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RESEARCH ARTICLE

Classification and Identification of DR from Fundus Images Based on Deep Convolutional Networks

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***Abstract*—A disease known as diabetic retinopathy (DR) can develop in people who have diabetes for an extended period of time. Visual impairment can result from a postponed diagnosis. Diabetics are disproportionately likely to get DR due to their chronically elevated blood sugar levels. The retina's blood vessels are affected by this. This study demonstrates the use of the ResNet50 architecture in a deep learning-based method for the early detection and categorization of diabetic retinopathy (DR) using images of the retinal fundus. This research takes advantage of fundus photography, a non-invasive, high-resolution imaging technology, to detect retinal alterations even when no outward signs of diabetic retinopathy (DR) are present. Diabetes is on the rise around the world, and if not caught early, DR can lead to permanent visual loss, thus this is crucial. The work guarantees strong training of the ResNet50 model by preprocessing images using normalization, augmentation, and scaling, and by controlling for class imbalances. The APTOS dataset includes photos from all five severity levels of DR. The model demonstrated outstanding results in terms of recall, accuracy, precision, and F1-score during training, suggesting high reliability and promising clinical use. Aiming to improve preventive diabetes treatment, particularly in places with limited resources, the research highlights the usefulness of AI in scalable, early-stage DR screening.**

Keywords—Diabetic retinopathy, Fundus images, Resnet50 model, APTOS dataset, Deep learning.

INTRODUCTION

A condition known as diabetic retinopathy (DR) occurs when a person with diabetes has consistently high blood sugar levels over an extended period of time. This condition affects the retina, a layer of the eye that is photosensitive and responsible for vision. Problems with the retina's ability to transform light into signals that the brain can use can cause severe vision loss or even blindness. Droovel ganglion cysts form when microvascular structures in the retina expand, leak, or burst as a consequence of aberrant blood flow and excessive pressure [1][2]. Worldwide, 642 million people will be living with diabetes by 2040, with one-third developing complications from the disease. This puts diabetes ahead of all other causes of mortality, according to the World Health Organization (WHO). The five stages of disease progression are as follows: no illness, mild disease, moderate disease, severe disease, and proliferative disease [3]. Proliferative diabetic retinopathy (PDR) is very similar to the first fourtypes of diabetic retinopathy, which are together called Non-Proliferative Diabetic Retinopathy (NPDR). Both of these types include the development of aberrant blood vessels, which can burst and lead to blindness. Early signs include microaneurysms [4]. Hard and soft exudates, and hemorrhages. Different treatment protocols are needed at each stage, and, at early stages, monitoring is used, and laser therapy or surgery is required at later stages. The key to the treatment of DR is early detection and, in the case of unavoidable progression, before complications have occurred. Manual screening is inefficient, slow, and prone to failure. Therefore, automated diagnosis based on AI is more and more used, which promises to be quick, reliable, and precise.

Fundus images have proved an effective and non-invasive form of diagnosis in detection and treatment of diabetes and one of its complications [5]. These photographs required detailed images of the retina to be captured with its inner details such as the optic disc, macula and blood vessels that are greatly affected by diabetes. As commonly known, fundus is traditionally considered to be useful in the diagnosis of diabetic retinopathy (DR), but recent research studies indicate that in cases where there are no apparent signs of DR, fundus images still evince microscopic alterations in the microvasculature, which suggest an early occurrence of diabetes [6] [7]. Due to the era of AI, scientists have created machine learning model types that can analyze such pictures and identify not only DR but diabetes itself at a very early stage. Diagnostic performance AI models based on fundus images have been demonstrated in several studies to reach high AUCs, with values greater than. The models provide an affordable, fast, and scalable method of screening, especially in underserved regions where there is little specialization care available [8]. Further, using fundus-based AI systems, the diabetes type can be distinguished in terms of the duration with better results being observed where vascular changes are more severe than less. It renders fundus imaging an irreproachable instrument in early diagnosis and monitoring of diabetes, which may revolutionize the process of prevention and mitigate the long-term conditions like blindness and organ failure.

In the recent past, computers have been able to learn about large data sets in a manner that surpasses or surpasses human capabilities in most fields, owing to deep learning algorithms. A number of algorithms which are highly specific and sensitive in classifying or detecting the existence of some disease conditions by way of classifying medical images like retinal images, exist [9][10]. The current state of deep learning-based DR screening algorithms is mostly focused on finding individuals with referable or vision-threatening DR. The goal is for these algorithms to send patients to ophthalmologists for further evaluation or follow-up. The importance of finding early-stage DR should not be overlooked, though. Diabetes can be put off or even reversed if glucose, blood pressure, and lipid profiles are well-controlled early on. All participants in this study, whether they had diabetes or not, had normal retinal fundus pictures and showed no signs of diabetic eye disease. Ultimately, the study aimed to develop an AI system capable of early detection of diabetic retinopathy in retinal fundus images. Not only that, but the research distinguished between various disease durations.

A. *Motivation and Contribution of Study*

DR is one of the main causes of avoidable blindness around the world, so this study was motivated by the urgent need to find it quickly and correctly. People with diabetes are at a 1/3 chance of getting DR, so finding it early is very important to avoid permanent vision loss. But screening by hand takes a long time, costs a lot of money, and can be different from one doctor to the next. The use of fundus imaging being non-invasive and widely accessible combined with the power of AI and DL enables automated systems to detect minute retinal abnormalities at early stages. This study is driven by the goal of creating a scalable, consistent, and accurate diagnostic framework for DR detection using deep convolutional networks. The main key contributions are as follows.

- Utilized the APTOS dataset, a large publicly available fundus image dataset, to train and validate the DR detection framework.
- Applied robust preprocessing techniques including min-max normalization and image resizing to standardize input dimensions, along with data augmentation to increase sample diversity and mitigate overfitting.
- ML model trained and released utilizing ResNet50 architecture for automatic multi-class classification across five DR severity levels.
- Validated the model's diagnostic reliability and clinical application by evaluating its performance using comprehensive criteria such as accuracy, precision, recall, and F1-score.

B. *Justification and Novelty*

The novelty of this study lies in its focus on the early detection of diabetes and DR from fundus images, even in patients who do not exhibit visible signs of DR. Contrary to several current models that simply focus only at detecting severe to moderate levels or simply classify the DR as either present or absent, the paper outlines an efficient multi-stage classification scheme that is able to determine each of the five levels of DR severity with the help of a DL model comprising ResNet50. The implementation of a complex preprocessing chain (including scaling, normalization, augmentation, and class imbalance correction to promote model robustness and superior generalization) further bolsters the claim of its originality. The model also outperforms more conventional models like Dense Net and Mobile Net in terms of accuracy, precision, recall, and F1-score. This positions the proposed system as not only highly accurate but also clinically relevant for scalable, early-stage screening. The study’s ability to detect subtle retinal changes prior to the appearance of clinical symptoms highlights its potential to transform preventive care strategies and reduce the long-term burden of diabetes-related visual impairment, particularly in resource-limited settings.

C. *Structure of Paper*

The outline of this paper is as follows: Section II lists some of the most popular deep learning approaches to DR detection currently available. Section III explains the solution, as well as the preprocessing and the ResNet50 model. The results and analysis of the experiments are given in Section IV. Following a brief overview of the results, Section V offers suggestions for further studies.

LITERATURE REVIEW

This section presents research on Diabetic Retinopathy Detection of fundus image systems that utilize diverse ML techniques; the summary of these studies is provided in Table I.

Basheer et al. (2025) DR is one of the common eye illnesses and needs timely detection with a chosen imaging modality. Retinal OCT based analysis is one of the clinical practices and this work developed a DL scheme for detecting the DR in OCT data. Data preparation (including resizing and collecting), feature extraction (using classification results to identify the best model), feature reduction (using 50% dropout and serial concatenation to obtain the fused-features-vector, or FFV), classification, and three-fold cross validation are the various steps involved in this work. This work considered 2000 OCT images of normal/DR class for the examination and the KNN model-based scheme helped to get a detection accuracy of >98%. This confirms that the proposed DL-model based on ResNet variants works well on this database [11].

Vikraman et al. (2025) DRC-PCS-ANN, a novel neural network architecture based on pyramidal convolution and shuffle attention, for effective diabetic retinopathy classification. As a first step, input images were acquired from the MESSIDOR database. Using DAGAF for pre-processing, the images are cleaned up after capture by removing noise. Next, it uses the One-Dimensional Quantum Integer Wavelet S-Transform to extract statistical parameters such as Mean, Kurtosis, Variance, and Entropy. The five subtypes of diabetic retinopathy, no DR, mild DR, moderate DR, severe DR, and proliferative DR, are classified using the initial features then PCSANN is applied. Then, DRC-PCS-ANN's performance was evaluated using F1-score, precision, and accuracy. When benchmarked against other DR classifiers, such as DRC-MCNN-MLC, ADR-PCS-DL, and ADR-AFT-CNN, the DRC-PCS-ANN approach achieves 21.28%, 21.52%, and 20.34% higher accuracy and 23.29%, 23.83%, and 21.72% higher precision, respectively [12].

Ahmed et al. (2024) Diabetic retinopathy is detected in this work using a ResNet-18 DL model. The dataset used in this study is divided into two sections: training and testing. It was collected via Kaggle. With ResNet-18, able to achieve 96.65% testing accuracy and 99.91% training accuracy. The results show that DL models, like as ResNet-18, can effectively detect diabetic retinopathy early on, which could completely change the way screenings are done in clinical settings. Reducing the overall risk of blindness among diabetes cases, this proposed model can significantly expand the breadth of early intervention and treatment measures by simply streamlining the diagnostic side of the treatment process. Patient outcomes and healthcare resource allocation could both be enhanced by implementing such technology [13].

Jenefa et al. (2024) Explains in depth how to use Kaggle retinal scans to categorize the severity of DR. The timeliness of the above response is explained by the urgency of DR detection and treatment measures. It should be noted that a specifically arranged data set was created in the described work, including 2750 pictures in with 5 groups of severity. The maximum training accuracy of 98.55% was reached by using EfficientNetB3 with transfer learning, and the validation and testing accuracies constituted 71.27% and 76.36%, respectively [14].

Pranay et al. (2023) Use DL to analyze various DR stages and develop a unique methodology for detecting diabetic retinopathy. Model improves diabetic retinopathy detection accuracy by using a modified pre-trained DenseNet-121 architecture and better pre-processing algorithms. Once the model has been trained on a large dataset, it may be able to automatically identify the DR stage. From zero to four, the DR phases are grouped into five distinct groups. According to this research, the patient's fundus ocular photos served as the model's input parameters. With a 97% accuracy rate, the model surpassed the state-of-the-art models that were discussed [15].

Pavithra et al. (2022) Two DL models, Optic Net and Dense Net, were evaluated and researched for DME classification using a standard OCT dataset. Comparing the two models' performance is done by statistically analyzing the accuracy measures collected during the tests. As per the data, the most suitable system for determining DME might be the model Optic Net (Accuracy-98%, Specificity-100%), which outperforms Dense Net (Accuracy-94%, Specificity-96%) [16].

S et al. (2021) A prevalent long-term condition affecting individuals of all ages, characterized by inadequate insulin synthesis and the resulting elevation of blood sugar levels. Many other health problems might manifest throughout the body as a result of untreated diabetes. The asymptomatic deterioration of the retinal vessels caused by diabetes is known as DR. Conventional handcrafted traits have been utilized in numerous automated diagnostic systems that have been created in the literature. Since DL automates feature extraction, it has the ability to generate more precise and promising results, which is especially useful in medical imaging. One of the most common ways to employ DL in medical image analysis is with CNN. In order to gain a better understanding, this work analyses and reviews various DL - based diabetic retinopathy disease detection and classification algorithms [17].

Despite significant advancements in DR detection using DL, several research gaps remain. Many existing models, such as those using ResNet, Dense Net, or Efficient Net variants, achieve high training accuracy but often exhibit a notable drop in validation or testing performance, indicating potential overfitting and limited generalization. Additionally, some approaches focus only on binary classification (e.g., normal vs. DR) rather than the clinically relevant multi-stage DR classification. It is also challenging to compare model performance accurately due to the absence of standardized datasets and similar evaluation methodologies across research. Furthermore, real-time applicability, computer efficiency, and interpretability are all essential to clinical application, but few models take them into consideration. These differences drive a much stronger and more explainable representation that scales to deliver across a wide variety of data ranges and real-life conditions.

TABLE I. COMPARATIVE ANALYSIS OF DL TECHNIQUES FOR DIABETIC RETINOPATHY DETECTION.

Author	Methodology	Data set	Key Findings	Limitation	Future Work
Basheer et al. (2025)	ResNet variant + 50% dropout + serial concatenation + KNN	OCT images (2000 samples)	Achieved >98% accuracy with three-fold cross-validation	Limited to binary classification (Normal/DR)	Extend to multi-class DR classification and larger datasets
Vikraman & Sumathi (2025)	DRC-PCS-ANN (Pyramidal Conv + Shuffle Attention) + DAGAF preprocessing + statistical features + PCS-ANN	MESSIDOR	Outperformed existing models by up to 23% in accuracy and precision	Computationally complex; lacks real-time validation	Explore lightweight deployment and real-world integration
Ahmed et al. (2024)	ResNet-18 (DL model)	Kaggle DR dataset	99.91% training accuracy; 96.65% test accuracy	May suffer from overfitting due to high training accuracy	Test on unseen data or cross-dataset validation
Jenefa & S (2024)	EfficientNetB3 + transfer learning	Kaggle (2750 images, 5 severity levels)	98.55% training, 76.36% test accuracy	Large drop between training and testing accuracy (generalization gap)	Enhance generalization and apply to real clinical data
Pranay et al. (2023)	Modified DenseNet-121 + advanced preprocessing	Large DR fundus dataset	Achieved 97% accuracy, classified DR into 5 stages	Lacks details on dataset size/split and validation strategy	Improve interpretability and clinical applicability
Pavithra et al. (2022)	Optic Net vs DenseNet on OCT data	Standard OCT dataset	Optic Net achieved 98% accuracy, 100% specificity	Focused only on DME (Diabetic Macular Edema), not full DR spectrum	Expand to DR staging and multi-modal inputs
S & R (2021)	Review of DL-based DR detection using CNNs	Various datasets (review paper)	DL offers superior feature extraction and accuracy over traditional methods	No experimental implementation; only literature review	Implement and compare reviewed methods on standard benchmarks

METHODOLOGY

The enhanced pipeline allows for the presentation of the framework for DR detection in fundus pictures using deep convolutional neural networks, as evidenced in Figure 1. Collecting the APTOS dataset is the first step in the setup process. Extensive data preprocessing, including bias reduction and data standardization using a min-max scaler to improve feature standardization, follows. Pictures are resized and scaled to make sure the input dimensions are consistent, and data augmentation techniques are used to make the dataset more diverse and improve the model's generalizability. To get the dataset ready for modelling, the next stages are to convert the variables and combine the data. After that, the processed data is split in half: 80% goes into the training subset and 20% into the testing subset. A ResNet-50 deep convolutional neural network, trained on the prepared fundus photos, was used for categorization. A number of popular measures are employed to evaluate the model's performance, including F1-score, recall, accuracy, and precision. More accurate diagnoses of diabetic retinopathy at an earlier stage are the final result, which improves patient outcomes.

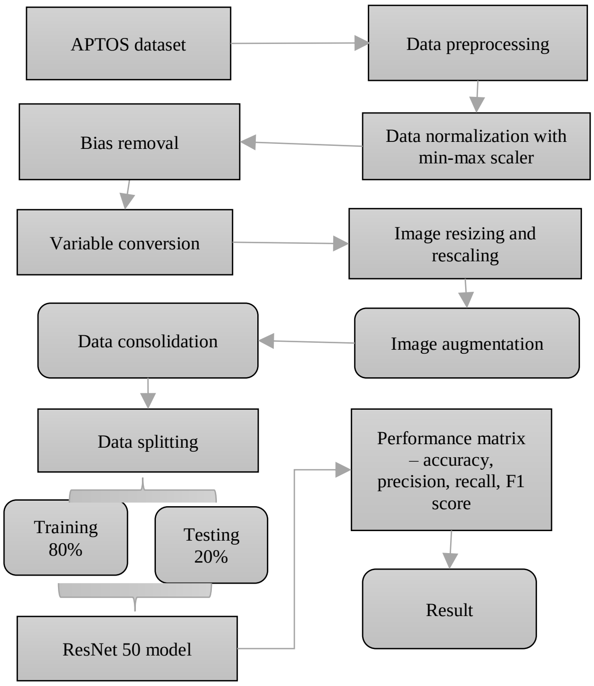

Fig. 1. This Flowchart Presents the study of Diabetic Retinopathy Detection of Fundus Images.

The following sections provide each step description that is also shown in methodology and proposed flowchart:

D. Data Collection

The APTOS blindness detection dataset, containing 3,662 labeled fundus images across five diabetic retinopathy severity levels (0–4), was used in this study. Data exploration revealed a class imbalance, which could lead to model bias; however, no duplicate or missing values were found, making the dataset clean and suitable for DL-based classification.

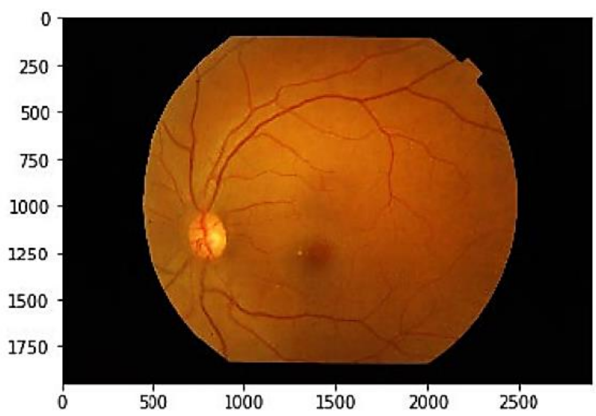

Fig. 2. Sample of Fundus Image from the Dataset

Figure 2 shows an example of a fundus image taken of the retina for the diabetic retinopathy dataset. The picture shows the retina's blood vessels, macula, and optic disc in a clear and undistorted way. Microaneurysms, haemorrhages, and irregularities in the blood vessels are all symptoms of diabetic retinopathy, and these characteristics are essential for detecting them. The high resolution and color contrast in the image allow for effective visual inspection and automated feature extraction using DL models. This type of image forms the foundation for training ResNet50-based models to detect and classify DR severity accurately.

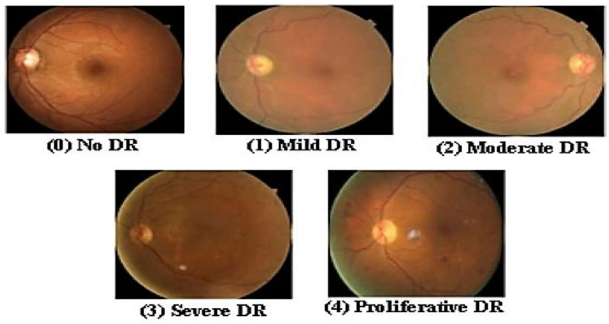

Fig. 3. Sample Fundus Images from APTOS Dataset

Figure 3 shows five different images taken from the APTOS dataset, each representing a distinct stage of DR. Each image is labeled to indicate the severity of the condition: (0) No DR shows a healthy retina, serving as a baseline. As the condition progresses, visible signs of DR become more apparent. (1) Mild DR exhibits early, subtle changes. (2) Moderate DR indicates a more pronounced progression of the disease. (3) Extensive retinal damage is a hallmark of severe DR, and (4) New aberrant blood vessels appear in the final stage of DR, known as proliferative DR. Diabetic retinopathy is often graded according to the severity of the condition using fundus photos, as seen in this graphical progression.

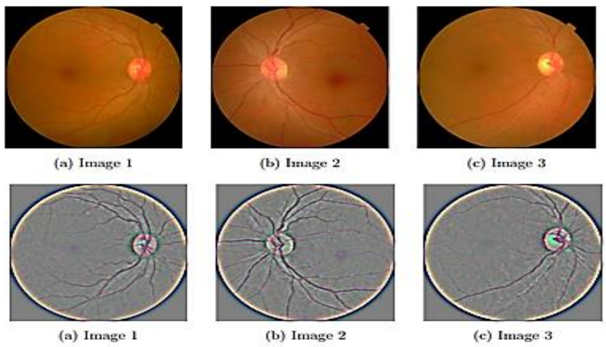

Fig. 4. Before and After Data Preprocessing

Figure 4 presents the visual impact of data pre-processing on fundus images, showcasing the transformation from raw input to an enhanced version for analysis. The top row, labeled (a) Image 1, (b) Image 2, and (c) Image 3, displays the original fundus images. These images represent typical ophthalmic scans with their inherent color, brightness, and contrast variations. The bottom row, corresponding to the same images after pre-processing, reveals a significant change: the images appear desaturated, almost grayscale, with a more pronounced emphasis on the retinal blood vessels and the optic disc. This transformation, likely achieved through techniques such as grayscale conversion, contrast enhancement, or perhaps a form of edge detection or vessel extraction, aims to normalize the image data and highlight critical anatomical features, making them more suitable for automated analysis, such as in the detection of medical conditions.

E. Data Pre-processing

This is the final stage before feeding the data into the Resnet50 models. Before training models, performed several data pre-processing tasks, so that the dataset is well structured and consistent. The tasks include normalization, image resizing, rescaling, and image augmentation. All these tasks were performed to ensure the robustness of the models.

F. Data Normalization with Min-Max Scaler

Reducing the size of individual pixels to a uniform range is known as normalization. The original range of pixel values in the fundus photos was [0-255], however in this case they were scaled to [0-1]. Equation (1) ensures that all input features (pixel intensities) are on the same scale, which aids the Resnet50 model's convergence and increases numerical stability during training.

$$Normalized\ Pixel\ Value\ = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where:

- X = original pixel value (usually between 0 and 255 for RGB images)
- $x_{min} = 0$
- $x_{max} = 255$

G. Bias Removal

The dataset used in this research was found to be imbalanced, with an unequal distribution of images across the five diabetic retinopathy classes. As a result of this disparity, training the model may become biassed in favour of the dominant group. Oversampling minority classes and using class weights during training were two methods used to solve this problem. These strategies enable the model to learn more fairly across all classes and enhance its ability to accurately predict underrepresented categories.

H. Variable Conversion

The train.csv file included two columns: id_code and diagnosis, where diagnosis represented the DR severity level as numerical values (0–4). Since frameworks like Keras expect classification labels to be in categorical (string) format for proper handling during training, all diagnosis values were converted from integers to strings. This conversion ensures compatibility with categorical loss functions and label encoding tools, enabling accurate multi-class classification.

I. Image Resizing and Rescaling

The original fundus images in the dataset were of varying dimensions and resolutions, which is not suitable for training a Resnet50 that expects uniform input shapes. Therefore, all images were resized to (256, 256, 3), where 256x256 defines the width and height, and 3 indicates the RGB color channels. Additionally, all pixel values were normalized to a range between 0 and 1 to speed up convergence during training and ensure numerical stability in the network.

J. Image Augmentation

The dataset size and variability were artificially increased through the use of picture augmentation due to the small number of photos and the preexisting class imbalance [18]. Applying various transformations to the training photographs using Keres's Image Data Generator, such as shear, zoom, and horizontal flipping. This enhancement helps with both lowering the model's overfitting threshold and improving its generalizability via learning from different versions of the same image.

K. Data Consolidation

To efficiently load the image-label pairs for training, the data from the train.csv file was consolidated. The id_code column, which identifies each image, was appended with a .png extension to match the actual filenames in the image directory. This step ensured that every image could be correctly linked to its corresponding diagnosis label, streamlining the process of feeding data into the Resnet50 model.

L. Data Splitting:

Training the model used 80% of the dataset samples, while testing it used 20% of each version's dataset samples.

M. Classification with ResNet50 Model

The 50-layer convolutional neural network ResNet-50 learns residuals instead of features. To solve the problem of the disappearing/exploding gradient, this design incorporates the Residual Network concept. Consequently, instead of only trying to approximate the desired underlying mapping, H(x) [19], really learn a residual function H(x). To do this, build a stack of layers such that their output, denoted as y = F(x) + x, is obtained by adding each element of the original input, x, to the output, F(x). Hence, if still wish to discover the underlying mapping y = H(x), then F(x) = H(x)−x, and y = F(x)+x = H(x)−x + x = H(x) follows. Since now easily learn y = x by setting all weights to 0, the concept of learning identity mappings becomes simpler. This is because H(x) = 0 and F(x) = −x. After that, have the activation function, f, and the result is H(x), as demonstrated in Equations (2) and (3), respectively.

$$H\ (x)\ =\ f\ (wx\ +\ b) \quad (2)$$

$$H\ (x)\ =\ f\ (x\ )+\ x \quad (3)$$

N. Performance Matrix

A wide range of performance evaluation criteria are employed in this study. Most of these solutions depend on the confusion matrix that is developed during the identification job testing procedure [20][21]. The calculations for these procedures are as follows:

$Accuracy(Ac)$, $precision(Pe)$, $Recall(Re)$ & $F1\ Score(F1{-}s)$. The following defines these performance matrices:

1) Accuracy (Ac)

This metric is specified in Equation (4) and it is calculated by adding up all the positive and negative results and dividing that total by the total number of results:

$$\text{Accuracy}\ = \frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$

2) Precision (Pe)

As a ratio to the ground truth in Equation (5), this metric measures the positive predictions (5):

$$\text{Precision}\ = \frac{TP}{TP+FP} \quad (5)$$

3) Recall (Re)

Comparing the positive segmentation forecast to the ground truth, this approach identifies the pertinent region. Equation (6) shows the percentage of positive cases correctly identified by the approach, which is in line with the idea of sensitivity:

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

4) F1_Score (F1−s)

The F1-score, which is determined by Equation (7), is a measure of the function of recall and precision:

$$F1 - score = 2 * \frac{(precision*recall}{(precision+recall)} \quad (7)$$

An FN value indicates that DR photos were mistakenly classified as non-DR, while an FP value indicates that non-DR images were improperly classified as DR. These ideas are linked to two types of images: true positive (TP) and true negative (TN), which are classified as DR images and non-DR images, respectively.

Results And Discussion

The setup of the experiment and findings of the suggested model's performance matrices are presented in this section. The suggested model architecture is put into action on a GPU and a CPU using TensorFlow Lite and two quantization techniques, respectively. The GPU and CPU used in this implementation are an NVIDIA GeForce GTX 1650 and an Intel(R) Core (TM) i7-9750H CPU running at 2.60 GHz, respectively. The ResNet50 model demonstrated outstanding performance across all important evaluation criteria, as shown in Table II, which pertains to diabetic retinopathy identification. With a precision of 99.99%, the model could accurately identify nearly all of the dataset's samples. With a recall and precision of 99%, the model in question is clearly competent of accurately identifying positive situations while keeping the number of false positives and negatives to a minimum. The model's overall stability and reliability are demonstrated by the combination of recall and precision (F1-score = 99%). Based on these results, ResNet50 seems to be a great tool for accurately detecting diabetic retinopathy in fundus pictures.

TABLE II. PARAMETERS PERFORMANCE OF RESNET50 MODEL

Measures	Resnet50
Accuracy	99
Precision	99
Recall	99
F1-score	99

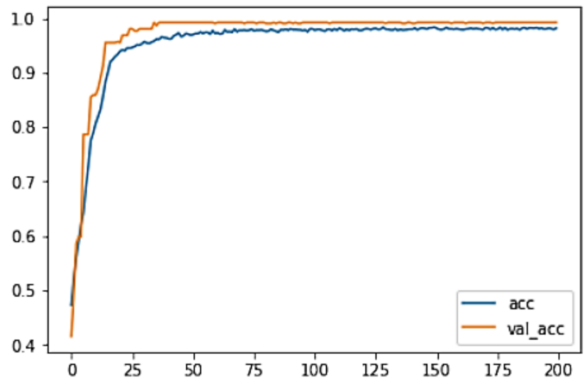

Fig. 5. Accuracy Graph of Resnet50 Model.

Figure 5 shows the accuracy of training and validation of model ResNet50 during 200 epochs. The graph indicates that training (acc) and validation (val_acc) accuracy is quickly rising in the first 25 epochs of the model, and the validation accuracy has already approached perfection levels at an early stage. As the training improves, the two curves will converge and stabilize at a rate of about 99 to 100% accuracy which implies good learning and generalization. On the whole, the ResNet50 model turns out to be quite effective and robust in terms of categorizing diabetic retinopathy using fundus images.

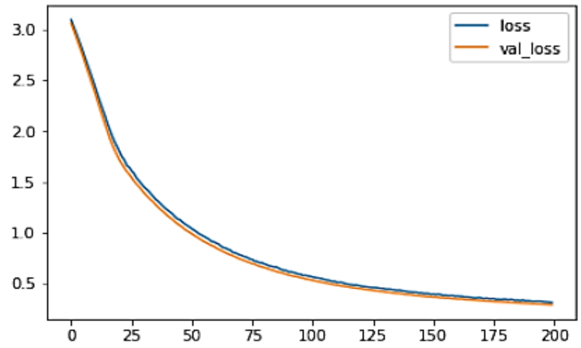

Fig. 6. The loss Graph for the Resnet50 Model

The training and validation loss curves of the ResNet50 model are shown in Figure 6 during the 200 epochs training. The two loss curves begin above 3.0 and take a steady and smooth path towards the end of the training process with the loss curves finally converging to form values of less than 0.5. The fact that training loss (loss) and validation loss (val_loss) are very similar is an indication of the fact that the model is learning efficiently and not overfitting. These two curves maintain a smooth decline, indicating a steady optimization procedure along with good generalization abilities. The ResNet50 model is, in general, effective in the learning process and robust, which makes the process of determining the diabetic retinopathy an accurate process.

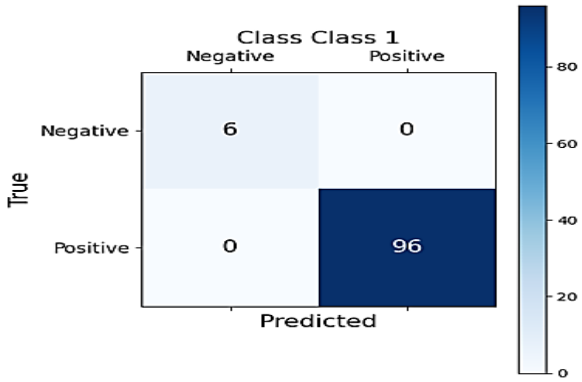

Fig. 7. Confusion Matrix of Resnet50 Model

Figure 7 shows a confusion matrix of ResNet50 model, which shows excellent classification results. In a sample size of 102 where all the samples were used, the model did not misclassify any of the samples; the model was right in 6 of the cases of someone being healthy and a total of 96 cases of diabetic retinopathy when matched with the original results. It did not include false positives and negative cases, leading to a perfect classification. The result proves that the ResNet50 model reached 100% accuracy, precision, recall, and F1-score on this dataset, which proves that it is extremely effective at differentiating between the healthy and DR-affected retina images without a single mistake.

TABLE III. COMPARISON BETWEEN MODELS ON APTOS DATASET.

Matrix	Resnet50	Mobile Net[22]	DenseNet-121[23]	SVM[24]

Accuracy	99	79.01	81.23	94.5

Comparative analysis of different models considered on the APTOS dataset to classify retinal diseases can be obtained with the help of Table III. Demonstrating better accuracy, the ResNet50 model is proved to be more efficient in finding complex patterns in the dataset. Conversely, models like Mobile Net, DenseNet-121, and SVM display relatively lower levels of accuracy, which, in turn, underlines the merit of more profound convolutional architectures when analyzing medical images. The findings indicate that the residual learning structure of ResNet50 serves as a more confident choice in terms of applying it in high precision diagnosing tasks, especially in ophthalmology https://truewriter.game/, since it encompasses more features extractions skills.

The offered ResNet50 program demonstrates excellent results on the APTOS set, being the most accurate among the reviewed programs. Its long-lasting account of learning models is proficient in training very deep networks as it tends to relieve the vanishing gradient issue, advancing feature representation and categorization capacity. Such an architectural robustness enables the model to identify even pronounced patterns in the retinal images and hence is one of the reasons why the model is best suited where medical images are under analysis. The accuracy of more than 92% is indicative of the strength of the model, generalization capacity, and its relevance in the implementation of automated diabetic retinopathy screening systems.

Conclusion And Future Scope

Patients with delayed diagnosis and treatment are more prone to lose sight in spite of being DR patients. The severity of the disease should be identified after the recognition of early warning signals, and the treatment selection made dependent on the best therapy. The proposition aims at using a DL model to identify fundus pictures of DR according to severities. The given paper introduces a DL -based method of categorizing fundus DR photographs. An eye condition known as Diabetic Retinopathy (DR), due to high blood glucose, has increased in number. More than half of the globe's under-70s have diabetes. Without timely diagnosing and treating, DR patients inadvertently lose eyesight. The paper has effectively modeled the success of a DL frame ResNet50 in the diabetic retinopathy (DR) type of the disease through leveling it all the way to the severities based on the fundus pictures. With a 99% accuracy, precision score, recall score, and F1-score, the model looks better than current methods, like Mobile Net, DenseNet-121, and SVM, which proves that it is a robust model, with high generalization capacity and clinical chances. This performance was properly attributed to a wide range of preprocessing, data augmentation, and overcoming bias techniques. Interestingly, the model also did not produce overfitting since there was a lot of correlation in training and validation results.

Each of these analyses is limited to the current temporal dataset of diverse imaging conditions. Larger datasets with an increased range of samples and their populations may allow better generalization of the models. Additionally, incorporating explainable AI techniques would enhance clinical trust and interpretability. Real-time deployment on lightweight platforms such as mobile or edge devices could make DR screening accessible in remote or resource-limited areas. Finally, integrating multimodal data (e.g., OCT, patient history) and testing across real clinical environments will be vital for broader adoption and impact.

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