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Convolutional Neural Network in Classifying Three Stages of Age-Related Macula Degeneration

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Abstract

Age-related macular degeneration (AMD) is an eye disorder that may blur the clear, central vision you use for things like reading and driving. It is one of several disorders that influence the retina. The word "age-related" applies to the reality that it is more prevalent among older persons. The term "macular" refers to a region of your eye named the macula. The term "degeneration" refers to the kind of eye injury that occurs. A disease that affects older people is age-related macular degeneration (AMD). In AMD, the macula produces a gradual accumulation of yellow deposits named drusen. Diagnosis with fluorescein angiography allows identifying and locating abnormal vascular processes. Most ophthalmologists now use consistent optical tomography to diagnose and evaluate follow-up in response to treatment with Avastin or Lucentis, which are injected into the eye's vitreous at different intervals. Early detection and care, as in other eye disorders, were found to reduce the risk of blindness and vision loss. Automated retinal examination devices save patients, time, resources, and vision as opposed to manual diagnosis procedures. The purpose of this study is to suggest an automated method using the Machine Learning (CNN) method to identify patients with macular degeneration AMD using images of the ODIR dataset. A convolutional neural network (CNN) was applied to extract the deep features from the fundus images present in the data set for the classification of the images to AMD different stages (Early, Intermediate, and Late), beside the Normal status of the eye. Specificity, Sensitivity, Accuracy, F-score, and Precision metrics were used to estimate classification efficiency the highest accuracy we will get is accuracy: 97%, sensitivity: 98.52%, specificity: 89.29%, area under the curve: 93.9%.

Conclusion:

CNN provided this study for AMD Diagnostics and Normal On images in the ODIR dataset
•CNN Network was trained on this image set to minimize the overfitting.
• The highest accuracy we will get is accuracy: 97%, sensitivity: 98.52%, specificity: 89.29%, area under the curve: 93.9% was obtained for the group of ODIR images on which the network was trained. Learning curves for accuracy training and test when the method was implemented on ODIR images.

Key words:
Age-related Macular Degeneration (AMD), Automatic Detection, Retinal Images, Convolutional Neural Network.

Citation:

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الشبكة العصبية التلافيفية في تصنيف ثلاث مراحل من تنكس البقعة الصفراء المرتبط بالعمر

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الخلاصة:

الضمور البقعي المرتبط بالعمر (AMD) هو اضطراب في العين قد يطمس الرؤية المركزية الواضحة التي تستخدمها لأشياء مثل القراءة والقيادة. وهو أحد الاضطرابات العديدة التي تؤثر على شبكية العين. تنطبق كلمة "متعلق بالعمر" على حقيقة أنها أكثر انتشارًا بين كبار السن. يشير مصطلح "البقعة الصفراء" إلى منطقة من عينك تسمى البقعة. يشير مصطلح "التنكس" إلى نوع إصابة العين التي تحدث. أحد الأمراض التي تصيب كبار السن هو الضمور البقعي المرتبط بالعمر .(AMD) في AMD ، تنتج البقعة تراكمًا تدريجيًا من الرواسب الصفراء المسماة .drusen يسمح التشخيص باستخدام تصوير الأوعية بالفلورسين بتحديد وتحديد عمليات الأوعية الدموية غير الطبيعية. يستخدم معظم أطباء العيون الآن التصوير المقطعي البصري المتسق لتشخيص وتقييم المتابعة استجابة للعلاج بأفاستين أو لوسنتيس، والتي يتم حقنها في الجسم الزجاجي للعين على فترات مختلفة. وُجد أن الاكتشاف المبكر والرعاية، كما هو الحال في اضطرابات العين الأخرى، يقللان من خطر الإصابة بالعمى وفقدان البصر. توفر أجهزة فحص الشبكية الآلية وقت المرضى ومواردهم ورؤيتهم بدلاً من إجراءات التشخيص اليدوية. الغرض من هذه الدراسة هو اقتراح طريقة آلية باستخدام طريقة التعلم الآلي (CNN) لتحديد المرضى الذين يعانون من الضمور البقعي AMD باستخدام صور مجموعة بيانات .ODIR تم تطبيق شبكة عصبية تلافيفية (CNN) لاستخراج السمات العميقة من صور قاع العين الموجودة في مجموعة البيانات لتصنيف الصور إلى مراحل مختلفة من AMDمبكر، متوسط، متأخر)، بجانب الحالة الطبيعية للعين. تم استخدام مقاييس الخصوصية والحساسية والدقة ودرجة F والدقة لتقدير كفاءة التصنيف. وقد تم تحقيق أعلى دقة نحصل عليها هي الدقة: 97٪ ، الحساسية: 98.52٪ ، الخصوصية: 89.29٪ ، المنطقة الواقعة تحت المنحنى: 93.9

الاستنتاجات:

قدمت CNN هذه الدراسة لتشخيصات AMD والصور العادية في مجموعة بياناتODIR

•تم تدريب شبكة سي إن إن على مجموعة الصور هذه لتقليل التجهيز الزائد.

أعلى دقة نحصل عليها هي الدقة: 97٪ ، الحساسية: 98.52٪ ، الخصوصية: 89.29٪ ، المنطقة الواقعة تحت المنحنى: 93.9٪. تم الحصول عليها لمجموعة صور ODIR التي تم تدريب الشبكة عليها. منحنيات التعلم للتدريب على الدقة والاختبار عند تنفذ الطريقة على صور ODIR.

الكلمات المفتاحية:

التنكس البقعي المرتبط بالعمر (AMD) ، الكشف التلقائي ، صور الشبكية ، الشبكة العصبية التلافيفية.

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INTRODUCTION

In the United Kingdom, age-related macular degeneration (AMD) is the primary cause of visual impairment, accounting for more individuals classified as "sight disabled" or "severely sight impaired" than any other ocular disorders combined [1], [2]. Between 2005 and 2050, AMD's global incidence is estimated to rise by threefold due to a projected threefold increase in the people number aged 60 and up [3]. Early AMD, also described as age-related maculopathy (ARM), is characterized by soft drusen and focal pigmentary shifts only [4]. Wet AMD manifests as choroidal neovascularization (wet AMD) or geographic atrophy (dry AMD), while dry AMD manifests as geographic atrophy (dry AMD). Only the wet (neovascular) type of AMD is currently treated, with anti-angiogenic pharmacotherapy being the most common option [5]. While there is currently no cure for dry AMD or early AMD, there is some indication that nutritional supplements might delay the disease's progression [6]. The ability to correctly diagnose AMD initiation and monitor disease development is critical for identifying candidates for care and assessing treatment results

There are three levels of AMD [7], Figure 1, the 2nd, 3ed, and 4th images showing AMD is defined by the presence of many tiny (63 m in diameter) or a few medium (63 to 124 m) drusen (Figure 1, 1st image demonstrates an illustration of a typical retinal image). Intermediate AMD is described by the existence of at minimum one wide (>124 m) and multiple moderate drusen. Non-neovascular AMD and neovascular AMD are the two forms of advanced AMD. Once drusen are available in the macula's nucleus, advanced non-neovascular (dry) AMD develops. Neovascular AMD is less frequent than non-neovascular AMD, but it is more serious since it involves bleeding and scarring of the eye. The neovascular type of AMD is the most common cause of vision loss in AMD patients.

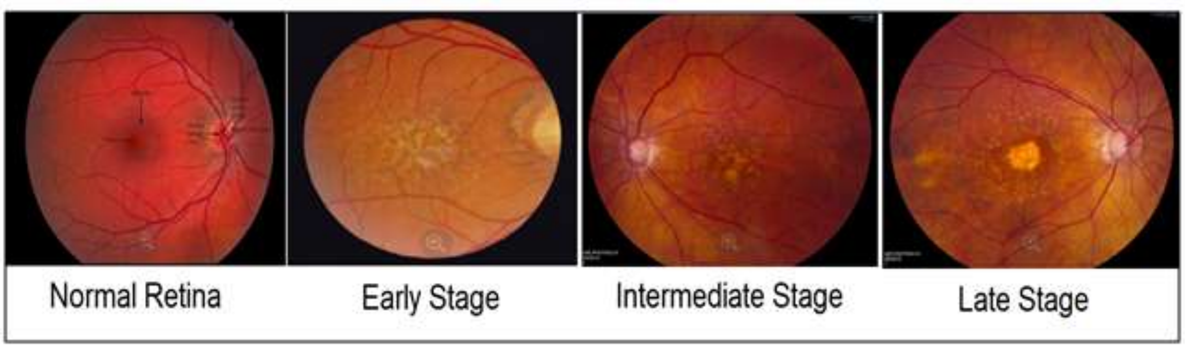

Figure 1. Images for Normal and AMD stages.

Traditional image feature extraction approaches depend on the researchers' previous experience, which has significant limitations. Deep learning algorithms have advanced exponentially in computer vision in recent years, and their results have vastly enhanced as opposed to conventional approaches. The convolutional neural network model is interesting since its strong representation efficiency, which compensates for the limitations of conventional feature extraction techniques. Convolutional neural networks (CNNs) can automatically acquire high-level image feature knowledge and have demonstrated promising results in image recognition, object detection, and other fields.

Wisaeng et al. [8] are specialist for specialist ophthalmologists to who identified diseases by automatically identifying the optic disc in optical retinal photos. Many approaches are capable of achieving successful results on retinal features that are easily noticeable. Regrettably, it is a common occurrence in Thailand for colour retinal photographs to be of low quality. The current algorithm is incapable of detecting images of low quality. As a result, this research is part of a broader initiative to provide a new approach for detecting the optic disc in low-resolution retinal photographs. The invention of a novel approach for detecting the optic disc in low-quality retinal images is identified. After the main pre-processing measures of colour standardization, contrast improvement, and noise reduction, the optical retinal images are identified using the morphological procedure and Otsu's algorithm. This distinguishes the suggested system from other methods, and the algorithm will produce decent results even with low-quality retinal photographs. The suggested approach was tested on a local dataset and a dataset from the STARE project that was made publicly accessible. The optic disc has been accurately observed in 91.35 percent of STARE dataset cases and 97.61 percent of local dataset cases. This device is designed to aid specialist ophthalmologists in the screening phase, allowing them to diagnose optic disc disease more quickly and effectively.

Stereoscopic fundus and visual acuity photos have traditionally been used to diagnose and grade AMD [4]. Nevertheless, Tan et al. [9] used a deep convolutional neural network to explore age-related macular degeneration identification in recent years. As is well established, the incidence of AMD is increasing as the world's population ages. As a result, early diagnosis is critical to preventing visual loss in the old. Organizing a thorough eye test to identify AMD in the aged, on the other hand, is time-consuming and difficult. To meet this need, we created a fourteen-layer deep Convolutional Neural Network (CNN) model that can detect AMD at an early stage automatically and accurately. The model's performance was assessed using a blindfold and ten-fold cross-validation techniques, which yielded a precision of 91.17 percent and 95.45 percent, respectively. This latest model may be used in a fast eye screening for the elderly to diagnose AMD early. It is both cost-effective and compact, allowing it to be used everywhere.

Both patients and ophthalmologists benefit from automatic monitoring for age-related macular degeneration (AMD). Using deep learning in a multiple instance learning environment, Liu et al. [10] suggested a Deep AMD for detecting early age-related macular degeneration. The role of detecting AMD from fundus images at an early stage has been the subject of this article. The challenge with this mission is that the early signals, such as drusen, are too small and slight to be identified by most modern approaches. To solve this issue, we use deep learning in multiple instances learning environments to identify AMD at an early stage using subtle features. Deep neural networks may develop a discriminative representation of AMD's subtle signals. In two instances, the multiple instance learning systems is beneficial. First, since it operates on image patches rather than the whole image, it may select the position where AMD occurs. Second, it uses a high-resolution camera rather than downsampling the image, which may make the tiny drusen invisible. The tests are conducted on a dataset that includes 3596 AMD and 1129 regular fundus photographs. The final average AUC is 0.79, equivalent to 0.74 for a neural network with multiple instance learning but no multiple instances learning.

Islam, et al., [11], suggested a novel approach for detecting eight different forms of ocular diseases using a convolutional neural network (CNN) and evaluated its results. Some diseases' infected areas may also be identified. The data is submitted to the network for thorough classification after certain normal pre-processing. On a brand-new dataset, the model was learned and evaluated using a high-end graphics processing unit (GPU). Our built model has an F-score of approximately 85 percent, a Kappa score of 31%, and an AUC value of 80.5 percent. There is no equivalent task to compare with and this is the first "real-life" (i.e. realistic for a clinical case with patients involving camera variation) estimation of various diseases in an eye depending on this dataset. Thus, we checked our model on a different dataset and it carried out admirably, with a persuasive F-score, Kappa score, and AUC magnitude.

This paper aims to suggest a system that automatically recognizes AMD based on the retina's fundus images. The system should be able to read the retina's fundus image from a computer, and based on its features, and it will give an acceptable level of accurate diagnosis of the eye's condition. Furthermore, whether it is healthy for having AMD when the eye has AMD, the system should include how severe the condition is. Meaning the system will classify the AMD into its three stages (Early, Intermediate, and Late), besides the Normal retina status. The approach to building this system will be based on Machine Learning (ML) techniques. Due to the efficient performance of ML algorithms in the classification of images. This work will require collecting a large dataset of healthy and AMD affected eyes retina to train the Machine Learning model.

WORK METHODOLOGY

The suggested system comprises of two stages; the first stage is the pre-processing, which includes converting the images into greyscale, changing the image size into 223 * 223 pixels, applying (Average Filtering) to remove the noise, and then scale the images by dividing by 255. Then it is used contrast limited adaptive histogram equalization (CLAHE) method to advance contrast.

The second stage is done using CNN, which is applied to several images, to extract the feature to identify the images, whether they are Normal, Early stage, Intermediate stage, or Late stage. The suggested model has been demonstrated in figure 2**.**

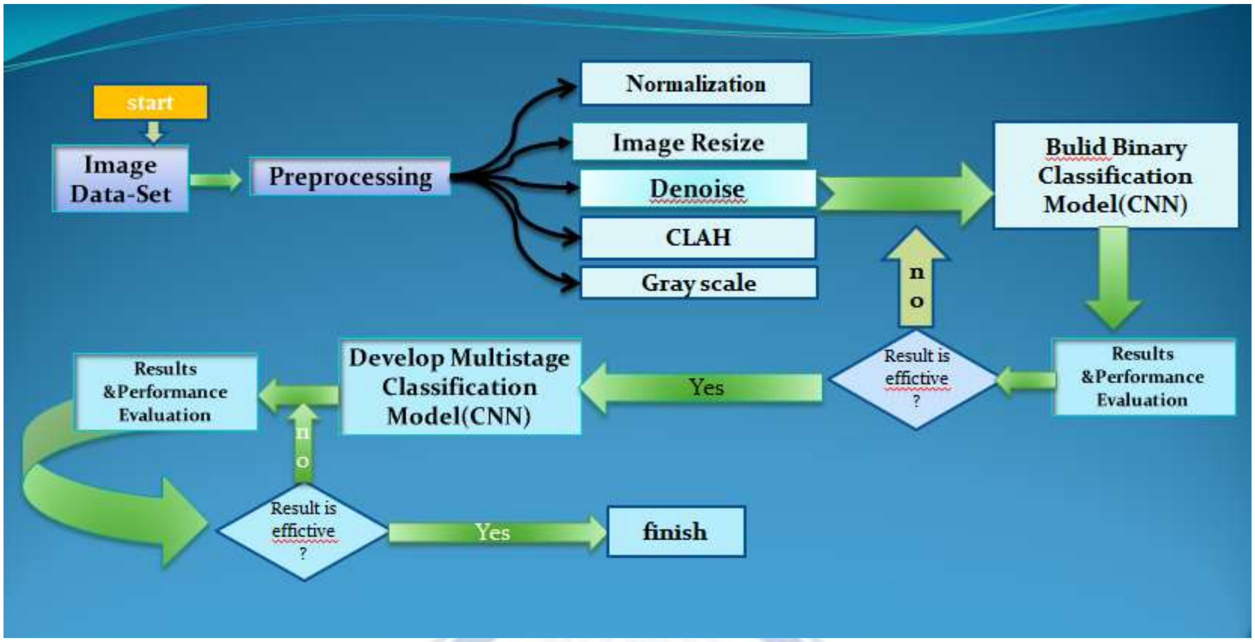

Figure (2): General diagram for our approach methodology.

Ocular Disease Intelligent Recognition (ODIR)

Ocular Disease Intelligent Recognition (ODIR) is a hierarchical ophthalmic database of era, color fundus images of the left and right feet, and physicians' diagnostic keywords. This dataset reflects a "real-life" collection of patient data gathered by Shanggong Medical Technology Co., Ltd. from various hospitals and medical centers in China. Fundus photographs are captured in these organizations utilizing a number of cameras on the market, including Cannon, Zeiss, and Kowa, resulting in a broad range of picture resolutions. It is a Microsoft Excel program that contains: identifier, disease type, Right-Diagnostic Keywords, Left-Diagnostic Keywords, Right-Fundus, Left-Fundus, Patient Sex and patient age. Trained human readers labelled annotations with quality control management. They classify patient into eight labels, including: Pathological Myopia (M), Hypertension (H), Age-related Macular Degeneration (A), Cataract (C), Glaucoma (G), Diabetes (D), Normal (N) and Other diseases/abnormalities (zO(

This work is focused on one type of eye disease, Age-related Macular Degeneration (AMD). This database contains 939 images (443 normal images, 116 early stage, 254 Intermediate stage, and 126 Late stage). The dataset is divided into 70% training dataset, and 30% test dataset. The table below demonstrates the statistics for dividing the dataset, and they used this dataset in many types of research [11]–[17].

Pre-processing

Pre-process the images from noise and crop their size. It is an important phase so that all images are clear and ready to be processed to extract features from them. There are different stages of image pre-processing to prepare them for the classification task.

Image Greyscale

The original images in the dataset are coloured images. Meaning there are three channels to represent the image (RGB). This will make the processing of the images longer. But the features required for the purpous of this work are present in each channel. So all the images is converted into greyscale to reduce the process time, and preserve the required features.

Image Resize

Since the size of certain photos taken by a camera and feeding to our AI algorithm varies, we can set a standard size for all images fed to our AI algorithms. The photographs have been reduced in scale to 223 * 223 pixels.

Remove noise (Denoise)

Images are noised during the capture and transmission. Image enhancement is the main and primary step in the image processing concept. It is used to develop the quality and brightness of an image. Moreover, the noise is removed using one of the filters, Average Filtering (Mean Filter): The mean filter is a linear type filtering method. The mean filter is smoothing the image data. Each pixel mask's performance is averaged together to make distinct pixel from other pixels; hence, it is called an average filter. Mainly in photographic images (i.e. In fundus photographic images), the grain noises are removed using this mean filter.

Images Enhancement

The major images enhancement techniques goal is to process a specific image in order to the outcome is more suitable comparison with the original image, or this is done by increasing the distinction between the details in the image, noting that the improvement process is done after the image correction process is carried out by removing the noise in the image. In this step, the fundus images were pretreated using the limited-contrast adaptive graph equation (CLAHE) technology. CLAHE is an effective contrast enhancement method that effectively increases image contrast] [12].

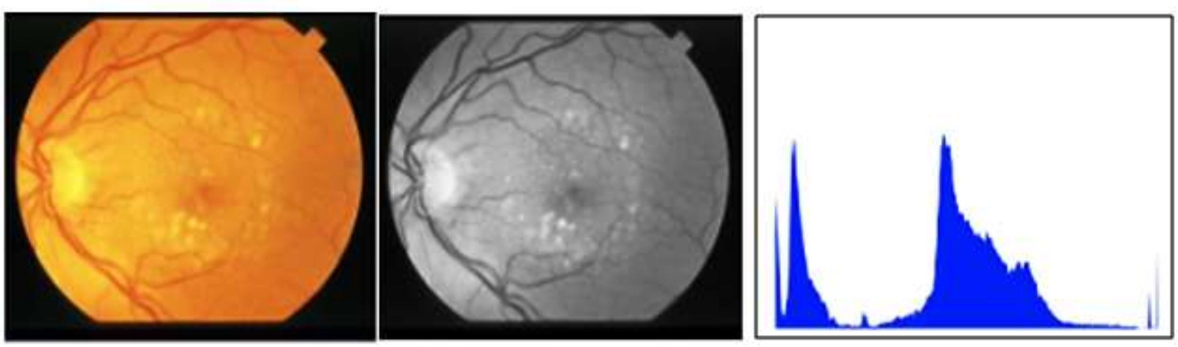

Figure 3. The suggested technique's Image pre-processing. (a) Original input (b) Contrast enhancement, (c) the image's histogram having better contras.

Feature Extraction

It uses a systematic method to define relevant shape details in a pattern, rendering model classification simpler. A feature extraction is a form of dimensional reduction used in pattern recognition and image processing. The primary aim of function extraction is to remove the most important data from the original data and depict it in a space of less dimensions. The model is classified depending on the features extracted. Convolutional neural networks are utilized to extract characteristics from the fundus images of macular degeneration disease of a dataset ODIR. There are some characteristics of fundus images for macular degeneration such as, Medium or large drusen deposits size, and change in retinal layers, and in rare cases, slight loss of vision, size of large prairie deposits, and changes in retinal layers, resulting in what is known as geographic atrophy (GA). It is the loss of some tissue in the retina layers due to progression to drusen. This could lead to vision loss, and large drusen will abnormally change the size of the eye blood vessels, causing them to bleed and leak. This is one of the most important characteristics of macular degeneration of the eye [13].

The CNN design includes the different layers in order to get the best feature extraction process. The layers of the CNN are as follows:

1. Layer 1 Convolutional layer (conv2D): the first layer is convolutional layer. With 16 filters the layer will learn. With 3*3 kernel size, padding(same). And the used activation function is ReLU. Since this is the first layer in our model, the parameter input_shape is used. Which is set to (s, s, 1). Where the s is the size of the image (223 for both the width and height of the image), and 1 for the single channel image. .
2. Layer 2 Convolutional layer (conv2D): : the second layer of the model is convolutional layer too. But the number of filters are 32. and have similar kernel size to layer 1 (3 * 3), padding(same), and reLU activation function. It should be noted that is no need to determine the input shape since the network will detect it automatically from the previous layer.
3. Layer2_1: this layer is inserted after layer_2. the size of this layer is (223, 223, 64). padding (same), and reLU activation function .
4. Layer 3 Max pool layer (maxpool2D): the third layer is max pooling layer. with (2 * 2) size. and stride value of (2 * 2).
5. Layer 4 Dropout: layer 4 is a dropout regulation layer. With 10% value.
6. Layer 5 Convolutional layer (conv2D): the fifth layer is convolutional layer with size (111, 111, 128). and kernel size of (3 * 3), padding (same), and reLU activation function .
7. Layer_5.1, with size (111, 111, 256). padding (same), and reLU activation function .
8. Layer 6 Convolutional layer (conv2D): the sixth layer is convolutional layer, with (111, 111, 512) size, padding (same), and reLU activation function.
9. Layer 7 Max pool layer (maxpool2D the seventh layer is max pooling layer. With (2 * 2) size. and stride value of (2 * 2).
10. Layer 8 Dropout: the eighth layer is a dropout regulation layer. With 10% value.
11. Layer 9 Convolutional layer (conv2D): the ninth layer is convolutional, with 256 filters and kernel size of (3 * 3), padding (same), and reLU activation function.

12. **12.** Layer 10 Max pool layer (maxpool2D the tenth layer is max pooling layer. with (2 * 2) size. And stride value of (2 * 2).
13. **13.** Layer 11 Dropout: the eleventh layer is layer is a dropout regulation layer. with 10% value.
14. **14.** Layer flatten: this layer will transform the previous feature map matrix into single column of values. So it will be appropriate to be entered to the next fully connected layer. The feature maps (three dimensions) will be converted to a vector (one dimension) so the output is 27 × 27 × 256 = 186624.
15. **15.** Layer 12 Dense layer: In the twelfth layer, the number of units (size of output layer) is set to 64. and the activation function is ReLU.
16. **16.** Layer 13 Dropout: the thirteenth layer is a dropout regulation layer. with 40% value to regulate and prevents the network from overfitting
17. **17.** Layer 14 Dense layer: In the fourteenth layer, the number of units is set to 2 (to represent the two classes of Normal and AMD and the activation function is Softmax. Figure 4 demonstrates the scheme of the CNN architecture

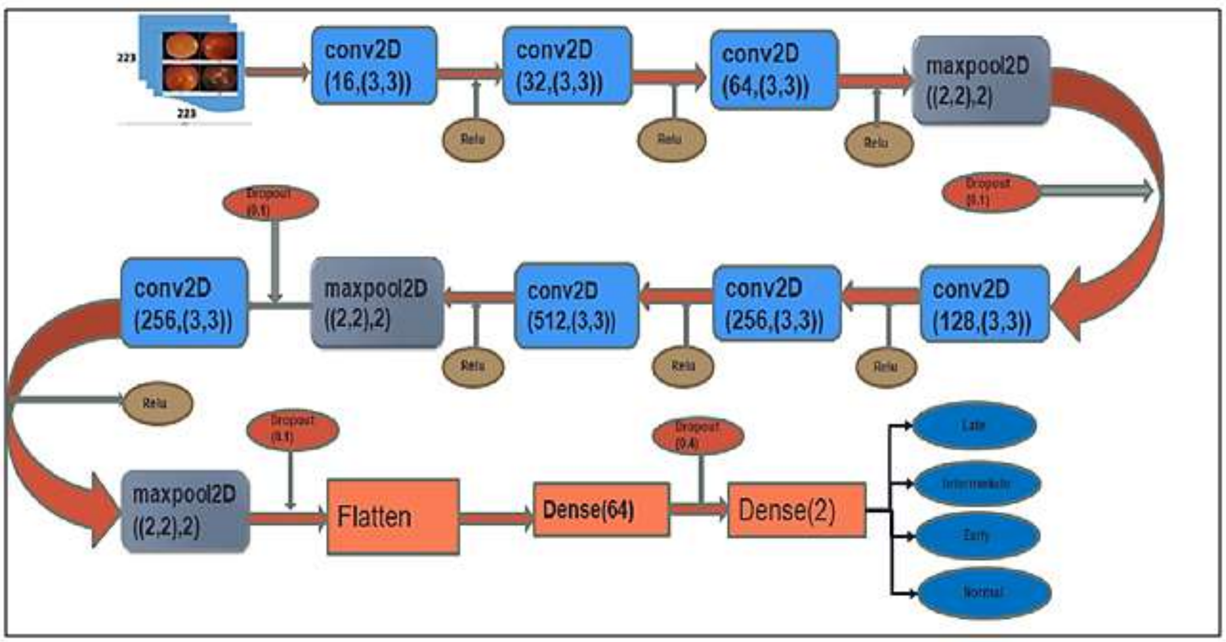

Figure 4. Show the architecture of the suggested model.

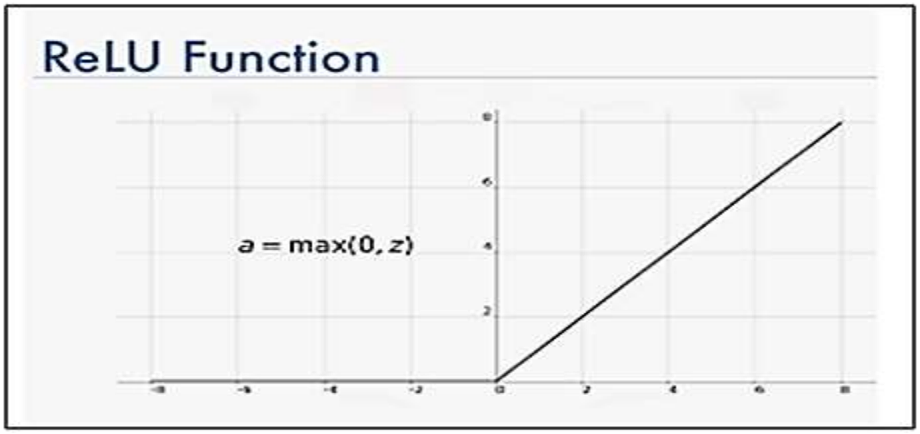

Figure 5. The Rectified Linear Unit function.

Pooling layers: It is one of the methods that is used to reduce feature maps to get more visible features to reduce overfitting. There are two common types of pooling: maximum and average pooling. Max pooling uses the maximum value for a group of neurons in the preceding layer, while the average pooling instead uses the average value [15]. In our work, we used the max-pooling property to reduce feature maps resulting from the previous layers [11], [17], as demonstrated in the Figure (6)

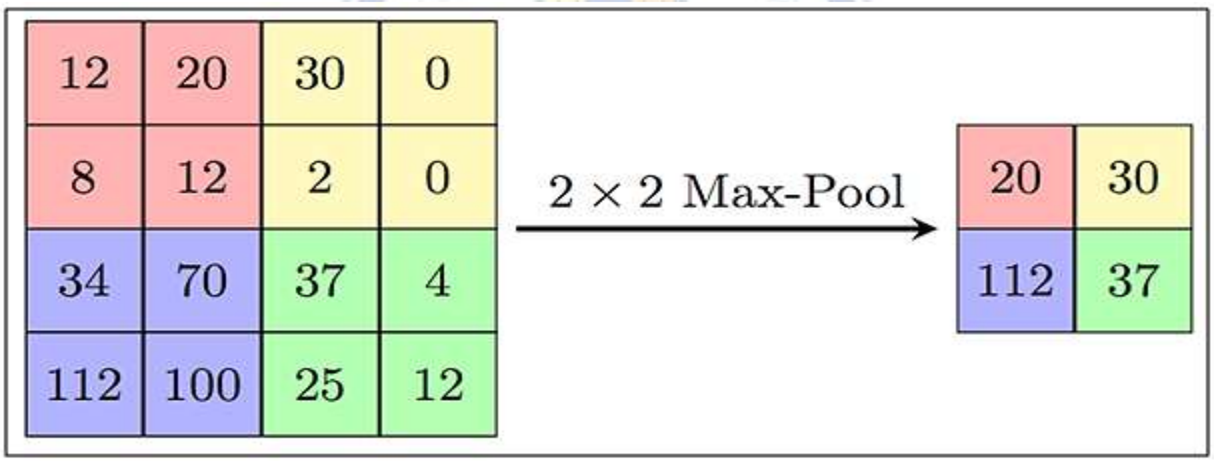

Figure 6. max pooling with (2×2 kernel size, stride 2) [11], [15]

The general properties of the fundus images present in the ODIR dataset are then better extracted by applying a trained CNN to the existing data.

1.1. Classification

For diagnosing cases with AMD, it should be extracting the features of the fundus images present in the ODIR dataset to gain the most relevant information from the original data and to characterize that information in a space with fewer dimensions and based on these extracted features; a prediction is made for the classification of AMD patients or Normal.

After the Flatten layer, there are three completely connected layers of dense structure with the activation function (Relu). Then the leakage layer is (0.1), and the last layer is the dense layer used for classification. We have used SoftMax as the activation function [16].

Evaluation Methodology

There are several metrics used to evaluate the performance:-

1. **Accuracy** is achieved when the classification is correct, whether the classification results are positive or negative.

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

2. **Sensitivity** is the rate at which a positive class is correctly classified.

$$\text{Sensitivity (Sen)} = \left(\frac{TP}{TP + FN}\right) \quad (2)$$

3. **Specificity** is the percentage of identification of negative examples rightly.

$$\text{Specificity (Spe)} = \left(\frac{TN}{TN + FP}\right) \quad (3)$$

4. **F1-score** demonstrates a compound of Precision and sensitivity for computing a balanced mean output .

$$\text{F1\_score} \;\&= \frac{2TP}{2TP + FP + FN} \quad (4)$$

$$\text{F}\,\beta_{\text{-score}} \;\&= \frac{(1+\beta^2)\times \text{Precision} \times \text{recall}}{\beta^2 \times \text{Precision} + \text{recall}} \quad (5)$$

$$\text{Kappa} \;\&= \frac{p_0 - p_e}{1 - p_e} \quad (6)$$

$$\text{Final\_score} \;\&= \frac{F1_{\text{score}} + \text{Kappa} + \text{Auc}}{3} \quad (7)$$

Depending on the sample and examination of eye images in the ODIR dataset, the correct classification of a positive diagnosis (normally classified as normal) is a true positive (TP), and false classification of a positive diagnosis (AMD classified as normal) is a false positive (FP). The correct classification For negative diagnosis (AMD classified as AMD) is a true negative (TN), and The wrong classification for negative diagnosis (Normal classified AMD) is a False Negative (FN) [18].

The rating report measures the quality of the classification algorithm's predictions. Table (2). demonstrates the main classification criteria for the suggested model.

Table 2. The classification report

	precision	recall	f1-score	support
Late	0.98	0.98	0.98	136
Interm	0.93	0.89	0.91	28
Early	0.96	1.00	0.98	79
Normal	1.00	0.95	0.97	39
accuracy			0.97	282
macro avg	0.97	0.95	0.96	282
weighted avg	0.97	0.97	0.97	282

The model was evaluated on the ODIR data set: (0.7) from the data selected to train the model (adjusting the values of weights and biases), (0.3) from the dataset selected to test the model) to optimize the parameters to obtain the best performance of the model measures, Through the test data, the final model is evaluated independently. Figure (7) demonstrates the confusion matrix for the features extracted by CNN,

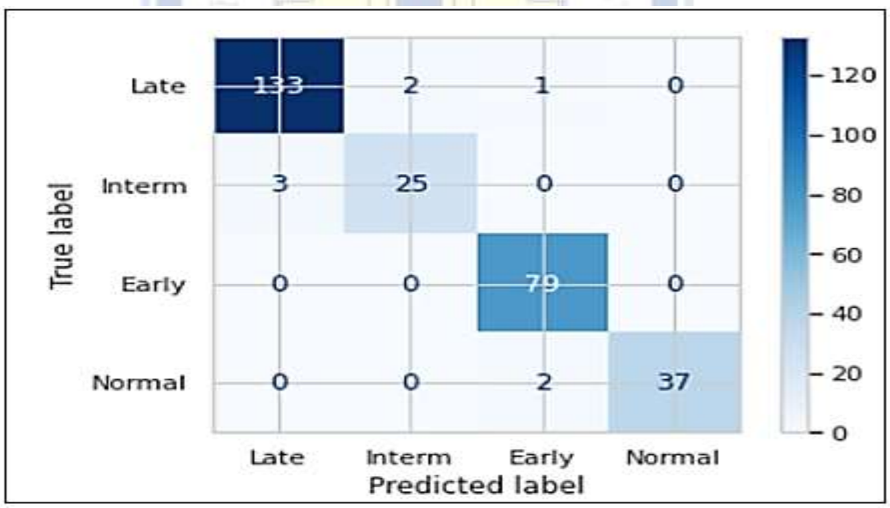

Figure 7. the confusion matrix for the features extracted by CNN.

Results and Discussion

From the confusion matrix to the test data, the highest accuracy we will get is accuracy: 97%, sensitivity: 98.52%, specificity: 89.29%, area under the curve: 93.9%.

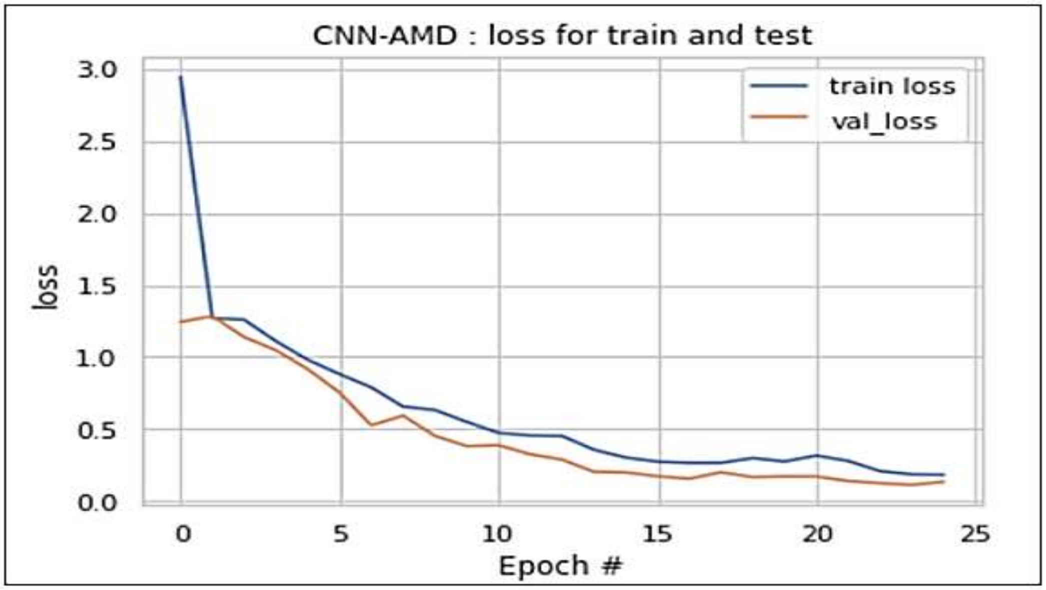

Figure 8. loss for train and test.

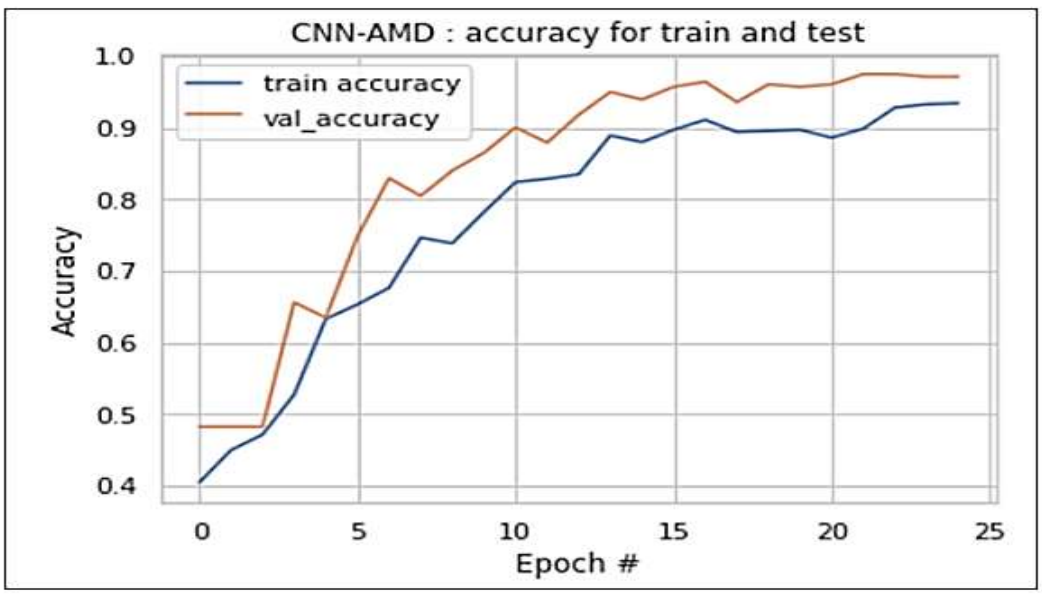

Figure 9. accuracy for train and test.

The chart demonstrates (loss for train and test) plot fig (8 and 9) a good and fit result because as it decreases loss for train (because loss function is the difference between the actual output and the prediction output, we train the network well to reduce the loss to get improved weights and thus get high accuracy

Table (3) compares different diagnosing AMD methods using deep learning algorithms with the suggested method's performance that uses the same data set. It was found that the suggested method achieved higher performance compared to the previous work of researchers who used the same data set in terms of the measures that are used for classification (accuracy, sensitivity, specificity, and area under the curve (AUC).

Table (3) Comparison of various diagnosing AMD methods using deep learning algorithms.

Research Study	Methodology	Accuracy %	Sensitivity %	Specificity %	Area under Curve AUC%
Ram, et al., [12].	Convolutional Neural Networks Retinal Images	0.819	0.714	0.663	-
Gour, et al. [13]	Two I/P VGG16	0.89	0.06	0.93	0.85
He, et al. [14]	AUBNet is composed of a feature extraction module (FEM)	Kappa=0.640, $F1$=0.913, and AUC=0.934			
He, et al. [15].	Backbone CNNs	Kappa=0.604, $F1$=0.907, and AUC= 0.928			
Islam, [11].	Convolutional neural network (CNN)	F-score: 0.85, Kappa score: 0.31, AUC value: 0.805			
Wang, et al. [16].	EfficientNet	0.89%	0.58	0.63	0.73
The current study	CNN	0.97	0.98	0.89	0.939

Conclusion

CNN provided this study for AMD Diagnostics and Normal On images in the ODIR dataset

•CNN Network was trained on this image set to minimize the overfitting.

•High classification accuracy of 97% was obtained for the group of ODIR images on which the network was trained. Learning curves for accuracy training and test when the method was implemented on ODIR images

Conflict of interests.

There are non-conflicts of interest.

References

[1] G. Zhang *et al.*, 'Reinforced concrete deep beam shear strength capacity modelling using an integrative bio-inspired algorithm with an artificial intelligence model', *Eng Comput*, pp. 1–14, 2020.

[2] C. Bunce and R. Wormald, 'Leading causes of certification for blindness and partial sight in England & Wales', *BMC Public Health*, vol. 6, no. 1, pp. 1–7, 2006.

[3] S. Moreland, E. Smith, and S. Sharma, 'World population prospects and unmet need for family planning', *Washington, DC Futur Gr*, vol. 62, 2010.

[4] A. C. Bird *et al.*, 'An international classification and grading system for age-related maculopathy and age-related macular degeneration', *Surv Ophthalmol*, vol. 39, no. 5, pp. 367–374, 1995.

[5] P. Mitchell *et al.*, 'Ranibizumab (Lucentis) in neovascular age-related macular degeneration: evidence from clinical trials', *Br J Ophthalmol*, vol. 94, no. 1, pp. 2–13, 2010.

[6] E. Y. Chew *et al.*, 'Long-term effects of vitamins C and E, β-carotene, and zinc on age-related macular degeneration: AREDS report no. 35', *Ophthalmology*, vol. 120, no. 8, pp. 1604–1611, 2013.

[7] R. D. Jager, W. F. Mieler, and J. W. Miller, 'Age-related macular degeneration', *N Engl J Med*, vol. 358, no. 24, pp. 2606–2617, 2008.

[8] K. Wisaeng, N. Hiransakolwong, and E. Pothiruk, 'Automatic detection of optic disc in digital retinal images', *Int J Comput Appl*, vol. 90, no. 5, 2014.

[9] J. H. Tan *et al.*, 'Age-related macular degeneration detection using deep convolutional neural network', *Futur Gener Comput Syst*, vol. 87, pp. 127–135, 2018.

[10] H. Liu, D. W. K. Wong, H. Fu, Y. Xu, and J. Liu, 'DeepAMD: detect early age-related macular degeneration by applying deep learning in a multiple instance learning framework', in *Asian Conference on Computer Vision*, 2018, pp. 625–640.

[11] M. T. Islam, S. A. Imran, A. Arefeen, M. Hasan, and C. Shahnaz, 'Source and camera independent ophthalmic disease recognition from fundus image using neural network', in *2019 IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON)*, 2019, pp. 59–63.

[12] A. Ram and d C. C. Reyes-Aldasoro, 'The relationship between Fully Connected Layers and number of classes for the analysis of retinal images', *arXiv Prepr arXiv200403624*, 2020.

[13] N. Gour and P. Khanna, 'Multi-class multi-label ophthalmological disease detection using transfer learning based convolutional neural network', *Biomed Signal Process Control*, p. 102329, 2020.

[14] J. He, C. Li, J. Ye, S. Wang, Y. Qiao, and L. Gu, 'Classification of Ocular Diseases Employing Attention-Based Unilateral and Bilateral Feature Weighting and Fusion', in *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*, 2020, pp. 1258–1261.

[15] J. He, C. Li, J. Ye, Y. Qiao, and L. Gu, 'Multi-label ocular disease classification with a dense correlation deep neural network', *Biomed Signal Process Control*, vol. 63, p. 102167, 2021.

[16] J. Wang, L. Yang, Z. Huo, W. He, and J. Luo, 'Multi-Label Classification of Fundus Images With EfficientNet', *IEEE Access*, vol. 8, pp. 212499–212508, 2020.

[17] E. H. Secondary, 'AEye Doctor : An Automated Diagnosis System for Ophthalmological Diseases', no. March, pp. 1–9, 2020.

[18] D. Luo and L. Shen, 'Vessel-Net: A Vessel-Aware Ensemble Network For Retinopathy Screening From Fundus Image', in *2020 IEEE International Conference on Image Processing (ICIP)*, 2020, pp. 320–324.