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# Diagnosis of Ophthalmic Diseases in Fundus Image by Using Deep Learning

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***Abstract: In the human eye, Damage in the retina may cause ophthalmic diseases like cataracts, AMD, Hypertensive retinopathy, myopia, etc. To cure these diseases, many ophthalmologists use retinal fundus images as an important information source to find out ophthalmic diseases. Multiple techniques have been introduced for the screening of ocular diseases. Today's world is in great demand to find out ocular diseases by using deep learning and machine learning techniques. This paper uses pre-trained deep neural networks to determine five categories of ophthalmic diseases such as cataract, AMD, Hypertensive retinopathy, myopia, and normal. Dataset is created into binary and multiclass, then trained on Resnet-101 of convolutional neural network (CNN) and evaluated. The accuracy of this model is found to be 90.38% and 88.5% for binary and multiclass respectively.***
***Keywords: Retinal fundus image, Ocular diseases, CNN, ResNet, deep learning. Image processing, Ensemble classifier.***

## I. INTRODUCTION

Fundus imaging is versatile for medical diagnosis. In the case of eye diseases, fundus imaging can help early detection of diseases, enabling preventive measures for impending blindness or eye health risk. The rate of several eye diseases is higher in the world. Specialist ophthalmologists can diagnose the disease by looking at the eye's symptoms but they are not found in many remote places around the world [1]. Therefore, researchers are eager to develop a smart, automated system that can provide diagnostic and therapeutic classification for the eye and the diagnosis of eye diseases. Early treatment and diagnosis of diseases can prevent millions of people from loss of vision. With the advancement of technology and image analysis, it is possible to make the diagnosis process more efficient and refer the patient to a physician for further consultation. The algorithms based on ' deep learning CNN' make changes in the evolution of the method by directly identifying features from the training data without the distinction of feature extraction and feature classification [2].

According to the World Health Organization, 2.2 billion peoples have vision impairment, of which 1.4 billion suffer from various ophthalmic diseases includes age-related macular degeneration, cataract, hypertensive retinopathy etc. [3] As population aging has emerged as a major demographic trend worldwide, patients suffering from chorioretinal diseases such as age-related macular degeneration (AMD) and hypertensive retinopathy (HR) are expected to increase in the future. AMD can cause blindness. Hypertensive retinopathy, which a common lifestyle disease, is also a major cause of blindness in patients with high blood pressure. Other retinal diseases including retinal vessel occlusion and retinitis are significant causes of vision impairment. If early diagnosis and treatment are implemented prior to the initial stage of blindness progression visual loss can be avoided in many cases. Many methods of obtaining ocular pathology diagnostic such as digital image processing and machine learning are widely used in automated diagnostics and decision-making processes to obtain the best and most accurate results. Deep learning (DL), as a small machine learning group, uses a neural network that enables the machine to make its own decisions, without human assistance. In the field of clinical ophthalmology, deep learning is used for data analysis, classification, automated diagnosis and possible outcome prediction. Deep learning emerges as a powerful tool for analyzing medical images. Diagnosis of retinal infections using computer-assisted diagnoses from a fundus image has emerged as a new approach.

The proposed framework is deep learning that can automatically detect features at different levels from the training dataset of retinal images. We considered five categories of ophthalmic diseases which further classified into two categories that are binary and multiclass. We have used the transfer learning approach of deep learning in which we'll use a pre-trained deep residual neural network (ResNet 101) and ensemble classifier was used.

The arrangement of this article is as follows. Section II presents the research method followed after surveying the articles. Section III describes our proposed methodology. Section IVshows the experimental result and quantitative analysis of our obtained model. Finally section V concludes the paper.

## II. LITERATURE REVIEW

A Many previous studies have focused on the automatic detection of ocular diseases using deep learning algorithms and study equipment to analyse the large number of fundus images taken in retinal screening programs. In more recent times, machine learning research has focused on diagnosing diseases such as diabetic retinopathy, glaucoma by removing features and dissecting the images as sick or healthy by developing system called LCDNet and successfully performed this binary classification [4]. Retinal fundus images were obtained from two sources, and eight data sets were created for testing. They found between 96.5% and 99.7% accuracy in those data sets. They also found that red-colored images have better effects than color, which is also the view of the medical community.

Other techniques such as artificial intelligence in ophthalmology mainly focus on diseases such as diabetic retinopathy, glaucoma, age-related macular degeneration, retinopathy of prematurity, age-related or congenital cataract, and a few with retinal vein occlusion. [5] Their study includes both types of classification algorithms such as decision tree, random forest, and neural approach so that the researcher can see the impact of how to propose a data model by precision classification. The data used was split into two sets as training and testing at a 70:30 ratio. In order to implement validation, the 10 fold cross-validation verification method must be used. But there is a general lack of recording of medical data. There is a need for a structured framework for providing professional data input and in particular, includes efficiency and therapeutic feasibility that can make it easier to differentiate. However, it is known as a critical challenge when using AI and Learning Applications to obtain information by many specialists in the diagnosis and interpretation of the disease.

In a subsequent study, a unique method was developed to diagnose eight types of ocular diseases using convolutional neural networks [6]. This diagnostic program is a prediction of the 'real life' of many eye diseases. Tests have passed on all types of images with different types of optic diseases. One study suggests a content-based visual recognition system based on facial images using image processing and machine learning techniques. [7] This automatically places part of the eyes on the front face image. They use two class learning methods: DCNN and SVM. And use PCA and t-SNE to select features and separate by SVM. They tested their system with seven visible eye diseases. A remote cataract system is provided to detect cataracts from fundus images and to provide different stages of cataracts to patients [8]. This focuses on improving system accuracy and providing a remote system for people in less developed areas so they can get their cataract status in a timely manner. Features are extracted from fundus images using wavelet transform and skeletonization through the DCT process. Subsequently, the extracted components are divided into two categories (cataract and non-cataract) and range in mild, moderate, and severe phases. Separately, a vector support machine algorithm (SVM) is used and grading is done using the MDA algorithm. In another study proposed the development of VGG eye diseases model and a model of recognition based on dense blocks. [9] This trial used the glaucoma dataset iChallenge-GON, the cataract dataset iChallenge-AMD, and the myopia dataset iChallenge-PM. Advantages of dense blocks is that the network is small and has a less no of parameters. By using the dense VGG network performance of network is improved. They get better performance by comparing this model with ResNet, AlexNet, and VGG. In order to successfully differentiate between different categories, the proposed model uses a variety of computer viewing features and a series of extracts to improve machine learning.

## III. PROPOSED METHODOLOGY

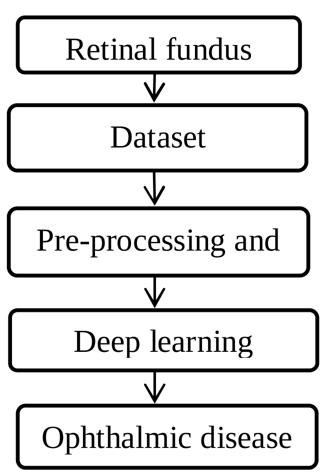


Fig 1. Shows the process flow of proposed method. Listing the major steps involved in the implementation of the system.

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### *A. Dataset*

In this trial we used a database representing a 'real-life' 'set of patient data collected by Shanggong Medical Technology, Ltd. at various hospitals / medical centres in China [10]. Ocular Disease Intelligent Recognition (ODIR) is a systematic ophthalmic database of 5,000 patients, left and right fundus images from doctors and key diagnostic eyes. Photos of fundus are sent by various cameras on the market, such as Canon, Zeiss and Kowa, which has led to various image processing. This database contains eight categories of diseases in which we have identified five categories namely cataract, age related macular degeneration, hypertensive retinopathy, myopia and generalized. In this dataset we can see that each eye can have one or more disease. We created a new dataset out of it, we took images from it which had another disease along with normal and we named that image as that disease. Again we reorganized it and created a new dataset divided into two categories that is binary and multiclass.

### *B. Pre-processing and Feature Extraction*

To ease the network environment for our model, we convert input images to the size of the image in layer to suit the architecture of the model. Here we have used ResNet-101 which is a convolutional neural network that is 101 layers deep. The network has 224-by-224 input image size. Utilizes domain knowledge to extract new features that will be used by the deep learning algorithm. We Use a pretrained resnet101 network and take the pool5 activation layer to extract the features. ResNet's main concept introduces the so-called "identity shortcut connection" that exceeds one or more layers [11]. Including a shortcut link [Fig 2] that converts the network into its remaining version of its counterpart. Identity shortcuts F (x {W} + x) can be used directly when input and output are the same size. Each ResNet block can be two deep layers (used in smaller networks like ResNet 18, 34) or 3 deeper layers (ResNet 50, 101, 152).


Fig 2. Architectural diagram of ResNet- 101 model.

### *C. Classification*

Dividing input into one of the many classes is one of the basic functions of identifying a mathematical pattern. The segregation function requires the creation of a mathematical model that represents a mapping from input data (usually defined by specific factors) for relevant results. The word ensemble is a Latin word meaning 'union of parts'. Commonly used classifiers tend to make mistakes as long as these inevitable errors can be minimized by proper construction of the learning classifiers [12, 13]. Ensemble learning is a way to produce a variety of basic classifiers where new classifiers are found that perform better than any local separator. These basic classifiers can vary in the algorithm used, hyper parameters, representation, or training set. The main purpose of the integration methods is to reduce bias and diversity.

## IV. RESULT AND DISCUSSION

The entire experiment was conducted on a system with an Intel(R) Core(TM) i5-6200U CPU @ 2.30GHz 2.40 GHz with RAM 12.0 GB. The entire model's result was implemented using MATLAB R2018b. We perform experiment on ODIR-5K a structured database of 5,000 patients. We have collected the images of five labels which is cataract, age related macular degeneration, hypertensive retinopathy, myopia and normal from this database. This dataset contains colour fundus photographs of left and right eye which have been collected from different hospitals/medical canters in china by Shanggong Medical Technology, Ltd. For this experiment we have used 260 images of this dataset.

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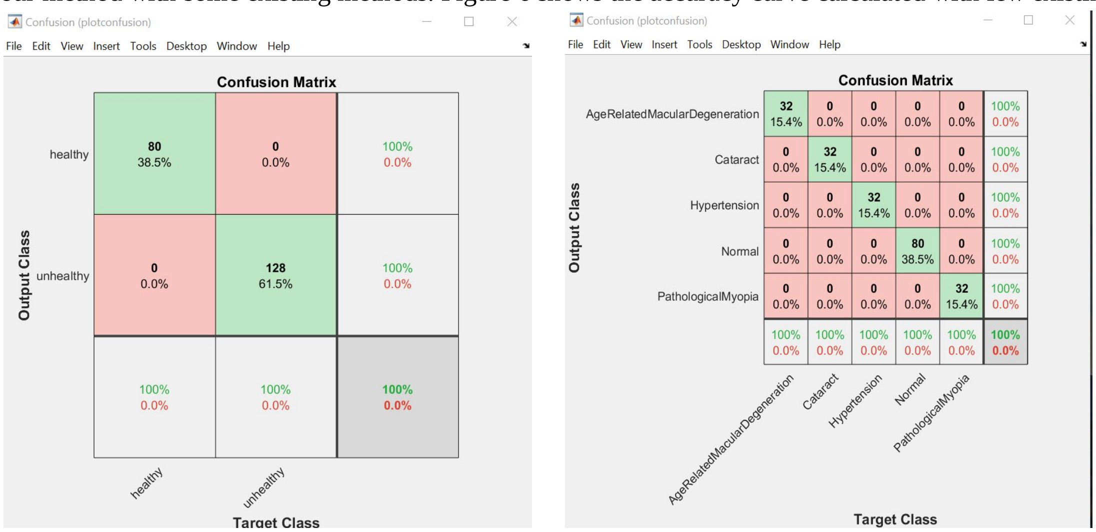
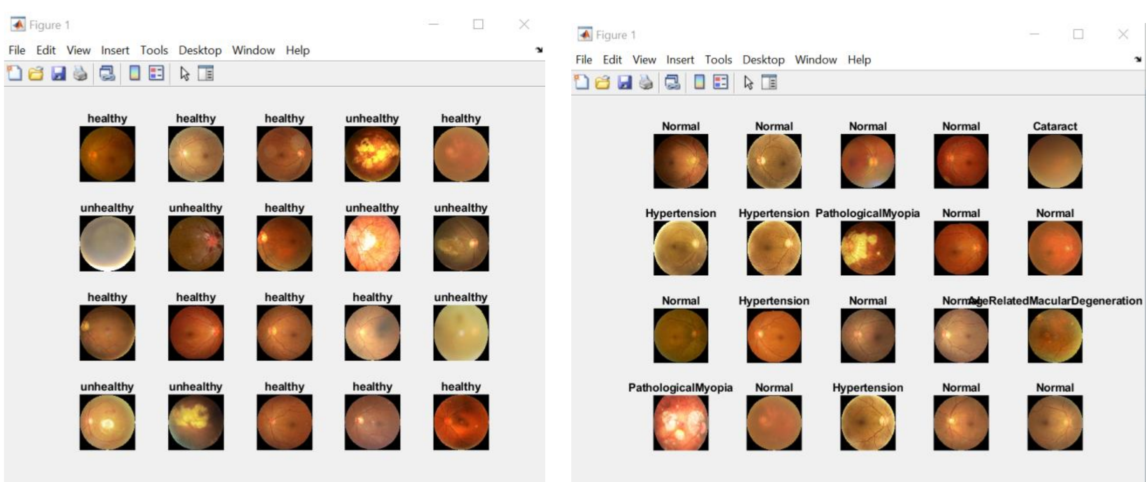
This dataset comprises images of five labels including varied image resolutions. Experiment is performing into two phases training and testing in the ratio of 80:20 with the two categories of dataset i.e. binary and multiclass.

For training first pre-trained ResNet 101 model load into the system and you get its input layer. The given dataset then split into training and testing. From the split dataset 80% dataset is used for training and 20% dataset used for testing for binary and multiclass as shown in fig (3) and (5). Every time dataset is trained random images are taken from it as shown in figure (4). The images are then resized while processing the split dataset, so that the image of that size fits in that layer. Then the feature extraction process is done using the deep learning model with the help of activation function. For this, the model's feature layer has to be loaded. We have used Pool 5 layer in our model as feature extraction which extracts class labels from training data. Then ensemble classifier is used [14]. Firstly image classifier is fit and trained into the model. Then trained images are given to the classifier where classification is done into two cases which are binary classification and multiclass. An image is classified into the respected labels and performance evaluated. We can see the performance evaluation of the classification algorithm in table 1. In the confusion matrix the number of positive and negative predictions is summarized in the calculation values and divided by each category. Table 2 shows the result of all the parameters of binary dataset and multiclass dataset that we have considered. In Table 3, we show the comparison of our method with some existing methods. Figure 6 shows the accuracy curve calculated with few existing methods.



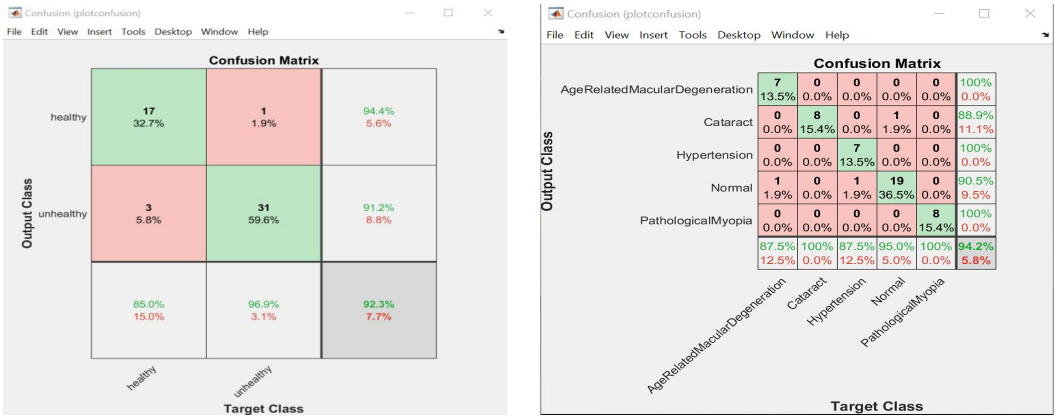

Binary (b) Multiclass

Fig 3. Confusion matrix of training dataset. (a) Confusion matrix of binary classification (b) Confusion matrix of category multiclass




(a) Binary (b) Multiclass

Figure 4. Fundus Images of (a) Binary and (b) Multiclass.




(a) Binary (b) Multiclass

Figure 5. Confusion matrix of test images of two categories (a) Confusion matrix of binary classification shows performance of healthy and unhealthy images. (b) Confusion matrix of category multiclass shows performance of five diseases.

TABLE I

Evaluation time for both the catagories

| Evaluation Time | Binary | Multiclass |
|---|---|---|
| Training | 112.65 | 87.82 |
| Testing | 26.20 | 24.20 |

TABLE III

Result of binary and multiclass classification

| Parameter | Values for Binary classification | Values for Multiclass Classification |
|---|---|---|
| Accuracy (%) | 92.30 | 94.2 |
| Error Rate (%) | 7.69 | 5.76 |
| Sensitivity | 90 | 94 |
| Specificity | 93.75 | 98.29 |
| F- score | 90 | 95.33 |
| Kappa score | 83.75 | 81.97 |

Table IIII

Comparison of Proposed Method and some Existing Method

| Reference | Ophthalmic diseases | Method used | Dataset | Accuracy (%) |
|---|---|---|---|---|
| [4] | Normal (N), diabetes (D), glaucoma (G), cataract (C), AMD (A), hypertension (H), myopia (M) and other diseases/abnormalities (0) | Deep CNN Model | ODIR-5K | Multiclass -80.5% |
| [6] | Cataract | MDA, SVM | 261 Images | Binary (cataract and non-cataract)- 84.66 % |
| This paper | AMD (A), Cataract (C), Hypertension (H), Pathological Myopia (M), Normal (N), | ResNet-101, Ensemble | 260 Images | Binary- 92.30% Multiclass- 94.2% |

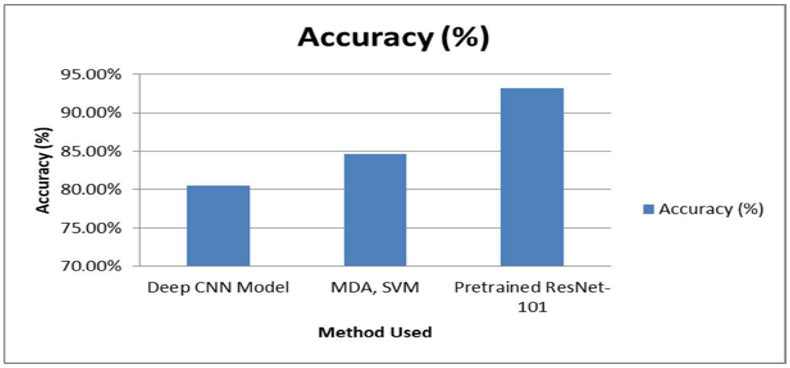



Figure 6. Accuracy curve.

## V. CONCLUSIONS

Ocular disease recognition and classification plays an important role in diagnosing disease in early stage. A conventional technique fails to predict these disease categories because this technique is time-consuming and required clinical experts to predict them. In this paper, we used pre-trained ResNet 101 network to predict ophthalmic diseases of five categories that is AMD (A), Cataract (C), Hypertension (H), Pathological Myopia (M), and Normal (N). We test our system for 260 images of different labels. In this experiment we have used two categories to predict these diseases. First is binary which shows healthy and unhealthy images from given dataset. And second is multiclass which shows exact labelling of given diseases. It is observed that the proposed system achieves maximum accuracy of 92.30% and 94.2% for both binary and multiclass respectively. In addition we can use this method to find out the large number of diseases. And we can use these methods with a large number of data which helps to achieve greater accuracy.

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## REFERENCES

[1] ManjulaSri Rayudu, Vaibhav Jain, MM.Rao Kunda. “Review of Image Processing Techniques for Automatic Detection of Eye Diseases”, Sixth International Conference on Sensing Technology (ICST), 2012.

[2] Triwijoyo, Bambang & Budiharto, Widodo & Abdurachman, Edi. (2017). “The Classification of Hypertensive Retinopathy using Convolutional Neural Network”. Procedia Computer Science. 116. 166-173. 10.1016/j.procs.2017.10.066.

[3] World Health Organization, "Blindness and Vision Impairment," 11October, 2018, [Online]. Available: https:/Iwww.who.intlnews-roomlfactsheets/detaillblindness-and-visual-impairment

[4] L. Jain, H. V. S. Murthy, C. Patel and D. Bansal, "Retinal Eye Disease Detection Using Deep Learning", 2018 Fourteenth International Conference on Information Processing (ICINPRO), Bangalore, India, 2018, pp. 1-6, doi: 10.1109/ICINPRO43533.2018.9096838.

[5] Dr. Kurikkil Veettil, Yooseff Ibrahim, “Investigate a Diagnosis of Eye Diseases using Imaging Ophthalmic Data”, GRD Journals- Global Research and Development Journal for Engineering | Volume 4 | Issue 11 | October 2019 ISSN: 2455-5703

[6] Md.Tariqul Islam, Sheikh AsifImran, Asiful Arefeen, Mahmudul Hasan, Celia Shahnaz, “Source and Camera Independent Ophthalmic Disease Recognition from Fundus Image Using Neural Network”, IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON), 28-30 November, 2019, Dhaka, Bangladesh.

[7] Ashrafi Akram, Rameswar Debnath, “An automated eye disease recognition system from visual content of facial images using machine learning techniques”. Turkish Journal of Electrical Engineering & Computer Sciences. (2020) 28: 917 – 932 © TÜBİTAK doi:10.3906/elk-1905-42

[8] Sucheta Kolhe, Shanthi K. Guru, “Remote Automated Cataract Detection System Based on Fundus Images”, International Journal of Innovative Research in Science, Engineering and Technology, 2016.

[9] Ye Mu, Yuheng Sun, Tianli Hu, He Gong, Shijun Li1, and Thobela Louis Tyasi. “Improved Model of Eye Disease Recognition Based on VGG Model”. Intelligent Automation & Soft Computing DOI:10.32604/iasc.2021.016569.

[10] Peking University, "Peking University International Competition on Ocular Disease Intelligent Recognition (ODIR-2019)”,[Online].Available: https:llodir2019.grand-challenge.org/datasetl.

[11] K. He, X. Zhang, S. Ren, and J. Sun. “Deep residual learning for image recognition”. arXiv preprint arXiv: 1512.03385,2015.

[12] Nikunj C. Oza, Kagan Tumer, “Classifier Ensembles: Select Real-World Applications”, Article in Information Fusion · January 2008 DOI: 10.1016/j.inffus.2007.07.002 · Source: DBLP

[13] Thomas G. Dietterich, “Ensemble Learning”, Department of computer science Oregon state university Carvallis, Oregon 97331-3202 USA September 4, 2002.

[14] Ishtiaque Ahmed Khan, Asaduzzaman Sajeeb, Shaikh Anowarul Fattah, “An Automatic Ocular Disease Detection Scheme from Enhanced Fundus Images Based on Ensembling Deep CNN Networks”, 2020 11th International Conference on Electrical and Computer Engineering (ICECE). 978-1-6654-2254-3/20/$31.00 ©2020 IEEE.