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Detection and Multiclass Classification of Ocular Diseases using Deep Learning-based Ensemble Model

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Abstract*:* The technological advances have made it possible to design and develop automated systems for the detection of diseases which saves time and enables early treatment, fostering good health. A lot of people in developing countries lose their vision to ocular diseases at an early age. To prevent irreversible damage to the eyesight timely detection and treatment are imperative. Nowadays, automatic detection of such vision-threatening diseases is possible with the help of artificial intelligence (AI) systems. Diabetic Mellitus or diabetes is one of the diseases which causes many ocular diseases such as diabetic retinopathy, diabetic macular edema, cataract, and glaucoma. The proposed work automatically detects three such ocular diseases: Choroidal neovascularization, Diabetic macular edema and Drusen. The proposed work uses an ensemble approach to detect ocular diseases wherein three models have been designed. The ensembles have been designed using the feature extractor method of the VGG16, Xception and mobilenet models and then extracted features are given to a convolutional neural network which then trains and classifies the input tomographic images into Choroidal neovascularization, Diabetic macular edema, Drusen and Normal. The proficiency of the ensemble models is assessed using the metrics- prediction accuracy, class-wise accuracy, precision, recall and f1-score. The ensemble model – MobileNet with CNN yields the best results with an average accuracy of 95.34%.

Keywords: *Automatic Detection, Artificial Intelligence, Deep Learning, Ocular Diseases, Optical Coherence Tomography, Choroidal Neovascularization, Diabetic Macular Edema, Drusen.*

1. Introduction

There is a surge in the number of cases of visual impairment around the globe. According to the recent statistics given by the World Health Organization (WHO) nearly 2.2 billion individuals suffer from ocular diseases and half of these impairments were preventable or could have been addressed if detection had been done earlier [1]. The ocular diseases occur due to damage in different parts like the retina, cornea, optic nerve, etc. Some of the common examples of ocular diseases are Cataracts, Glaucoma, Macular Degeneration, Retinal Detachment, Refractive Errors, Retinopathy, Keratitis, Conjunctivitis, and others. The causes, symptoms, and treatments of these illnesses vary, while some are linked to ageing, others stem from infections, injuries, genetic factors, or underlying health problems like diabetes mellitus. Consistent eye check-ups and immediate medical care for any eye-related concerns play a vital role in sustaining good eye health and safeguarding vision [2].

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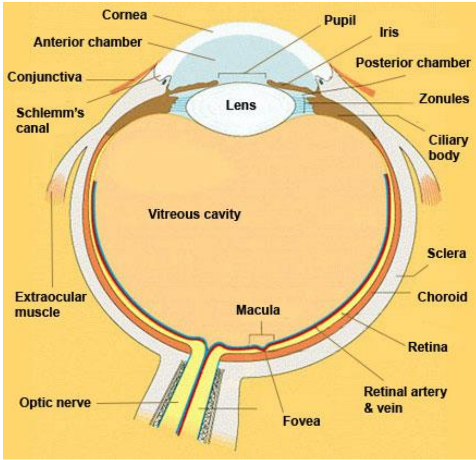
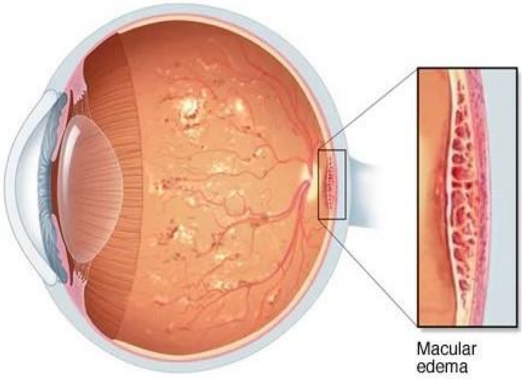
Age-related ocular diseases are a primary reason for vision loss at an early age, typically worsening as one gets older. The authors [3] studied the causes of blindness in Indians and found that approximately 17% of the Indians above 30 years of age suffered blindness due to ocular diseases. The retina is a very thin layer of light-sensitive tissues located on the back side of the eye as shown in Fig. 1(a). The layer consists of two types of cells known as rods which facilitate vision in dim light and cones that operate in brighter light. Therefore, the retina plays a crucial role in human vision and acts similarly to the film of a camera. The retina captures the incoming light signals and transmits them to the brain in the form of electrical and chemical signals which help in identifying and understanding the light images formed on the retina [4]. Many diseases of the retina develop at different age groups which significantly impact the eye-sight and consequently reduces the quality of life[5]. Some of the retinal diseases that occur during different age groups are Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME) and Drusen which impact vision. These retinal diseases are detected with the help of Retinal Optical Coherence Tomography (OCT) [6] and Magnetic Resonance Imaging (MRI) [7].



(a)



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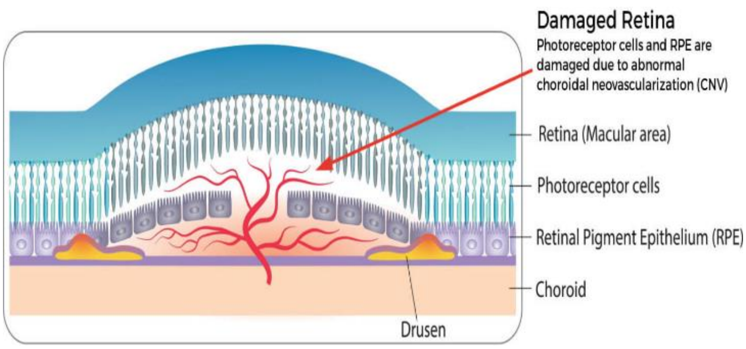


(c)

Fig. 1. (a) The representation of the anatomy of the human eye (normal human eye without disease) (Trobe, n.d.), (c) representation of the Choroidal Neovascularization and Drusen disease (Kelley, n.d.) (c) representation of the Diabetic Macular Edema disease (Mayo Foundation, n.d.).

Choroidal Neovascularization (CNV) is an eye problem which is caused by a defect in the Bruch's membrane which is the innermost layer in the choroid which can be identified as a hollow space in the membrane as shown in Fig. 1 (b). There is an abnormal growth of new blood vessels in the choroid which causes problems in the central vision. The central vision is responsible for converting light to images with the help of millions of cells that further enable the brain to identify objects. The abnormal growth of vessels is due to the excessive production of Vascular Endothelial Growth Factor (VEGF) signals which hampers the eye's central vision [8]. The central vision suddenly deteriorates due to CNV. The sufferers of CNV experience a sudden deterioration in the central vision in a short period of only a few weeks. This can be accompanied by colour disturbance and seeing straight lines as wavy known as metamorphopsia [9].

Drusen is another complication of the eyes in which extracellular deposits are built within the layers of the retina. These deposits contain proteins, lipids and cellular debris and their appearance is in the form of small yellow-coloured residues visible like tiny pebbles. As depicted in Fig. 1 (b). these deposits are formed in the inner layers of the Bruch Membrane due to ageing and macular degeneration, which further results in central vision loss [10], [11].

Diabetic Macular Edema (DME) as the name suggests occurs in diabetes sufferers and is caused by high sugar levels. It is one of the most prevalent stimulants of sight loss among diabetic patients. The retina thickens or swells due to the accumulation of intraretinal fluid in the inner layers of the retina. This thickening causes the macula to swell and the centre of the macula known as the fovea is affected. This defect of the macula is easily visible in the form of small holes in the membrane as shown in Fig. 1 (c). The main symptoms of DME are blurriness of the vision, waviness and double vision, eye floaters seen as small spots in the vision, and problems in perceiving correct colours [10], [12], [13].

Artificial Intelligence (AI) has become an invaluable asset in disease detection and diagnosis. Traditionally, these tasks require substantial time and effort when done manually by healthcare professionals. Yet, AI-driven automated systems have notably boosted the efficiency and accuracy of these processes. By swiftly analysing extensive medical data- like imaging scans or patient records- AI algorithms rapidly detect patterns or irregularities that could indicate diseases. This accelerated analysis not only speeds up diagnoses but also heightens the precision in identifying potential health concerns. Consequently, the integration of AI in healthcare holds promise for transforming how diseases are identified and diagnosed, offering a more efficient and effective approach than conventional manual methods [14], [15], [16].

In the healthcare sector, prompt reactions play a vital role in various situations, where quick responses can be pivotal in preserving lives. Identifying and treating conditions early on are foundational aspects of healthcare practices, highlighting the importance of technologies such as AI in speeding up the detection of diseases. AI's ability to rapidly identify potential health concerns empowers healthcare professionals to start treatments swiftly, potentially influencing patient outcomes significantly. This accelerated response, made possible through AI-driven diagnostic tools, meets the urgent demand for precise and immediate actions in healthcare, playing a substantial role in safeguarding human life [17], [18], [19].

Machine Learning (ML) and Deep Learning (DL) models play a crucial role in developing automated systems capable of early disease detection, consequently facilitating timely treatment[20], [21]. For instance, ocular diseases occurring at various life stages typically require manual detection by ophthalmologists, involving substantial time investment for comprehensive analysis and diagnosis. However, with the integration of Deep Learning AI systems, ophthalmologists can harness technology to expedite disease identification within a shorter timeframe[22]. This technological support not only aids in faster disease detection but also enables professionals to allocate their time more efficiently, potentially leading to quicker interventions and treatments. Ultimately, the implementation of AI-driven systems in healthcare, particularly in the field of ophthalmology, significantly enhances the diagnostic process, allowing for timelier interventions and improved patient care [23], [24], [25].

The following outlines the contribution of the paper:

- The work detects and classifies ocular diseases- Choroidal Neovascularisation, Diabetic Macular Edema and Drusen automatically using deep learning-based ensemble models.
- The ensemble model is constructed using pre-trained feature extraction methods- VGG16, Xception and MobileNet; and then utilizes a convolution neural network for classification.
- The productivity in terms of prediction accuracy, precision, recall and f1-score is compared for the three ensemble approaches. The MobileNet with CNN model-based ensemble is found to be more proficient when contrasted with VGG16 with CNN and Xception with CNN models.

This article starts with an introduction in Section 1, explaining the ocular diseases under the scanner and eventually the significance of AI, ML and DL in the automatic detection of these ocular diseases. The next section - Section 2 describes the state-of-the-art literature in ocular disease detection with regards to the techniques used by them, followed by an in-depth explanation of the materials used and methods applied in Section 3. Section 4 analyses the results obtained by applying the methodology elaborated in Section 2 and then after a detailed investigation of the obtained outcomes, conclusions are drawn in Section 5.

2. Related Work

Researchers have harnessed the capabilities of deep learning to identify ocular diseases, some of such works have been mentioned in this section.

In the research paper by [26] age-related macular degeneration is detected using deep learning strategies. The primary objective of the study was to design and develop a multi-scale CNN for automated detection. They used CNNs to identify variations in the scale and then applied a feature-fusion technique to improve the performance of the CNNs used to identify diseased eyes from OCT images.

The study presented by [27] also selects AI for designing and developing an automated system to first detect fluid in the macula and then quantify it. The authors have presented that by detecting the presence of intraretinal fluid and subretinal fluid, age-related macular degeneration and diabetic macular edema can be detected. The basic idea is that the presence of these fluids leads to diseases. A deep convolutional neural network is utilized for implementing the mapping of images to the corresponding disease labels. A high accuracy of prediction is achieved in this experimental study.

A non-invasive imaging technique known as Spectral Domain Optical Coherence Tomography is also used in ophthalmology to capture high-resolution, cross-sectional images of the retina and other layers of the eye to detect retinal diseases. A novel approach has been devised by [28] using convolutional neural networks to classify SD-OCT scans into DME, CNV, AMD, Drusen and Normal classes. The classifier used in the multiclass-classification task is the softmax classifier and the prediction accuracy is considerably good.

The authors in [29] worked to automatically diagnose non-proliferative diabetic retinopathy (NDPR). The retrospective experiment done in the study was to analyse whether machine learning can be of practical use in detecting NPDR by demographic data and clinical images of the eyes. The random forest classifier was used after the feature extraction to build the complete design used for the binary class classification problem. Then the obtained results were compared with the clinical grades of the disease. The system developed in the experimental setup proves to be highly proficient. The dataset has been procured manually from a hospital in the USA and graded by gold-standard ophthalmologists.

Another study [30] has been carried out on a private database obtained by the authors and an open-source public database. The authors propose to use CNNS for classification. First, the noise in the images was reduced and then, thresholding was applied. Next, the images are subjected to morphological dilation to extract features. After all this, surrogate images are formed which are then fed to the CNN model for training. The local database used has achieved a good accuracy score and the algorithm works better on the public database.

3. Materials and Methods

The current section provides a detailed explanation of the approach taken to accomplish multiclass classification, along with a description of the input set of images.

3.1 Dataset Description

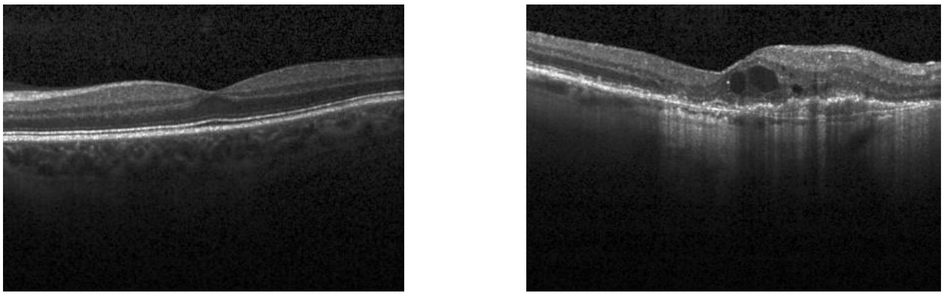
The dataset used in the experiment has been taken from a popular open-source repository- Kaggle, it is quite famous amongst the machine learning evangelists and the researchers' community. The dataset is divided into three subsets for training, testing and validation. Each subset contains four bifurcations one for each class: CNV, Drusen, DME and Normal. The dataset is a curation of 84,495 Retinal Optical Coherence Tomography (OCT) images. Retinal OCT captures retinal cross-sectional images in high resolution which are then studied to obtain the inference regarding whether the images of the subject are normal or have some retinal disorder.

Table 1. Labels of Ocular Disease Classes

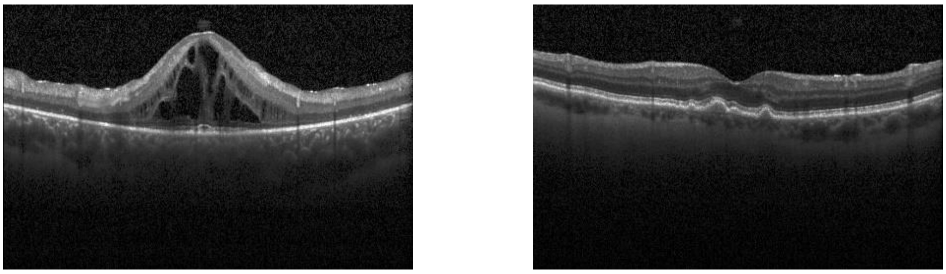
Class Number	Class Name
0	Normal
1	CNV
2	DME
3	DRUSEN

Table 2. Bifurcation of the dataset into training, testing and validation images

	Normal	CNV	DME	DRUSEN
Training	26315	37205	11348	8616
Testing	242	242	242	242
Validation	8	8	8	8



(a) (b)



(c) (d)

Fig. 2. Original images of Optical Coherence Tomography from the dataset. (a) Normal Eye (b) Choroidal Neovascularization (CNV) (c) Diabetic Macular Edema (D) Drusen

Fig. 2 is from the dataset and shows the four retinal maladies: DRUSEN, DME, CNV and Normal and the labelling of the classes is shown as given in Table 1. The 3 diseases are assigned labels as Class 1, Class 2 and Class 3 and the normal class is labelled as Class 0. Table 2 shows the bifurcation of images of the dataset as training, testing and validation.

3.2 Methods

In the current scenario, three ensemble models have been used and trained on an image dataset, the algorithms utilised for extracting features are VGG16, Xception and MobileNet model and then Convolutional Neural Network layers are added for classifying the images into 4 categories: Normal, CNV, Drusen or DME. The complete methodology has been depicted using a flow chart as shown in Fig. 3.

The raw dataset is procured from open repositories available online and then this raw data is pre-processed into similar dimensions to get uniformity. Thereafter, this pre-processed data is used to derive features using the VGG16 model layers, and then Convolutional Neural Network layers are added to classify the images. The same process is repeated but now the Xception model layers are added instead of the VGG16 layers; again, followed by Convolutional Neural Network Layers. Then the third model is implemented, and the layers for feature derivation are from the MobileNet model; after features are obtained the classification task is assigned to a convolutional neural network.

The feature extraction from the images is done in batches of 32 images each. Batch processing proves to be beneficial for confronting extensive data volumes with repetitive operations in computing. After the features are extracted from the processed image set, classification must be performed for which Convolutional Neural Networks are utilised. The output features derived after the feature extraction are contained in a multi-dimensional array. Therefore, before providing the features as input to the convolutional neural network, the multidimensional array is flattened to form a one-dimensional array which can be further processed by the neural network.

The neural network contains four layers where the first layer is the input layer and the features extracted from the models are given to this layer as their input data. The second and the third layers are hidden layers. These hidden layers have further two layers: a dense layer and a dropout layer. Here, the dropout layer is added to overcome the over-fitting problem and the dropout rate is 0.5. The dense layers contain 512 units and 256 units of neurons for the purpose of classification. The activation function used in the fully connected layers or the dense layers is the ReLU activation function.

After that, the output layer with a Softmax activation does the task of decision-making for classifying the images into four categories. The Softmax activation is customarily used in multi-class classification problems since it converts raw scores (logits) into probabilities, where each class probability is independent of the others and the sum of all probabilities is 1. The model is trained for several epochs, again in batches, to improve the efficiency of learning, after the learning the trained model is tested on a set of images. The performance of the trained ensemble models on the basis of testing is analysed using a confusion matrix and calculating various metrics used to compare the performance of the implemented models. The metrics used to compare the performance of the ensemble models are- the accuracy of prediction, precision and recall score.

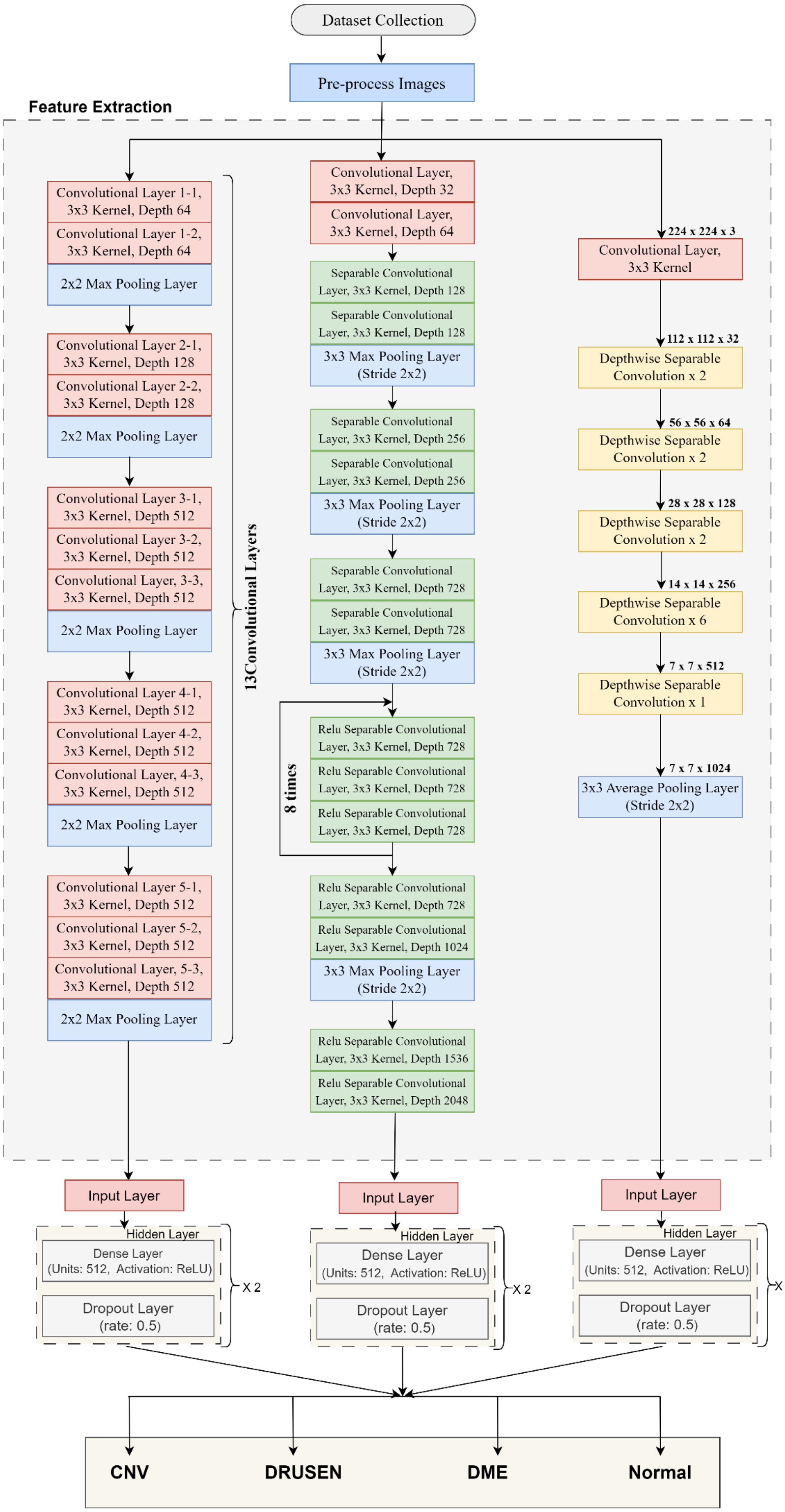


Fig. 3. The illustration of the proposed methodology followed for the Detection and Classification of Choroidal Neovascularisation, Diabetic Macular Edema and Drusen using Deep Learning-based Ensemble Model.

4. Results and Discussion

The present section emphasizes the assessment criteria employed to compare the effectiveness of ensemble models generated using the methodology outlined in the preceding section. Subsequently, a thorough examination of the obtained results is conducted to conclude the superiority of one of the three ensemble models.

4.1 Evaluation Metrics

Confusion Matrix: This tool assesses how well a classification task performs. It is a two-dimensional grid where specific data points are plotted. Various metrics are derived from these points to analyse and make inferences about the effectiveness of the learning models.

- True Positives represent instances where the classification algorithm correctly predicted a positive outcome.
- False Positives indicate the number of results that were negative, but the algorithm incorrectly predicted them as positive.
- True Negatives signify the instances where the algorithm accurately predicted a negative outcome.
- False Negatives represent the instances where the algorithm mistakenly classified positive outcomes as negative.

Table 3. Confusion Matrix in table form

	Actual Values	
Predicted Values	True Positives (TP)	False Negatives (FN)
	False Positives (FP)	True Negatives (TN)

Accuracy: defines the proportion of correct outputs, both positive and negative given by the classifier.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{total} \quad \text{(i)}$$

Precision: This measures the algorithm's frequency of accurate predictions for a "Yes" outcome.

$$\text{Precision} = \frac{TP}{Predicted{:}Yes} \quad \text{(ii)}$$

Recall: It is often referred to as the True Positive Rate since it denotes the proportion of correctly identified positive cases among all actual positives.

$$\text{Recall or Sensitivity} = \frac{TP}{Predicted{:}Yes} \quad \text{(iii)}$$

F1-Score: The F1 score is derived by computing the Harmonic Mean between Precision and Recall, and a superior F1 Score signifies improved performance.

$$\text{F1-Score} = \left(\frac{\frac{1}{precision}+\frac{1}{recall}}{2}\right)^{-1} = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} = \frac{2*precision*recall}{precision+recall} \quad \text{(iv)}$$

4.2 Result Analysis

The methodology mentioned in the previous section is used to find out at what number of epochs the prediction accuracy is the highest and a record as shown in Table IV is obtained. It is quite evident from the table that on varying the number of epochs the accuracy of prediction is affected.

Table 4. Confusion Accuracies were obtained at different numbers of epochs for the three ensemble models

No. of Epochs	VGG16 with CNN	Xception with CNN	MobileNet with CNN
10	87.24	90.17	92.93
15	88.62	90.34	93.97
20	86.90	88.97	94.66
25	89.31	90.34	95.00
30	90.69	92.07	95.34
35	88.97	91.90	94.83
40	90.34	91.72	94.14
45	90.17	91.03	93.97
50	89.66	91.21	93.79
AVG	**89.10**	**90.86**	**94.29**

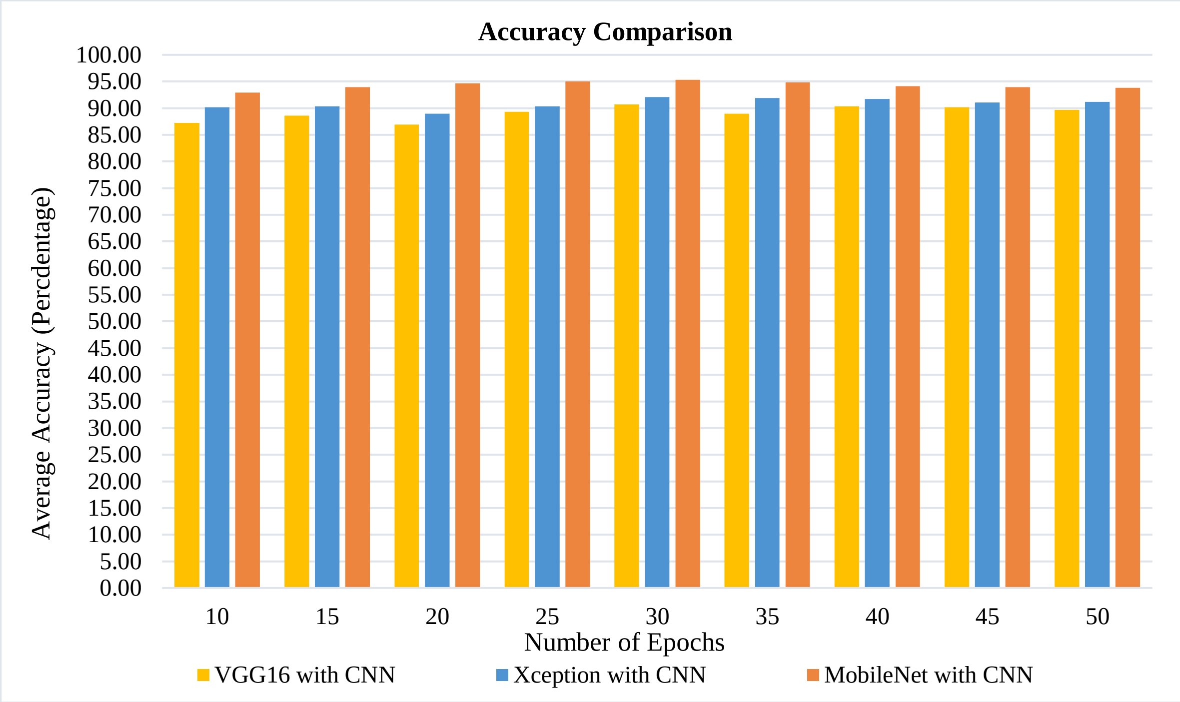


Fig. 5. The accuracy comparison of the ensemble models at different epochs.

Initially, the accuracy keeps increasing, starting from 10 epochs and at 30 epochs score surges to its peak which starts to decline after the number of epochs increases from 30 to 50 epochs. Also, it can be seen from Fig. 6 that the MobileNet with CNN ensemble model outperforms the ensemble models- VGG16 with CNN and Xception with CNN in all the cases. Therefore, the ensemble of MobileNet feature extraction and CNN is the best suited based on the accuracy of prediction.

Table 5. The class-wise accuracy, precision, recall and f1-score at 30 epochs.

	VGG16 with CNN	**Xception with CNN**	**MobileNet with CNN**
	Class-wise Accuracy		
CNV	0.96	0.99	0.99
DME	0.89	0.90	0.94
DRUSEN	0.88	0.87	0.91
Normal	0.91	0.93	0.97
	VGG16 with CNN	**Xception with CNN**	**MobileNet with CNN**
	Class-wise Precision		
CNV	0.98	0.98	0.99
DME	0.90	0.91	0.97
DRUSEN	0.86	0.87	0.97
Normal	0.91	0.93	0.90
	Class-wise Recall		
CNV	0.96	0.99	0.99
DME	0.89	0.90	0.94
DRUSEN	0.88	0.87	0.91
Normal	0.91	0.93	0.97

Class-wise F1-Score			
CNV	0.97	0.98	0.99
DME	0.89	0.90	0.95
DRUSEN	0.87	0.90	0.94
Normal	0.91	0.90	0.93

Table 5 shows the values of Accuracy, Precision, Recall and F1-score calculated from the confusion matrix obtained at 30 epochs for classifying the images into CNV, DRUSEN, DME and Normal. The chart depicted in Fig. 7 presents a comparison among ensemble models based on different classes. It is evident from the graph that the models excel particularly in detecting the CNV class. Both the Xception with CNN and MobileNet with CNN ensemble models exhibit strong proficiency in identifying CNV disease in the images. Yet, when evaluating all four classes collectively, the accuracy of detecting the remaining three classes is notably higher with the MobileNet and CNN ensemble model. Consequently, the ensemble featuring MobileNet for feature extraction surpasses the other two ensemble methods.

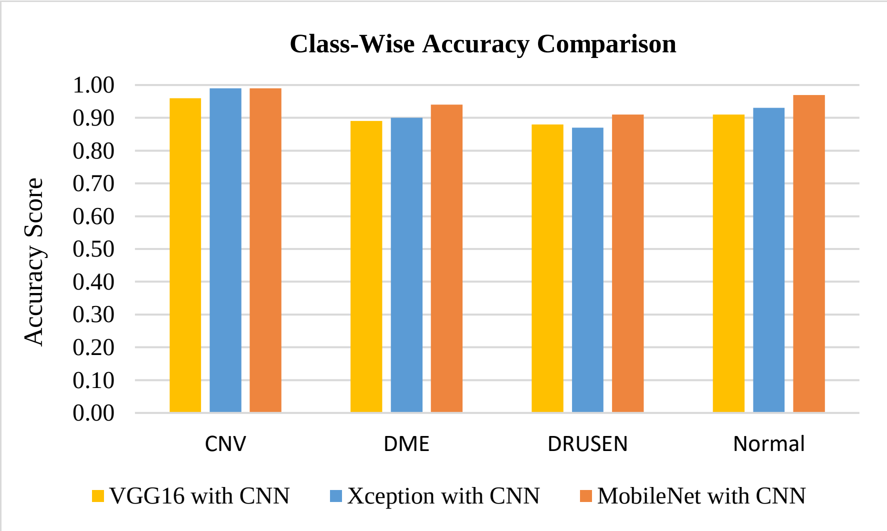


Fig. 6. The class-wise accuracy comparison at 30 epochs.

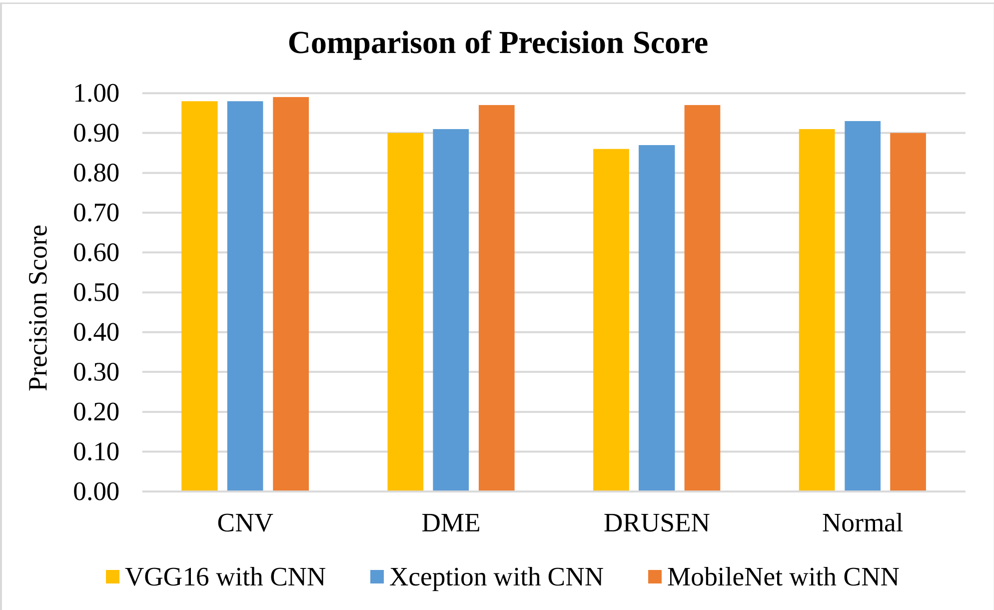


Fig. 7. The precision score of various classes at 30 epochs.

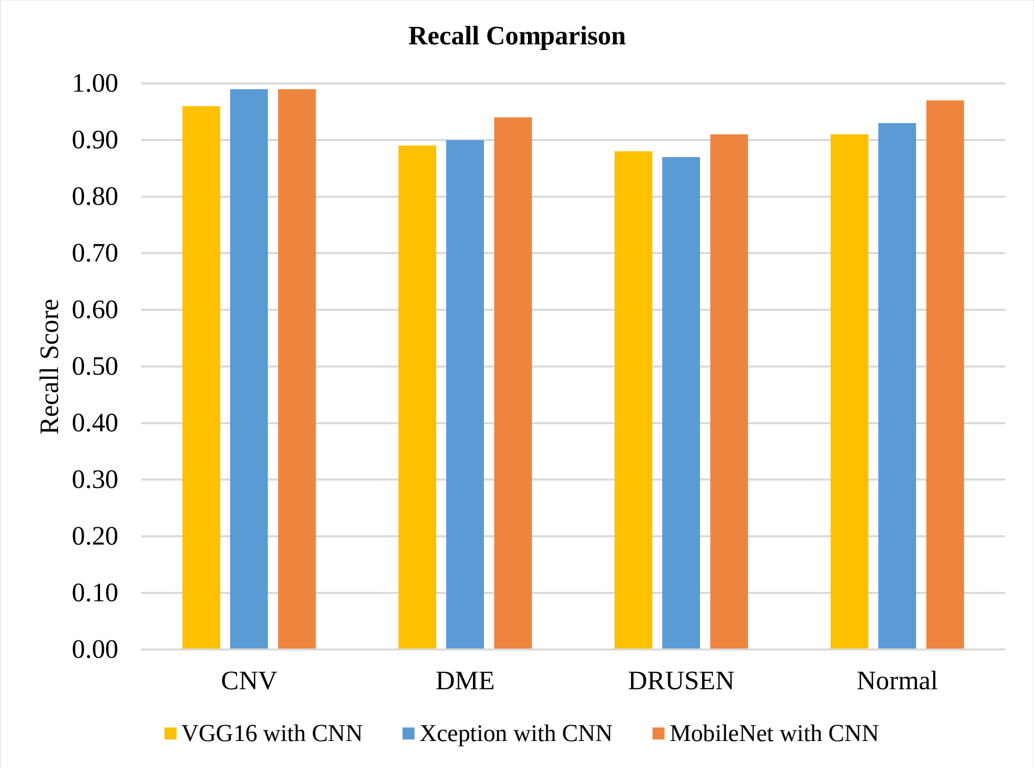


Fig. 8. The recall score comparison at 30 epochs.

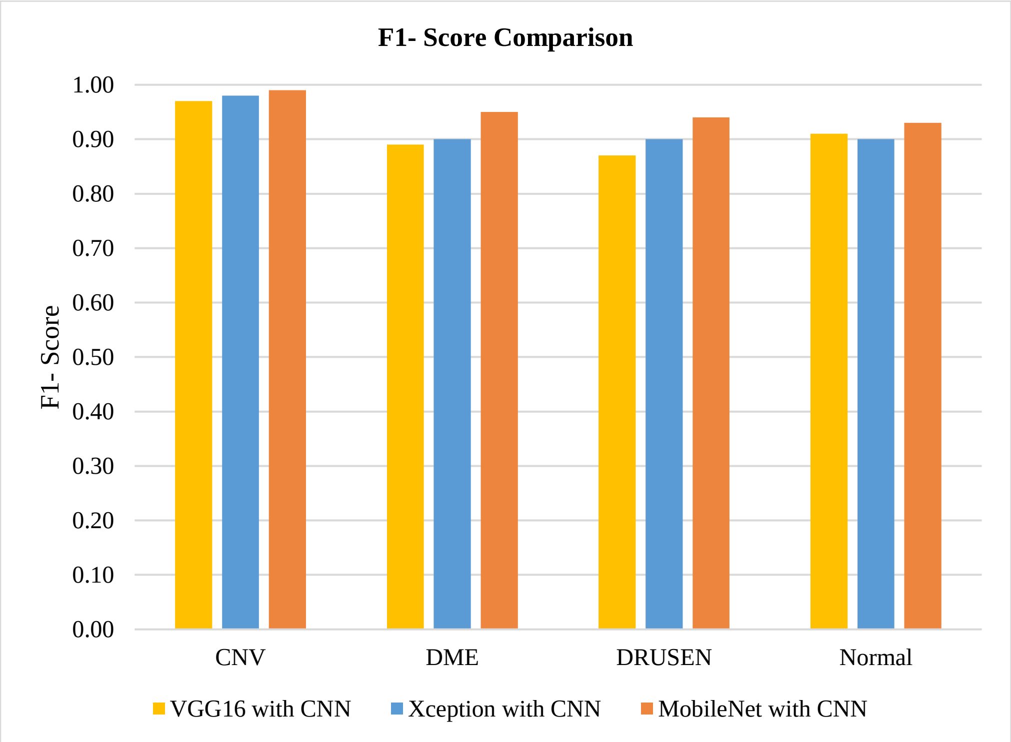


Fig. 9. The F1-score obtained at 30 epochs being compared.

The precision score chart depicted in Fig. 8 highlights that the MobileNet with CNN model once more demonstrates superior performance when dealing with images of diseased eyes. However, in classifying normal eye images, the Xception with CNN feature extraction method exhibits a higher precision score. Overall, the analysis of precision scores reinforces that the MobileNet with CNN model remains the optimal choice for classifying images of ocular diseases.

Examining the recall score illustrated in Fig. 9, it is evident that the MobileNet with CNN ensemble stands out as a superior performer, securing higher scores across three classes: DME, Drusen, and normal. Specifically, in CNV-diseased eyes, both the Xception with CNN and

MobileNet with CNN exhibit equal performance. Consequently, when considering recall, the MobileNet with CNN model consistently demonstrates notably superior performance on average compared to the Xception and VGG16 with CNN models. The f1-score, being the final parameter considered for performance evaluation, is graphically depicted in Fig. 10. It is apparent that across all four classes, the MobileNet with CNN ensemble model achieves the highest f1-scores. Upon comprehensive analysis of all metrics, it is evident that the ensemble model- MobileNet with CNN model excels as the top performer in the classification of ocular disease images, followed by the Xception with CNN and VGG16 with CNN models.

5. Conclusion

Ophthalmic disorders are a cause of concern for lot many people and these ocular diseases usually cause blurriness and other symptoms in the eye-sight and disturb the sufferer's life. These diseases develop with the progression of age and many of these ocular diseases cause irreversible harm to the eyes and may also lead to complete loss of vision. The timely detection is inevitable to avoid permanent loss of the eyesight of the persons suffering from these diseases. Machine Learning comes to aid, the automated detection systems can assist ophthalmologists and reduce the time to process all images of the patients. Many pieces of research using either fundus images or OCT images have been carried out to identify these diseases automatically using machine learning and deep learning. The proposed work involves the identification of ocular diseases - diabetic macular edema, drusen, and choroidal neovascularization using three deep-learning-based ensemble models: VGG16 with CNN, Xception with CNN, and MobileNet with CNN. These models employ feature extraction followed by classification through convolutional neural networks. Subsequently, the performance assessment of these three ensembles involves evaluating prediction accuracy, precision, recall, and f1-score. The comprehensive analysis of these metrics aims to determine the most suitable model for the task. Upon examination, it is evident that out of the three ensembles- the MobileNet with CNN ensemble model, achieves the highest average accuracy, precision, recall, and f1-score. Conclusively, the performance of the third ensemble utilizing the MobileNet with CNN technique, boasting an average accuracy of 95.34%, surpasses the others in comparison.

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