InceptionV3 Based Approach for the Recognition of Age-related macular degeneration Disease

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***Abstract*— Millions of people around the world are infected with age-related macular degeneration (AMD) disease. It is not easily detected in the intermediate stage, as it is typically asymptomatic. Moreover, the ideal learning trends for AMD professional advice are identifying those who are at this stage of the condition, instructing them on ways to screen the early diagnosis of the choroidal neovascular level before significant vision loss is incurred, and encouraging them to think about taking nutritional supplements that may lessen the likelihood that the condition will extend from the intermediate to the mature phase. However, conventional identification of this disease can be time-intensive and necessitates knowledgeably competent individuals to carry out the task. Since retinal fundus images have proven beneficial in detecting AMD, automated methods for AMD detection from retina fundus images can be developed by applying a novel application of deep transfer learning (DTL) to leverage on the artificial intelligence advances. In this investigation, deep convolutional neural networks (DCNN) specifically trained for automated AMD evaluation were contrasted with deep transfer learning (DTL), a different deep learning (DL) technique that included common characteristics with a diagnostic grader. In order to differentiate between the age-related macular degeneration (AMD) stage and the Normal stage, automated identification was used on a 2-class classification issue. The study proposed using deep learning (DL) models, and compared them to the DTL model. The proposed DTL model with transfer learning approach yielded an accuracy of 96.41%, area under receiver operator characteristics curve (AUC) of 0.9633, precision of 94.24%, specificity of 94.82% and false positive rate (FPR) of 0.0518 on the test dataset, which specified a considerable agreement with the gold standard Age-related Eye Disease investigation data set. Implementing an automatic DTL-founded AMD evaluation from fundus scans can yield outcomes that are on par with human effectiveness. This research confirms that automated techniques could perform a task in the current administration of AMD that is self-sufficient of knowledgeable human graders and could take into account the expenses of inspection or surveillance, availability to medical care, and the evaluation of effective therapeutics that resolve the advancement of AMD.**

Keywords— Age-related macular degeneration, Deep learning, Deep transfer learning, Automated system, Retinal images

I. INTRODUCTION

Microscopic and color eyesight are strongly tied to the macula, which is situated in the posterior pole of the retina. Appearance of lesions around the macula region will bring about vision decline, dysmorphia, or dark shadows. Age-related macular degeneration (AMD) is a worsening syndrome that affects the macular region, mainly occurring in older people around 45 years old [1]. The AMD's etiology is not fully known, although multiple factors such as genetics, nutritional disorders, and chronic photo destruction effect have been observed to have links to it [2-4]. According to clinical characteristics, AMD can be divided into early, intermediate, and advanced stages [5]. Drusen and pigmentary disorders are the primary symptoms of initial and mid AMD, and individuals with these conditions often have good or almost perfect eyesight. In contrast, mature AMD is linked to substantially worse macular degeneration.

There are two classes of AMD: neovascular AMD (also known as wet AMD) and geographic atrophy (also known as dry AMD) [6]. In advanced dry AMD, the appearance of choroidal retinal atrophies usually leads to impairment of central vision. On the other hand, Wet AMD is characterized by active neovascularization under retinal pigment epithelium, consequently leading to hemorrhages, exudates, and scarring. The ocular sensory neurons will end up suffering irreparable harm if neglected, and macular degeneration will occur quickly [7]. For prompt detection, management, and prediction of AMD, an early discovery is essential. Fundus imaging is a popular non-invasive test, thereby making it an essential resource for detecting eye ailments. Eye doctors utilize fundus radiographs to examine the condition of the retinal area and identify the presence of AMD if they notice any symptoms which include drusen, wounds, blood clots, hyphae, geographic muscles atrophy, angiogenesis, etc. However, it takes a while and demands skill to examine fundus photographs qualitatively.

Hence, this research suggested a DTL technique that can detect binary common ascribable fundus ailments and situations (2 classes) by utilizing 5748 ocular disease fundus

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images obtained from Kaggle repository. Two models are proposed, InceptionV3 with transfer learning (TL) technique and InceptionV3 without TL technique. The research's primary contributions include:

1. A proposed pretrained model InceptionV3 which used transfer learning, and fine-tuning techniques to advance the model performance.
2. The study introduced the early stopping, and dropout techniques to reduce over fitting of the model.
3. Data augmentation approach was introduced to increase the ocular disease dataset images to increase and balance the dataset for improve accuracy and reduce overfitting of the model.

The rest of the article is prearranged as follows: section 2 highlights the materials and methods employed to implement the study. Section 3 discusses the implementation outcomes and interpretation. Section 4 concludes the work and presents future work.

II. Literature Review

Automation approaches for fundus computer vision have been more interesting to researchers due of the rapid breakthroughs and innovations in computer vision techniques [8]. In order to instantly, categorically, and innately convey the fundus architecture to a specialist at the preliminary phase, local thresholding or extent tends to set optimization techniques for macula and cup segmentation [9, 10] or eye lens clustering techniques rely on eye characteristics like spiral segmental centrosymmetric assessments [11] have demonstrated reliable sufficiently. Complementary methodologies by other strategies that concentrate on recognizing disorder symptoms include ways for recognizing hemorrhoids [13] and drusen [12]. In contrast, illness identification techniques were first built on calculating characteristics from the whole image to classify it utilizing a specific classifier. For instance, Mookiah et al. [14] suggested an automatic AMD discovery procedure founded on the discrete wavelet transform (DWT) in which image-level characteristics included first four-order statistical values, momentum, entropy, and Gini indicator characteristics from the DWT coefficients.

These approaches for disease identification and lesion segmentation can deliver an important AMD therapeutic indication. Their reliance on additional functionality created to preserve certain sensory attributes, grayscale intensity, or places inside the fundus architecture in the imagery, meanwhile, had hampered their entire effectiveness and capacity for generalization.

AMD can be diagnosed through the identification of drusen from the retinal fundus imageries [13]. To automate the diagnostic process, it is essential to automatically segment drusen and its measurement [14]. For this reason, numerous scholars have projected AMD recognition utilizing automatic drusen segmentation [15–22].

Using 249,620 fundus photos labeled with 275,543 annotations from diverse sources, Cen et al. 2021 built a DL platform (DLP) able to recognize several prevalent attributable fundus illnesses and disorders (39 classes). Their DLP attained the acceptable rating of retina experts, with a resonance average F1 score of 0.923, sensitivity of 0.978, specificity of 0.996, and AUC of 0.9984 in the basic test dataset.

The authors Kadry, Rajinikanth, Crespo, and Verdu [23] suggested employing a DL strategy utilizing sequentially concatenated deep and handmade characteristics to create an efficient AMD diagnosis approach. Preliminary data treatment, deep image acquisition employing VGG16, manual feature extraction (FE), best FE utilizing Mayfly-Algorithm, serial feature fusion, and binary classification and assessment are all parts of the investigation. In this study, manually created characteristics including the DWT, pyramid histogram of oriented gradients (PHOG), and local image pattern (LBP) are retrieved from experimental photos and integrated with the features extracted of VGG16. Optical coherence tomography (OCT) pictures and fundus macular imaging (FMI) are used to assess the effectiveness of the suggested scheme independently. The optimum experimental outcome using a binary categorization and fivefold cross-validation is selected as the final product. Following that, the effectiveness of VGG16 is contrasted with that of VGG19, ResNet50, and AlexNet. The study's implementation results demonstrate that the proposed VGG16 with fused characteristics obtains AMD identification accuracy for FRI and OCT pictures of 97.08 and 97.50, correspondingly.

Multi-level analysis was proposed to isolate drusen from the retinal images in the investigation conducted by Brandon and Hoover [24]. Although their model showed an accuracy of 87.00%, this method is subject to fluctuations in the blood vessels and optic disc (OD). Sbeh et al. [25] applied mathematical morphology to the segmentation of bright spots. The drusen were separated from these spots using shape, contrast, and area criteria. However, their method's performance metrics are not disclosed. In [26], drusen with both ambiguous and minute boundaries are segmented using the Adaptive Local Thresholding (HALT) operator. Their technique claimed to have a sensitivity of 98.00%. According to [27], drusen was identified using Gaussian derivative filters and k-NN classifier. Although their approach yielded sensitivity and specificity of 77.00% and 88.00% correspondingly, the technique is ineffective in identifying all drusen spots. Soliz et al. [28] obtained an accuracy of 100% when Independent Component Analysis (ICA) was used on only 12 fundus images to detect drusen phenotypes. In [29], drusen identification was carried out using Amplitude Modulation (AM)–Frequency Modulation (FM) based multi-scale features. An AUC of 1 was obtained. Their technique can identify fundus images with modest, fluctuating brightness. In [30], drusen are identified from normal and AMD images using the Mexican Hat Wavelet and Support Vector Data Description (SVDD). Seven images were used to test their method, and accuracy of 100% was reported. An intensity-based drusen segmentation technique was projected by Liang et al. [31]. In their approach, removing the blood vessel and locating the macula are crucial to getting a better outcome. Sensitivity and specificity of 75.00% were recorded by their method. To segment drusen spots, a multi-resolution locally adaptive segmentation approach is suggested. Their technique yielded a sensitivity of 95.00% and a specificity of 96.00% when using a physically selected threshold [32]. In [33], a drusen segmentation method based on statistical modeling is used, and an AUC of 0.99 was reported. The method also applied post-processing to remove false positives. In [34], Gaussian function and Sobel operator are used to

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segment drusen. A kappa agreement of 0.60 was obtained by their method. The thresholding technique used created a lot of false positives. To distinguish between drusen and flecks, an optimal filter bank is created in [35]. Their approach led to an AUC of 0.85. BIF was suggested by Cheng et al. [36] to identify drusen in fundus images. Using Gabor functions, the developed BIF's sensitivity and specificity were reported to be 86.30% and 91.90%, respectively. It obvious that all the cited literature merely does drusen segmentation. They did not encompass their techniques to notice AMD. With the exemption of [26, 35], where Authors segmented the drusen before detecting the AMD class.

Further, a segmentation accuracy of 90.00% was reported when inverse anomaly segmentation was used to locate AMD lesions in [37]. In order to distinguish between the AMD and normal classes, Case-Based Reasoning (CBR) and Dynamic Time Warping (DTW) techniques are used [38]. The approach recorded a sensitivity of 86.00%. In [39], AMD images are analyzed using inverse segmentation with statistical texture information to separate healthy and diseased regions in the images. Both the classification and retrieval stages reported accuracy levels of 92.76% and 96-100%, respectively. To categorize normal and AMD images, spatial histogram and hierarchical image decomposition techniques are used in [40]. These methods recorded 74.00% and 100% accuracy respectively. Wavelet, Weighted Frequent Sub-Graph Mining (WFSM), color, GLCM, and histogram-based features are employed in [41] to categorize normal and AMD classes. Their technique obtained an accuracy of 99.90%. AMD was automatically detected by Zheng et al. [42] using tree-founded hierarchical decomposition and WFSM, with a claimed accuracy of 99.60%. Histogram percentiles, statistical moments, and AM-FM-based decomposition are employed as features in [43] to distinguish between classes of diabetic retinopathy (DR) and AMD. Using RIST and UTHSCSA, respectively, an AUC of 0.84 and 0.77 was obtained. To distinguish between the normal and AMD classes, [44, 45] uses texture- and DWT-based features. Their approach similarly produced accuracy results of 93.70% and 95.07%, respectively.

A. Motivation of the Study

For AMD disease, previous research has employed a variety of ML and DL techniques to precisely detect OCT and fundus images. There hasn't been much prior research on how to use deep transfer learning algorithms to obtain high prediction accuracy. This work focuses on fundus imaging for the identification of AMD disorder utilizing fine-tuning methods based on InceptionV3 DL classification techniques and TL.

III. Materials and Methods

This section outlines the proposed DTL model's framework as well as the performance metrics that will be utilized to measure the efficiency of the suggested system.

A. Proposed InceptionV3 TL Model Framework

This study proposes a novel, powerful and robust pre-trained approach for ADM disease detection. This Pretrained model is employed to determine whether a given ocular disease image of a patient has AGM or not. The proposed model used in this study is InceptionV3 which was fine-tuned by unfreezing some layers for implementation. The model consists of 42 layers and a lower error rate than its predecessors. This work focuses on fundus imaging for the identification of AMD disorder utilizing fine-tuning methods based on InceptionV3 DL classification techniques and TL. The Rectified Linear Unit (ReLU) and max pooling layers follow the convolutional layers. ReLU activation function is used in the proposed design because it has been the de facto standard activation function for image classification problems. The 2-dimensional feature vector created by the fully connected layer is provided as an input to the Softmax classifier, which determines whether or not AMD illness is present. The output layer comprises of 2 neurons as this model tries to classify an image into 2 classes: AMD (+) or Normal (-). The size of the input images that are forwarded into the pretrained model implemented is 224x224x3. Stochastic Gradient Descent (SGD) Momentum is employed as the optimization method.

B. Transfer Learning (TL)

Less samples are needed for the model training process using the transfer learning (TL) approach since the expertise collected by a pre-trained network is transmitted to the network that has to be trained. An already-trained network, typically for a significant image classification task is referred to as a pre-trained technique. In order to successfully use a technique as a baseline technique for image classification, it must first be trained on a substantial general dataset. The learnt characteristics can be employed in a new job, generally including data from a relatively small population, to build a CNN from the beginning [46-48].

C. Performance Assessment Matrix

After performing classification using the proposed pretrained DL approach, it is vital to analyze the effectiveness of the classification technique. This paper employs the confusion matrix to do this. Confusion matrix gives useful details about the actual and projected image labels that the classification technique proposes. Using this valuable information, several elements of the classification effectiveness can be measured.

Different values are diagonally placed on the confusion matrix to show true positives (TP), True Negative (TN), False Negatives (FN), and False Positives (FP). TP is the proportion of samples that are labeled as true when they are actually true. TN is the proportion of samples that are labeled as false when they are actually false. FP is the proportion of samples that are labeled as true when they are actually false. FN is the proportion of samples that are classified as negatives when they are actually true.

Accuracy, Specificity, False Positive Rate (FPR), and AUC are the most often utilized performance evaluation indicators. The associated formulas for these metrics are displayed in (1) through (4) [49, 50].

$$Accuracy = (TP + TN) \,/\, (TP + TN + FP + FN) \quad (1)$$

$$Specificity = (TN) / (TN + FP) \quad (2)$$

$$FPR = (FP) \,/\, (FP + TN) \quad (3)$$

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$$Precision = (TP) / (TP + FP) \quad (4)$$

IV. Implementation Outcomes and Interpretation

In this section, the dataset used for the implementation of this study is presented.

A. Dataset

The dataset used for the detection and classification of AMD disease was obtained from Kaggle repository. The data set is a benchmark data called Ocular Disease Intelligent Recognition (OCIR). It is an organized ophthalmic database with information on 5000 individuals, including age, color images of the fundus in the left and right eyes, and diagnostic terms used by clinicians.

The dataset is imbalance one with 266 images for the AMD classes and 2873 images for the Normal class. Image data augmentation technique was employed to increase the AMD image so as to balance the dataset for the experiment performed in this study. In summary, a total of 5748 images which comprises of two classes was obtained after the data augmentation procedure. The first class is AMD with 2875 images while the second class is Normal with 2873 images. The dataset employed in this study is available to the public courtesy of Kaggle repository.

Data augmentation is done to enhance the data size. Several studies have investigated the role of data augmentation in deep learning [51, 52]. The techniques employed for the image data augmentation procedure and value set is shown in table I.

TABLE I. Image Augmentation Techniques

Techniques	Values
Horizontal_flip	True
Rotation_range	40
Width_shift	0.2
Height_shift_range	0.2
Zoom_range	0.2

B. Implementation Configuration and Time Consumption

The configuration employed in this investigation involves using a 64 bits windows PC. Other configuration includes an intel core i7 vPro processor and 16GB RAM. The programming language used for the study implementation is Python with the use of some libraries such as Tensorflow, Keras, Numpy, Matplotlib and so on. The elapsed time for image (4152) training using the InceptionV3 pretrained DL model with and without TL is shown in table II.

TABLE II. Implemented Model Time Consumption

Model	Time
InceptionV3 with TL	2h 15m 03s
inceptionV3	5h 12m 35s

C. Results

After splitting the image datasets into training, validation and test sets, the pretrained DL technique is trained, validated and tested using the split datasets. The training set is used to train the network, the validation set is employed to validate the network, and the test set is used for testing the already trained and validated models and parameter optimization procedures.

After balancing the dataset, it was split into three set such as training, validation and testing sets of 4152, 733 and 863 respectively that is ratio 70:15:15. This implies that 70% of the images are used for training, 15% for validating the model during training procedure and lastly 15% of the images was used for the testing procedure.

At the pre-processing stage, fundus images were rescaled to a size of 224 x 224. Figures 1 and 2 show accuracy and entropy graphs for the task of AMD (+) image vs. Normal (-) image. After 11 epochs, the pretrained DL approach with TL process obtains a 97.52% classification accuracy overall. This outcome demonstrates the architecture's capacity to identify AMD illness.

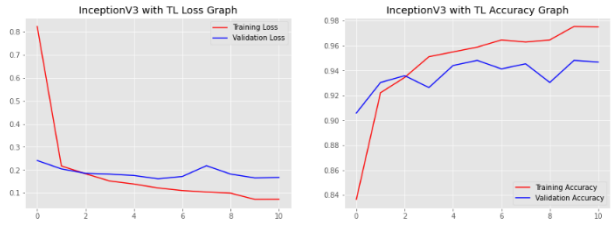


Fig. 1. Accuracy and entropy graphs for the proposed model with TL

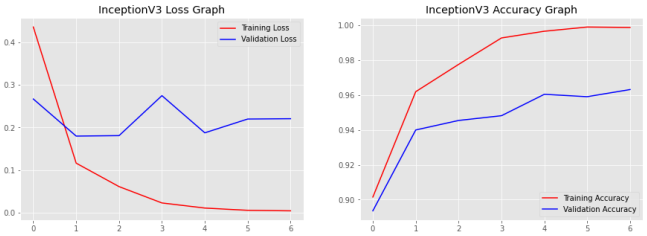


Fig. 2. Accuracy and entropy graphs for the proposed model without TL

The performance of the system was visualized using confusion matrix as shown in Figures 3 and 4. The predicted values are represented by the horizontal axis (X-axis), which represents the system output, and the actual labels are represented by the vertical axis (Y-axis), which represents the ground truth values. The proposed models' performance is evaluated using metrics such as Accuracy, Sensitivity, Specificity, and Precision. These metrics are calculated using the confusion matrix results and are shown in Table III. The InceptionV3 model with TL outperformed that of the model without TL with a Precision, Specificity and FPR value of 94.24%, 94.82% and 0.0518 respectively to classify AMD (+) and Normal (-). The Receiver Operation Characteristic Curve (ROC) curve is another technique for evaluating the effectiveness of the proposed models. The value of AUC is observed to be 0.9933 for the model with TL and 0.9955 for the model without TL. Fig. 5 and 6 shows ROC curves for the proposed model with and without transfer learning technique.

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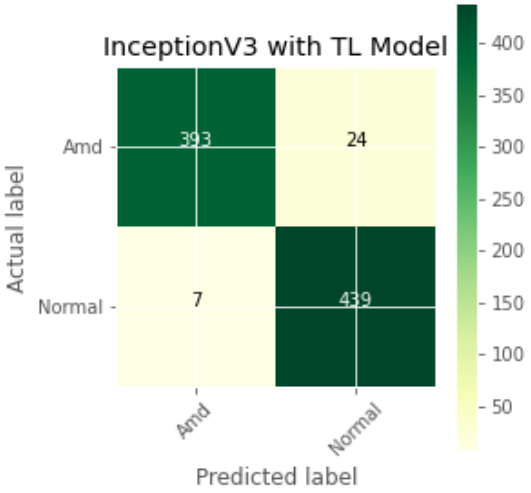


Fig. 3. Confusion for the proposed model with TL

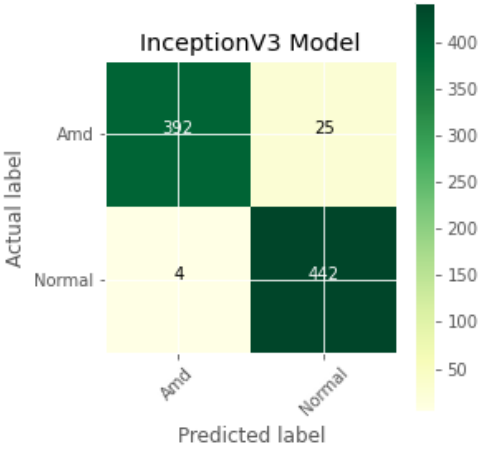


Fig. 4. Confusion matrix for the proposed model without TL

TABLE III. PERFORMANCE METRIC FOR THE MODELS

Model	Accuracy	Specificity	Precision	FPR
InceptionV3 with TL	96.41%	**94.82%**	**94.24%**	**0.0518**
InceptionV3 without TL	**96.64%**	94.65%	94.00%	0.0535

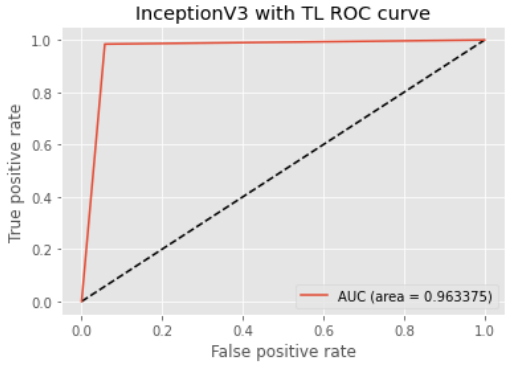


Fig. 5. ROC curve for the proposed model with TL

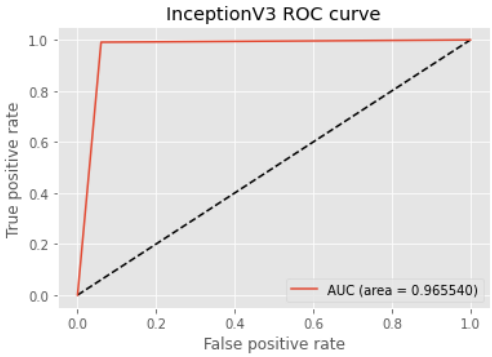


Fig. 6. ROC for the proposed model without TL

D. Proposed Model Comparison with Existing Studies

There are quite a few studies that focus on AMD ocular disease detection using pretrained DL. This is due to the need for more data and images. For instance, as shown in table IV, Burlina et al., 2016 used GA and support vector machine to classify AMD fundus images as either early stage or immediate stage. Their work achieved an accuracy of 95.00% overall. Saha et al., 2019 suggested a three deep convolutional neural network (Inception, ResNet and IncResNet) models for AMD disease detection. They obtained a classification accuracy of 87%. Khan, Sajeeb and Fattah, 2020 adopted ResNet50 for detection of multi-class dataset and obtained an accuracy of 82.57%. However, the performance of proposed model in this study is 96.18% on the test dataset which surpasses the above results.

TABLE IV. COMPARATIVE ANALYSIS WITH EXISTING SYSTEMS

Authors	Disease	Method	Accuracy
Burlina et al. [53]	AMD	GA and SVM	95.00%
Saha et al. [54]	AMD	Inceprion, ResNet and IncResNet	87.00%
Khan, Sajeeb and Fattah [55]	Ocular disease	ResNet50	82.57%
Proposed Model	**AMD**	**InceptionV3**	**96.18%**

CONCLUSION

A fully automatic study using deep transfer learning technique for Age-related macular degeneration (AMD) disease detection is presented in this paper. This study develops a new, potent, and reliable DTL approach for detecting AMD ocular illness using publicly accessible datasets. Detection of AMD (i.e., fundus images classification into AMD (+) and Normal (-) images) is achieved with high accuracy values of 98.92% on the training dataset, 94.82% on the validation dataset, and 96.18% on the test dataset. It can be deduced that the introduction of transfer learning, fine-tuning, early stopping, data augmentation, and dropout techniques assisted in producing a better system performance and reduced overfitting of the model (figure 1) when compared with the InceptionV3 without the TL and other methods. The model suggested in this research can be easily applied in practice to assist ophthalmologists in diagnosing AMD ocular illness because of its simplicity and flexibility.

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REFERENCES

[1] J. L. Haines, N. Schnetz-Boutaud, S. Schmidt, W. K. Scott, A. Agarwal, E. A. Postel, ... & M. A. Pericak-Vance (2006). Functional candidate genes in age-related macular degeneration: significant association with VEGF, VLDLR, and LRP6. Investigative ophthalmology & visual science, 47(1), 329-335.

[2] J. Ambati & B. J. Fowler (2012). Mechanisms of age-related macular degeneration. Neuron, 75(1), 26-39.

[3] H. M. Zając-Pytrus, A. Pilecka, A. Turno-Kręcicka, J. Adamiec-Mroczek & M. Misiuk-Hojło (2015). The dry form of age-related macular degeneration (AMD): the current concepts of pathogenesis and prospects for treatment. Adv Clin Exp Med, 24(6), 1099-1104.

[4] V. K. Rapalli, S. Gorantla, T. Waghule, A. Mahmood, P. P. Singh, S. K. Dubey, ... & G. Singhvi (2019). Nanotherapies for the treatment of age-related macular degeneration (amd) disease: recent advancements and challenges. Recent patents on drug delivery & formulation, 13(4), 283-290.

[5] F. L. Ferris III, C. P. Wilkinson, A. Bird, U. Chakravarthy, E. Chew, K. Csaky,... & Beckman Initiative for Macular Research Classification Committee. (2013). Clinical classification of age-related macular degeneration. Ophthalmology, 120(4), 844-851.

[6] L. S. Lim, P. Mitchell, J. M. Seddon, F. G. Holz & T. Y. Wong (2012). Age-related macular degeneration. The Lancet, 379(9827), 1728-1738.

[7] I. Maruko, T. Iida, M. Saito, D. Nagayama & K. Saito (2007). Clinical characteristics of exudative age-related macular degeneration in Japanese patients. American journal of ophthalmology, 144(1), 15-22.

[8] T. Li, W. Bo, C. Hu, H. Kang, H. Liu, K. Wang & H. Fu (2021). Applications of deep learning in fundus images: A review. Medical Image Analysis, 69, 101971.

[9] J. Anitha (2014, February). A region growing method of optic disc segmentation in retinal images. In 2014 international conference on electronics and communication systems (ICECS) (pp. 1-5). IEEE.

[10] N. Thakur & M. Juneja (2019). Optic disc and optic cup segmentation from retinal images using hybrid approach. Expert Systems with Applications, 127, 308-322.

[11] X. Guo, H. Wang, X. Lu, X. Hu, S. Che & Y. Lu (2020). Robust fovea localization based on symmetry measure. IEEE Journal of Biomedical and Health Informatics, 24(8), 2315-2326.

[12] M. U. Akram, S. Mujtaba & A. Tariq (2013, November). Automated drusen segmentation in fundus images for diagnosing age related macular degeneration. In 2013 International Conference on Electronics, Computer and Computation (ICECCO) (pp. 17-20). IEEE.

[13] M. García, M. I. López, D. Álvarez & R. Hornero (2010). Assessment of four neural network based classifiers to automatically detect red lesions in retinal images. Medical engineering & physics, 32(10), 1085-1093.

[14] M. R. K. Mookiah, U. R. Acharya, J. E. Koh, C. K. Chua, J. H. Tan, V. Chandran, ... & L. Tong (2014). Decision support system for age-related macular degeneration using discrete wavelet transform. Medical & biological engineering & computing, 52(9), 781-796.

[15] E. S. Barriga, V. Murray, C. Agurto, M. S. Pattichis, S. Russell, M. D. Abramoff, ... & P. Soliz (2009, August). Multi-scale AM-FM for lesion phenotyping on age-related macular degeneration. In 2009 22nd IEEE international symposium on computer-based medical systems (pp. 1-5). IEEE.

[16] D. E. Freund, N. Bressler & P. Burlina (2009, June). Automated detection of drusen in the macula. In 2009 IEEE International Symposium on Biomedical Imaging: From Nano to Macro (pp. 61-64). IEEE.

[17] Z. Liang, D. W. Wong, J. Liu, K. L. Chan & T. Y. Wong (2010, August). Towards automatic detection of age-related macular degeneration in retinal fundus images. In 2010 Annual international conference of the IEEE engineering in medicine and biology (pp. 4100-4103). IEEE.

[18] P. Burlina, D. E. Freund, B. Dupas & N. Bressler (2011, December). Automatic screening of age-related macular degeneration and retinal abnormalities. In 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 3962-3966). IEEE.

[19] H. Santos-Villalobos, T. P. Karnowski, D. Aykac, L. Giancardo, Y. Li, T. Nichols,... & E. Chaum (2011, January). Statistical characterization and segmentation of drusen in fundus images. In 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 6236-6241). IEEE.

[20] A. D. Mora, P. M. Vieira, A. Manivannan & J. M. Fonseca (2011). Automated drusen detection in retinal images using analytical modelling algorithms. Biomedical engineering online, 10(1), 1-16.

[21] Q. Quellec, S. R. Russell & M. D. Abràmoff (2010). Optimal filter framework for automated, instantaneous detection of lesions in retinal images. IEEE Transactions on medical imaging, 30(2), 523-533.

[22] J. Cheng, D. W. K. Wong, X. Cheng, J. Liu, N. M. Tan, M. Bhargava, ... & T. Y. Wong (2012, September). Early age-related macular degeneration detection by focal biologically inspired feature. In 2012 19th IEEE International Conference on Image Processing (pp. 2805-2808). IEEE.

[23] I. P. Cen, J. Ji, J. W. Lin, S. T. Ju, H. J. Lin, T. P. Li... & M. Zhang (2021). Automatic detection of 39 fundus diseases and conditions in retinal photographs using deep neural networks. Nature communications, 12(1), 1-13.

[24] L. Brandon & A. Hoover (2003, November). Drusen detection in a retinal image using multi-level analysis. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 618-625). Springer, Berlin, Heidelberg.

[25] Z. B. Sbeh, L. D. Cohen, G. Mimoun & G. Coscas (2001). A new approach of geodesic reconstruction for drusen segmentation in eye fundus images. IEEE Transactions on medical imaging, 20(12), 1321-1333.

[26] K. Rapantzikos, M. Zervakis & K. Balas (2003). Detection and segmentation of drusen deposits on human retina: Potential in the diagnosis of age-related macular degeneration. Medical image analysis, 7(1), 95-108.

[27] M. Niemeijer, B. Van Ginneken, S. R. Russell, M. S. Suttorp-Schulten & M. D. Abramoff (2007). Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis. Investigative ophthalmology & visual science, 48(5), 2260-2267.

[28] P. Soliz, S. R. Russell, M. D. Abramoff, S. Murillo, M. Pattichis & H. Davis (2008, March). Independent component analysis for vision-inspired classification of retinal images with age-related macular degeneration. In 2008 IEEE Southwest Symposium on Image Analysis and Interpretation (pp. 65-68). IEEE.

[29] E. S. Barriga, V. Murray, C. Agurto, M. S. Pattichis, S. Russell, M. D. Abramoff, ... & P. Soliz (2009, August). Multi-scale AM-FM for lesion phenotyping on age-related macular degeneration. In 2009 22nd IEEE international symposium on computer-based medical systems (pp. 1-5). IEEE.

[30] D. E. Freund, N. Bressler & P. Burlina (2009, June). Automated detection of drusen in the macula. In 2009 IEEE International Symposium on Biomedical Imaging: From Nano to Macro (pp. 61-64). IEEE.

[31] Z. Liang, D. W. Wong, J. Liu, K. I. Chan & T. Y. Wong (2010, August). Towards automatic detection of age-related macular degeneration in retinal fundus images. In 2010 Annual international conference of the IEEE engineering in medicine and biology (pp. 4100-4103). IEEE.

[32] P. Burlina, D. E. Freund, B. Dupas & N. Bressler (2011, December). Automatic screening of age-related macular degeneration and retinal abnormalities. In 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 3962-3966). IEEE.

[33] H. Santos-Villalobos, T. P. Karnowski, D. Aykac, L. Giancardo, T. Li, T. Nichols, ... & E. Chaum (2011, January). Statistical characterization and segmentation of drusen in fundus images. In 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 6236-6241). IEEE.

[34] A. D. Mora, P. M. Vieira, A. Manivannan & J. M. Fonseca (2011). Automated drusen detection in retinal images using analytical modelling algorithms. Biomedical engineering online, 10(1), 1-16.

[35] G. Quellec, S. R. Russell & M. D. Abràmoff (2010). Optimal filter framework for automated, instantaneous detection of lesions in retinal images. IEEE Transactions on medical imaging, 30(2), 523-533.

[36] J. Cheng, D. W. K. Wong, X. Cheng, J. Liu, N. M. Tan, M. Bhargava, ... & T. Y. Wong (2012, September). Early age-related macular degeneration detection by focal biologically inspired feature. In 2012 19th IEEE International Conference on Image Processing (pp. 2805-2808). IEEE.

[37] C. Köse, U. Şevik & O. Gençalioğlu (2008). Automatic segmentation of age-related macular degeneration in retinal fundus images. Computers in Biology and Medicine, 38(5), 611-619

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[38] M. H. A. Hijazi, F. Coenen & Y. Zheng (2010, July). Retinal image classification using a histogram-based approach. In The 2010 international joint conference on neural networks (IJCNN) (pp. 1-7). IEEE.

[39] C. Köse, U. Şevik, O. Gençalioğlu, C. İkibaş & T. Kayıkıçıoğlu (2010). A statistical segmentation method for measuring age-related macular degeneration in retinal fundus images. Journal of medical systems, 34(1), 1-13.

[40] M. H. A. Hijazi, F. Coenen & Y. Zheng (2012). Data mining techniques for the screening of age-related macular degeneration. Knowledge-Based Systems, 29, 83-92

[41] M. H. A. Hijazi, F. Coenen & Y. Zheng (2014). Data mining for AMD screening: A classification based approach. International Journal of Simulation: Systems, Science and Technology, 15(2), 57-69.

[42] Y. Zheng, M. H. A. Hijazi & F. Coenen (2012). Automated "disease/no disease" grading of age-related macular degeneration by an image mining approach. Investigative ophthalmology & visual science, 53(13), 8310-8318.

[43] C. Agurto, E. S. Barriga, V. Murray, S. Nemeth, R. Crammer, W. Bauman, ... & P. Soliz (2011). Automatic detection of diabetic retinopathy and age-related macular degeneration in digital fundus images. Investigative ophthalmology & visual science, 52(8), 5862-5871.

[44] M. R. K. Mookiah, U. R. Acharya, J. E. Koh, V. Chandran, C. K. Chua, J. H. Tan, ... & A. Laude (2014). Automated diagnosis of age-related macular degeneration using greyscale features from digital fundus images. Computers in biology and medicine, 53, 55-64.

[45] M. R. K. Mookiah, U. R. Acharya, J. E. Koh, C. K. Chua, J. H. Tan, V. Chandran, ... & L. Tong (2014). Decision support system for age-related macular degeneration using discrete wavelet transform. Medical & biological engineering & computing, 52(9), 781-796.

[46] R. O. Ogundokun, R. Maskeliūnas & R. Damaševičius (2022). Human Posture Detection Using Image Augmentation and Hyperparameter-Optimized Transfer Learning Algorithms. Applied Sciences, 12(19), 10156.

[47] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Transactions on knowledge and data engineering, vol. 22, no. 10, pp. 1345–1359, 2009.

[48] R. O. Ogundokun, R. Maskeliūnas, S. Misra & R. Damasevicius (2022). A Novel Deep Transfer Learning Approach Based on Depth-Wise Separable CNN for Human Posture Detection. Information, 13(11), 520.

[49] M. F. Ak (2020, April). A comparative analysis of breast cancer detection and diagnosis using data visualization and machine learning applications. In Healthcare (Vol. 8, No. 2, p. 111). MDPI.

[50] R. O. Ogundokun, S. Misra, M. Douglas, R. Damaševičius & R. Maskeliūnas (2022). Medical Internet-of-Things Based Breast Cancer Diagnosis Using Hyperparameter-Optimized Neural Networks. Future Internet, 14(5), 153.

[51] F. Garcea, A. Serra, F. Lamberti & L. Morra (2022). Data augmentation for medical imaging: A systematic literature review. Computers in Biology and Medicine, 106391.

[52] R. O. Ogundokun, R. Maskeliūnas, S. Misra & R. Damasevicius (2022). Hybrid InceptionV3-SVM-Based Approach for Human Posture Detection in Health Monitoring Systems. Algorithms, 15(11), 410.

[53] P. Burlina, D. E. Freund, N. Joshi, Y. Wolfson & N. M. Bressler (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.

[54] S. Saha, M. Nassisi, M. Wang, S. Lindenberg, S. Sadda & Z. J. Hu (2019). Automated detection and classification of early AMD biomarkers using deep learning. Scientific reports, 9(1), 1-9.

[55] I. A. Khan, A. Sajeeb & S. A. Fattah (2020, December). An Automatic Ocular Disease Detection Scheme from Enhanced Fundus Images Based on Ensembling Deep CNN Networks. In 2020 11th International Conference on Electrical and Computer Engineering (ICECE) (pp. 491-494). IEEE.

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