

IMPROVING RETINAL DISEASE DETECTION USING AN ENSEMBLE OF CNN-BASED DEEP LEARNING MODELS

Aqsa¹, Muhammad Rizwan Anwar², Muhammad Arslan Khan³, Taskeen Zahra⁴,
Muhammad Jawad Yousaf^{*5}¹MS Scholar, Department of Computing, Riphah International University, Faisalabad, Pakistan²Assistant Professor, Department of Computing, Riphah International University, Faisalabad, Pakistan³ ⁴ ⁵Department of Computing, Riphah International University, Faisalabad, Pakistan¹aqzahid229@gmail.com, ²rizwan.anwar@riphahfsd.edu.pk, ³muhammad.arslan1080@gmail.com,⁴zahrabsc@gmail.com, ⁵muhammadjy981@gmail.comDOI: <https://doi.org/10.5281/zenodo.20047076>**Keywords**

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Muhammad Jawad Yousaf,
Muqaddas Salahuddin**Abstract**

Diabetic Retinopathy is a severe form of retinal diseases that cause vision impairment in most of the world. Timely diagnosis is the key to success in treatment and prevention of blindness. Nevertheless, the diagnosis of retinal fundus images manually involves the use of professional ophthalmologists and does not allow large-scale and timely screening, particularly in resource-limited settings. The present study presents an automated retinal disease detection model using DL methods. The model proposed combines three pre-trained CNN architectures and fine-tuning on retinal fundus image datasets with transfer learning. Resizing, normalization, and augmentation are employed to preprocess the input data to enhance the generalization and minimize overfitting. Focal loss and class weighting methods are used in the training to overcome the issue of imbalance class. The models are trained separately and their performance. The last prediction is derived under a soft voting ensemble strategy which involves the output of the individual models. The experimental results indicate that the proposed model is better than individual networks with an accuracy of 97.54 and AUC of 0.98 in the test data. The results indicate the usefulness of ensemble DL techniques to enhance the diagnostic results and minimize erroneous classification. The suggested system will be able to help medical staff with early screening and diagnosis, which will eventually lead to better patient outcomes and decrease the risk of vision loss.

1. INTRODUCTION

Diabetes mellitus is a long-term metabolic disease that is marked by a deficiency in insulin production or poor utilization of insulin that results in increased blood glucose levels. Prolonged hyperglycemia may cause irreparable damage to other organs, especially the nerves, blood vessels, kidneys and eyes. It is also among the most common international health issues, impacting millions of people around the world. Retinal disease, especially diabetic retinopathy and diabetic macular edema (DME) is one of the most severe diabetes complications and may

result in the loss of vision and irreversible blindness in case of early diagnosis (Alam et al., 2021; Teo et al., 2021). The cause of diabetic retinopathy is the long-term damage to retinal blood vessels in the condition of elevated blood glucose, which results in the leakage of blood vessels, their swelling, and abnormal growth (Mayo Clinic, 2023).

Likewise, DME is defined by the presence of fluid on the macula leading to thickening of the retina and inability to see the center (Browning et al., 2018). The conditions usually exhibit no symptoms until in their early stages and thus it

becomes difficult to detect them early. Research shows that almost 90 percent of retinopathy-induced vision impairment could be avoided due to early diagnosis and treatment (Ting et al., 2017; Li et al., 2022). Conventionally, the diagnosis of retinal diseases was done manually by ophthalmologists using fundus images. Nevertheless, it is a time-consuming, subjective, and extremely clinical expertise-dependent method. In Pakistan, early diagnosis and mass screening are even more complicated by the lack of access to specialized healthcare services in a range of developing countries (Khan et al., 2021). These restrictions make it clear that automated, efficient, and reliable diagnostic systems are needed.

The recent developments in the field of AI, especially DL, have greatly enhanced the analysis of medical images. CNNs have been shown to perform well in auto-detecting hierarchical features of retinal images and thus detecting a disease (Esteva et al., 2017; Gulshan et al., 2016). Transfer learning methods also improve their performance by using the knowledge of large datasets to increase the accuracy of classification in medical imaging problems (Dubey et al., 2023). Irrespective of such improvements, single deep learning models are also prone to overfitting, reduced generalization, and imbalance in classes. Ensemble learning has become one of the effective methods to solve these limitations by aggregating the models to enhance predictive performance and robustness. Ensemble techniques minimize the variance, reduce bias, and increase the accuracy of classification since they combine the results of numerous models (Zhou, 2023). This research paper suggests an ensemble learning scheme using several architectures of CNN to detect retinal diseases. The given strategy will enhance the accuracy and reliability of the diagnosis, which will help to perform the early screening and help healthcare professionals to avoid the loss of vision.

The main contributions of this research are:

- Created an intelligent system based on deep learning for automatic diagnosis of retinal diseases.
- This approach used three models (ResNet50, DenseNet121 and EfficientNetB0) to improve results.

- Employed focal loss to address the issue of imbalanced data and make the detection of diseased cases better.

- Evaluated the model with various metrics such as accuracy, precision, recall and F1-score. The ensemble model was more accurate than single models.

- This research helps automate disease detection and can be used in future studies and practice.

2. LITERATURE REVIEW

The application of deep learning (DL) has dominated recent progress in detecting retinal diseases. The goal of these studies has been to develop automated diagnostic systems that are reliable, accurate, and generalise well. Convolutional neural networks (CNNs) and Vision Transformers have gained popularity because they effectively learn abstract features directly from retinal fundus images (Muchuchuti and Viriri, 2023). Yet, despite their effectiveness, DL-based models still struggle with lesion detection and model interpretability, prompting the use of ensemble learning. In recent years, ensemble learning methods have been extensively used to enhance the performance of classification models. These approaches involve the combination of multiple learning models, which can provide improved feature representation and increased robustness and generalisation (Ghosh and Chatterjee, 2023). There has also been recent work on automated systems for multi-disease detection on fundus images to facilitate early diagnosis of retinal diseases. These systems have shown potential in clinical practice, showing the need for ensemble-based models in medical image analysis (Ejaz et al., 2024).

Moreover, recent studies have aimed to enhance computational efficiency and accuracy. Efficient ensemble models have been created to provide good accuracy while maintaining low computational complexity, allowing for practical applications (Wang et al., 2024). Novel architectures like EfficientNet enhance feature extraction, while multimodal and hybrid methods enhance detection accuracy by integrating multiple data and techniques (Arora et al., 2024; Yu & Dong, 2025). However, issues like overfitting, computational demands, and

lack of interpretability remain, suggesting the need for more efficient and scalable methods for retinal disease detection (Akhtar et al., 2025;

Soft Computing Study, 2025; Expert Systems Study, 2025).

Table 1: Critical Literature Review

Sr. No	Study	Methods & Models	Dataset	Accuracy / Results	Limitations & Future Work
1	Alam, T. M., Qureshi, W. S., & Iqbal, M. (2022).	Ensemble (EfficientNet + ResNet + Inception)	EyePACS (Kaggle)	92%	Deep ensemble not limited feature extraction; Future: deeper CNNs, hybrid ensemble
2	Ghosh, A., Dutta, S., & Chakraborty, S. (2023).	Hybrid Ensemble (CNN + DenseNet variants)	APTOS	94%	ensemble, imbalance between classes, transfer learning.
3	Ghosh and Chatterjee, 2023	CNN method	Images fundus 43,055	~79.2%	Multi-disease is not specialized in APTOS binary detection, making it more difficult; Future: increased datasets, improved representation learning.
4	Ejaz et al., 2024	CNN-based method	RFMiD (~ few thousand fundus images)	88.7%–90.3%	ensemble, imbalance between classes, transfer learning.
5	Wang et al., 2024	Ensemble learning under limited resources	Public retinal image sets	78%	Low-resource context; Future: generalize to additional types of diseases, increase dataset.
6	Ejaz et al., 2025	Feature concatenation, classical ensemble	RFMiD & RFMiD 2.0 (~ various disease classes)	~93.4%	Deep ensemble not limited feature extraction; Future: deeper CNNs, hybrid ensemble
7	Singh et al., 2025	CNN + Transformer method	~20 fundus images of retinal disease	~91.7%	improved methods, hybrid clinical evaluation.

3. Proposed Methodology

This paragraph outlines the ensemble learning system to be used to detect retinal disease. Figure 2 demonstrates the general flow of the suggested approach that involves dataset acquisition,

preprocessing, feature extraction with the help of DL models, and performance evaluation.

1. To evaluate the retinal images, the publicly available datasets are gathered. This aids the model to learn and to generalize well with unknown data.

2. The preprocessing of the input images involves resizing and normalization of these images in order to ensure consistency and

3. The feature extraction and classification are performed using three CNN models, namely DenseNet121, ResNet50, and EfficientNetB0 that are pre-trained. Transfer learning is used to fine-tune these models to fit retinal image information.

4. The models are trained individually and produce prediction probabilities per class. The variety of the models assists in the representations of various features of the images.

enhance training stability. Data augmentation methods are used to minimize overfitting and maximize the diversity of the data.

5. The soft voting technique is used as an ensemble learning method, in which the prediction probabilities of all the models are summed up. This will increase the overall accuracy, decrease bias and increase model robustness.

6. Predictions are finally tested on performance measures. These measures are a complete evaluation of the model.

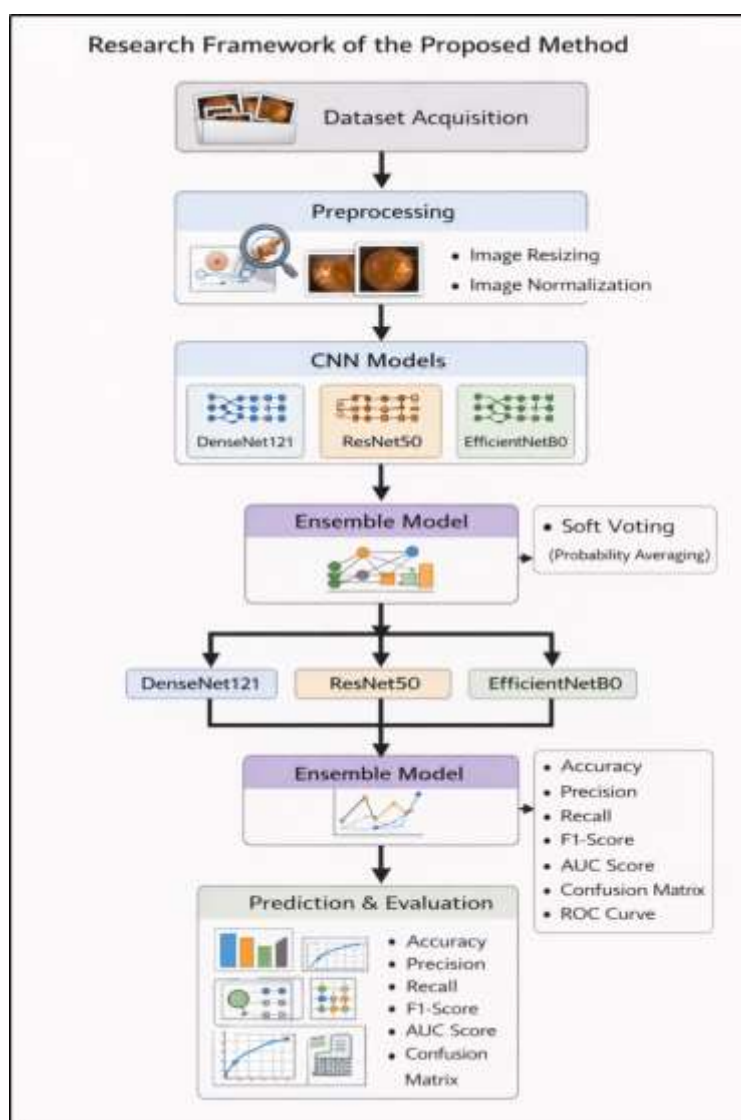


FIGURE 1: CLOUD-BASED CYBERSECURITY OF PROPOSED METHODOLOGY

3.1. Data Collection

The data, which was used in this research, is the publicly available Blindness Detection dataset, a data set that is used to examine retinal disease.

The dataset consists of retinal images that were captured with the various cameras under different acquisition conditions of the image. In this study, total images of 3,296 retinal. Two

thousand and nine hundred and thirty pictures are used as trainers and three hundred and sixty-six pictures are used as validation. The data set will be configured in two groups: Healthy retinal images and Retinal images with an abnormality of the disease. APTOS dataset is particularly problematic due to the problems with illumination and imaging artifacts. This kind of diversity resembles a clinical situation in the real world in many ways and, thus, is suitable when the effectiveness of automated diagnostic systems is tested. Even more recent studies still use the APTOS data as a reference point when identifying DL-based procedures to identify retinal disease.

3.2. Data Preprocessing:

Data preprocessing is a crucial step in stable and successful training of DL models. Retinal fundus images are generally noisy, non-uniformly lit and contain background regions which may affect learning. So, a systematic pipeline of the preprocessing system is applied.

- Resizing where the images are resized to a fixed resolution of 224 x 224 pixels, which is the expected input size of the pre-trained CNN models used in this research. This allows for consistent usage across models and simplifies calculations.

- Normalization where the intensity values of the pixels are scaled to [0, 1] by dividing the values by the maximum intensity value. This helps mitigate the internal covariate shift, leads to more stable gradient updates, and faster training in deep convolutional neural networks (Zhou, Zheng, & Li, 2023).

- Data Augmentation To enhance generalization and prevent overfitting, real-time data augmentation is performed during training. Random rotations, horizontal flips, zooms, and brightness changes are used. Data augmentation has demonstrated the ability to enhance robustness in medical image classification by training models with a variety of transformations, preventing overfitting to the training data (Chen, Liu, & Gao, 2024).

Table 3.1: Dataset Distribution Before and After Data Augmentation

Dataset Stage	Normal Images	DR Images	Total Images
Original Training Dataset	1465	1465	2930
After Data Augmentation	4395	4395	8790
Validation Dataset	183	183	366
Test Dataset	183	183	366

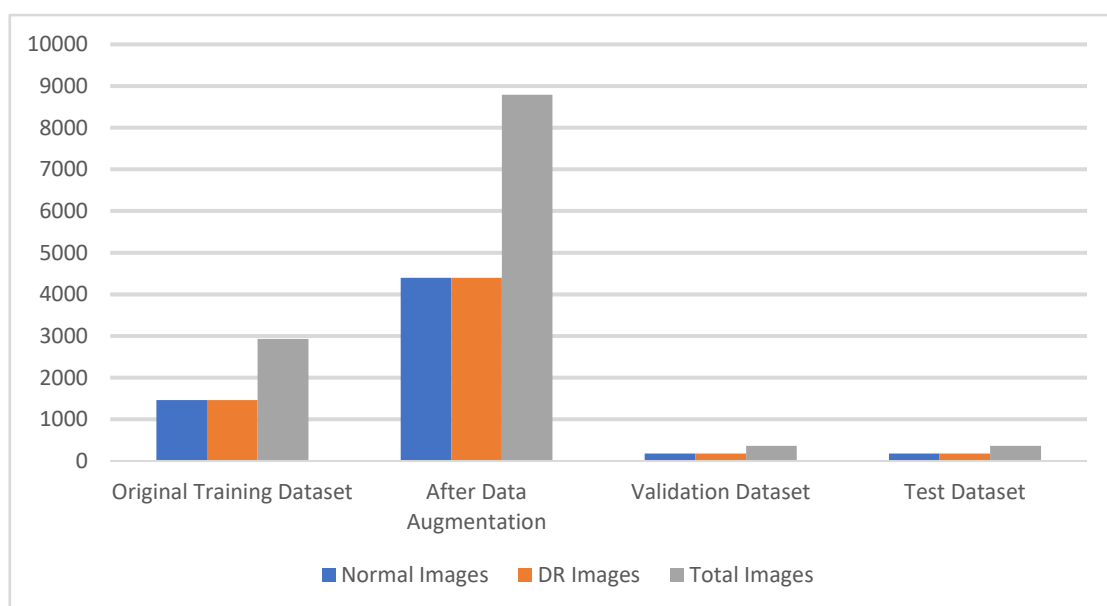


Figure 3.5: Graphical Representation of Before and after augmentation

- **Class Imbalance:** Medical data can be imbalanced, skewing the model. This is addressed by class weighting, where errors in detecting disease cases are weighted higher.
- **Feature Learning:** CNNs learn features from images, with initial layers identifying simple shapes (edges, textures) which are then combined by later layers to form complex structures (lesions, blood vessels).
- **Several CNNs for Variety:** We use three different CNNs to learn different features as they have different structures. This enhances the ensemble learning (Zhou, 2022), where the combination of multiple models results in better accuracy and generalisation.

4. Classifications of CNN Architecture

4.1. DenseNet121

DenseNet121 is a type of deep CNN that suggests dense connectivity between the network layers. Here, the current layer takes inputs of any other layer before it resulting in higher feature reusability and lower redundancy as well as avoiding the vanishing gradient problem. The DenseNet121 can be used in the detection of microaneurysms and hemorrhages in the context of retinal diseases due to its ability to capture fine-grained details. Moreover, this model is able to identify the tiniest dissimilarity of the retinal images as it is in a position to maintain both the high and low-level features.

4.4. Evaluation Metrics

For evaluating DL models in the process of medical diagnosis, it is not enough to rely only on the accuracy of the model. A number of metrics are needed.

- **Accuracy**

Accuracy measures the proportion of correctly classified samples and is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy is a good indicator of the model's performance, but it is not always the only metric that should be used, especially in cases where the dataset is imbalanced.

- **Precision**

Precision indicates the proportion of correctly predicted diseased cases among all predicted diseased cases:

$$\text{Precision} = \frac{TP}{TP + FP}$$

High precision reduces false positives, which is important to avoid unnecessary clinical follow-ups.

- **Recall (Sensitivity)**

Recall measures the ability of the model to correctly identify diseased cases:

$$\text{Recall} = \frac{TP}{TP + FN}$$

4.2. ResNet50

ResNet50 is one of the popular DL models that address the degradation problem of deep models through residual learning. The shortcut connections allow the neural network to learn the residual mapping, instead of the normal mapping. It enables gradient flow and allows more profound networks to be trained. Compared to classifying retinal images, ResNet50 can effectively extract rich semantic features. The shortcut connections created ensure that information recorded in the model by the early layers is retained. Early information is retained thus simplifying the process of identifying patterns in the images.

4.3. EfficientNet

EfficientNet is an advancement in CNN architecture design in that it uses a compound scaling architecture that optimally scales the network. Although the techniques used in the past worked on enhancing one of the above, the proposed technique optimizes everything in a balanced fashion leading to greater efficiency. The use of EfficientNet in the identification of retinal diseases can be explained by the fact that the model is capable of making correct forecasts with the number of parameters being minimal. This aspect guarantees that the algorithm can be easily applied in practice with minimum computing resources.

Recall is particularly critical in medical screening systems, as false negatives can lead to delayed diagnosis and severe health consequences.

- **F1-Score**

The F1-score represents the harmonic mean of precision and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

It provides a balanced measure of model performance, especially when class distribution is uneven.

3.8.1 Confusion Matrix

Confusion matrix is a detailed classification outcome table that shows true positives, true negatives, false positives, and false negatives. It is used for analyzing errors and understanding false classification, which is very important in the evaluation of diagnostic systems.

5. Discussion and Results:

This part provides an in-depth discussion of the experimental findings of the individual CNN models and the proposed system in detecting retinal diseases. The measures of performance of every model are assessed with the help of such

standard metrics to estimate the efficiency of every model in classification tasks. The findings indicate that individual models can perform well, but each possesses some shortcomings when used to different image conditions. The suggested ensemble model is much better at the overall performance as it merges the advantages of several models, leading to increased accuracy, enhanced generalization, and more dependable predictions. It underscores the ability of ensemble learning to improve diagnostic accuracy and minimize misclassification of retinal disease detection systems.

TABLE 3: PERFORMANCE OF CNN MODELS

Model	Accuracy	Precision	Recall	F1-Score	AUC
ResNet50	0.948	0.95	0.94	0.94	0.95
DenseNet121	0.956	0.96	0.95	0.95	0.96
EfficientNetB0	0.956	0.94	0.93	0.93	0.94
Ensemble Model	0.9754	0.98	0.97	0.98	0.98

Table 4 offers the performance analysis of separate CNN models and the suggested model to detect retinal diseases. Individual models DenseNet121 and EfficientNetB0 are more accurate than ResNet50, and moreover, DenseNet121 exhibits a better recall and AUC performance since it is densely connected and capable of reusing the features. ResNet50 is also a good classifier but exhibits weaknesses when working in challenging image conditions. EfficientNetB0 is more consistent, but with low-

quality images, it is less efficient. Conversely, the proposed ensemble model beats all the single models in all the evaluation measures with the highest accuracy (97.54%). This enhancement underscores the efficacy of using a combination of several DL models since an ensemble model minimizes weaknesses of individual models, leads to better generalization and offers more effective and dependable predictions regarding retinal disease detection.

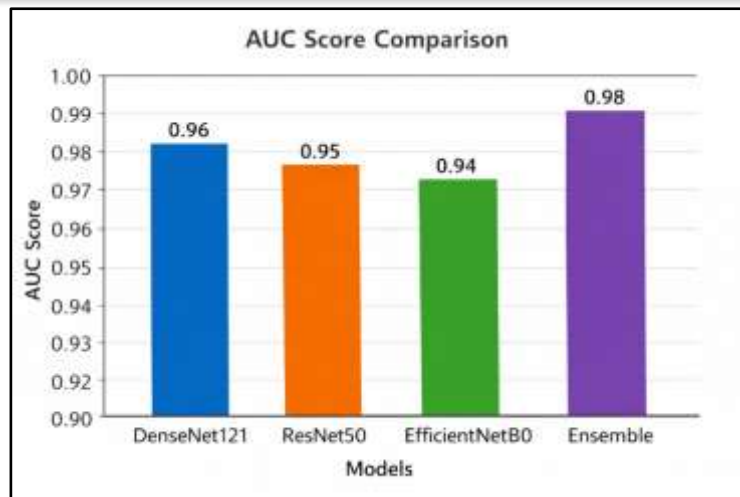


Figure 2: AUC Score Comparison of Individual Models and Ensemble Model

The figure 2 makes a comparative study of the AUC values of the models of different DL methods and the proposed model. These bars are employed to show the performance of a model in terms of classification to distinguish diseased images. The model has the highest AUC score as compared to other models and

this means that it is more effective in classifying positive and negative cases. This underlines how ensemble learning works successfully in fusing various models because it enhances the overall predictive accuracy and the provides more confident results than that of the single models.

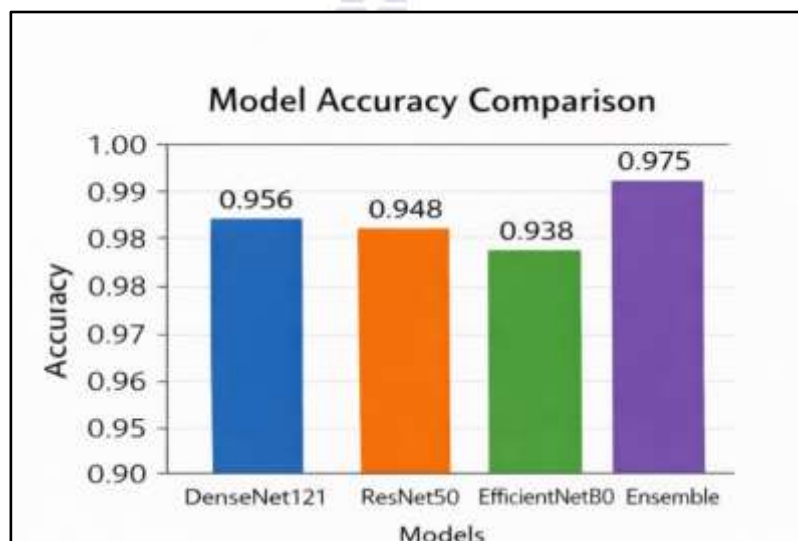


Figure 4.2: Model accuracy comparison

This chart shows the accuracy of DenseNet121, ResNet50, EfficientNetB0 and the Ensemble model. The ensemble model has the highest accuracy (0.975), and suggests that model integration enhances predictive accuracy.

DenseNet121 achieves the highest accuracy (0.961), followed by ResNet50 (0.959) and EfficientNetB0 (0.957). These findings indicate that model ensemble improves classification performance.

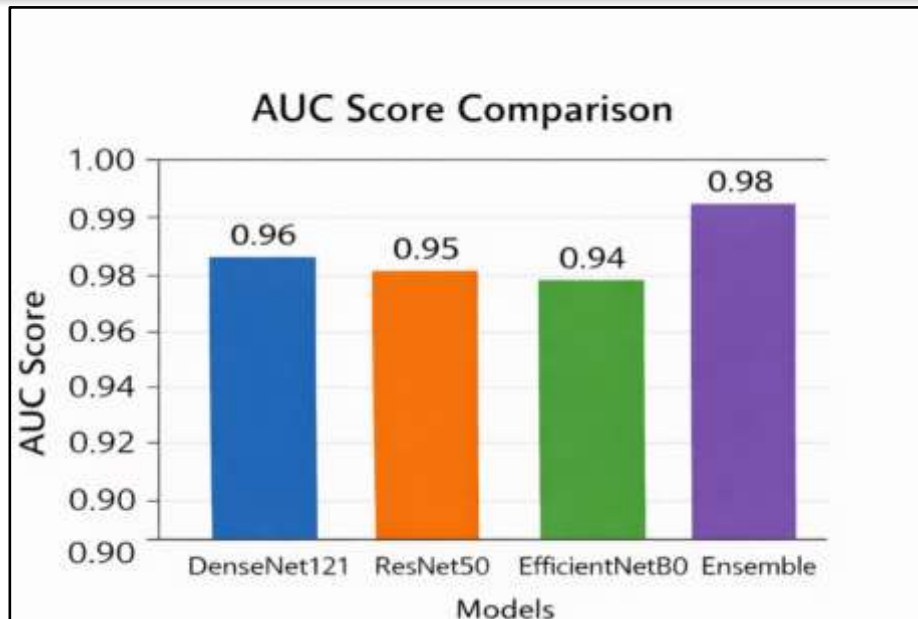


Figure 4.3: AUC score comparison

This graph shows the AUC scores of the four models, which represent their discriminative power. The ensemble model has the highest AUC (0.98), once again demonstrating better discriminative power. DenseNet121 and

ResNet50 are the next best performers, with EfficientNetB0 performing the worst. In summary, the ensemble model outperforms in capturing the class separability

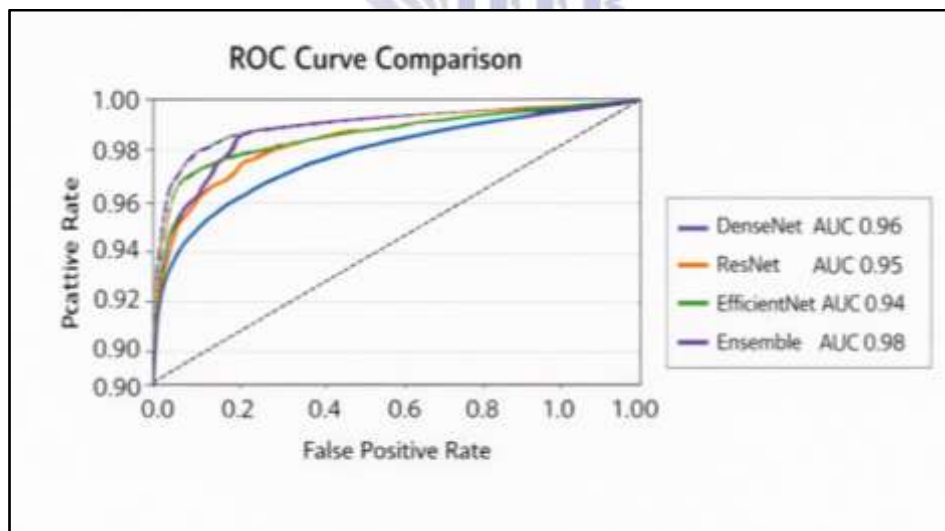


Figure 3: ROC Curve Comparison

The ROC curves are used to plot the trade-off between the FPR and TPR in each model. The ensemble model curve is nearest to the top-left corner, which means the most optimal performance at thresholds. It is always higher

than the individual models, the curves of which are slightly lower. This establishes that the ensemble model has more robust and reliable classification results.

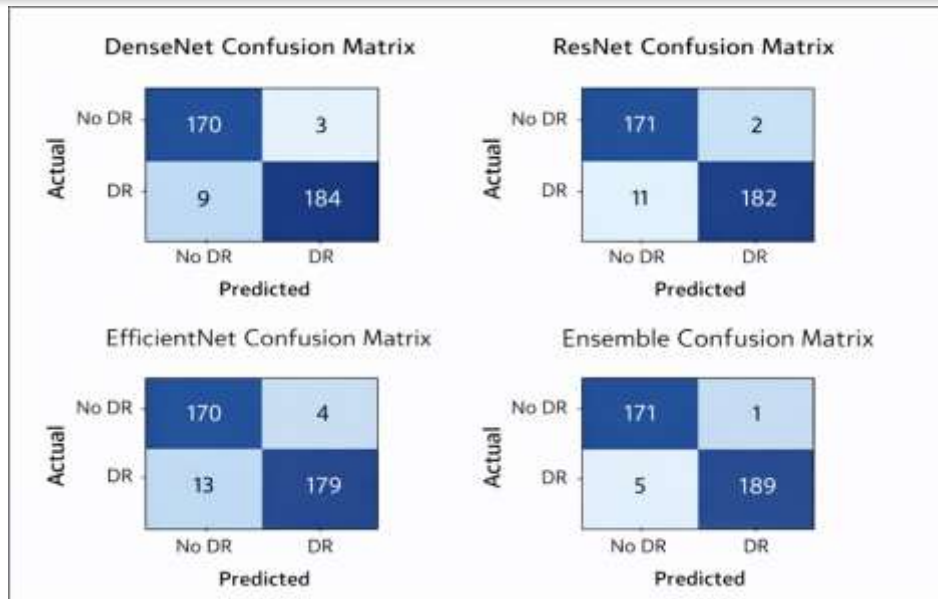


Figure 4: Confusion matrix of models

Figure 4 is comprised of four confusion matrices that depict the performance of different DL architectures and Ensemble to classify the cases. In each confusion matrix, both correct and incorrect results are presented where the Y-axis is marked with the actual classes and the X-axis indicates the predicted classes. The misclassification of both DenseNet and EfficientNet is worse compared to ResNet, particularly with regards to predicting cases of DR. ResNet can be reasonably well-performing in terms of the lower counts of misplaced predictions. The Ensemble model comes out the best of the rest and yields the best results with the highest accuracy since the model predicts best and low counts of misclassification errors.

6. CONCLUSION

This paper has provided a solid model of identifying retinal disease under an DL models. The suggested approach combines several CNN models using a soft voting mechanism to enhance the classification results. Transfer learning, systematic preprocessing of data and the use of focal loss helped improve the learning of the model and address the issue of class imbalance. The experimental outcomes indicate that the model is much better than the individual models with high accuracy and better precision, recall and AUC. This once again validates the idea that ensemble learning is a useful method of minimizing model weaknesses

including overfitting and inaccurate generalization that is often experienced in single-model deep learning systems. Moreover, the results clarify how the suggested system may be practically useful in aiding in the early detection of retinal disorders, especially in resource-constrained environments where expertise in ophthalmologists is scarce. The constructed model offers a powerful and automated system that has the potential to guide healthcare providers to screen and make decisions in a timely manner, which would eventually help to minimize the chance of vision loss. Although it was effective, the study recognizes some limitations, such as the use of one dataset, binary classification, and clinical validation. The next generation of work can be centered on the multi-class disease classification model, the applications of explainable AI methods, and testing the system on the real-world clinical setting. In general, this study illustrates that DL models provide a potential and scalable method of precise and credible retinal disease detection.

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