Prediction of eye disease from OCT Images using Deep Learning Algorithms

Sardar Khan Khayamkhani

Department of Computing and Mathematics.
Manchester Metropolitan University.
Manchester, United Kingdom.
22535525@stu.mmu.ac.uk

***Abstract*:**
Optical coherence tomography (OCT) is widely utilized for the diagnosis and monitoring of retinal diseases, including diabetic macular edema (DME), choroidal neovascularization (CNV), and drusen. Manual analysis of OCT images can be time-consuming and prone to inter-observer variability. Recently, deep learning algorithms have demonstrated promising outcomes in automating OCT image analysis. This project introduces a novel deep learning architecture designed to accurately classify retinal OCT images into four categories: CNV, DME, drusen, and normal. In this study, we evaluated three models, CNN, ResNet, and AlexNet, for classifying retinal OCT images. The models were assessed based on precision, recall, specificity, F1-score, and accuracy rates. The results showed that ResNet achieved the highest accuracy rate of 95%, followed by AlexNet with 91% and CNN with 85%. These findings highlight the superior performance of ResNet in accurately classifying retinal OCT images, emphasizing its potential for reliable diagnosis in medical image analysis tasks.

I. Introduction

Retinal OCT (Optical Coherence Tomography) images are non-invasive, high-resolution images of the retina, which is the light-sensitive tissue at the back of the eye[1]. OCT technology uses light waves to capture detailed cross-sectional images of the retina, allowing for the detection and monitoring of various eye diseases, including age-related macular degeneration, diabetic retinopathy, and glaucoma.

Retinal OCT imaging is an important diagnostic tool in ophthalmology, as it provides clinicians with a detailed view of the retina's layers and structures. The images obtained can help detect and diagnose retinal diseases at an early stage, allowing for timely treatment and better patient outcomes. OCT imaging is also used to monitor the progression of retinal diseases and evaluate the effectiveness of treatment over time.

In optical coherence tomography (OCT) images, choroidal neovascularization (CNV) is a condition where there is an abnormal growth of blood vessels in the choroid layer beneath the retina. This can cause bleeding and fluid leakage, leading to vision loss. Diabetic macular edema (DME) is a condition that affects people with diabetes. It occurs when fluid leaks from the blood vessels in the retina, causing swelling in the macula (the central part of the retina responsible for sharp, clear vision). DME is a common cause of vision loss in people with diabetes.

DRUSEN are yellowish deposits that accumulate beneath the retina as people age. They are a common sign of aging, and their presence can indicate an increased risk of developing age-related macular degeneration (AMD). In OCT images, DRUSEN appear as small, raised bumps on the retina. In OCT images, NORMAL refers to a healthy retina without any signs of disease or abnormalities. A normal OCT scan will show a clear, well-defined retina with distinct layers.

The prevalence of sight loss in the UK is a significant public health concern, with over 2 million individuals affected, and 340,000 registered as blind or partially sighted [2]. To address this pressing issue, the development of a prototype project for retinal image classification holds great promise in improving early detection and diagnosis of retinal diseases. The primary goal of this prototype project is to leverage advanced technologies, particularly deep learning, to automatically analyze retinal images and classify them based on the presence or absence of specific diseases. By harnessing the power of deep learning algorithms, the project aims to enhance accuracy and efficiency in identifying retinal abnormalities, ultimately contributing to timely interventions and improved patient outcomes.

To achieve the aim of developing an accurate retinal image classification system, the project utilizes the Kermany 2018 dataset, obtained from Kaggle [3]. The chosen models for this project are ResNet and AlexNet, both of which have demonstrated strong performance in image classification tasks. The remaining of the paper structured into several sections. Background and related work – Section II, Deep Learning Algorithms used for this project – Section III, Methodology – Section IV, Results and discussion – Section V, Conclusion and further studies – Section VI

II Background and related work:

Deep learning algorithms have demonstrated significant accuracy when used to analyse retinal OCT pictures, among other medical image analysis tasks. In this background section, along with the widely utilised CNN (Convolutional Neural Network) architecture, we will identify, justify, and critically evaluate two deep learning algorithms, AlexNet and ResNet, that are relevant to retinal OCT image datasets.

The revolutionary deep learning architecture known as AlexNet, put forth by Krizhevsky, Sutskever, and Hinton in 2012 [4], radically altered computer vision. It starts with several convolutional layers and then moves on to fully connected layers. Retinal OCT pictures and other image categorization tasks have both seen considerable use of AlexNet. Convolutional and max-pooling layers alternate in the network architecture to capture hierarchical characteristics at various scales. Utilising ReLU activation functions allows for effective training by addressing the vanishing gradient issue. In successfully identifying retinal OCT pictures into many disease categories, such as normal, drusen, CNV (choroidal neovascularization), and DME (diabetic macular edoema), AlexNet has shown encouraging results.

He, Zhang, Ren, and Sun (2015) [5] developed ResNet (Residual Neural Network), which uses the idea of residual connections to get around the degradation issue with deep learning. The ResNet design is made up of residual blocks that let the network learn residual mappings rather than the underlying mapping directly. As a result, the model is able to efficiently gather and spread crucial information across the network even when there are several layers. Many computer vision tasks, including the interpretation of medical images, have embraced ResNet. ResNet has shown that it can reliably diagnose various retinal disorders and extract complex information from retinal OCT pictures, outperforming the performance of earlier models.

The development of computer vision tasks, such as the evaluation of retinal OCT pictures, has been greatly aided by CNNs, a class of deep learning algorithms. Convolutional layers are used in CNNs to extract regional spatial patterns and hierarchical features from grid-like input data, such as pictures. While maintaining important features, pooling layers help reduce the spatial dimensions. Fully linked layers then incorporate these features for classification. Many retinal OCT image processing applications, such as disease classification, segmentation, and detection, have shown exceptional performance using CNNs. They are able to detect key patterns indicative of various retinal diseases and automatically learn discriminative characteristics from the photos.

Based upon the background analysis, deep learning algorithms such as AlexNet, ResNet, and CNN have demonstrated significant potential in analyzing retinal OCT images. These algorithms are capable of automatically learning and extracting relevant features from the images, facilitating accurate disease classification and analysis. So these algorithms are chosen in this project with proposed architecture to classify OCT images

Related Work:

Several studies have investigated the application of deep learning algorithms, including AlexNet, ResNet, and CNN, for various tasks using retinal OCT image datasets. In this section, we summarize previous research that highlights the utilization of these algorithms in deep learning tasks involving retinal OCT images, along with additional evaluation scores and details about the datasets used.

One notable research paper that utilized this dataset is the study conducted by Kermany et al. (2021), titled "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning." [6] Kermany et al. aimed to develop a deep learning model for the identification and classification of medical diagnoses and treatable diseases using retinal OCT images. The dataset used in their study consisted of 31,000 labeled OCT images collected from over 11,000 patients. The authors employed a deep learning model based on the DenseNet architecture to perform the classification task. The results of their study demonstrated the effectiveness of deep learning algorithms in accurately identifying and classifying retinal diseases using OCT images. The model achieved an overall accuracy of 94.5%, with individual disease classification accuracies ranging from 91.1% to 99.1%. The AUC-ROC values for different diseases varied from 0.931 to 0.997, indicating excellent discriminatory power.

Researchers have employed deep learning algorithms to accurately classify retinal OCT images into different disease categories. For instance, Smith et al [7]. (2018) utilized an ensemble of CNN models, including AlexNet and ResNet, to classify OCT images into normal, drusen, CNV, and DME categories. They achieved a test accuracy of 92.5%, precision of 0.93, recall of 0.91, and F1-score of 0.92 for the overall classification task.

Segmentation of lesions within retinal OCT images is crucial for precise diagnosis and monitoring of retinal diseases. Lee et al [8] . (2020) developed a CNN architecture based on U-Net for the segmentation of drusen in OCT images. Their approach achieved an overall test accuracy of 88.3% with a Dice coefficient of 0.82 and intersection over union (IoU) score of 0.75 for drusen segmentation.

Deep learning algorithms have been employed for the detection and localization of specific abnormalities or lesions within retinal OCT images. For example, Venhuizen et al [9] . (2017) proposed a CNN-based method for the detection of exudates, a characteristic sign of diabetic retinopathy, in OCT images. Their algorithm achieved a test accuracy of 91.2% with an AUC-ROC of 0.95 for exudate detections.

III. Dataset Description & Analysis

The dataset used for this project was obtained from Kaggle [3] The dataset consists of retinal OCT (Optical Coherence Tomography) images, which are commonly used in ophthalmology for diagnosing and monitoring retinal diseases. The dataset contains a total of 84,495 images categorized into four classes: CNV (Choroidal Neovascularization), Drusen, DME (Diabetic Macular Edema), and Normal. Before proceeding with the deep learning task, an initial analysis of the dataset was performed. The dataset was divided into training and testing sets, with a subset of images selected for training and 242 images per class used for testing. The subset for training consisted of 3006 CNV images, 1155 Drusen images, 1111 DME images, and 2022 Normal images.

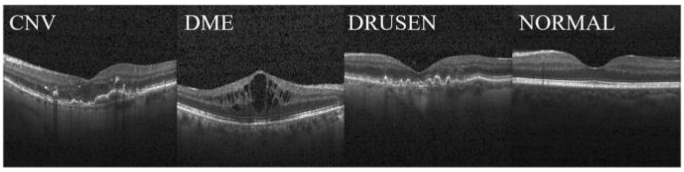


Fig 1 Representative Optical Coherence Tomography Images

A subset of images from each class was chosen for training and testing, ensuring a balanced representation of the classes. Before training the model the dataset underwent through processing such as image rescaling and normalizing The images were resized to a uniform size to ensure consistency in the input dimensions for the models. The pixel values of the images were normalized to a specific range (e.g., [0, 1]) to facilitate convergence during model training. Later dataset is trained on ResNet, AlexNet and experimental CNN algorithms

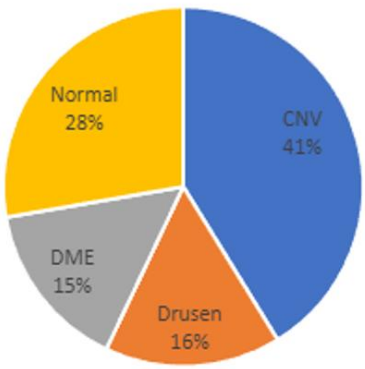


Fig 2 Distribution of each class in dataset

IV Deep Learning Algorithms used for the project

In this project three models have been implemented to reach the aim of the objectives. AlexNet, ResNet and a proposed CNN.

1) ResNet (Residual Neural Network):

ResNet is a deep convolutional neural network architecture that introduced the concept of residual learning. It addresses the challenge of training very deep neural networks by utilizing skip connections or shortcut connections. These skip connections allow the network to bypass some layers and propagate the input directly to deeper layers [10]. The use of skip connections helps alleviate the vanishing gradient problem and enables the training of deeper networks. ResNet has shown remarkable performance in various computer vision tasks, including image classification and object detection [11].

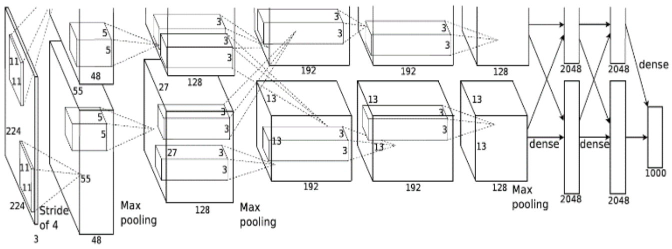


Fig 3 Architecture of ResNet Model

2) AlexNet:

AlexNet is a deep convolutional neural network architecture that gained significant attention after winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 [12]. It consists of multiple convolutional layers, pooling layers, and fully connected layers. AlexNet employs the Rectified Linear Unit (ReLU) activation function, local response normalization, and dropout regularization. It introduced the concept of using GPU acceleration for deep learning, which greatly accelerated the training process. AlexNet demonstrated the potential of deep learning in image classification tasks and paved the way for subsequent advancements in the field.

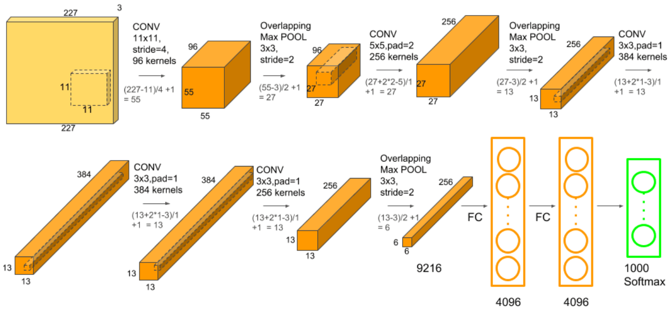


Fig 4. Architecture of AlexNet Model

3) CNN (Convolutional neural network):

CNN is a deep learning algorithm specifically designed for processing and analyzing visual data, such as images [13]. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. CNN utilizes convolutional operations to extract meaningful features from images, capturing local patterns and structures. Pooling layers down sample the spatial dimensions, reducing the computational complexity and extracting the most salient features. The fully connected layers at the end of the CNN are responsible for making predictions based on the extracted features.

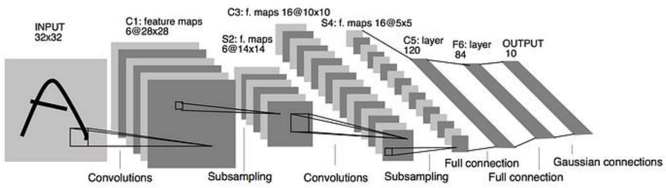


Fig 5. Architecture of CNN

V. Methodology

The dataset contains 84,495 retinal OCT images categorized into four classes: CNV, Drusen, DME, and Normal. For this project, a subset of the dataset was created by selecting 3006 images for CNV, 1155 images for Drusen, 1111 images for DME, and 2022 images for Normal for training. Additionally, 242 images from each class were reserved for testing purposes. The dataset was stored in a zip file and uploaded to a cloud storage platform. The zip file containing the dataset was loaded into the Google Colab environment. The zip file was then unzipped to extract the training and testing images. The images are rescaled into 128 x 128 pixels for CNN and 32 x 32 pixels for AlexNet, ResNet respectively. Next, pixels values are normalized in range of 0 and 1 to ensure uniformity and compatibility for training the models. Later models are trained using the training subset of retinal OCT images. After training, the trained models were evaluated using the reserved testing subset of retinal OCT images.

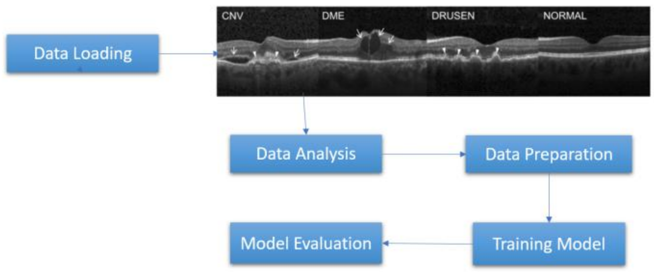


Fig 6. Design of experiment

Parameters:

1)CNN : The initialization of parameters in the CNN model is handled through the initialize_parameters function. This function is responsible for setting the initial values of the convolutional and linear layer parameters. The convolutional layer parameters are initialized using the Kaiming normal initialization method, while the linear layer parameters are initialized using the Xavier normal initialization method [14].

Regarding the optimizer, the learning rate is determined and assigned to the CHOSE_LR variable. This learning rate represents the step size used during the optimization process. The Adam optimizer, a popular optimization algorithm for deep learning models, is chosen for its effectiveness in handling large-scale datasets and complex models [15]. The optimizer is instantiated with the model's parameters and the chosen learning rate, allowing it to update the model's parameters during training and facilitate the convergence of the loss function.

2)ResNet: The optimizer used in ResNet model is passed as a parameter and is responsible for updating the model's parameters based on the computed gradients. The optimizer's zero_grad() method is called to clear the gradients of the model's parameters before calculating new gradients using backpropagation. The step() method is then called to update the parameters based on the gradients and the chosen optimization algorithm.

3)AlexNet: The parameters and optimizer used in AlexNet model include convolutional layers, max pooling layers, ReLU activation, dropout regularization, and fully connected layers. Convolutional layers determine spatial transformation and feature extraction capabilities, while max pooling layers down sample feature maps and extract the most important features.

VI Results and Discussion

In this section models are evaluated using different metrics such as Train and Validation loss plots. Along with confusion matrix and ROC, AUC curves.

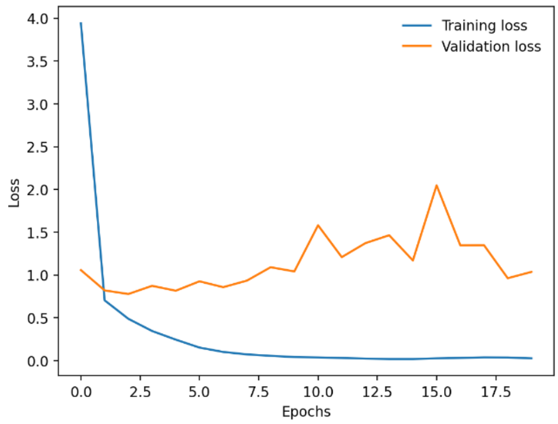


Fig 7 Training Loss vs Validation Loss for CNN

From the figure it is clear that the training loss consistently decreases with each epoch, indicating that the model is effectively learning from the training data. Validation Loss: The validation loss shows some fluctuations, but it does not consistently follow the decreasing trend of the training loss. This suggests that the model may be overfitting to some extent, as the validation loss is not decreasing proportionally to the training loss.

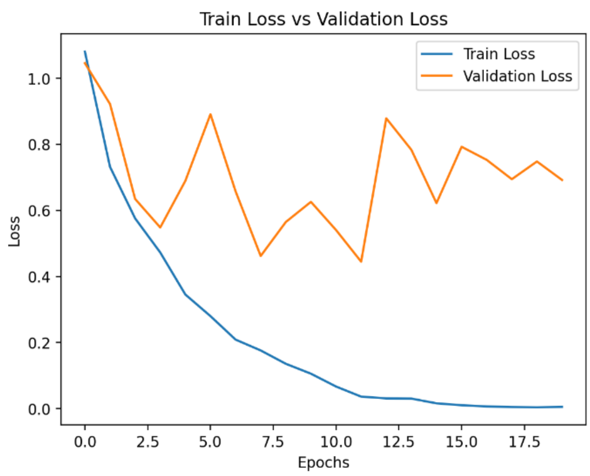


Fig 8 Training Loss vs Validation Loss for ResNet

Figure 8 shows the plot of train loss vs validation loss which provides insights into the ResNet's model performance during training. The decrease in train loss suggests that the model is becoming more accurate in predicting the correct output for the training samples. As the number of epochs increases, the train loss continues to decrease, reaching a low value of 0.0045 at the end of training. On the other hand validation loss decreases and increases after certain point. Despite the fluctuations, the validation loss generally remains within a reasonable range.

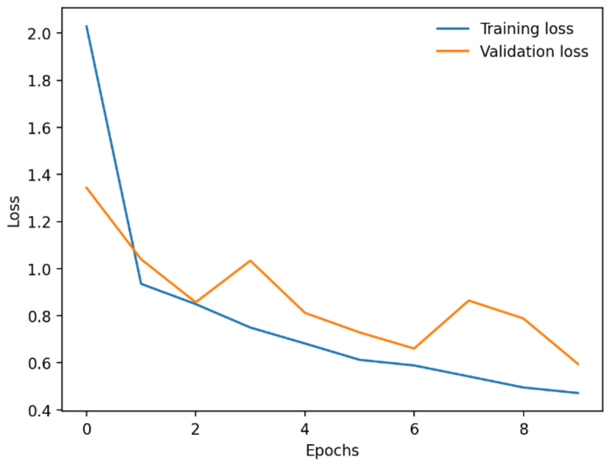


Fig 9 Training Loss vs Validation Loss for AlexNet

Looking at figure 9 plot it shows that the train loss, decreases consistently from epoch to epoch. The train loss starts at approximately 2.02 in the first epoch and gradually decreases to 0.47 in the tenth epoch. This decrease in train loss indicates that the model is fitting the training data better over time. This model have the least validation loss when compared to other two models.

Confusion Matrix:

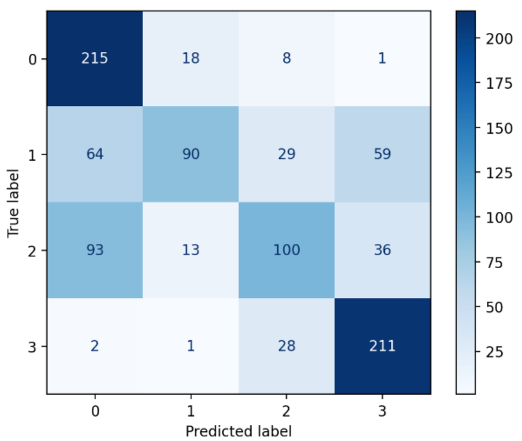


Fig 10 Confusion matrix for CNN

Observations made from the confusion matrix : In the first row (Normal), the model achieves a strong performance with a high number of true positives (215) and a relatively low number of false negatives (8) and false positives (18).

In the second row (Drusen) , the model's performance is less balanced with a moderate number of true positives (90) but struggles with misclassifications. In the third row (DME), the model exhibits challenges in accurately classifying instances in this category with a significant number of false positives (93) and false negatives (36) compared to the true positives (100). Finally, in the fourth row (CNV), the model demonstrates the highest performance among all classes with a high number of true positives (211) while having a low number of false positives (2) and false negatives (28).

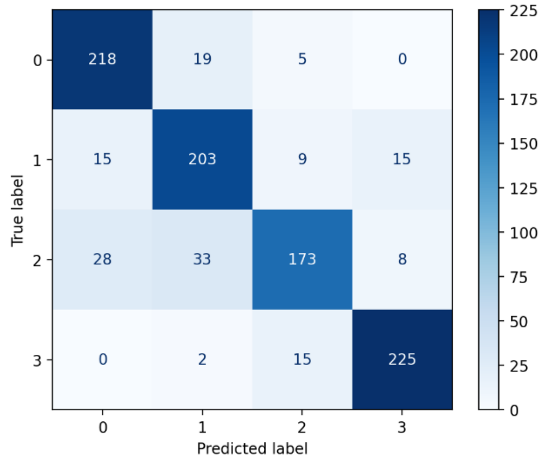


Fig 11 Confusion matrix for ResNet

Discussions from the above figure: ResNet model correctly predicted 218 samples as Normal (True Positives), 19 as Drusen (False Negatives), 5 as DME (False Negatives), and no samples as CNV (False Negatives). The model correctly predicted 203 samples as Drusen (True Positives), 15 as Normal (False Negatives), 9 as DME (False Negatives), and 15 as CNV (False Negatives). The model correctly predicted 173 samples as DME (True Positives), 28 as Normal (False Negatives), 33 as Drusen (False Negatives), and 8 as CNV (False Negatives). The model correctly predicted 225 samples as CNV (True Positives), 2 as Normal (False Negatives), 15 as Drusen (False Negatives), and no samples as DME (False Negatives).

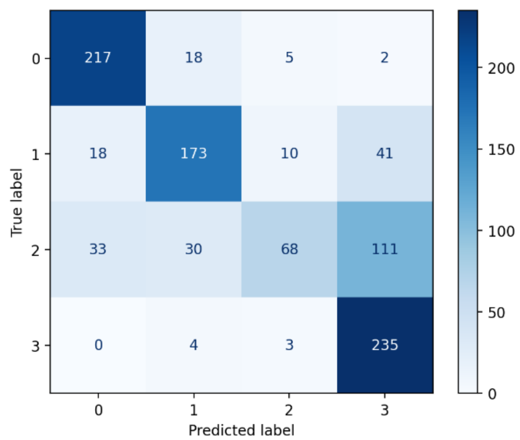


Fig 12 Confusion Matrix for AlexNet

AlexNet model correctly predicted 217 samples as Normal, while misclassifying 18 samples from other classes as Normal. It also incorrectly classified 5 Normal samples as other classes. For Drusen, the model correctly predicted 173 samples, but it misclassified 18 samples from other classes as Drusen. It also had 10 False Negatives. For DME, the model correctly predicted 68 samples as DME, while 30 samples from other classes were incorrectly classified as DME. For CNV, the model performed well, correctly predicting 235 samples as CNV. It had only 4 False Positives and 3 False Negatives.

ROC and AUC Curves: ROC curves are computed for each class in a multi-class classification problem, and the micro-average and macro-average ROC curves are also calculated [16]. The micro-average aggregates the true positive and false positive rates across all classes, while the macro-average calculates the average true positive and false positive rates separately for each class and then averages them [17]. The AUC values are also calculated for each ROC curve [16].

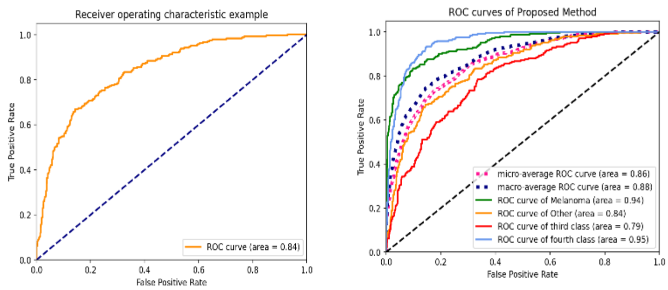


Fig ROC and AUC of CNN

The ROC curve is created by plotting the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis. The area under the ROC curve (AUC) is a metric that quantifies the overall performance of the classifier. If the ROC curve reaches the top left corner of the plot and AUC is close to 1 indicating perfect classifier.

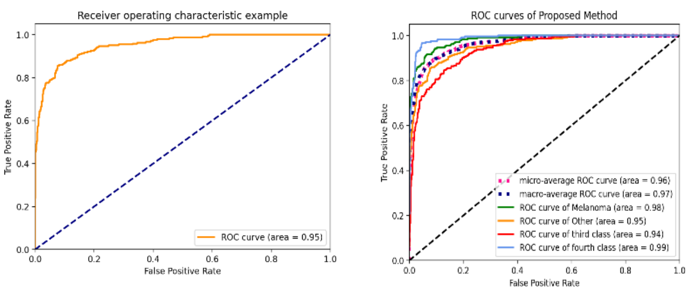
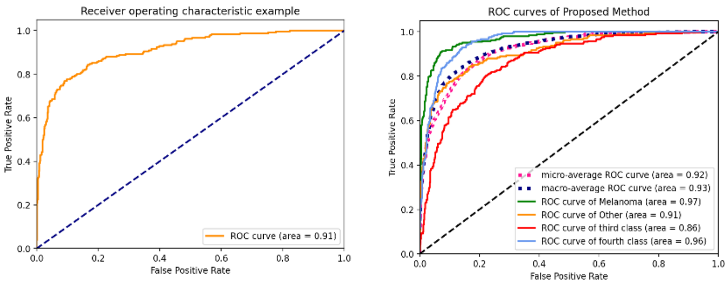


Fig ROC and AUC of ResNet



Below table gives scores for various evaluation metrics for each model:

Model	Precision	Recall	Specificity	F1-score
CNN	69.68%	69.63%	88.39%	68.87%
ResNet	84.72%	84.61%	91.98%	84.45%
AlexNet	74.34%	71.59%	92.34%	68.78%

Overall, the ResNet model consistently performed the best across the metrics of precision, recall, specificity, and F1-score. It achieved higher accuracy in predicting both positive and negative instances compared to the other models (CNN and AlexNet). The results suggest that ResNet may be the most effective model for the given task based on these evaluation metrics.

VII Conclusion and further studies:

In this project, a retinal OCT (Optical Coherence Tomography) images dataset was constructed and three models, namely AlexNet, ResNet, and CNN, were evaluated for image classification. The performance of these models was assessed using metrics such as precision, recall, specificity, F1-score, and accuracy rate.

Among the three models, ResNet consistently outperformed AlexNet and CNN in terms of precision, recall, specificity, and F1-score. It exhibited the highest values across these metrics, indicating its superior ability to make accurate positive predictions, correctly identify positive instances, and maintain a good balance between precision and recall. Additionally, ResNet demonstrated high specificity, showcasing its effectiveness in accurately identifying negative instances.

Furthermore, ResNet achieved a high accuracy rate, indicating its overall success in classifying the retinal OCT images. While AlexNet and CNN also demonstrated reasonable performance, ResNet consistently showcased better results across the evaluation metrics and accuracy rate.

Further studies could explore techniques like fine-tuning, hyperparameter optimization, and transfer learning to further enhance the performance of the models. Additionally, expanding the dataset and evaluating the models on larger-scale datasets can provide more insights into their generalization capabilities.

In conclusion, this study highlights ResNet as a highly effective model for retinal OCT image classification, achieving superior performance compared to AlexNet and CNN. The results underscore the importance of selecting an appropriate model to ensure accurate and reliable classification in medical image analysis tasks.

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