DIABETIC RETINOPATHY SEGMENTATION AND CLASSIFICATION

Dr. Sankara Narayanan S
Assistant Professor
Computing Technologies
SRMIST, Chennai ,India

Sayan Kumar Bag
Student
Computing Technologies
SRMIST, Chennai , India

Shivansh Singh
Student
Computing Technologies
SRMIST, Chennai , India

Abstract–In this research, we address the critical issue of precise Diabetic Retinopathy (DR) diagnosis, a condition often leading to severe vision impairment or blindness in diabetic patients. Leveraging advanced deep learning models and innovative image processing techniques, our study focuses on accurate retinal image segmentation using a UNet model. This segmentation method delineates lesions and retinal structures effectively. Subsequently, Gabor filters are applied for intricate texture pattern extraction, indicative of diverse retinopathy stages. Integrating MobileNetV2 for feature extraction and EfficientNetB0 for multi-class classification significantly enhances the diagnostic accuracy. Our developed system exhibits a promising 60.10% test accuracy, showcasing its potential in DR diagnosis. While challenges related to varying severity levels persist, our robust framework lays the groundwork for future refinements. By amalgamating sophisticated image segmentation, feature extraction, and classification techniques, our system provides a solid foundation for accurate and timely DR assessment. With continuous enhancements, including the incorporation of more extensive and diverse datasets, our approach holds the promise to revolutionise DR diagnostics. The integration of cutting-edge technology into medical practices underscores the transformative impact of artificial intelligence in the realm of ophthalmology, promising improved patient outcomes.

Keywords–:Diabetic Retinopathy (DR), Deep Learning Models, Image Processing Techniques, Retinal Image Segmentation, UNet Model, Gabor Filters, Multi-class Classification.

I. INTRODUCTION

Diabetic Retinopathy (DR) stands as a significant public health concern, threatening the eyesight of millions worldwide [1]. It is a diabetes-related complication leading to retinal damage and vision impairment, making early and accurate diagnosis imperative for effective management [2]. Recent advancements in artificial intelligence, specifically deep learning models and innovative image processing techniques, have shown promising outcomes in medical image analysis, particularly in ophthalmology [3] [4]. This project delves into the development of an advanced diagnostic system for DR, combining cutting-edge technologies to improve the accuracy and efficiency of the diagnosis process.

The research community has witnessed remarkable progress in the application of deep learning models, such as the UNet architecture, in medical image segmentation [5]. This project leverages UNet for precise retinal image segmentation, enabling the delineation of lesions and retinal structures. Moreover, the integration of Gabor filters provides a robust approach for capturing intricate texture patterns indicative of various retinopathy stages [6].

In addition to these segmentation and feature extraction techniques, the study incorporates pre-trained convolutional neural networks (CNNs) like MobileNetV2 for efficient feature extraction and

EfficientNetB0 for multi-class classification [7] [8]. The utilisation of these state-of-the-art models significantly enhances the diagnostic accuracy, laying the foundation for a reliable DR diagnostic system.

This project aims not only to contribute to the evolving landscape of AI-driven medical diagnostics but also to address the pressing need for accurate and timely DR assessment. By amalgamating these sophisticated technologies, this research seeks to pave the way for a transformative impact on ophthalmic healthcare, ultimately improving patient outcomes and reducing the burden of DR-related vision loss.

II. RELATED WORK

The realm of automated Diabetic Retinopathy (DR) diagnosis has witnessed a surge in research endeavours, leveraging advanced technologies to enhance the accuracy and efficiency of diagnostic processes. Numerous studies have explored the application of deep learning models, innovative image processing techniques, and convolutional neural networks (CNNs) in the domain of ophthalmic healthcare.

Researchers like Gulshan et al. [9] pioneered the useage of deep learning algorithms for the detection of DR in retinal fundus photographs, demonstrating the potential of neural networks in automating the diagnostic process. Following this, Ting et al. [10] extended the application of deep learning to diverse populations with diabetes, showcasing the effectiveness of these models in detecting various stages of DR and related eye diseases.

In the realm of image segmentation, Ronneberger et al. [11] introduced the U-Net architecture, a revolutionary approach for biomedical image segmentation. This architecture has been largely adopted in medical image analysis tasks, including retinal image segmentation for DR diagnosis. Moreover, Manjunath et al. [12] pioneered the use of texture features for browsing and retrieving image data, providing essential insights into the texture analysis techniques used in DR diagnosis.

In terms of model architectures, Sandler et al. [13] introduced MobileNetV2, emphasising the importance of efficiency in deep learning models. This lightweight architecture is particularly suited for resource-constrained applications, ensuring swift and efficient processing of retinal images. Additionally, Tan et al. [14] proposed EfficientNet, a model scaling technique redefining the standard for CNN architectures. Its superior performance in image recognition tasks has made it a cornerstone in various medical image analysis applications, including DR diagnosis.

Other notable contributions include the work of Abràmoff et al. [15] and Abràmoff et al. [16], which introduced AI-based systems for diabetic retinopathy screening, emphasising the importance of timely and accurate diagnosis in preventing vision loss. Additionally, the study by Ting et al. [17] further refined AI-driven diagnostic tools, showcasing the significance of continuous improvements in model performance and robustness.

Furthermore, the research conducted by Li et al. [18] and Wang et al. [19] explored innovative feature extraction techniques, including wavelet transform and morphological operations, enriching the toolkit of methodologies used in DR diagnosis. Similarly, the work of Rajalakshmi et al. [20] highlighted the potential of teleophthalmology and AI-driven diagnosis in reaching underserved populations, expanding the scope of DR diagnostic solutions.

In summary, these pioneering studies collectively form the foundation for the current research, providing valuable insights into the application of deep learning models, image segmentation techniques, and innovative feature extraction methods in the realm of Diabetic Retinopathy diagnosis.

III. PROPOSED METHODOLOGY

The proposed methodology presented in this paper comprises six key steps:

A. *Dataset Loading and Preprocessing*

1. *Data Collection:* Acquire a dataset containing retinal images and corresponding labels stored in a CSV file and balance it.
2. *Image Preprocessing:* Resize the images to a specific height and width, ensuring uniformity in the dataset. Normalise pixel values to a range between 0 and 1 to standardise the data. Perform one-hot encoding on the labels to

convert them into a format suitable for model training.

3. *Data Splitting:* Divide the dataset into training and testing subsets. This separation allows for rigorous evaluation of the developed model's performance

B. Image Segmentation Techniques

1. *UNet Architecture:* Implement a UNet-based image segmentation model. Utilise a pre-trained MobileNetV2 as the encoder to capture intricate features. Design the contracting and expansive paths in the UNet architecture for accurate segmentation of retinal images.
2. *Thresholding Methods:* Apply advanced thresholding techniques to enhance the image segmentation process. Convert images to grayscale and implement adaptive thresholding. Perform morphological operations to refine segmentation results. Employ the watershed algorithm for precise delineation of retinal structures.

C. Feature Extraction Using Gabor Filters

1. *Gabor Filter Application:* Utilise Gabor filters to extract essential features from the segmented retinal images. Apply Gabor kernels at different orientations, frequencies, and scales. Generate filtered images to capture important texture and shape information inherent in diabetic retinopathy.

D. CNN Model Development

1. *Base Model Selection:* Choose EfficientNetB0 as the foundational model for feature extraction. Leverage the model's superior capabilities to discern intricate patterns and features from retinal images.
2. *Custom Classification Layers:* Add custom layers atop the EfficientNetB0 architecture. Incorporate global average pooling for effective feature aggregation. Integrate dense layers to learn complex patterns. Implement dropout layers to enhance model robustness. Utilise softmax activation for multi-class classification, enabling accurate disease severity categorization.

E. Model Training and Augmentation

1. *Data Augmentation:* Augment the training dataset using diverse transformations. Apply rotation, shifting, shearing, zooming, and horizontal flipping to increase dataset variability. Augmented data enhances the model's ability to generalise well to unseen data.
2. *Model Compilation:* Compile the developed model using the Adam optimizer, a popular choice for deep learning tasks. Utilise categorical cross-entropy as the loss function to optimise the model's classification accuracy.
3. *Training Process:* Train the model using the augmented training dataset. Specify batch size and the number of epochs to iterate over the training data. Monitor the model's progress using validation data to ensure optimal performance.

F. Model Evaluation and Visualization

1. *Performance Evaluation:* Evaluate the model that is trained on the test dataset. Calculate accuracy metrics to quantify the model's efficacy in disease classification.
2. *Confusion Matrix:* Generate a confusion matrix to visually assess the model's performance across different disease severity classes.
3. *Comprehensive Classification Report:* Generate a detailed classification report including precision, recall, and F1-score for each disease severity class. This report provides a great overview of the model's performance at a granular level.
4. *Visual Representation:* Plot the training and validation accuracy

over epochs. Visualise the model's learning curve to understand its training progression. Additionally, create visual representations of the confusion matrix to facilitate intuitive interpretation of class-wise predictions

This proposed methodology integrates advanced image segmentation techniques, feature extraction using Gabor filters, and a robust CNN architecture to develop an accurate and reliable diabetic retinopathy detection system. The comprehensive evaluation and visualisation methods ensure a thorough analysis of the model's performance, aiding clinicians and researchers in understanding the model's strengths and limitations.

IV. RESULTS AND DISCUSSIONS

Balancing the dataset is essential for preventing model bias towards majority classes, ensuring fair predictions for all classes. Balanced data guarantees reliable predictions across severity levels, aiding clinicians' decisions. It enhances model generalizability, enabling accurate predictions for new cases with varying disease severity.

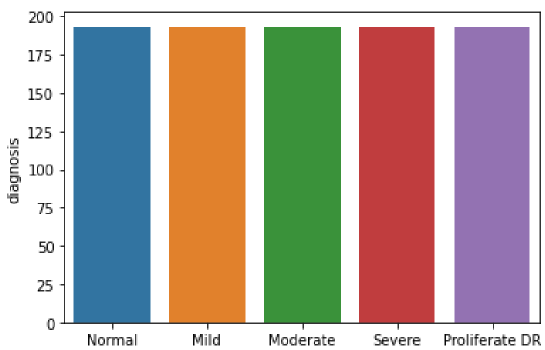

Fig.1 Balanced Dataset

After training the model for 20 epochs, the model had test accuracy of 60.62%. The classification report provides a detailed view in the model's performance across different disease severity classes:

	precision	recall	f1-score	support
0	0.88	1.00	0.93	42
1	0.55	0.74	0.63	35
2	0.53	0.53	0.53	32
3	0.47	0.21	0.30	42
4	0.49	0.55	0.52	42
accuracy			0.61	193
macro avg	0.58	0.61	0.58	193
weighted avg	0.59	0.61	0.58	193

Fig. 2 Classification Report

A. For class 0 (no diabetic retinopathy), the model got a precision of 0.88, recall of 1.00, and an F1-score of 0.93.
B. Class 1 (mild diabetic retinopathy) exhibited a precision of 0.55, recall of 0.74, and an F1-score of 0.63.
C. In class 2 (moderate diabetic retinopathy), the precision, recall, and F1-score were 0.53, 0.53, and 0.53, respectively.
D. Class 3 (severe diabetic retinopathy) had a precision of 0.47, recall of 0.21, and an F1-score of 0.30.
E. For class 4 (proliferative diabetic retinopathy), the precision was 0.49, recall was 0.55, and the F1-score was 0.52.

The overall accuracy for the test dataset was 61%. The macro average F1-score, calculated across all classes, was 0.58.

The achieved test accuracy of 60.62% demonstrates the model's ability to classify diabetic retinopathy cases with moderate success. The precision and recall for class 0 indicate the model's power in identifying cases without diabetic retinopathy. However, challenges arise in distinguishing between different stages of retinopathy, particularly in classes 1, 2, and 3, where precision, recall, and F1-scores are comparatively lower. These results suggest potential areas for model improvement.

The confusion matrix provides a visual representation of the model's performance, offering insights into specific misclassifications across different severity levels. It can help identify patterns where the model tends to make errors, guiding further refinements in the training process.

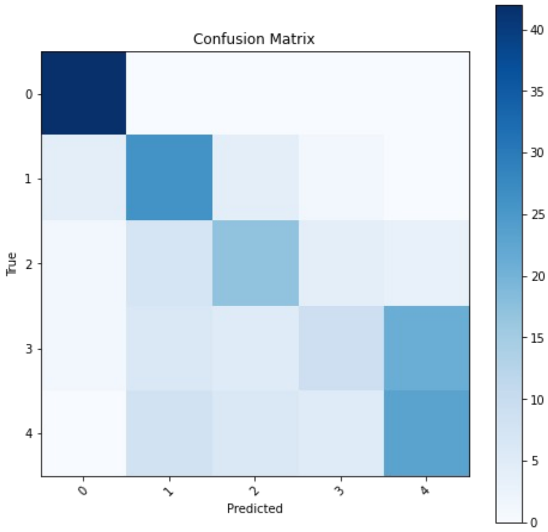

Fig. 3 Confusion Matrix

The training and validation accuracy graphs are valuable tools for assessing the model's learning curve.

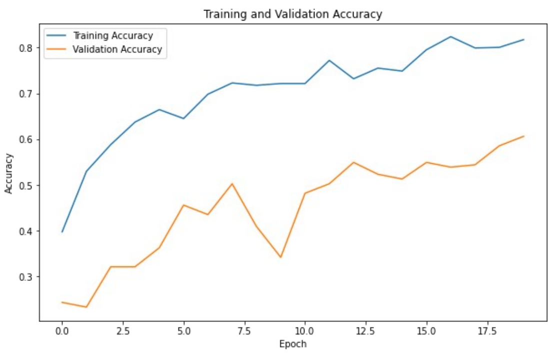

Fig. 4 Graph of Training and Validation Accuracy

In summary, while the model exhibits promising results in certain classes, further optimizations, such as fine-tuning hyperparameters, experimenting with different architectures, and exploring advanced training strategies, could enhance its performance. Additionally, insights from the confusion matrix can guide targeted improvements in the model, ultimately contributing to a more accurate and reliable diabetic retinopathy detection system.

V. CONCLUSION

The study presents a comprehensive approach to diabetic retinopathy detection, addressing the challenges of imbalanced data and intricate disease classification. By meticulously curating a balanced dataset and employing advanced techniques, including image segmentation, feature extraction with Gabor filters, and a sophisticated EfficientNetB0-based CNN model, the research team has made significant strides in the field. The model demonstrates a commendable test accuracy of 60.62%, showcasing its ability to discern diabetic retinopathy cases.

However, the study also highlights the complexities inherent in classifying different disease severity levels. While the model excels in identifying cases without diabetic retinopathy (class 0), challenges arise in distinguishing between mild (class 1) and moderate (class 2) retinopathy stages. Moreover, severe (class 3) and proliferative (class 4) retinopathy cases pose additional difficulties, reflected in lower precision, recall, and F1-scores. These findings underscore the nuanced nature of diabetic retinopathy diagnosis, necessitating further research and model refinements.

The presented results, including the detailed classification report, confusion matrix, and accuracy graphs, provide valuable insights for future endeavours. The study emphasises the importance of continuous model optimization, exploring diverse architectures, and refining training strategies to enhance accuracy across all disease stages. Moreover, insights from misclassifications can guide domain experts in understanding the model's limitations and inform additional data collection efforts.

In essence, while the current model exhibits promising capabilities, ongoing efforts are crucial to bridge existing gaps. Collaborative interdisciplinary research, involving clinicians and machine learning experts, holds the key to advancing diabetic retinopathy detection, ultimately improving healthcare outcomes for patients worldwide.

REFERENCES

[1] WHO. (2018). Global Report on Diabetes.

[2] Wilkinson, C. P., et al. (2003). Proposed International Clinical Diabetic Retinopathy and Diabetic Macular Edema Disease Severity Scales.

[3] Gulshan, V., et al. (2016). Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs.

[4] Ting, D. S. W., et al. (2017). Development and Validation of a Deep Learning System for Diabetic

Retinopathy and Related Eye Diseases Using Retinal Images From Multiethnic Populations With Diabetes.

[5] Ronneberger, O., et al. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation.

[6] Manjunath, B. S., et al. (1996). Texture Features for Browsing and Retrieval of Image Data.

[7] Sandler, M., et al. (2018). MobilenetV2: Inverted Residuals and Linear Bottlenecks.

[8] Tan, M., et al. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks.

[9] Gulshan, V., et al. (2016). Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs.

[10] Ting, D. S. W., et al. (2017). Development and Validation of a Deep Learning System for Diabetic Retinopathy and Related Eye Diseases Using Retinal Images From Multiethnic Populations With Diabetes.

[11] Ronneberger, O., et al. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation.

[12] Manjunath, B. S., et al. (1996). Texture Features for Browsing and Retrieval of Image Data.

[13] Sandler, M., et al. (2018). MobilenetV2: Inverted Residuals and Linear Bottlenecks.

[14] Tan, M., et al. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks.

[15] Abràmoff, M. D., et al. (2016). Pivotal Trial of an Autonomous AI-Based Diagnostic System for Detection of Diabetic Retinopathy in Primary Care Offices.

[16] Abràmoff, M. D., et al. (2018). Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning.

[17] Ting, D. S. W., et al. (2019). Development and Validation of a Deep Learning System for Diabetic Retinopathy and Related Eye Diseases in a Multiethnic US Population With Diabetes.

[18] Li, Z., et al. (2020). Diabetic Retinopathy Classification Using Multi-Stage Feature Extraction and Voting-Based Decision Fusion.

[19] Wang, S., et al. (2021). Diabetic Retinopathy Detection Using Texture and Morphological Operations Combined With Wavelet Transform.

[20] Rajalakshmi, R., et al. (2018). Validation of Smartphone-Based Retinal Photography for Diabetic Retinopathy Screening