An Empirical Study on Cataract Multiclass Grading Assessment with Slit Lamp Bio-microscope Images Using Neural Network Models

Likhitha D. Atada[1*], S. Joshi Manisha[1], A. J. Dayananda[2]

[1]*Department of Medical Electronics Engineering*
B. M. S. College of Engineering
Bengaluru, Karnataka 560019, India
E-mails: likhitha29atada@gmail.com, msj.ml@bmsce.ac.in

[2]*Department of Ophthalmology*
K. C. General Hospital
Bengaluru, Karnataka 560003, India
E-mail: daya7979@gmail.com

[*]*Corresponding author*

Received: September 02, 2023 **Accepted: April 02, 2024**

Published: June 30, 2024

Abstract: *Cataract, an age-related eye disease, poses a significant ophthalmological public health challenge in both developed and developing nations. Tailoring treatment or surgery plans helps accurately categorise the cataract's developmental stage. Precise cataract grading helps in diagnosing cataracts and subsequently scheduling surgical intervention. In this project endeavour, a solution is presented to automate the cataract grading process utilizing slit lamp bio-microscope data sets acquired through smartphones. This innovation is particularly valuable for novice practitioners and non-specialist doctors/experts who may struggle with proficiently interpreting cataract progression, leading to potential misdiagnoses. To address this challenge, a Neural Network model is harnessed to automatically predict the grade of cataracts. The study employs multi-class image classification models, including the Convolutional neural network (CNN) model, the Efficient Net B0 model, and the ResNet50 model, for this purpose. Notably, the ResNet50 model outperforms the other models in terms of accuracy and prediction capability for the provided data set. Achieving an accuracy rate of 0.8611, the ResNet50 model demonstrates superior performance in classifying cataract grades, after augmenting the data set with 544 images. This performance comparison establishes the ResNet50 model as the most robust choice among the considered models and data sets.*

Keywords: *Cataract grading, CNN model, Efficient net B0 model, Multi-class classification, ResNet50, Slit lamp Bio-microscope images.*

Introduction

The human eye in its adult form takes on a nearly spherical shape. Its anatomical structure comprises three distinct layers: the outer sclera, the middle choroid, and the inner retina. Within the eyeball, a transparent crystalline lens is positioned, securely anchored by ligaments connected to the ciliary body.

Cataract is characterized by the presence of opacity in the typically transparent lens of the human eye. Cataracts are one of those eye disorders that lead to blindness if not treated correctly and quickly [9]. However, cataract grade classification is necessary to control risk and avoid blindness [6]. In the majority of cataract cases, this condition progresses gradually over several years. The primary manifestation of cataracts is a decline in visual clarity, akin to viewing the world through a misted window. When an individual develops a cataract that interferes with their daily activities, the cloudy lens can be substituted with a clear synthetic lens. This procedure is generally conducted on an outpatient basis and is considered safe. Decision-making for cataract surgery is a major challenge for clinicians [7]. The principal catalyst for cataract development is the deterioration of proteins and fibres within the lens, leading to a blurred or obscured field of vision. Cataract early detection and treatment could greatly reduce the risk of deterioration and blindness [4]. According to the NPCB (National Program for Control of Blindness) survey, a considerable backlog of over 22 million blind eyes (representing 12 million individuals with blindness) exists in India, with cataracts being accountable for 80.1% of these cases. The paper [8] utilizes the visibility cue by proposing grey-level image gradient-based features for automatic grading of nuclear type of cataract. Along with the development of information technology, computer-aided healthcare by integrating medical devices and healthcare information systems to improve healthcare quality and productivity is getting more and more attention [1]. Advances in computing and AI technology have promoted the development of connected health systems, indirectly influencing approaches to cataract treatment [10].

The aim is to develop an automated system for categorizing cataracts using a data set obtained from slit lamp bio-microscope examinations. This solution is intended to assist novice or non-specialist medical practitioners who may struggle with accurately grading cataracts. The grading of cataracts through slit lamp evaluations remains relatively uncharted territory, and the resulting system could be especially valuable for enhancing diagnostic capabilities in primary health centres, clinics, hospitals, and during large-scale eye screening events. A clinician needs a quick, easy grading system which will help to guide surgical decisions and parameters [5]. Automatic cataract grading can help the government assist the poor population more accurately [11]. In any screening or telemedicine program, misclassification results create unnecessary referral and burden to the healthcare system [12] and the proposed method addresses this problem.

Materials and methods

High level architecture

Fig. 1 illustrates the overarching architecture, encompassing elements such as the data set, data labelling, image pre-processing, data augmentation, and the neural network models utilized for cataract grading.

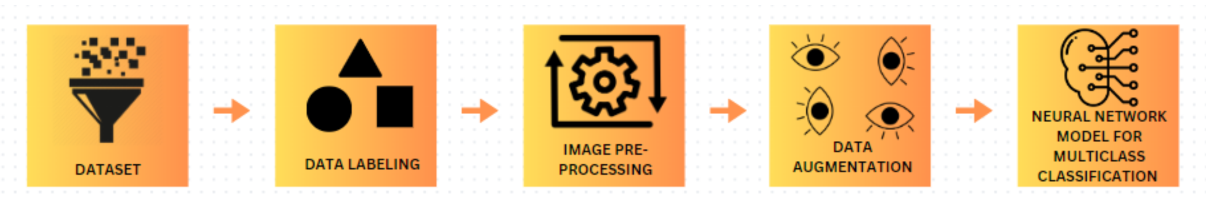


Fig. 1 High level architecture of the proposed methodology

Data-set information

The dataset is sourced from the Department of Ophthalmology at K. C. General Hospital in Bengaluru. This study has collected an extensive compilation of 136 slit lamp images. These images were acquired using a smartphone camera, capturing them through the eyepiece of the slit lamp bio-microscope device. All the slit lamp images sourced from the hospital are authenticated as cases of cataract disease by the experts.

Data labelling

Data labelling involves the task of identifying and affixing labels to unprocessed data, encompassing various formats like images, videos, text, and audio. This labelling process serves to facilitate the model's learning by providing clear annotations. To streamline this process, a user interface (UI) has been designed, allowing the dataset to be labelled manually under the guidance of medical professionals and experts. The UI is developed specifically for this project using PyQt, a Python (programming language) module that allows to building of Graphical User Interface applications. This UI has been developed with the specific goal of expediting the labelling process and minimizing time consumption.

Fig. 2 provides an initial view of the UI upon its launch, indicating its purpose as "Data labelling for cataract grading". The UI prominently displays several buttons, as depicted.

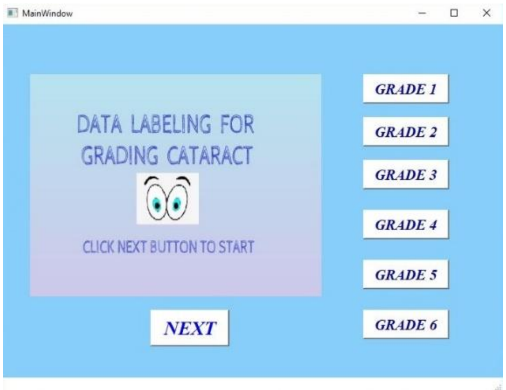


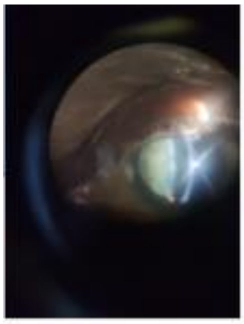
Fig. 2 Screenshot of the first page of the UI

Fig. 3 portrays the UI showcasing slit lamp bio-microscope images. These images are sequentially presented as the NEXT button is clicked. When an image is shown, the user has the option to select a grade. For instance, if the GRADE 3 button is chosen, the corresponding image will be stored in a distinct folder within the local storage named GRADE 3. Similarly, selecting the GRADE 5 button will lead to the image being stored in a separate local storage folder named GRADE 5.

Upon completion of the data labelling procedure, the dataset statistics are as follows: GRADE 1 comprises 11 images, GRADE 2 – 16 images, GRADE 3 – 23 images, GRADE 4 – 34 images, GRADE 5 – 28 images, and GRADE 6 – 24 images.

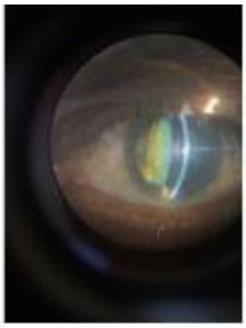
Fig. 3 Working screenshot of UI

Fig. 4 displays the sample data representing each of the grades of cataracts. As depicted in Fig. 4, the grading is determined by the progress of opacification of the lens leading to cataracts. Fig. 4 illustrates observable changes in the central region of the lens, from GRADE 1 to 6.



a) GRADE 1 of cataract

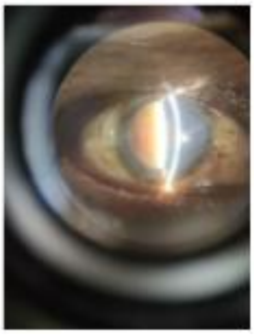
b) GRADE 2 of cataract



c) GRADE 3 of cataract

d) GRADE 4 of cataract

e) GRADE 5 of cataract



f) GRADE 6 of cataract

Fig. 4 Sample data for all 6 grades of cataract

Image pre-processing

The image pre-processing phase involves the execution of the following operations:

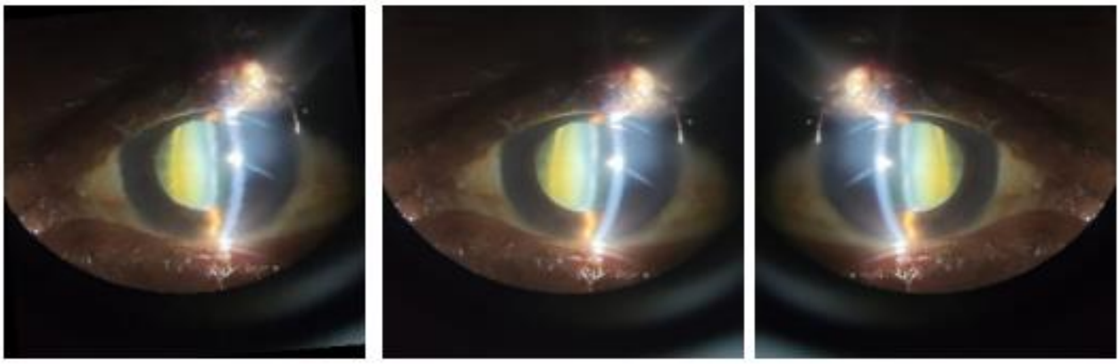
- Cropping operation: The original image is cropped to obtain the region of the cataract. The reason for utilizing this operation is to remove the unnecessary blank regions in the surroundings apart from the region of interest.
- Resizing operation: The cropped image is resized to the dimension of 256×256. Since the acquired images from a smartphone are not of the same dimensions, resizing to a fixed dimension.

This resized image is then utilized as input for the subsequent stages of the models.

Data augmentation

Various image processing techniques have been applied in the project to augment the data set, including operations namely horizontal flipping, rotating by 5 degrees, and adjusting brightness by 5 units. The original image is acquired from the smartphone at a specific position. The reason to perform data augmentation is to increase the data size for training the model and suppose if the acquired image is flipped (right or left eye) or slight rotation of smartphone position while acquiring the image or variation in the light intensity in the surroundings, the model should be trained enough to provide the correct result. Following the data augmentation process, the cumulative number of images employed for training the models amounts to 544 (comprising 136 original images, 136 horizontal flip images, 136 rotated images, and 136 images with adjusted brightness).

Fig. 5 illustrates the three data augmentation operations employed, which include a 5-degree rotation, a brightness increase of 5 units, and a horizontal flip.



a) b) c)

Fig. 5 Rotation of 5-degree image (a), brightness increased image (b), and horizontally flipped image (c)

Neural network models for cataract grading

Multi-class classification refers to a classification task within the domains of machine learning and deep learning, involving the categorization of data into more than two distinct output classes. The final assignment of an input is determined by identifying the class with the highest probability. In the scope of this study, three models have been taken into account: the CNN model, the Efficient Net B0 model, and the ResNet50 model. Both the Efficient Net and ResNet models share a fundamental convolutional neural network (CNN) architecture. This project involves comparing the results of a basic CNN architecture with the advanced architectures of Efficient Net and ResNet.

Convolutional neural network model

A CNN belongs to the category of neural network architectures within Deep learning (DL) and finds widespread application in the field of Computer vision. A CNN is composed of several layers, including the input layer, the convolutional layer, the pooling layer, and fully connected layers. CNN models are mainly used for classification tasks [3].

Efficient Net B0 model

Efficient Net B0 is a CNN that has been trained on an extensive collection of images from the ImageNet database. This network is configured to accommodate input images with dimensions of 224×224 pixels. Efficient Net is a CNN that uses a scaling method called compound scaling that aims to improve the efficiency of an existing ConvNet [13]. The Efficient Net approach involves commencing with a foundational network (N) and subsequently expanding the network's length (L), width (C), and resolution (W, H) while preserving the core architecture. This expansion necessitates a uniform scaling of all layers using a consistent ratio.

ResNet50 model

The ResNet architecture is considered to be among the most popular CNN architectures around [14]. ResNet, short for Residual neural network, represents a distinct category within the CNN framework. ResNet50, a specific variant, entails a CNN comprising 50 layers, including 48 convolutional layers, one MaxPool layer, and one average pool layer. ResNet constitutes a subset of artificial neural networks (ANNs) constructed through the assembly of residual blocks. The ResNet architecture adheres to two foundational design principles:

1. The quantity of filters within each layer remains consistent, contingent upon the desired output feature map size.
2. In scenarios where the feature map's dimensions are reduced by half, the number of filters is doubled to maintain the time complexity of each layer.

In [2], the pre-trained ResNet50 model is used for 2-class and 3-class classification with maximum accuracy of 99.9% and 97.3%, respectively.

Table 1 displays the details of CNN, Efficient Net B0 and ResNet50 models. The details of each model provided are input image size, weights used, total number of convolution layers, number of filters at each convolution layer, pooling layer and activation functions.

Table 1. Details of CNN, Efficient Net B0, and ResNet50 models

Models	**CNN**	**Efficient Net B0**	**ResNet50**
Input image size	(256, 256, 3)	(224, 224, 3)	(224, 224, 3)
Weights	none	none	'Imagine'
Convolution layers	3	1	6
Number of filters at each convolution layer (in order from 1st to last layer)	128, 64, 32	128	64, 128, 256, 512, 1024, 2048
Pooling layer	Max Pooling with (2, 2) size	None	Average Pooling with (2, 2) size
Activation function at convolution layer	'relu'	'relu'	'relu'
Activation function at classifier	'softmax'	'softmax'	'softmax'

Results and discussion

Comparative results of CNN, Efficient Net B0 and ResNet50 models

All 3 models adhere to common parameters which include the use of Rectified Linear Unit (Relu) activation function, Max Pooling and Adam optimizer.

CNN model contains 3 layers with convolution layer size starting with 128. The Efficient Net B0 model contains one layer with a convolution layer size of 3. The ResNet50 model contains 5 layers with a convolution layer size of 64.

Accuracy and loss of training and testing dataset

Table 2 displays the epochs, training, and testing accuracy, as well as the training and testing loss metrics for the CNN, Efficient Net B0, and ResNet50 models. Analysis of the provided table leads to the observation that the ResNet50 model achieves notably superior accuracy with a reduced number of epochs in comparison to the other models.

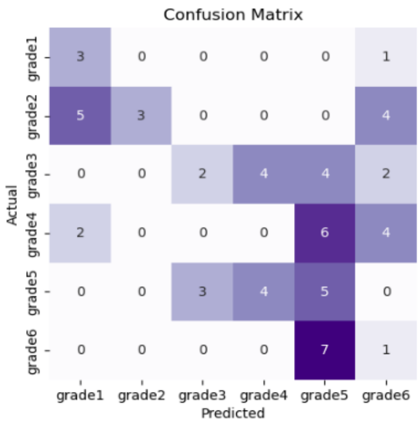
Table 2. Epochs, accuracy and loss of CNN, Efficient Net B0 and ResNet50 models

Models	**CNN**	**Efficient Net B0**	**ResNet50**
Epochs	30	60	7
Training accuracy	0.9602	0.9460	1.000
Training loss	0.2162	0.1714	0.0669
Testing accuracy	0.2333	0.4667	0.8611
Testing loss	13.5937	2.2015	0.3701

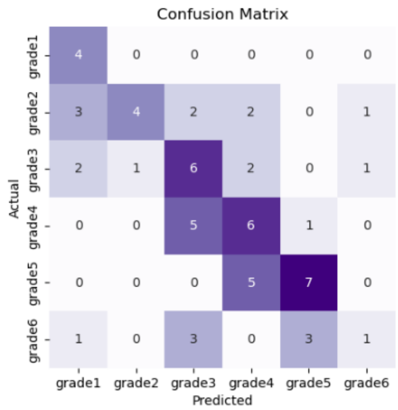
Confusion matrix

A confusion matrix is a matrix with dimensions $m \times m$, employed to assess and scrutinise the effectiveness of a classification model, where m represents the number of distinct target classes. This matrix facilitates a comparison between the authentic or true target values and the predictions made by the machine learning or deep learning model.

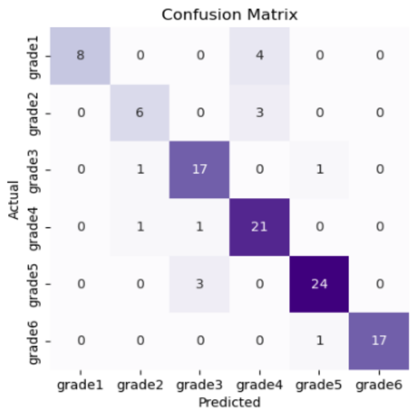
Fig. 6 illustrates the confusion matrices encompassing the classes ranging from grade 1 to grade 6 for the CNN model, Efficient Net B0 model, and ResNet50 model.



a) CNN model



b) Efficient Net B0 model



c) ResNet50 model

Fig. 6 Confusion matrices

Based on the provided confusion matrix data, it can be deduced that the ResNet50 model exhibits a higher count of true positives and true negatives, signifying accurate predictions. Furthermore, the ResNet50 model demonstrates fewer incorrect predictions, indicated by the lower values of false positives and false negatives. This places the performance of the ResNet50 model in a relatively superior position when compared to both the CNN model and the Efficient Net B0 model.

Multi-class classification report

The confusion matrix metrics encompass accuracy, precision, sensitivity, specificity, and F1-score. The formulae and definition for these metrics are mentioned in the below table as shown.

Table 3 represents the different formulae derived from true positives (TN), true negatives (TN), false positives (FP) and false negatives (FN) to obtain accuracy, sensitivity/recall, specificity, precision and F1-score.

Table 3. Table of parameters with respective formulae and definition

Parameters	Formulae	Definition
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Accuracy measures how frequently the classifier makes the correct prediction. The ratio between the number of correct predictions and the total number of predictions is accuracy.
Precision	$\frac{TP}{TP+FP}$	Precision can be defined as the total number of correctly classified positive classes divided by the total number of predicted positive classes.
Sensitivity or recall	$\frac{TP}{TP+FN}$	Recall or sensitivity is defined as the total number of correctly classified positive classes divided by the total number of positive classes.
Specificity	$\frac{TP}{TN+FP}$	Specificity is the number of true negatives by all negative outcomes.
F1-score	$\frac{2*Precision*Recall}{Precision+Recall}$	The F1-score is a number between 0 and 1, and is the mean of harmonic recall and precision.

Fig. 7 showcases a screenshot of the multi-class classification report, featuring key metrics such as TP, TN, FP, FN, sensitivity/recall, accuracy, specificity, precision, and F1-score.

The TP means when the actual/true value is positive and the prediction is positive as well. The TN means when the actual/true value is negative and the prediction is negative as well. The FP means when the actual is negative whereas the prediction is positive. The FN means when the actual is positive whereas the prediction is negative.

TP and TN are the correct predictions which is good. But FP are dangerous because actually the patient does not have the disease but the prediction says that the patient has the wrong disease. The patient might undergo unnecessary treatments and diagnosis. Also, the FN are dangerous too because actually the patient has the disease but the prediction says that the patient does not have a disease which is wrong as well. The patient/subject is left untreated and non-diagnosed.

Fig. 7c implies a conclusive observation that the ResNet50 model exhibits superior accuracy and other parameters, contributing predominantly to correct predictions (TP and TN).

	grade1	grade2	grade3	grade4	grade5	grade6
TP	3.000000	3.00	2.000000	0.000000	5.000000	1.000000
TN	49.000000	48.00	45.000000	40.000000	31.000000	41.000000
FP	7.000000	0.00	3.000000	8.000000	17.000000	11.000000
FN	1.000000	9.00	10.000000	12.000000	7.000000	7.000000
Sensitivity or Recall	0.750000	0.25	0.166667	0.000000	0.416667	0.125000
Accuracy	0.866667	0.85	0.783333	0.666667	0.600000	0.700000
Specificity	0.875000	1.00	0.937500	0.833333	0.645833	0.788462
Precision	0.300000	1.00	0.400000	0.000000	0.227273	0.083333
F1 Score	0.428571	0.40	0.235294	NaN	0.294118	0.100000

a) CNN model

	grade1	grade2	grade3	grade4	grade5	grade6
TP	4.000000	4.000000	6.000000	6.000000	7.000000	1.000000
TN	50.000000	47.000000	38.000000	39.000000	44.000000	50.000000
FP	6.000000	1.000000	10.000000	9.000000	4.000000	2.000000
FN	0.000000	8.000000	6.000000	6.000000	5.000000	7.000000
Sensitivity or Recall	1.000000	0.333333	0.500000	0.500000	0.583333	0.125000
Accuracy	0.900000	0.850000	0.733333	0.750000	0.850000	0.850000
Specificity	0.892857	0.979167	0.791667	0.812500	0.916667	0.961538
Precision	0.400000	0.800000	0.375000	0.400000	0.636364	0.333333
F1 Score	0.571429	0.470588	0.428571	0.444444	0.608696	0.181818

b) Efficient Net B0 model

	grade1	grade2	grade3	grade4	grade5	grade6
TP	8.000000	6.000000	17.000000	21.000000	24.000000	17.000000
TN	96.000000	97.000000	85.000000	78.000000	79.000000	90.000000
FP	0.000000	2.000000	4.000000	7.000000	2.000000	0.000000
FN	4.000000	3.000000	2.000000	2.000000	3.000000	1.000000
Sensitivity or Recall	0.666667	0.666667	0.894737	0.913043	0.888889	0.944444
Accuracy	0.962963	0.953704	0.944444	0.916667	0.953704	0.990741
Specificity	1.000000	0.979798	0.955056	0.917647	0.975309	1.000000
Precision	1.000000	0.750000	0.809524	0.750000	0.923077	1.000000
F1 Score	0.800000	0.705882	0.850000	0.823529	0.905660	0.971429

c) ResNet50 model

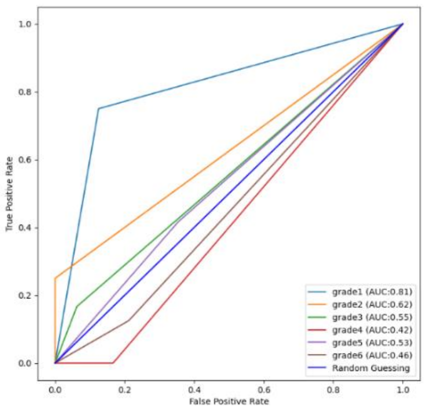
Fig. 7 Screenshots of multi-classification report

Receiver operating characteristic curve

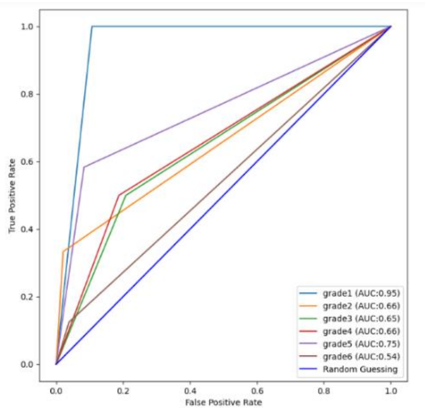
The Receiver Operating Characteristic (ROC) curve is a graphical portrayal that contrasts the True Positive Rate (TPR) against the False Positive Rate (FPR).

Fig. 8 displays a captured image of the ROC curve for the CNN model, Efficient Net B0 model, and ResNet50 model. The probability of any model that an actual positive will test positive is called TPR (TPR = TP / (TP + TF)). The probability of any model that a positive result will be given when the true value is negative is called FPR (FPR = FP / (FP + TN)). The ROC curve shows the separability of the classes by all possible thresholds or in other words, how well the model is classifying each class. Upon analysing the graphs depicting the relationship between TPR and FPR, it is evident that the ResNet50 model showcases superior performance, as evidenced by the provided area under the curve (AUC) values. Notably, the ResNet50 model attains the highest AUC value for GRADE 6.

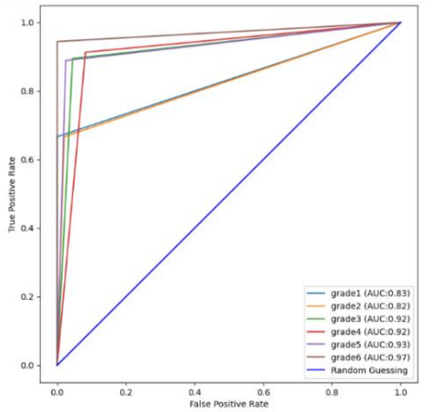
 doi: 10.7546/ijba.2024.28.2.000959



a) CNN model



b) Efficient Net B0 model



c) ResNet50 model

Fig. 8 Screenshots of ROC curves

Conclusion

Cataract is a condition characterized by the clouding of the eye's otherwise clear lens. Timely detection and diagnosis during the initial stages are crucial for effective treatment and management. The process of assigning labels to raw data, including images, videos, text, and audio, to facilitate the model's learning is known as data labelling. To accomplish this, a user-friendly interface has been developed, allowing manual labelling of the dataset with the assistance of medical professionals. The creation of this UI serves to optimize the labelling process and minimize time expenditure.

Subsequently, the data undergoes image pre-processing, a pivotal phase aimed at enhancing the model's training efficacy. Data augmentation becomes imperative in scenarios of limited data set availability, and it contributes to improved model training by accounting for variations in image capture angles, lighting conditions, and distinctions between left and right eyes.

A contrastive analysis has been performed involving three distinct models for multi-class image classification, specifically the CNN model, the Efficient Net B0 model, and the ResNet50 model. The results indicated that the ResNet50 model achieved superior predictive outcomes in terms of accuracy. This superiority could potentially be attributed to the consistent number of filters in each layer, which is determined by the output feature map size, rendering the ResNet model more effective. Additionally, this model demonstrates expedited training and testing periods for the dataset under consideration.

Acknowledgements
Taking immense pleasure in thanking the Department of Medical Electronics Engineering and the Department of Ophthalmology, for guiding, inspiring, and giving opportunity to work on this project. I would like to be grateful and thank our institute for their support in working on the topic of medical image processing and neural networks.

References
1. Guo L., J. J. Yang, L. Peng, J. Li, et al. (2015). A Computer-aided Healthcare System for Cataract Classification and Grading Based on Fundus Image Analysis, Computers in Industry, 69, 72-80.
2. Hamlili F. Z., M. Beladgham, M. Khelifi, A. Bouida (2022). Transfer Learning with Resnet-50 for Detecting COVID-19 in Chest X-ray Images, The Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), 25(3), 1458-1468.
3. Kaur P., B. S. Khehra, A. P. S. Pharwaha (2020). Evaluation of Base Networks for Object Classification and Detection, International Journal of Advanced Research in Engineering and Technology (IJARET), 11(12), 3132-3141.
4. Lai C. J., P. F. Pai, M. Marvin, H. H. Hung, et al. (2022). The Use of Convolutional Neural Networks and Digital Camera Images in Cataract Detection, Electronics, 11(6), 887.
5. Mandelblum J., N. Fischer, A. Achiron, M. Goldberg, et al. (2020). A Simple Pre-operative Nuclear Classification Score (SPONCS) for Grading Cataract Hardness in Clinical Studies, Journal of Clinical Medicine, 9(11), 3503.
6. Saju B., R. Rajesh (2022). Eye-vision Net: Cataract Detection and Classification in Retinal and Slit Lamp Images Using Deep Network, International Journal of Advanced Computer Science and Applications, 13(12), 211-221.
7. Son K. Y., J. Ko, E. Kim, S. Y. Lee, et al. (2022). Deep Learning-based Cataract Detection and Grading from Slit-lamp and Retro-illumination Photographs: Model Development and Validation Study, Ophthalmology Science, 2(2), 100147.
8. Srivastava R., X. Gao, F. Yin, D. W. Wong, et al. (2014). Automatic Nuclear Cataract Grading Using Image Gradients, Journal of Medical Imaging, 1(1), 014502-014502.
9. Tawfik H. R., R. A. Birry, A. A. Saad (2018). Early Recognition and Grading of Cataract Using a Combined Log Gabor/Discrete Wavelet Transform with ANN and SVM, International Journal of Computer and Information Engineering, 12(12), 1038-1043.
10. Wan Z. W. M. D., H. A. Mutalib, L. A. Ramlan, A. Hussain, et al. (2022). Towards a Connected Mobile Cataract Screening System: A Future Approach, Journal of Imaging, 8(2), 41.
11. Zhang H., K. Niu, Y. Xiong, W. Yang, et al. (2019). Automatic Cataract Grading Methods Based on Deep Learning, Computer Methods and Programs in Biomedicine, 182, 104978.
12. Zheng C., X. Xie, Z. Wang, W. Li, et al. (2021). Development and Validation of Deep Learning Algorithms for Automated Eye Laterality Detection with Anterior Segment Photography, Scientific Reports, 11, 586.
13. Efficient Net B0 Model Architecture, https://iq.opengenus.org/efficientnet/ (Last Access June 10, 2024).
14. ResNet50 Model Architecture, https://towardsdatascience.com/the-annotated-resnet-50-a6c536034758 (Last Access June 10, 2024).

Likhitha D. Atada, M.Tech.
E-mail: likhitha29atada@gmail.com

Likhitha D. Atada is a highly motivated individual with a strong educational background with an M.Tech. Degree in Biomedical Signal Processing and Instrumentation branch from B. M. S. College of Engineering, B.E. Degree in Medical Electronics from Ramaiah Institute of Technology. Her objective is to secure a role in the healthcare industry where she can provide high-quality solutions while leveraging her expertise in medical image processing and imaging.

Prof. S. Joshi Manisha, M.D.
E-mail: msj.ml@bmsce.ac.in

Dr. Joshi Manisha S. is a highly accomplished Professor with a Ph.D. Degree in Electronics Engineering, specializing in Medical Image Processing and Machine Learning. She earned her M.Tech. Degree in Biomedical Instrumentation Engineering and a B.E. Degree in Electronics Engineering from reputed institutions in India. She has made significant contributions to the field with her research, including publications and a book chapter on diabetic foot assessment using infrared thermography. She has received numerous awards and recognitions for her work, including the SAP Top Performer Award from the Indian Institute of Technology – Bombay and the Karnataka State Innovation Council Award for healthcare innovation.

Dr. A. J. Dayananda
E-mail: daya7979@gmail.com

Dr. Dayananda A. J. is a Senior Specialist Ophthalmologist at the Department of Ophthalmology, K. C. General Hospital, Bengaluru. He is a trusted, patient-focused and experienced practitioner with a long history (rich experience of 27+ years as a doctor) of serving patients by successfully diagnosing, treating and also managing their illnesses and diseases. He also has 7 years of duty in rural health service, as well as experience in the day-to-day management of a busy doctor’s practice surgery. Dr. Dayananda A. J. is an excellent team player and enthusiast, as well as capable leader and staff motivator.