced image analysis capabilities without significant infrastructure changes. By automating the segmentation of eye diseases, TMUnet streamlines the diagnostic process, reduces manual effort, and improves the overall efficiency of healthcare services. Fig. 3 depicts the view of TMUnet-NL for segmentation.

4.3. Cup and disc segmentation using TMUnet-NL function

TMUnet-NL architecture combines the efficiency of MobileNet, the contextual understanding of transformers, and the segmentation capabilities of U-Net to create a powerful model for accurate and contextually informed pixel-wise classification in images. Segmentation of medical images, such as cup and disc segmentation in retinal images, is a critical task in computer vision and healthcare. Utilizing TMUnet and designing a novel loss function can indeed helped to improve the accuracy of segmentation tasks. The choice of loss function is critical for training a segmentation model.

Loss functions play a critical role in assessing the performance by quantifying how effectively they capture underlying patterns in the data. They enable the models to learn and adapt their parameters in order to minimize the loss, ultimately leading to better performance in either predicting continuous values in regression or classifying data into discrete categories in classification. The Mean Square Error (MSE) of residuals is used instead of just taking the Sum of Squares of Residuals to make the loss function independent of the number of data points in the training set. MSE is often favored over Mean Absolute Error (MAE) in

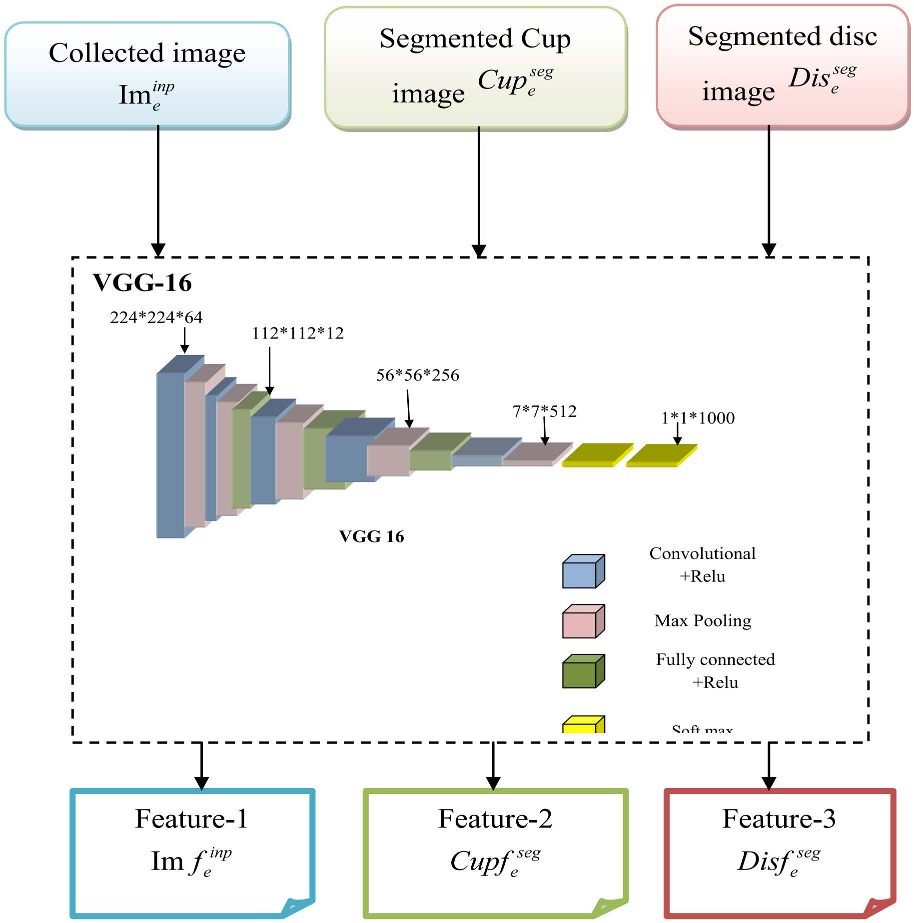

Fig. 4. An architectural representation of VGG16.

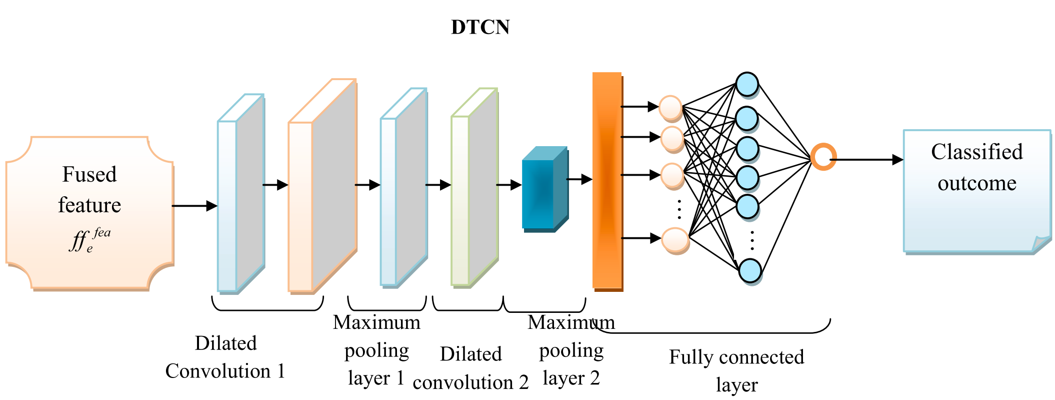

Fig. 5. Architectural view of DTCN.

certain contexts due to the ease of calculating derivatives. This preference arises because calculating derivatives of functions containing absolute values can be more challenging, primarily because the absolute function is not differentiated at its minimum point. Here the MAE is calculated using Eq. (4).

$$MAE = \frac{\sum_{i=1}^{m} |x_i - \overline{x}_i|}{n} \tag{4}$$

Mean Bias Error (MBE) provides insights into whether a model exhibits a positive bias or a negative bias when making predictions, which is mathematically defined in Eq. (5).

$$MBE = \frac{\sum_{i=1}^{m} |x_i - \overline{x}_i|}{n} \tag{5}$$

Cup and Disc Segmentation using TMUnet-NL offers significant advantages in the precise analysis and detection of eye diseases, particularly those affecting the optic nerve head. This advanced algorithm combines the strengths of Trans-MobileUnet with loss function to improve the segmentation accuracy of cup and disc regions, providing valuable benefits in the field of ophthalmology. One key advantage of TMUnet-NL is its enhanced segmentation accuracy for cup and disc regions in eye images. By incorporating a novel loss function, the algorithm can effectively optimize the segmentation process, ensuring more

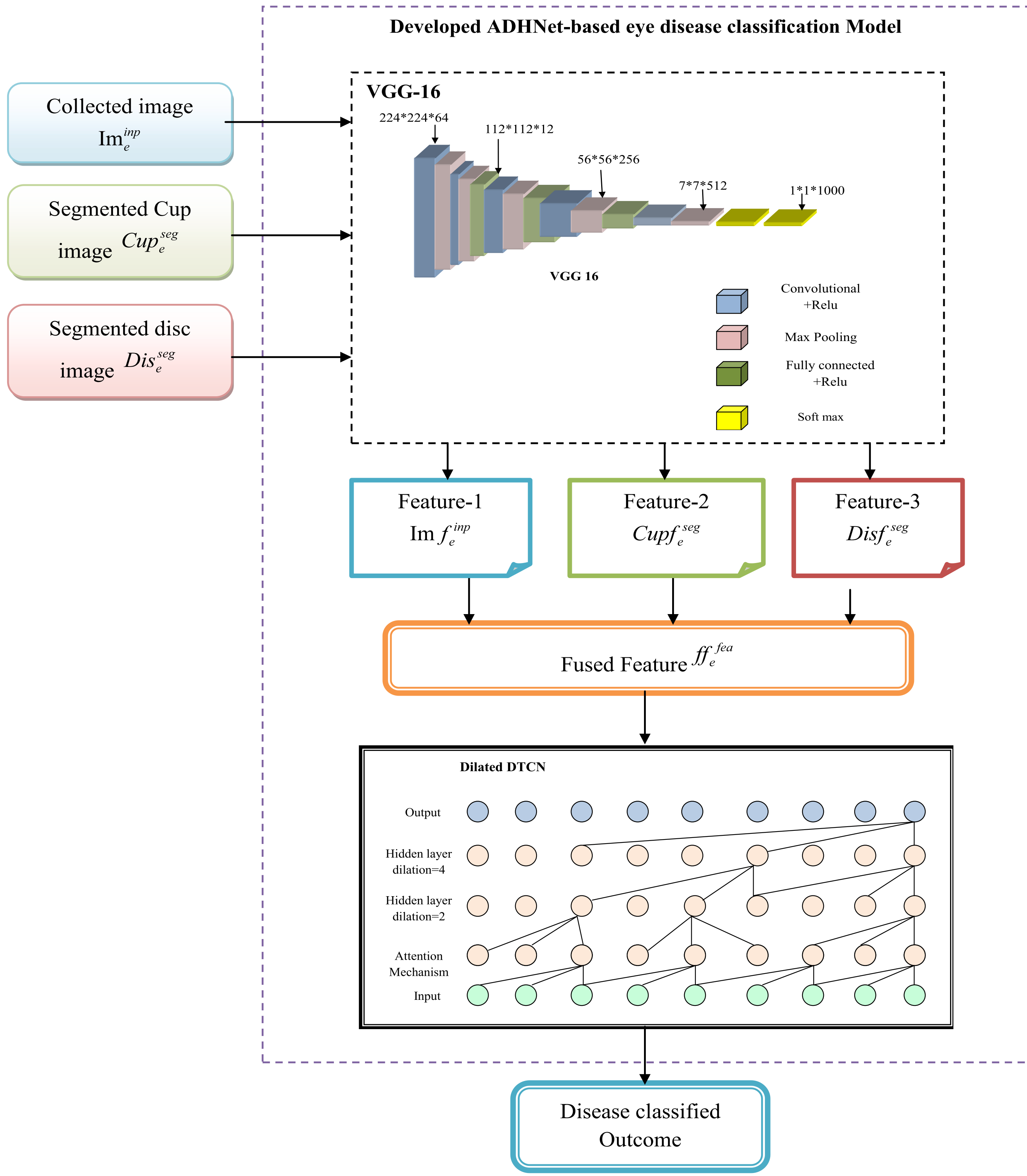

Fig. 6. The proposed view of deep learning based ADHNet Model for eye disease classification.

precise delineation of the optic cup and disc structures. This improved accuracy is crucial for monitoring the eye diseases like glaucoma, where changes in the cup-to-disc ratio can indicate disease progression. With TMUnet-NL, healthcare professionals can rely on more accurate segmentation results, leading to better clinical decision-making and patient care. Moreover, TMUnet-NL acquires robust generalization capabilities, allowing the algorithm to perform well on diverse datasets and across different imaging modalities. The novel loss function adapt to variations in image quality, lighting conditions, and patient demographics, ensuring consistent and reliable segmentation results. This adaptability is essential in clinical settings where image quality may vary, and accurate segmentation of cup and disc regions is critical for diagnosing and monitoring eye diseases. Additionally, TMUnet-NL provides scalability and efficiency in cup and disc segmentation tasks, making it suitable for

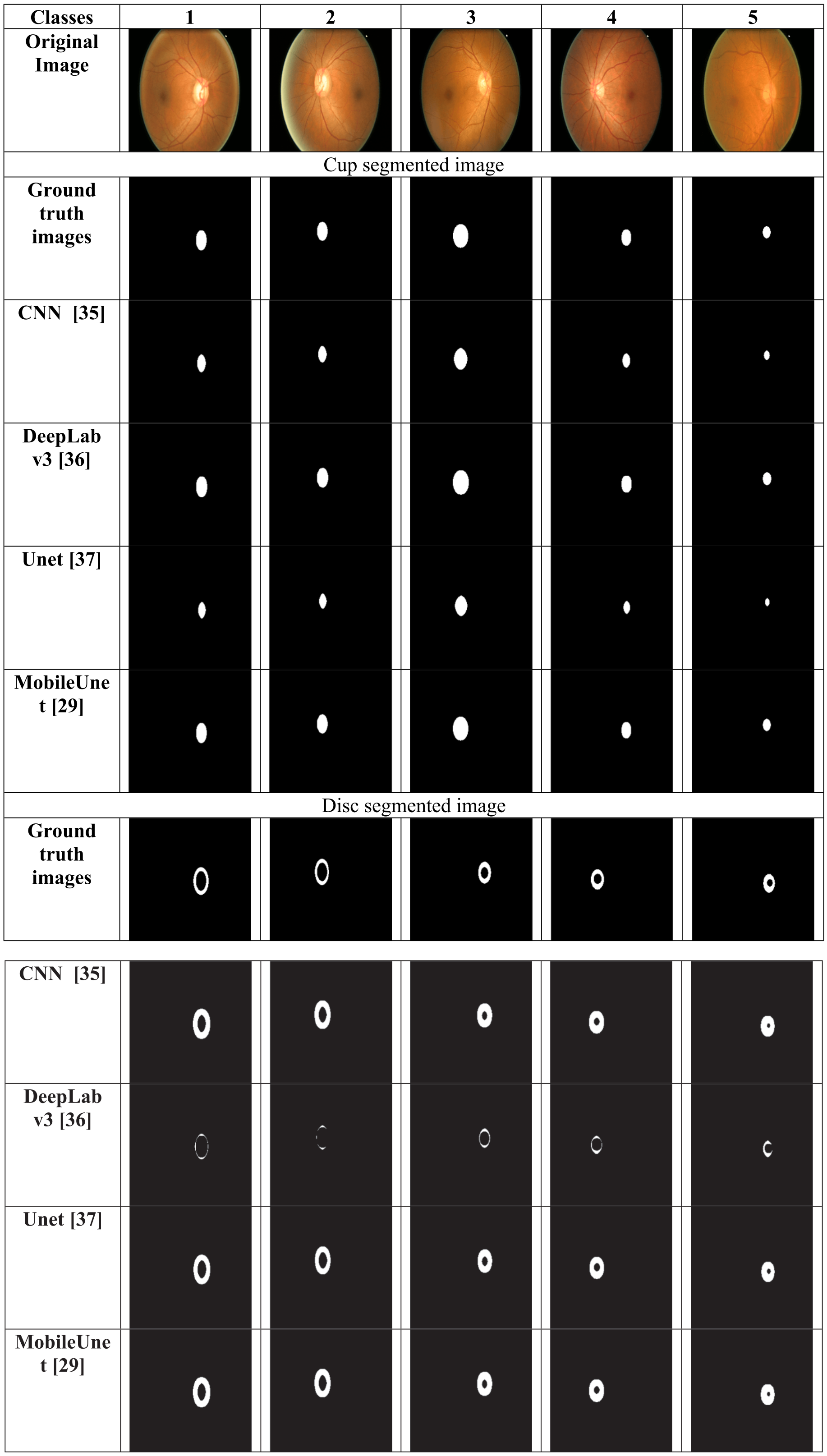

Fig. 7. Resultant images of eye disease classification system model.

integration into existing medical imaging systems. The algorithm's mobile-friendly design ensures that it can run efficiently on a range of devices, enabling healthcare providers to perform rapid and accurate segmentation of optic nerve head structures. By automating the segmentation process with TMUnet-NL, healthcare facilities can improve workflow efficiency, reduce manual effort, and enhance the overall quality of eye disease diagnosis and management.

Table 4
Software and hardware requirements of the developed model of eye disease segmentation and classification model.

Software requirements	
Software	Pycharm
version	3.11 and anaconda v3
Hardware requirements	
Machine	Windows
ROM	500 GB
Processor	i3
Version	11
RAM	8 GB
Libraries	operncv-python Matplotlib Keras tflearn TensorFlow NumPy prettytable

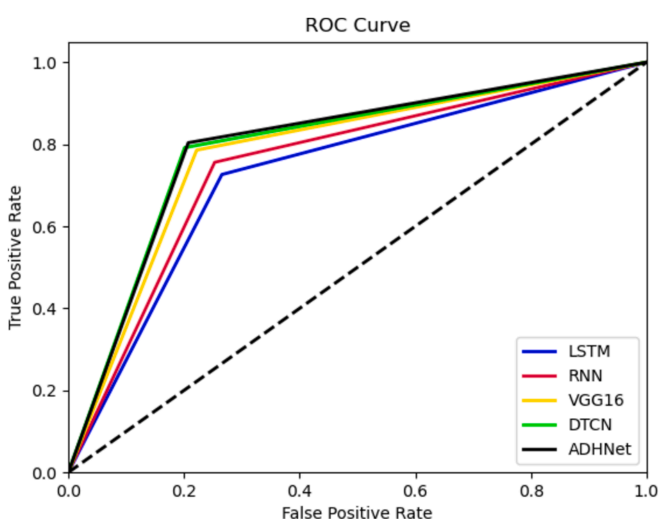

Fig. 8. The examination of the ROC curve for the eye disease classification model is conducted across a range of traditional classifiers.

5. Describing the attention-based Dilated hybrid network for classifying the eye disease

5.1. VGG16

VGG-16 [33] is conceived to delve into the impact of network depth on the efficacy of CNNs in deciphering image recognition challenges. Its purpose was to scrutinize the advantages brought by increased depth compared to shallower counterparts like AlexNet. Before the advent of VGG-16, models like AlexNet had exhibited promise in large-scale image classification tasks, yet they possessed a smaller number of layers. Here the collected image Im_e^{inp}, the segmented images Cup_e^{seg} and Dis_e^{seg} act as the input to this phase, VGG-16 was meticulously crafted to be more profound, boasting a total of 16 layers, with the explicit goal of ascertaining whether heightened depth could translate to superior performance.

In its architectural construction, VGG-16 adopted a uniform approach, consistently employing 3x3 convolutional filters across the network. This strategic decision is pivotal in enabling the network to grasp intricate and hierarchical features embedded within input images. This architectural choice led to an elevated aptitude for feature acquisition and amplified representational capacity.

The input to VGG-16 consisted of images with dimensions 224 x 224 x 3, wherein 224x224 denoted the spatial resolution, and 3 signified the RGB color channels. The design incorporated 13 convolutional layers, each coupled with a Rectified Linear Unit (ReLU) activation function to introduce non-linear transformations. Max-pooling layers ensued after sets of convolutional layers, serving the dual purpose of diminishing spatial dimensions, thereby enhancing translational invariance, and mitigating computational complexity.

Ultimately, the architecture culminated in a fully connected layer that typically underwent a softmax activation function, facilitating the conversion of network outputs into class probabilities. VGG-16′s accomplishments spanned an array of image recognition tasks for detecting object. Its exceptional achievements underscored the pivotal role of depth within CNN architectures and catalyzed the development of more intricate models. In totality, VGG-16′s architectural blueprint and the insights it furnished and stand as pivotal milestones in shaping subsequent advancements in the realms of deep learning and CNNs. Finally obtained the three features, which are represented as Imf_e^{inp}, $Cupf_e^{seg}$ and $Disf_e^{seg}$. Fig. 4 gives architectural view of VGG16.

5.2. Feature fusion

The central objective of feature fusion is to gather complementary or pertinent information from multiple sources, potentially resulting in enhanced performance. By integrating information from different features, can create a more robust and informative representation of the underlying data. The obtained three features are multiplied with respective constant values and then summed finally obtained the fused feature and shown mathematically as Eq. (6)

$$ff_e^{fea} = 0.3 \times Imf_e^{inp} + 0.3 \times Cupf_e^{seg} + 0.4 \times Disf_e^{seg} \tag{6}$$

From the above equation, the term Imf_e^{inp} , $Cupf_e^{seg}$ and $Disf_e^{seg}$ defines the obtained collected image-based feature, cup-based feature, and disc-based feature.

5.3. Deep temporal convolution network

The distinctive feature of DTCN [34] is its integration of temporal convolutional layers. These layers are adept at capturing sequential dependencies and temporal evolutions present in sequences of images. The obtained fused feature ff_e^{fea} is the input to this phase, by convolving across both spatial and temporal dimensions, DTCN becomes proficient in discerning intricate spatiotemporal patterns that would be elusive to traditional CNNs. DTCN's architecture might involve stacking multiple temporal convolutional layers, each extracting progressively higher-level temporal features. In addition, these layers can be interspersed with pooling operations to distill essential information and minimize computational overhead. Activation functions like ReLU can introduce non-linearity, enabling the network to grasp complex temporal dynamics. Mathematically, the convolution operation $K(l)$ executed for the l_{th} time step in a dilated causal TCN layer can be expressed using the following Eq. (7).

$$K(l) = \sum_{i=1}^{s} w(i).y(l-(b.i)) \tag{7}$$

Here, the term s denotes the kernel size of the convolutional layer $w(i)$ is the weight of the i_{th} element within the kernel and $y(l-(b.i))$ corresponds to the input value at the shifted time step accounting for the dilation factor b.

The convolutional operation conducted by a dilated DTCN layer, pertaining to step l and denoted as $M(l)$ can be expressed using Eq. (8). In this equation, the convolution is performed within the range from $y_{l-b.\frac{s-1}{2}} to y_{l+b.\frac{s-1}{2}}$.

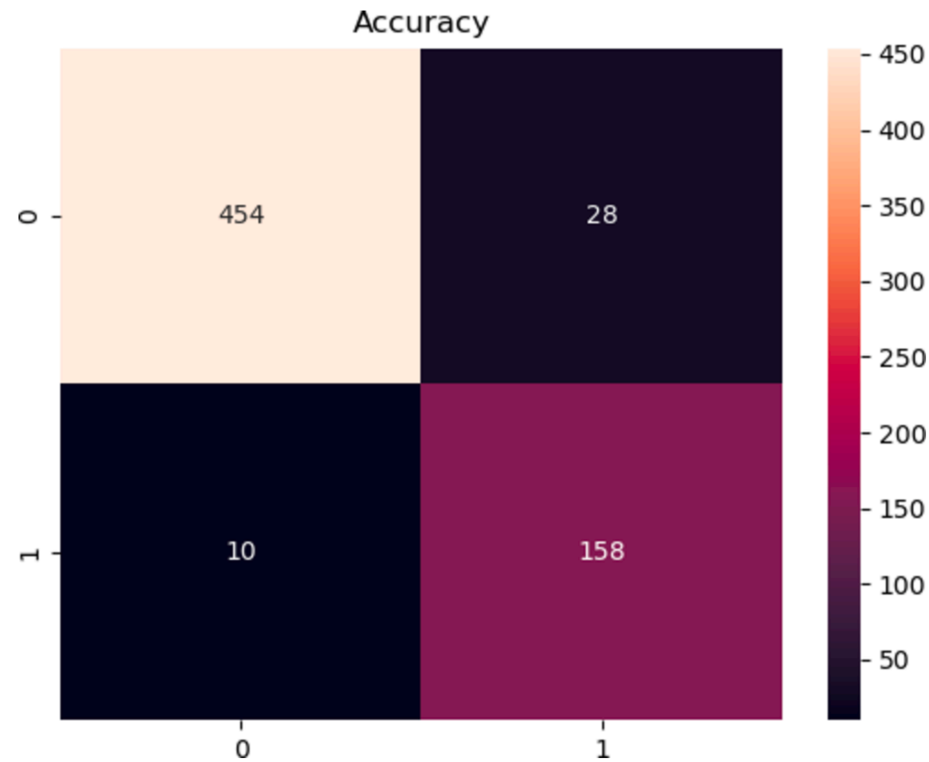

Fig. 9. The examination of the confusion matrix for the eye disease classification model is conducted across a range of traditional classifiers.

$$M(l) = \sum_{y_{l-b.\frac{s-1}{2}}}^{y_{l+b.\frac{s-1}{2}}} w(i - l + s.\frac{s-1}{2} + 1).y(i) \tag{8}$$

Here, the term $M(l)$ represents the output of the convolutional operation at the time step l and s is the kernel size of the convolutional layer. Also, the term $\sum_{ly_{l-b.\frac{s-1}{2}}}^{ly_{l+b.\frac{s-1}{2}}} w(i - l + s.\frac{s-1}{2}+1)$ signifies the weight associated with the i_{th} element in the kernel.

The convolution is performed over a specific range, defined by the shifting of indices in the input sequence to account for the dilation and kernel size. This captures the essence of how a DTCN layer operates in modeling sequence data, finally obtaining the classified outcome, to achieve accurate and reliable predictions in the realm of eye disease classification from medical images. Fig. 5 shows the architectural view of DTCN.

5.4. Description of proposed ADHNet model

Dilated and attention-based VGG16: The Dilated and Attention-based VGG16 combine these two enhancements with the original VGG16 architecture. This typically involves replacing some of the standard convolutional layers with dilated convolutional layers and introducing attention mechanisms at specific points in the network. The dilated convolutions help capture a broader range of spatial information, while attention mechanisms enable the network to adaptively focus on relevant features. This hybrid architecture is particularly effective for tasks that require both a comprehensive understanding of image context and the ability to concentrate on specific details.

Dilated and attention-based DTCN: A Dilated and Attention-based DTCN integrate both dilated convolutions and attention mechanisms into the architecture. Dilated convolutions help the network to capture temporal dependencies over extended time horizons, allowing it to recognize patterns and trends occurring at different scales. Attention mechanisms enable the model to dynamically weigh the importance of different time steps, focusing on relevant information and ignoring noise or irrelevant data. This combined approach results in a powerful model for processing and understanding complex temporal sequences, making it well-suited for various applications.

ADHNet is a deep-learning architecture designed specifically for the classification of eye diseases in medical images. Also, this process involves a combination of deep learning architectures such as VGG16 and DTCN, here VGG16 is used for feature extraction and DTCN for classification. By combining the feature extraction capabilities of VGG16 with the classification expertise of DTCN, ADHNet effectively leverages the strengths of both architectures to achieve accurate and reliable predictions in the realm of eye disease classification from medical images. Here the VGG 16 provides the fused feature to the DTCN model, both network influences the concept of attention mechanisms and dilated convolutions to capture important features in the input images and make accurate disease predictions.

Moreover, in the context of eye disease classification, the attention mechanism plays a crucial role in streamlining the process. It allows the network to focus on specific regions of the input image that are essential for detecting eyes. Instead of treating all parts of the image equally, the attention mechanism enables the network to prioritize areas that are more likely to contain eyes. This selective attention helps in reducing the overall complexity of the task by highlighting important details and disregarding irrelevant information. By integrating the attention mechanism into the process of eye disease classification, the network can effectively manage the complexities associated with using multiple complex models. The attention mechanism enhances the network's ability to handle intricate tasks by guiding it to concentrate on the most relevant features, leading to more precise and efficient eye detection outcomes. In practical terms, the attention mechanism works by assigning weights to different parts of the input image based on their importance for the task at hand. These weights are learned during the training process, allowing the network to dynamically adjust its focus as needed. By giving more weight to areas that are critical for eye disease classification, the attention mechanism helps the network make more informed decisions and improve its overall performance.

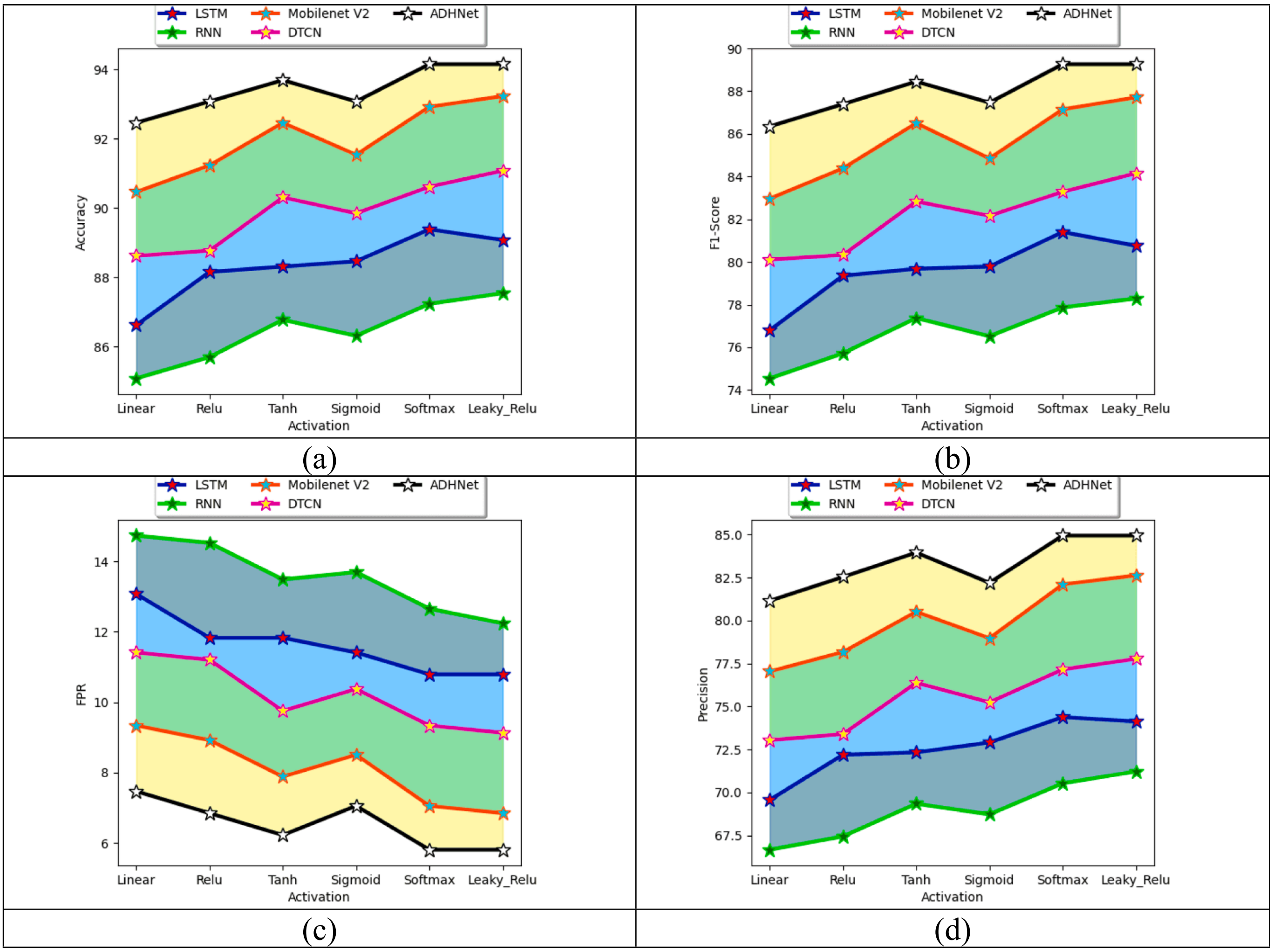

Fig. 10. Determining the activation function of the given eye disease classification model when assimilated with classical models regarding (a) Accuracy b) F1-Score, c) FPR and d) precision.

Eye disease classification using the ADHNet presents several advantages in accurately categorizing and diagnosing eye diseases by leveraging a hybrid network that combines Dilated and attention-based versions of VGG16 and DTCN models. This innovative approach enhances the classification performance and efficiency in identifying various eye conditions, offering significant benefits in the field of ophthalmology. One key advantage of ADHNet is its superior classification accuracy for eye diseases. By integrating both Dilated and attention-based architectures of VGG16 and DTCN models, the hybrid network can effectively capture intricate features and patterns in eye images, enabling more precise disease classification. This enhanced accuracy is crucial for distinguishing between different eye conditions such as diabetic retinopathy, macular degeneration, and retinal vascular diseases, leading to more targeted and effective treatment strategies. Furthermore, ADHNet's attention mechanism allows the network to focus on relevant regions within the input images, thereby improving the model's interpretability and performance. The attention-based components in both the VGG16 and DTCN models enable the network to selectively highlight important features during the classification process, enhancing the overall understanding of the classification decisions. This attention mechanism not only boosts the network's performance but also provides valuable insights into the factors influencing the classification outcomes, aiding healthcare professionals in making informed diagnostic decisions. Moreover, the hybrid nature of ADHNet combining dilated and attention-based architectures offers versatility and adaptability in handling diverse datasets and different types of eye images. The fusion of these advanced models allows for comprehensive feature extraction and representation, enabling the network to effectively classify a wide range of eye diseases with high accuracy and robustness. This flexibility is essential in real-world clinical scenarios where the diversity of eye conditions and imaging modalities requires a versatile and reliable classification system. Fig. 6 shows the proposed view of deep learning-based ADHNet Model for eye disease classification.

5.5. *Resultant images*

The executed eye disease classification model is carried out, and the resulting images are gathered and shown in Fig. 7.

6. Results and discussion

6.1. *Simulation Setup*

The implementation of an eye disease classification system was conducted using Python, and subsequent analysis was performed. This newly proposed model incorporated a variety of classifiers, including LSTM [37], MobileNetV2 [38], RNN [39], DTCN [40], U-Net [31], CNN [35], DeepLab3 [36], MobileUNet [29], Artificial Neural Networks [41], and Gated Recurrent Unit [42], for the classification task. The hardware

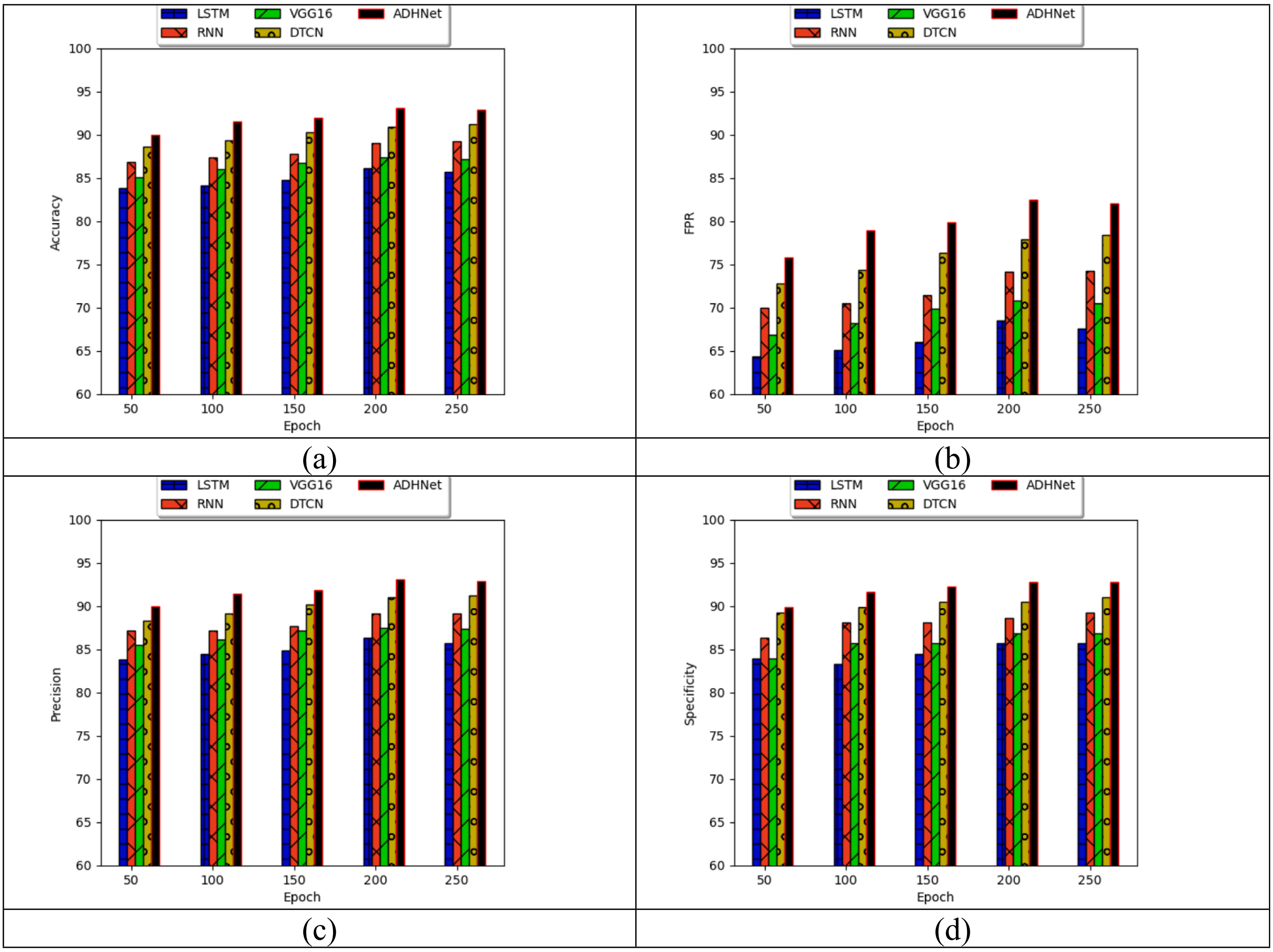

Fig. 11. Determining Epoch value of the given eye disease classification model when assimilated with classical models regarding (a) Accuracy b) FPR, c) precision and d) specificity.

and software requirements of the developed model are shown in Table 4.

6.2. Determining ROC validation of the suggested eye disease classification model over distinct traditional classifiers

Fig. 8 presents a visual representation of how well the improved eye disease classification framework performs when compared to various classifiers on traditional datasets using ROC analysis. The analysis of ROC is widely performed by plotting the true positives and false positives at different threshold values. This figure is crucial for demonstrating the effectiveness of the proposed framework to understand the classification performance. It quantifies to visually assess the differentiation of healthy and eye affected regions at different decision points to enhance the accuracy outcomes. The curve closer to the top left corners shows the model perform better sensitivity outcomes while minimizing the false rates. In clinical analysis, the optimal cut off value shows the medical experts to provide the accurate treatment for eye disease effectively. This shows that the developed model is adept at processing large volumes of eye images efficiently, allowing for comprehensive analysis and insights, and can personalize treatment plans based on individual patient data and specific disease characteristics, leading to more tailored care.

6.3. Determining confusion matrix for the developed eye disease classification model

The confusion matrix provides valuable insights into the model's performance, allowing the calculation of various metrics like accuracy, precision, recall, F1-score, and more. These metrics help to understand how well your classification model is performing and whether it is making specific types of errors more frequently than others. In the context of confusion matrix analysis, the medical expert helps to classify eye disease based on retinal images for enhancing diagnosis accuracy in medical sector. The medical expert can identify different patterns in confusion matrix analysis to enhance the diagnosis performance. Fig. 9 is likely a graphical representation of a confusion matrix, which can be a helpful way to visualize and interpret the model's performance. This shows that the developed model excels in achieving high accuracy levels in classifying various eye diseases, providing more reliable diagnoses, and detecting subtle signs of eye diseases outcomes.

6.4. Determining eye disease classification system using a diverse classifier

In Fig. 10, Fig. 11, and Fig. 12, a graphical representation illustrates the evaluation of the eye disease classification system model across various classifier models. When examining the accuracy values depicted on the linear activation function, it is evident that the proposed ADHNet outperforms models such as LSTM, MobileNet V2, RNN, and DTCN by a

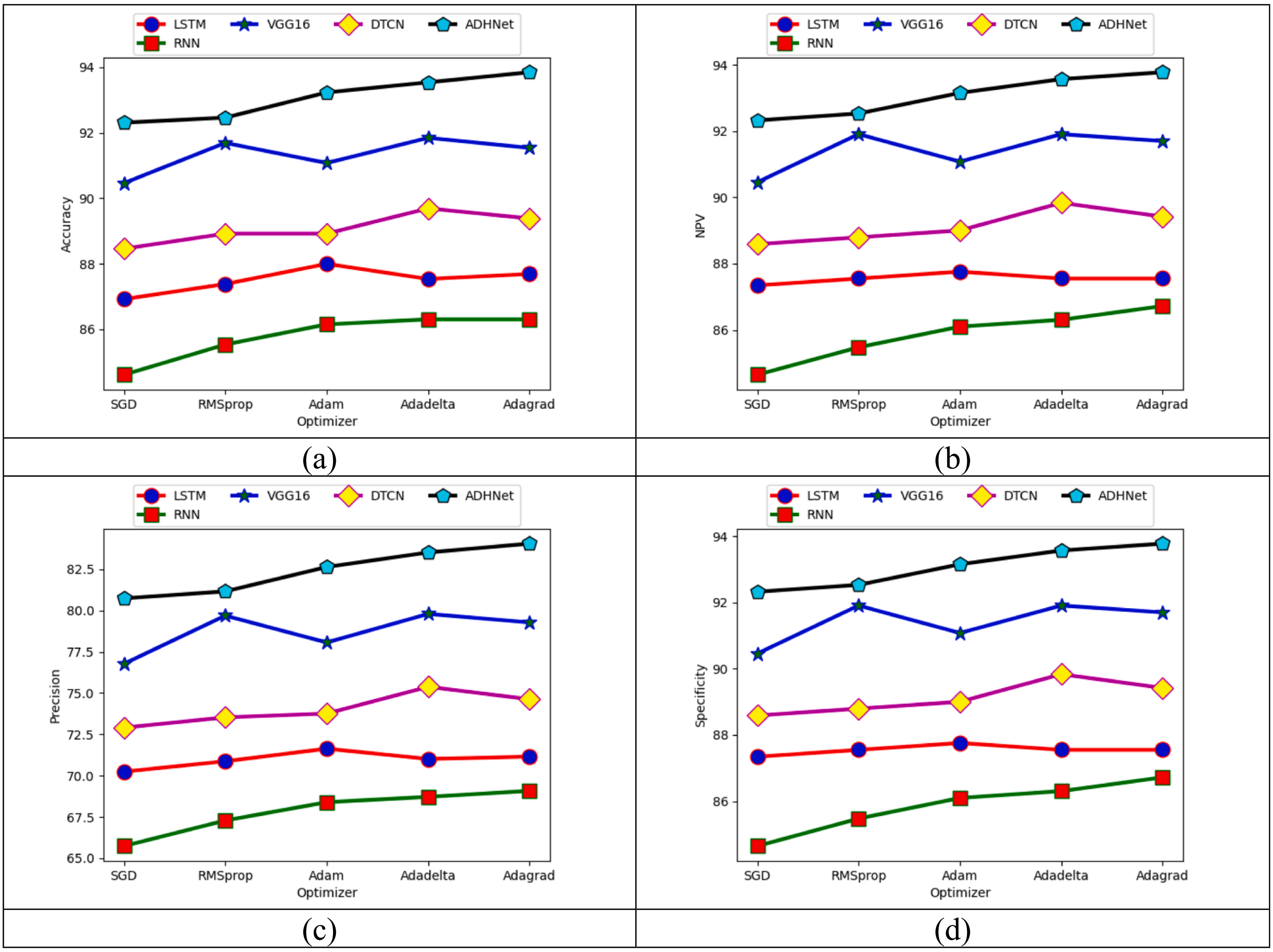

Fig. 12. Determining the given eye disease classification model when assimilated with classical models regarding (a) Accuracy b) NPV, c) Precision and d) Specificity.

margin of 7 %, 5 %, 4 %, and 3 %, respectively. In Fig. 10, the x-axis represents activation functions including linear, tanh, sigmoid, and ReLU, while the y-axis displays diverse performance metrics. By examining different analysis, the consideration of activation function plays the crucial role to evaluate the accurate diagnostic performance in eye disease. The examination of higher activation function in the developed model helps to learn complex features in the retinal images to identify the disorder like glaucoma and other related disease. Considering ReLU activation function, it effectively performs in learning the edges and boundaries of retina images to identify the essential features in the developed model. The lower performance in activation function can greatly impact the diagnosis treatment that causes loss of eye sight. Considering Fig. 11, the epoch-based analysis is initiated with different variations like 50, 100, 150, 200 and 250 in terms of diverse performance metrics. However, the epoch analysis is progressed by analyzing the whole dataset during training. In eye disease classification model, the increasing number of epoch can significantly enhance the models accuracy that helps the medical professionals to cure the disease at the right time. If the model shows poor performance, the generalization of the model is reduced within the unseen data. This makes the accurate diagnosis is not been exactly performed by the clinicians. In this experimental validation, the developed method model shows superior performance in eye disease classification model. In Fig. 12, the optimizer based analysis is performed by evaluating the deep learning models. By selecting the optimal features, the developed model can learn the intrinsic features to avoid from the occurrence of misclassification issues. Higher accurate rate analysis helps the developed model shows accurate performance in which the exact classification performance is done in the eye disease model. Consequently, the novel eye disease classification system model demonstrates superior performance outcomes. This shows that the developed model speeds up the classification process, resulting in faster diagnosis and treatment for patients, and provides consistent and reproducible results in classifying eye diseases, ensuring reliability in diagnoses. Also, it can provide real-time analysis of eye images, allowing for immediate decision-making in critical situations.

6.5. Determining eye disease segmentation system using a diverse classifier

In Fig. 13, and Fig. 14, a graphical representation illustrates the evaluation of the eye disease cup and disc segmentation system model across various classifier models. The x-axis represents statistical analysis, including best, worst, mean, median, and standard deviation, while the y-axis displays diverse performance metrics. Training significant amount of data can perform effective and accurate outcomes in the developed model. The examination of statistical analysis incurs most prominent outcomes by segmenting the accurate locations of the disease affected regions. The accurate segmentation of eye disease can greatly achieve the effective results of the developed model to minimize the

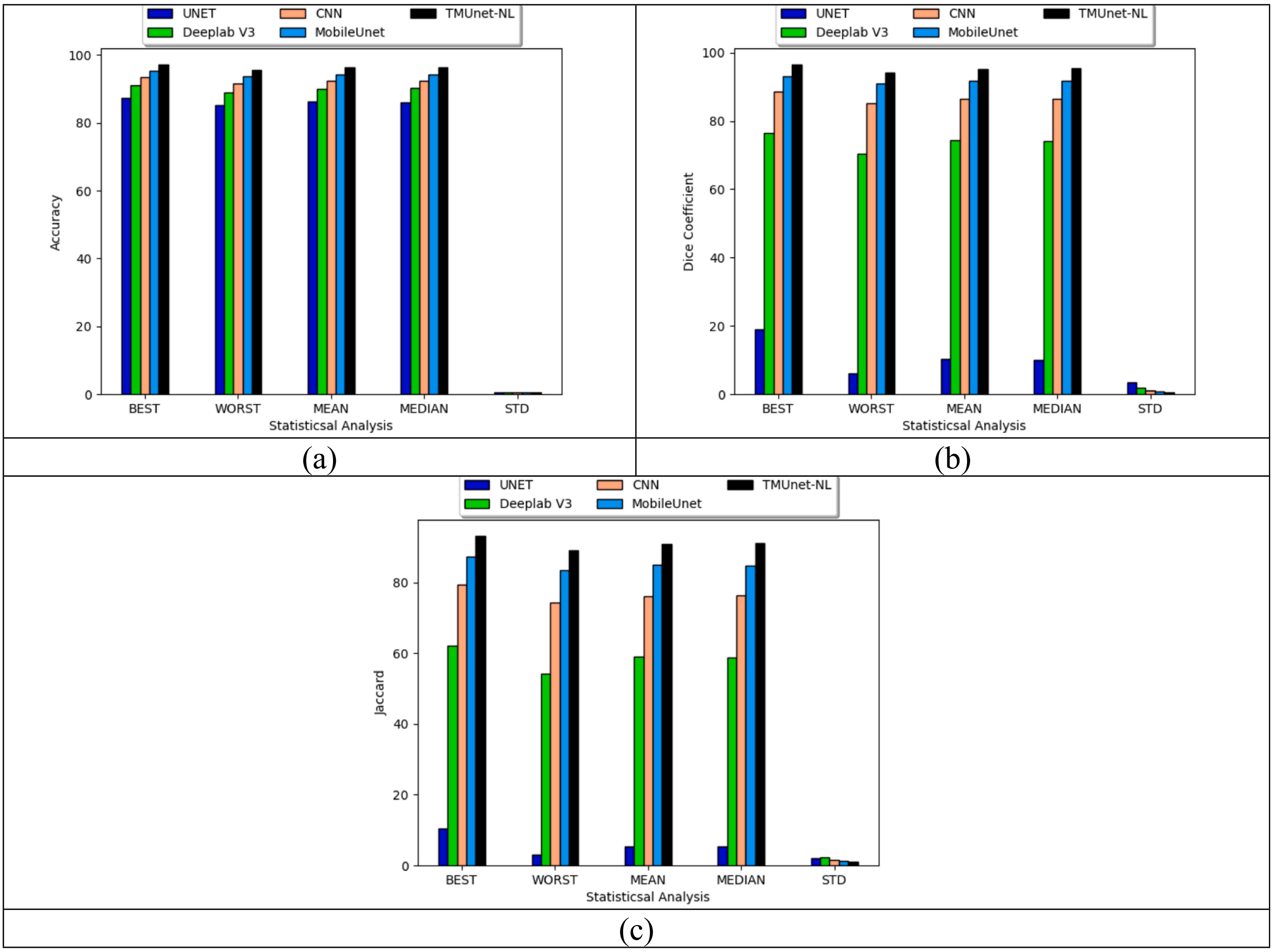

Fig. 13. Determining the given eye disease cup segmentation model when assimilated with classifier models regarding (a) Accuracy b) Dice-coefficient and c) jaccard coefficient.

overfitting issues. When examining the accuracy values depicted on the best activation function, it is evident that the proposed TMUnet-NL outperforms models such as U-Net, CNN, DeepLab3, and MobileUNet by a margin of 7 %, 5 %, 4 %, and 3 %, respectively. Consequently, the novel eye disease segmentation system model demonstrates superior performance outcomes. This shows that the developed model reduces the risk of human errors in the diagnosis process, enhancing accuracy, and can extract complex features from images, aiding in the accurate classification of eye diseases. Additionally, the developed approach enables non-invasive diagnosis of eye diseases through image analysis, making the process more patient-friendly.

6.6. Ablation Experiment on the recommended method

Table 5 shows an ablation evaluation of the developed model. This evaluation is carried out using accuracy with existing models. Here, the accuracy of the recommended framework is 94.15 %, which this more than other models. Thus, it proved that the developed model can lead to better treatment outcomes and overall improved patient care, and enabling comprehensive analysis of large datasets, fostering advancements in the field. In analysis, the accuracy of the model could greatly depend on the models performance. The developed model ensures to classify the eye disease at earlier stage with certain time limit. This performance enhancement of the developed model allows providing prompt treatment to prevent from vision loss and enhance the quality of life. The inaccurate detection are often made by the existing techniques to causes health related problems so, the timely and monitoring the patients health becomes crucial task for the medical expert. The recommended framework has the ability to treat the disease at the earlier stage with the help of medical experts.

6.7. Overall validation of the proposed model using diverse classifiers

In Table 6, the determination of the proposed model in accordance with diverse classifier models is depicted. When assimilated over other classifiers like LSTM, MobileNet V2, RNN, and DTCN, the given ADHNet model for the value over MCC is 18 %, 14 %, 11 %, and 6 % higher. Thus, it has proved the efficiency level of the given eye disease classification model. The overall analysis is done by considering the standard models like LSTM, RNN, MobileNet and DTCN. In this validation, the developed model performs 94.1 % that seems to be present the highest value to enrich the classification performance. This enhanced performance helps to neglect the occurrence of falsely outcomes in the classification. Hence, the effective classification can provide the developed model more stable and enrich the models generalizability outcome. This proves that the developed model has the potential to reduce healthcare costs by streamlining the diagnostic process and improving efficiency, and also analyzing a large number of eye images efficiently, accommodating varying data volumes.

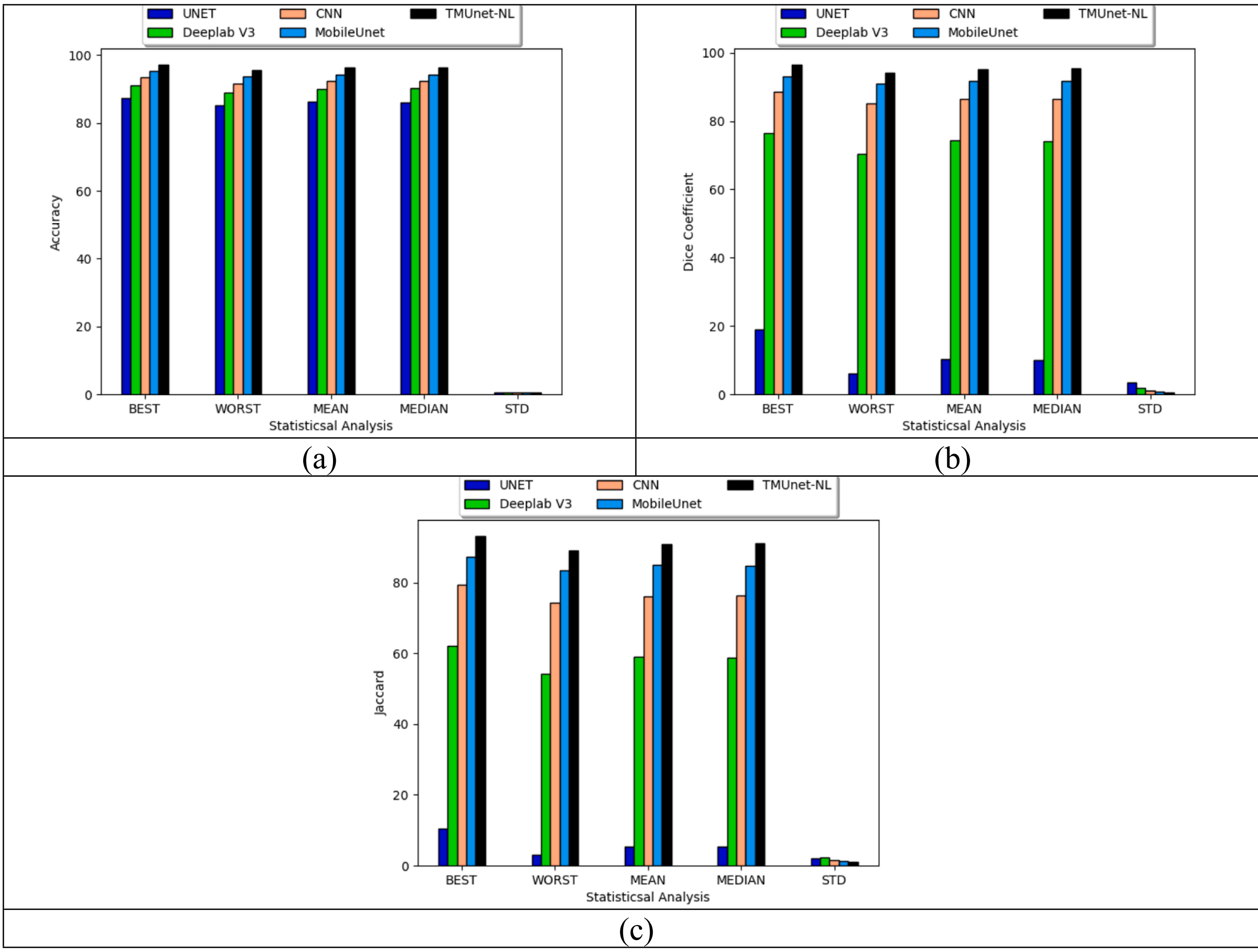

Fig. 14. Determining the given eye disease disc segmentation model when assimilated with classifier models regarding (a) Accuracy b) Dice-coefficient and c) jaccard coefficient.

Table 5
Ablation Experiment on the Developed Model.

Models	Accuracy (%)
GRU [42]	94
LSTM [37]	91
RNN [38]	92.1
CNN [35]	90.5
ANN [41]	91.2
ADHNet	94.15

Table 6
Overall determination for the proposed eye disease classification model compared over existing classifiers.

Measures	LSTM [37]	RNN [38]	Mobilenet V2 [39]	DTCN [40]	ADHNet
Accuracy	89.38462	87.23077	92.92308	90.61538	94.15385
Recall	89.88095	86.90476	92.85714	90.47619	94.04762
Specificity	89.21162	87.3444	92.94606	90.6639	94.19087
Precision	74.38424	70.5314	82.10526	77.15736	84.94624
FPR	10.78838	12.6556	7.053942	9.3361	5.809129
FNR	10.11905	13.09524	7.142857	9.52381	5.952381
NPV	3.803132	4.96614	2.608696	3.532009	2.155172
FDR	89.21162	87.3444	92.94606	90.6639	94.19087
F1-Score	25.61576	29.4686	17.89474	22.84264	15.05376
MCC	81.40162	77.86667	87.15084	83.28767	89.26554

Table 7
State-of-the-art analysis comparison for the proposed eye disease classification model.

Measures	CANN [19]	PCA [18]	TBUT-based detection model [25]	Inception-v3 [28]	ADHNet
Accuracy	88.60000	89.20000	90.20000	91.05000	94.15385
Specificity	88.42213	89.24180	90.47131	90.98361	94.19087
Precision	88.94325	89.68566	90.82840	91.38100	84.94624
FPR	11.57787	10.75820	9.52869	9.01639	5.809129
FNR	11.23047	10.83984	10.05859	8.88672	5.952381
NPV	88.24131	88.69654	89.55375	90.70480	2.155172
FDR	11.05675	10.31434	9.17160	8.61900	94.19087
F1-Score	88.85630	89.42214	90.38273	91.24694	15.05376
MCC	0.77188	0.78392	0.80397	0.82091	89.26554

6.8. State-of-the-art comparison analysis on the developed model

State-of-the-art analysis comparison analysis for the proposed eye disease classification model is given in Table 7. Here, the precision of the suggested model is 6.52 %, 5.54 %, 4.11 %, and 3.52 % more than CANN, PCA, TBUT-based detection model, and Inception-v3. From this analysis, the analysis of deep learning model facilitates to allow effective treatment from the medical professionals. The early detection of eye disease plays the crucial role that helps to prevent from serious

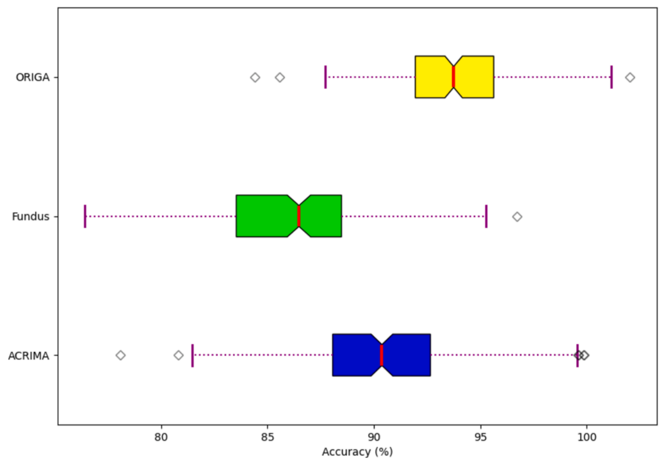

Fig. 15. Generalizability of the developed model.

consequences. The performance enhancement of the developed model shows the accuracy rate of 94.15. This helps the developed to prevent from false observations in the eye disease classification model. This proved that the developed model can provide insights into the features used for classification, aiding in understanding the decision-making process, and can be integrated into telemedicine platforms, enabling remote diagnosis and consultation for patients in underserved areas.

6.9. Generalizability of the developed model

The generalizability of the developed model in the eye disease segmentation and classification model is shown in Fig. 15. The generalizability of the model is validated by considering different classes like ACRIMA, Fundus, and ORIGA to evaluate the model's efficiency. This generalizability helps the model to improve the scalability of the model and enhance the model's effectiveness. It effectively performs in the larger data to analyze the complex patterns to strengthen the model ability in eye disease segmentation and classification model.

6.10. Experimental analysis of learning curves

The experimental analysis of the learning curve of the developed model in terms of training/ validation and accuracy/loss is illustrated in Fig. 16. Based on epoch count, the performance of training and validation is performed to enrich the model stability in the classification model.

6.11. Comparative analysis from recent literature study

The comparative analysis of the developed model is validated with recent literature works is tabulated in Table 8. In this comparative analysis, the developed model shows efficient and accurate performance in which the developed model offers reliable and efficient outcomes in eye disease segmentation and classification model. In this developed model, the accuracy of the model shows 94.15 % that provide reliable performance. This enhanced accuracy of the developed model ensures better treatment in eye disease classification model.

6.12. Possibility of validating the approach with medical experts

The clinical application of the deep learning-based ADHNet model for eye disease classification is a groundbreaking development in the field of ophthalmology. In clinical settings, the medical experts are highly involved in the diagnosis and treatment of eye diseases. Its high accuracy and efficiency streamline the diagnostic process, allowing for quicker assessments and more informed decision-making. By providing detailed insights into the characteristics of different eye conditions, the developed model supports clinicians in developing personalized treatment plans tailored to each patient's specific needs. This targeted approach enhances the model's precision in identifying specific diseases, leading to early diagnosis and timely intervention.

Furthermore, there are several ways to enhance diagnostic accuracy

Table 8
Comparative analysis of the developed model with recent state-of-the-art-methods.

Terms	CANN [19]	DenseNet121 [18]	Modified Inception-v3 [43]	ADHNet
Accuracy	88.20	89.47	90.07	**94.15385**
Specificity	88.44	89.25	89.92	**94.19087**
Precision	88.55	89.45	90.09	**84.94624**
FPR	11.56	10.75	10.08	**5.809129**
FNR	12.04	10.32	9.79	**5.952381**
NPV	87.85	89.49	90.04	**2.155172**
FDR	11.45	10.55	9.91	**94.19087**
F1-Score	88.25	89.56	90.15	**15.05376**
MCC	76.40	78.93	80.13	**89.26554**

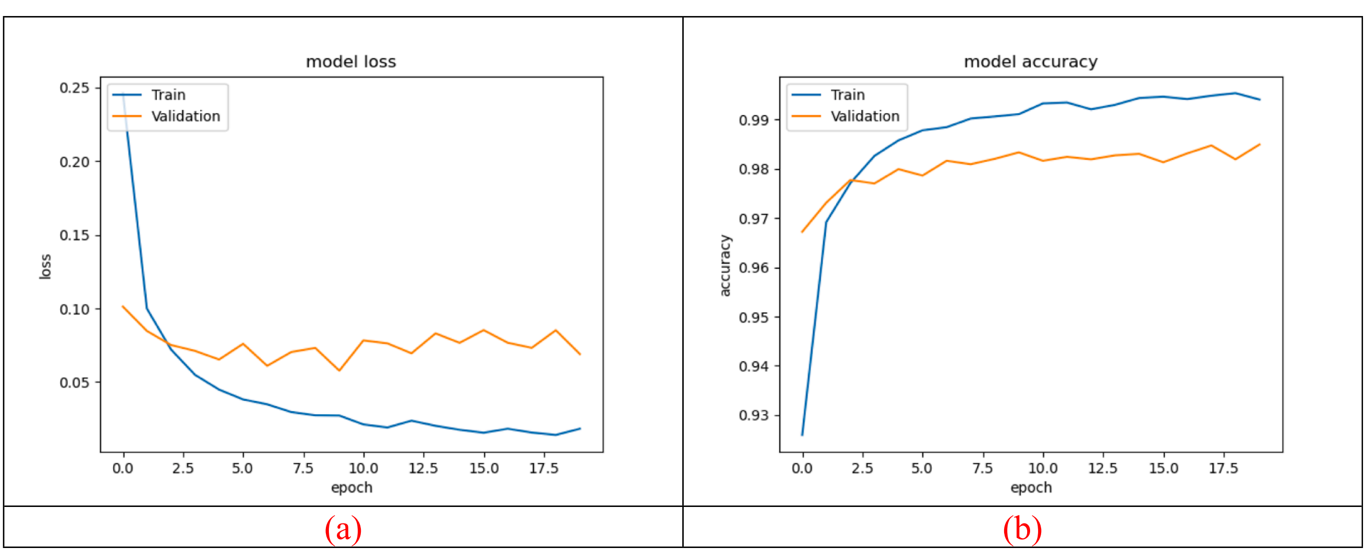

Fig. 16. Experimental analysis in the developed model in terms of (a) loss and (b) accuracy.

and improve patient outcomes in the field of ophthalmology. The medical experts needs to conduct the routine eye exam helps to detect variety of severe conditions like pupil size, cancers, giant cell arteritis, and heart disease. In medical sector, the RetinaLyze is one of the software screening applications, in which the medical experts can perform the signs of pathology in a safety manner.

6.13. Discussion

The solutions given by the research question are described below. Focusing on RQ.1, the eye disease classification is done by the ADHNet model employed by the combination of VGG16 and DTCN to provide reliable performance. The consideration of VGG16 model provides high accuracy to boostup the classification performance. With different scale variations, the developed ADHNet model offers robust to image variations. Capturing the complex patterns in the images leads to better classification performance. So, the robust classification performance helps the model to provide appropriate treatment from the medical professionals.

In RQ2, the segmentation is conducted through the TMUnet-NL model. We know that, the primary advantage of MobileNet and UNet model relies on providing accurate segmentation for complex boundaries and provides faster processing time by considering high and low level features. By considering these advantages, the MobileNet and Unet models are integrated to form an effective TMUnet-NL model. Considering RQ3, the focusing of retinal images in the implementation process can meticulously enhance the accuracy of the model. The consideration of developing new deep learning model can effectively work well in detecting and classifying the eye disease. Development of these model helps to solve overfitting and data imbalance issues whereas it step towards to reach the higher accuracy outcome. Selecting essential features can strengthen the developed model to show better accurate performance. Overall the accuracy of the developed model shows 94.1 %.

Issues and limitations (such as overfitting/ underfitting) in the training model: While training the model, overfitting and underfitting issues occur when it is not effectively dealing with data quality issues like noise, data imbalance, data leakage, and insufficient training data. In general, the overfitting issues occur when the model learns the training data too closely to provide poor performance on new data. Underfitting issues means when the model is too simple and failed to capture the significant patterns in the data. The emergence of overfitting and underfitting issues impacts the model's ability to generalize the unseen data. **In this research work,** issues like overfitting and underfitting are rectified by training the larger amount of data with the ratio of 75 % (training) and 25 % (testing). However, the implementation of the result has been evaluated based on the models generalizability that helps to estimate different classes to minimize the overfitting and underfitting issues in the developed model. Monitoring and managing the validation loss helps the developed model to find the optimal value in order to capture the complex patterns of unseen data. Selecting the most appropriate features helps to eradicate unnecessary features that might lead to decrease the overfitting issues.

7. Conclusion

The research paper has developed a deep learning-based eye disease classification system for detecting Glaucoma. It enabled automated and efficient diagnosis of eye diseases, reducing the reliance on manual interpretation and potentially decreasing human error. It first collected relevant images and given to Trans-MobileUnet, which integrated with a loss function to segment the optic cup and disc. The ADHNet was then designed for eye disease classification, combining VGG16′s feature extraction capabilities with DTCN's classification expertise. The ADHNet outperformed traditional models such as LSTM, MobileNet V2, RNN, and DTCN by 4 %, 12 %, 14 %, and 3 % in precision values on the linear activation function. The system proved highly effective in delivering accurate and reliable predictions in the field of eye disease classification using medical images. One key advantage of the developed model was its high accuracy in identifying various eye diseases from medical images. This accuracy can lead to early detection and timely treatment, potentially improving patient outcomes. Also, it could efficiently analyze large and complex datasets, making them well-suited for detecting subtle patterns in eye images that may indicate different diseases. Additionally, the developed model had the potential to automate the diagnosis process, saving time for healthcare professionals and increasing the speed of patient care. However, there are also some disadvantages to be aware of. The designed approach required a substantial amount of labelled data for training, which can be challenging and time-consuming to acquire in the medical field. Moreover, the interpretability of the model could be limited, making it difficult to understand the reasoning behind the model's predictions. Looking into the future, the scope of developed eye disease classification using deep learning is promising. Advancements in deep learning techniques, such as transfer learning and explainable AI, can address current limitations that aid to improve the model's performance and interpretability. Moreover, the integration of multimodal data sources, such as genetic information or patient history, could further improve the accuracy and personalized treatment of developed eye disease classification. Future extensions will be enhanced by providing the substantial improvements by incorporating the contrastive learning and vision transformer models [43]. Additionally, developing algorithms can effectively handle rare diseases and prevent bias in predictions that will be crucial for the accuracy of the models. The consideration of data augmentation technique in eye disease segmentation and classification model will be recommended in the upcoming works.

CRediT authorship contribution statement

C. Venkataiah: Conceptualization. **M. Chennakesavulu:** Conceptualization. **Y. Mallikarjuna Rao:** Conceptualization. **B. Janardhana Rao:** Conceptualization. **G. Ramesh:** Conceptualization. **J. Sofia Priya Dharshini:** Conceptualization. **Manjula Jayamma:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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