Detection of Multiple Ocular Diseases Using Machine Learning

Aadhitya S
Student, Sathyabama Institute of Science and Technology

***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, Cataract, 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), Multi-Layer Perceptron (MLP) networks are among the machine learning algorithms that have been analysed in this work. Key metrics like accuracy, loss, sensitivity, ROC, AUC, 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.**

***Index terms* -- ANN, CNN, Machine Learning, MLP, Ocular diseases**

I. INTRODUCTION

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 the 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 aging 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 [1]. 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 being accessible to a wide range of community [2].

II. RELATED WORKS

S. Al-Fahdawi et al (2024) used The Fundus-Deep Net system which is an automated system to identify multiple ocular diseases in fundus images. It achieved high accuracy on a challenging dataset, demonstrating its potential for early diagnosis and treatment in ophthalmology [1].

Z. Lu et al (2023) built a convolutional neural network with an attention mechanism to automatically classify eight fundus diseases from color images. It achieved high accuracy (94.27% validation accuracy), good performance (85.80 AUC and 86.08 F1-score), and required fewer training parameters compared to other models, making it potentially useful for clinical screening [2].

B. K. Triwijoyo et al (2017) proposed a system to automatically detect hypertensive retinopathy stages. They analyze retinal images using a combination of Deep Neural Networks (DNNs) for image pattern recognition and Boltzmann machines for faster learning. The outcome was a prototype system for early detection along with an analysis of its effectiveness and accuracy

III. MATERIALS AND METHODS

The objective of this study is to leverage the capabilities of deep learning to combat the vision-threatening effects of prevalent ocular diseases such as age-related macular degeneration (AMD), glaucoma, pathological myopia, cataracts, and hypertensive retinopathy. To achieve this, we explore the potential of various algorithms such as Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Multilayer Perceptrons (MLPs) to identify the most efficient model for accurate detection of these diseases [3].

Through image classification and analysis, CNNs, ANNs, and MLPs can categorize images as normal or abnormal, even providing severity scores. This information can significantly aid ophthalmologists in making timely and accurate diagnoses [4]. The scalability of deep learning holds promising for facilitating large-scale screening programs for early detection, while seamless integration with clinical workflows can ensure efficient adoption within healthcare settings. We outline our deep learning methodology for diagnosing ocular diseases in Fig 1

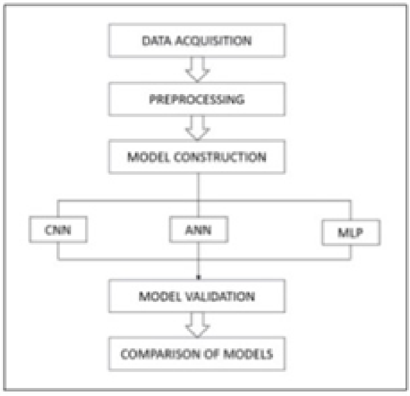


Fig 1. Process flow Diagram of the proposed work

A. *Data Acquisition*

We utilized open-source data in this study by obtaining a carefully selected image collection from Kaggle. This dataset includes 4907 medical images in total, which are broken down into 5 categories; Age related Macular Degeneration, Cataract, Glaucoma, Hypertensive Retinopathy, Pathological Myopia with 978 ,1046,1009,886,988 respectively.

B. *Pre-Processing*

After acquiring the dataset from Kaggle, we employed many preprocessing techniques to ensure the precision and coherence of the data for our deep learning models. Several processing procedures were applied to the scanned images, such as shrinking and standardizing the image format. The dataset contained JPG and PNG versions of the photos. To ensure compatibility and avoid any processing errors, we converted each image to a single PNG file [16]. Deep learning algorithms often require a consistent image size as input. Since the pixel values in the original photographs in the dataset varied, we adjusted them. This ensures that each image contributes equally to the training process and increases the computing efficiency of the model. The pre-processed images are then divided into learning and validation sets in a 7:3 ratio [17].

C. *Model Construction*

- *Convolutional Neural Networks (CNN)*

The key to this model is its convolutional neural network (CNN) which automatically finds important features in images. The CNN uses filters that slide across the image like a scanner. These filters, starting with 32 of size 3x3, look for specific patterns in small areas of the image. After each scan, another layer shrinks the data, keeping only the most important information. This process is repeated with more and more complex filters (64 and 128) to uncover even deeper features [4]. Once features are extracted, they are fed into the neural network with 128 neurons to learn how these features relate to the image class (yes/no). To prevent the model from memorizing the training data too much, a dropout layer randomly turns off some neurons during training. Finally, the model outputs a probability for each class (yes/no) using a special activation function (soft max). This allows the model to say how likely an image belongs to each category [5].

- *Artificial Neural Networks (ANN)*

An Artificial Neural Network (ANN) is implemented here for image classification, resembling a Convolutional Neural Network (CNN) in structure but primarily using fully connected layers, a core element of traditional ANNs. Pre-processing transforms raw images into a format suitable for the ANN [6]. A sequential ANN architecture is then constructed with interconnected layers, allowing the network to learn relationships between image features and class labels. During training, the ANN receives pre-processed images and iteratively adjusts its internal parameters to improve its classification ability [7]. This process, called backpropagation, allows the network to learn from the data. Following training, the model's performance is evaluated on unseen data to assess its generalization capability. The code also visualizes the training process

- Multi-Layer Perceptron (MLP)

The methodology comprises an established workflow beginning with data loading and preprocessing. The MLP model, an essential element of the system, takes on a sequential architecture with a flatten layer to transform image data followed by dense layers with Re LU activation for non-linearity, and dropout layers to prevent overfitting [8]. During the training process, the Adam optimizer and sparse categorical cross-entropy loss are employed, with early stopping to monitor validation loss and terminate training if it plateaus. This approach is highly indicative of the application of MLPs for image classification tasks within a deep learning framework [14].

D. Model Validation

After training, the model's performance is assessed using a separate testing dataset [9]. The model makes predictions for various eye diseases like Age-related Macular Degeneration, Cataract, Glaucoma, and others, indicating whether they are detected or not [15]. To evaluate the model's effectiveness, key metrics like accuracy, loss, sensitivity, ROC curve, AUC, and scalability are calculated.

E. Comparison Of models

Once all the models (CNN, ANN, MLP) are trained and evaluated, their performance is compared using key parameters like accuracy, loss, sensitivity, ROC curve, Area Under the Curve (AUC), and scalability. Based on this comparison, the model that achieves the best balance between these metrics is recommended as the most suitable deep learning model for real-time healthcare applications [18].

IV. RESULTS AND DISCUSSIONS

To determine the most effective model for real-time detection, we conducted a thorough evaluation of several key performance metrics. This included a detailed analysis of Accuracy, Loss, Sensitivity, Scalability, ROC (Receiver Operating Characteristic), and AUC (Area Under the Curve). We then plotted the results in graphical form to showcase the performance of three different models: CNN (Convolutional Neural Network), ANN (Artificial Neural Network), and MLP (Multilayer Perceptron) across five distinct diseases.

The graphs we created provide a comprehensive illustration of the accuracy, loss, scalability, ROC, AUC, sensitivity, and confusion matrices for each individual model. By examining these key performance metrics in detail, we were able to gain a better understanding of the strengths and weaknesses of each model, allowing us to make an informed decision regarding which one is most suitable for real-time detection in a given scenario.

TABLE I COMPARISON OF CNN, ANN, MLP MODELS FOR AGE RELATED MACULAR DEGENERATION PREDICTION

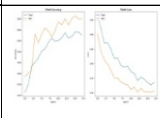
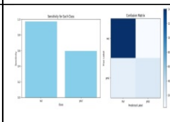
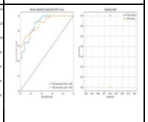
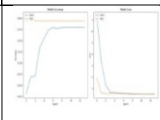
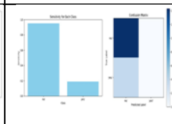
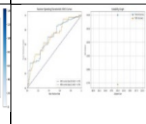
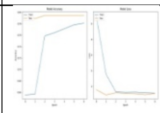
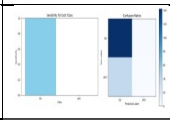
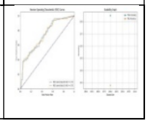
Model	Accuracy and loss	Sensitivity and confusion matrix	ROC and AUC
CNN			
ANN			
MLP			

Table 1 gives graphical representation of the performances of CNN, ANN, MLP model that has been trained to identify age related macular degeneration. It shows that the CNN, ANN and MLP achieved an accuracy of 89%,79% and 78% respectively. The sensitivity of each model is calculated by the formula given in (1). From the table it is evident that CNN has achieved good sensitivity of 99% in no class and 75% in Yes class and it was also able to detect 140 True Negatives (TN) and 22 True Positives (TP) and 3 False Negatives (FN) and 15 False Positives (FN). CNN’s AUC under ROC in both the classes were 0.90, whereas ANN and MLP fall shorter in sensitivity [12] and ANN predictions were 143(TN),0(TP), 37(FN) and 0(FP). MLP predicted 142(TN),0(TP),0(FP),37(FN). ANN and MLP achieved AUC under ROC as 0.70, 0.73

respectively. This infers that, the CNN model appears to have the best performance, with a higher number of correctly classified cases than the ANN and MLP.

Sensitivity = True Positives / (True Positive + False Negatives) … (1)

TABLE II COMPARISON OF CNN, ANN, MLP MODELS FOR CATARACT DETECTION PREDICTION

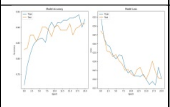
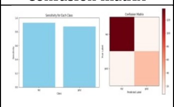
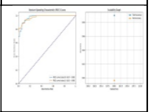
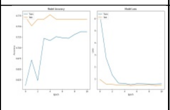
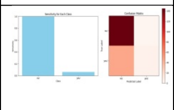
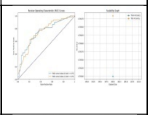
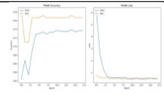
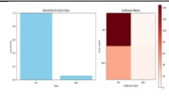
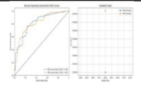
Model	Accuracy and loss	Sensitivity and confusion matrix	ROC and AUC
CNN			
ANN			
MLP			

Table 2 gives graphical representation of the performances of CNN, ANN, MLP model that has been trained to identify cataract. It shows that the CNN, ANN and MLP achieved an accuracy of 91, 76% and 76% respectively. The sensitivity was calculated from (1) and it is evident that CNN has achieved greater accuracy, sensitivity and AUC under ROC 91%, > 95% in both classes and 0.98 respectively. CNN predicted 137 TN,39 TP,8 FP, 9FN, ANN predicted 145 TN,3 TP,0 FP, 45 FN and MLP predicted 145 TN,3 TP,0 FP,45 FN. It is inferred that CNN is performing well when compared to other models.

TABLE III COMPARISON OF CNN, ANN, MLP MODELS FOR GLAUCOMA DETECTION

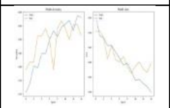
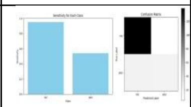
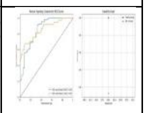
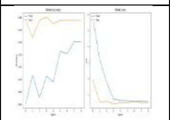
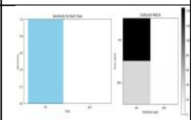
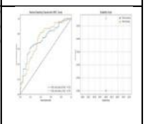
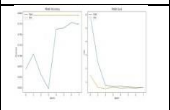
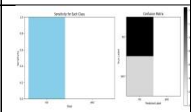
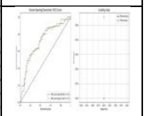
Model	Accuracy and loss	Sensitivity and confusion matrix	ROC and AUC
CNN			
ANN			
MLP			

Table 3 gives graphical representation of the performances of CNN, ANN, MLP model that has been trained to detect glaucoma. It shows that the CNN, ANN and MLP achieved an accuracy of 87%, 80%, 78% respectively. The sensitivity was calculated from (1) and it is evident that CNN has achieved greater accuracy, sensitivity and AUC under ROC 87%, 99% in no class and 78% in yes class and 0.85 respectively. CNN predicted 139 TN,18 TP, 5 FP, 19 FN, ANN predicted 144 TN,1 TP,0 FP, 36 FN and MLP predicted 144 TN,0 TP,0 FP and 37 FN. CNN is comparatively providing good results.

TABLE IV COMPARISON OF CNN, ANN, MLP MODELS FOR HYPERTENSIVE RETINOPATHY PREDICTION

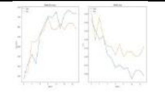
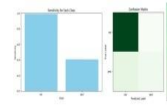
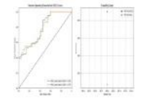
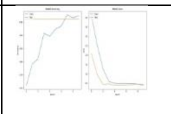
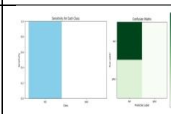
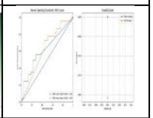
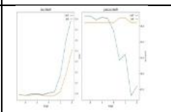
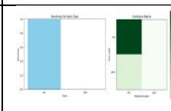
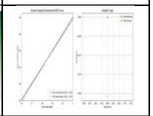
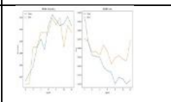
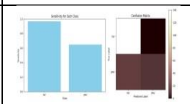
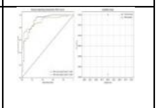
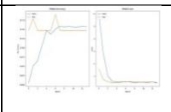
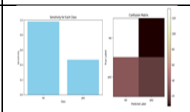
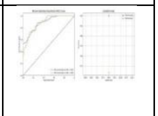
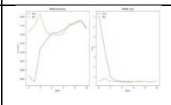
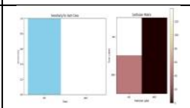
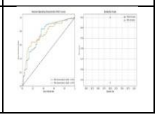
Model	Accuracy and loss	Sensitivity and confusion matrix	ROC and AUC
CNN			
ANN			
MLP			

Table 4 gives graphical representation of the performances of CNN, ANN, MLP model that has been trained to detect hypertensive retinopathy. It shows that the CNN, ANN and MLP achieved an accuracy of 90%, 80%, 85% respectively. The sensitivity was calculated from (1) and it is evident that CNN has achieved greater accuracy, sensitivity and AUC under ROC 90%, > 75 % in both classes and 0.79% respectively [14].

TABLE V COMPARISON OF CNN, ANN, MLP MODELS FOR PATHOLOGICAL MYOPIA DETECTION

Model	Accuracy and loss	Sensitivity and confusion matrix	ROC and AUC
CNN			
ANN			
MLP			

The sensitivity of ANN and MLP is very low less than 20%. CNN predicted 140 TN,22 TP,0 FN,0 FP, ANN predicted 140 TN,23 TP,15 FN,0 FP, and MLP predicted 140 TN,22 TP,15 FN and FP. This clearly illustrates that ANN and MLP fail to predict the presence and absence of ocular diseases accurately. CNN is also highly scalable. Again, CNN has proved to be effective when compared to other algorithms.

Table 5 gives graphical representation of the performances of CNN, ANN, MLP model that has been trained to detect Pathological Myopia. It shows that the CNN, ANN and MLP achieved an accuracy of 92%,75% and 74% respectively. The sensitivity was calculated from (1) and it is evident that CNN has achieved greater accuracy, sensitivity and AUC under ROC 92%, 80%,0.90 respectively whereas ANN's and MLP sensitivity is 50% and 10% on yes class. CNN predicted 140 TN, 20 TP,13 FP,9 FN, ANN predicted 139 TN,1 TP,46 FP,0 FN and MLP predicted 139 TN,1 TP,46 FP and 0 FN. Once again CNN has derived best outcomes on comparison.

V. CONCLUSIONS

In conclusion, after analyzing various algorithms for ocular disease detection, it is clear that each approach has its own strengths and weaknesses. However, Convolutional Neural Networks (CNNs) are distinguished for their exceptional accuracy of more than 90% for most of the diseases, along with low model loss and efficient training. This suggests that the model can perform well on new data, making it a reliable solution for real-world applications. Although Artificial Neural Networks (ANNs) and Multi-Layer Perceptron (MLPs) show improvements in accuracy during training, their peak accuracies are still lower than that of CNNs. Therefore, based on the presented data, CNNs are the most promising candidate for accurate and efficient multiple ocular disease detection, with their superior combination of accuracy, low loss, and efficient training making them suitable for practical use.

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