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Optical coherence tomography with the best deep properties for finding age-related macular degeneration

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Abstract

Background

An ocular ailment impacts the entirety of sensory functioning, and an undetected and untreated ocular ailment might result in visual impairment. The objective of this study was to create an automated system for detecting age-related macular degeneration (ARMD) using deep-learning (DL) method that combines optimal deep features selected using the arithmetic optimizer (AO).

Methods

The main stages of the proposed scheme include; image collection from the chosen dataset and resizing, feature extraction using the DL scheme, feature optimization with AO and serial features fusion, and bi-level data classification and five-fold cross validation. The performance of the developed DL system is verified using conventional-, optimal-, and fused-features and the importance of these methods are established based on the chosen performance metrics.

Results

This study is executed using 1200 numbers of optical coherence tomography images of Normal/ARMD class and the scheme helps in achieving accuracy of >90% and >91% with conventional- and optimal features. Further, the fused-features based classification provided an accuracy of >99% with the support vector machin.

Conclusions

The achieved results of this study confirm the importance of the developed procedure on the examination of retinal optical coherence tomography images.

Keywords: ocular ailment; age-related macular degeneration; optical coherence tomography image; arithmetic optimizer; classification.

Introduction

Science and technology have made great strides in improving people's quality of life by developing new medications and monitoring systems. These developments have been extremely helpful in enabling early sickness diagnosis and treatment. The above described improvements have made a substantial difference in the treatment of several anomalies, including viral and non-infectious diseases, especially in the medical domain. The ability to monitor illnesses in persons has been made possible by the availability of advanced medical equipment and suitable health interventions.[1] The occurrence rate of aging-related diseases (ADs) in humans is unavoidable, even with the use of several preventative measures to succeed different diseases. Diseases are less severe and occur less frequently when modern medical procedures and prevention measures are used. Scholarly literature has several in-depth analyses of AD together with relevant clinical data. Of these conditions, age-related macular degeneration (ARMD) is one of the most common and concerning; it primarily affects middle-aged and older people, namely those who are 45 years of age and older. Based on where it occurs, the ARMD is divided into two groups: dry and wet.[2,3] The eye's field of vision is reduced in both classes, and an unprocessed, uncertain picture is produced.

Earlier research has demonstrated the importance of treating and diagnosing ARMD early. When patients attend ophthalmology clinics, ophthalmologists often do eye exams and may recommend specific diagnostic tests to find any ocular disorders. Using a selected imaging modality, image-assisted diagnosis is a commonly authorized procedure in the clinics to assess and validate eye illnesses. One of the often used imaging modalities is optical coherence tomography (OCT), which is extensively used to scan for abnormalities in the eye for assessment and therapy. The information about the retina that the OCT serves to offer is essential for analysing and determining the abnormalities and severity of the eye illness.[4,5]

The goal of this study is to create a deep-learning (DL) algorithm that will identify ARMD in selected OCT pictures. For the purpose of classifying OCT images into normal and ARMD classes, this work implements an ARMD detection tool supported by transfer learning. The stages of this tool are as follows: image collection and resizing; deep features extraction using the selected DL technique; feature reduction using the Arithmetic Optimizer (AO); serially combining the AO selected features to achieve deep features fusion; and five-fold cross validation to verify the effectiveness of the developed system. In this study, 1200 OCT-images from the normal and ARMD classes are examined, and before the classification task is carried out, the relevant features are mined, optimized, and serially fused.[6,7] The tool that is being described makes it easier to obtain the initial evaluation result from the chosen OCT-database. The obtained result is then confirmed by the ophthalmologist, who takes over the task of formulating and administering the necessary medication for the management of ARMD. By analysing and then merging the component features of the generated tool, its performance is evaluated. Choosing the best value obtained from the cross-validation process determines the outcome in the end.

For analysis, this study looked at both the lightweight and conventional deep learning (DL) systems. The results that are acquired are shown by means of individual and feature fusion methods. Using the SoftMax classifier is the first step in the classification process. Other methods like Naïve Bayes (NB), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbour (KNN), and Random Forest (RF) are then assessed. The results of these techniques are then discussed and examined.[8,9]

This research demonstrates how well the suggested technique works in determining its overall correctness for the database that is being examined. The recommended research's experimental findings verify that the Support Vector Machine (SVM) performed satisfactorily in categorizing individual features and more satisfactorily in recognizing fused-deep features. When using the SoftMax classifier, the incorporation of deep features results in better accuracy rate. This paper gives an evaluation of retinal OCT-images with the proposed approach, showing enhanced results by using fused deep features.[10]

The investigational outcome of this study is established using different feature set, like conventional, optimized with AO, and fused-features and the merit of these methods are confirmed by computing the classification accuracy. This study was performed with 1200 OCT images of dimension$150 \times 150 \times 3$ pixels using the labelled Normal/ARMD class images and this work helped in achieving accuracies of >91% with conventional-, and optimized-features. During the fused-features based classification, the Support Vector Machine (SVM) classifier provided a recognition accuracy of and >99%, which is higher compared to other methods. The achieved results in this research confirm the importance of propose method on the examination of retinal OCT images.

The following are some ways in which this research contributes:

i. Traditional DL and lightweight DL methods are used to show the development of an efficient retinal OCT examination.
ii. The AO is used to implement deep features optimization, and the reduced features are then taken into account to form the fused feature vector.
iii. Conventional, optimized, and fused features are used to confirm the worth of the developed system, and the OCT image database is used to confirm the obtained results.

The other portions of this are organized as follows: Section 2 provides background information; Section 3 details the technique; and portions 4 and 5 offer the results and conclusion of the experiment. According to the World Health Organisation (WHO), over 2.2 billion individuals suffer from a visual impairment, either near or far, with common causes including refractive errors, cataracts, diabetic-retinopathy, glaucoma, and ARMD. The ARMD is recognized as a significant factor contributing to vision-related problems. Therefore, researchers have devised ARMD detection systems employing a specific strategy. The utilization of computer algorithm-supported methodologies is prevalent in the analysis of ARMD through the analysis of clinical grade retinal pictures.[11]

Prior research on ARMD detection focused on utilizing Machine-Learning (ML) and DL methods to classify labelled images into normal and ARMD classes. This classification is crucial in alleviating the diagnostic workload for doctors during patient screening for ARMD detection. The significance of ARMD has led to the proposal and development of many computerized approaches for its detection. The majority of these methods emphasize the necessity of an algorithm-based screening and grading system for disease diagnosis and treatment planning. The study examined in.[12] offers a complete examination of the diagnosis of ARMD and emphasizes the necessity of implementing computerized screening methods for early and effective detection of ARMD.

The previous studies conducted on retinal image inspection have provided evidence supporting the efficacy of computerized diagnosis for retinal abnormalities, including ARMD. Burlina et al. (2016) conducted a study where they utilized deep learning (DL) to identify ARMD using 5600 fundus-retinal pictures. They reached an accuracy rate of up to 95%.[13] González-Gonzalo et al. (2020) utilizes deep learning (DL) to detect retinopathy and age-related macular degeneration (ARMD) in fundus images. The study achieves a mean error (SE) of 91.8% and a standard deviation (SP) of 87.5%.[14] The study conducted by Xie et al. (2020) utilized the ARMD-GAN model to autonomously identify the presence of ARMD in ophthalmoscopy images, resulting in a remarkable accuracy rate of 91.97%.[15] The study conducted by Rim et al. (2021) provides empirical evidence supporting the efficacy of the DL-technique in improving the ROC-curve value to 0.952.[16] In their study, Kadry et al. (2022) introduced a DL approach for the identification of ARMD in fundus images and ocular cochlear implants (OCT) using the VGG16 model.[17] Their findings validate the superior diagnostic accuracy achieved through the utilization of the DL technique in comparison to alternative methodologies.

The implementation of this work involved the utilization of integrated deep-features and handcrafted-features for classification. Various binary classifiers were employed to assess the performance. The fundus-imaging and OCT were used to check the accuracy of the results. The analysis was conducted using the MATLAB software, and the findings of this study validate that the implementation of the SVM-RBF classifier resulted in a detection accuracy of 97.5%. This study verifies that the classification based on fused features acquired an accuracy of only 98%. Therefore, the objective of this research is to enhance this accuracy by utilizing fused deep features improved with the AO.

The proposed study examines the detection of ARMD using both conventional and lightweight deep learning models. The analysis focuses on individual and fused features and evaluates the performance of the chosen classifier using quality metrics such as accuracy (AC), precision (PR), sensitivity (SE), specificity (SP), and F1-Score (FS). The performance of the implemented technique is then verified based on these values.

Methods

In this section of the paper, an analysis is conducted on the various steps encompassed within the suggested technique. The succinct structure of this technique is illustrated in Figure 1. The required optical coherence tomography (OCT) images were acquired from the benchmark datasets. The test images are acquired from.[7], while the ARMD images are derived from.[6] The dimensions of these photographs are subsequently reduced to 150x150x3 pixels before to being examined by the proposed architecture. Firstly, the required deep-feature (DF) with dimensions of 1x1x1000 is mined with selected DL scheme. Subsequently, the efficiency of the DL approaches is assessed using the SoftMax classifier. After choosing the suitable deep learning strategy for the selected optical coherence tomography (OCT) data, a feature reduction is performed using the AO technique, resulting in the acquisition of the required fused feature. The verification of ARMD detection from the selected OCT pictures, as seen in Figure 1, is subsequently undertaken. Throughout this process, the requisite metrics are calculated. The metrics that have been attained are subsequently evaluated in order to establish the importance of the implemented technique on the selected OCT-image database.

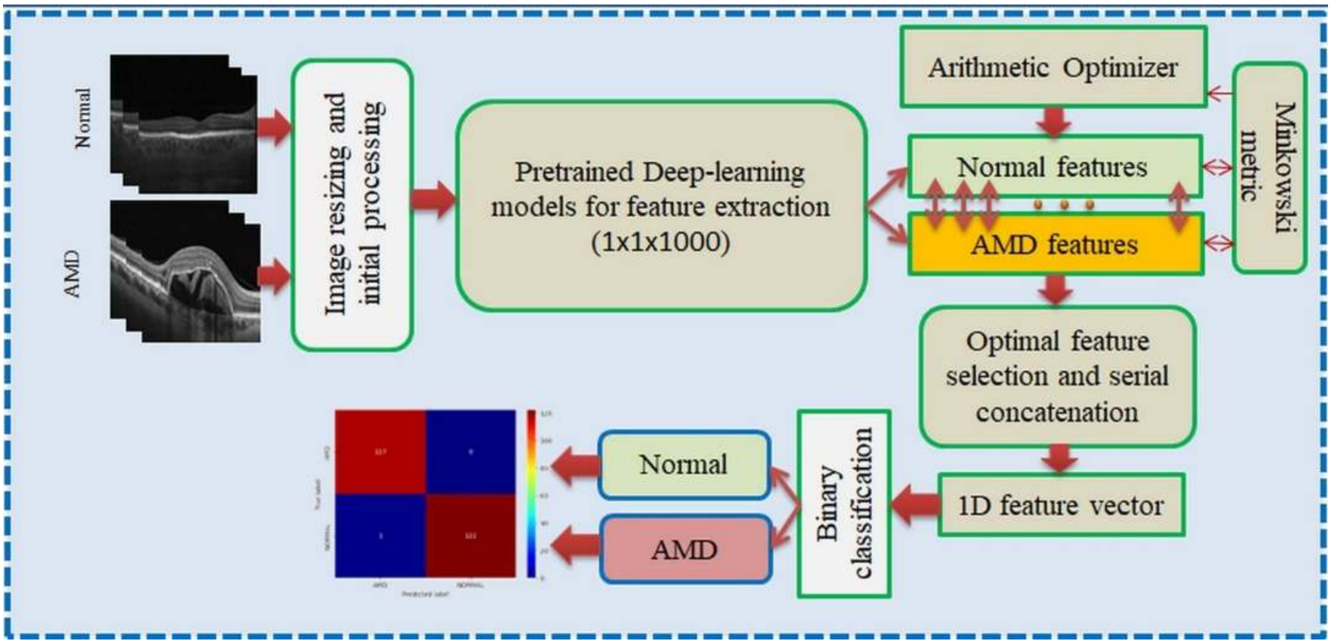


Figure 1. Developed OCT image examination architecture with deep-learning scheme

OCT image database

Selecting a suitable database that closely resembles the clinical images is crucial for the training and validation procedure of the DL-scheme. Once the DL scheme has been effectively trained using a selected database, the subsequent clinical implementation of the model becomes straightforward and requires little modifications. Therefore, the disease examination processes mostly rely on the benchmark database that is available for research purposes. The normal class OCT images are acquired from.7], whereas the ARMD class images are sourced from.[7] Once the image is gathered, each image is resized to 150x150x3 pixels (RGB) and evaluated to assess the effectiveness of the devised scheme.

The performance of traditional and lightweight DL algorithms with a binary classification is examined in this study utilizing the OCT dataset. A supervised training and validation procedure is utilized, wherein each image is allocated a label denoting Normal/ARMD. The images used for analysing the developed model are presented in Table 1, whereas Figure 2 displays the sample images from the OCT database that were employed in this study.

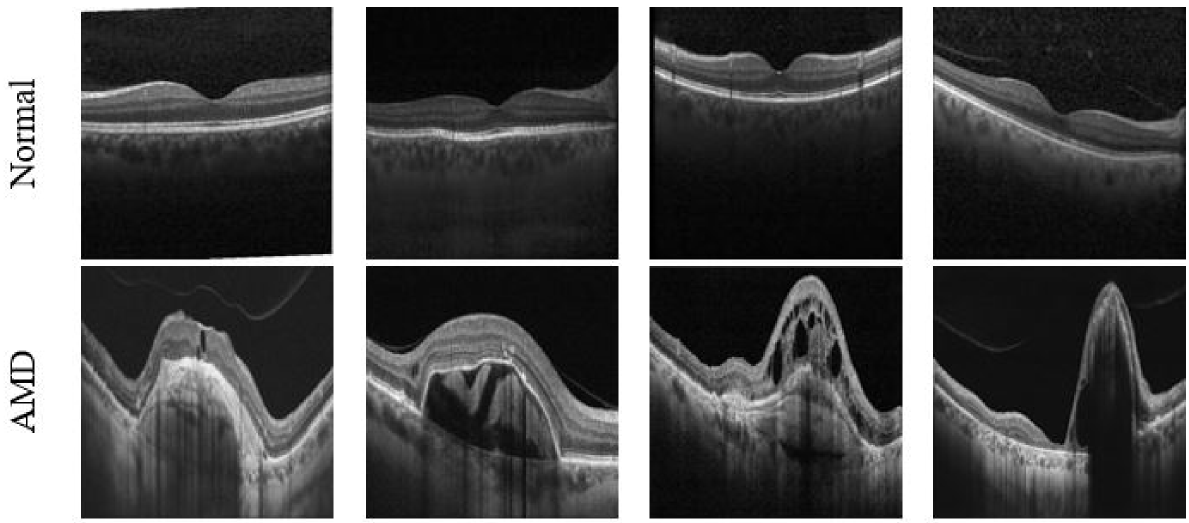


Figure 2. OCT images available in the chosen database

Table 1. Images from chosen OCT-database for the DL scheme examination

Class	Dimension	Images			
		Total	Training	Validation	Testing
Normal	150x150x3	1200	960	120	120
ARMD	150x150x3	1200	960	120	120

Deep-learning scheme

The existing pre-trained DL methods utilized in the literature are readily available for examination and immediate implementation. Various tools can be utilized to implement these models, depending on the specific requirements. The present work utilizes the Python programming language to implement the DL schemes under investigation. One of the key benefits associated with pre-trained DL methods is their pre-optimized parameters, which require relatively minimal hyperparameter adjustment based on the specific task being addressed. Furthermore, the success of these models is assessed by employing the highly acknowledged ImageNet benchmark dataset. Moreover, the said models exhibit proficient performance on both grayscale and RGB-scale photos, consistently yielding the expected outcomes when employed on suitably labelled and scaled image data. The primary objective of this study is to examine the analysis of various DL methods found in the literature.[18,19]

After assessing the chosen models using the OCT images, they are then compared to various DL models, including lightweight DL models. The evaluation of the initial and end quality metrics calculated using the CM is used to assess the performance of these models. Furthermore, the assessment of these models is further validated through the application of the receiver operating characteristic (ROC) value acquired during the analysis.[20]

Initially, common image augmentation process is executed to improve the performance during the training process, such as a 30-degree flip and rotation of the image, a 0.3-fold zoom, a 0.3-fold shift in width and height, and the application of a 0.2-fold shear factor. This methodology facilitates the effectiveness of the DL model in precisely detecting the fundamental components of the image. Each DL-scheme is first configured with the following settings: The weights of the model are configured as ImageNet, the number of epochs is set to 80, the optimizer is set to Adam, the batch size is set to 16, the learning rate is set to 1e-4, max pooling is performed, the activation is set to ReLU, the classifier is set to SoftMax and then other methods, like NB, DT, RF, KNN, and SVM are also verified.[21,22]

Features Selection and Fusion

The developed DL-model provides a 1x1x1000 DF that is considered to appraise the merit of the SoftMax assisted binary classification process. Following confirmation of the DL-scheme's performance, the best model is chosen for additional research.

The conventional DF achieved with the chosen DL-scheme is depicted in Eqn. (1);

$$DL_{1\times1\times1000} = DL_{(1\times1)} + DL_{(1\times2)} + \dots + DL_{(1\times1000)} \quad (1)$$

This equation confirms that the normal/ARMD based analysis achieves a feature vector with dimension; 1x1x1000 and it is then utilised to classify the OCT images. After confirming the performance, the feature value is then optimized (reduced) using the chosen heuristic technique and the reduced feature vector is then considered for further analysis with SoftMax classifier and the accomplished results are compared with the conventional scheme.

The feature optimization executed using the AO is implemented and the reduced feature for VGG16 is shown in Eqn. (2);

$$DL_{1\times1\times317} = DL_{(1\times1)} + DL_{(1\times2)} + \dots + DL_{(1\times317)} \quad (2)$$

$$Fused\ Features_{1\times1\times N} = Best\ Model1 + Best\ Model2 \quad (3)$$

By eliminating less significant features, the optimization process that has been put in place helps to lower the complexity of the features that are taken into account for categorization. This subsection discusses the required feature optimization procedure that was used for this work.

Abualigah et al. (2021) created this algorithm by applying addition, subtraction, multiplication, and division, among

other fundamental arithmetic operations. The AO algorithm from.23] is used in this study to determine the binary AO and optimal DF with the following parameters: agent size = 50, search dimension = 2, total iterations = 2500, and monitoring cost value = Minkowski distance among features. The required details regarding feature reduction are available in.24,25], and this technique aids in lowering the feature value in this study.
Based on the classification AC, the optimal DL scheme with decreased feature is next determined. The two optimal DL schemes (best model 1 and best model 2) with the highest accuracy are then serially combined to produce the fused feature vector for additional analysis; its expression is provided in Eqn. (3).

Performance Verification

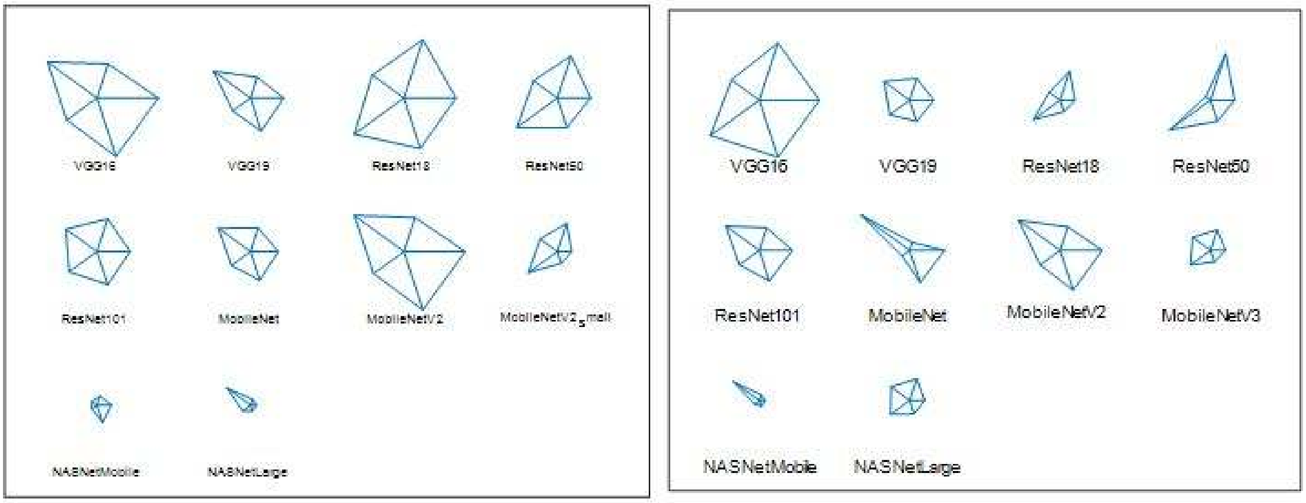
The efficacy of the conceptualized ARMD detection methodology relies on the performance metrics achieved during the classification task. The verification method considers the fundamental metrics, specifically AC, PR, SE, SP, and FS, as outlined in Eqns. (4) to (8). In order to get additional metrics as described in reference.[26], the initial measurements obtained from the CM, including TP, TN, FP, and FN, was considered.

$$AC = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (4)$$
$$PR = \frac{TP}{TP+FP} \times 100 \quad (5)$$
$$SE = \frac{TP}{TP+FN} \times 100 \quad (6)$$
$$SP = \frac{TN}{TN+FP} \times 100 \quad (7)$$
$$FS = \frac{2TP}{2TP+FN+FP} \times 100 \quad (8)$$

Result and Discussion

The study was conducted utilizing an Intel i5 CPU workstation equipped with 16GB RAM, 4GB VRAM, and Python®. A total of 2400 photos, including both normal and ARMD, were selected for the purpose of assessing the efficacy of the proposed deep learning technique. In order to choose the optimal deep learning model for subsequent analysis, the performance of the selected scheme is initially assessed using the SoftMax classifier in conjunction with the traditional deep learning framework.
Subsequently, the AO is utilized for feature optimization in order to decrease the number of features. Following this, the SoftMax algorithm is employed to conduct a comparable classification task. The performance of the selected DL models is then calculated and documented. Ultimately, two optimal models are chosen from these deep learning techniques. The features of these models are then combined in a sequential manner to obtain the fused features (FF). The effectiveness of these models is then assessed by evaluating their performance using different binary classifiers in a five-fold cross validation process. This section solely focuses on the categorization outcome obtained using the FF and the OCT classification using the SoftMax algorithm is initially performed on a feature size of 1x1x1000. The best result obtained during the cross-validation process is then selected for further analysis. Table 2 displays the metrics obtained for the selected models, so confirming the efficiency of the applied approach in achieving an accuracy exceeding 88%. The enhancement of this outcome can be achieved by the optimization of features and the incorporation of serial features.
To verify the overall performance for Table 2 values; a Glyph-plot is constructed and achieved better outcome with VGG16 and MobileNetV2. Similar process is then applied on the chosen image and the achieved results are presented in Table 3. This Table confirms a slight increase in the detection accuracy compared to the conventional features as in Table 2. From Figure 3, it is detected that the feature optimization performance is better compared to other methods.
Once the performance of the selected scheme has been verified, the binary classification task is carried out using the fused-features of VGG16 and MobileNetV2. The obtained results for several binary classifiers are presented in Table 4. The findings of this investigation validate that the SVM classification method has an accuracy rate (AC) of 98%.
The training and validation accuracy using the fused-features are depicted in Figure 4, providing confirmation that the adopted approach yields superior outcomes. Figure 4(a) displays the accuracy, while Figure 4(b) illustrates the loss. Figure 5 displays the acquired convolutional result. Figures 5(a) to (d) depict the diverse outputs of the layers for a selected model. Figure 6 displays the ultimate outcome using the suggested approach, which further validates

the improved CM and ROC-curve. This study demonstrates that the utilization of fused features yields superior outcomes in comparison to alternative results.



(a) Plot1 (b) Plot2

Figure 3. Overall performance measure with Glyph-plot

Table 2. Classification result for the OCT database with conventional features and SoftMax

Scheme	TP	FN	TN	FP	AC (%)	PR (%)	SE (%)	SP (%)	FS(%)
VGG16	110	8	109	13	91.2500	89.4309	93.2203	89.3443	91.2863
VGG19	109	10	107	14	90.0000	88.6179	91.5966	88.4298	90.0826
ResNet18	109	12	107	12	90.8333	90.9091	90.9091	90.7563	90.9091
ResNet50	107	12	109	12	90.0000	89.9160	89.9160	90.0826	89.9160
ResNet101	109	11	107	13	90.0000	89.3443	90.8333	89.1667	90.0826
MobileNet	111	11	108	14	89.7541	88.8000	90.9836	88.5246	89.8785
MobileNetV2	110	8	109	13	91.2500	89.4309	93.2203	89.3443	91.2863
MobileNetV3	106	13	108	13	89.1667	89.0756	89.0756	89.2562	89.0756
NASNetMobile	109	11	105	15	89.1667	87.9032	87.5000	87.5000	89.3443
NASNetLarge	107	12	107	14	88.7967	87.7049	89.9160	87.7049	88.7967

Table 3. Classification result for the OCT database with reduced features and SoftMax

Scheme	TP	FN	TN	FP	AC (%)	PR (%)	SE (%)	SP (%)	FS(%)
VGG16	111	11	109	9	91.6667	92.5000	90.9836	92.3729	91.7355
VGG19	108	11	108	13	90.0000	89.2562	90.7563	89.2562	90.0000
ResNet18	107	13	108	12	89.5833	89.9160	89.1667	90.0000	89.5397
ResNet50	108	14	108	10	90.0000	91.5254	88.5246	91.5254	90.0000
ResNet101	109	10	108	13	90.4167	89.3443	91.5966	89.2562	90.4564
MobileNet	110	8	109	13	90.4959	88.0000	93.2203	87.9032	90.5350
MobileNetV2	110	9	108	13	90.8333	89.4309	92.4370	89.2562	90.9091
MobileNetV3	107	12	108	13	89.5833	89.1667	89.9160	89.2562	89.5397
NASNetMobile	108	11	106	15	89.1667	87.8049	90.7563	87.6033	89.2562
NASNetLarge	108	12	107	13	89.5833	89.2562	90.0000	89.1667	89.6266

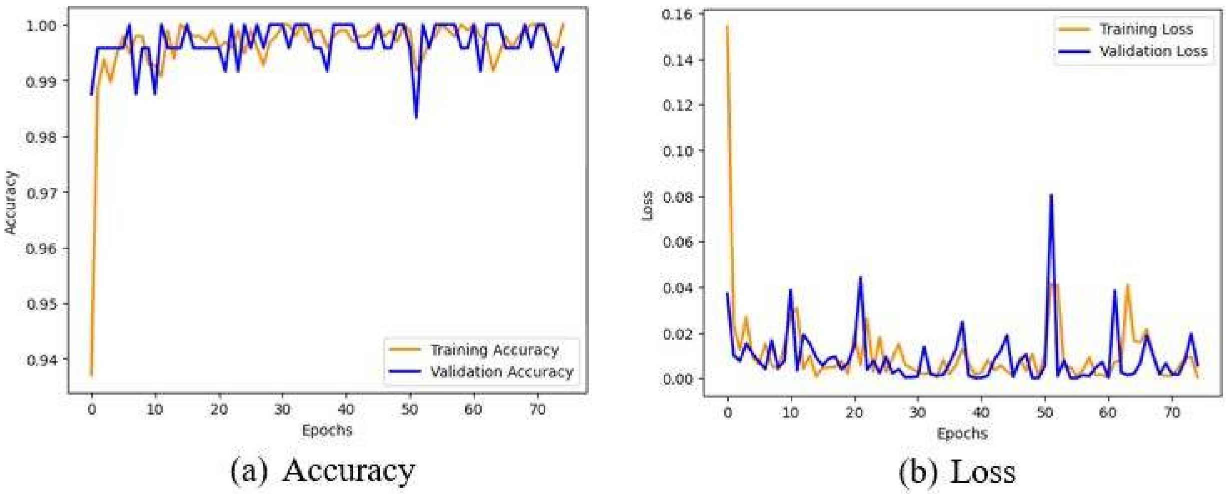


Figure 4. Accuracy and Loss attained with features-fusion for a chosen epoch of 80.

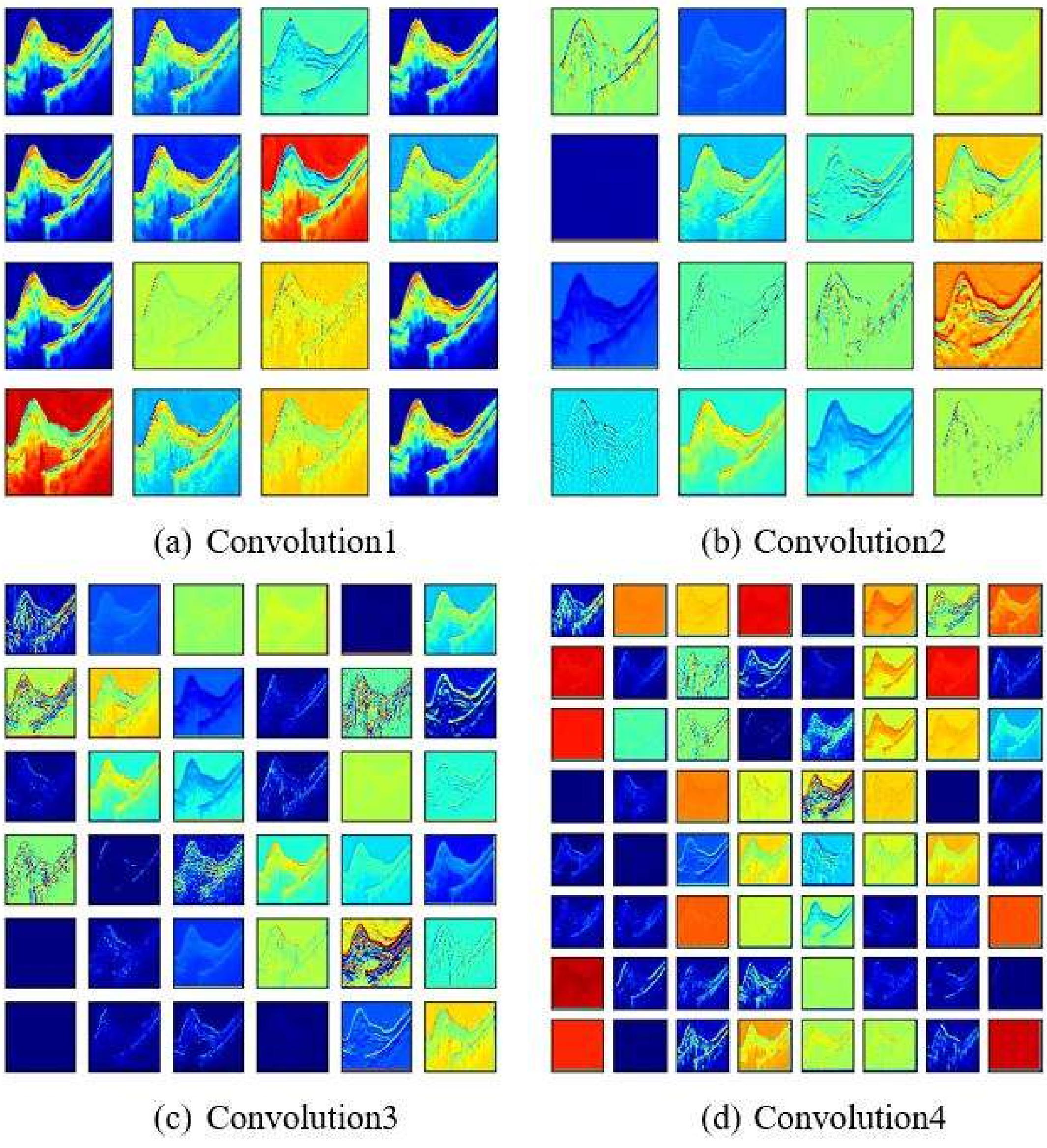
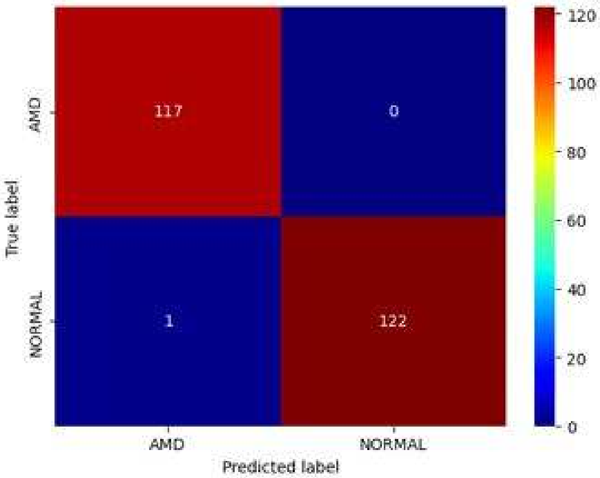
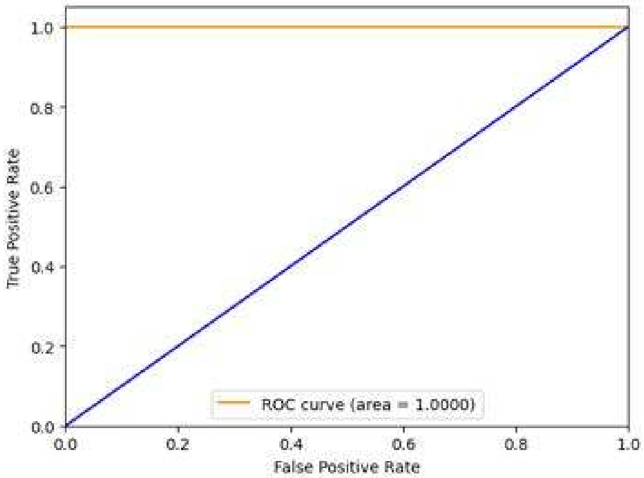


Figure 5. Various convolution layer outcomes for a chosen image



(a) CM



(b) ROC

Figure 6. Confusion matrix obtained with the SVM classifier and the corresponding ROC

Table 4. Classification result for the OCT database with fused features

Scheme	TP	FN	TN	FP	AC (%)	PR (%)	SE (%)	SP (%)	FS (%)
SoftMax	118	1	118	3	98.3333	97.5207	99.1597	97.5207	98.3333
NB	117	3	119	1	98.3333	99.1525	97.5000	99.1667	98.3193
DT	119	1	118	2	98.7500	98.3471	99.1667	98.3333	98.7552
RF	118	3	117	2	97.9167	98.3333	97.5207	98.3193	97.9253
KNN	120	0	118	2	99.1667	98.3607	100	98.3333	99.1736
SVM	122	1	117	0	99.5833	100	99.1870	100	99.5918

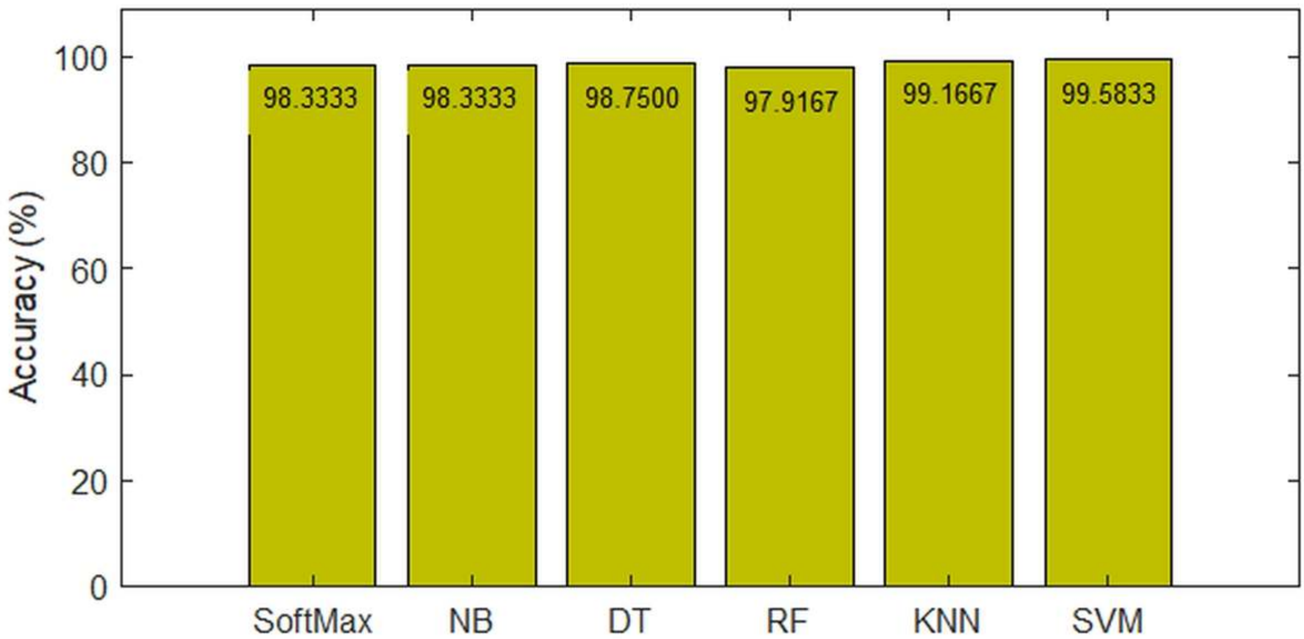


Figure 7. Comparison of the AC achieved with various classifiers

Based on the data shown in Table 4 and Figure 7, it is evident that the Support Vector Machine (SVM) classifier achieved a detection accuracy of 99.5833%. This performance surpasses that of other classifiers and previous findings documented in the existing literature. This validates that the suggested classification method, which combines characteristics, offers improved detection of OCT images. In the future, the feature optimization component can be enhanced by employing other contemporary heuristic techniques. Moreover, it is worth considering the ensemble of deep features in order to assess the effectiveness of the constructed system.

Conclusion

The objective of this study is to provide a systematic analysis of retinal abnormalities utilizing contemporary deep learning techniques. The DL approach under consideration is utilized for the detection of labelled OCT images into two classes: normal and ARMD. This is achieved by employing conventional, optimum, and fused features. The study encompasses a grand total of 1200 annotated photos for every category. This study involves an initial implementation of conventional feature-based classification, followed by the execution of AO-based feature optimization. The experimental inquiry is then repeated. This study validates the superior performance of the VGG16 and MobileNetV2 models in detecting AC and overall performance. Therefore, the implementation of serial features integration is then employed to obtain a novel feature vector that amalgamates the reduced feature vectors of VGG16 and MobileNetV2. SoftMax, NB, DT, RF, KNN, and SVM are employed to perform the classification task. The results collected are subsequently compared. The results of this study confirm that the Support Vector Machine (SVM) algorithms produce similar levels of test accuracy (>99%) when utilized on the chosen Optical Characteristics Transform (OCT) data. The effectiveness of the proposed methodology can be evaluated by utilizing OCT images received from clinical sources. Moreover, the efficacy of the performance can be assessed and validated through the utilization of an ensemble of deep characteristics.

References

1. Stoumpos, A. I., Kitsios, F., & Talias, M. A. (2023). Digital transformation in healthcare: technology acceptance and its applications. *International journal of environmental research and public health 20*(4), 3407.
2. Sarkar, A., Sodha, S. J., Junnuthula, V., Kolimi, P., & Dyawanapelly, S. (2022). Novel and investigational therapies for wet and dry age-related macular degeneration. *Drug Discovery Today 27*(8), 2322-2332.
3. Acharya, U. R., Hagiwara, Y., Koh, J. E., Tan, J. H., Bhandary, S. V., Rao, A. K., & Raghavendra, U. (2017). Automated screening tool for dry and wet age-related macular degeneration (ARMD) using pyramid of histogram of oriented gradients (PHOG) and nonlinear features. *Journal of Computational Science*, *20*, 41-51.
4. Hirabayashi, K., Hannah, J. Y., Wakatsuki, Y., Marion, K. M., Wykoff, C. C., & Sadda, S. R. (2023). OCT risk factors for development of atrophy in eyes with intermediate age-related macular degeneration. *Ophthalmology Retina*, *7*(3), 253-260.
5. Ricardi, F., Oakley, J., Russakoff, D., Boscia, G., Caselgrandi, P., Gelormini, F., ... & Borrelli, E. (2024). Validation of a deep learning model for automatic detection and quantification of five OCT critical retinal features associated with neovascular age-related macular degeneration. *British Journal of Ophthalmology*.
6. Mikhail Kulyabin, Aleksei Zhdanov, Anastasia Nikiforova, Andrey Stepichev, Anna Kuznetsova, Vasilii Borisov, Mikhail Ronkin, Alexander Bogachev, Sergey Korotkich. (2023). OCTDL: Optical Coherence Tomography Dataset for Image-Based Deep Learning Methods. IEEE Dataport. https://dx.doi.org/10.21227/fpvs-8n55
7. https://www.kaggle.com/datasets/paultimothymooney/kermany2018
8. Umer, M. J., Sharif, M., Raza, M., & Kadry, S. (2023). A deep feature fusion and selection-based retinal eye disease detection from oct images. *Expert Systems*, *40*(6), e13232.
9. Kadry, S., Crespo, R. G., Herrera-Viedma, E., Krishnamoorthy, S., & Rajinikanth, V. (2023). Deep and handcrafted feature supported diabetic retinopathy detection: A study. *Procedia Computer Science*, *218*, 2675-2683.
10. Chen, M., Jin, K., Yan, Y., Liu, X., Huang, X., Gao, Z., ... & Ye, J. (2022). Automated diagnosis of age-related macular degeneration using multi-modal vertical plane feature fusion via deep learning. *Medical Physics*, *49*(4), 2324-2333.
11. Kawasaki, R., Yasuda, M., Song, S. J., Chen, S. J., Jonas, J. B., Wang, J. J., ... & Wong, T. Y. (2010). The prevalence of age-related macular degeneration in Asians: a systematic review and meta-analysis. *Ophthalmology*, *117*(5), 921-927.
12. Chakravarthy, U., Wong, T. Y., Fletcher, A., Piault, E., Evans, C., Zlateva, G., ... & Mitchell, P. (2010). Clinical risk factors for age-related macular degeneration: a systematic review and meta-analysis. *BMC ophthalmology*, *10*, 1-13.

13. Burlina, P., Freund, D. E., Joshi, N., Wolfson, Y., & Bressler, N. M. (2016, April). Detection of age-related macular degeneration via deep learning. In *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)* (pp. 184-188). IEEE.
14. González-Gonzalo, C., Sánchez-Gutiérrez, V., Hernández-Martínez, P., Contreras, I., Lechanteur, Y. T., Domanian, A., ... & Sánchez, C. I. (2020). Evaluation of a deep learning system for the joint automated detection of diabetic retinopathy and age-related macular degeneration. *Acta ophthalmologica*, *98*(4), 368-377.
15. Xie, J., Chen, Q., Yu, J., Zhou, H., He, J., Wang, W., ... & Xu, X. (2020). Morphologic features of myopic choroidal neovascularization in pathologic myopia on swept-source optical coherence tomography. *Frontiers in Medicine*, *7*, 615902.
16. Rim, T. H., Lee, A. Y., Ting, D. S., Teo, K., Betzler, B. K., Teo, Z. L., ... & Cheung, C. M. G. (2021). Detection of features associated with neovascular age-related macular degeneration in ethnically distinct data sets by an optical coherence tomography: trained deep learning algorithm. *British Journal of Ophthalmology*, *105*(8), 1133-1139.
17. Kadry, S., Rajinikanth, V., González Crespo, R., & Verdú, E. (2022). Automated detection of age-related macular degeneration using a pre-trained deep-learning scheme. *The Journal of Supercomputing*, *78*(5), 7321-7340.
18. Shrestha, A., & Mahmood, A. (2019). Review of deep learning algorithms and architectures. *IEEE access*, *7*, 53040-53065.
19. Khamparia, A., & Singh, K. M. (2019). A systematic review on deep learning architectures and applications. *Expert Systems*, *36*(3), e12400.
20. Carrington, A. M., Manuel, D. G., Fieguth, P. W., Ramsay, T., Osmani, V., Wernly, B., ... & Holzinger, A. (2021). Deep ROC analysis and AUC as balanced average accuracy to improve model selection, understanding and interpretation. *arXiv preprint arXiv:2103.11357*.
21. Moraes, G., Fu, D. J., Wilson, M., Khalid, H., Wagner, S. K., Korot, E., ... & Chopra, R. (2021). Quantitative analysis of OCT for neovascular age-related macular degeneration using deep learning. *Ophthalmology*, *128*(5), 693-705.
22. Lee, C. S., Baughman, D. M., & Lee, A. Y. (2017). Deep learning is effective for classifying normal versus age-related macular degeneration OCT images. *Ophthalmology Retina*, *1*(4), 322-327.
23. Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., & Gandomi, A. H. (2021). The arithmetic optimization algorithm. *Computer methods in applied mechanics and engineering*, *376*, 113609.
24. Xu, H., Zeng, W., Zeng, X., & Yen, G. G. (2018). An evolutionary algorithm based on Minkowski distance for many-objective optimization. *IEEE transactions on cybernetics*, *49*(11), 3968-3979.
25. Saeedi, A., Moridani, M. K., & Azizi, A. (2021). An innovative method for cardiovascular disease detection based on nonlinear geometric features and feature reduction combination. *Intelligent Decision Technologies*, *15*(1), 45-57.
26. Kansal, V., Armstrong, J. J., Pintwala, R., & Hutnik, C. (2018). Optical coherence tomography for glaucoma diagnosis: an evidence based meta-analysis. *PloS one*, *13*(1), e0190621.