RESEARCH PAPER

Artificial Intelligence-based Early Diabetic Retinopathy Detection - AIDER

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ABSTRACT
After so many significant advancements in diabetes treatment, DR continues to be one of the leading causes of blindness in the world that is preventable. Identifying the disease early and evaluating its progression stage accurately are essential for developing an appropriate course of action. My model combines deep learning algorithms along with image processing techniques to identify DR based on fundus photographs. My neural network classifies images into five stages of DR: No_DR, Mild_DR, Moderate_DR, Severe_DR, Non-Proliferative, and Proliferative_DR. In order to allow the neural network to distinguish even very small lesions, CLAHE is used for improving contrast in images, Gaussian filter for reducing noise, and edge detection to emphasize the regions that are affected by the disease. Moreover, I introduced additional data augmentation through random rotations and flips of the images to diversify my dataset. The features of the images are extracted using ResNet and DenseNet architecture.Given its accuracy of around 93.60% when tested on a publicly available retinal fundus image dataset. The proposed system demonstrates potential for reliable clinical utilization for early detection severity grading of DR to minimize misdiagnosis and enhance patients' quality of life.

Keywords: Diabetic Retinopathy, Deep Learning, Fundus Images, ResNet, DenseNet, CLAHE, Image Classification.
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I. INTRODUCTION

Diabetes Retinopathy (DR) is a severe complication of diabetes that may result in the loss of an individual's eyesight if diagnosed late. It happens as a consequence of the injury to the blood vessels of the retina, which may be caused by chronic hyperglycemia. Existing diagnostic techniques are based on a largely manual analysis of retinal images by trained personnel, therefore being not only subjective but also susceptible to human error. With the rise in diabetes globally, there is an urgent need to enhance the sensitivity and specificity of existing diagnosing methods to improve early detection and timely treatment and to prevent any complications associated with it.

Advancements in deep learning models to detect diabetic retinopathy always require a good amount of training data to achieve high efficiency, a major challenge in medical research is the limited availability of data to privacy concerns. Tariq et al. [1] addressed this issue by using Siamese Neural Network built on pre-trained models like VGG16, ResNet50, and DenseNet121. Their approach relies on similarity-based learning where the model determines whether two retinal images are similar or not. They did the test on the APTOS 2019 dataset and achieved approximately 80% accuracy for five-stage classification.

Recent AI-based approaches utilize machine learning and image processing to detect diabetic retinopathy. These models are trained on large datasets of retinal images. It helps them learn patterns that are linked to diabetic retinopathy and provide faster and consistent outcomes. When these models are combined with feature extraction and preprocessing such as normalization, augmentation, and resizing, image is enhanced and models efficiency improves [2].

The Artificial Intelligence based Early Diabetic Retinopathy (AIDER) system is designed to analyse signs of diabetic retinopathy using image processing and machine learning techniques. It trains deep CNN models on a variety of retinal images and combines with image processing steps to enhance accuracy. This model helps identify DR in the early stage and sorts it into the five standard stages: No_DR, Mild_DR, Moderate_DR, Severe_DR, and Proliferative_DR. This helps doctors in the decision making process and helps avoid major vision problems. I also have added techniques which helps to prevent overfitting, this resulted in consistent predictions no matter which stage it detects.

It is ranked as the biggest cause of blindness for diabetics between ages 20 and 64. Spotting it early will open up real treatment options. It is necessary to timely act, given that 3.4% of the world's population is affected. Concentrating on the adoption of CNN-based learning paradigms together with sophisticated data preprocessing in order to enhance the detection of initial traces of non-proliferative

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diabetic retinopathy (NPDR) prior to its progression into proliferative diabetic retinopathy (PDR), which can cause irreversible vision loss.

We have the opportunity to develop an accurate and fully automated solution to improve care of diabetic patients so that clinicians can make decisions in a timely manner, thus decreasing the possibility of permanent visual impairment.

In general, the Diabetes Retinopathy Symptoms Analysis proposed model by using ML and IP strives to utilize advanced technology to achieve better diagnostic precision as well as patient treatment. Through the application of stage-level taxonomy and the design of optimized CNN architectures, we help further the development of AI-based healthcare solutions for patients with Diabetes.

II. THEORETICAL REFERENCE

II.1 Literature Survey

Many authors in recent years have done work related to deep learning (Table 1). We will review and learn from the solutions proposed by various researchers within the machine learning community in this chapter. Current Use of IDX-DR equipment in Diabetic Retinopathy Detection [3]: Currently, about 90 percent of physicians use this equipment for diagnosing diabetic retinopathy.

Current Use of this device in diabetic retinopathy Detection [3]: In contemporary medical practice, approximately 90% of doctors utilize the IDX-DR equipment for diagnosing it. This device employs image processing techniques to analyse retinal images provided by patients. Although the pre-processing stage often relies on trial and error to identify the most effective methods, a significant limitation of this device is its dependency on human interpretation, which can introduce errors in diagnosis. Even so, the IDX-DR device gives quick results. It produces reports in just seconds. This speed comes mostly from AI, which makes up about 60% of how it works. The other 40% handles image processing..

Isabel Diez and Ahnaf Kazi[4], these authors proposed a DR staging system which is based on DenseNet-121 and Xception models. The results are good, but it requires high computing power which is usually missing in rural health centers. Ayesha Jabbar and Irma Azpiroz[5] followed a similar path using GoogleNet and ResNet-16 along with additional ML classifiers. They got decent accuracy score, but the system didn't hold up well when it was tested with different datasets.

Zekai Wang and Bing Yao [6] addressed challenges related to missing data and class imbalance in large electronic health records. They have used MB-TCN-TC approach yet their method is computationally expensive and requires 10 hours of training even on high GPUs. The IFERP study [7] proposed a customised CNN model for both binary and multi-class classification. By achieving the accuracy of 84.84% on multi-class tasks. The authors emphasize on the testing on more datasets to prove it's efficiency.

The IJCA study [8] integrates deep learning with clustering to identify diabetic retinopathy features like microaneurysms, while showing promising results. However, its performance is limited when applied to new datasets. Thanikachalam et al. [9] enhance dataset images using DWT and segmentation before classification. Providing an effective approach for early detection, though it is computationally expensive and only works on single dataset. ISRAA Y. Abushawish et al. [10] applied DenseNet201 with transfer learning and got 81.76% accuracy. But the model shows limited accuracy when tested against a variety of dataset.

Cam-Hao Hua and Kiyoung Kim [11] proposed an improved approach for detecting DR by combining multi-modal features from both spatial and frequency domains. This technique helped him get better precision and recall. But the consumption of the computing power was their limitation while scaling it up. The Faster R-CNN uses fusion features to accurately localize lesions. Improving the detection performance, but it requires longer period of training time and higher computation resources [12]. Also an XAI-based model has been introduced for transparent detecting diabetic retinopathy. It only focuses on transparency to build trust amongst the doctors, while maintaining the accuracy. [13]

The paper uses a two-stage transfer learning approach. It fine-tunes VGG19, ResNet152, and DPN107 models to achieve high accuracy. It is limited by its dependency on transfer learning and the corresponding computing resources required for fine-tuning.[14] Another study shows a hybrid CNN model is used for automatic detection of diabetic retinopathy. It blends CNN layers with feature fusion to boost prediction quality. However, working with big image collections still requires solid preprocessing steps. [15]

Here we combine deep learning image processing to improve efficiency. By using convolutional neural networks (CNNs), along with preprocessing and data augmentation, the system focuses on identifying non-proliferative DR before it turns into proliferative. This approach helps doctors make solid decisions quickly and prevent the patient from losing their vision for good.

Research gaps from the literature survey we studied:

1. In addition, the majority of existing models only focus on the binary detection, while multi-stage detection in DR is clinically more important.
2. Little attention to the early stages development of DR, thus limiting possibilities for early interventions.
3. Dataset Generalizability: Based on the single datasets like EyePACS which limits the model to understand across diverse populations.

Based on the above research gaps, we have proposed the following objectives:

1. To develop a CNN-based system able to perform strongly multi-stage DR grading (No_DR, Mild_DR, Moderate_DR, Severe_DR, Proliferative_DR).
2. In order to make more use of preprocessing and augmentation, such as morphological operations, to categorize and present the feature in a better format..
3. We have made the model more efficient by combining deep learning with smart image processing. This helps the whole setup so we get high accuracy without needing a massive amount of computing power to run it.

II.1.2 AIDER System Architecture

Our model AIDER combines deep learning and image processing to predict and stage diabetic retinopathy in its early stages. Once the fundus images are collected, we run them through a basic preprocessing steps. We use median filtering to reduce noise and histogram equalization to bring important details. This pipeline is designed to improve the visibility of the retinal vessels. To summarize, this procedure helps remove artifacts from the image before feeding them to the model.

After the preprocessing stage, I segment the blood vessels, optic disc, and lesion area (Figure 1). Thus, the presence of disease symptoms is identified precisely. Then, by performing morphological procedures and edge detection, I emphasize such abnormalities as microaneurysms, small hemorrhages, and exudates. Such characteristics allow verifying the existence of diabetic retinopathy and its level of severity.

The obtained features are directly fed into the neural network for classification. The convolutional layers detect the image patterns, the pooling layer decreases the dimensionality, and fully connected layers generate a final prediction.

Overall, this pipeline classifies fundus images according to five grades of diabetic retinopathy, namely: No_DR, Mild_Non_Proliferative_DR,
Moderate_Non_Proliferative_DR,
Severe_Non_Proliferative_DR, and Proliferative_DR.

The preprocessing pipeline works smoothly with the classifier. Each phase is important for the resulting output, producing an effective pipeline to detect diabetic retinopathy.

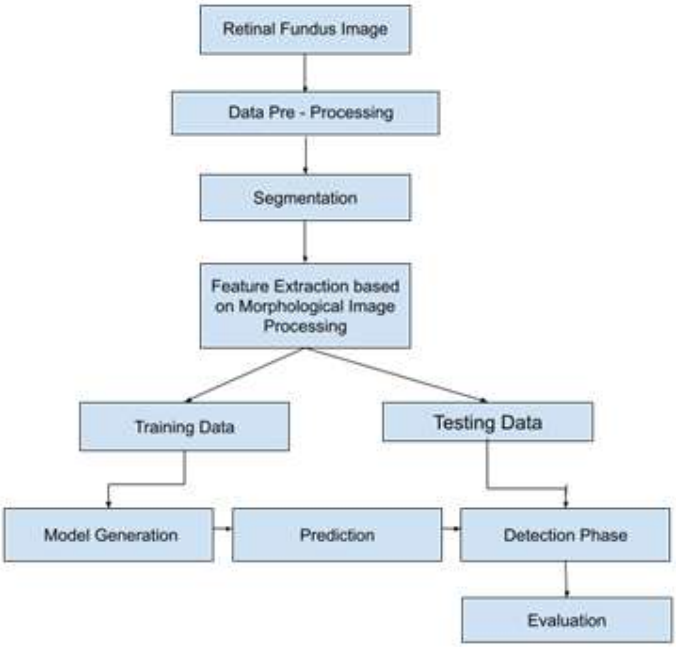

Figure. 1: The AIDER System Architecture

III. MATERIALS AND METHODS

I started by getting the retinal fundus images from the APTOS database. In order to preprocess the images, resizing, normalization, and augmentation were performed for each image. In order to detect the essential DR features responsible for the disease grading, feature extraction using convolutional neural network learning along with morphological operations was utilized.

III. 1. Data Acquisition and Preprocessing

The dataset has over 3,500 annotated retinal fundus images [17]. It includes various patient demographics and imaging environments, which makes the classification algorithm more resilient to challenges when training and testing.

For improving the clarity of the image, I have used normalization, median filtering, and histogram equalization on the images. I have also changed the color space in order to make the important features stand out

more. For preventing overfitting, I have created more varied training data through rotations, flips, and scaling. Each image was labeled into one of the five DR severe stages, which allows the model to perform multi-class classification.

Segmentation: The enhanced images are divided into regions of interests by applying region-based segmentation. Also by morphological operations that enhance the appearance of structures such as blood vessels and the optic disc within the retina. This is an important step that allows for simpler representation, but also for a stronger feature extraction.

Feature Extraction: The pathological features are significant to the diagnosis of DR, microaneurysms, haemorrhages, and exudates are emphasized. Canny edge detection and morphological processing are performed for fine-tuning, but differently from handcrafted features, the CNN learns spatial discriminative representations on its own.

III. 2. Deep Learning-Based Classification

1. Model Selection and Training: A CNN-based model is employed as a core model to analyze retinal images into multiple stages of diabetic retinopathy.
2. Architecture: The network is built with convolution, pooling, and dense layers that help learn image features, recognize abnormalities, and improve classification accuracy.
3. ResNet50: Applies residual pathways to maintain gradient flow, enabling the model to learn complex features in deeper layers.
4. DenseNet121: Uses dense connections where each layer receives inputs from all previous layers, improving feature propagation and reuse.
5. Feature Learning: The extracted features are directly passed through CNN layers, where the network learns distinguishing characteristics for each DR severity stage.
6. Severity Classification: The developed model predicts five classes of No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR, which allows for stage-based diagnosis as needed for treatment.

III. 3. Prediction and Output

1. This system determines the existence of diabetic retinopathy and rates its severity using a five-level grading scheme.
2. Diagnostic predictions allow for early detection and referral to an ophthalmologist to avoid progression to permanent vision loss.
3. To make lesion size measurements accurate, we apply a reference scale for pixel to metric calibration. This improves the reliability of our diagnosis.

My model uses a straightforward workflow with high-quality retinal fundus images. The initial stages will aim at minimizing any noise and manipulating the color space for better detailing. Following this, segmentation methods will be applied to separate regions of interest from others. The feature extraction stage involves extracting key parameters such as microaneurysms and hemorrhages. Classification of the problem using machine learning classifiers such as CNN or SVM is then applied.

III. 4. Working Principles

[A] Image Preprocessing and Normalization

Equation (1) - Image Normalization:

$$X_{norm} = \frac{X}{255.0} \quad (1)$$

where X represents the raw pixel intensity values in the range [0, 255], and X norm represents the normalized pixel values in the range [0, 1].

[B] Image Augmentation Transformations

Equation (2) - Rotation Transformation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x - c_x \\ y - c_y \end{bmatrix} + \begin{bmatrix} cx \\ cy \end{bmatrix} \quad (2)$$

where (x, y) represent the original positions, (x′, y′) denote the new coordinates after transformation, and θ ∈ [0°, 5°] indicates the rotation angle, and represents the center of the image.

$$x_{flip} = w - x - 1 \quad (3)$$

where w is the image width and x is the original horizontal coordinate.

[C] CLAHE Enhancement

Equation (4) - Adaptive Histogram Equalization:

$$I_{CLAHE}(x,y) = clip\left(\frac{CDF(I(x,y)) - CDF_{min}}{CDF_{max} - CDF_{min}} \times L\right) \quad (4)$$

where I(x,y) is the input grayscale intensity, CDF is the cumulative distribution function, L is the maximum intensity level, and the clip limit is set to 2.0 for an 8×8 tile grid.

[D] Gaussian Blur

Equation (5) - Gaussian Filtering:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$I_{blurred} = I \times G \quad (5)$$

where G(x,y) is the Gaussian kernel with σ\sigma σ determined by kernel size (5×5), and * denotes the convolution operation.

[E] Canny Edge Detection

Equation (6) - Gradient Magnitude:

$$|\nabla I| = \sqrt{G^2x + G^2y} \quad (6)$$

Equation (7) - Gradient Direction:

$$\theta = arc\tan\left(\frac{Gx}{Gy}\right) \quad (7)$$

where Gx and Gy are the gradients in x and y directions, with thresholds T1=50 and T2=150

[F] Image Fusion

Equation (8) - Weighted Overlay:

$$I_{combined} = \alpha \cdot I_{original} + \beta \cdot I_{edges} + \gamma \quad (8)$$

where α=0.8, β=0.5, γ=0, representing the weights for original image, edge-enhanced image, and bias, respectively.

Equation (9) - Dense Layer with L1 Regularization:

$$H = \sigma(Wx + b) \quad (9)$$

Equation (10) - L1 Regularization Loss:

$$L_{reg} = \lambda \sum_{i=1}^{n} |w_i| \quad (10)$$

where λ=0.0001 is the regularization parameter, W are the trainable weights, b is the bias term added to the layer, and σ is the ReLU nonlinear activation.

[G] Batch Normalization with Renormalization

Equation (121 - Batch Normalization:

$$\hat{x} = \frac{x - \mu_B}{\sqrt{\sigma^2_B + \epsilon}} \quad (11)$$

Equation (12) - Affine Transformation:

$$y = \gamma \hat{x} + \beta \quad (12)$$

where μB and σ²B represent the mean and variance of the batch, ϵ is a small value added for numerical stability, and γ and β are parameters learned during training. The "renorm = True" parameter applies additional normalization constraints.

[H] Dropout Regularization

Equation (13) - Dropout Operation:

$$h_{drop} = h \odot m,\ m \sim Bernoulli(p) \quad (13)$$

where p=0.7 (keep probability), ⊙ indicates component-wise multiplication, with m being a binary-valued mask.

[I] Loss Function

Equation (14) - Sparse Categorical Cross-Entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N} \log(p_{yi}) \quad (14)$$

where N is the number of samples, is the true class label, and is the predicted probability for the true class.

[J] Optimizer Update Rule

Equation (15) - RMSprop Update:

$$vt = \rho v_{t-1} + (1 - \rho)\, g_t^2 \quad (15)$$

$$\theta_{t+1} = \theta t - \frac{\eta}{\sqrt{v_t + \epsilon}}\, g_t \quad (16)$$

where η=0.0001 is the learning rate, ρ=0.9 is the decay rate, gt stands for gradient at time t, and vt is the moving average of squared gradients.

IV. RESULTS AND DISCUSSIONS

Performance evaluation is the organized activity associated with determining how well and how accurately a given model performs; in this case, a deep learning or machine learning model to identify diabetic retinopathy (Figure 2). It is important to have some evaluation of the model in order to understand how accurately the model responds to previously unseen inputs. It helps us find what works and what doesn't on the model, in order to further improve and better adjust it. When assessing the performance for diabetic retinopathy detection specifically, it is critical to determine how accurate the model is in detecting and classifying retinal abnormalities to enable appropriate clinical response. Here are the metrics we used to evaluate the performance[16]:

IV. 1. Standard Evaluation Metrics

To evaluate our AIDER model we used a standard classification metric. These are based on four basic outcomes (TP) True Positive, (TN) True Negative, (FP) False Positive, and (FN) False Negative.

- **True Positives:** This simply means the model correctly identifies that a patient has diabetic retinopathy when the disease is actually present in the image.
- **True Negatives:** This means the model correctly shows the absence of diabetic retinopathy when it is actually absent.
- **False Positives:** This means the model incorrectly shows the availability of diabetic retinopathy when it is not available.
- **False Negatives:** This means the model incorrectly shows the absence of diabetic retinopathy when it is actually available.

1. **Accuracy:** It represents the percentage of images identified correctly, indicating overall effectiveness (As seen in table 2). It is given as in Eq.17

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP+TN+FN+F} \quad (17)$$

2. **Precision:** It measures how accurately the model identifies all true positives, signifying the reliability of positive diagnostic outcomes. It is given as in Eq.18

$$Precision = \frac{True\ Positive\ (TP)}{TP+FP} \quad (18)$$

3. **Recall (Sensitivity):** It measures how accurately the model identifies all actual positive cases. It is given as in Eq.19

$$Recall = \frac{True\ Positive\ (TP)}{TP+FN} \quad (19)$$

4. **F1 Score:** A single metric that combines Precision and Recall, measures how well the model avoids false alarms and also catches real cases. It is given as in Eq.20

$$F1 - Score = 2\frac{Precision*Recall\ (Sensitivity)}{Precision+Recall\ (Sensitivity)} \quad (20)$$

5. **Execution Time:** The temporal efficiency required to process and analyze images for DR detection, essential for evaluating real-time clinical feasibility.

6. **ROC-AUC Score:** Tests the models ability to recognize different classes by analyzing the trade-off between the true positive rate and the false positive rate. This is particularly relevant for multi-class ranking performance.

Table 2: Performance results of "Combined" Technique

DL Algorithm	Dataset	Training Ratio (%)	Testing Ratio (%)	Accuracy (%)
ResNet50	APTOS	80	20	72.29%
DenseNet121	APTOS	80	20	72.29%

Table 3: Performance results of "Improved Combined" Technique

DL Algorithm	Dataset	Training Ration (%)	Testing Ratio (%)	Accuracy (%)
ResNet50	APTOS	80	20	93.60%
DenseNet121	APTOS	80	20	92.94%

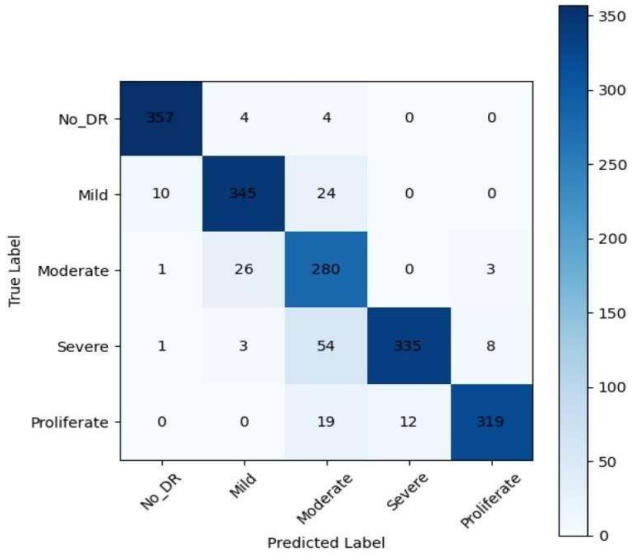

Figure 2: Confusion Matrix for Hybrid AIDER Model

Figures 3 and 4 indicate the use of Explainable AI by converting the original DR image into Grad-CAM and Heatmap, which helps for better interpretation of how the model predicts the output.

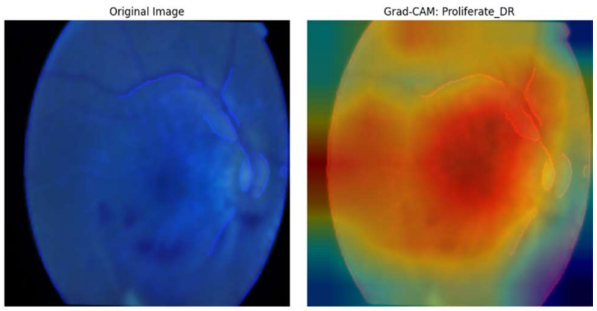

Figure 3: Grad-CAM of a sample Proliferate_DR image.

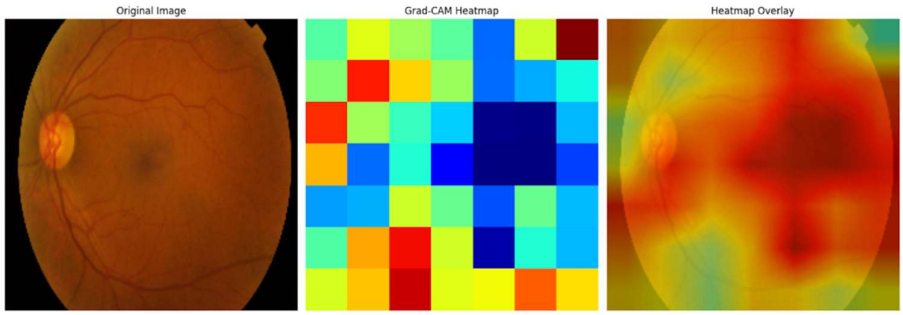

Figure 4: Grad-CAM and Heatmap for a sample of DR image.

IV. 2. Implementation Platform

Machine Learning Model with Advanced Image Processing: We plan to build our solution using a machine learning model that takes advantage of sophisticated image processing techniques, deploying Python as the programming language and utilizing OpenCV for the image processing and Keras to build the model. OpenCV contains many more computer vision and machine learning algorithms and is continually being improved. OpenCV interfaces are currently in development to allow for fast GPU processes. The OpenCV-Python API has the power of the OpenCV library and the simplicity of the Python programming language [17].

TensorFlow as the Machine Learning Platform: For this implementation, we are going to collect large images for retinal images, in the realm of machine learning, TensorFlow serves as a robust end-to-end open source platform. [19] It's a complete and adaptive machine learning ecosystem for researchers pushing the boundaries of the field and for developers deploying and building ML-powered applications. TensorFlow has several levels of abstraction, and the user can choose the most appropriate for his/her needs. For example, the high-level API Keras makes building and training models easier for people who are starting to use TensorFlow and machine learning in general. [20]

Development Environment: Python IDE: The implementation of this process is achieved using Python IDE as the development environment. The code is written and tested in Python's ide, which offers a built-in editor environment. This setup simplifies writing and running Python code [21].

IV. 2. Limitations and Future Scope

The AIDER model is capable of achieving around 93% accuracy in classification of diabetic retinopathy through multiple phases, but there are three major limitations that need to be considered. Firstly, generalizability becomes an issue because the findings were obtained using only one dataset called APTOS. Also for clinical reliability, the report precision, recall, and F1-score per stage, especially for tough proliferative cases can be enhanced. Lastly, the testing on real-world speed using clinical computers or low-power devices to ensure practical rollout.

Future work targets precisely on the multi-stage DR classification. Early stages have subtle signs which are easy to miss, so improvements will enable earlier intervention of DR. Severe-stage images are scarce, that is why we will use advanced augmentation and morphological operations to create synthetic examples of features like microaneurysms. This maintains strong performance despite limited data. We will also optimize deployment with pruning and network quantization to reduce the computation needs while maintaining the accuracy high specifically for the rural clinics or low-power devices.

IV. 3. Discussions

In a five-category classification task of diagnosing diabetic retinopathy, the proposed AIDER model achieved an accuracy rate of 93.60%, which shows its potential in clinical use. Unlike many machine learning algorithms that perform only binary classifications, the proposed model divides the output classes into No_DR, Mild, Moderate, Severe, and Proliferative stages. In addition, the model prioritizes recall for advanced diabetic retinopathy stages to help identify patients early and prevent any harm. The use of specific pre-processing procedures ensures

accurate diagnoses by using techniques such as CLAHE to increase contrast, applying Gaussian filters to suppress noise, and applying edge detection to emphasize important lesions. As the backbone model, both ResNet50 and DenseNet121 provide very accurate predictions while remaining computationally efficient.

V. CONCLUSIONS

Diabetic Retinopathy (DR) is considered among the most significant complications of diabetes. Untreated DR results in irreversible vision loss. Unfortunately, at its earlier stages, the condition is difficult to diagnose, which makes accurate and prompt detection a must. Existing detection approaches fail to be reliable enough and do not manage to track the progression of the disease. By introducing multi-class classification and advanced CNN layers in conjunction with good image preprocessing, AIDER overcomes these drawbacks. In addition, it helps detect early DR markers such as microaneurysms and hemorrhages, which helps initiate treatment to prevent permanent vision impairment. Being developed as a diagnostic tool for all five stages of the disease, namely No_DR through to Proliferative_DR, AIDER delivers valuable insights that can be applied for clinical decision-making.

To meet these requirements, it is intended to deliver:

1. Accurate Multi-Class Classification: AIDER allows classifying not only the presence but also the stages of NPDR and PDR.
2. Efficient Augmentation: The use of morphological operations improves the quality of training data by adding to their diversity.
3. Computationally Efficient Approach: An optimal balance between deep learning and preprocessing makes the approach energy-efficient.

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