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An Automated Wavelet Scattering Network Classification Using Three Stages of Cataract Disease

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Abstract

A cataract is an eye disease that causes visual distortion and the late stage of this disease can lead to blindness. It is considered a silent disease that can occur without the appearance of symptoms. Therefore, the most effective way to detect cataracts is through accurate and timely detection to prevent hurting, expensive operations, and to stop blindness. The purpose of this paper is to propose an automated system based on the wavelet scattering network which categorizes the patients into four classes: early cataract, intermediate cataract, late cataract, and non-cataract conditions using 512 images of the ODIR dataset (212 Cataract and 300 of Normal). The first step in this technique is the preprocessing step for the retinal image was a mean filter, which was utilized to reduce the image's noise. The limited contrast adaptive histogram equalization (CLAHE) method was then employed to improve the image's contract level. Then, Low-variance characteristics can be extracted from image data using a wavelet scattering network for use in deep learning applications. In this network, lowpass scaling filters and predefined wavelets are employed. The average accuracy of the suggested method was 100% for four classes (Normal, Early, Moderate, and Severe). The results are promising compared with other similar works.

Keywords: Cataract disease, Cataract category, Deep learning network, Retinal fundus images, wavelet scattering.

Introduction

Ocular fundus images can reveal information on pathological alterations due to several eye diseases as well as early indicators of many systemic illnesses, including hypertension and age-related eye disease. Researchers are increasingly focusing on automating the fundus image analysis step of the ophthalmology diagnostic process. The early detection of these disorders is crucial for ophthalmologists because some of them have the potential to cause blindness in patients [1]. Medical imaging today plays a significant role in many areas of medicine; it makes it possible and simple to acquire, transmit, and analyze medical images while also aiding in medical diagnosis. Medical imaging is continually growing with the addition of novel imaging modalities and ongoing device capabilities advancements [2-4]. Cataract is an age-related eye disease and is the most prevalent ophthalmological public health issue in both industrialized and developing countries. Early cataract detection is essential to protect vision and stop global cataract-related blindness from rising [5]. In human eyes, cataract is a lenticular opacity that obscures the transparent lens. The lens typically converges light to the retina. Poor visual acuity is the result of this light being blocked by the cataract and not reaching the

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lens. It is the most common eye condition in the world, and it does not immediately impair vision. But over time, it can impair vision and even result in vision loss in persons over 40 [6]. According to recent data published by WHO (World Health Organization), more than 40,000,000 individuals are predicted to become blind during the next ten years. According to WHO statistics, cataract symptoms or severity were detected in about half of all blind individuals. Typically, many people put off having their cataracts surgically for a couple of years after they are discovered, but they should be aware that the severity worsens over time [7]. Early identification of cataracts is essential for effective treatment and can significantly reduce the chance of going blind. It's a challenging task to create an autonomous system that can recognize cataracts. Based on color fundus images, automated and effective diagnosis algorithms are critically needed because there aren't many symptoms of sickness in the early stages [8]. By observing the structural differences occurring in the retina, this diagnosis is made. After cataracts have been discovered, the severity of cataracts can be estimated by comparing the original retinal image to the reference images [9].

As indicated in Fig 1, there are typically four severity degrees for cataracts: normal, early, moderate, and severe.

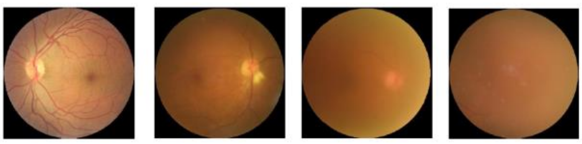

Figure 1. Degree of cataract.

This paper suggests a technique that uses retinal fundus images to automatically detect cataracts as a solution to this problem. This system should be able to read the fundus image of the retina based on its features. It should be able to accurately determine the eye's status and whether it is healthy or has a cataract together with the cataract grade.

The remaining sections of this paper are organized as follows:

Section 2 introduces related works, while Section 3 describes wavelet scattering. The methodology is the main topic for Section 4. The result and discussion are presented in Section 5, and Section 6 concludes the paper.

The Contributions

The proposed approach concentrated on creating a wavelet scattering network to identify the stages of a cataract (Mild, Moderate, and Severe) utilizing funds images. Also, this approach using fewer parameters than the most recent models result in a quick prediction time of about 2.1 **secs**, allowing the system to be employed in real time. Regrading to classification system accuracy, the proposed method produced great results for disease diagnosis, when compared to earlier researchers.

Related Work

Turimerla P. and Priyanka K.[10] suggested cataract identification approach using a convolutional neural network (CNN) that was trained to recognize different stages of the cataract. The retrieved features were then applied to a support vector machine (SVM) classifier after being extracted using a pre-trained CNN model. The acquired accuracy for the four stages of categorization was 92.91%.

In 2020 Jing W. et al. [11] proposed a technique that used CNN-style model imaging of fundus images to identify one or more fundus disorders without the use of additional labeling information. The approach was divided into two parts, with the first using an effective net-based feature extraction network and the second using a specially designed classification neural network that worked well in multi-label classification. This method had an accuracy of 0.89.

Dense-Net and U-Net were proposed by Jayachitra S. et al.[12] in 2021 to identify and categorize eye cataracts.
Additionally, 200 ocular image samples were taken to categorize the severity of the different stages of cataract.
. U-Net's accuracy was 93.5, while Dense-Net's was 89.5. As a result, it has been demonstrated that U-Net produces findings that are 10% more accurate than those of Dense-Net.

For automatic cataract diagnosis in fundus images, Junayed M. et al. [13] proposed a deep neural network named CataractNet. Its accuracy was 98.62%.

Kamrul H. et al. [14], used convolutional neural networks to classify cataract illness using a publicly available image dataset. During this test, the TensorFlow object identification framework was employed to apply four different convolutional

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neural network meta-architectures, containing DenseNet121, InceptionV3, InceptionResnetV2, and Xception.

In 2022 Hind H. et al. [15] used convolution neural network for identification and classification of cataract grading in retina images, and devised a method for the automatic diagnosis of cataract. The model was trained using the Adam optimizer with the (ODIR) dataset. According to the findings of the experiments, the four groups (Normal, Mild, Moderate, Severe) had an average accuracy of 96.9%.

In 2022 Richard B. et al. [16] compared different CNN architectures, including ResNet, GoogLeNet, MobiLeNet, and the proposed CNN model, to explore the grading of cataracts using fundus images. Adam Optimizer with a 0.001 learning rate, was regularly used to compare the four architectures. The proposed CNN model gave the best performance with an accuracy of 0.92.

Utilizing deep neural networks for detecting the stage of a cataract, Yaroub E [17] in 2022 suggested three networks of convolutional deep neural (MobileNet-V2, InceptionV3 and NasNet-Mobile) which stacked to provide better performance grading. The proposed framework has a 93.97% accuracy and a 94.89% F-measure for grading cataracts.

Wavelet Scattering

Mallat first introduced the null-parameter convolution network known as wavelet scattering [18]. Low-variance characteristics can be extracted from image data using a wavelet scattering network for use in applications of deep learning. In the network, lowpass scaling filters and pre-defined wavelets are employed. Data representations created by the scattering transform result in fewer disparities within a class while maintaining class discrimination.

When there is a shortage of training data, scattering can be applied successfully. For the wavelet scattering transform, three primary operations are required successively as illustrated in Fig 2.

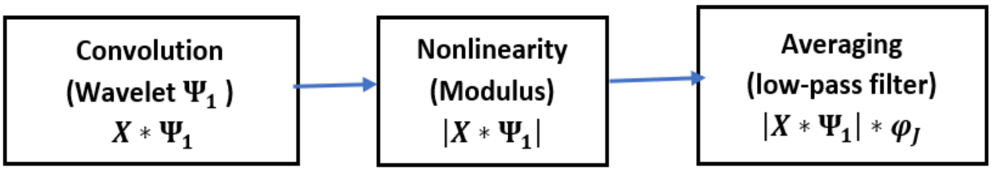

Figure 2. Processes of wavelet scattering transform.

Where X is the input data, $\Psi 1$ acts as a wavelet function, and φJ is an averaging low-pass filter.
Wavelet low-pass filters are used to first average the input signal; this is the layer zero scattering characteristic feature, and the high-frequency information is lost during the averaging step. The details that were lost in the first phase are captured at the following layer by applying a continuous wavelet transform for the signal to produce a scalogram coefficients set. In this instance, a set of layer 1 scattering coefficients is produced by applying a modulus to the scalogram coefficients and then filtering the output with a wavelet low-pass filter.

To get the layer 2 scattering coefficients, the same procedure is used again, the operations in the following layer always use the output of the scalogram coefficients from the previous layer as their input.

Depending on a number of layers the user defines, this nonlinear process continues, the wavelet modulus coefficients are averaged by a low-pass filter φ to produce the wavelet scattering transform coefficient, as shown in Fig 3.

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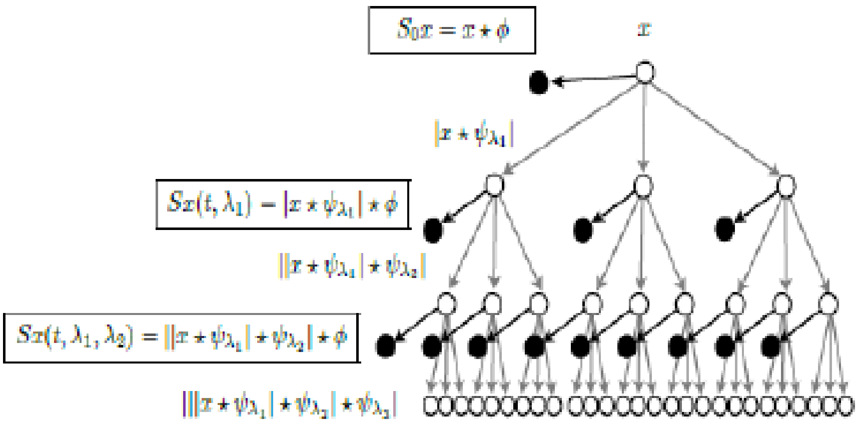

Figure 3. Hierarchical representation of wavelet scattering coefficients at multiple layers [19].

Methodology

The architecture of the proposed model is shown in Fig 4. In this proposal ODIR dataset which contains 512 images was used, these images were divided into 357 training images and 155 testing images.

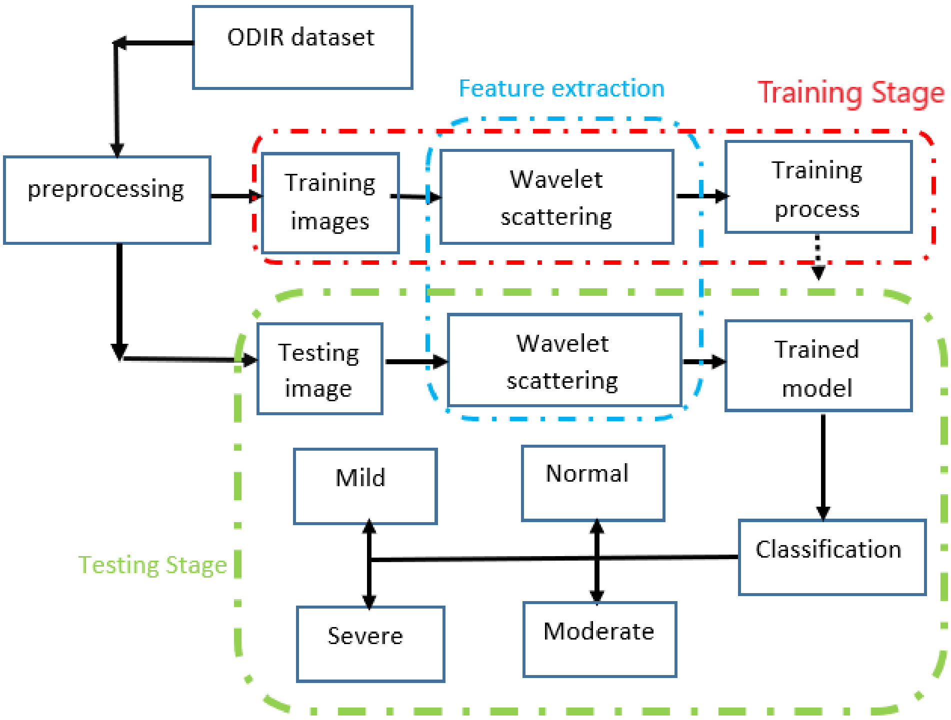

Figure 4. The proposed model architecture.

Pre-processing Stage

It is an important stage so that all images must be clear and ready to be processed to extract features from them. It has been applied on images to prepare the dataset for classification tasks. There are different stages of pre-processing which are:

Image Greyscale

Each image in the dataset consists of three channels (RGB). So all the images are converted into

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greyscale to speed up the task and preserve the required features.

Image Resize

Due to the size of camera images being different, therefore for all images, a uniform size can be established. The size of the images has been scaled down to (28 × 28) pixels which is suitable for wavelet scattering.

Removing Noise (Denoise)

The major and most important step in the idea of image processing is image enhancement by removing unwanted pixels. This is done by using average (Mean) filtering.

Images Contrast Enhancement

The purpose of the image enhancement method is to manipulate a chosen image so that the outcome is better than the original image. This can be accomplished by improving the contrast between the details in the image's details. In this stage, the fundus images were pre-treated using the limited-contrast adaptive histogram equalization (CLAHE) technique. CLAHE is a technique for improving contrast that successfully increases the contras of the image.

Training Stage

In this stage, images are input into the wavelet network and trained on classifying the retina into four classes. The proposed wavelet employed 30 epochs, a batch size of 64 with a learning rate of 0.0001. The numerous setup parameters that are provided in Table 1 were used to fine-tune the learning models.

Table 1. Parameters configuration.

Configuration Parameters	Value
Epochs	30
Learning rate	0.0001
Batch size	64

Testing Stage

This is the final stage in this proposal, the trained model will be fed with an image that has not been seen before, and classified into one of the four classes.

Results and Discussion

There are 512 fundus images in the ODIR database (212 Cataract images and 300 Normal images). The categories of cataract fundus images include (51 early, 61 Moderate, and 100 Severe). The retinal fundus images are divided into four classes using a wavelet scattering network: normal, early, moderate, and severe.
A percent of 30% of the dataset is used for testing, while 70% is used for training. Table 2 displays the statistics used to divide the data set.

Table 2. Dividing ODIR data set.

	Normal	Early	Moderate	Severe	Total
Train	210	35	42	70	357
Test	90	16	19	30	155
Total	300	51	61	100	512

In the train and test datasets, Table 2 displays the number and proportion of each class (Normal, Early, Moderate and Severe) for each part.
According to the confusion matrix, as shown in Fig 5, the suggested system will classify fundus images from the ODIR dataset as (Normal, Early, Moderate, or Severe) with 100% accuracy, 100% sensitivity, and 100% specificity.
The test data were used to independently to evaluate the final model.

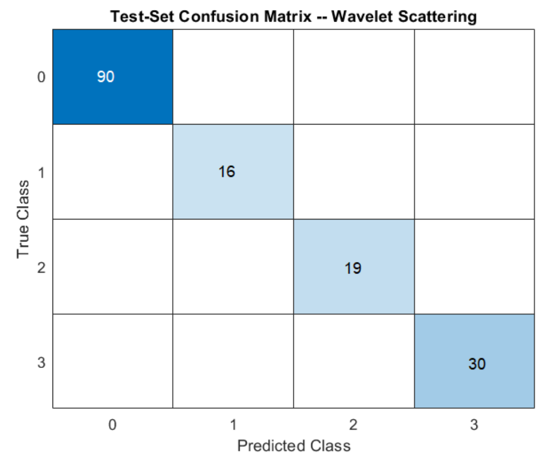

Figure 5. The confusion matrix for testing the proposed method.

The performance of the proposed classification algorithms was measured as listed in Table 3.

Table 3. The classification reports for the ODIR dataset.

Severity of Cataract	Sensitivity%	Specificity %	Support
Normal	100	100	90
Early	100	100	16
Moderate	100	100	19
Severe	100	100	30

Table 3 shows the performance measurements findings for the major performance metrics of specificity and sensitivity when the proposed system classified retina images into four classes using data from the ODIR dataset.

Also, compared the proposed method for diagnosing cataract disease based on retinal images with some of the previous similar methods was done as shown in Table 4.

Table 4. Comparison of several cataract detection techniques.

Author	Year	Method	Class	Accuracy
Jing W. et al. [11]	2020	CNN	Normal, Early, Moderate, and Severe	0.89
Jayachitra S et al.[12]		Dense-Net U-Net	Normal, Early, Moderate, and Severe	89.5 93.5
Hind H. et al. [15]	2022	CNN	Normal, Early, Moderate, and Severe	96.9
Richard B. et al. [16]	2022	CNN	Normal, Early, Moderate, and Severe	92%
Proposed Method	2023	wavelet scattering network	Normal, Early, Moderate, and Severe	100%

The primary factor for obtaining these achieved results are firstly, the suggested model architecture's Fig. 4 structure, which is based on a wavelet scattering network that divides patients into four classes. The proposed system produces better-quality, more accurate, and more general results. Second, the network was trained using preprocessed retina images, which produces more accurate results because it concentrated on the retina, where the illness is present.

Conclusion

This research proposes a wavelet scattering network for the categorization of cataracts based on fundus images from the ODIR dataset. The proposed method can detect stages of cataracts in retinal fundus images (Early, Moderate, and Severe). On this set of images, a wavelet scattering network was trained to reduce overfitting. For RGB images used to train the network, a high classification accuracy of 100% was attained. The classification accuracy attained in the current study is more efficient when compared to earlier studies that divided detectable cataract classes into four categories (Normal, Early, Moderate, and Severe). The proposed method is very fast, the fundus images prediction time takes approximately 2.1 **secs**. Results in comparison to other similar research are promised. It is anticipated that this method will aid ophthalmologists in early cataract identification to prevent the potentially dangerous consequences of cataracts and adequate medical treatment because it was able to diagnose cataracts more rapidly and accurately with fewer parameters and less computing power. For the future works, the expantion of the proposed approach was suggested to cover more eye conditions based on funding photographs, such as eye hypertension, age-related macular degeneration (AMD), glaucoma, and others. Also, the dividing of the cataracts into three types was suggested, these types were nuclear cataracts (NC), cortical cataracts (CC), and posterior subcapsular cataracts (PSCs), based on the location of the lens opacity.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in University of Babylon.

Authors' Contribution Statement

E. H., A. N. K. and L. H. participated in the designing and execution of the work, analysis of the results, and manuscript writing.

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التصنيف الالي لثلاث مراحل من مرض إعتام عدسة العين بالاعتماد على شبكة نثر المويجات

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الخلاصة

إعتام عدسة العين وهو مرض يصيب العين حيث يسبب تشوهًا بصريًا ويمكن أن تؤدي المرحلة المتأخرة من هذا المرض إلى العمى. ويعتبر مرضًا صامتًا يمكن أن يحدث دون ظهور الأعراض. لذلك ، فإن الطريقة الأكثر فاعلية للكشف عن إعتام عدسة العين هي من خلال الكشف الدقيق في الوقت المناسب لمنع الأذى والعمى والعمليات المكلفة. ان الغرض من هذه البحث هو اقتراح نظام آلي يعتمد على شبكة نثر المويجات التي تصنف المرضى إلى أربع فئات: إعتام عدسة العين المبكر وإعتام عدسة العين المتوسط وإعتام عدسة العين المتأخر وعدم إعتام عدسة العين باستخدام 512 صورة لقاعدة البيانات ODIR (212 شخص مصاب و300 شخص غير مصاب). الخطوة الأولى في هذه التقنية هي خطوة المعالجة المسبقة لصورة الشبكية التي كانت عبارة عن مرشح المتوسط ، والذي تم استخدامه لتقليل ضوضاء الصورة. ثم بعد ذلك استخدام طريقة معادلة الرسم البياني التكيفية محدودة التباين (CLAHE) لتحسين مستوى عينات الصورة. بعد ذلك ، يمكن استخراج الخصائص منخفضة التباين من بيانات الصورة باستخدام شبكة تشتت المويجات لاستخدامها في تطبيقات التعلم العميق. في هذه الشبكة ، يتم استخدام مرشحات تحجيم تمرير منخفض وموجات موجية محددة مسبقًا. كان متوسط دقة الطريقة المقترحة 100٪ لأربع فئات (غير مصاب، مبكر، متوسط، شديد). علما ان النتائج موعودة مقارنة مع أعمال أخرى مماثلة.

الكلمات المفتاحية: مرض اعتمام عدسة العين، فئة اعتمام عدسة العين، شبكة التعلم العميق، صور قاع الشبكية، تشتت المويجات.