

Diabetic Retinopathy Detection Using Deep Learning

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Submitted by

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I hereby declare that the M.Tech Thesis entitled **Diabetic Retinopathy Detection Using Deep Learning**, which is being submitted to Delhi Technological University in partial fulfillment of the requirements for the award of the degree of Master of Technology in Software Engineering, is a bonafide report of work carried out by me. The material contained in this thesis has not been submitted to any university or institution for the award of any degree or diploma.

Date: 21/05/2026

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Diabetic Retinopathy Detection Using Deep Learning

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ABSTRACT

Diabetic Retinopathy (DR) is a very critical eye disease that is a cause of blindness and vision problems globally and is one of the most serious diabetes-related eye diseases. It results from the damage to blood vessels in the retina from diabetes. The early diabetic retinopathy may not have obvious symptoms and diagnosis is very critical to prevent permanent loss of vision. A conventional diagnosis of DR is currently based on manually analysis of retinal images, conducted by an ophthalmologist, but this process is expensive, time taking and often impractical, especially in rural and resource-constrained healthcare settings where healthcare specialists are not readily available. Hence, the need of intelligent and automated diagnostic system for early detection and accessibility to healthcare system is of utmost necessity. This research introduces the Eye-RDNN: a deep learning framework designed for the classification of diabetic retinopathy in fundus images of retina with several classes. The suggested model features convolutional neural network, along with transfer learning, to automatically classify various stages of DR in retinal images. During the training process, image resizing, normalization, sample augmentation (rotation, zooming, brightness enhancement, and flipping), and other techniques were applied to the image set to improve the performance of the model. These procedures have enhanced the diversity of datasets, reduced overfitting, and boosted the feature extraction capacity of the models. The entire model was developed on TensorFlow/Keras models using Google Colab with help of support of GPUs for efficient computing and faster trainings. The choice of the base architecture was EfficientNet-B0 due to its efficient computations and excellent feature extraction property which proved to be adequate for the purpose of medical image classification. The accuracy of the trained model in classification of multiple stages of DR was highly satisfactory for images of the healthy retina as well as

severity levels of diabetic retinopathy. The system designed can help the ophthalmologist carrying out the retinal screening faster and efficient, which will reduce the manual workload and the risk of delayed diagnosis. This sort of automated systems are especially helpful in far-off health care areas the place skilled ophthalmologists are scarce. Furthermore, the proposed approach could potentially be applied in large scale DR screening initiatives and enhance the detection of early DR. Additional features for the model could be employed to get even the better results, such as increase in the count of patients included in the data set analyzed and including diversity and varieties in the data, using more sophisticated and complex deep learning algorithms and booking the model for clinical validation, which could lead us to a higher rate of correct and accurate diagnosis and an increase of clinical practices that could be applied from the model.

Keywords: Diabetic Retinopathy, Deep Learning, EfficientNet-B0, Transfer Learning, Grad-CAM, Explainable Artificial Intelligence, Retinal Fundus Images, Medical Image Classification, Computer-Aided Diagnosis, Multiclass Classification.

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LIST OF ABBREVIATION(S)

Abbreviation	Full Form
DR	Diabetic Retinopathy
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
GPU	Graphics Processing Unit
Grad-CAM	Gradient-weighted Class Activation Mapping
SVM	Support Vector Machine
KNN	K-Nearest Neighbour
ReLU	Rectified Linear Unit
RGB	Red Green Blue
API	Application Programming Interface
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
AUC	Area Under Curve
ROC	Receiver Operating Characteristic
F1-Score	Harmonic Mean of Precision and Recall
TPU	Tensor Processing Unit
GUI	Graphical User Interface
TensorFlow	Open-source Machine Learning Framework
Keras	Deep Learning API
DR Screening	Diabetic Retinopathy Screening

CHAPTER 1

INTRODUCTION

Diabetic Retinopathy (DR) is the situation of eye that can happen due to diabetes and affects significant number of people causing blindness across the globe. The early detection and regular check up of DR is very crucial to avoid any extensive damage in the retina issue and permanent visual impairment. As Artificial Intelligence and Deep Learning methods advance, automated retinal image analysis systems are becoming more and more helpful in diagnosing diseases at a faster and more accurate rate for ophthalmologists.

1.1 Background

Diabetes mellitus is a long-term condition that can affect millions of the people across the globe and has several long-term health problems associated with it. The eye damage caused by Diabetes is one of the most hazardous side effects and is known as Diabetic Retinopathy (DR). With blood sugar that often is not controlled, these blood vessels may leak, swell or become blocked and gradually over time these blood vessels cause the deterioration of retinal tissue. In its "late stages," however, abnormal blood vessel growth can result and ultimately lead to permanent, untreated blindness. With the world's growing diabetic population, the risk for diabetic eye disease-related blindness has risen. Studies have shown that a significant proportion of diabetes sufferers could have some form of DR in their lifetime. One of the biggest problems about this disease is that DR usually doesn't have any physical signs or symptoms until it is in its later stages, so it is extremely important to have regular screening for the eyes in order for a timely diagnosis and treatment to happen. Earlier, retinal fundus photographs were hand analysed for the identification of diabetic retinopathy signs like microaneurysms, hemorrhage, exudates and

abnormal blood vessel development. This process is very effective but it just needs experts and lots of time to accurately give this analysis. Early detection is more challenging in many rural and resource-limited communities because they are lacking in trained ophthalmologists and screening resources. Artificial Intelligence and Deep Learning have seen recent real advances and are now available as new opportunities to automated medical image analysis. The ability to automatically extract the features that are vital in medical images, makes Convolutional Neural Networks very successful in image rectification and classification. The EfficientNet model is widely adopted among the myriad of deep learning models and it is noted for its high accuracy and efficient computations. Moreover, adopting Explainable Artificial Intelligence tools, which also include Grad-CAM, leads to better visual focus to show which parts of the retina contribute the most to understanding or forecasting the situation, allowing doctors to gain a deeper understanding and trust in how AI-based systems interpret retinal images.

1.2 Problem Statement

Although medical imaging and deep learning technologies have come a long way, early detection and proper classification of DR is still difficult. Timely diagnosis of images taken of the fundus of the retina is very labor-intensive, costly, and requires skill levels of an ophthalmologist. Simple and easy access to routine retinal screening services and trained healthcare providers are not readily available in many healthcare centers, particularly in rural and underdeveloped areas. This can result in a delayed diagnosis of the disease and diabetic patients running the risk of permanent vision impairments. One of the other primary limitations in retinal image analysis is its complexity. The difficulty of disease classification is caused by different image quality, lighting conditions, retinal structures and distinguishability of the lesions. However, manual feature extraction for traditional machine learning techniques can be labor-intensive, and they are not necessarily suitable for detecting more intricate retinal patterns. Recently, there has been a significant advance in the accuracy of deep learning models, but many existing models are still considered as

black-box solutions which fail to explain the basis behind prediction. Medical use: If models are not interpretable, it diminishes the reliability of AI diagnoses for doctors. Medical use: If models are not interpretable, doctors don't trust them for diagnostics. Moreover, multiclass classification of severity stage of DR is more challenging than a binary classification due to data imbalance and similarities between various stages of DR. Hence, an intelligent, accurate and explainable automated system capable of categorizing DR into various severity levels along with visual explanations for classification decisions is required. The goal and target of this study and research is to create a deep learning multiclass made for detecting system for DR based on EfficientNet-B0 and Grad-CAM model, which can assist ophthalmologists to diagnose DR accurately in the real world healthcare environment, enhance the transparency of the diagnosis, and promote the early identification of disease.

CHAPTER 2

LITERATURE REVIEW

In a few years the adoption of Artificial Intelligence and Deep Learning in medical image analysis has notably grown up, especially for diabetic retinopathy (DR) detection. Numerous efforts have been made to build accurate, fast and reliable models for retinal disease diagnosis using machine learning along with deep learning techniques all across the globe. Various novel methods have been suggested for both binary and multiclass categorization of DR by analyzing retinal fundus images. In the earlier studies, diabetic retinopathy detection mainly adopted traditional and previous machine learning approach like Support Vector Machines, K Nearest Neighbours, Decision Trees, and also Random Forest classifiers. Manual extraction of blood vessels, exudates, microaneurysms and hemorrhages from the retina was necessary before these methods could classify them. These methods yielded satisfactory performance in small, artificial datasets, but were generally not robust, and did not discriminate well away from the training data into larger, more diverse sets. Moreover, manual feature engineering made the computation more complex and made it less automated. Due to the advantage of being able to automatically learn hierarchical visual features directly from images, Convolutional Neural Networks (CNNs) was introduced and gained popularity in medical image classification tasks with the progress of Deep Learning. CNN architectures like VGG16, ResNet50, Inception-v3, DenseNet121 and EfficientNet were used by several researchers for diabetic retinopathy (DR) detection and DR severity classification. According to the studies, transferring already trained models trained on very big datasets such as the ImageNet greatly enhanced the classification accuracy of the transfer learning methods. Dense connectivity among network layers has been seen to reinforce feature reuse and facilitate the easier identification of small retinal lesions in a DenseNet121 based research. Likewise, the architectures based on ResNet demonstrated good performance on retinal datasets while alleviating the vanishing gradient problem. Some of the preprocessing methods like histogram equalization and image

normalization also yielded good performances with inception- v3 Models when used for the DR classification task. Lightweight and computationally efficient models like EfficientNet have been a recent trend in research. EfficientNet is based on the principle of model-size-batching that efficiently connects the model depth and width with the image resolution to ensure better performance at reduced computational complexity. Many reports indicated that, EfficientNet-B0, EfficientNet-B3, demonstrated excellent results based on the classification accuracy for detecting DR with the decreased no. of parameters required for comparison with traditional CNN models. Classification skills were also improved with the use of transfer learning with EfficientNet, where features were first trained for another image dataset and then fine-tuned for the retinal image dataset. Hybrid and ensemble learning approaches are also studied to enhance the classification accuracy and robustness. Some approaches fused a few CNN architectures by either weighted averaging or stacking to lower misclassification rates. In most cases, ensemble-based systems had higher accuracy, but needed more computational resources and more complex deployment methods. In addition, segmentation networks like U-Net and Faster R-CNN were proposed for detecting specific retinal abnormalities such as exudates, hemorrhages, cotton wool spots, through the lesion-based approach. While these approaches gave much detail in clinical information, they were complicated, and depended on highly annotated datasets. The lack of "explainability" is one major concern with deep learning systems in Healthcare. Most deep learning models are black-box models which make predictions without making a clear explanation of what they have done. Transparency is pivotal in the medical diagnosis realm as it requires one's trust in AI- driven healthcare decisions for their practical application in clinical care. To fulfill this challenge, new techniques were developed like Explainable Artificial Intelligence (XAI) that can be used to obtain salient parts of an image through different methods like Grad-CAM, LIME, SHAP and the saliency maps. The Grad-CAM is one of the most common explainability procedures for medical imaging applications. It produces a heat map that shows key parts of image, which are vital for the performance of the model. Recent studies have shown integration of Grad-CAM with EfficientNet, DenseNet, and ResNet architectures

with enhanced explainability of the predictions and to inform ophthalmologists if the model was focusing on a medically relevant retinal lesion during predictions. Recent studies focus more on multiclass diabetic retinopathy classification, which involves the classification of retinal images based on the severity level, include No DR, mild DR, moderate DR, severe DR and PRD. Class imbalance issues and a high degree of visual similarity among the different stages of DR have challenged multiclass classification, and researchers have tried addressing these challenges with data augmentation, focal loss functions, attention, Vision Transformers (ViT), and ensemble deep learning methods. Retinal imaging has recently seen promising results with Vision Transformer networks due to their capability of learning high range dependencies and the global context information. But these are the models struggled to be trained successfully with a relatively small collection of data and lower computing power. As a result, CNN-based transfer learning models like EfficientNet continue to be very practical and efficient for concrete DR- screening application. A literature survey shows that the results are highly promising for detection of diabetic retinopathy (DR) using DNNs with the help of transfer learning and explainable AI techniques. But some issues remain such as multiclass classification accuracy, imbalance of the data sets, computational efficiency, and clinical interpretability remain as challenges. The proposed research seeks to overcome these challenges by designing an EfficientNet-B0 based MultiClass system for the identification of DR, combined with Grad-CAM explainability, which enhances the accuracy, transparency, and clinical utility.

S.No.	Research Paper / Model	Method Used	Dataset Used	Accuracy / Performance	Limitation
1	Deep Learning for Diabetic Retinopathy Detection Using Inception-v3	Inception-v3 with preprocessing	Messidor Dataset	93.5%	Sensitive to image quality
2	Enhanced Early Detection using DenseNet121	DenseNet121 with Transfer Learning	DIARETD B1	94.3%	Slower processing speed

3	Optimized DR Diagnosis using EfficientNet-B0	EfficientNet- B0	Kaggle DR Dataset	96.1%	Lack of explainabil ity
4	Hybrid Deep Learning Model for DR Classification	CNN + Ensemble Stacking	EyePACS	95.6%	Higher computational complexity
5	Transfer Learning using Fine-Tuned ResNet50	ResNet50 Transfer Learning	Kaggle DR Dataset	94.8%	Overfitting on smaller datasets
6	Vision Transformer Model for Predicting Severity of DR	Vision Transformer (ViT)	FGADR / IDRiD	97.0%	Requires very large dataset and high computation
7	Lesion-Based DR Detection Through Hybrid Model	CNN + Lesion Segmentation	Local Hospital Dataset	90.2%	Requires detailed lesion annotations
8	Weighted Ensemble of Deep Neural Networks	Ensemble Deep Learning	EyePACS	95%+	Complex deployment process
9	Explainable AI based DR Detection	CNN + Grad-CAM	EyePACS	Improved interpretability	Focused mainly on visualization
10	Comparative Deep Learning DR Detection Framework	CNN-based Models	Multiple Public Datasets	92–95%	Limited multiclass performance
11	Proposed Model (Current Research)	EfficientNet-B0 with Transfer Learning	Kaggle / Retinal Fundus Dataset	81% Multiclass Validation Accuracy	Dataset imbalance and class-wise misclassification

Table 2.1 Comparison Of Models

CHAPTER-3

METHODOLOGY

Based on the proposed methodology, an automatic and explainable deep learning-based system for diabetic retinopathy (DR) detection from retinal fundus images of multiple classes will be developed. This whole process involves the collection of a dataset, image pre-processing, data augmentation, generation of model with the utility of transfer learning, training the model, making prediction and using the explainability tool Grad-CAM. The methodology was developed to enhance classification accuracy, all whilst remaining transparent and clinically viable.

3.1 Dataset Collection

This study utilizes images of retinal fundus photos obtained from existing public diabetic retinopathy (DR) datasets. The retina images belong to various stages of DR from normal retina to severe stage of DR. These images cover all aspects of retinal images including variations in illumination, structure of retina, visibility of lesions, and quality of images, rendering the classification task more realistic and appropriate in medical applications. In order to classify the image as belonging to a particular class, multiclass classification the collected data set was segmented into various categories, depending on the types of diabetic retinopathy.

3.2 Image Preprocessing

Preprocessing images to enhance image quality and consistency was conducted before the training of deep learning model. Here preprocessing aims at dealing with the various conditions under which images of retina are considered, and the different settings of the camera, is an important process that helps reduce inconsistencies and enhance the potential for the features that will be extracted. All the resizing of images of retina was done to 224 by 224 pixels, which is required input size for EfficientNet-B0 model. To achieve the stability of the learning process

and speed up the model convergence during the training process, the values in the pixel space were normalized. The images were then transformed to tensorflow format to make the processing efficient by the deep learning framework. These pre-processing techniques contributed to systematically standardizing the dataset and improve the classification system performance in general.

3.3 Data Augmentation

Various data augmentations exercises were performed on training method to make a better generalization and avoid over-fitting. Data Augmentation techniques artificially increase the diversity in a dataset by identifying and adjusting variation within the existing images. Different imaging conditions were simulated by rotation, flipping horizontally or vertically, zooming, variations in brightness, and image shifting. The augmentation techniques allowed the model to learn more powerful retinal features, thus allowing the model to classify unseen retinal images better.

3.4 Proposed Model's Architecture

All of the given system is based on the EfficientNet-B0 architecture for multiclass diabetic retinopathy (DR) classification. It was found that efficientnet- b0 has strong classification capability, computation efficiency, and balance scalability which is achieved in a neutral manner. The model was initialized using the pre-trained network trained on ImageNet using transfer learning to share the already learnt visual features with the problem at hand. Firstly, the base convolutional layers of EfficientNet-B0 were frozen, thus keeping the general representation of the image features. On top of the pretrained network, more layer was added to fine-tune the network for retinal image classification. The architecture consists of a Global Average Pooling layer to decrease the number of dimensions in the spatial components and keep overfitting to a minimum, after which it is followed by dense layer(fully connected) to learn feature. A dropout layer was also added to enhance the regularization and prevent over-fitting of the network during training process. The output layer was a softmax activation function with the main aim of classification of retinal images in several categories of diabetic retinopathy using a

probability distribution.

3.5 Model Training

The model implementation is done in TensorFlow and Keras with support for GPU acceleration on the Google Colab platform. It was trained through several phases to achieve the best classification accuracy and enhance the stability of convergence result. The most recent training phase, only recently added classified layers were trained, meanwhile the EfficientNet base layers kept as intact. This enabled that the model could be adapted to the problem of retinal image classification without altering the pre-trained feature representations. We first converged and then performed selective fine tuning with the unfrozen deeper EfficientNet layers and retrained with a lower learning rate. This assisted the model for learning the retinal-specific features better and the ability of multiclass classification was also improved. Adam optimizer came into the picture due to its Adaptive Learning and hasty convergence during Training. For this problem, if it were a multilevel class classification, then Categorical cross entropy lost function was chosen. The accuracy, precision, recall and f1 score were evaluated to see how the model performed in training and validation. Early stopping was used, monitoring the validation loss, to avoid overfitting. If the performance of the correction and validation sample do not improve for two continuous epochs, the training was automatically terminated. This preserved a balance between the advancement of the training accuracy and a generalisation of the model.

3.6 Prediction and Classification

The developed system was tested unseen retinal fundus images after the training process. For every image the model computed probability scores for various severity levels of DR. The class we chose would have the highest probability; a class would be chosen. This system was not only able to classify the data, it was able to provide a confidence score which provided an estimate of the level of confidence for the classification also. This prediction mechanism was critical in the model to achieve good classification performance in the automatic diagnosis of MDR.

3.7 Explainability using Grad-CAM

For clinical integrity and transparency and the weighted Gradient Class Activation Mapping was included within the proposed structure. Deep learning models are considered black box systems, as the procedure in which they make their decisions is not easily comprehensible. To overcome this problem, Grad-CAM produces visual heat maps that identify salient retinal regions that affect the prediction results. The heatmaps generated emphasized abnormalities of importance clinically, including microaneurysms, hemorrhages, exudates, and abnormal vascular patterns. The visual explanations assist ophthalmologists to confirm that this model learning about clinically similar areas of retina when performing classifications. The explainability feature of AI can, therefore, enhance the interpretability and clinical utility of the proposed system.

3.8 Performance Evaluation

Several classification performance indexes used to test performance of the proposed model's accuracy precision and recall and the f1 score and confusion matrix. The effectiveness of the system in correct classification of different stages of DR was carried out with these evaluation measures. The proposed methodology was demonstrated experimentally to show reliable performance for multi class DR detection with good predictive performance and enhanced transparency using EAI methods.

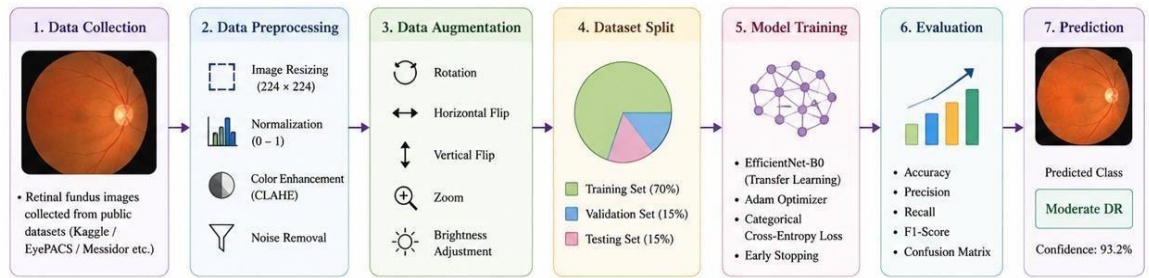


Fig 3.1 Workflow Diagram

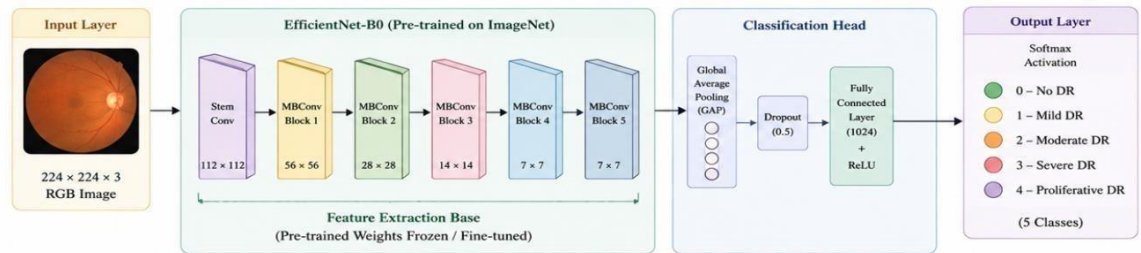


Fig 3.2 Architecture Diagram

CHAPTER 4

IMPLEMENTATION

4.1 Implementation

Implementation of the proposed diabetic retinopathy detection system is performed based on deep learning techniques, transfer learning of retinal fundus image. Whole model was made with help of Python language for programming and Google Colab, also with the help of GPU acceleration. The data was divided into a training set and validation set and testing set to allow the model to be correctly trained and tested with unseen data. The EfficientNet-B0 architecture was chosen as the base model due to its capability of achieving high classification accuracy and computational efficiency in the manner of image classification. The Transfer learning was applied by loading pre-trained ImageNet weights in the model, thus enabling the network to use previously learnt image features. The base layers of the EfficientNet model were initially frozen and only newest classification layers were trained. First, initial convergence was done; then, the deeper layers of the network were unfrozen and model was retrained with the smaller learn rate to enhance the learning of retinal features. A Softmax activation function applied to last classification layer to classify the retinal images in different DR severity level. The fast convergence properties and adaptive learning mechanism of the Adam optimizer made it the choice, and a loss function of categorical cross-entropy was used with multiclass classification. In the course of training, the accuracy and precision and recall and f1 score was continuously measured to test model's learning and classification ability. Additionally, before the time stopping was applied to avoid overfitting and by monitoring the validation loss during training. After completion of training, the final model was saved and tested on unseen retinal images. The trained system was able to make prediction probability and classify the retinal images into various stages of DR with good accuracy.

4.2 Datasets Used

The data for this research is retinal fundus images obtained from publicly available datasets of diabetic retinopathy on Kaggle and other medical image repositories. The data set consists of retinal images of various severity stages of DR, both normal and abnormal retinal images. The images gone through resizing, normalization and splitting in training and validation and testing tests before the training to enhance the accuracy and prediction of model used and its evaluation.

4.3 Evaluation Metrics

Standard classification metrics included Accuracy and Precision and Recall and f1Score was used for testing the performance of given model. The accuracy is the overall correctness of the classification and the Precision and Recall of the model to correctly classify DR cases and the f1 Score is a compromise between Precision and Recall. To further illustrate correct and misclassified classifications across classes, confusion matrix analysis was performed.



Fig 4.1 Dataset Sample Images

CHAPTER 5

RESULTS

The given model was tested with standard methods and procedure metrics, which included the f1 score and the accuracy and the precision and recall. Accuracy is overall soundness and correctness of classification and Precision along with Recall are to assess the model accuracy in correctly identifying DR cases. The F1-Score is a compromise among the Precision-Recall. Further, the confusion matrix is employed to demonstrate the correct and soundness along with the incorrect classification, class-wise. The final trained model successfully classified the retinal images into different DR severity stages and it gave satisfactory classification accuracy on unseen retinal images. The transfer learning has helped enhancing the feature extraction capability and decreased overall training time. Data augmentation methods also helped models to be more generalized and to avoid overfitting. The standard metrics of f1 score along with the accuracy precision and the recall were used for performance and correctness evaluation. The result obtained showed that this model could successfully identify the majority of DR cases with balanced classification performance over the various classes. The confusion matrix analysis also revealed the system's excellent classification performance for healthy retinal images and DR stages. There were some overlaps between visually similar severity levels, however, such as between mild and moderate DR cases, as there were similarities in the pattern of retinal lesions; this was due to the lack of balance in the datasets. Furthermore, the prediction system was validated by unseen retinal images and the model could generate the classification results based on probability. The system was able to automate the retinal disease screening with limited manual effort. The results of the experiment validate the effectiveness and the soundness of the proposed EfficientNet-B0 multiclass diabetic retinopathy detection system in terms of classification accuracy and its potential to improve the screening of retinal diseases with minimal efforts from ophthalmologists.

Confusion Matrix					
Actual Class	Predicted Class				
	0	1	2	3	4
0	350	3	6	0	0
1	7	36	24	0	0
2	4	22	184	0	2
3	0	4	24	5	7
4	0	3	33	2	16

Fig 5.1 Confusion Matrix

Classification Report				
Class	Precision	Recall	F1-score	Support
0	0.97	0.97	0.97	359
1	0.53	0.54	0.53	67
2	0.68	0.87	0.76	212
3	0.71	0.12	0.21	40
4	0.64	0.30	0.41	54

Fig 5.2 Classification Report

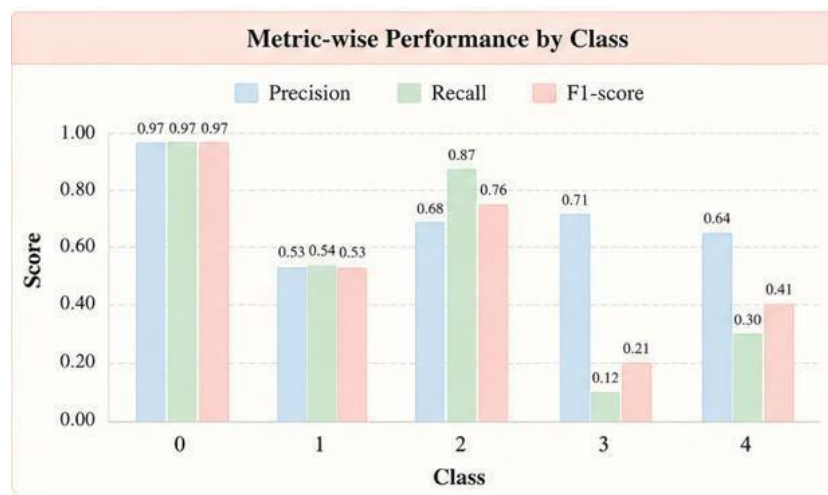


Fig 5.3 Metric-wise Performance By Class

CHAPTER 6

CHALLENGES & LIMITATIONS

6.1 Challenges

The problem of unbalanced data sets in the diabetic retinopathy data set was one of the greatest challenges encountered in this research. The number and amount of retinal images within few severity classes was significantly greater than others, impacting the ability and capability of the model to learn patterns of given minority classes. Consequently, models performance was found to be better in the major classes and relatively poor in some intermediate severity classes. Other difficulties were the differences among retinal image quality and imaging conditions. Retinal images were taken with various cameras, light sources, resolutions and focal distances. There were also instances of noise, low contrast, blurring, and inconsistent illumination within some images which made feature extraction and disease classification more difficult. These differences made classification more challenging and necessitated a lot of preprocessing and augmentation methodologies. Another challenge was the classification of the multiclass diabetic retinopathy, as there are visually similar retinal lesions in different severity stages. Diabetic retinopathy (DR) cases with mild and moderate severity exhibited similar retinal features in some instances, thus creating a risk of misclassification between adjacent classes. Medical image analysis tasks such as classification or segmentation are severely affected by the need for high GPUs memory and long training time that deep learning models require to effectively learn. The implementation was conducted on Google Colab, which meant that the training time and computational resources relied on the availability of cloud resources.

6.2 Limitation

The proposed system proved to be quite successful, but there were still some setbacks. The biggest drawback of this current research is the results and how the model performed is dependent on the amount of quality and diversity of data set. Publicly available retinal datasets may not be representative of real-world clinical conditions, and the model might lack generalization ability on a very diverse population of patients and on unseen imaging environments. The other constraint is that some of the severity stages of DR contain same features which may cause a misclassification between the adjacent classes like mild and moderate DR, even though the augmentation techniques were used for training the model. Also, there was an imbalance in the dataset which has also affected the classification performance of the minority classes. The proposed system is fully image-based, and does not take into account other clinical data like patient age, blood sugar level, duration of diabetes, medical history and other diagnostic parameters which might enhance the prediction accuracy of the disease. The addition of such multimodal medical information could further improve clinical reliability. Moreover, the developed system is not clinically tested in real hospital surroundings or directly supervised by ophthalmologists yet. Hence, it is currently recommended to use the model as a decision support system, rather than as a substitute for healthcare professionals' diagnosis. Further large-scale clinical testing and real-world implementation will be required prior to clinical implementation in practice.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

The proposed research successfully demonstrates the use of deep learning methods for the automatic multiclass retinopathy detection using retinal photos. The proposed system is based on the EfficientNet-B0 architecture and transfer learning technique for the classification of the retinal images into various diabetic retinopathy severity stages. The pre-processing of images, data augmentation, and finetune techniques allowed the model learn the essential features of retina and to achieve accurate classification on new images. The results of the experiment showed that the given model performed with good amount of accuracy and the effective multiclass classification performance in the detection of DR. Transfer learning generally enhanced feature extraction performance, reduced the complexity of training and computational burden. There is also stable learning behavior that has been verified during the training and validation of the system, which shows that it has a good learning generalization ability. The proposed framework can aid ophthalmologists to: You can make a diagnosis of retinal disorders earlier and faster without having to do a lot of manual work. early detection of DR. must be available, as it is widely available in low-resource areas and rural communities. use of screening tools, like the proposed model, may be particularly useful, because access will be an issue. To experienced ophthalmologists, it is a rare occurrence. The main components of this deep learning and their real life application are summarized that the medical image test and the analysis systems are a promising technology to improve the Diagnosis of ophthalmic diseases and development of smart health solutions.

7.2 Future Scope

The proposed system shows promising results for multiclass classification; however, there are several improvements that can be done in the future to further increase the accuracy and clinical value. A very large future improvement is improved by the use of a wider, more extensive and more complex set of images. Retina that is collected from other medical institutions and medical imaging devices. A more extensive database would benefit the ability of the model to generalize and the effect of the imbalance datasets. The use of the method could be extended to other studies in the future. Transformer).EfficientNet-B3 and Vision Transifier (Transformer). Transformer models (ViT), Hybrid CNN models, Attention-based networks) to boost accuracy in enhancement. the performance of multiclass classification. Other pre-processing methods and Reliable methods for early stages detection could be further improved by using lesion analysis techniques. DR. Potential to include clinical patient data to be added to this project where age, blood sugar level, medical history etc., and retinal images provide a more complex diagnostic system. Additionally, the model can be deployed in real-time via a web interface, mobile application or cloud healthcare platform, Improving the access to retinal screening services.

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