

# Deep Convolutional Neural Network and Transfer Learning to Classify Cataract Based on Fundus Images

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## Abstract

Ocular diseases have crippled many lives ubiquitously. Cataract is one of the major contenders for impaired vision, which creates a cloudy area in the lens of the eye leading to a decrease in normal vision. Fundus images of the eye help to distinguish between normal eyes and cataract eyes. The development of cataract identification using a traditional algorithm based on feature representation is highly dependent on the classification process carried out by an eye specialist so the method is prone to misclassification. Deep learning algorithms help in the automatic and very early detection of such diseased eyes using pattern recognition. In this paper, transfer learned RESNET-50, in addition to other various models such as VGG-16, VGG-19, and model from scratch are applied to compare the results to classify 14000 images. The best model, RESNET- 50, attained an accuracy of 95.9% with 12 million parameters.

**Keywords:** Deep learning, Transfer Learning, Pattern Recognition, RESNET-50, VGG-16, Cataract.

## 1. Introduction

Novel Cataract is one of the leading causes of blindness worldwide. With age, the condition becomes even more severe, ranging from 3.6% among 55-64 years to 92.6% among those 80 years and older [1]. There were 10.8 million cataract-blind people in the year 2010, and this number is expected to surge to 40 million in 2025. Dementia, the likelihood of road traffic crashes and impaired quality of life of an individual are the severe effects of cataracts. Faster identification of cataracts is very crucial to avoid such disasters. With the advancement of deep learning techniques, it is possible for automated and rapid detection of the cataract eye

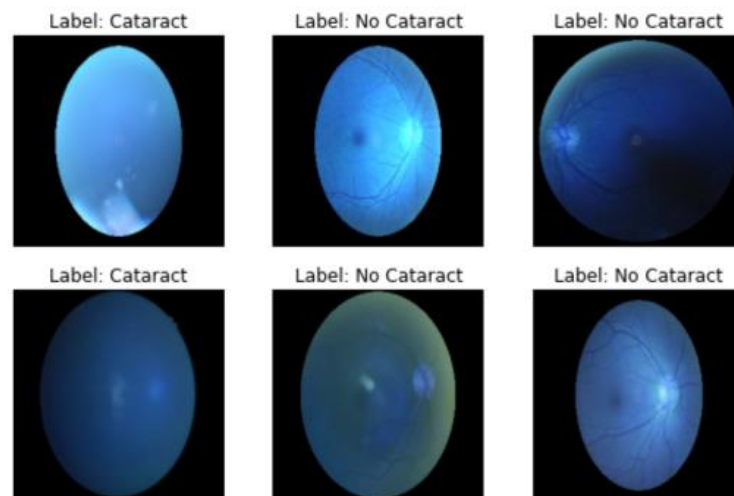
so that proper measures can be taken to reduce the risk. The proposed method, transfer learned deep learning models, will help to classify healthy eyes from cataract eyes.

This study has been conducted on an ocular dataset by building a CNN (convolutional neural network) model to classify cataract eyes from normal eyes. 380 fundus images consisting of 240 images of cataracts and 140 images of normal eyes were fit into the model which returned an average accuracy of 88% in about 50 epochs [2].

## 2. Materials and Methods

### 2.1 Dataset

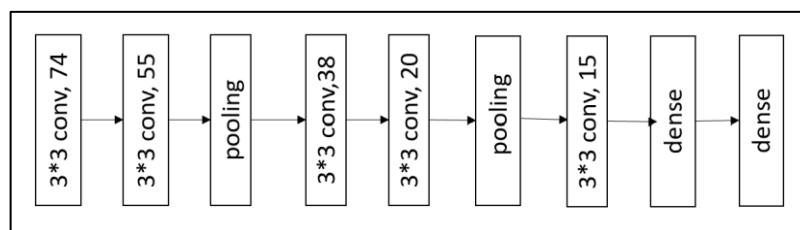
This dataset consists of fundus images of normal and cataract-infected eyes. A total of 14000 samples were used for the experiment. The images were obtained from Kaggle Repository. 7000 images were used as train data, 6000 images were used as validation data and the remaining 1000 images were used as test data. The average image size was  $224 \times 224 \times 3$ . Figure 1 shows a few data samples.



**Figure 1.** Few samples of cataracts and normal eyes.

### 2.2 Model from scratch

This is a simple implementation of the CNN model prepared to train the model and test its accuracy of the model. This model consisted of 5 convolutional layers and 2 max pooling layers. The illustration of this model from scratch is shown in figure 2 below.



**Figure 2.** The architecture of model from scratch.

### 2.3 Transfer Learning

Transfer learning is the reuse of a pre-trained model on a new problem. In transfer learning, the machine uses the knowledge acquired in the previous task to improve the generalizability of another task. For example, by training a classifier to predict whether an image contains food, we can use the knowledge it gained during training to identify soft drinks. This process will tend to work if the features are general, meaning suitable to both base and target tasks, instead of specific to the base task [3].

**Table 1.** Comparison of various models 224 × 224 input image.

Model Name	Test Accuracy (%)	Number of trainable	Number of convolutional layers	Epoch number
Model from scratch	71.54	22 parameters (in millions)	5	181
GG-16	82.68	15	13	105
VGG-19	91.87	5	16	177
RESNET 50	95.92	12	48	205

## 3. Results

Implementation of the model from scratch with 22 million trainable parameters provided a test accuracy of 71.54%. The accuracy was increased when the VGG-16 model was implemented with fewer parameters than the scratch model. VGG-19 provided an increased test accuracy of 91.87% in just 5 million trainable parameters. Finally, the highest accuracy was obtained in RESNET 50 model. Test accuracy of 95.92% was obtained in the RESNET 50 model consisting of 12 million trainable parameters.

## 4. Conclusion

In this work, a model from scratch, as well as transfer, learned VGG 16, VGG 19 and RESNET 50 on Imagenet were used to classify fundus images of eyes. These models classified the normal eyes from the cataract eyes efficaciously. By varying the number of trainable parameters, fine-tuning the hyperparameters of the models, and testing on various deep convolutional neural network models, we attained a maximum accuracy of 95.92% in the dataset. The various models discussed above are used in the ocular illness categorization system. The most appealing thing about this method is that it can be easily applied to other types of medical image-based disease classification.

## References

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