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Revolutionizing Diabetic Retinopathy Detection: A Deep Learning Approach with CNN and ResNet50

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ABSTRACT
Diabetic Retinopathy (DR), a leading cause of blindness and visual impairment, is one of the major consequences and significant causes of Diabetes Mellitus (DM), a metabolic disease characterized by elevated blood sugar. In order to guarantee appropriate intervention, early identification of DR is crucial, and screening is an essential part of this procedure. This study introduces a sophisticated deep learning system that uses Convolutional Neural Networks (CNN) and transfer learning techniques to classify DR using the ResNet50 model. To help ophthalmologists, we suggested a framework that divides patients into five stages: no DR, mild DR, moderate DR, severe DR, and proliferative DR. We attained 96.93% precision during training and 93.59% test precision by training our model on a very diverse set of retinal picture dataset. In addition, the findings significantly aid in the diagnosis of DR by providing an automated method that results in scalable and accurate identification with the possibility for better early onset and prevention of diabetics' irreversible visual impairment.

Keywords: Diabetic Retinopathy, Diabetes Mellitus, Automated Diagnosis, Deep Learning, Metabolic Disease, Convolutional Neural Network, ResNet50

INTRODUCTION

Diabetes Mellitus (DM) is a lifelong metabolic disorder with multisystemic involvement, including the eye that can culminate in Diabetic Retinopathy (DR)[1], which remains one of the major causes for blindness globally. DR is the primary cause of reduced vision at all age levels in nearly half of Western countries, and DR prevalence will continue to grow worldwide as diabetes rates rise. The major cause of blindness caused by diabetes is DR followed by macular edema[2] and diabetics have a nearly increase in risk than non-diabetics. Drusen typically causes no symptoms until late in its development, when it offers few treatment options and significant vision loss has already occurred.Cotton wool patches, hemorrhages, microaneurysms, and hard exudates are among the distinctive lesions that occur from damage to the retinal blood vessels, fluid, and blood leaks[3]. Since DR therapy is most successful when started early, early diagnosis is essential. Since direct screening is costly and time-consuming, automated methods are being promoted more and more. Organizations like the ADA [5] and the AAORP[6] have recognized the need and developed guidelines that emphasize routine screening and follow-up for people with diabetes [4]. The high-risk group still has difficulty accessing the

current screening procedures, which are costly and time-consuming. Despite their promise, automated detection methods frequently fall short in correctly identifying the several stages of DR. Currently, due to the tremendous development in dentistry [7], treatment techniques and methods, and the use of technology and artificial intelligence in treatment, which has led to the diversity of dental materials [8]. This requires care to meet the needs of the patient and consider the sensitivity of patients to these dental materials in the Kingdom of Saudi Arabia and all over the world. This study uses CNN and transfer learning with the ResNet50 model to propose a deep learning-based automated detection solution for DR. The framework, which has good accuracy rates of 96.93% during training and 93.59% on test data, divides DR into five different stages: no DR, mild, moderate, severe, and proliferative. By providing an effective and economical screening tool that can give early therapies before diabetes patients experience significant vision impairment, this study offers ophthalmologists easily accessible alternatives. MAs are the initial sign of DR and manifest as tiny red dots in the retina that have a diameter of less than 125 μm and distinct boundaries. The six distinct forms of MAs that have been found using AOSLO reflectance and conventional fluorescein are categorized in Figure 1 [9][10][11][12]. Greater than 125 μm in size, larger hemorrhages manifest as uneven, patchy retinal lesions. There are two types of them: flames, which are surface hemorrhages, and blots, which are deeper hemorrhages in Figure 2. Apart from bleeding, plasma leakage produces hard exudates, which are bright yellow lesions; soft exudates, often known as "cotton wool" lesions, are spherical, white lesions linked to the growth of nerve fibers. Based on these retinal alterations, the Diabetic Retinopathy Early Treatment Research Group (DRETR) and International Diabetic Retinopathy Clinical Study (IDRC) have classified DR severity levels in **Table 1**.

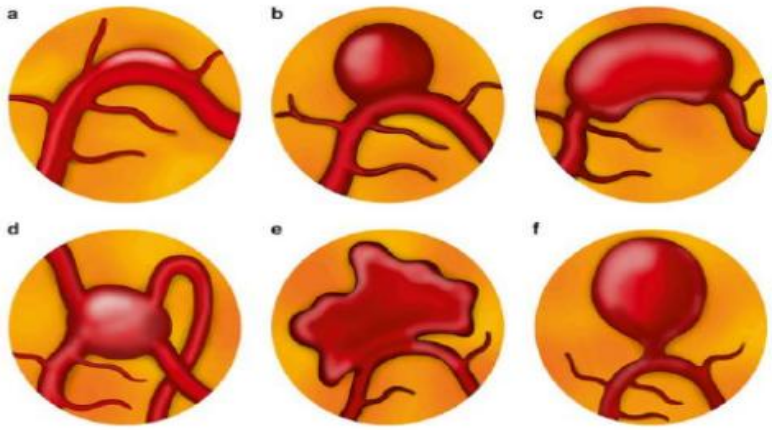

Figure 1. Focal bulge (a) Saccular (b) Fusiform (c) Mixed Saccular/Fusiform (d) Irregular (e) and Pedunculated (f) types of MA [13]

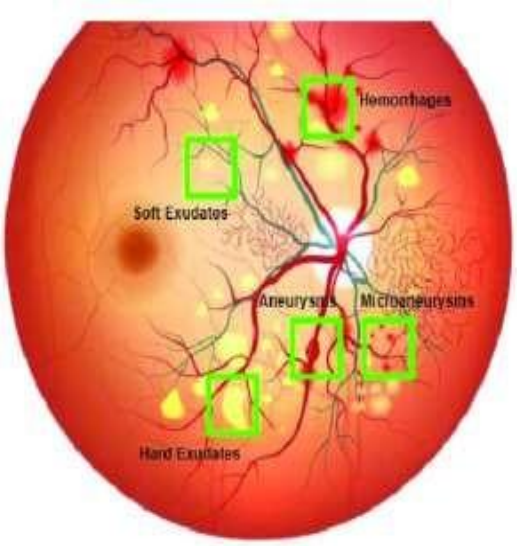

Figure 2: Blot (deeper HM) and flame

Table 1: Diabetic Retinopathy Early Treatment (shallow HM)Research Group (DRETR)

Stage	Dilated Ophthalmoscopy Observable Signs	Severity
I	No Signs	No DR
II	Micro-aneurysms	Mild DR
III	Micro-aneurysms, retinal dot and blot hemorrhages, hard exudates or cotton wool spots **without** signs of severe non-proliferative diabetic retinopathy	Moderate DR
IV	More than 20 intra-retinal hemorrhages in each of 4 quadrants, definite venous beading in 2 or more quadrants, prominent intra-retinal microvascular abnormality (IRMA) in 1 or more quadrants **without** signs of proliferative retinopathy	Severe DR
V	Neovascularization or Vitreous/pre-retinal hemorrhage	Proliferative DR

RELATED WORK

In the interdisciplinary domains of ophthalmology, endocrinology, and machine learning, the recognition of diabetic retinopathy (DR) from medical data is achieved. This section examines contemporary developments in DR detection and the literature, including everything from early conventional approaches to the use of machine learning algorithms on medical imaging data in the present day. Numerous methods have been used in the literature to construct intelligent systems for the detection and categorization of diabetic retinopathy [18]. Multiple works addressing the central theme of this investigation have been analyzed and evaluated. Suvajit et al. [13] focused on extracting statistical information from raw RGB images and converting them to grayscale for edge detection and image filtering. The methodology includes the utilization of Convolutional Neural Network (CNN) [15] on preprocessed images, as well as the implementation of Deep Neural Network (DNN) and Feed Forward Neural Network (FNN) models for image categorization. The study aims to develop an automated diagnostic model for diabetic retinopathy using a dataset comprised of fundus images of the human retina. According to Mustapha et al. [14], DR classifications that include proliferative, mild, moderate, severe, and normal eyes are made possible, allowing ophthalmologists to make a preliminary diagnosis. Results for the categorization of DR via color retinal backdrop pictures with the VGG-16 and ResNet50 algorithms claimed classification accuracy of 25% and 70%, respectively. A dataset of retinal pictures of DR annotated with relevant treatment courses was established by Gao et al. [16]. They used this dataset in their study to create models of deep convolutional neural networks to evaluate the degree of DR in retinal photos. They remarkably classified these photos into four severity levels with an accuracy of 88.72%. An intelligent strategy developed by the authors of [17] divided up potential geographical regions in order to identify and categorize DR using the Fuzzy C Means (FCM) clustering technique. On a dataset of 140 retinal images, the proposed system produced results that varied in accuracy between 82.53% and 97.05%, sensitivity between 74.28% and 97.14%, and specificity between 78.57% and 100%.

METHODOLOGY

Input Data and Data processing

A low-power microscope and a camera are combined to create the optical system known as a fundus camera, which records retinal fundus pictures. It may be used in combination to both image and lighten the retina. The primary regions of the eye that were meant to be photographed were the macula, posterior pole, optic disc, and retina. The APTOS 2019 Blindness Detection data collection, available through the Kaggle platform, has been utilized by us. It is 10GB in size. In the dataset, 5,593 color fundus images captured through fundus photography are included. Tests and training of our model were conducted using this photo collection the foundation. An expertly trained physician assigned an integral value, ranging from 0 to 4, to each image in the collection, depending on the severity of the sickness, as you can see in Table 2& Figure 3. of them, 1,931 photos were used for testing, whereas 3,662 images were used for training.

Table 2: Description of the data used

Class	Name	No. of images	Size in Percentage
Class-0	Normal	1805	49.3%
Class-1	Mild NPDR	999	5.3%
Class-2	Moderate NPDR	370	8.1%
Class-3	Severe NPDR	295	10.1%
Class-4	PDR	193	27.3%

- ✓ 0 - Normal: Diabetic retinopathy is not present in the patient.
- ✓ Moderate Non-Proliferative DR (Mild_NPDR): Within the retina's small blood veins are tiny patches of inflammations shaped like balloons.
- ✓ At stage two, known as moderate non-proliferative DR (moderate_NPDR), the blood arteries supporting the retina are obstructed.
- ✓ Severe Non-Proliferative DR (severe): At this point, numerous retinal areas are without blood flow due to an increased number of occluded blood vessels. In addition, the number of retinal hemorrhages has sharply increased.
- ✓ Proliferative Diffuse Retinal Degeneration (PDR): Abnormal blood vessels developed on the surface of the retina. The newly formed blood vessels exhibit fragility and susceptibility to bleeding, perhaps leading to haemorrhages that may compromise vision.

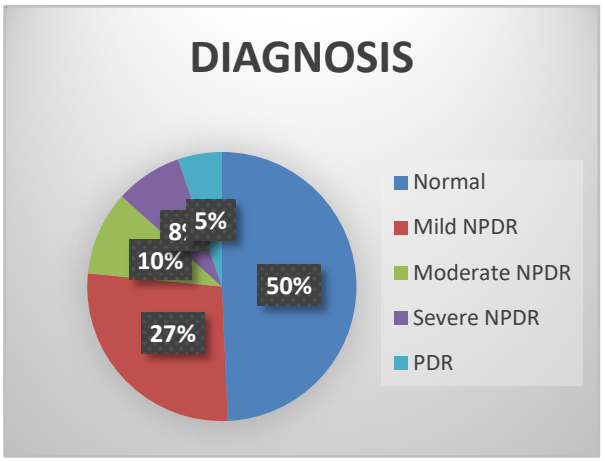

Figure 3. Distribution of classes in the training dataset

CNN Architecture Performance & Results

The Convolutional Neural Network is frequently employed in utilized for retinal imaging because of its breakdown of visual imagery. Generally speaking, a CNN is a convolutional neural network. an amazing multilayered neural network designed to recognize difficult elements in the data. When compared to other classification techniques, a Convolutional Neural Network (CNN) necessitates far less pre-processing. The four fundamental layers of CNN architecture consist of convolutional, pooling, dropout, and fully- connected layers.

The sequential CNN model has been constructed by us. The first layer is the Conv2d layer, whose parameters are 64 filters and a kernel of size (3,3), a 2-tuple that defines the 2D convolution window's width and height. To maintain spatial dimensions, the input shape parameter is supplied together with the train's shape, and the padding value is set to be the same as the activation parameter, which is set to Relu.

The pooling layer known as max pooling is thought to enhance the receptive field on the filters and downsample the resultant feature maps [2,2].

These two layers are again relayed in the same way.

- Currently, a conv2d layer with 128 filter parameters and a (3,3) kernel with padding and activation should be the same as Lu and the same, respectively.
- Next, a pooling layer is added, and max pooling is carried out there.
- These two layers are re-layered twice using the same technique.

Along with the validation and training precision, the image illustrates the VGG-16 model's training and validation loss. This was acquired using the VGG-16 model and the APTOS 2019 blindness detection dataset. We have a 67% precision rate with the VGG-16. The picture illustrates additional performance evaluation indicators for each stage of diabetic retinopathy, including recall, precision, and f1-scoreas shown in **Figure 4**collected input data based on Sample images of diabetic's retinopathy

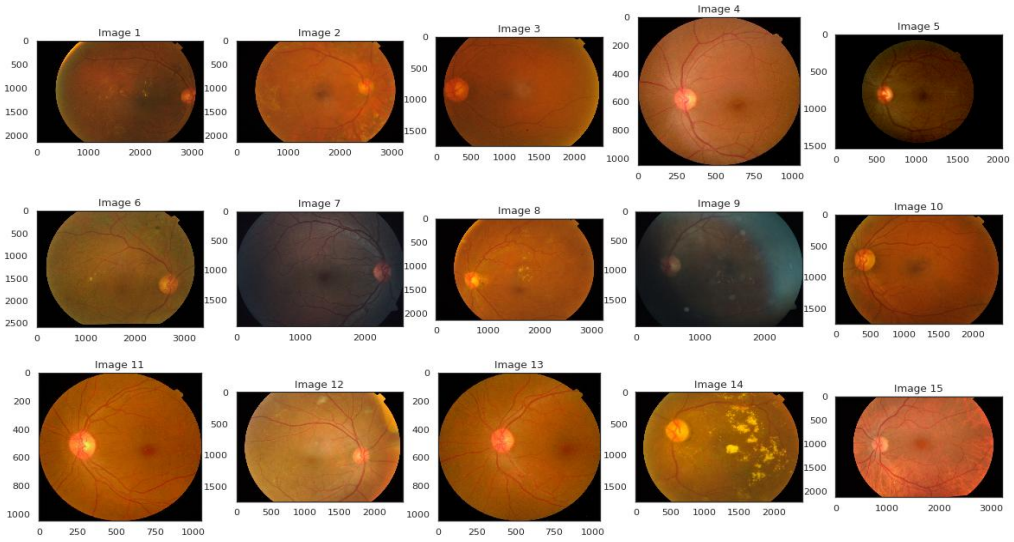

Figure 4: Sample images of diabetics retinopathy

Using CNN and ResNet50, a deep learning-based model was created for the identification of diabetic retinopathy (DR). It was trained and evaluated using 5,593 retinal fundus pictures from the APTOS 2019 Blindness identification dataset. Compared to the conventional CNN and VGG-16 models, which only obtained 67% accuracy under comparable conditions, the ResNet50 model demonstrated a significant increase with training accuracy of 96.93% and test accuracy of 93.59%. Each model's accuracy and loss metrics for training and validation are displayed in Figures 5, 6, and 16. Significantly, the deeper architecture and transfer learning of the ResNet50 model are responsible for its higher performance, which enables detailed feature extraction even in intricate, high-dimensional medical pictures. These findings show that ResNet50 is a viable technique for clinical usage when accurate DR stage identification is crucial since it can successfully categorize DR throughout its several phases, from no DR to proliferative DR.

Table 3: CNN Model Evaluation

	precision	recall	f1-score	support
Normal	0.94	0.99	0.96	74
Mild_NPDR	0.88	0.88	0.88	74
Moderate_NPDR	0.86	0.86	0.86	74
Severe_NPDR	0.88	0.92	0.90	39
PDR	0.91	0.81	0.86	59

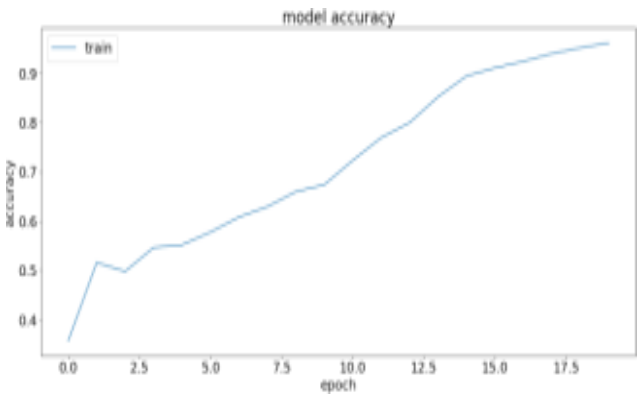

Figure-5: Graph on CNN Model Accuracy

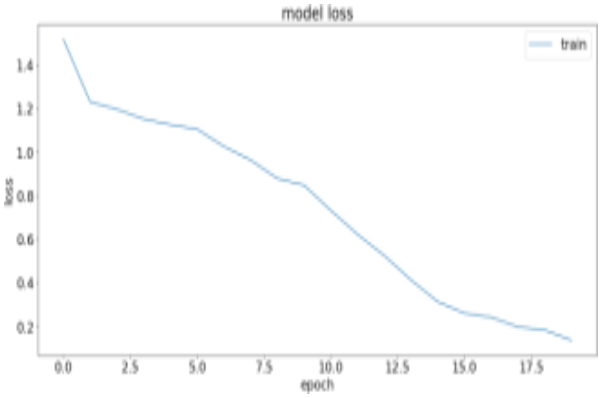

Figure-6: Graph on CNN Model Loss

VGG-16 Architecture Performance & Results

The well-known convolutional neural network known as VGG-Net is adapted into the VGG-16 version. The layers that makeup VGG-16 are three fully linked layers and thirteen convolutional layers. A colour image with dimensions of 224 x 224 pixels is fed into the system, and it is classified into one of 1000 classes. The probability of belonging to each class is consequently included in a vector of size 1000 that is returned by it.Colour filters with a 3x3 px size and a 1-pixel step are used in each convolutional layer. In order to maintain consistent output dimensions for the input volumes, a zero-padding value of 1 is applied. Depending on whatever "block" the layer is placed in, there are different numbers of filters. Furthermore, each filter's convolution product includes a bias parameter. ReLU activation is the purpose of each convolutional layer. Stated differently, after a convolution layer is invariably a ReLU rectification layer. To ensure that the cells do not overlap, the pooling procedure is carried out using cells that are 2 x 2 px in size and a step of 2 px. Rectified Linear Unit (ReLU) layer is positioned after the initial two completely connected layers, where each layer calculates a vector of dimensions 4096. The Softmax function is ultimately employed to yield a probability vector with a size of 1000, corresponding to the entire number of classes. Furthermore, each member of the output vector is subject to a bias parameter across all three layers. In our instance, we added Softmax as an activation function while maintaining the same architecture.
VGG-16 has a 67% accuracy rate. The picture displays more performance assessment indicators, including f1-score, recall, and accuracy shown in Table 4

Table 4: VGG-16 Model Evaluation

	precision	recall	f1-score
Normal	0.93	0.92	0.93
Mild_NPDR	0.59	0.88	0.71
Moderate_NPDR	0.60	0.59	0.60
Severe_NPDR	0.64	0.54	0.58
PDR	0.74	0.39	0.51

The well-known convolutional neural network known as VGG-Net is adapted into the VGG-16 version. The layers that makeup VGG-16 are three fully linked layers and thirteen convolutional layers. A color image with dimensions of 224 x 224 pixels is fed into the system, and it is classified into one of 1000 classes.

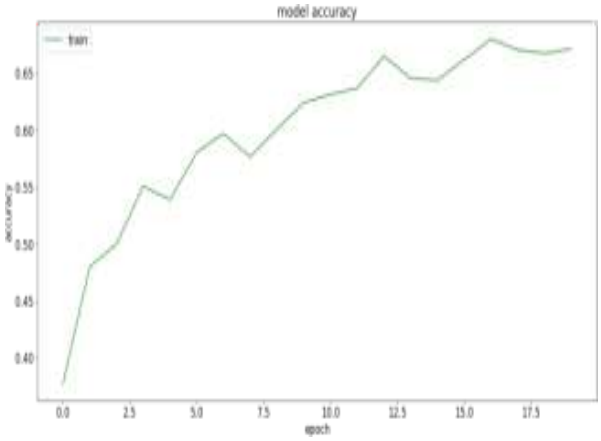

Figure-7: Graph on VGG-16 Model Accuracy

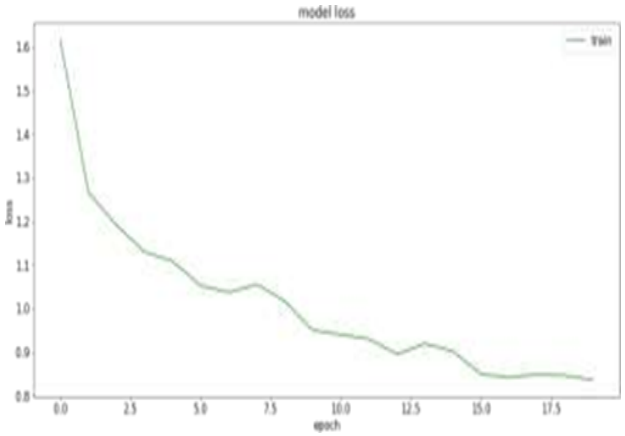

Figure-8: Graph on VGG-16 Model Loss

The probability of belonging to each class is consequently included in a vector of size 1000 that is returned by it. In Figure 7 & 8shown the performance for above dataset using VGG-16.

ResNet-50 Architecture

The Microsoft-developed ResNet50, often known as the Residual Network, was victorious in the yearly ILSVRC (ImageNet Large Scale Visual Recognition Competition) in 2015. Annually, numerous teams engage

in the ILSVRC competition with the aim of inventing the most superior algorithm for computer vision predicaments. The ResNet50 model consists of almost 25.6 million parameters and has a depth of 50 layers. The set consists of a convolution, an identity block where the input is equal to the output, and a fully connected layer. The variable x represents the input value of the first block or signal. Therefore, the block's input value is added to the output values of its internal layers to determine the remaining block's output value.

Table 5: Performance of ResNet-50 Model for 10 Epochs

Epoch	Accuracy	Validation Accuracy	Loss	Validation Loss
1	0.9801	0.9828	0.2072	0.1011
2	0.9835	0.9828	0.0701	0.0570
3	0.9835	0.9828	0.0737	0.0601
4	0.9834	0.9828	0.0645	0.0610
5	0.9835	0.9829	0.0565	0.0495
6	0.984	0.983	0.0533	0.0529
7	0.984	0.983	0.0530	0.0519
8	0.984	0.983	0.0528	0.0519
9	0.984	0.983	0.0528	0.0519
10	0.984	0.983	0.0528	0.0519

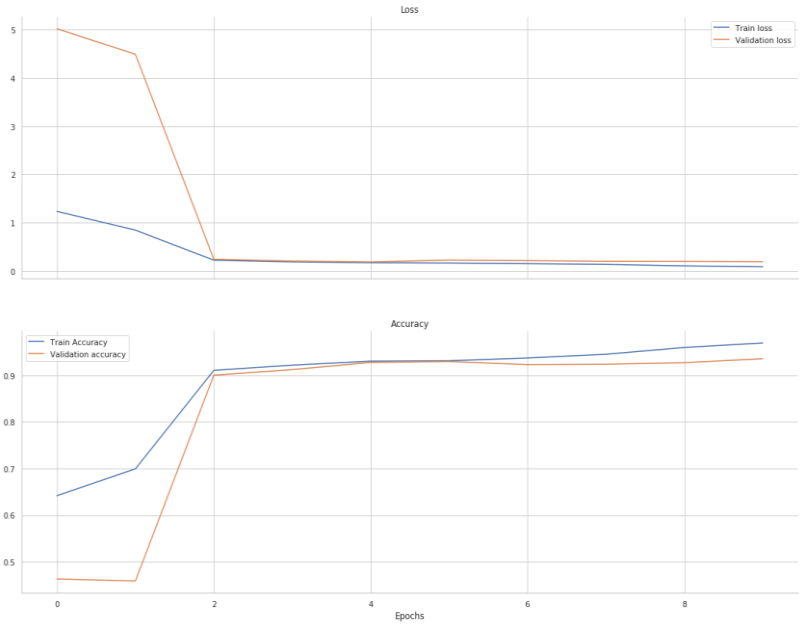

Figure 9: Accuracy and validation loss graphs

With the entire model tweaked, ResNet-50 achieved 93.59% accuracy on test data and 96.93% on training data. The following graph shows the model's accuracy and loss graphs for ResNet-50 model shown in **Table 5 & Figure 9** Performance of ResNet-50 Model for 10 Epochs.

Comparison with Existing Literature

Our findings are in good agreement with those of recent deep learning experiments on DR categorization. For example, Mustapha et al. also used the ResNet50 and VGG-16 architectures, and they achieved 70% accuracy with VGG-16, which is close to our VGG-16 findings, and 93% accuracy with ResNet50, which is equivalent to our 93.59%. Even across various datasets, this consistency shows that ResNet50 is very well-suited for DR detection tasks in medical imaging. Additionally, using a similar dataset, Gao et al. used a deep convolutional network and obtained an accuracy of 88.72%, which is less than our ResNet50 model's performance. This implies that the depth of ResNet50's architecture and transfer learning offer a benefit in detecting minute differences in retinal pictures linked to various DR stages. The efficacy of our method over conventional neural network models was demonstrated by the much lower accuracies obtained by research employing simpler models, such as Suvajit et al.'s study with basic CNNs. Similarly, segmentation-based methods, such as Saha et al.'s Fuzzy C-Means clustering, exhibit limits in classification accuracy, highlighting the benefit of utilizing

ResNet50 for a more reliable classification.

Implications and Significance of Study

According to the results, the suggested ResNet50-based model offers an automated, highly accurate method of DR screening, which may save ophthalmologists' manual labor and aid in early intervention initiatives. The approach has substantial therapeutic benefit by accurately categorizing DR into five separate stages, allowing for more prompt and focused patient therapy and lowering the risk of severe vision impairment. This work emphasizes how deep learning is becoming more and more significant in medical imaging, especially in automated DR screening. Real-time monitoring and explainable AI characteristics might be added to this model in future research to improve its interpretability and reliability in clinical contexts.

CONCLUSION

Automated screening techniques not only save ophthalmologists money and effort, but they also significantly reduce the time required for diagnosis enabling prompt patient care. The CNN, VGG16 and ResNet-50 models were compared in this work We achieved 67% accuracy with the CNN and VGG-16 models and 96% accuracy with the ResNet-50 model using the APTOS dataset. ResNet50 is an efficient architecture for image classification, particularly in systems with huge datasets, since it yielded the best results. Here are some suggestions for enhancements that will increase the detection system's scalability, accuracy, and resilience. Combining Federated Learning, Explainable AI (XAI), Real-time Monitoring, Early Detection, and Multi-modal Data for Data Privacy.

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