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Hybrid Image Features Supported Normal/Abnormal Retinal Optical Coherence Tomography Image Classification

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Abstract

Background

Eye is one of the primary sensory organs, responsible to provide the necessary visual information to the brain. Any abnormality in eye cause mild to severe vision issues and hence appropriate detection and treatment is preferred. Clinical level examination of the eye is commonly performed using image examination procedures and this work considered the Optical Coherence Tomography (OCT) for the study. In the present study, the proposed system aims to develop a tool to classify the OCT-images into normal and abnormal class using the traditional deep-learning (DL) and machine-learning (ML) features.

Methods

This tool consists the following stages; OCT-image collection and resizing based on the chosen DL scheme, image features extraction using DL and ML methods, DL feature reduction using 50% dropout and serially fusing the deep- and machine-features to generate hybrid-features, and binary classification using 5-fold cross-validation.

Results

The developed tool's merit is verified using; (i) deep-features, (ii) machine-features, and (iii) hybrid-features. The merit of the developed scheme is verified using different binary classifiers and the overall quality metric is considered to verify the tool's performance.

Conclusions

The study confirms that the hybrid-features based detection provides 97.6% accuracy, when Random Forest classifier is employed, which verifies the tool's merit on the chosen OCT database. In the future, this tool can be considered to detect the common AEAs, like AMD and the DME.

Keywords: retinal abnormality, Optical Coherence Tomography, deep learning, hybrid features

Introduction

The eye, a prime organ of human physiology, serves as dynamic sensory organs accountable for converting visual information into bio-electric signals for the brain for the understanding. This complicated procedure is performed by the specific cells named photoreceptors translate light into electrical impulses. These indicators are then communicated through the optic nerve to the brain. Despite its significant abilities, the eye is susceptible to several abnormalities and disorders, which can impair vision. The prime cause of the eye illness is the ageing and other associated reasons, like infection, accident and diabetes also influence the chances of eye abnormalities.[1]

It is authoritative to promptly regulate the irregularities in vision to guarantee good eye healthiness. Several medical procedures have been developed to accomplish this, highlighting practices, like frequent eye exams, early diagnosis of abnormalities/infections, and prompt treatment. Moreover, as age increases, it is significant to manage appropriate eye-health, which includes regular check-ups to monitor for age-related changes in eye. By remaining proactive and seeking appropriate medical consideration when essential, people can significantly decrease their risk of developing eye abnormalities.[2]

Awareness programs are essential for encouraging systematic health check-ups and eye care, particularly for Age-related Eye Abnormalities (AEA). These programs highlight the significance of premature recognition and management. By encouraging recurrent eye inspections, they support avoid vision loss and advance overall eye health in the public. Compared to other common AEA, the occurrence of Age-related Macular Degeneration (AMD) is common and it is a deteriorating illness in retina which leads to considerable central visual impairment.[3] The Choroidal-neovascularization (CNV) is a factor of exudative AMD, which initiates the irregular development of blood vessels from the choroid layer of the eye into the neurosensory retina.[4] Early detection of the CNV is essential for appropriate treatment planning to control the irregularity in blood vessels.

The clinical level diagnosis of the CNV is performed using image supported examination and the methods like, Fluorescein-Angiography (FA) and Optical Coherence Tomography (OCT) are commonly executed to record the abnormal eye section for further examination. The execution of OCT is common compared to the FA and due to its significance, a number of earlier research considered the OCT to examine the CNV.[5]

Recently, a number of Artificial-Intelligence (AI) supported tools are developed to examine the retinal collected using a chosen imaging modality, like fundus-imaging and OCT. The AMD can be examined using the fundus-imaging technique[6] and the CNV is commonly examined using the OCT.[7] The recent literature confirms the examination of these images using the chosen machine-learning (ML) and deep-learning (DL) methods. Compared to the ML-schemes, the DL-methods helps in achieving a better detection accuracy and the availability of a number of pre-trained models suggests in implementing the chosen DL methods for the image examination tasks.

The earlier works in the literature confirms that the DL-approaches are efficient in providing a clinically significant detection results on the chosen image database.[8] Further, the integration of the deep-features and machine-features helps to improve the detection accuracy to a higher level. The proposed research aims in develop an OCT examination scheme using the deep- and machine-features and verifying its performance using the chosen benchmark retinal images. The different phases of the developed tool include; (i) OCT image collection from the database and resizing it to an appropriate dimension, (ii) mining the image features using the chosen DL and ML techniques, (iii) integrating the DL and ML features to obtain a new feature vector to obtain enhanced detection result, and (iv) binary classification and performance confirmation using a five-fold cross validation process.

In this work, the necessary DL-features is collected using the commonly adopted DL-models in the literature,[9,10] and the essential ML-feature is obtained using the Gray-Level Co-occurrence Matrix (GLCM) and to achieve this the binary section of the retinal is extracted from the chosen OCT using the Marker-controlled watershed Algorithm (MWA). To generate the hybrid feature vector, the DL-features are reduced using 50% dropout and then it is serially combined with the GLCM features. The significance of developed tool is verified using; (a) deep-features, (b) GLCM-features, and (c) deep+GLCM features and during this task, the necessary metrics are computed and based on its value, the performance is verified.

This research considered the benchmark OCT images found in[8] for the assessment, and this task is executed using 15000 images (7500 normal and 7500 CNV class). The experimental result authorizes that achieves a detection accuracy of 97.6% when the Random-Forest (RF) classifier is considered along with deep+GLCM features. This result confirms that, the proposed tool performance well on the chosen OCT database and provides significant detection accuracy during the normal and CNV detection task.

The significant contribution includes;

1. Development of a novel OCT examination procedure using the pre-trained DL model and the GLCM-features obtained from the MWA segmented OCT section,
2. Demonstration of the DR detection process using DL, ML and hybrid features.

The other part of this work is organized as; Section 2 presents the review on earlier works, Section 3 demonstrates the materials and methods, Section 4 displays the execution of the tool, and Sections 5 and 6 shows the outcome and conclusion.

The disease occurrence rates in elderly individual are commonly more and appropriate diagnosis and treatment is essential to confirm a healthy life. AEA is one of the common issues in elderly and hence scheduled eye testing and, management is widely recommended. AMD and CNV are the common AEA and clinical level diagnosis of these images is normally performed using the image supported schemes.

Compared to the fundus-imaging, the OCT provides the necessary insight regarding the retinal and its abnormality and hence, a number of OCT examination schemes are discussed in the literature.[11-13] Recently, the ML- and DL-tool based examination of the OCT is common and this section outlines few chosen earlier works and the achieved results.

The work of Li et al. (2019) discussed VGG16 based DL-method with transfer learning to examine the ADM and Diabetes-Related Macular Edema (DME) class OCT images and achieved satisfactory classification results.[14] Wang et al. (2020) implemented computerized examination and segmentation of the CNV from the OCT-images using Convolutional Neural-Network (CNN) and achieved better sensitivity (100%) and specificity (95%).[15] Research by Ran et al. (2021) presented a short review on the DL-based examination of the OCT to detect the retinal abnormalities and this work confirms the merit of the DL-technique compared to the ML-schemes.[16]

Research by Maunz et al. (2021) discussed ML-based CNV detection in OCT images and achieved a better Area Under the Receiver Operating Characteristic (AUROC) of 0.99.[17] The research by Tasnim et al. (2019) provides a detailed analysis on DL-based examination of the OCT using different pre-trained DL schemes and it shows a detection accuracy of 98%.[18] Kang et al. (2021) discussed DL-based multimodal imaging scheme for the ARA detection and it offered a CNV detection AUC of 0.996.[19] Research by Rastogi et al. (2019) presented a DL-based examination of DME and CNV and achieved a test accuracy of 97.65% using the pre-trained DL-scheme.[20] Maunz et al. (2020) implemented a ML-based examination of CNV using OCT examination and achieved an AUROC of 0.99.[21] The research by Abirami et al. (2022) presented CNV detection from the OCT-images using the VGG16 and DenseNet approach and achieved an accuracy of 97.53%.[22] Jin et al. (2022) discussed the CNV activity identification from the AMD using DL-scheme and achieved an initial accuracy of 95.5% and final accuracy of 100%.[23] Schlegl et al. (2028) implemented DL-based evaluation of OCT for macular fluid examination and achieved an AUC of 0.94.[24] Hassan et al. (2022) presented a fully automatic analysis of the OCT using joint segmentation and classification and achieved better F1-score.[25] Recently, the research by Nagamani and Rayachoti (2024) implemented segmentation and classification of the OCT images for the abnormality detection using the ResNet50 and LSTM and obtained a better result.[26] A detailed meta-analysis on OCT examination form DME with DL-methods are presented and discussed in[27] and this work confirms the need for the DL-approaches for the real time disease examination using the OCT.

All these earlier works confirm the needs for an effective examination of the OCT to discover the abnormality for the disease diagnosis and treatment. Further, these works confirm the need for a DL- and ML-based procedure for the automatic examination of the chosen images. Based on the motivation from the earlier works, which integrated the ML- and DL-features, this work also aims to develop a tool to examine the CNV from the chosen OCT using the hybrid-features based classification.

Materials and Methods

The proposed research implements a simple and effective tool to classify the OCT-images into normal and CNV class using the hybrid-features and this work employs a binary classification using the chosen classifiers.

Figure 1 depicts the proposed tool's architecture, which utilizes the ML- and DL-features based classification. Initially, the necessary images are collected from the chosen benchmark database and then resized to a required level based on the chosen DL-scheme. The AlexNet needs an image size of 227×227 pixels and other methods needs 224×224 pixels. These images are then examined using the chosen DL-scheme, which helps in extracting $1 \times 1 \times 1024$ numbers of features. These features are then reduced using 50% dropout and the remaining features are considered for the hybrid feature development. In order to mine the GLCM-features, the chosen OCT images are segmented using the MWA as discussed in [28]. This extracted binary section is then considered to mine the GLCM features of the dimension; $1 \times 1 \times 25$. This feature is then combined with the reduced DL-feature to get a hybrid feature of dimension; $1 \times 1 \times 537$, which is considered for the classification using a chosen classifier. The outcome of this task helps in achieving the confusion matrix (CM) and these values are then considered to compute the other measures. Based on these measures, the performance of the developed tool on the chosen OCT database is confirmed.

OCT database

This research work considered the OCT images available in [8] for the research. Similar database can also be found in.[29] The total images considered in this study for the experimental investigation can be found in Table 1. In this work, the necessary data split is implemented as; 80% for training, 10% for validation and remaining 10% data for the testing and verifying the performance of the developed tool. The sample images of normal and CNV category found in the database is depicted in Figure 2. Every image is resized to an appropriate size (227x227 - for AlexNet examination and (224x224 for other DL-models). For the MWA segmentation and GLCM feature mining task, the image with dimension 224x224 is considered.

Deep-transfer learning

Due to its availability, the execution of DL-based image examination is widely executed by the number of researchers to examine the data using binary-class and multi-class classification task. In the proposed work, the schemes, like AlexNet, VGG16, VGG19, ResNet18, ResNet50, and ResNet101 are considered for the investigation.[30,31] The other parameters for these algorithms are assigned as follows; the learning rate= 0.001, epochs= 150, optimizer= Adam, activation= ReLu, and classifier= SoftMax,

In this research, the pre-trained models found in MATLAB-software are considered for the investigation and the achieved results are verified to choose the best model among the chosen schemes.

Watershed algorithm

In the literature, a number of automatic and semi-automatic segmentation methods are proposed and implemented to extract the required section from the chosen image frame. Compared to the semi-automatic technique, the automatic methods are very popular, since it does not require the operator's involvement in selecting and extracting the image section.

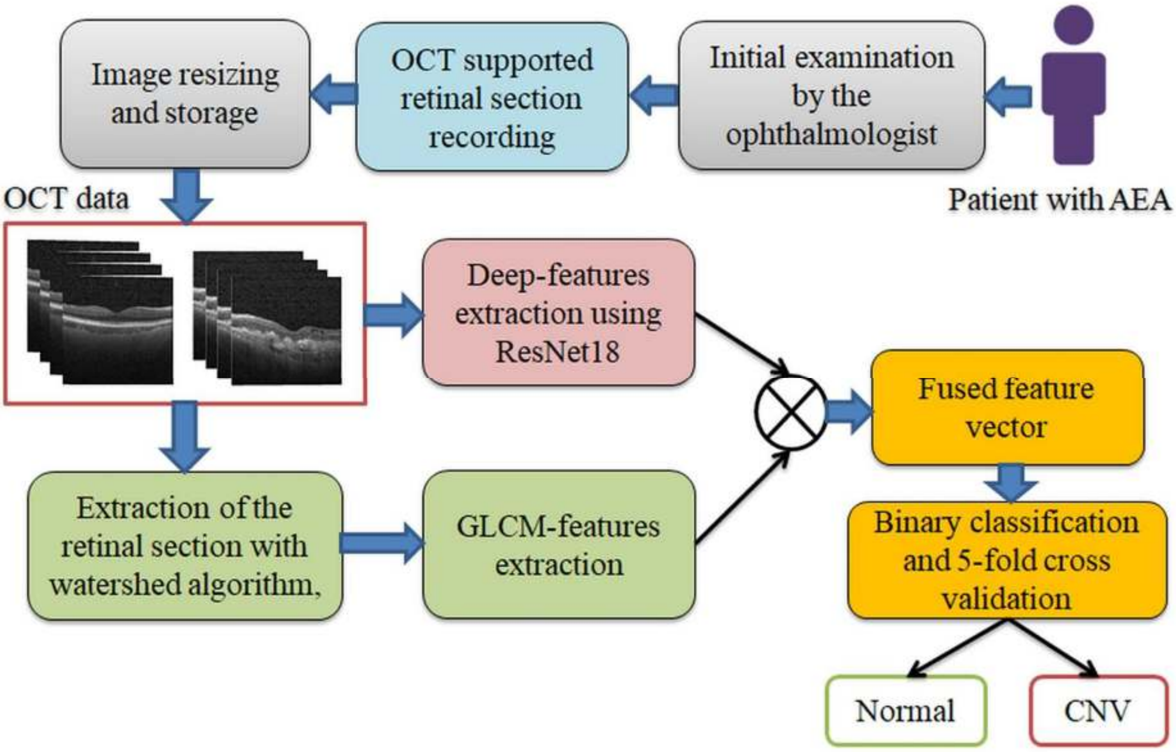


Figure 1. Proposed Oct examination tool with ResNet18 and hybrid features

Table 1. OCT images considered in this research work

OCT group	No. of Images			
	Total	Training	Validation	Testing
Normal	7500	6000	750	750
CNV	7500	6000	750	750

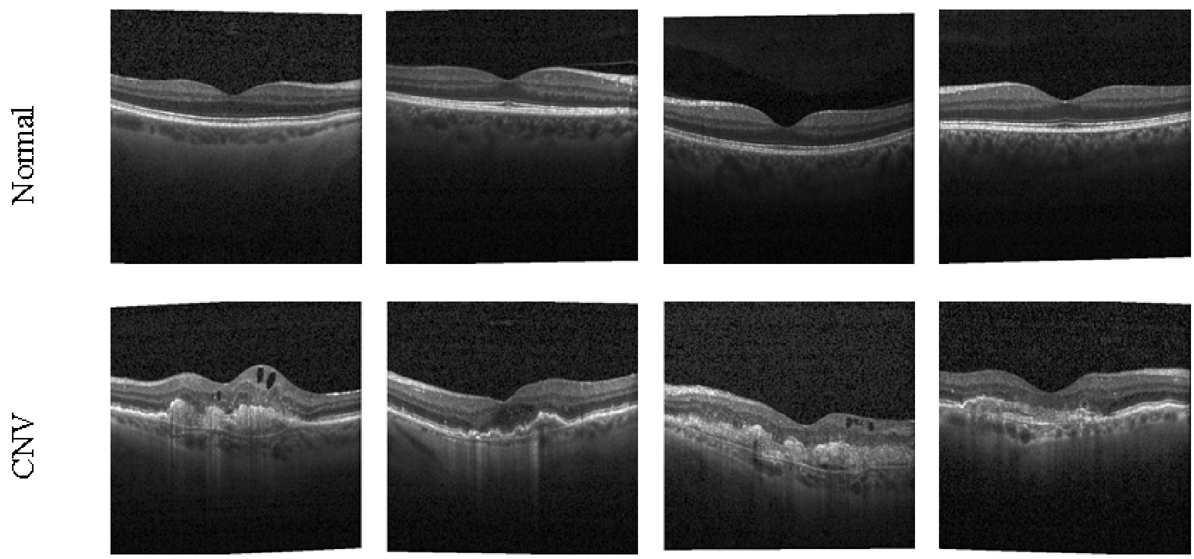


Figure 2. Sample retinal OCT test images

MWA is one of the commonly employed traditional automatic segmentation technique and it helps to extract the required region from the chosen Oct image. The MWA consist various sections as depicted in Figure 3. Fig 3(a) presents the initial process in MWA, edge detection, which identifies the possible sections in the image which is to be mines. Fig 3(b) presents the filling of the watershed in the edges shown in Fig 3(a). Figs. 3(c) and (d) show the morphological operation to highlight the retinal section and enhanced image for the segmentation, respectively. Finally, the binary form of the retinal is then automatically extracted and it is then considered to get the necessary GLCM features, which is then chosen as the ML-feature to create the hybrid feature vector. The essential information on MWA can be accessed from.[32,33]

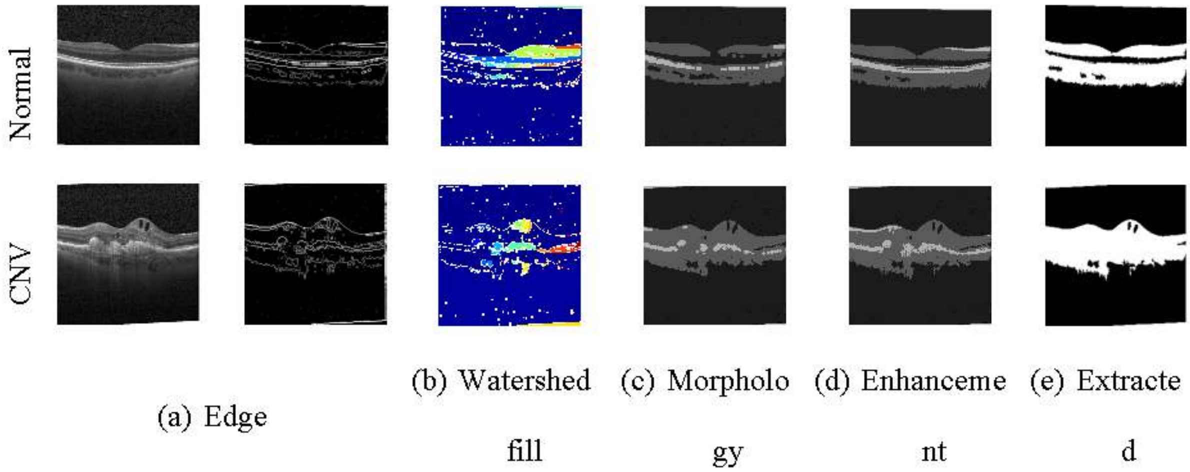


Figure 3. Implementation of Watershed segmentation to extract retinal section

Features extraction

Image features play a major role in the automatic segregation of the chosen images and in this work, both the deep- and machine-features are considered to develop the proposed OCT examination tool.

The deep-features of size; $1 \times 1 \times 1024$ is directly obtained from the chosen DL model. Every model of this study extracts this feature and it is then saved as the.csv file for the further investigation. The features are the numerical data, which provides distinct values for the normal and CNV image case. The necessary ML-feature in this research is obtained using the MWA segmented binary image. The binary image is then evaluated by the GLCM technique, which provides a feature vector of dimension $1 \times 1 \times 25$. Essential information regarding the GLCM-features can be found in.[34,35] The GLCM- and DL-features are then combined to get the necessary hybrid image feature vector.

Implementation

This part presents the implementation and evaluation of this research for OCT examination and the merit of the applied tool is verified using the Normal and CNV images. The investigation presented in this section is achieved using MATLAB-software and this work considered a PC having Intel-i7, 20GB of RAM and 8 GB of VRAM.

The classification task is initially performed using the SoftMax classifier. After identifying the appropriate DL-model for the tool, other classifiers, like Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), Support Vector Machine-Linear Kernel (SVM-L), and SVM with radial basis function (SVM-RBF) are considered and the achieved results are compared.[36]

The performance of the developed image examination scheme can be verified using the necessary metrics obtained during the classification task. The OCT examination performance of the developed tool is verified using the necessary quality metrics obtained in this study. When the detection task is executed, the binary classification process gives a CM, which comprises the necessary measures, like true- (TP) and false-positive (FP) and true- (TN) and false-negative (FN). From these measures, other associated values depicted in Eqns. (1) to (5) are computed and based on Eqn. (1), the performance of the tool is confirmed using different features.[37]

$$\text{Accuracy (ACC)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

$$\text{Precision (PRE)} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Sensitivity (SEN)} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{Specificity (SPE)} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

$$\text{Negative Predictive Value (NPV)} = \frac{\text{TN}}{\text{TN+FN}} \quad (5)$$

Result and Discussion

This tool is initially executed using the AlexNet as the processing model and the achieved outcome for the testing task is recorded for the examination. Similar procedure is executed with the chosen DL-schemes and every achieved result is recorded and examined. Table 2 shows the result achieved using the ResNet18-model and it confirms that this model helps to achieve an accuracy of 92.4667%, which a 5-fold cross validation is implemented. Further, it offers an aggregable PRE, SEN, SPE and NPV. The graphical result of this investigation is shown in Figure 4, which confirms that the Fold4 offers a better result than other folds, which is then chosen as the final result. Similar task is then executed with other DL-methods and obtained result is recorded for further investigation.

Table 2. Results achieved during 5-fold cross validation with ResNet18 and SoftMax classifier

Cross validation	TP	FN	TN	FP	ACC	PRE	SEN	SPE	NPV
Fold1	683	67	674	76	90.4667	89.9868	91.0667	89.8667	90.9582
Fold2	679	71	682	68	90.7333	90.8969	90.5333	90.9333	90.5710
Fold3	688	62	693	57	92.0667	92.3490	91.7333	92.4000	91.7881
Fold4	696	54	691	59	92.4667	92.1854	92.8000	92.1333	92.7517
Fold5	690	60	687	63	91.8000	91.6335	92.0000	91.6000	91.9679

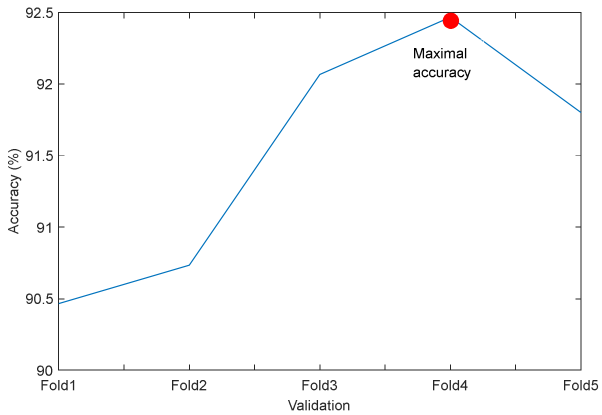
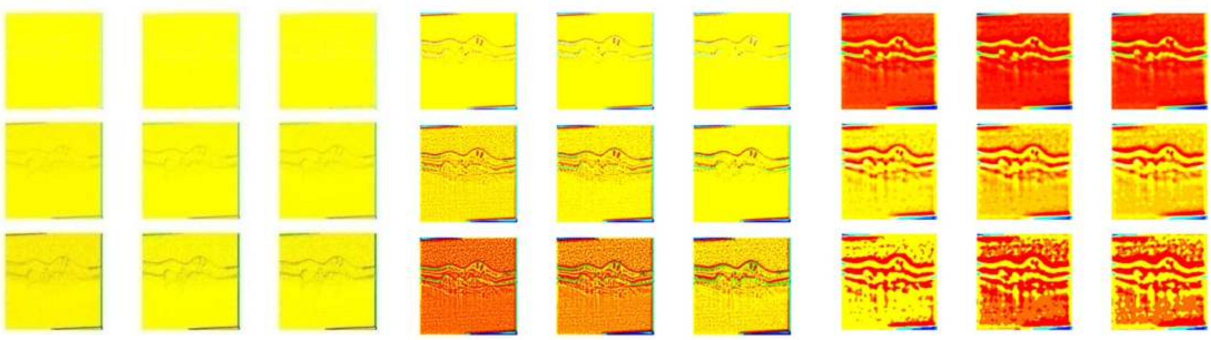


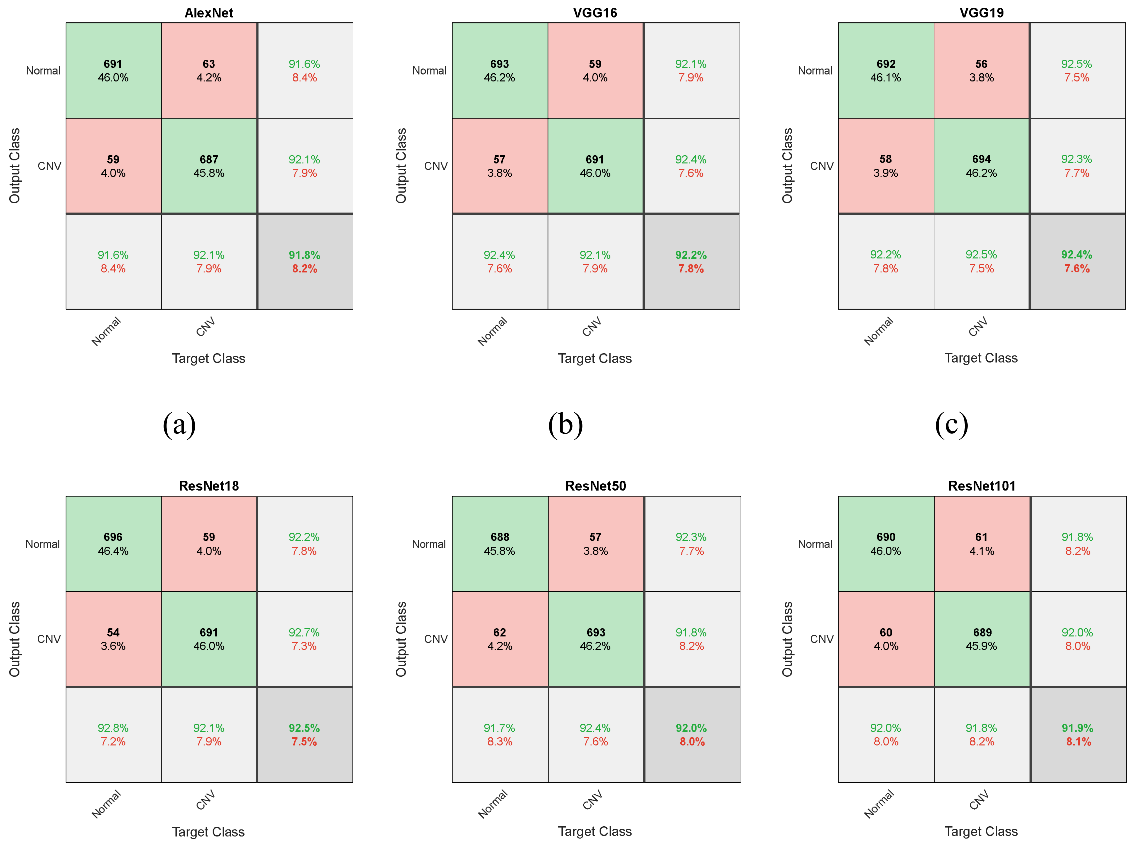
Figure 4. Comparison of accuracy achieved during the cross validation

Figure 5 depicts the different convolutional layer (Conv) results of ResNet18 and this confirms that the chosen image is converted into features as shown in Figs 4(a) to (c), which depicts Conv1 to Conv3. The experimental outcome of the chosen model with SoftMax classifier is executed on the OCT data and the outcomes are presented and discussed, Figure 6 depicts the CM attained with the proposed technique with the chosen test images of size 750 each. Fig 6(a) to (f) presents the two-class CM achieved with, AlexNet, VGG16, VGG19, ResNet18, ResNet50, and ResNet101, respectively. Along with the necessary measures, like TP, TN, FP, and FN, the CM helps in achieving the other metrics, like ACC, PRE, SEN, SPE, and NPV in pictorial form.
These CM values are then tabulated as in Table 3 and compared by choosing the ACC as the prime measure, which confirms that the ResNet18 offers better detection accuracy on the chosen OCT data. Hence, the deep-features of the ResNet18 are then chosen for the hybrid-feature generation, after a 50% dropout.



(a) Conv1 (b) Conv2 (c) Conv3

Figure 5. Convolutional layer results obtained from pre-trained ResNet18



(d) (e) (f)

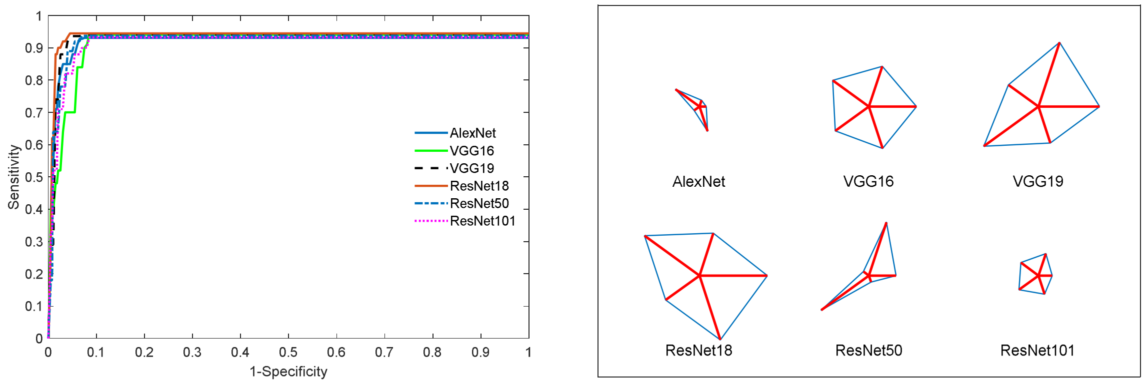
Figure 6. Confusion matrix achieved for the pre-trained schemes with SoftMax based binary classification

Table 3. Binary classification results of pre-trained deep-learning schemes with SoftMax

Scheme	TP	FN	TN	FP	ACC	PRE	SEN	SPE	NPV
AlexNet	691	59	687	63	91.8667	91.6446	92.1333	91.6000	92.0912
VGG16	693	57	691	59	92.2667	92.1543	92.4000	92.1333	92.3797
VGG19	692	58	694	56	92.4000	92.5134	92.2667	92.5333	92.2872
ResNet18	696	54	691	59	92.4667	92.1854	92.8000	92.1333	92.7517
ResNet50	688	62	693	57	92.0667	92.3490	91.7333	92.4000	91.7881
ResNet101	690	60	689	61	91.9333	91.8775	92.0000	91.8667	91.9893

To verify the performance of the chosen DL-models on the OCT data with the SoftMax classifier, the Receiver Operating Characteristic (ROC) curve is also then constructed as in Figure 7(a), which also verifies that the ResNet18 shows a better value compared to other chosen methods. Figure 7(b) presents graphical representation in Glyph-plot for the overall evaluation of the Table 3 values, which verifies that the ResNet18's merit is better than other DL-models of this study. As per this diagram, the AlexNet and ResNet101 show a poor examination result on the chosen image database.

Finally, the ResNet18 model is considered to verify the merit of the developed tool using the deep, GLCM-, and hybrid image features using the different binary classifiers presented in Table 4. The deep-features based detection confirms that the KNN presents detection ACC of 93.8%, whereas the GLCM-feature offered 89.07% ACC with the KNN. These ACC values are lesser compared to other existing works in the literature. Hence, hybrid-features based OCT classification is executed and this process offered and ACC of 97.6%, which is higher than all other techniques executed in the proposed work. To verify overall performance of the proposed too, the achieved result in Table 4 is graphically evaluated using the Glyph-plot as shown in Figure 8.



(a) ROC (b) Glyph-plot to compare the performance

Figure 7. Performance evaluation of the pre-trained deep leaning systems

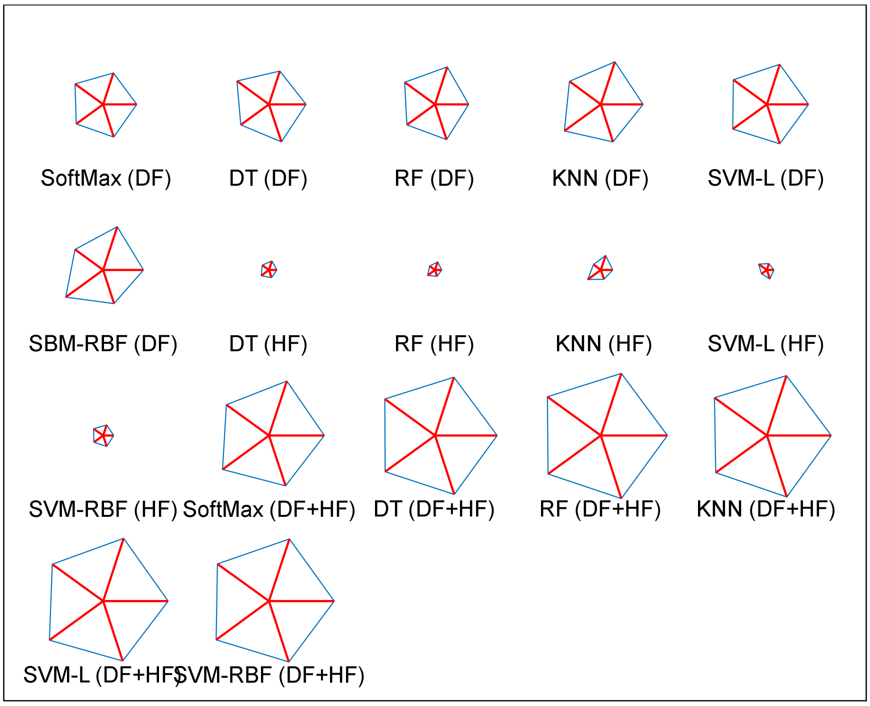


Figure 8. Glyph-plot to present the overall performance of the proposed system with different feature vector

Figure 8 confirms that the hybrid-features based result is superior compared to other two-features used in this research. This work presented a study to classify the normal and CNV class OCT images using the developed tool. In the future, this tool can be considered to examine the AMD and DME using the OCT images. Further, the performance of the tool can be verified using the existing pre-trained lightweight DL-models. The clinical significance of the tool can also be confirmed using the clinically collected OCT images.

Conclusions

The occurrence rate of the AEA is gradually rising in elderly; hence a number of diagnostic methods are proposed and implemented for early detection and treatment. This work considered the CNV detection from the OCT for the study and to automate this process, DL-method based tool is developed using the ResNet18. In this work, ResNet18 based technique is implemented to verify the performance of the OCT classification task using the chosen binary classifier and a 5-fold cross validation. The performance of the developed tool is separately verified using the deep, GLCM-, and hybrid-features with the classifiers like, SoftMax, DT, RF, KNN, SVM-L, and SVM-RBF and the achieved results are compared to identify the suitable classifier based on the achieved ACC. The experimental outcome of this tool verifies that the developed tool with hybrid-features is efficient in providing a significant result on the chosen OCT data with normal and CNV class. In the future, this tool can be considered to detect the common AEAs, like AMD and the DME.

Table 4. Performance evaluation of proposed tool with different image features using different binary classifiers

Features	Cross validation	TP	FN	TN	FP	ACC	PRE	SEN	SPE	NPV
Deep features	SoftMax	696	54	691	59	92.4667	92.1854	92.8000	92.1333	92.7517
	DT	702	48	693	57	93.0000	92.4901	93.6000	92.4000	93.5223
	RF	699	51	693	57	92.4603	93.2000	93.2000	92.4000	93.1452
	KNN	701	49	706	44	93.8000	94.0940	93.4667	94.1333	93.5099
	SVM-L	704	46	702	48	93.7333	93.6170	93.8667	93.6000	93.8503
	SVM-RBF	696	54	707	43	93.5333	94.1813	92.8000	94.2667	92.9041
GLCM features	DT	665	85	662	88	88.4667	88.3134	88.6667	88.2667	88.6212
	RF	663	87	661	89	88.2667	88.1649	88.4000	88.1333	88.3690
	KNN	666	84	670	80	89.0667	89.2761	88.8000	89.3333	88.8594
	SVM-L	667	83	658	92	88.3333	87.8788	88.9333	87.7333	88.7989
	SVM-RBF	669	81	664	86	88.8667	88.6093	89.2000	88.5333	89.1275
Deep+GLCM features	SoftMax	717	33	721	29	95.8667	96.1126	95.6000	96.1333	95.6233
	DT	728	22	726	24	96.9333	96.8085	97.0667	96.8000	97.0588
	RF	733	17	731	19	97.6000	97.4734	97.7333	97.4667	97.7273
	KNN	731	19	728	22	97.2667	97.0784	97.4667	97.0667	97.4565
	SVM-L	729	21	732	18	97.4000	97.5904	97.2000	97.6000	97.2112
	SVM-RBF	730	20	729	21	97.4000	97.4633	97.3333	97.4667	97.3369

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