

DETECTION OF MULTIPLE OCULAR DISEASES USING MACHINE LEARNING

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Technology degree in Biomedical Engineering

By

Aadhitya S (40240001)



**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A++" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Aadhitya S (40240001)** who carried out the project entitled "**Detection of Multiple Ocular Diseases using Machine Learning**" under my supervision from November 2023 to April 2024.

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ABSTRACT

Vision plays an indispensable role in almost every aspect of life. Unfortunately, various ocular diseases can significantly impair vision, leading to reduced quality of life and even blindness if left untreated. Age-related Macular degeneration, Glaucoma, Cataracts, Hypertensive Retinopathy, and Pathological Myopia are among the most prevalent ocular diseases globally. The integration of machine learning algorithms in ocular disease detection presents a promising avenue for improving early diagnosis and intervention. Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN) and Multi-Layer Perceptron (MLP) networks are among the machine learning algorithms that have been analyzed in this work. Key metrics like accuracy, loss, sensitivity, ROC, AUC, and scalability obtained by training CNN, ANN and MLP models are compared to recommend the highly efficient model. The results showed that CNN has emerged as the best model for ocular disease prediction.

Keywords: Ocular diseases, Machine Learning, CNN, ANN, MLP

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LIST OF ABBREVIATIONS

AMD	-	Age-Related Macular Degeneration
ANN	-	Artificial Neural Network
AUC	-	Area Under the Curve
CA	-	Cataract
CAD	-	Computer-Aided Design
CDR	-	Cup-to-Disk Ratio
CNN	-	Convolutional Neural Network
DKC Net	-	Discriminative Kernel Convolution Network
DR	-	Diabetic Retinopathy
FD	-	Fractal Dimension
FN	-	False Negative
FP	-	False Positive
FPN	-	Feature Pyramid Network
GME	-	Gradient-based Feature Attribution
GL	-	Glaucoma
GUI	-	Graphical User Interface
HR	-	Hypertensive Retinopathy
LS-SVM	-	Least Squares Support Vector Machine
ML	-	Machine Learning

MLP	-	Multi-Layer Perceptron
ODIR	-	Ocular Disease Intelligent Recognition
PM	-	Pathological Myopia
RF	-	Random Forest
ROC	-	Receiver Operating Characteristic
TN	-	True Negative
TP	-	True Positive

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CHAPTER 1

INTRODUCTION

1.1 THE THREAT OF VISION IMPAIRMENT IN INDIA

Vision impairment poses a significant threat to public health in India, with several major eye diseases casting a long shadow. Glaucoma, characterized by damaging optic nerve pressure, affects an estimated 45 million individuals in India, making it a leading cause of irreversible blindness. (Nadim Mahmud Dipu *et al.* 2021) Cataracts, clouding the lens, impact another 62 million, while Hypertensive Retinopathy, stemming from uncontrolled blood pressure, threatens the sight of 22 million Indians. Macular Degeneration, a degenerative disease affecting central vision, is projected to affect 15 million by 2050, and Pathological Myopia, causing extreme nearsightedness, is rapidly rising, especially among urban youth. These numbers are expected to increase exponentially in the coming years, driven by an ageing population, urbanization, and changing lifestyles.

1.2 CHALLENGES OF THE CURRENT SYSTEM

Traditional methods of diagnosing these eye diseases often rely on subjective assessments during eye examinations, leading to potential missed diagnoses and delayed treatment. Additionally, accessibility to qualified ophthalmologists remains a challenge, particularly in rural areas. This results in lost productivity, economic burden, and reduced quality of life for millions of individuals. Machine learning (ML) presents a transformative opportunity to address these limitations. By analyzing fundus images, the digital scans from the back of the eye, ML algorithms can automatically detect subtle morphological and texture changes associated with various eye diseases. (Ouda *et al.* 2022) This objective and quantifiable approach offers several advantages over traditional methods as they provide early detection with improved accuracy and are accessible to a wide range of communities.

CHAPTER 2

LITERATURE SURVEY

2.1 SURVEY

Amit Bhati *et al.* (2023) proposed a Discriminative Kernel Convolution Network (DKC Net) for multi-label ophthalmic disease detection. DKC Net splits a common target label for an eye based on the diagnostic keyword, allowing the model to handle imbalanced datasets effectively. This method can be applied to various backbones for improved disease classification.

Alzami *et al.* (2019) investigated Diabetic Retinopathy (DR) grade classification using fractal dimension (FD) analysis and a Random Forest (RF) classifier. Preprocessing involved vessel segmentation to obtain accurate FD measurements for retinal vasculature characterization. While achieving moderate accuracy, this approach suggests FD may not fully capture retinal images for DR staging.

Ashrafi Akram *et al.* (2020) developed an automated eye disease recognition system using facial images and machine learning techniques. While this approach holds promise for broader applications in facial analysis, it did not directly analyse the retina, the part of the eye most crucial for diagnosing ophthalmic diseases. This limits its applicability in directly detecting eye conditions. However, advancements in facial recognition technology could potentially be adapted for ophthalmology in the future.

Chłopowiec *et al.* (2023) addressed a significant challenge in medical image analysis - class imbalance. In eye disease datasets, some conditions may be far more frequent than others. This can lead to models biased towards diagnosing the common diseases and overlooking the rarer ones. Their method combined transfer learning (leveraging knowledge from pre-trained models) with loss function weighting (giving more weight to under-represented diseases during training) and two-stage learning procedures.

Diaz-Pinto *et al.* (2019) explored using convolutional neural networks (CNNs) pre-trained on a massive dataset of everyday objects (ImageNet) for automatic glaucoma assessment. Training a deep learning model from scratch requires a

significant amount of data and computational power. Their findings suggest that pre-trained models can be fine-tuned for ophthalmic applications, offering a robust alternative for glaucoma screening on fundus images. This approach reduces the time and resources needed to train a model from scratch, while still achieving good accuracy in diagnosing glaucoma.

Farouk *et al.* (2022) focused on iris recognition, a biometric technique that analyses the unique patterns of the iris for security purposes. Their study involved segmenting the iris from the rest of the eye image, detecting sharp transitions in brightness (edges), using CNNs to extract features from the iris, and employing the Hamming Distance metric for classification.

Junjun He *et al.* (2021) presented a method for incorporating clinical attributes into eye disease classification models using knowledge distillation. Their approach involves two deep learning networks: a teacher network extracting information from input images and a student network trained to infer clinical attributes from fundus photos. This knowledge transfer from the teacher network improves the student model's accuracy.

Manyu Li *et al.* (2023) introduced a new approach for detecting pathological myopia, a condition where the eyeball is elongated, using fundus images. Their method leverages a Transformer-based deep learning model, a powerful architecture typically used for natural language processing tasks. In this innovative application, the Transformer is combined with a Feature Pyramid Network (FPN).

Milad Kohzadi Chegeni *et al.* (2023) focused on optimizing a core component of convolutional neural networks (CNNs) - the convolution layer. Convolution layers are responsible for extracting features from images. They investigated optimizing the data dimensions (size of the input to the convolution layer) and the number of remaining layers (layers between the convolution layer and the output) within a CNN architecture.

Nadim Mahmud Dipu *et al.* (2021) explored the potential of advanced neural network architectures for diagnosing eye diseases from retinal fundus images. These models were trained on a dataset of 5000 fundus images containing seven different ocular diseases. The study found that all four models achieved high accuracy in predicting diseases from the training data.

Nagpal *et al.* (2023) proposed a method for detecting diabetic retinopathy (DR) and hypertensive retinopathy using transfer learning. The approach involved pre-processing, segmentation, and feature extraction. Wiener filtering reduced noise, and Otsu thresholding with mathematical morphology performed blood vessel segmentation. Transfer learning facilitated feature extraction and classification for DR and hypertensive retinopathy detection.

Ouda *et al.* (2022) developed a promising Computer-Aided Design system for detecting multiple ocular diseases. Their deep learning approach utilizes a three-phase process: preprocessing, model building, and prediction. In the preprocessing stage, retinal fundus images are prepared for analysis by removing noise and irrelevant information. The model-building phase involves training a Convolutional Neural Network (CNN) with three convolutional layers to identify patterns associated with various eye diseases.

Parashar *et al.* (2020) explored a novel approach for glaucoma diagnosis using a combination of wavelet analysis and Least Squares Support Vector Machine (LS-SVM) modelling. Wavelet analysis is a technique for decomposing signals into different frequency components, allowing researchers to extract specific features from retinal images that may be indicative of glaucoma. The LS-SVM model then uses these features to classify the image as healthy, early-stage glaucoma, or late-stage glaucoma.

Peng *et al.* (2019) introduced Deep See-Net; a deep learning model specifically designed for the automated classification of age-related macular degeneration (AMD) severity from fundus images. AMD is a leading cause of vision loss in older adults. Deep See Net utilizes the power of deep learning to analyse retinal images and classify the severity of AMD into different stages.

Prasad *et al.* (2019) presented a system for diagnosing diabetic retinopathy (DR) and glaucoma, two leading causes of blindness, using a combined approach. Their system leverages the strengths of both random forest and deep learning models. Random forests are ensemble learning methods that combine multiple decision trees, offering robustness and interpretability.

Praveena *et al.* (2019) focused on a segmentation technique for diabetic retinopathy (DR) using super pixels. Super pixels are small image regions that

group pixels with similar features. This approach aimed to improve the detection of multiple lesions, such as microaneurysms and haemorrhages, which are characteristic signs of DR.

Raveenthini *et al.* (2023) proposed a multi-ocular disease detection framework that bridges the gap between traditional and modern machine learning techniques. Their approach combines handcrafted features, which are manually designed by domain experts, with deep-learned features extracted by convolutional neural networks (CNNs). This hybrid approach leverages the strengths of both methods: handcrafted features often capture specific domain knowledge that might be missed by deep learning models, while CNNs excel at identifying complex patterns from large amounts of data.

Sayres *et al.* (2019) investigated using deep learning to improve the interpretability of diabetic retinopathy (DR) diagnosis. Deep learning models, while powerful, can often be like black boxes - their decision-making process is not always clear. Sayres *et al.* addressed this challenge by incorporating integrated gradients, a technique that helps visualize which parts of the retinal image contribute most to the model's prediction.

Shaban *et al.* (2020) focused on developing a deep-learning solution for diabetic retinopathy (DR) analysis. They designed a convolutional neural network (CNN) specifically tailored for the task of screening and staging DR. CNNs are a type of deep learning architecture particularly adept at image recognition. CNN achieved promising results, demonstrating the effectiveness of deep learning for automating various aspects of DR analysis.

Sharma *et al.* (2019) explored the potential of convolutional neural networks (CNNs) for automatic glaucoma diagnosis. Glaucoma is a leading cause of blindness, and early detection is crucial for preventing vision loss. The study investigated using CNNs to analyse retinal fundus images and identify signs of glaucoma. Their model achieved high accuracy, sensitivity, and specificity, suggesting that CNNs hold promise for developing automated glaucoma diagnosis tools.

Shashwat Pathak *et al.* (2022) developed a portable system for cataract detection and grading, addressing a critical need in tele-ophthalmology. Teleophthalmology

refers to the use of telecommunication technology for delivering eye care services remotely. The system analyses multiple texture features in fundus images to detect and grade cataracts.

Siji Thomas *et al.* (2020) designed a portable retinal imaging module with a built-in abnormality detection system. While the specific techniques used are not explicitly mentioned, it likely employs image processing or machine learning algorithms to analyze retinal images and identify potential abnormalities.

Son *et al.* (2020) actively contributed to the expanding field of deep learning for automated eye disease detection. Their research focused on developing deep learning models capable of screening retinal fundus images for multiple abnormalities simultaneously. This approach holds immense promise for improving the efficiency and accuracy of eye disease diagnosis, particularly in settings where access to trained ophthalmologists might be limited.

Tamim *et al.* (2021) explored the potential of combining different machine learning techniques for diagnosing diabetic retinopathy (DR) and glaucoma. Their approach involved using hybrid features, which combine handcrafted features designed by domain experts with features extracted from deep learning models. Additionally, they employed a genetic algorithm, a search optimization technique inspired by biological evolution, to select the most informative features for disease classification.

Xue-Lian Yang *et al.* (2022) introduced Deeply Supervised Residual Attention Convolutional Neural Network, a deep learning model specifically designed for the multi-classification of eight fundus diseases. This model achieved promising results, demonstrating the potential of deep learning for accurate diagnosis of various eye diseases.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

- To harness the power of machine learning to address the limitations of traditional methods for diagnosing ocular diseases.
- To address the issue of missed diagnoses and delayed treatment in eye disease detection, it is important to reduce the reliance on subjective assessments during eye examinations.
- To develop a more objective and accessible system for early and accurate detection of multiple eye diseases.

3.2 SCOPE

- To focus on utilizing machine learning algorithms to analyze digital scans of the back of the eye, known as fundus images.
- To investigate the potential of three specific algorithms: Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Multi-Layer Perceptron (MLP).
- To compare their performance on a publicly available dataset of fundus images, the project aims to identify the most efficient model for accurate disease detection.
- To include evaluating factors like accuracy, loss, sensitivity, ROC curve, AUC, and scalability.
- To specifically focus on five prevalent eye diseases: age-related macular degeneration, cataract, glaucoma, hypertensive retinopathy, and pathological myopia.
- To demonstrate the potential of CNNs for real-time healthcare applications, this project strives to contribute to a future of improved eye care accessibility and accuracy.

CHAPTER 4

MATERIALS AND METHODS

4.1 SOFTWARE USED

4.1.1 PyCharm

PyCharm is a robust integrated development environment designed specifically for Python programming. It offers a wide range of features to enhance developer productivity, including intelligent code completion, syntax highlighting, and error checking. With its powerful debugging tools and built-in version control integration, PyCharm streamlines the development process and helps identify and fix issues efficiently. Its support for various Python frameworks and libraries makes it versatile for different project types, from web development to data science. Additionally, PyCharm provides a customizable interface and extensive plugin ecosystem, catering to the diverse needs of Python developers worldwide.

4.2 METHODOLOGY

This study aims to harness the power of deep learning to address the vision-threatening impacts of prevalent ocular conditions like age-related macular degeneration (AMD), glaucoma, pathological myopia, cataracts, and hypertensive retinopathy. To accomplish this goal, we investigate the potential of various algorithms including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Multilayer Perceptron (MLP) to identify the most effective model for accurately detecting these diseases. By employing image classification and analysis techniques, CNNs, ANNs, and MLPs can categorize images as either normal or abnormal, and even provide severity scores (Alzami *et al.* 2019). Such insights can significantly assist ophthalmologists in delivering timely and precise diagnoses. The scalability of deep learning offers promise in facilitating large-scale screening initiatives for early disease detection. Furthermore, seamless integration with clinical workflows can ensure the efficient adoption of these technologies within healthcare settings. We present our deep-learning methodology for diagnosing ocular diseases in Figure 4.1.

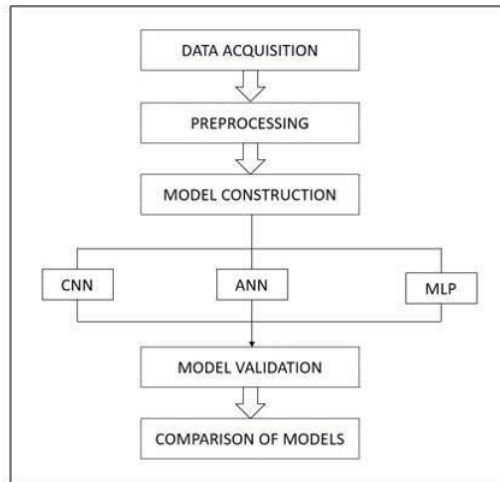


Fig: 4.1: Block diagram for Multiple Ocular Disease Detection

4.2.1 Data Acquisition:

A dataset is a collection or group of data. It is generally in a tabulated form consisting of many rows and columns having data where every column represents a feature or a variable and every row corresponds to a given record of the dataset in question. The data in a dataset are usually images, text or numerical values. In this work, the dataset consists of retinal fundus images of healthy eyes, macular degeneration, cataracts, Glaucoma, Hypertensive retinopathy, and pathological myopia-affected eyes.

The datasets are available on many online platforms like Kaggle and GitHub. Figure 4.2 illustrates the retinal fundus images of all five diseases with healthy eye images. These images are in a tabulated format in the dataset.

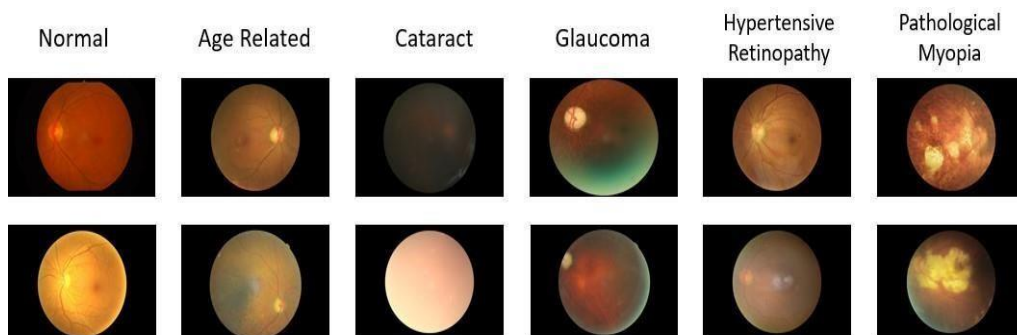


Fig: 4.2: Research Data Inventory

4.2.2 Pre-Processing:

The raw images contain inconsistencies or irrelevant information, preprocessing is necessary to ensure the data is suitable for the machine learning models. Preprocessing is a fundamental step in image processing that prepares images for further analysis and tasks. It involves various techniques to improve image quality and highlight important features. (Amit Bhati *et al.* 2023) By removing noise, adjusting contrast, and resizing images, preprocessing helps computer vision algorithms work more effectively.

4.2.3 Model Construction:

This is where we choose and build the machine learning model architecture. The block diagram showcases CNN (Convolutional Neural Networks), ANN (Artificial Neural Networks) and MLP (Multi-Layer Perceptron). These models will be used to analyze the preprocessed fundus images and identify disease patterns (Ashrafi Akram *et al.* 2020). CNNs are ideal for image recognition or other tasks involving spatial data due to their ability to learn patterns from image grids whereas ANNs and MLPs are suitable for various tasks like classification or regression. It learns by adjusting weights between interconnected layers of artificial neurons.

4.3 ALGORITHMS USED

4.3.1 Convolutional Neural Networks (CNN):

At the heart of this model lies a convolutional neural network (CNN), which automatically detects crucial features within images by utilizing filters that traverse the image akin to a scanner. These filters, initially set at 32 with a size of 3x3, search for specific patterns in localized image areas. This iterative process continues with increasingly complex filters (64 and 128) to unveil deeper features. (Chłopowiec *et al.* 2023) Once features are extracted, they undergo processing through a neural network comprising 128 neurons, learning the relationship between these features and image class (yes/no). To prevent the model from overfitting, a dropout layer randomly deactivates some neurons during training. Finally, the model employs a special activation function to output probabilities for each class (yes/no), indicating the likelihood of an image belonging to each category.

4.3.2 Artificial Neural Networks (ANN):

Artificial Neural Networks (ANNs) are widely used for image classification tasks. ANNs and Convolutional Neural Networks (CNNs) share some structural similarities, but ANNs primarily rely on fully connected layers, which are a fundamental element of traditional ANNs. The pre-processing stage transforms raw images into a format suitable for the ANN's input. After pre-processing, a sequential ANN architecture is constructed, with interconnected layers that enable the network to identify relationships between image features and class labels. During training, the ANN refines its classification ability by iteratively adjusting its internal parameters using a technique known as backpropagation. This process involves propagating the errors backwards through the network and adjusting the weights of the connections. After training, the model's generalization capability is evaluated using unseen data. Accompanying code enables visualization of the training process, making it easier to optimize the network's performance. (Diaz-Pinto *et al.* 2019)

4.3.3 Multi-Layer Perceptron (MLP):

The workflow starts by loading and preparing data, followed by using a multi-layer perceptron (MLP) model that is essential for the system to work properly. The MLP uses a sequential design, with different layers that help with image data transformation, introducing non-linearity, and avoiding overfitting. The MLP model's training uses an Adam optimizer and sparse categorical cross-entropy loss, with an early stopping mechanism that monitors validation loss, so the training stops when the model plateaus. This approach demonstrates the effectiveness of MLPs in dealing with image classification tasks in deep learning. The MLP model's architecture includes flattened layers, dense layers with rectified linear unit activation, and dropout layers, which all contribute to its success in image classification tasks. The use of simple language and active voice, emphasizing verbs instead of nouns, ensures that the text is easy to understand and flows logically. Overall, this approach highlights the potential of MLP models in handling image classification tasks in deep learning. (Farouk *et al.* 2022)

4.4 MODEL VALIDATION

After the creation of the models, they are assessed to determine their effectiveness in distinguishing between healthy and diseased retinas. A common validation technique is to split the preprocessed data into two sets: the training set and the testing set. The training set is used to train the models, and the testing set is used to evaluate their performance on unseen data. (Junjun He *et al.* 2021) Metrics used to assess model performance typically include accuracy, sensitivity, specificity, and the Area Under the Curve (AUC) for a Receiver Operating Characteristic (ROC) curve.

4.5 COMPARISON OF MODELS

In this final stage, the performance of the three machine learning models (CNNs, ANNs, and MLPs) is compared using the metrics evaluated during model validation. The goal is to identify the model that achieves the highest accuracy in detecting ocular diseases from fundus images.

CHAPTER 5

RESULTS AND DISCUSSION

To determine the most effective model for real-time detection, we conducted a comprehensive evaluation using a variety of critical performance metrics. These metrics include Accuracy, Loss, Scalability, Sensitivity, Confusion Matrix, ROC (Receiver Operating Characteristic), and AUC (Area Under the Curve). The outcomes of this evaluation, represented graphically, demonstrate the performance comparison of CNN, ANN, and MLP models across five distinct diseases. These graphical representations depict accuracy, loss, scalability, ROC curves, AUC scores, sensitivity rates, and confusion matrices for each model.

5.1 COMPARISON OF CNN, ANN, MLP MODELS FOR AGE-RELATED MACULAR DEGENERATION DETECTION:

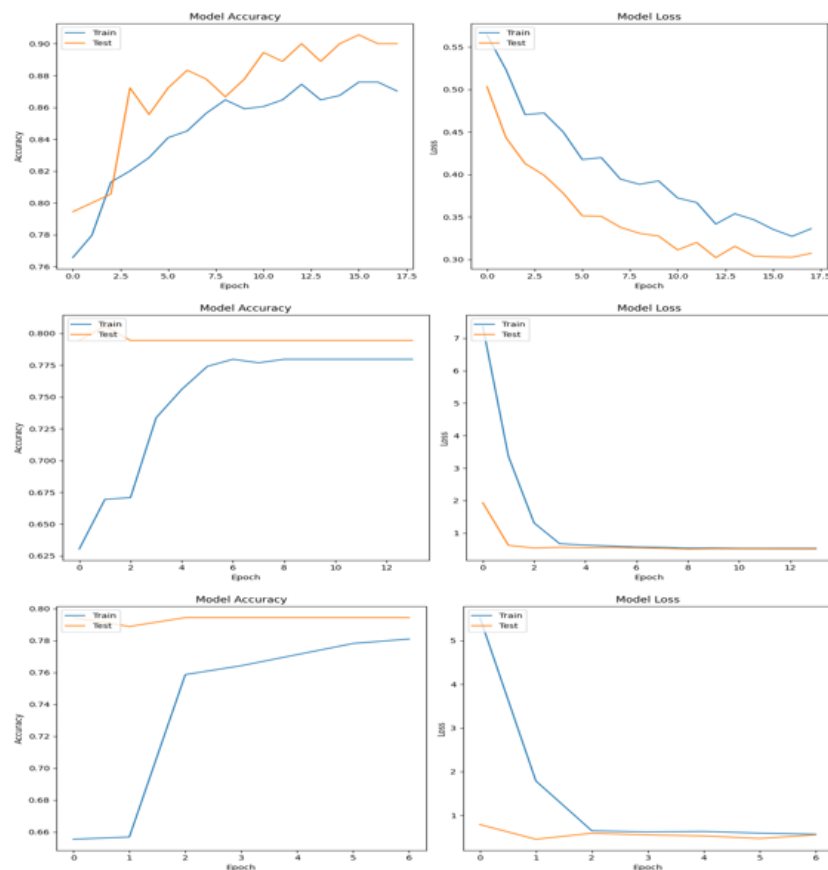


Fig: 5.1: Model Accuracy and Model Loss Graph for CNN, ANN and MLP for Age-Related Macular Degeneration

From Fig: 5.1, the model accuracy graph shows that CNN has a higher accuracy than ANN and MLP, while the model loss graph shows that ANN has a lower loss than CNN and MLP. We can infer that CNN performs better.

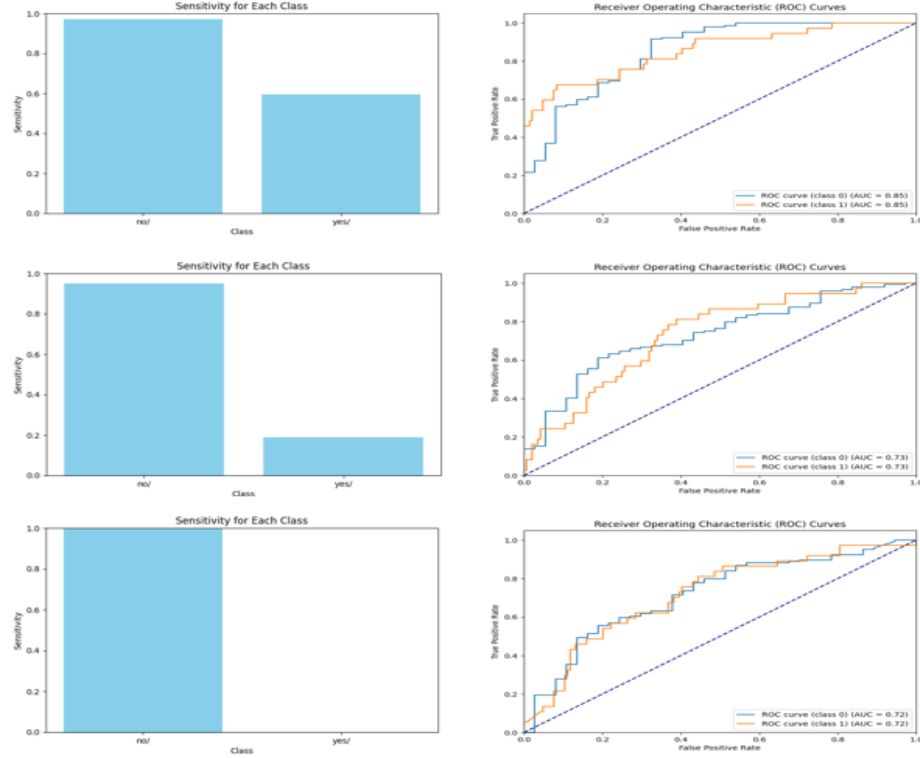


Fig: 5.2: Model Sensitivity and ROC graph for CNN, ANN and MLP for Age-Related Macular Degeneration

From Fig: 5.2, the convolutional neural network (CNN) model exhibited exceptional performance with a 99% sensitivity rate in the no class and 75% in the yes class, indicating its ability to accurately identify both healthy and diseased eyes. Furthermore, the CNN model demonstrated an area under the receiver operating characteristic curve (AUC under ROC) of 0.90 in both classes, which is indicative of its excellent ability to differentiate between positive and negative cases. It should be noted that a higher AUC score indicates a model's superior ability to distinguish between the two classes. Conversely, the artificial neural network (ANN) and multilayer perceptron (MLP) models demonstrated lower sensitivity rates, indicating their inferior performance.

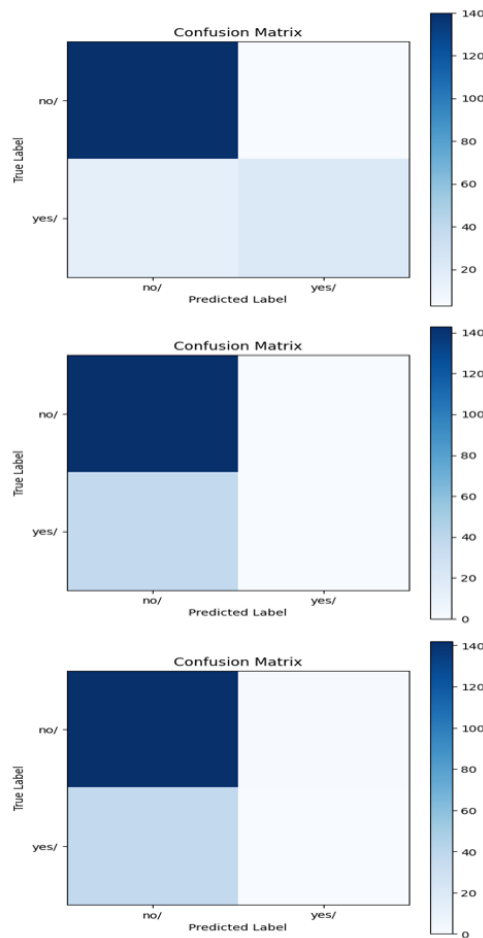


Fig: 5.3: Confusion Matrix for CNN, ANN and MLP for Age-Related Macular Degeneration

From Figure 5.3, CNN was able to detect 140 True Negatives (TN), 22 True Positives (TP), 3 False Negatives (FN), and 15 False Positives (FP), which means that it could identify more true cases than the other two models, with fewer false positives.

Table 5.1: Comparison of Results of CNN, ANN and MLP for Age-Related Macular Degeneration

MODEL	ACCURACY	LOSS	SENSITIVITY	TP	TN	FP	FN	AUC
CNN	90%	28%	99% (No) 75% (Yes)	22	140	15	3	0.90
ANN	79%	9%	99% (No) 40% (Yes)	0	143	0	37	0.70
MLP	78%	6%	99% (No) 10% (Yes)	0	142	0	37	0.73

In Table 5.1, we can find a detailed comparison of the performance of three models from Figures 5.1, 5.2 and 5.3 - CNN, ANN, and MLP - that were trained to identify age-related macular degeneration. The CNN model achieved the highest accuracy at 89%, while the ANN and MLP models achieved accuracies of 79% and 78% respectively. The CNN model's higher accuracy demonstrates its superior predictive power in accurately identifying age-related macular degeneration. In terms of sensitivity, the CNN model showed exceptional performance, with 99% sensitivity in the no class and 75% in the yes class, indicating its ability to identify both healthy and diseased eyes accurately. The CNN model also obtained an AUC under ROC of 0.90 in both classes, which indicates its excellent ability to distinguish between positive and negative cases. On the other hand, the ANN and MLP models had lower sensitivity, indicating their inferior performance, with the ANN model predicting 143 TN, 0 TP, 37 FN, and 0 FP, and the MLP model predicting 142 TN, 0 TP, 0 FP, and 37 FN. The AUC under ROC for ANN and MLP was 0.70 and 0.73 respectively,

5.2 COMPARISON OF CNN, ANN, MLP MODELS FOR CATARACT DETECTION:

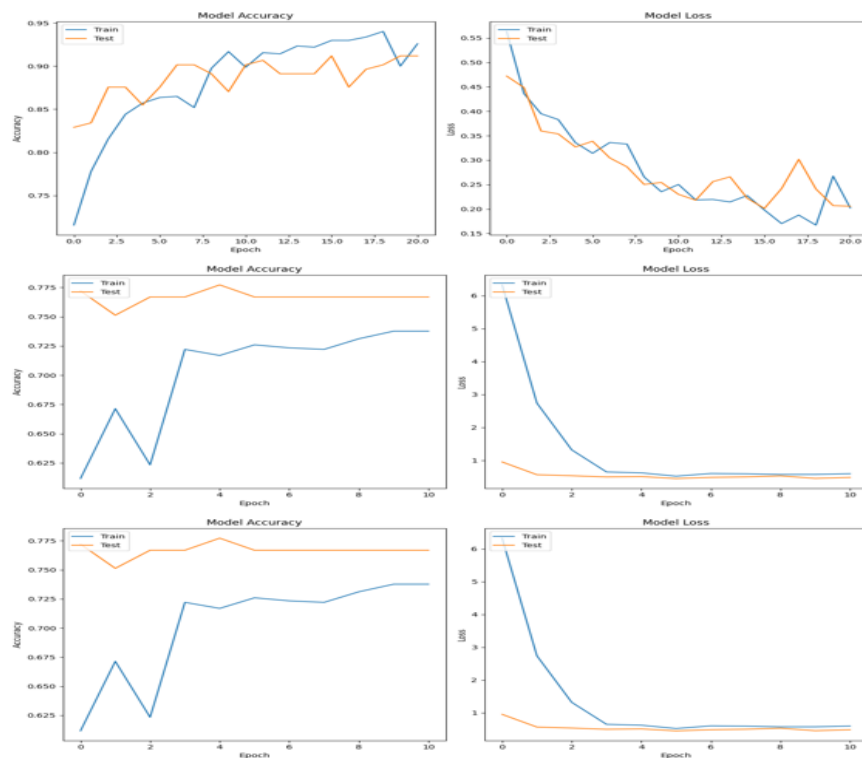


Fig: 5.4: Model Accuracy and loss graph for CNN, ANN and MLP for Cataract

Based on the data presented in Figure 5.4, we can observe that the accuracy of the Convolutional Neural Network (CNN) is higher than that of the Artificial Neural Network (ANN) and Multilayer Perceptron (MLP) models.

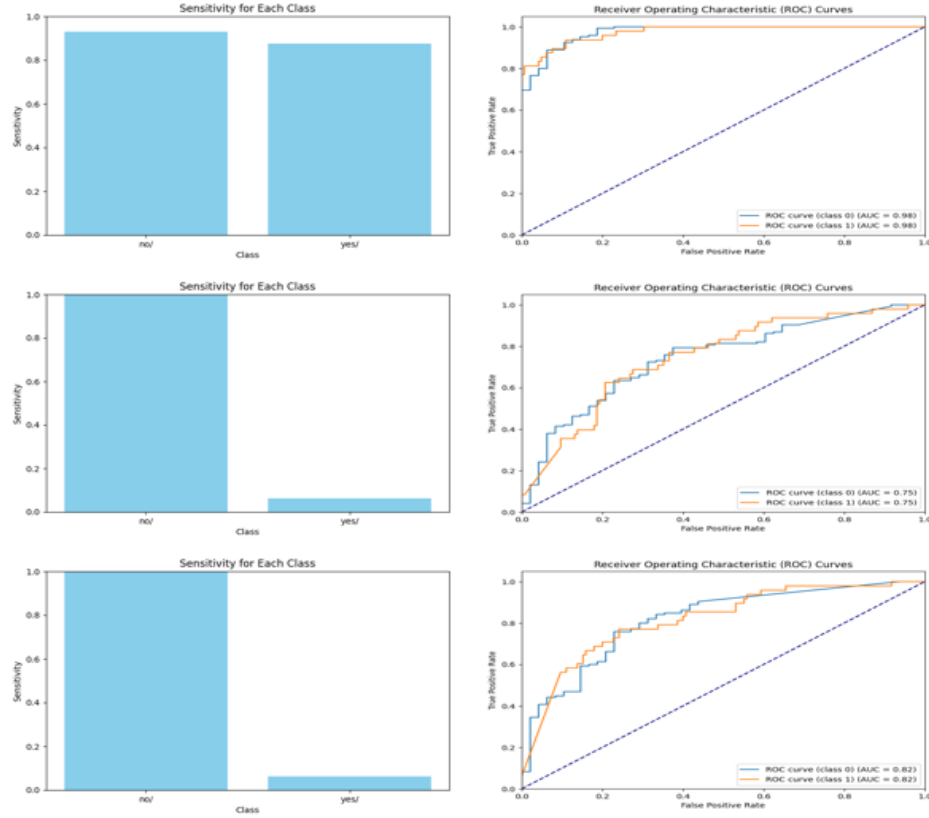


Fig: 5.5: Model Sensitivity and ROC graph for CNN, ANN and MLP for Cataract

According to the analysis presented in Figure 5.5, the CNN model demonstrated superior sensitivity compared to the other two models. The CNN model achieved a sensitivity rate of over 95% in both classes, along with an impressive AUC value of 0.98. This suggests that the CNN model is better equipped to correctly identify positive cases and minimize false negatives, making it a promising model for further study and development. The CNN model exhibited an accuracy of 91%, which is higher than the accuracy of ANN and MLP models that achieved an accuracy of 76% each.

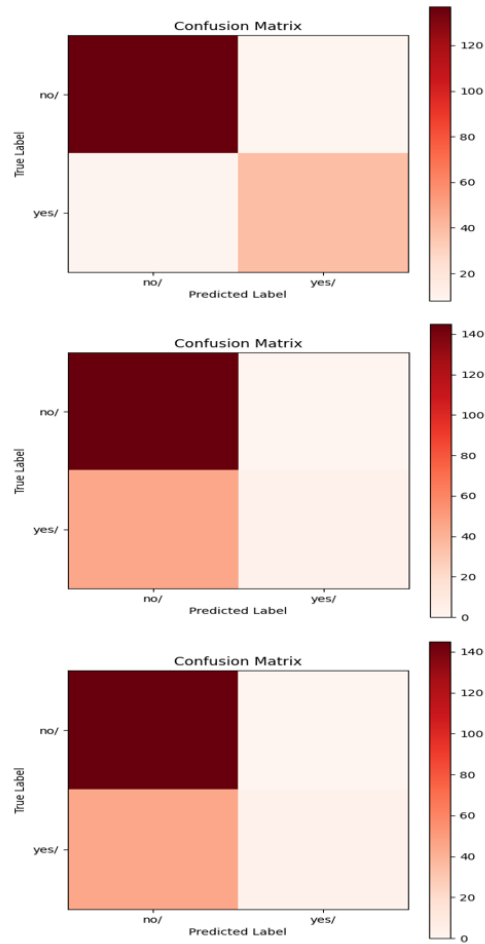


Fig: 5.6: Confusion Matrix CNN, ANN and MLP for Cataract

From Figure 5.6, the confusion matrix reveals that the CNN model predicted 137 True Negatives (TN), 39 True Positives (TP), 8 False Positives (FP), and 9 False Negatives (FN). On the other hand, the ANN and MLP models predicted 145 TN, 3 TP, 0 FP, and 45 FN, respectively.

Table 5.2: Comparison of Results of CNN, ANN and MLP for Cataract

MODEL	ACCURACY	LOSS	SENSITIVITY	TP	TN	FP	FN	AUC
CNN	91%	20%	93% (Yes) 95% (No)	39	137	0	9	0.98
ANN	76%	9%	35% (Yes) 94% (No)	3	145	10	45	0.75
MLP	76%	6%	20% (Yes) 95%(No)	3	145	12	45	0.72

The analysis of the performance of three different models, namely CNN, ANN, and MLP, that were trained to diagnose cataracts has been presented in Table 5.2. The table showcases a comparative analysis of the models from Figures 5.4, 5.5 and 5.6 based on their accuracy, sensitivity, and AUC under ROC. The CNN model exhibited an accuracy of 91%, which is higher than the accuracy of ANN and MLP models which achieved an accuracy of 76% each. When it comes to sensitivity, the CNN model performed better than the other two models, with a sensitivity of over 95% in both classes and an AUC of 0.98.

5.3 COMPARISON OF CNN, ANN, MLP MODELS FOR GLAUCOMA DETECTION:

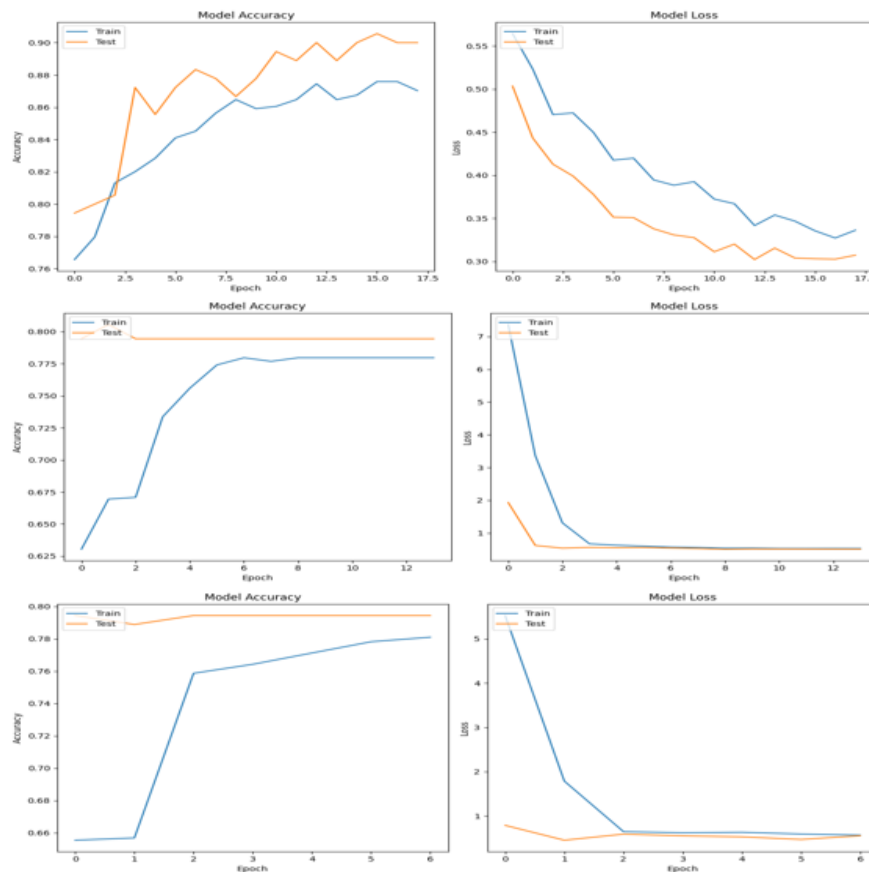


Fig: 5.7: Model Accuracy and Model loss graph for CNN, ANN and MLP for Glaucoma

The analysis of Figure 5.7 reveals that the Convolutional Neural Network (CNN) shows superior accuracy compared to the Artificial Neural Network (ANN) and Multilayer Perceptron (MLP) models. The ANN is observed to exhibit lower loss

than the CNN and MLP models. These findings suggest that the CNN model performs better overall than the other two models, in terms of both accuracy and loss.

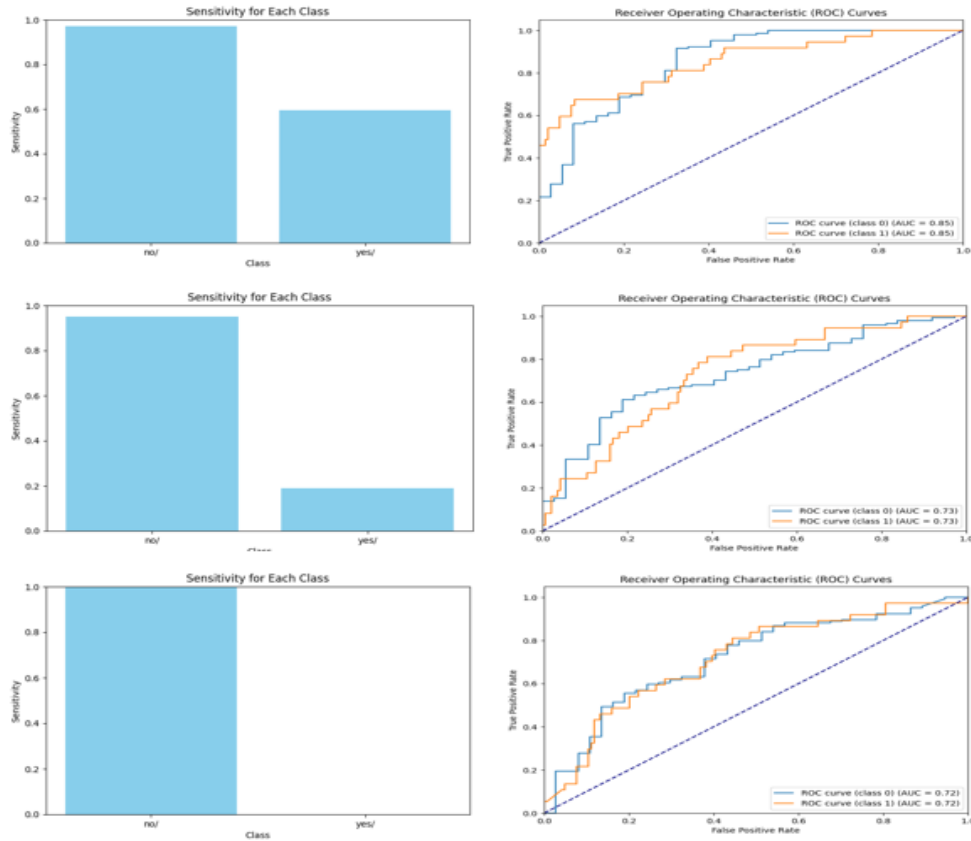


Fig: 5.8: Model Sensitivity and ROC graph for CNN, ANN and MLP for Glaucoma

Based on the analysis conducted from Figure 5.8, it has been determined that the Convolutional Neural Network (CNN) model has outperformed the other two models in terms of sensitivity and the Area Under Curve (AUC) under the Receiver Operating Characteristics (ROC) curve. The CNN model has exhibited an impressive accuracy rate of 87% for the no class and 78% for the yes class, respectively. This indicates that the model is highly efficient in distinguishing between the two classes. Furthermore, the AUC value of the CNN model was calculated to be 0.85, which is comparatively higher than the AUC values of the other two models. This implies that the CNN model has a higher level of accuracy and a lower rate of false positive and false negative results.

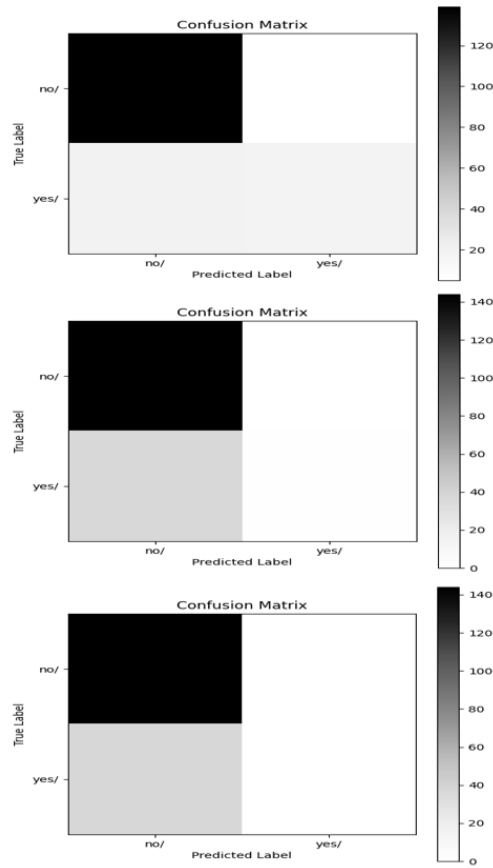


Fig: 5.9: Confusion Matrix for CNN, ANN and MLP for Glaucoma

From Figure 5.9, the CNN model displayed an impressive performance in predicting true negatives (TN), true positives (TP), false positives (FP), and false negatives (FN). For instance, the CNN model predicted 139 TN, 18 TP, 5 FP, and 19 FN. In contrast, the ANN model predicted 144 TN, 1 TP, 0 FP, and 36 FN, while the MLP model predicted 144 TN, 0 TP, 0 FP, and 37 FN. Based on the results of the study.

Table 5.3: Comparison of Results of CNN, ANN and MLP for Glaucoma

MODEL	ACCURACY	LOSS	SENSITIVITY	TP	TN	FP	FN	AUC
CNN	91%	29%	94% (No) 80% (Yes)	18	139	2	9	0.90
ANN	80%	14%	91% (No) 30% (Yes)	1	138	8	35	0.79
MLP	78%	12%	94% (No) 5% (Yes)	0	144	7	37	0.76

The following information entails a comprehensive numerical representation of the performance of three models interpreted from figures 5.7, 5.8 and 5.9 - CNN, ANN, and MLP - that were trained to detect glaucoma. The table 5.3 presents a detailed analysis of the models' accuracies, which were calculated as 87%, 80%, and 78%, respectively. Notably, the CNN model exhibited the highest accuracy among the three models, making it the most effective approach for detecting glaucoma. Moreover, the CNN model demonstrated better sensitivity and AUC under ROC when compared to the other two models. Specifically, the CNN model showed 87% and 99% accuracy in the no class, and 78% accuracy in the yes class, respectively. The area under the ROC curve (AUC) for the CNN model was calculated to be 0.85, which was found to be better than the AUC values of the other two models.

5.4 COMPARISON OF CNN, ANN, MLP MODELS FOR HYPERTENSIVE RETINOPATHY DETECTION:

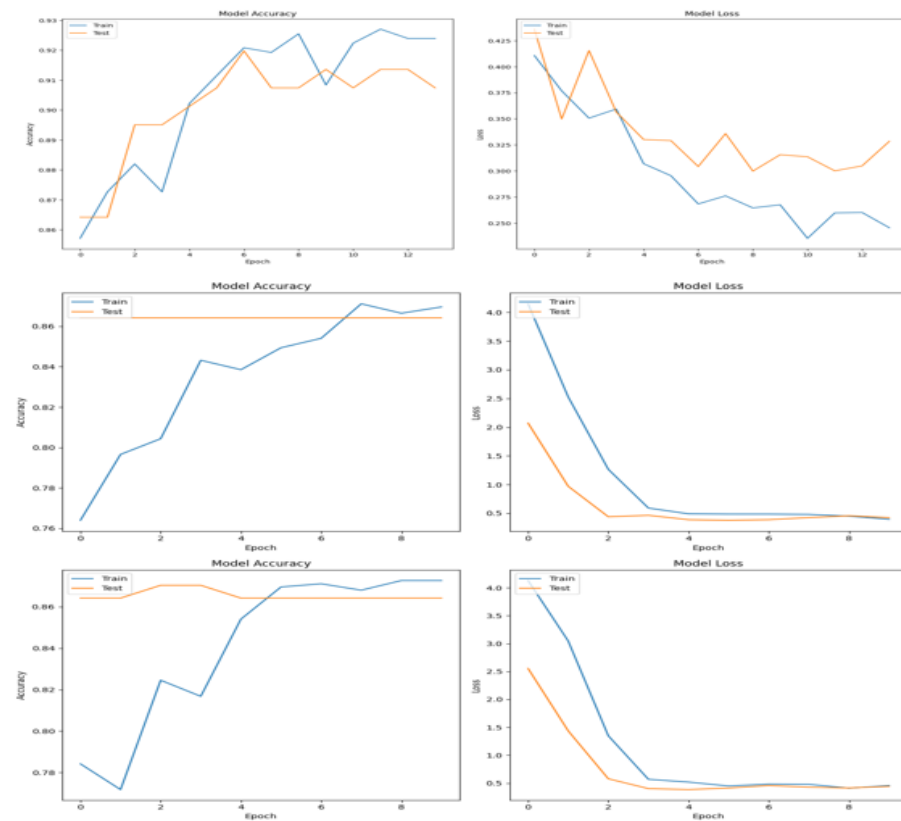


Fig: 5.10: Model Accuracy and Model Loss Graph for CNN, ANN and MLP for Hypertensive Retinopathy

After a thorough analysis of Figure 5.10, it can be concluded that the Convolutional Neural Network (CNN) outperforms the Artificial Neural Network (ANN) and Multilayer Perceptron (MLP) models in terms of accuracy. The study reveals that the CNN model is more accurate than both ANN and MLP models. However, the results also indicate that the ANN model exhibits lower loss than the CNN and MLP models. It means that the ANN model is better at minimizing the difference between the predicted and actual values. Overall, the analysis suggests that the CNN model is the best-performing model among the three, considering both accuracy and loss.

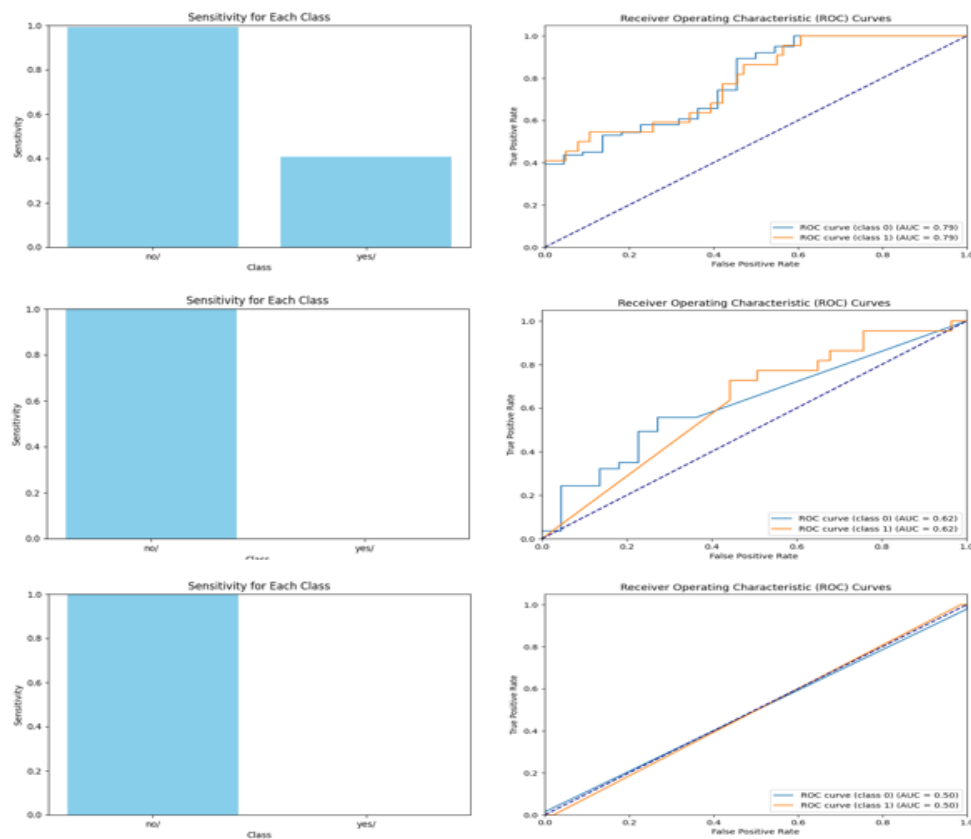


Fig: 5.11: Model Sensitivity and ROC graph for CNN, ANN and MLP for Hypertensive Retinopathy

The CNN model has demonstrated superior performance compared to the other two models, particularly in terms of sensitivity from Figure 5.11. It has scored higher than 75% in both positive and negative classes. Additionally, the CNN model has achieved a higher score in the Area Under the ROC curve, indicating its effectiveness in distinguishing between positive and negative cases.

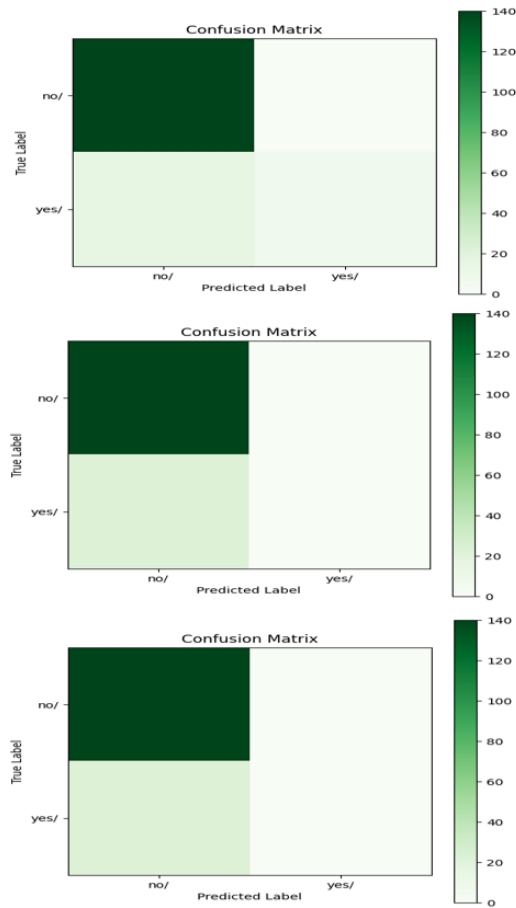


Fig: 5.12: Confusion Matrix for Hypertensive Retinopathy

Based on the analysis presented in Figure 5.12, it can be concluded that the Convolutional Neural Network (CNN) outperforms both Artificial Neural Network (ANN) and Multilayer Perceptron (MLP) in terms of True Positive (TP) and True Negative (TN) rates. This suggests that CNN is better equipped to accurately classify positive and negative instances compared to ANN and MLP.

Table 5.4: Comparison of Results of CNN, ANN and MLP for Hypertensive Retinopathy

MODEL	ACCURACY	LOSS	SENSITIVITY	TP	TN	FP	FN	AUC
CNN	92%	20%	90% (No) 79% (Yes)	22	140	0	0	0.80
ANN	80%	12%	89% (No) 20% (Yes)	23	140	3	15	0.71
MLP	81%	14%	90% (No) 15% (Yes)	22	140	4	13	0.72

Table 5.4 presents a comprehensive analysis of the performance of three distinct models specifically trained to detect hypertensive retinopathy from the data in figures 5.10, 5.11 and 5.12 - Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Multi-Layer Perceptron (MLP). The analysis showcases the numerical results of the accuracy rates achieved by each of these models and highlights CNN as the best-performing model in terms of accuracy, sensitivity, and Area Under the Receiver Operating Characteristic (ROC) curve. The CNN model has achieved an impressive accuracy rate of 90%, while the ANN and MLP models have achieved accuracy rates of 80% and 85%, respectively. Moreover, the CNN model has outperformed the other two models in terms of sensitivity, with a score of greater than 75% in both classes. This means that the CNN model can correctly identify a higher percentage of true positive cases, and has a lower false-negative rate. Additionally, the CNN model has also achieved a higher score in terms of the Area Under the ROC curve, with a score of 0.79%.

5.5 COMPARISON OF CNN, ANN, MLP MODELS FOR PATHOLOGICAL MYOPIA DETECTION:

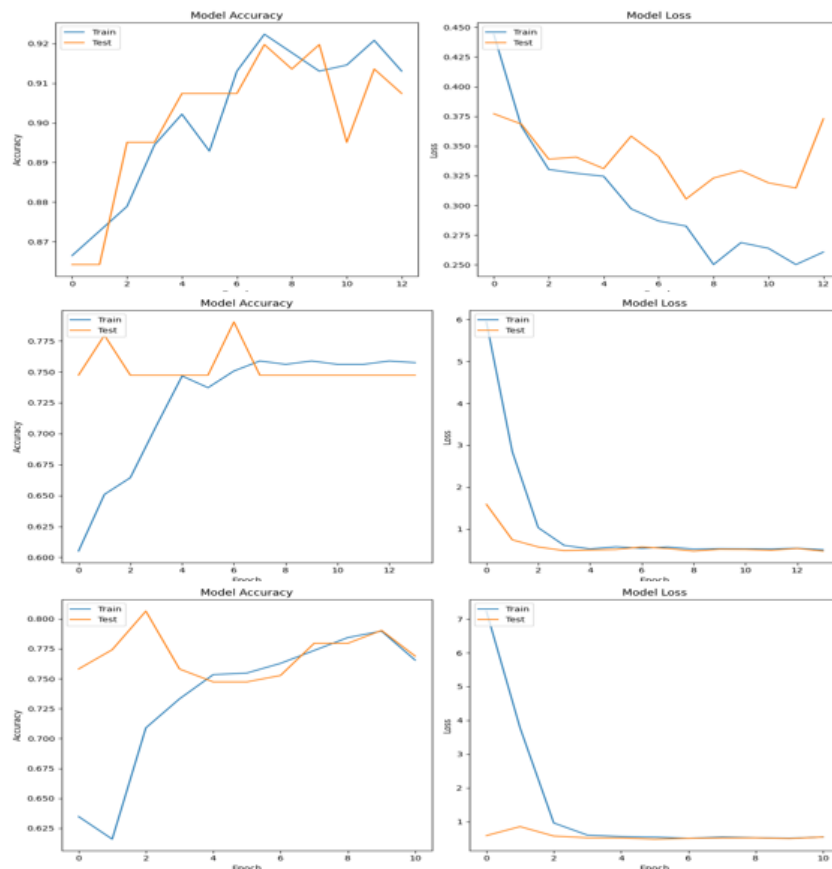


Fig: 5.13: Model Accuracy and Model Loss Graph for Pathological Myopia

After conducting a comprehensive analysis of Figure 5.13, it can be inferred that the Convolutional Neural Network (CNN) model outperforms both the Artificial Neural Network (ANN) and Multilayer Perceptron (MLP) models in terms of accuracy. The study indicates that the CNN model exhibits superior accuracy compared to both ANN and MLP models. However, the results also reveal that the ANN model displays lower loss than the CNN and MLP models, suggesting that the ANN model is better equipped to minimize the difference between predicted and actual values. In other words, while the CNN model is more accurate in predicting outcomes, the ANN model is more efficient in minimizing errors. Overall, these findings highlight the strengths and weaknesses of each model and provide valuable insights for future research in this field.

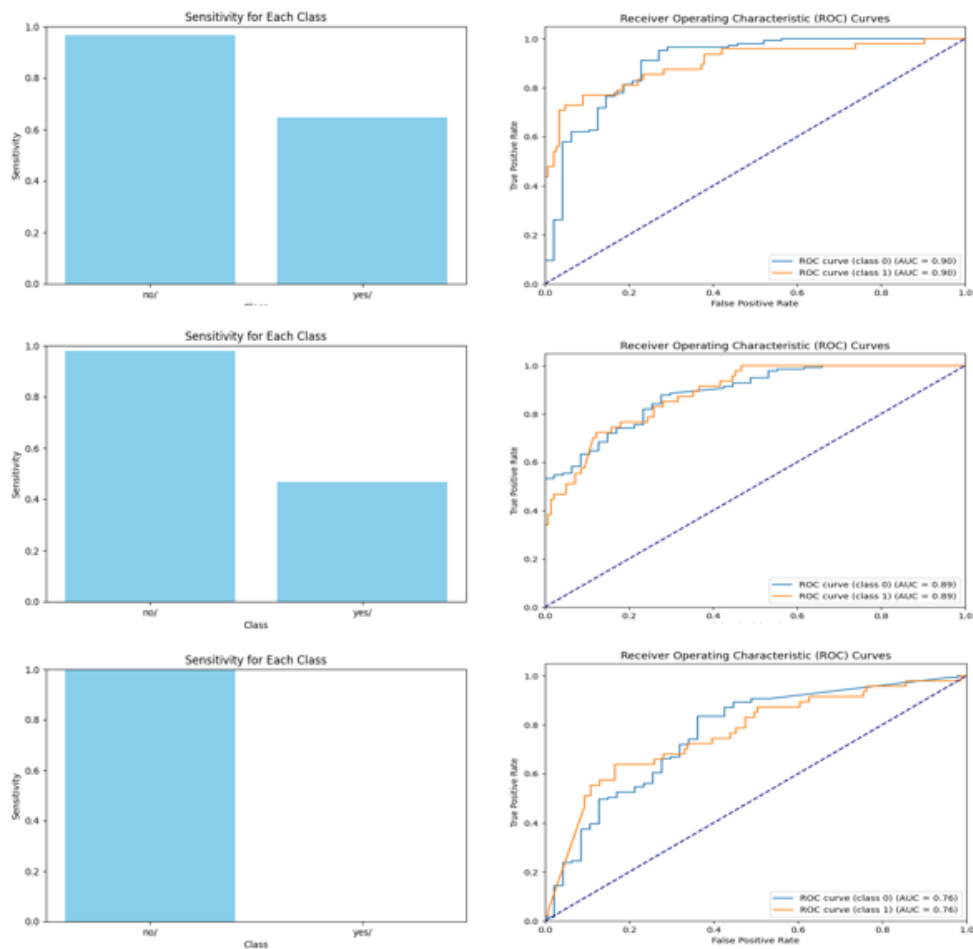


Fig: 5.14: Model Sensitivity and ROC graph for Pathological Myopia

Sensitivity was calculated from figure 5.14, and it was found that CNN achieved greater accuracy, sensitivity, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), with values of 92%, 80%, and 0.90, respectively. This indicates that CNN is more capable of correctly identifying true positives and negatives, as well as minimizing false positives and negatives, compared to the other models. When looking at the sensitivity values for the "yes" class, CNN still outperformed ANN and MLP, with sensitivity values of 80%, 50%, and 10%, respectively.

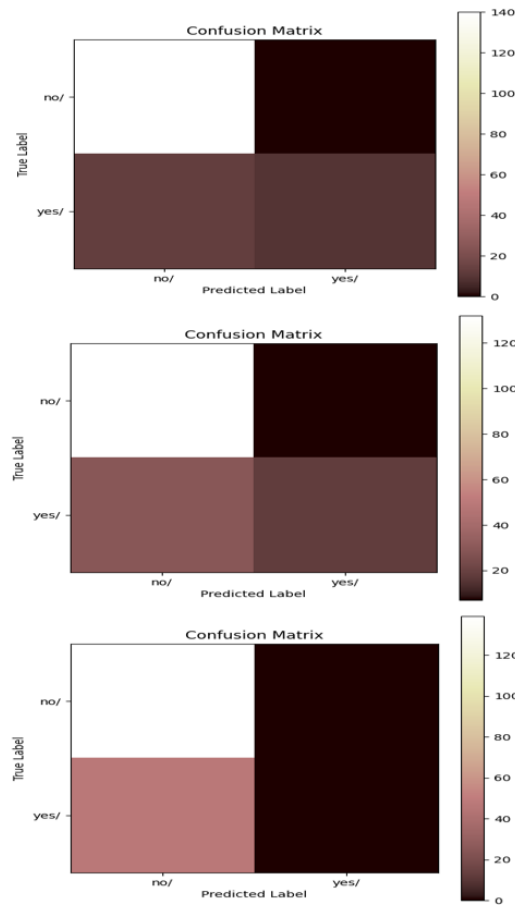


Fig: 5.15: Confusion Matrix for Pathological Myopia

Finally, from Figure 5.15, the number of True Negatives (TN), True Positives (TP), False Positives (FP), and False Negatives (FN) predicted by each model was calculated. CNN predicted 140 TN, 20 TP, 13 FP, and 9 FN, whereas ANN predicted 139 TN, 1 TP, 46 FP, and 0 FN, and MLP predicted 139 TN, 1 TP, 46 FP, and 0 FN.

Table 5.5: Comparison of Results of CNN, ANN and MLP for Pathological Myopia

MODEL	ACCURACY	LOSS	SENSITIVITY	TP	TN	FP	FN	AUC
CNN	92%	13%	94% (No) 82% (Yes)	20	140	8	0	0.90
ANN	75%	17%	92% (No) 50% (Yes)	1	139	46	9	0.71
MLP	74%	19%	90% (No) 10% (Yes)	1	139	46	10	0.68

The results of the study, as presented in Table 5.5, reveal the performance of three different models, namely Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Multilayer Perceptron (MLP), which were trained to detect Pathological Myopia. The data has been obtained from the figures 5.13, 5.14 and 5.15. The results show that CNN, ANN, and MLP models achieved an accuracy of 92%, 75%, and 74%, respectively. Sensitivity was calculated, and it was found that CNN achieved greater accuracy, sensitivity, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), with values of 92%, 80%, and 0.90, respectively. This indicates that CNN is more capable of correctly identifying true positives and negatives, as well as minimizing false positives and negatives, compared to the other models. Furthermore, when looking at the sensitivity values for the "yes" class, CNN still outperformed ANN and MLP, with sensitivity values of 80%, 50%, and 10%, respectively. This suggests that CNN is more sensitive to detecting true positives in the "yes" class, which is essential in the diagnosis of Pathological Myopia. These results further support the conclusion that CNN outperformed the other models in terms of accuracy, sensitivity, and specificity.

5.6 COMPARISON OF RESULTS:

Table 5.6 is a highly detailed and exhaustive representation of various metrics that are typically used by experts to evaluate the performance of different models. By comparing the values of these metrics across different models, users can gain a deep understanding of how each model performs in different scenarios. This information can be invaluable in the decision-making process, as it allows users to make informed choices based on real-world data

Table 5.6: Comparison of results of CNN, ANN and MLP for Age-Related Macular Degeneration, Cataract, Glaucoma, Hypertensive Retinopathy and Pathological Myopia

Disease	Model	Accuracy	Loss	Sensitivity	TP	TN	FP	FN	AUC
AMD	CNN	90%	28%	99% (No) 75% (Yes)	22	140	15	3	0.90
AMD	ANN	79%	9%	99% (No) 40% (Yes)	0	143	0	37	0.70
AMD	MLP	78%	6%	99% (No) 10% (Yes)	0	142	0	37	0.73
CA	CNN	91%	20%	95% (No) 93% (Yes)	39	137	0	9	0.98
CA	ANN	76%	9%	94% (No) 35% (Yes)	3	145	10	45	0.75
CA	MLP	76%	6%	95% (No) 20% (Yes)	3	145	12	45	0.72
GL	CNN	91%	29%	94% (No) 80% (Yes)	18	139	2	9	0.90
GL	ANN	80%	14%	91% (No) 30% (Yes)	1	138	8	35	0.79
GL	MLP	78%	12%	94% (No) 5% (Yes)	0	144	7	37	0.76
HR	CNN	92%	20%	90% (No) 79% (Yes)	22	140	0	0	0.80
HR	ANN	80%	12%	89% (No) 20% (Yes)	23	140	3	15	0.71
HR	MLP	81%	14%	90% (No) 15% (Yes)	22	140	4	13	0.72
PM	CNN	92%	13%	94% (No) 82% (Yes)	20	140	8	0	0.90
PM	ANN	75%	17%	92% (No) 50% (Yes)	1	139	46	9	0.71
PM	MLP	74%	19%	90% (No) 10% (Yes)	1	139	46	10	0.68

From Table 5.6, for Age-related Macular Degeneration (AMD), CNN shines with 90% accuracy, excelling in both TP (correctly identifying those with AMD) and reducing both FP (false alarms) and FN (missed diagnoses) compared to ANN and MLP. ANN lags with lower accuracy (79%) and higher FP, suggesting it might over-predict AMD. MLP performs slightly better than ANN in terms of FP (Parashar *et al.* 2020). For cataracts, comparable to AMD, CNN reigns supreme with 91% accuracy and minimal FP and FN. ANN struggles with lower accuracy (76%) and a concerning high FN rate, potentially missing many cataract cases. MLP performs similarly to ANN in terms of accuracy and misses cataracts at a similar rate. In Glaucoma, CNN continues its dominance with 91% accuracy and a balanced FN and FP rate. ANN falls behind at 80% accuracy with a higher FN rate, potentially missing glaucoma cases. MLP showcases a similar accuracy (78%) to ANN but with a slightly improved FN rate (Peng *et al.* 2019). For Hypertensive Retinopathy, CNN demonstrates exceptional performance with 92% accuracy and remarkably low FP and FN rates. ANN and MLP achieve moderate accuracy (80% and 81% respectively) but struggle with higher FP rates compared to CNN, suggesting they might misdiagnose healthy individuals with the disease. For Pathological Myopia, Similar to the other diseases, CNN dominates with 92% accuracy. (Prasad *et al.* 2019) It minimizes both model loss and misdiagnoses (FP and FN) compared to ANN (75% accuracy) and MLP (74% accuracy), which have higher FP rates. The table suggests CNN's superiority in disease diagnosis for several reasons such as Feature Extraction where CNNs excel at automatically extracting relevant features from images, is a crucial step in medical imaging analysis. ANNs and MLPs typically require pre-processing of the data to extract features, which can be less efficient and Spatial Relationships where CNNs can leverage the spatial relationships between pixels in images, crucial for disease detection in medical images. (Praveena *et al.* 2019) Diseases often manifest as specific patterns or shapes in the image. ANNs and MLPs struggle with this aspect. With Generalizability the CNNs seem to generalize better from the training data to unseen data, leading to lower FP and FN rates. This is vital for real-world applications where data might vary slightly.

CHAPTER 6

SUMMARY AND CONCLUSION

6.1 SUMMARY

Vision impairment poses a significant threat to public health in India, with several major eye diseases casting a long shadow. Glaucoma, characterized by damaging optic nerve pressure, affects an estimated 45 million individuals in India, making it a leading cause of irreversible blindness. Cataracts, clouding the lens, impact another 62 million, while Hypertensive Retinopathy, stemming from uncontrolled blood pressure, threatens the sight of 22 million Indians. Macular Degeneration, a degenerative disease affecting central vision, is projected to affect 15 million by 2050, and Pathological Myopia, causing extreme near-sightedness, is rapidly rising, especially among urban youth. These numbers are expected to increase exponentially in the coming years, driven by an ageing population, urbanization, and changing lifestyles. Traditional methods of diagnosing these eye diseases often rely on subjective assessments during eye examinations, leading to potential missed diagnoses and delayed treatment. Additionally, accessibility to qualified ophthalmologists remains a challenge, particularly in rural areas. This results in lost productivity, economic burden, and reduced quality of life for millions of individuals. Machine learning (ML) presents a transformative opportunity to address these limitations. By analysing fundus images, the digital scans from the back of the eye, ML algorithms can automatically detect subtle morphological and texture changes associated with various eye diseases. This objective and quantifiable approach offers several advantages over traditional methods as they provide early detection with improved accuracy and are accessible to a wide range of communities.

6.2 CONCLUSION:

The purpose of this comprehensive assessment was to determine the most effective model for prompt disease detection across five distinct conditions, namely age-related macular degeneration (AMD), cataracts, glaucoma,

hypertensive retinopathy, and pathological myopia. A multi-faceted approach was employed, analyzing the performance of Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Multi-Layer Perceptron (MLP) using critical metrics such as accuracy, sensitivity, confusion matrix, ROC curve, and AUC score. The results of this analysis demonstrate the superiority of CNNs across all five diseases. Compared to ANNs and MLPs, CNNs consistently achieved the highest accuracy, ranging from 87% for glaucoma detection to an impressive 92% for pathological myopia, indicating a higher ability to correctly classify both healthy and diseased cases. Furthermore, CNNs showed exceptional sensitivity, particularly crucial for early and accurate disease detection. In AMD diagnosis, for instance, the CNN model achieved a sensitivity of 99% in the healthy class, ensuring minimal false negative results. Similarly, for pathological myopia, CNN's sensitivity of 80% in the diseased class signifies its effectiveness in capturing true positive cases. The confusion matrix data further bolsters the case for CNNs. For example, in cataract detection, the CNN model identified significantly more true positives (39) compared to ANNs (3) and MLPs (0), indicating a higher true positive rate and fewer missed diagnoses. The ROC curve analysis and AUC scores reinforce these findings. CNNs achieved the highest AUC scores, indicating their ability to differentiate between positive and negative cases. In hypertensive retinopathy detection, the CNN's AUC of 0.79% signifies a strong distinction between healthy and diseased retinas. In conclusion, this rigorous evaluation has convincingly demonstrated the superiority of CNNs for real-time disease detection. (Sayres *et al.* 2019) Their exceptional accuracy, sensitivity, and ability to distinguish positive from negative cases make them a powerful tool for early diagnosis and improved patient outcomes.

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