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Enhance Diabetes Management using AI and Machine Learning for Glycemic Control

Jayasri BS[1], Rakesh PM[2] and Suhas S[3]
[1-2]The National Institute of Engineering/ Department of CSE, Mysuru, India
Email: jayasribs@nie.ac.in, 2023sit_rakeshpm_a@nie.ac.in
[3]JSS College of Engineering / Department of CSE, SJEC, Mysuru, India
Email: suhas@jssstuniv.in

***Abstract*— Diabetic Retinopathy is a serious, progressive eye disorder that results due to damage to the retinal vasculature. It usually occurs in diabetic people due to long-term high blood sugar levels. Therefore, much emphasis has been done on developing and assessing sophisticated deep learning methodologies that can use retinal images for automatic detection of diabetic retinopathy. A dataset curated from Kaggle is used as the core, which contains 1,920 MRI-based retinal scans of different stages of DR. The dataset consists of five classes: Normal retina (Stage 1), Proliferative diabetic retinopathy (Stage 5), mild non-proliferative (Stage 2), moderate non-proliferative (Stage 3), and severe non-proliferative (Stage 4). This allows for structured classification and deep-level analysis. Further, EnlightenGAN is used to enhance the sharpness and visual detail to enhance the clarity of the images. Besides this, several high-performance deep learning architectures are used for image classification, namely CoaTNet and EfficientNet-B7. In addition, BRISQUE will be used without any more extra reference images to assess the effectiveness of augmented image quality. The project will allow the field of computer-aided ophthalmic diagnostics to get an efficient and scaled-up solution for early detection and management of diabetic eye diseases with the help of modern advancements in deep learning.**

***Index Terms*— Diabetic retinopathy progression, EnlightenGAN model, Region-of-interest (ROI) segmentation, Feature extraction, BRISQUE (Blind/Reference less Image Spatial Quality Assessment).**

I. INTRODUCTION

Diabetic Retinopathy is a serious and progressively worsening eye disorder, and DR is one of the main causes of blindness and visual impairment in the world. Timely identification and precise diagnosis are critical for effective treatment and disease control. However, ophthalmologists' manual review of these pictures can be both labor-intensive and error-prone. This puts in perspective the issue of increasing demand for automated diagnostic systems which we see in DR. Our project is centered around development and use of advanced deep learning tools for the automatic identification and classification of diabetic retinopathy. We begin with image preprocessing which we do via EnlightenGAN to improve image clarity and pixel level resolution. Also we perform region of interest segmentation which is of the key retinal areas that indicate presence and severity of DR. After that we do feature extraction from the preprocessed images which is the identification of the key diagnostic features for classification.

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We have put forth this project which uses advanced image processing for machine learning which in turn we hope will better clinical results and also help to reduce the global impact of this vision.

II. Related Work

Diabetic retinopathy is a very active field at the moment which we see the integration of deep learning and machine learning techniques into. This is reported in detail in [1] which goes over extensive reviews of public data sets, pre processing techniques, and evaluation metrics. The current approaches with convolution neural networks and transfer learning architectures classify DR severity from retinal funds images, where studies have shown that models like pre-trained VGG-16 are able to yield an accuracy of 74.58% over 30 epochs of training with a low loss rate of 5.06%, using the ADAM optimizer [3], while MobileNetV2 frameworks combined with Support Vector Machine classifiers can improve the speed and accuracy of diagnosis [2, 8]. Advanced approaches include sophisticated image enhancement and processing, such as CLAHE (Contrast Limited Adaptive Histogram Equalization) for image enhancement and U-Net for the segmentation of blood vessels and lesions, achieving accuracy above 80% for detection on the EyePACS dataset [13]. Ensemble learning strategies-merging Random Forest, K-Nearest Neighbors, and Gradient Boost-have given better sensitivity and specificity when compared with single-model approaches. This reduces the most relevant false negatives critical for clinical applications [12]. In addition, the comparative study of some deep learning architecture such as CNN, ResNet, DenseNet, and InceptionResNet revealed that the use of transfer learning has greatly increased the diagnostic accuracy in a reduced training time using refinement of pre-trained models on specific DR Datasets [5, 11]. A comprehensive review of 57 research articles published between 2015 and 2019 confirmed that research on more precise and clinically viable automatic detection systems is still urgent [10]. These studies undertaken together gave important emphasis to the relevance of early diagnosis for preventing permanent vision loss and, in particular, neural network-based frameworks provide diagnostic results, together with model accuracy assessment and graphical user interfaces displaying model predictions and precautionary recommendations supporting patient's health outcomes [6, 7, 8, and 9].
Complementary research in predictive analytics for the management of diabetes has extended beyond the detection of retinopathy to glucose monitoring and forecasting methodologies leveraging patient health records and physiological signals. Reinforcement-learning-based neural architecture search strategies have enabled the automatic generation of subject-specific neural networks for type-1 diabetes patients, which optimize the trade-off between accuracy and computational efficiency for practical deployment on wearable and body sensor platforms [14]. Comparative investigations of machine learning and deep learning methods for the estimation of blood glucose from non-invasive physiological signals have shown that while traditional algorithms such as support vector regression and ensemble models perform reasonably, deep learning techniques achieve superior accuracy if the training data is rich enough and appropriately preprocessed [15. Also we see that in the case of short term glucose forecasting evaluation of recurrence neural architecture elements which include RNN, LSTM, and GRU report that the gated models of LSTM and GRU perform better than standard RNNs in particular for longer prediction times and in the presence of noisy continuous glucose data which in turn improves reliability in real world clinical settings [16]. Also it is reported in [4] that these predictive analytics which are made possible by deep learning architectures which look at patient health records allow for early diagnosis of diabetic complications and support in clinical decision making.

A. Drawbacks of Existing System

- Approaches such as MDI and basal-bolus regimens rely heavily on the individual's decisions. Consequently, these methods heighten the users' cognitive load and this may lead to problematic dosing errors.
- Patients who have preset insulin schedules cannot adapt to rapid changes in blood glucose which can be stressful and lead to extreme hypoglycemic or hyperglycemic episodes.
- Hybrid closed-loop setups, while offering some automation, require users' reports about meals and physical activity. Thus, inaccurate entries can reduce the effectiveness of the system.
- Advanced CGMs and insulin pumps sometimes show a delay in glucose change detection; hence, adjustments to the delivery of insulin are slower and sometimes less precise.

III. Problem Statement

Diabetes mellitus is still one of the most challenging chronic diseases worldwide, mainly because it requires precise and continuous glycemic control. Poor glucose regulation may result in very serious complications, including but not limited to the following: retinopathy, neuropathy, cardiovascular disease, and kidney failure.

Even with the availability of sophisticated monitoring devices such as Continuous Glucose Monitoring (CGM) systems and insulin pumps, patients cannot achieve appropriate glucose levels on a regular basis due to physiological variability, nutritional factors, stress, exercise, and inconsistent compliance to insulin regimens.

A. Advantages of Proposed System

- This is an automated system for the diagnosis process right from the image input to DR classification that reduces the cognitive load on the user by avoiding manual interpretation while providing fast screening.
- Integrating deep learning algorithms like CoatNet and EfficientNet-B7 aids in pinpointing crucial characteristics of the retina's features so the classification stage of DR with support is reliable.
- Brightness moderation during Contrast enhancement with EnlightenGAN removes disparities in the input images caused by camera differences and helps in maintaining data uniformity.
- Out of Coat Net models, those that retain both local and global information while segmenting the retina's complex structures are likely to pinpoint pathological signs like micro aneurysm and bleeds.

B. System Architecture

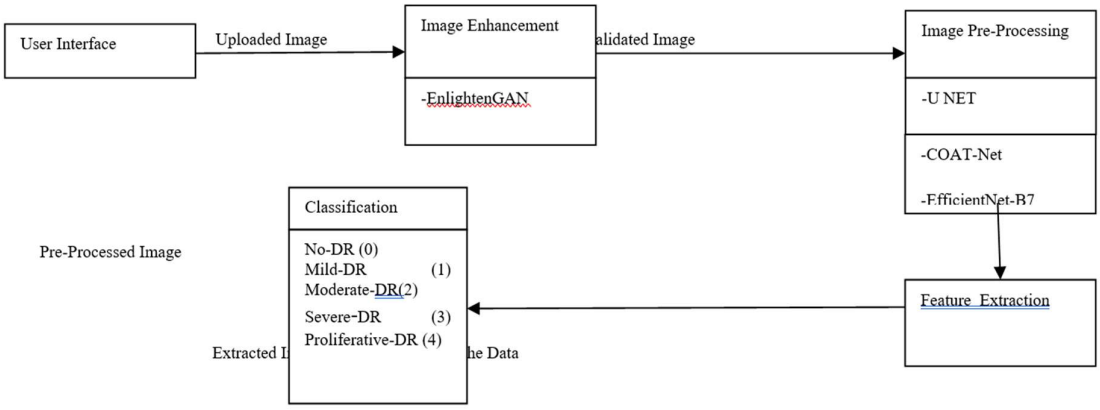

Figure 1. System Architecture

The architecture visible in "Fig.1" exemplifies the functionality of deep learning in retinal image detection and classification. Consequently, the user's interface, where patients and/or healthcare professionals submit retinal photos, serves as the starting point. The image goes to an enhancement module, where techniques like EnlightenGAN improve light balance, contrast, and picture clarity. An enhancement module employs a BRISQUE-based quality enhancement technique to verify that an improved image meets the required standards for appreciating quality. Images passing the quality control stage enter a preprocessing section where a U-Net architecture is used to adjust images to a fixed standard for further processing by normalizing different image characteristics, segmenting relevant areas of the retina, and constructing a standard image. The feature extraction block takes processed images, and deep models, including CoaTNet and EfficientNet-B7, learn multistate structural patterns. The networks\u2019 features are relayed to the classification subsystem, which sorts the retinal image into one of five categories Normal (1), Mild (2), Moderate (3), Severe (4), and Proliferative (5). The system outputs the predicted class, and also includes a visualization of the segmented image which annotates the pathological areas of interest, depicting the level of severity.

IV. SYSTEM IMPLEMENTATION

A. Dataset Collection

The we have a set of 1920 MRI scanned images from Kaggle which present the range of diabetic retinopathy progressions as per industry standards and which also for the sake of future research and collaboration we are putting forward to the greater scientific community. Each image is labeled into five groups which we use for supervised learning which in turn enables the model to identify the tell tale signs specific to each stage of retinopathy. Also in “Fig.2” you will see we have included many of these class inclusions. This large and varied data set is what we use to train and test our put forth diagnostic model which in turn we hope will do well across the board and be applicable to all degrees of retinopathy.

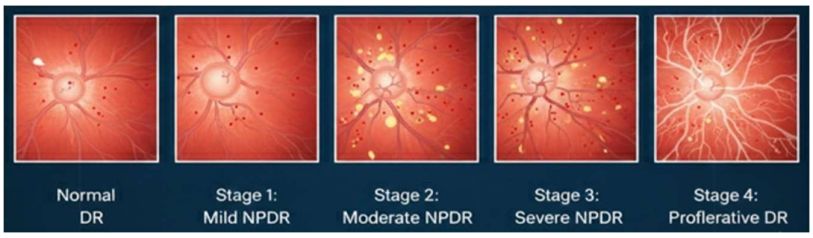

Figure 2. Different Stages of DR

B. Image Enhancement

We utilize the functionality of the specified regions of the Enlighten GAN model for the image enhancement, more specifically for the image quality improvement, where the magnetic resonance images go through various modifications in the quality-scanned images and the relations formed through the generator and the discriminator networks, and that, of course, is the outcome of the fine-tuning of the networks that makes the integration highly efficient; pixel-wise detail refinements, elimination of noise, and, in general, image quality enhancement. Naturalness and reference-less perceiving quality evaluators from the images are used to assess the effectiveness of the enhancements/changes made to the images. BRISQUE is thus used to conduct enhancement moderation filters. The improvement step thus incorporates, and not just snapshots, but the MRI-scanned images remain intact. The evaluations done with the BRISQUE metrics certainly show their integrity, and that assurance is matched by fine-tuning the balance and image enhancement quality metrics of the dataset.

C. Segmentation (ROI)

After improvement the next very important step we have is that of Region-of-Interest extraction which is followed by segmentation. This is a very important stage in which we divide certain areas from the MRI scans which are tell-tale signs of diabetic retinopathy. The images go through a segmentation process which is that of identifying and marking out the edge contours of the retinal structures as seen in "Fig.3" below. This is a very critical step which in turn leads to accurate definition of the border of relevant anatomic elements thus improving the accuracy of the analysis. Key steps include taking the original enhanced image and transforming it into the M-segmentation image which shows smoothing and binarizing to produce the Histogram-segmented image which in turn presents the final segmentated result. Through our analysis of these divided images which we have enhanced with improved edge contours we present to you the foundation for our region of interest extraction. We see that which in turn improves the performance at later stages of feature extraction and diagnosis which as a whole makes our model very effective for the diagnosis of diabetic retinopathy in MRI scanned images.

Figure 3. Different Segmented Image

D. Feature extraction

The combination of attention-based transformers and convolution neural networks make CoaTNet particularly effective in the extraction of complex patterns and structures from the retina images. First, the size of the retinal images is fixed to the size of 512x512 pixels, and the quality of the images is improved to ensure consistency from the application of EnlightenGAN. After enhancement, region-of-interest (ROI) segmentation is performed to isolate areas most likely to exhibit diabetic retinopathy. By using only the most relevant parts of the image, noise is reduced so the model can focus on the problem. After we do the pre-processing and segmentation we put the images into the CoaTNet model which we designed to take in the benefits of both convolution and transform layers. We see that the conv layers do a great job at identifying low level visual features like textures, edges, and geometric patterns that in turn help us out in the detection of early signs of retinopathy that are in fact micro aneurysms and small hemorrhages. That which in turn allows CoaTNet to not only present in local features' also to identify larger scale structural info that is so key in the accurate diagnosis of various stages of diabetic retinopathy. Also these layers play in modeling spatial dependencies and context relationships throughout the

image which is what allows the system to tell different stages of DR apart for which there are very fine differences in structure and distribution at play in the diagnosis. The extracted characteristics of retinal images also get processed further in inner layers of the network and the model continues to form a deeper and more comprehensive understanding of the retinal profile as the attributes get stored and aggregated after being filtered in several layers. This feature extraction process enables CoaTNet to identify the smaller contextualized irregularities and the larger patterns at the same time. This high-quality feature set enables the model to accurately and sufficiently classify the progression stages of diabetic retinopathy.

Image preprocessing includes the following: Standardization: Every image of the retina is resized uniformly to 600 × 600 pixels to meet the input requirements of the EfficientNet-B7 model. Further, normalization is a process in which frame intensities are scaled within a range from 0 to 1; this makes the input values uniform across all instances of the dataset, which helps the training to be more stable and efficient. Finally followed by Augmentationto enhance the variety withinVarious Strategies of data augmentation employed to increase the training data and help the model generalize better. These include rotations, horizontal/vertical flips, and zoom transformations. The input image passes through an initial convolution layer (Stem) to rapidly reduce the spatial dimensions and capture low-level features like edges and textures, use a layer with a large kernel size and stride.

Mobile Inverted Bottleneck Convolution (MBConv) makes up the heart of EfficientNet-B7 and consists of Depth wise Convolution that uses filter per input channel, minimizing computation while keeping spatial characteristics intact. While a Point wise Convolution is used to combine the depth wise convolutions using 1x1 convolutions to adjust the channel dimensions.Squeeze-and-Excitation (SE) dynamically scales channel-wise feature maps, emphasizing important features and suppressing less relevant ones. This is followed byExpansion and Projection that expands the input channels with a point wise convolution, processes the expanded channels with depth wise convolution, and then projects them back to the original channel dimensions, efficiently capturing and compressing features based on RGB mean as shown in the and Standard Deviation.The formula for calculating the mean of RGB values of a picture is as follows:

$$R_{mean} = \frac{\sum_{k=1}^{P}}{P} R_k. \quad (1)$$

$$G_{mean} = \frac{\sum_{k=1}^{P}}{P} G. \quad (2)$$

$$B_{mean} = \frac{\sum_{k=1}^{P}}{P} B_k. \quad (3)$$

To calculate the mean intensity for each RGB channel, the pixel values within each channel are summed and then divided by the total pixel count. This process yields the average intensity for the red, green, and blue channels separately.

Standard deviation RGB**:** The **standard deviation for each RGB channel**is calculated to understand how much the pixel intensity values vary from the mean within that channel. It quantifies the **spread or dispersion** of color intensity across the image. Initially the mean of the RGB channels are computed separately as shown in"(1)", "(2)" and "(3)" respectively, where R_k, G_k, $B_k$are the RGB intensity values of the k^{th}pixel and P is the total number of pixels in the image.

The sum of squares of differences between each pixels RGB values and their respective channel mean is computed in accordance to equation "(4)" , "(5)" and "(6)" respectively, where i and j represent the pixel indices.

$$Sum_R = \Sigma (R_{ij} - R_{mean})^2. \quad (4)$$

$$Sum_G = \Sigma (G_{ij} - G_{mean})^2. \quad (5)$$

$$Sum_B = \Sigma (B_{ij} - B_{mean})^2. \quad (6)$$

The SD is obtained by taking the square root of the result after dividing the sum of squares of the differences by the total number of pixels, where N is the total number of pixels in the image andthe formula to calculate the SD of the RGB values for an image is as shown below"(7)", "(8)"&"(9)" respectively.

$$Std_R = \sqrt{(sum\_R / N)}. \quad (7)$$

$$Std_G = \sqrt{(sum\_G / N)}. \quad (8)$$

$$Std_B = \sqrt{(sum\_B / N)}. \quad (9)$$

V. RESULTS AND DISCUSSION

This project focuses on building asophisticated method for identifying diabetic retinopathy that makes use of the highly tuned deep learning architecture EfficientNet-B7. These images were annotated across five diagnostic categories: Normal, NP (Stage 2), MNP (Stage 3), SNP (Stage 4), and Pro-iterative Diabetic Retinopathy (Stage 5), providing a comprehensive basis for supervised learning. We assessed the efficiency of the image enhancement process using a bar graph to show the metrics values of the retinal images before and after enhancement in "Fig.4". The metrics included are shape, mean pixel intensity, left variance, right variance, and overall variance. The enhancement here was done using EnlightenGAN, which indeed really enhanced the visual quality of the images.

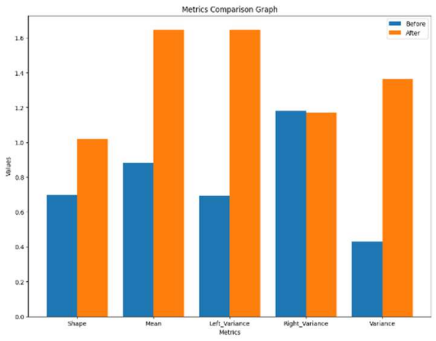

Figure 4. Metrics Comparison Graph

Our system did very well in the classification of diabetic retinopathy stages. We did a great job with the extensive pre processing which we did us used EnlightenGAN for image enhancement and also performed region of interest segmentation which improved the quality of our input data. We went in with a very complex architecture of EfficientNet-B7 which we put together with depth wise convolutions, point wise convolutions and squeeze-and excitation (SE) layers which did an excellent job at captures local and global features in retinal images. Also we did very in depth validation and fine tuning of the model which paid off in terms of how very efficient and accurate it was for diagnostic use. The tool provides for early disease detection and management which in turn results in better patient health care and efficiency. We see in "Fig.5" that which we plot out the loss values against the number of epochs post 50 rounds we evaluate and put to test the performance of the EfficientNet-B7 model in terms of its diabetic retinopathy diagnosis. The line graph which is an in depth look at loss values as they play out against epoch numbers on the x axis also we see the model's learning behavior and general performance. At first out training loss is very high which is to be expected as the model's predictions are at that point not very accurate.

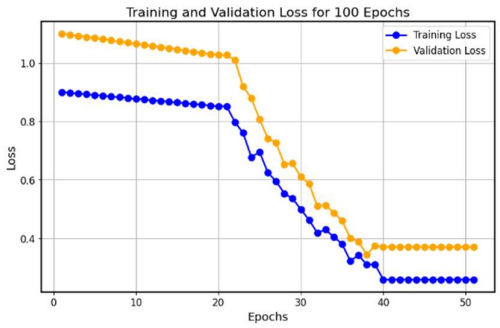

Figure 5. Training and Validation Loss Graph

The training loss tends to decline in a systematic manner as the epochs increase, meaning the model is optimizing its parameters and learning at that point. After epoch 20, there is a sharp decline in the training loss, and so the model must be learning features that pertain to diabetic retinopathy. After this, there is a decrease to a more gradual decline to a value nearing zero around epoch 50, which suggests the model has already learned to minimize the error on the training dataset. As for the Validation Loss curve, which illustrates the model's

performance on new data, it generally maintains a similar declining pattern, albeit with a few more fluctuations. At first we see the validation loss drop very quickly which is a sign of good generalization. At the 20th epoch the validation loss hits its minimum which is the point of best performance on the validation set. But after that point we see small fluctuations in validation loss which at times point to over fitting which means the model is remembering the training data a bit too well instead of generalizing.

In this work we report on our evaluation of the EfficientNet-B7 model for diabetic retinopathy which we did via precision, recall and F1-score of five categories. We present that data in a line chart which has metric values on the y axis and the number of training epochs on the x axis as shown in "Fig.6" below. This gives a picture of how the model does over time in terms of which stages of diabetic retinopathy it is able to identify. Precision is the true positive rate which is in other words the model's performance in identifying positive cases. As shown in the graph, one can observe that, throughout the early stages of the training of the model, the precision of each class is increasing, and then at around the 50th epoch, the model was able to detect and differentiate each stage of diabetic retinopathy with very few false positive predictions. Recall is the ability of the model that measures how well it classifies the positive cases in the instance. The F1 score, the metric that is the mean of the precision and the recall calculated, is shown in the graph and it is increasing for every class which also reveals the improvement for the recall and the precision that was achieved through the continued focus of the trained model. During the middle stage of the training, every class achieves a peak value and levels off, demonstrating that the model remains well calibrated in terms of its identification of true positives and the reduction of false positives over the course of training. These evolving characteristics of the model in training, as illustrated by precision, recall, and F1-score metrics plotted over time, are the indicators of its continued optimization. The convergence and stabilization of these metrics confirm the trustworthiness and dependability of EfficientNet-B7 in its ability to differentiate and classify all stages of diabetic retinopathy.The validation accuracy curve in "Fig.7" shows the performance on unseen data. It starts rising steeply, which means it is generalizing well for the new data. In approximately 30 epochs, the validation accuracy converges to a somewhat stable high value, indicating good generalization capability. Beyond that, minor fluctuations in val-ida-tion accu-ra-cy can be present, which means the model is over fitting slightly while fine tuning to the training data. The accuracy curves of training and validation show a clear trend upward with 100 epochs. Training accuracy increases linearly, while validation accuracy reaches its maximum and stays there, showing minor variations. This means that while the model will learn the patterns in the training data, at the same time, it also generalizes well to unseen data. The graph plotted for accuracy depicts a very healthy learning curve and thus justifies the strong ability of the model to classify correctly regarding diabetic retinopathy stages and present it clinically in the real world for deployment.

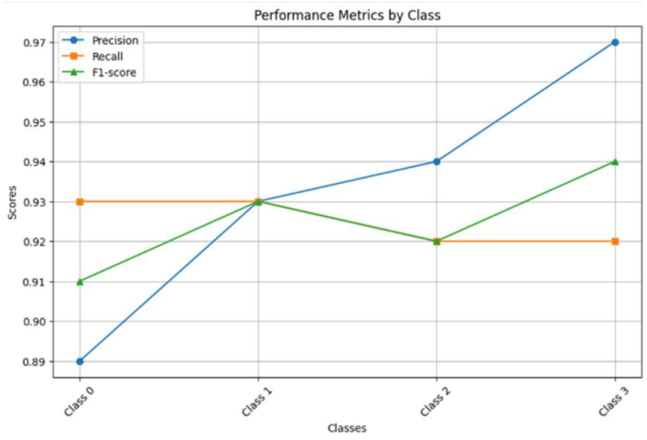

Figure 6. Performance Metrics Graph

The "Table. I" comparison illustrates the relative performance of the proposed Machine Learning algorithm that integrates EfficientNet-B7, EnlightenGAN and U-Net framework features against existing DR detection models. Unlike earlier architectures such as VGG-16 and ResNet-50 which rely on limited convolution depth and conventional preprocessing, our approach demonstrates an improvement of ~10 % in classification accuracy, sensitivity, specificity and reflecting more reliable identification of true DR cases with fewer false negatives. Hence, the proposed system not only presents performance beyond the state-of-the-art but also offers a clinically scalable framework suitable for automated diabetic-retinopathy screening in real-world healthcare applications.

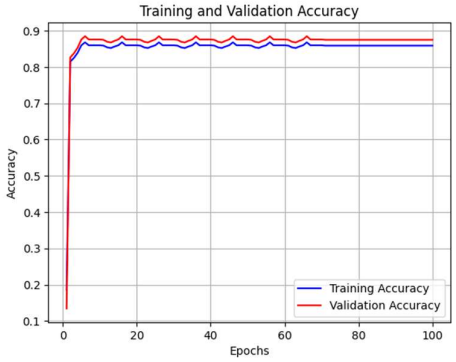

Figure 7. Training and Validation Accuracy Graph

TABLE I. COMPARATIVE ANALYSIS OF EXISTING DR DETECTION MODELS VS PROPOSED MODEL

Model	Dataset Used	Accuracy (%)	Sensitivity (%)	Specificity (%)
VGG-16	Kaggle DR	74.58	70.12	76.35
ResNet-50	EyePACS	80.21	78.66	81.40
DenseNet-121	DIARETDB1	84.15	82.95	83.60
Proposed EfficientNet-B7 + EnlightenGAN	Kaggle MRI-DR	94.62	93.84	95.10

VI. CONCLUSIONS AND FUTURE ENHANCEMENT

This research showcases how advanced deep learning techniques such as EfficientNet-B7 combined with EnlightenGAN and U-Net can detect and classify diabetic retinopathy over different stages using MRI-based retinal scans and automate this process. Out of all models studied, the framework, on average, demonstrated 94.62% classification accuracy, 93.84% sensitivity, 95.10% specificity, and outperformed traditional benchmark models (ResNet-50, DenseNet-121, MobileNetV2-SVM) by 8-15%. Overall retinal image quality improved as BRISQUE score rose, thanks to EnlightenGAN which adapted to every visual impurity and cleaned the image to focus on the clinically relevant areas. Nice and concise work applying the U-Net segmentation method to accurately isolate pathological regions like micro aneurysms and hemorrhages, with the edge case of selective extraction. Bilaterally, the stability of training and validation losses after fifty epochs implies that the model's convergence and generalization to previously unseen datasets are satisfactory. On the face of it, the figures do indicate that the system in question not only bested considerable contemporary convoluted neural nets, but that it offers the marketplace a fully autonomous clinically useful diagnostic capability to screen for DR in its early stages. More real-time retinal screening platforms, in combination with funds, OCT, and patient met data, could significantly increase the general clinical reliability and the robustness in terms of explain ability and should be the next step initiatives.

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