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Research Article

Eye Disease Classification using Integrated Deep Learning Approaches - CNN and Transfer Learning (ResNet50 and MobileNetV2)

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Abstract

To avoid irreparable vision loss, it is imperative to diagnose eye diseases early. Ophthalmologists typically manually screen the images of the diseases. An increase in the number of patients and a shortage of skilled ophthalmologists are detrimental to the treatment of patients. In this study, the classification of the images into cataract, glaucoma, normal, and diabetic retinopathy-infected eyes is the main objective. In a number of issues including disease classification, the Convolutional Neural Network – CNN model has been shown to be successful. The aim of this paper is to use CNN and transfer learning (MobileNetV2 and ResNet50) models to classify images of eye diseases into four categories: normal, cataract, glaucoma, and diabetic retinopathy through Data and image pre-processing and data augmentation, CNN will be used to extract features from the dataset, using CNN and pre-trained models for the classification of eye diseases, comparison of CNN and pre-trained models and with models used for multiclass classification by some other authors. The suggested CNN models combined with Transfer Learning models (names written above) extract a variety of distinct properties from the images. The dataset for this research was gotten from Kaggle. The performance of the models improved after introducing several hyper-tuning approaches on the parameters and the highest accuracy gotten for the CNN model was 88% while 94% and 93% were gotten for ResNet50 and MobileNetV2 respectively.

Keywords: Eye Disease; Blind; ResNet50; MobileNetV2

Introduction and Background

By 2020, 596 million persons with vision impairment were expected worldwide, of which 43 million are blind. Statistically, untreated nearsightedness affected an additional 510 million people because of no reading glasses. There are scores of eye conditions – ranging from common to rare ones. Nearly two million people live with sight loss in the UK. Nevertheless, it is heartening to know that more than 90% of those who suffer from vision impairment causes that are preventable or treatable, and there are already extremely affordable solutions available to do so. Eye diseases affect all ages, although young children and the elderly are most vulnerable. Additionally, people who live in rural areas and belong to ethnic minorities are more susceptible to impairment of vision. By 2050, it is projected that 895 million people will have distance vision impairment, and 61 million will be blind due to population aging and urbanization [2]. Now is the time to prioritize eye health (Matthew., *et al*. 2020). According to [14], there are several ophthalmic illnesses relating to the eyes –glaucoma, uveitis, cataracts, diabetic retinopathy, ocular hypertension, macular degeneration, keratitis, and trachoma. These eye diseases and the spread of blindness or vision impairment are not confined by geography, economics, or cultural boundaries. Early identification and treatment of eye diseases can prevent loss of vision.

Brief description of the diseases that this project encompasses: In 2019, it was estimated that the number of people aged 16 years or older who have diabetes in England was 4,029,407. It is said to be 4,398,883 by 2025 and 4.9 million by 2035 (which is almost 10% of the population over 16). Diabetes is more prevalent in men than women in ratio of 9.6% to 7.6% (Public Health England).

Damage to the blood vessels feeding the retina, the light-sensitive layer at the back of the eye leads to diabetic retinopathy. Type 1 and type 2 diabetics are both susceptible to this disease.

Damage to the optic nerve which links the eyes with the brain, leads to glaucoma. More than 700,000 persons in the UK have glaucoma. Half of them don't know they have it. It is one of the main causes of blindness in the world. About 2% of people over 40 in the UK have the illness. Glaucoma can cause visual loss if it is not identified and treated at an early stage. Adults in their 70s and 80s are the most frequently impacted, yet it can affect anyone.

Glaucoma rarely exhibits any symptoms at first. Peripheral vision or the outer edges of the field of vision, is often initially affected and takes years to grow slowly. Because of this, glaucoma is frequently only identified during a normal eye exam [11], and many people are not aware they have it. Additionally, it is the most typical reason for permanent blindness. The two main risk factors for glaucoma, which is actually a small group of diseases that all result in the same loss of vision, are high eye pressure and old age.

Cataract

About 51% of blindness worldwide is caused by cataracts, which is the most common cause of blindness [12]. A total of 0.314 billion people worldwide are blind due to cataracts [9]. The majority of people who develop cataracts are over the age of 40, and this ratio rises as people get older. There are an additional 2 million cases of cataracts added each year [13]. When the lens, a little transparent tissue inside the eye, scatters light, causing your eyes to appear foggy or milky to other people and the optometrist when they look into your eyes, you have a cataract. Cataract sufferers may see view as through clouded lenses to looking through a frosty or fogged-up window.

Medical errors are already an issue that affects every country in the world. In 1999, the American Institute of Medicine (IOM) released a report titled "To Err is Human" [3] that stated: First, the number of medical errors is staggering; they are now the fifth leading cause of death; and second, the majority of medical errors are caused by human error and can be prevented by using computer technology. Hence, a need to explore and maximize Artificial Intelligence with respect to eye diseases. It has been applied in medical diagnosis; for skin disease, fetal delivery, and metabolic synthesis [7] and has demonstrated high accuracies and outstanding track records.

Classifying these diseases is important because patients or individuals with any of them can easily be diagnosed/identified, and treated to avert further conditions or total loss of vision. Hence CNN and transfer learning models will be used for the classification. The diseases are Diabetic Retinopathy, Glaucoma, and Cataract from the normal eyes.

Literature Review

Eye disease classification with deep-learning neural networks is a very important project that has been worked on by many individuals in the past. This section focuses on studies that classify two or more eye diseases that are more pertinent to this line of work.

Authors in [5] used five eye conditions - Ptosis, Goonderson Flap, Strabismus, Ocular Surface, and Dermoid Cyst —were chosen to be identified using HOG features and Convolutional Neural Network (CNN) techniques on a dataset of 7244 labeled images gathered from Gujarat, India's Drashti Netralaya Eye Hospital and got an accuracy of 75-77%.

In [10], authors classified eye diseases with Machine Learning (ML) algorithms and deep learning neural networks. The ML algorithms used were Decision Tree, Naive Bayes, Random Forest, and the Neural Network algorithm and they gave an accuracy of 85.81%, 81.53%, 86.63%, and 85.98% respectively for correctly classified instances.

Esmail., *et al*. (2023) used a pre-trained model of ResNet50 and CNN model to classify Diabetic Retinopathy (DR) and Choroidal Nervus (CN) and for binary and multi-class classification of DR, they got an accuracy of 97% and 81%, and 82.5% accuracy for binary classification for CNN after using SHapley Additive exPlanations (SHAP) analysis approach to detect areas of an eye image that contribute the most to the DR and CN prediction using transfer learning.

Authors in [15] classified Diabetic Retinopathy, Macular Disease of the eye, and Glaucoma Suspects with Deep Learning algorithms and got accuracies of 96.3%, 92.9%, and 94.6% for their specificity respectively.

Authors in [5] classified seven eye diseases which are conjunctivitis, sub-conjunctival, cataracts, stye, dilated pupil, corneal ulcer, pterygium using CNN and the best accuracy of 87.1428% was achieved.

In [1], authors used Retinal Fundus photograph of 1,748 images and used AlexNet and VGG network architectures, accuracies of 87.2% and 90.7% were obtained respectively.

In [4], the authors also used Retinal Fundus photograph using CNN and a pre-trained model of InceptionV3 architecture on 128,175 images, after tuning some hyperparameters, the best accuracies obtained were

97.5% and 93.9%.

Deep Learning algorithm was created by [8] with Inception V3 architecture on 30,000 images based on the Australian Tele-eye care DR database, DiaRetDB1, EyePACS, and other training datasets. A primary care clinic in Australia treated 193 patients, and the performance of the DL algorithm was tested prospectively.

The low prevalence of Diabetic Retinopathy in their cohort led to a specificity of 92%.

Methodology

Data Collection and Description: The dataset used is composed of real-time data obtained from Kaggle. It contains 4,270 eye disease images with 4 classes of diseases. The preprocessing step is a crucial step to getting the data into the right shape, format, and accuracy level for the model. Its label is indicated by the image filename and folder name saved in the file system. According to their folder index, the labels were assigned to all of the imported images. Data Transformation: The research's data transformation phase is normalization, involves dividing the images by 255 so that the image will be represented using a range of 0–1. Model Description: After getting the base model using the Adam optimizer and other parameters, different models were generated by tweaking the necessary parameters to improve the result that was initially gotten from the base model. By so doing, different optimizers were used, dropouts changed, learning rates tuned, different training times/epochs, and convolutional layers were used. The dataset was augmented- rotated, flipped at different directions and dimensions, and trained to check for any betterment in the result. Evaluation: Accuracy, F1-score and sensitivity are the metrics that are used. The ability of the model to identify those who have the condition is known as the model's sensitivity, sometimes referred to as the true positive rate. The ability of the model to correctly identify people who do not have the disease is known as the true negative rate [6].

Discussion and Results

As aforementioned, the classes of disease worked on were cataract, diabetic retinopathy, glaucoma and normal eyes as visualized below.

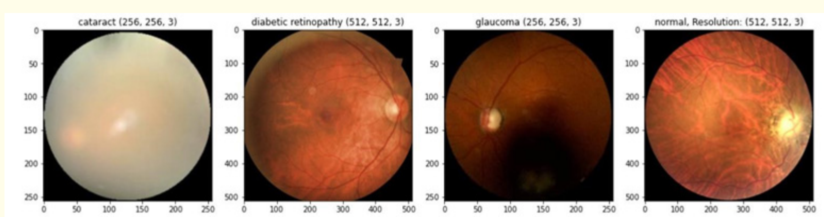

Figure 1: Showing the classes of eye diseases in the dataset.

The dataset contains 4,217 images, split into ratio 3 to 1 for training and validation respectively hence 3,374 images were used for the former and 843 used for the latter.

```
Found 4217 files belonging to 4 classes.
Using 3374 files for training.
Found 4217 files belonging to 4 classes.
Using 843 files for validation.
```

CNN Models and Results

The base model

The base model had the below parameters, training and validation accuracy and loss respectively, classification report and confusion matrix.

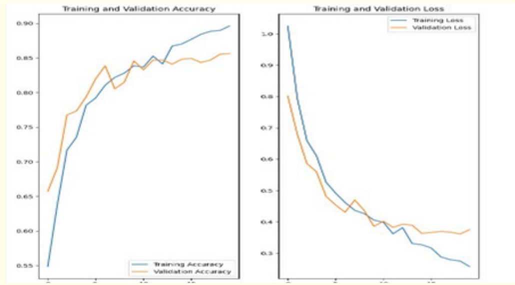

Figure 2: Showing training and validation accuracies.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       202
           1       1.00      1.00      1.00       214
           2       0.86      0.67      0.75       205
           3       0.79      0.86      0.83       222

    accuracy                           0.86       843
   macro avg       0.86      0.85      0.85       843
weighted avg       0.86      0.86      0.85       843

Confusion Matrix:
 [[180   0   9  13]
 [  0 213   1   0]
 [ 29   1 137  38]
 [ 18   0  12 192]]
```

Figure 3: Showing classification report and confusion matrix.

Optimizer	Activation Function	Epochs	Dropout	Learning Rate	Accuracy	Convolutional block
Adam	ReLu	20	0.5	0.001	86%	3

Table 1: Showing the metrics of the CNN base model.

The base model gave an accuracy of 86%. In the quest to improve the performance of the model, the base model's training time was increased to be 30 (epochs) from 20, and the below results were gotten.

Training the model for more times (30) never had any effect on the accuracy, it remained 86% as it was when the epoch was 20.

After this, there was data augmentation, where images were randomly flipped horizontally, and rotated at 0.2. Data augmentation had to be done because the number of images in the dataset was not so numerous hence had to be augmented to get more images/flipping. Here, the accuracy increased by 1% making it 87%.

Optimizer	Activation Function	Dropout	Epochs	Accuracy	Convolutional block	Learning Rate
Adam	ReLu	0.4	30	86%	3	0.001

Table 2: Showing metrics of a more trained model from the base model.

Data augmentation table

The dataset was augmented and shown in figures below with corresponding results.

There were more hyperparameter tunings of the base model to check further for better accuracies from the one gotten initially. Using Adam Optimizer for nine other models built whose results are shown in the tables below.

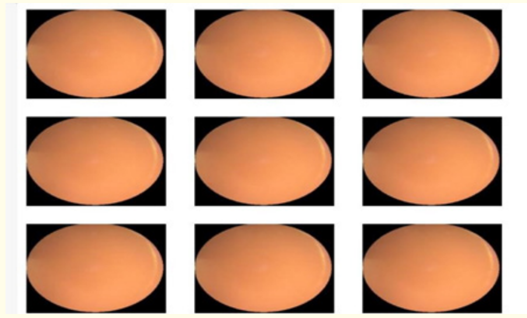

Figure 4: Shows augmented data.

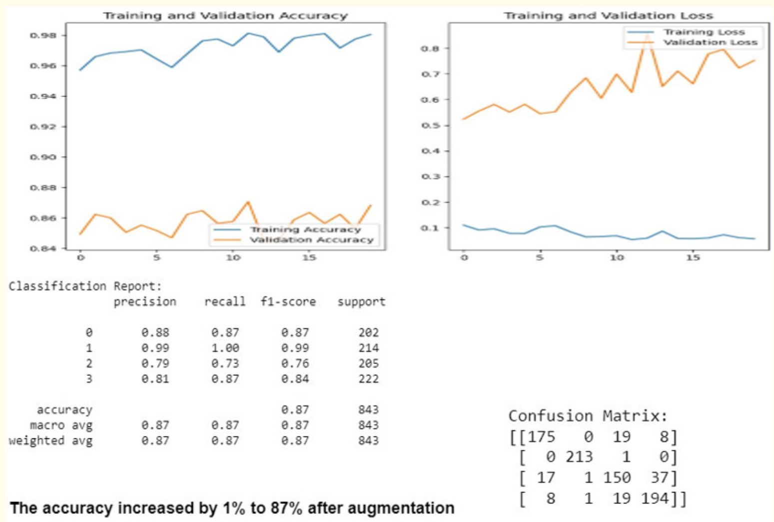

Figure 5: Show training and validation accuracies, classification report and confusion matrix of model of data augmentation.

Optimizer	Activation Function	Epoch	Learning Rate	Accuracy
Adam	ReLu	20	0.001	87%

Table 3: Showing performance of data augmentation model.

The first three models and accuracies

From the first three models run with Adam optimizer, the one that gave the best accuracy (although with more training time) was the third with 84%, Learning rate = 0.001, epoch = 20, and every other parameter held constant as the rest.

The second three models and accuracies

The learning rate was slightly tuned to 0.002 to see if there would be better accuracy to the model, but there was no better accuracy than the 84% gotten previously.

MODELS	First_model	Second_model	Third_model
Learning Rate	0.001	0.001	0.001
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Layer	3	3	3
Accuracy	81%	82%	84%

Table 4: Showing the performance of the first three models using Adam optimizer and different parameters.

MODELS	Seventh_model	Eigth_model	Nineth_model
Learning Rate	0.003	0.003	0..003
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional layers	3	3	3
Accuracy	80%	79%	78%

Table 6: Shows the performances of the seventh to nineth models with Adam optimizer with different parameters.

The last three models and accuracies with Adam optimizer

The learning rate again was changed to 0.003 to probe further if it could better the accuracy, but rather the highest and best accuracy gotten here was 80%. The best accuracy using Adam optimizer was 84% when the learning rate was 0.001. This will be further tuned to see if better accuracy could be obtained. To be discussed later in this section.

Now, the Stochastic Gradient Descent optimizer was used also and the results are as shown in the tables below.

The first three models using SGD and their accuracies

When a learning rate of 0.001 was used, the best accuracy obtained was 61% at 20 epochs.

MODELS	First_model	Second_model	Third_model
Learning Rate	0.001	0.001	0.001
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Layer	3	3	3
Accuracy	46%	53%	61%

Table 7: Shows the performances of the first to third models with SGD optimizer with different parameters.

The second three models with SGD optimizer and accuracies.

Upon changing the learning rate and training for 10, 15, and 20 times, the accuracy of the SGD optimizer never improved. The best accuracy here was 58%, which is poorer that the previous table with 61%.

The third three models of SGD optimizer and their respective accuracies

When the learning rate was changed further at different training times, the accuracy never improved. The best accuracy gotten

MODELS	Fourth_model	Fifth_model	Sixth_model
Learning Rate	0.002	0.002	0.002
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Layer	3	3	3
Accuracy	57%	54%	58%

Table 8: Shows the performances of the fourth to sixth models with SGD optimizer with different parameters.

MODELS	Seventh_model	Eigth_model	Nineth_model
Learning Rate	0.003	0.003	0.003
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Layer	3	3	3
Accuracy	57%	59%	60%

Table 9: Shows the performances of the seventh to ninth models with SGD optimizer with different parameters.

here was 60%. The accuracies obtained from SGD optimizer models are poor and would never be recommended as the best accuracy obtained from the entire models run with SGD was 61% at learning rate of 0.001.

Using RMSprop optimizer and the parameters shown below, the first three models are.

In the first three models with the parameters listed above, the best accuracy obtained was 82%. Tuning the learning rate to 0.002 and others left constant, results below are obtained.

The best accuracy here was 77%. There was no improvement in the accuracy. Again, learning rate was tuned further to check any improvement in the accuracy as shown below.

MODELS	First_model	Second_model	Third_model
Learning Rate	0.001	0.001	0.001
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Block	3	3	3
Accuracy	79%	81%	82%

Table 10: Shows the performances of the first to third models with RMSprop optimizer with different parameters.

MODELS	Fourth_model	Fifth_model	Sixth_model
Learning Rate	0.002	0.002	0.002
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Block	4	4	4
Accuracy	77%	74%	75%

Table 11: Shows the performances of the fourth to sixth models with RMSprop optimizer with different parameters.

MODELS	Seventh_model	Eigth_model	Nineth_model
Learning Rate	0.003	0.003	0.003
Epoch	10	15	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Block	3	3	3
Accuracy	61%	64%	67%

Table 12: Shows the performances of the seventh to ninth models with RMSprop optimizer with different parameters**.**

Upon changing the learning rate, the accuracy never improved rather the best accuracy gotten was 67%.

Comparison of the best accuracies obtained so far from the three optimizers are.

The model with the highest accuracy obtained so far was from Adam Optimizer as shown above (although with Data Augmentation – named model_aa for future referencing in the paper), the parameters (of model_aa) were hyper-tuned further to check if there could be any performance improvement. The results below were gotten.

The accuracy never improved at all upon tuning the dropout, rather it dropped to the three accuracies above. Furthermore, the patience in the early_stopping parameter was tuned at a dropout of 0.3 as it gave the highest accuracy from previous table and got the results below.

Optimizer	SGD	RMSprop	Adam+ Augmentation (model_aa)
Learning Rate	0.001	0.001	0.001
Epoch	20	20	20
Dropout	0.5	0.5	0.5
Patience	5	5	5
Convolutional Block	3	3	3
Activation Function	ReLu	ReLu	ReLu
Accuracy	61%	82%	87%

Table 13: Shows the performances of the best models with the three optimizers with different parameters.

Dropout	0.2	0.3	0.4
Epoch	20	20	20
Learning Rate	0.001	0.001	0.001
Patience	5	5	5
Convolutional Block	3	3	3
Activation Function	ReLu	ReLu	ReLu
Accuracy	82%	86%	85%

Table 14: Shows the performances of the model_aa after parameters were hyper-tuned.

Patience	2	3	4
Epoch	20	20	20
Learning Rate	0.001	0.001	0.001
Dropout	0.3	0.3	0.3
Convolutional Block	3	3	3
Activation Function	ReLu	ReLu	ReLu
Accuracy	86%	85%	88%

Table 15: Shows the performances of the model_aa after patience values were hyper-tuned.

There was an improvement in the accuracy from 87% to 88% at patience of 4 and dropout of 0.3.

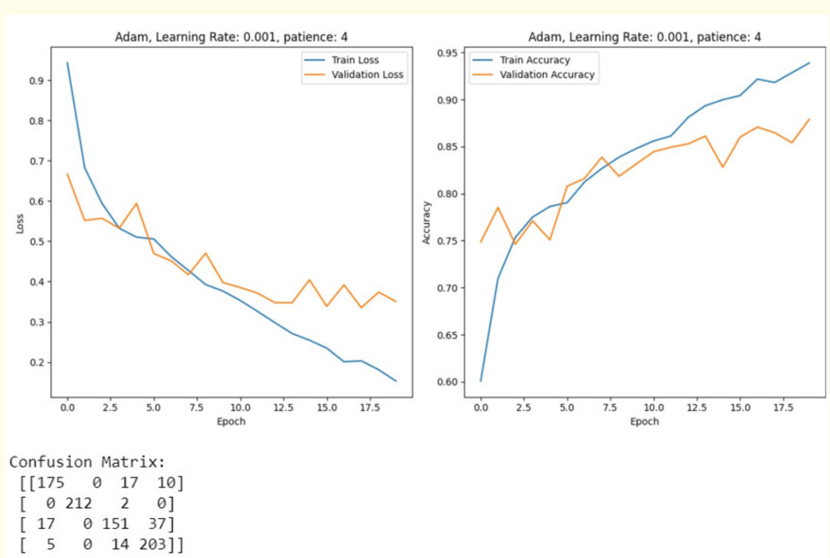

Figure 6: Shows training and validation accuracies, and confusion matrix of the model with the best performance for patience of 4.

The RMSprop optimizer model was tuned for any improvement in accuracy, the dropout first.

Dropout	0.2	0.3	0.4
Epoch	20	20	20
Learning Rate	0.001	0.001	0.001
Patience	5	5	5
Convolutional Block	3	3	3
Activation Function	ReLu	ReLu	ReLu
Accuracy	84%	86%	86%

Table 16: Shows the performances of the RMSProp model after parameters were hyper-tuned.

The RMSprop optimizer improved in accuracy from the initial highest value of 82% to 86% at dropouts of 0.3 and 0.4. Again, patience was tuned and the accuracies in the table were obtained.

Also, same accuracies were gotten and the highest accuracy was still 86% at 3 and 4 patience.

Patience	2	3	4
Epoch	20	20	20
Learning Rate	0.001	0.001	0.001
Dropout	0.4	0.4	0.4
Convolutional Block	3	3	3
Activation Function	ReLu	ReLu	ReLu
Accuracy	84%	86%	86%

Table 17: Shows the performances of the RMSProp model after patience were hyper-tuned.

So far, the CNN model with highest accuracy was 88%.

Pre-trained models and results

With MobileNetV2, the results and parameters were obtained.

First model with Adam optimizer of 91% accuracy was tuned further and the results below were gotten.

After tuning, the accuracy improved to 93% which is the highest for MobileNetV2.

Optimizer	Adam	RMSprop	SGD
Learning Rate	0.0001	0.0001	0.0001
Epoch	25	25	25
Dropout	0.5	0.5	0.5
Accuracy	91%	75%	86%

Table 18: Shows the performances of the MObileNetV2 models with different optimizers.

Optimizer	Adam	Adam	Adam	Adam
Learning Rate	0.0002	0.0002	0.0002	0.002
Epoch	25	30	25	25
Dropout	0.5	0.5	0.4	0.3
Accuracy	93%	91%	80%	89%

Table 19: Shows the performances of the MObileNetV2-Adam model with different learning rate with.

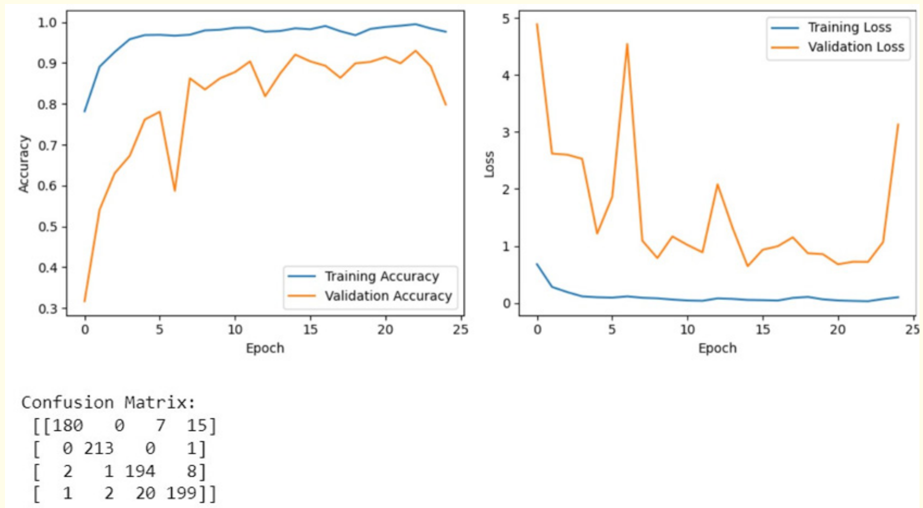

Figure 7: Shows training and validation accuracies, and confusion matrix of the best performance of MObileNetV2.

ResNet50

The parameters and results below were obtained.

The model with best accuracy was 94% and was tuned further with results below.

Optimizer	Adam	RMSprop	SGD
Learning Rate	0.0001	0.0001	0.0001
Epoch	25	25	25
Dropout	0.5	0.5	0.5
Accuracy	94%	93%	86%

Table 20: Shows the performances of the ResNet50 models with different optimizer.

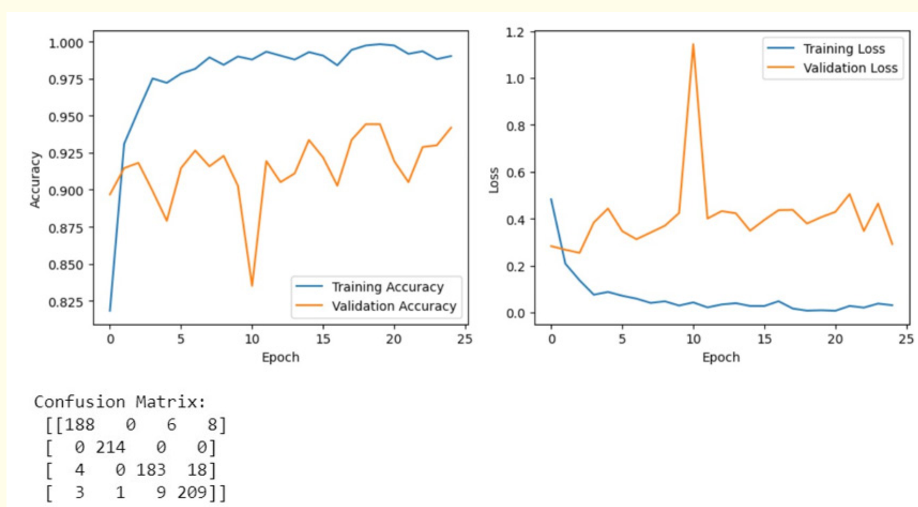

Figure 8: Confusion matrix, training and validation accuracies of the best performing model from ResNet50.

Optimizer	Adam	Adam	Adam
Learning Rate	0.0001	0.0001	0.0002
Epoch	25	25	25
Dropout	0.4	0.3	0.5
Accuracy	93%	92%	90%

Table 21

There was no improvement after tuning, and the best accuracy for the ResNet50 model was 94%.

According to the confusion matrix performance of the best-performed models of CNN, MobileNetV2, and ResNet50, the ResNet50 model classified the classes in the dataset best than the other two models.

Comparison of models with best accuracies

Model Name	Best Accuracy Obtained
ResNet50	94%
MobileNetV2	93%
CNN	88%

Table 22

Comparison of CNN and Pre-trained Models with Previous Researches.

Dataset	Number of Images	Classifier	Accuracy	Author
Retinal Fundus photograph	1,748	VGG16	90.7%	Abràmoff., *et al*. (2016) [1]
DIARETDB0, HRF Image and STARE	2,848	CNN	92%	Karthikeyan., *et al*. (2019)
Akdeniz Eye University Hospital Diseases Department	9,565	Xception with multilayer perceptron	81%	Bulut., *et al*. (2020)
STARE and DRIVE	440	VGG19+Augmentation	93.58%	Das., *et al*. (2019)
Kaggle	600	ResNet50+Augmentation	60%	Santra T. (2019)
Kaggle	4,270	CNN	88%	This research
Kaggle	4,270	ResNet50	94%	This research
Kaggle	4,270	MObileNetV2	93%	This research

Table 23: Shows the performances of the best model in this research in comparison with other authors'.

Deductions

This research sought to classify eye disease images into different classes of 4; diabetes retinopathy, normal eyes, glaucoma, and cataract. CNN and pre-trained models were used for this classification; the highest accuracy obtained so far in all of the CNN models was 88% and the pre-trained models were able to classify the images more accurately giving accuracies of 94% and 93% for ResNet50 and MobileNetV2 respectively.

Conclusion and Future Work

To expand the number of images in each class, it should be intended to integrate more classes into the dataset that are similar in future work and more number of images in each class; multiple datasets can be integrated to create a more accurate and reliable model. Due to the fact that Cataracts, Glaucoma, and diabetic retinopathy affect three distinct eye structures— the Optic disc, Optic nerve, and retina—this structure can be segmented from the images and later trained using the CNN model. This would be useful because, although the images of normal and diseased eyes appear similar, there may be a small area of the image that represents the beginning of the disease. Therefore, classifying the images will be more accurate if the segmented data are trained using the models.

Bibliography

1. Abràmoff MD., *et al*. "Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning". *Investigative Ophthalmology and Visual Science* 57.13 (2016): 5200.

2. Burton MJ., *et al*. "The Lancet Global Health Commission on Global Eye Health: vision beyond 2020". *The Lancet Global Health* 9.4 (2021): e489-e551.

3. GRUEN R. "To Err Is Human". Eds. L. T. Kohn, J. M. Corrigan and M. S. Donaldson. National Academy Press Washington, D.C (2000): 287.

4. Gulshan V., *et al*. "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs". *JAMA* 316.22 (2016): 2402.

5. Hanaa Mohsin Ahmed and Hameed SR. "Eye Diseases Classification Using Hierarchical MultiLabel Artificial Neural Network". (2020).

6. Hanung Adi Nugroho., *et al*. "Analysis of Texture-based Features for Image Classification of Retinal Exudates". (2017).

7. Kabari LG and Nwachukwu EO. "Neural Networks and Decision Trees For Eye Diseases Diagnosis". *InTech eBooks* (2012).

8. Kanagasingam Y., *et al*. "Evaluation of Artificial Intelligence–Based Grading of Diabetic Retinopathy in Primary Care". *JAMA Network Open* 1.5 (2018): e182665.

9. Louis P., *et al*. "Global initiative for the elimination of avoidable blindness". (2000).

10. Malik S., *et al*. "Data Driven Approach for Eye Disease Classification with Machine Learning". *Applied Sciences* 9.14 (2019): 2789.

11. NHS. "Glaucoma" (2017).

12. Pascolini D and Mariotti SP. "Global estimates of visual impairment: 2010". *The British Journal of Ophthalmology* 96.5 (2012): 614–618.

13. Sahana M and Gowrishankar SN. "Identification and Classification of Cataract Stages in Old Age People Using Deep Learning Algorithm". 8.10 (2019): 2767-2772.

14. Zhang Z., *et al*. "A survey on computer aided diagnosis for ocular diseases". *BMC Medical Informatics and Decision Making* 14.1 (2014).

15. Ruoan X., *et al*. "Deep Learning for Eye Disease Classification: Diabetic Retinopathy, Macular Disease, and Glaucoma". *Journal of Medical Imaging* 35.4 (2022): 123-135.