Advance Deep Learning Approach for Diabetic Retinopathy Detection and Severity Classification Utilizing ResNet50

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Abstract- Diabetic Retinopathy (DR) is a common eye condition that occurs in people with Diabetes Mellitus. If this illness is not treated, there is a greater chance of blindness, either entire or partial. DR has broad range of levels and to identify and categories these levels in its early stages are challenging so it is important to have an automated system that can identify DR timely to prevent this disease from developing, but automated DR detection system has its own short comings such as limited data, small dataset and distortions in images due to size, colour and others. To overcome this problem, we proposed ResNET50 model with customized classification block to accurately identify DR and categories its levels. During the experiment we used two Datasets i.e. DR benchmark dataset and APTOS-19 and we validate the effectiveness and reliability of our proposed approach and the results of our experiment demonstrate that our proposed model generated better results to accurately identify DR and its states.

Index Terms- Image Classification, Diabetic Retinopathy, Resnet50, Fundus Images and Deep Learning.

I. INTRODUCTION

The medical community has focused a great deal of emphasis on the complex issues presented by diabetes mellitus, a metabolic disease that affects a lot of people and puts a pressure on healthcare systems worldwide. Diabetes is a disease that is influenced by both genetic predispositions and environmental variables. It is now ranked as the ninth most dangerous disease by the World Health Organization [1]. Tissues become less sensitive to the hormone insulin, which controls blood sugar levels, as a result. The metabolic imbalance, increased susceptibility to cardiovascular complications, and various eye problems—the most notable of which being DR—are all caused by the high blood sugar levels that is the outcome of uncontrolled diabetes.

One consequence of uncontrolled diabetes is DR, a condition where boosted blood sugar levels are chronic and have a detrimental effect on eye health. High blood sugar is the main cause of this sickness because it increases blood vessel permeability and leads to the formation of small aneurysms in the blood vessels that supply the retina. By starting a chain of events that includes ischemia, neovascularization, and bleeding, microscopic angiopathy leads to progressive retinal degeneration and, ultimately, irreversible blindness.

Patients usually do not show symptoms of the disease until it has progressed to severe stages, which hides the fatal effects of its insidious beginning. To reduce the incidence of disease and death related to this vision-threatening condition, it is imperative that the condition be identified early. Ophthalmologists primarily use fundus image analysis to diagnose DR. By carefully examining the retinal morphology, vascular anomalies can be found and subtle signs of neuroretina dysfunction can be found using this method. There are a few drawbacks to this method, despite its diagnostic use; the most important of these is the time and effort required for interpretation, which is inherently subjective due to individual variances in observation. Consequently, cutting-edge technical solutions are required to improve upon existing diagnostic procedures in order to hasten diagnosis, increase diagnostic accuracy, and provide prompt intervention to forestall long-term visual consequences.

The fast-expanding area of AI could be a game-changer in the treatment of diabetic retinopathy given the current state of affairs. Artificial intelligence (AI) powered diagnostic systems have the ability to replace labor-intensive manual evaluation with quick, objective, and easily extendable DR screening using large image datasets and advanced deep learning algorithms. These tools give doctors a new level of insight into retinal pathology by using innovative image processing methods and convolutional neural networks (CNNs). As a result, patients can have tailored treatments based on their unique profiles, and subtle symptoms of disease can be detected earlier. When everything is considered, DR presents a major risk to global healthcare systems. However, a new era of precise medical procedures for diagnosing and treating this illness may be marked by fusions of clinical expertise and technical improvement. Medical professionals, researchers, and legislators' collaborations are the only way to mitigate the consequences of DR and protect vision and eye health for later generations.

II. Related Work

Several AI and computer vision solutions have been developed to address these limitations in the diagnostic process. Harun et al. [2] utilized a neural network with multiple layers of perceptron. The system was trained with two classification methods: Levenberg-Marquardt (LM) and Bayesian regularization (BR). When comparing the classification accuracy, the Multilayer Perceptron (MLP) trained with the Backpropagation method (BR) outperformed the Levenberg-Marquardt algorithm (LM). Identifying the optimal nodes during the classification phase proved to be quite difficult. The authors explored a deep learning approach to identify the ideal number of nodes for achieving optimal results. According to research conducted by Aqib et al. [3], DR was categorized into five stages using machine learning classifiers and fundus images. With this method, we successfully classified the attributes into four distinct categories. For assessing the method, a data fusion tool generated a hybrid feature dataset. An ensemble machine learning model was used to categorize DRs in reference [4]. Initially, the DR Dataset underwent normalization using the min-max method. After that, a normalized dataset was used to train an ensemble model. This model was tested on a dataset with a small number of records. Vijayan et al. [5] aimed to identify DR through the analysis of retinal images from a database that was accessible to the public. They attained a 70% accuracy rate by using decision rules, decision trees, and instant-based learners.

The Convolutional Neural Network (CNN) approach has demonstrated substantial efficacy in anomaly identification, particularly in the diagnosis of DR. Sungheetha et al. [6] developed a CNN model to detect early stages of DR conditions in retinal fundus pictures and created an algorithm for this purpose. Unfortunately, the algorithm was unable to analyze unprocessed real-time images for diagnostic purposes. Gayathri et al. [7] examined a CNN model that was enhanced with ML classifiers to accurately identify and classify DR by extracting and analyzing its features. Drawbacks of this strategy encompass the substantial expense and the ability to identify minuscule abnormalities during the initial phases of DR. A different automatic classification technique called Coarse-to-fine DR network (CFDRNet), based on CNN, was introduced in [8]. The research incorporated two interrelated subnetworks to classify and assess the severity of DR based on fundus images: 1) the Coarse Network and 2) the Fine Network. The current model lacks the ability to reliably distinguish different levels of DR severity. A more comprehensive Fine Network can be built to overcome this restriction. To categorize the degrees of DR severity, Karki et al. [9] used the Efficient Net model. The APTOS 2019 data set was used to test the given model. To identify diabetic retinopathy (DR), Suchetha et al. [10] presented a CNN model. Two datasets, one from a medical facility and one from a traditional DR dataset, were used to evaluate the model. According to reference [11], DR detection was carried out using OCTA photos and various CNN models. We compared the model's performance against that of more conventional machine learning models to ensure its usefulness. Using a Synergic deep learning model (SDL), Shankar et al. [12] were able to filter images in real-time. To enhance and ensure precise identification and prediction of the severity degrees of DR, in [13], a specialized model with a gated attention mechanism was introduced, based on a multichannel deep neural network model. The model's performance is inadequate for greater levels of DR severity. Zhang et al. [14] showcased a sophisticated ensemble method for identifying Diabetic Macular Oedema and DR by utilizing retinal fundus pictures. The utilization of the majority decision for the evaluation of retinal pictures in this study is subject to several constraints, including the potential for grader bias.

Gangwar et al. [15] introduced a hybrid deep-learning method to automatically diagnose diabetic retinopathy (DR). The model employed Transfer Learning by utilizing a bespoke block based on a Convolutional Neural Network (CNN) and a pre-trained Inception-ResNet-v2. The evaluation was conducted using the APTOS-2019 dataset. Resnet models utilize deep learning architecture for the purposes of classification and feature extraction. Millions of images, divided into multiple groups, make up the ImageNet collection. The Resent50 model's 177-layer design includes skip connections, which let input to go from early levels to later ones. By utilizing 11 convolutional layers, the model's size and number of parameters are reduced. The Resnet50 model has two main problems: it is too deep, which makes error detection challenging, and it may lead to inefficient learning if the network isn't deep enough. By Using DenseNet121's Transfer Learning capabilities, Ayala et al. [16] trained a deep-learning classification model to classify retina fundus pictures for the detection of DR. An efficient architecture for Deep Neural Networks, InceptionResnet-V2, was presented in the publication [17, 18] for the aim of DR discrimination. Handayani et al. [19] explored the issue of delayed identification of DR using the MobileNetV2SVM model. Utilizing the APTOS-2019 dataset, the effectiveness of the given technique was evaluated. Zhang et al. [20] used the Inception V3 model to classify the severity of DR using fundus images. When non-proliferative diabetic retinopathy (NPDR) was found to be severe, the condition's functioning was inadequate. Diabetic retinopathy (DR) can be automatically identified by the model developed by Qureshi et al. [21]. Active Deep Learning's (ADL) multi-layer architecture served as the foundation for the model. A model was created by Deter et al. [22] using a modified Xception deep feature extractor. The DenseNet-169 algorithm was utilized. Gupta et al. [23] presented a combined method for DR detection that included deep learning and conventional machine learning approaches.

The detection and categorization of diabetic retinopathy (DR) from retinal images has been approached with various machine learning and deep learning approaches. These algorithms need to be improved because they have only been tested on small datasets with no more than four categories. Most existing methods can identify four main types of diabetic retinopathy (DR). Hence, a method is needed to accurately identify and classify all types of DR, such as EarlyPDR, HighriskPDR, Mild-NPDR, MOD-NPDR, NonDR, and SEV-NPDR. In light of these present difficulties, we have proposed a method for the accurate detection and classification of diabetic retinopathy (DR) by means of retinal images. Medical practitioners and healthcare systems alike will reap the benefits of this approach. The "DR benchmark dataset" is used to categorize and identify instances of diabetic retinopathy in the proposed study. A total of 1,445 extremely high-resolution photographs illustrating healthy and sick humans are produced by the procedure using non-mydriatic fundus shots. What follows is a breakdown of our roles in this study project. Introducing an optimized ResNet50 model for computational efficiency: We have created a customized ResNet50 architecture to reliably identify fundus images of DR into six distinct categories. This specialized model enhances the efficiency of ResNet50 to better detect subtle changes indicating varying levels of DR severity. The diversity of imagery resilience: Our proposed method showcases the natural variability in DR fundus images, such as variations in image sizes, distortions, and color palettes. Our model's resilience allows it to consistently perform well across a variety of image attributes, making it valuable in real world clinical situations where image quality can vary significantly.

Thorough experimentation was carried out to validate our proposed technique, using two well-known datasets: APTOS2019 and the DR benchmark dataset. We compared our model's output to the latest cutting-edge techniques, showcasing its superior accuracy and resilience through thorough testing and validation. Below is a detailed overview of the key research points:

Part III delves deeper into the methodology, offering a detailed explanation of the technical specifications and theoretical foundations behind our customized ResNet50 model. Part IV provides a detailed description of the experimental framework used in our investigation. It presents an analysis of the experimental findings along with details of the experimental setup, data sets, and evaluation criteria used. Section V summarizes important findings, explains their implications for clinical practice and future research, and highlights the significance of the contributions to the field of DR diagnosis and categorization, concluding the research attempt.

III. PROPOSED METHODOLOGY

This section offers a detailed explanation of the proposed methodology. The proposed method consists of several processes, as seen in Figure 1, which are image preprocessing, data augmentation, DR detection using a customized ResNet50 with dense layers, and prediction. The preprocessing stage involves resizing all of the dataset's images to 128 x 128 pixels. To further enhance image quality and preserve smoothness, we also used a diverge regularized filter. Postprocessing is essential for ensuring the quality of training data and enhancing the performance of the trained model. Additionally, the exclusion of smaller image samples during training is done to enhance accuracy by preventing the model from overfitting the data, hence ensuring its effectiveness on unknown data. Data augmentation is employed on the training samples to mitigate overfitting problems and address the scarcity of training data. Data augmentation is the most widely used and direct approach to artificially expand the training dataset without relying on costly computational resources. By increasing the amount of data, the number of training samples is expanded by 200%, resulting in enhanced accuracy without the risk of overfitting. We significantly improved the training examples by employing various approaches such as rotation, flip, skew, scale, and translation (see to Figure 2 for example images). The dataset was partitioned into two subsets, allocating 80% of the data for training purposes and reserving the remaining 20% for testing.

In order to address the limitations of conventional machine learning methods, which necessitate segmentation and substantial manual feature engineering, we have put up a tailored ResNet architecture.

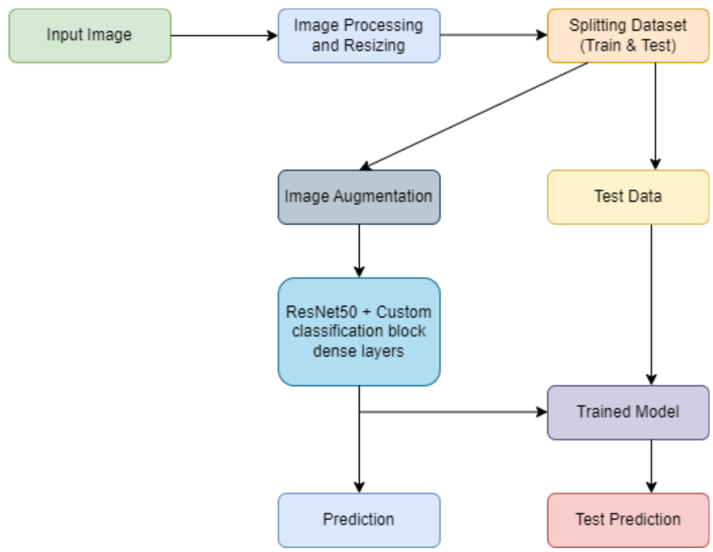

Figure 1: Overview of Diabetic Retinopathy Detection

The current ResNet model comprises 50 layers, including 48 Convolution layers, 1 Max-Pool layer, and 1 Average Pool layer. An important advancement of ResNet is its ability to enable researchers to train neural networks with more than 150 layers. The Vanishing Gradient Problem poses a notable drawback for CNNs. Backpropagation considerably decreases the gradient value, resulting in little changes to the weights. The issue is addressed by employing ResNet, which utilizes skip connections. We implemented a classification block with numerous layers in order to enhance the performance and accuracy of our system's categorization. Figure 3 illustrates the proposed network architecture in which the average pooling layer is responsible for generating a reduced-size feature map obtained from the preceding convolutional layer. The dropout layer serves to mitigate overfitting during the training phase. The 6 dense layers calculate the weighted average of each input and apply the 'ReLU' activation function to aid in image classification. To achieve precise multi-class detection, the SoftMax layer is employed. In Figure 3 the input preprocessed image is transmitted to the ResNet-50 architecture.

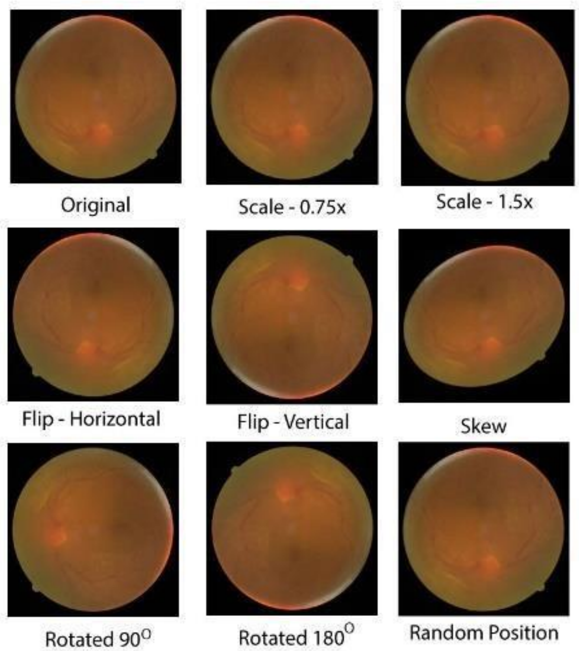

Figure 2: Image results after Data Augmentation techniques

Initially, the ResNet-50 model is meticulously prepared by undergoing a series of sequential procedures. To ensure the preservation of all data, the initial stage involves doing zero padding. At stage 1, the image is convolved, the batch is normalized, the image is sent through the ReLU function, and finally, Max pooling is performed. The max pooling function is employed to reduce the size of image samples in order to minimize computational expenses. This is performed during the process of selecting hidden layers. We have minimized the number of concealed layers and determined the most effective quantity of these layers. Subsequently, we adjusted them accordingly. In addition, the utilization of max pooling yielded optimal results without compromising the overall performance. This is because max pooling selects the highest value from each pool, ensuring that the best maximum value is chosen for matching purposes. At the second stage, the system performs a convolution on the block and generates an ID Block. This stage involves performing a convolution operation for the ResNet50 network. From stage 1 to stage 5, all stages in this network utilize convolution. The next step in model training involves conducting more convolutions using the hidden layers. The ResNet-50 network consists of numerous concealed layers, and each block is sequentially processed through all of these layers. This generates a distinctive and discernible feature vector that produces the most optimal feature representation for classification. Following the hidden layers, additional functions are executed to enhance the features. The processes involved are average pooling and passing via the drop-out layer. Next, a Dense layer with 6 units is generated to ensure accurate classification. The Dense layer is determined by the number of available classes. Given that the dataset has 6 classes, the Dense (6) function is utilized in this context. Ultimately, we opted for the SoftMax function due to the presence of six distinct classes.

IV. EXPERIMENTS AND RESULTS

This section discusses the details of datasets, evaluation metrics, and a discussion on experimental results used to assess the performance of our method.

A. Dataset Description

We evaluated our proposed model using two distinct datasets: 1) the DR benchmark dataset [20], and 2) the APTOS 2019 dataset. The first dataset utilized in the proposed research has been gathered by the Department of Ophthalmology at RMU in the format of digitized retinal images. A group of five expert ophthalmologists analyzed the image collection obtained from a sample consisting of 40% male and 60% female individuals. This dataset comprises 1445 high-quality fundus pictures of retinal imaging, collected over a span of two years from patients who

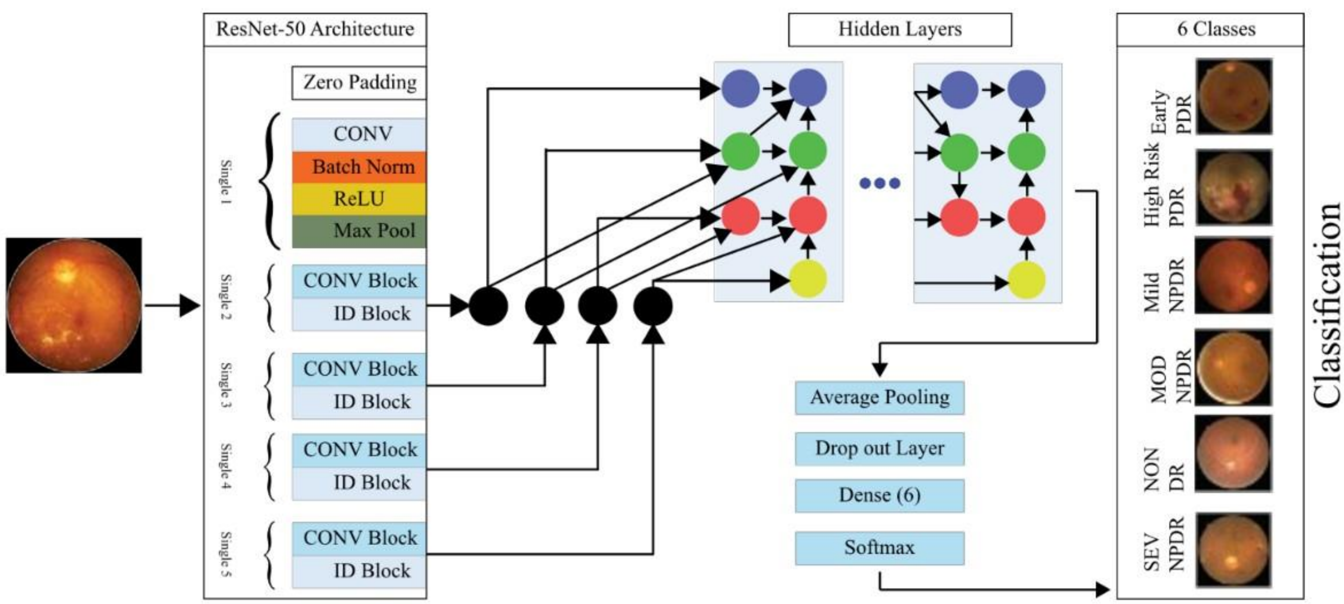

Figure 3: Proposed Network Architecture

visited the Department of Ophthalmology at Holy Family Hospital in Rawalpindi. Furthermore, it provides samples for each stage of the DR process. A team of five experienced ophthalmologists conducted the task of annotating 1445 digitized retinal images with excellent precision. Every image possesses an 8-bit colour gamut and a pixel resolution of 2976 × 2976. Figure 4 demonstrates that the dataset consists of 650 photographs that are considered healthy or normal. Additionally, the panel of experts identified clinical evidence of DR in 631 images, which were thus classified as abnormal, as shown in Figure 5. The second dataset utilized in this study is APTOS-2019. This dataset was created from 3662 DR photos obtained by the Aravind Eye Hospital in India. The fundus photos were captured over an extended duration, encompassing various settings and circumstances. The samples were later assessed and categorized by a team of proficient physicians. The APTOS-2019 samples are classified into five categories: No DR, mild NPDR, moderate NPDR, severe NPDR, and proliferative DR. The collection consists of 1805 images with no diabetic retinopathy (No DR), 370 images with mild stage non-proliferative diabetic retinopathy (NPDR), 999 images with moderate stage NPDR, 193 images with severe stage NPDR, and 295 images with proliferative stage diabetic retinopathy (DR).

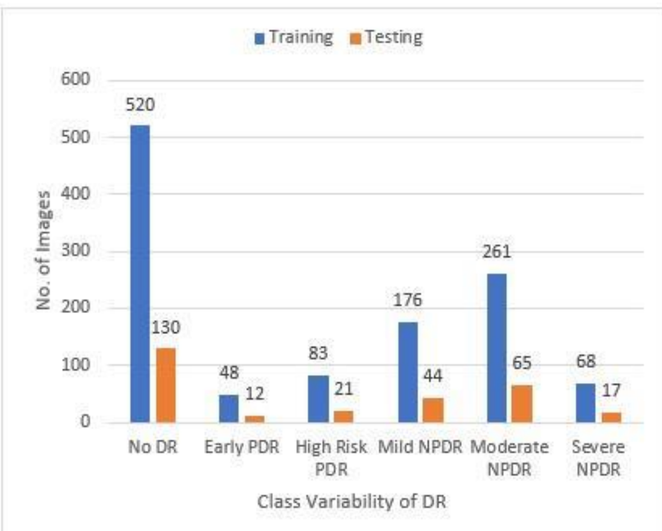

Figure 4: Label distribution of the DR benchmark dataset

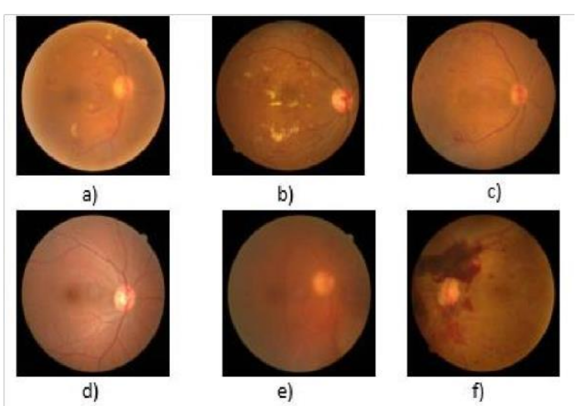

Figure 5: Sample images from the Diabetic Retinopathy benchmark dataset exhibiting classes

B. Performance Metrics

We evaluated the performance of the developed model using four assessment metrics i.e., Accuracy, Precision, F1 Score and Recall.

C. Evaluation of Proposed Technique

For the purpose of determining whether or not the proposed method is effective, we carried out an experiment consisting of two stages, using two typical benchmark datasets. In the beginning, we used the DR Benchmark Dataset to determine whether or not the methodology that we proposed was really effective. In order to accomplish this goal, the dataset was split into two sets: a set for training purposes and other sets for assessment purposes. 80% of the time was spent on training, while the remaining 20% was used for testing. Over the course of a maximum of fifty epochs, the training procedure makes use of a batch size of ten photographs and is carried out repeatedly. A total of 228 iterations are included in each epoch. This model was trained with the assistance of a free GPU Tesla K80 that was donated by Google Collaboratory.

An accuracy of 88%, a recall of 92%, and an F1-score of 88% were demonstrated by the model, which is indicative of the robustness of the network that we proposed. The particulars of the outputs of the model trained on the DR benchmark dataset, both in terms of class-wise and overall performance, are presented in Table 1 and Figure 6 which is the graphical visualization of Table 1 indicates that the proposed method has achieved a precision of 85% when applied to the benchmark dataset. In light of this, it is clear that the model has demonstrated satisfactory performance on the diabetic retinopathy benchmark dataset. We were able to improve the robustness of our model by including the Resnet50 model, which features dense layers and a max pooling function. By training and testing the DR benchmark dataset in less than 270 seconds, the proposed model presents evidence of its applicability to real-time environments. This results in a reduction in the number of computational resources required. Due to the fact that this dataset is being used for the very first time, there are no previous research that have been reported in the literature that have utilized it. The effectiveness of our suggested model was evaluated within the context of the APTOS-2019 dataset during the second phase of the project. The outcomes are detailed in Table 2 and visually presented in Figure 7, and the demonstration of the robustness of our method is provided by the performance of our proposed model on this diverse dataset. When compared to the accuracy of Mild NPDR, which is just 52.28%, the accuracy of Proliferative DR is really lower than 50%. This is because these samples are located in close proximity to other classes while the visual representation is being created. It is not possible to properly utilize the visual pattern of PDR to correctly classify things because it does not contain any separate elements. On the other hand, the results of the other four classes were significantly better. The training and testing of the model that we have suggested could be finished in one minute and two hundred and fifty seconds. Consequently, this demonstrates that our methodology is very effective and appropriate for applications that take place in real time.

Class	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
High-Risk PDR	48.72	65	49	56
Moderate NPDR	94.62	81	95	87
Mild NPDR	53.93	75	54	63
Non-DR	97.69	99	98	98
Severe NPDR	63.54	85	64	73
Early PDR	98.32	91	98	94
Overall	88	85	92	88

Table 1: Class-Specific performance of the proposed model using DR benchmark dataset

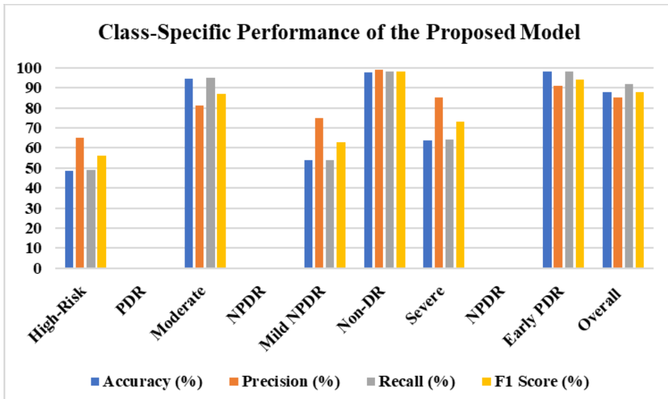

Figure 6: Class-Specific performance of the proposed model

Class	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Moderate NPDR	92.12	75	92	83
Mild NPDR	52.28	70	52	60
Non-DR	97	98	98	98
Severe NPDR	49.61	72	48	58
Proliferative DR	45	62	45	52
Overall	87	84	89	86

Table 2: Performance of the model in a specific class using the APTOS-2019 dataset

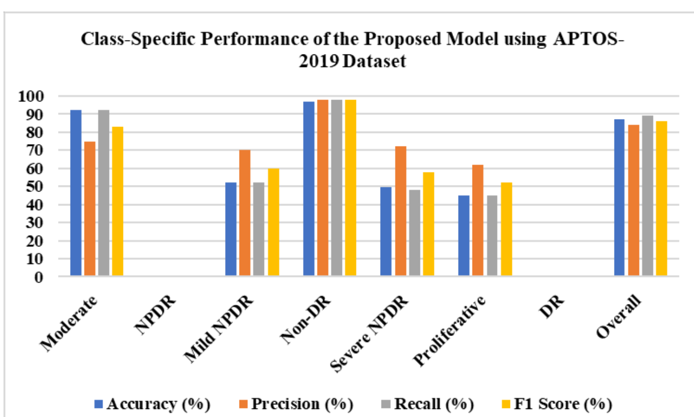

Figure 7: Class-Specific performance of the proposed model using APTOS-2019 dataset

D. Comparative Analysis with Existing Methods

In order to evaluate the importance of our approach for DR in comparison to current approaches, we conducted a performance comparison between our method and the most recent methods cited as [13], [15], [19], and [22]. The APTOS 2019 dataset was used to assess all of these approaches. Based on the information presented in Table 3 and Figure 8, our suggested network has demonstrated outstanding performance in terms of accuracy, precision, recall, and F1 score compared to the other techniques. The enhanced performance is a result of using data augmentation techniques and adding extra layers to the model. Expanding the dataset is a method that increases the number of samples to improve training by utilizing a variety of data. By incorporating additional layers into the ResNet50 network architecture, it enhances the identification of crucial features and enhances the categorization process.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Bodapati et al. [13]	82.54	82	83	82
Gangwar et al. [15]	82.18	Nil	Nil	Nil
Handayani et al. [19]	85	Nil	Nil	Nil
Ralph et al. [22]	83.09	Nil	Nil	Nil
Proposed work	87	84	89	86

Table 3: Performance comparison over APTOS dataset

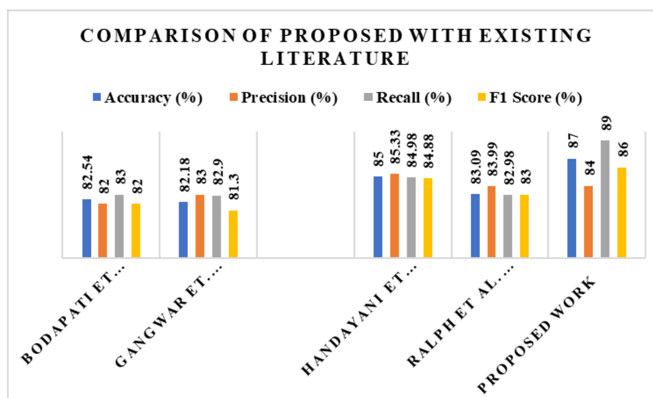

Figure 8: Comparison of proposed model with existing literature

V. CONCLUSION

Featuring a novel method to enhance the diagnosis and classification of DR. Proposing a combination of an enhanced ResNet50 model with a CNN-based classification block. We have created a unique method to differentiate between proliferative and non-proliferative forms of diabetic retinopathy (NPDR). After carefully examining the DR and APTOS-2019 benchmark datasets, we have gained valuable insights into the efficacy and longevity of our proposed method. Our study's key results highlight how data augmentation techniques can improve the effectiveness of DR classification. Our model outperforms competitors when trained with data augmentation techniques, showing that synthetic data can improve a model's resilience and adaptability. In addition, it was discovered that obtaining high classification accuracy necessitates incorporating dense layers into our model architecture. Highlighting the significance of feature extraction and abstraction in accurately identifying subtle changes related to different levels of drug resistance severity. It is visible from our results on the APTOS-2019 dataset and the DR benchmark dataset that our methodology outperforms other existing methodologies. The remarkable robustness of our methodology in accurately detecting DR severity levels underscores its promise as a substantial therapeutic tool for early diagnosis and prognosis of DR related issues. In the future, our research plan involves a strong emphasis on incorporating advanced deep learning models and methods to enhance the effectiveness and scalability of our approach. Through the adoption of state-of the-art methods in combining models and fusion techniques, our goal is to explore uncharted territories in the diagnosis of diabetic retinopathy. This will lead to a new era of precise medical treatment and personalized healthcare delivery.

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