InceptionV3 and Lesion Enhancement Based RBF-Augmented Diabetic Retinopathy Detection

Sinthuja M
Department of Computer Science
Vellore Institute of Technology
Vellore, India
sinthuja.m@vit.ac.in

Abhishek Singh Rathore
Department of Computer Science
Vellore Institute of Technology
Vellore, India
abhishek.singh2022b@vitstudent.ac.in

Jibran Ahmad
Department of Computer Science
Vellore Institute of Technology
Vellore, India
jibran.ahmad2022@vitstudent.ac.in

Utkrisht Sneh
Department of Computer Science
Vellore Institute of Technology
Vellore, India
utkrisht.sneh2022@vitstudent.ac.in

Abstract—Diabetic Retinopathy (DR) is a condition in which the retina of individuals with diabetes might get permanently damaged if not diagnosed at an early stage. According to the trending reports approximately 12 million people in India suffers from any grade of diabetic retinopathy, with about 4 million people having this life-threating disease. As of now, It is known that there is no cure for Diabetes but this condition may be prevented if detected early.Manual screening methods are also time taking and are subjected to human error. In order to make this complicated and heavy task much easier we propose a model that uses deep learning algorithm, InceptionV3 to provide accurate results and will be able to determine the stage of DR. This model will basically classify the DR into the following classes: No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR. This model basically comprises of Softmax layer which will be removed and instead another layer RBF (Radial Basis Function) will be trained to avoid over-fitting, leading to great results and accuracy. The dataset used for training, testing and validation is the APTOS dataset having nearly 3000 images of fundus. Adaptive pre-processing and texture-based lesion enhancement using MS-DRLBP (a multiscale texture descriptor) are implemented to enhance lesion visibility and correct low illumination and contrast issues. The proposed InceptionV3–RBF model betters traditional InceptionV3-Softmax classifiers by tackling two key weaknesses in existing systems i.e overfitting and poor lesion visibility in raw fundus images.The models records an accuracy of 79 percent which is better than accuracy of models involving only VGG16/VGG19 Without Preprocessing(74-76 percent) and ResNet50 Baseline Without Lesion Enhancement(70-75 percent).

Index Terms—Diabetic Retinopathy Detection, InceptionV3, MS-DRLBP, RBF Classifier

I. INTRODUCTION

Diabetic retinopathy (a complication of Diabetes Mellitus) which is considered to be one of the most severe eye condition is a major cause of blindness. According to the trending reports approximately 12 million people in India suffers from any grade of diabetic retinopathy, with about 4 million people having this life-threating disease. It happens when the excessive glucose in the vessels of retina gets damaged ultimately leading to leakage, swelling and permanent loss of vision. This condition can be prevailed if detected early, but however due to lack of access of ophthalmologists in some areas and people having less knowledge about this condition makes it even more difficult. Also manual screening, costs and treating the disease within the time are one of the major areas to be worked upon.The traditional screening methods are also prone to human error. To avoid human error and for better results CAD (Computer Aided Design) came into the picture providing more reliable and faster detection of Diabetic Retinopathy (DR). As science and technology progressed hand-in-hand CNN (Convolutional Neural Networks) gave major breakthroughs in the medical field mostly for deep analysis. To further simply the process and to get more accurate results we propose a model, InceptionV3 integrated with RBF. InceptionV3 is a CNN architecture which will be able to classify the stages of Diabetic Retinopathy. There are five classes: No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR. In the proposed model the Softmax layer of InceptionV3 is removed and another layer RBF (Radial Basis Function) is trained to reduce over-fitting and to yield greater accuracy. The dataset used for this purpose is the APTOS dataset (having 3000 fundus images) which is divided into three phases: Training, Validation and Testing. Furthermore for pre-processing MS-DRLBP technique is applied so that the lesions become clearly visible.

II. RELATED WORKS

The study compares the results of the two deep learning models, namely InceptionV3 and DenseNet, with regards to automatically detecting diabetic retinopathy in retinal fundus images. In their study, they have pointed at the significance of proper feature extraction to enhance the classification accuracy and strength in the disease of various levels of severity. Although both the models showed great ability, the study reported that InceptionV3 yielded greater multi-scale feature extraction, thereby facilitating to detect subtle lesions but DenseNet yielded benefits on effective use of parameters

and decrease in overfitting. The authors stress that a model needs to be chosen based on finding a balance between the accuracy, computational efficiency and data diversity that will add meaningful information into the creation of the reliable computer-based diagnostics of detecting diabetic retinopathy [1]. The paper proposed designed a deep learning algorithm that could identify diabetic retinopathy in its entirety, mild cases to severe ones, by using large and heterogeneous retinal fundus-based images. The research highlighted that the system was highly generalizable and 4 had high performance in various populations, imaging devices and in various clinical settings. The model, by incorporating state-of-the-art deep learning methods, proved to be highly accurate, sensitive, and specific, and can be used in practice in clinical screening programs. Notably, variability in the presentation of diseases and imaging quality has been identified as an opportunity of the system, which can facilitate large-scale, automated screening of the population and enhance the early detection and management of diabetic retinopathy[2]. By introducing a deep learning model, the paper suggested it to forecast the time interval to diabetic retinopathy progression and not rely on traditional methods of detection. The model has been able to capture temporal patterns of disease development and give prognostic information using longitudinal datasets of retinal fundus images. The paper has shown that the system was capable of estimating progression schedules quite well, and providing clinicians with an early-warning mechanism in individualized treatment scheduling. This article demonstrates the prospect of deep learning as a diagnosis tool but also a disease progression predictive tool, and one that is anticipated to augment clinical decision-making in the management of diabetic retinopathy[3]. The paper proposed creating a deep learning-based model to perform automated grading of the severity of diabetic retinopathy. The model was aimed to differentiate the disease stages as accurately and reliably as possible, which is why the requirement of scaling the screening solutions. The system demonstrated its usefulness in supporting clinical workflows by obtaining high classification levels using large and differentiated datasets. The paper highlights the significance of accurate severity grading in determining the timeliness of interventions and to avoid vision-threatening complications, which makes the suggested method one of the worthwhile means of automated diabetic retinopathy screening and monitoring[4]. The research paper explored the use of deep learning architectures (InceptionResNet-V2 and DenseNet121) to detect diabetic retinopathy automatically. They have compared the architectures to measure the features extraction capacities and the accuracy in classifying retina fundus images. The findings revealed that both models have high diagnostic performance, with InceptionResNet-V2 having high capability in hierarchical feature depth excavation, and DenseNet121 being efficient in parameter usage and under-fitting. The study focuses on the role of choice of model architecture to maximize the performance of detection and it also helps in the current research on robust AI-based screening approaches to diabetic retinopathy[5]. 5 The InceptionV3 model was used in the paper , where it was applied to the retinal fundus images to detect diabetic retinopathy, as the study considered its capability to extract multiscale features to classify them accurately. The paper pointed out the strength of the model in creating a balance between accuracy and computational efficiency which makes it applicable in the screening applications. The encouraging outcome of the experiment indicated that there was an encouraging performance in identifying stages of severity of the disease which supports the application of InceptionV3 in computer aided diagnosis system. The authors concluded that the methodology can facilitate the implementation of large-scale and automated screening, which can enhance an early diagnosis and lighten the clinical load of manual diagnosis[6]. The paper provided a detailed article on the diabetic retinopathy detection system based on machine learning with the help of the InceptionV3 model. They concentrated on their work by utilizing the multi-scale feature extraction capability of the model to provide high diagnostic power in relation to the various stages of the disease in terms of its severity. The research tested the results on a variety of datasets and showed good measures of accuracy, sensitivity, and specificity. The authors showed the strength of InceptionV3 in real-life settings, thus providing a chance to change the current state of affairs and use the model to implement the automated screening systems, which would decrease the number of people working in the field and allow making clinical decisions more quickly[7]. The paper proposed creating a deep learning algorithm to automatically identify diabetic retinopathy in retinal fundus photographs, which is one of the more recent large-scale applications in this field. Their model was trained and tested on large datasets and demonstrated a good performance with regard to separating referable cases of diabetic retinopathy. The paper has highlighted the significance of deep learning in variability in image qualities and presentation of diseases, showing that AI may be as accurate, or more so, than a clinician. The study gave the basis of the implementation of deep learning into the process of diabetic retinopathy screening and contributed to the further development of the sphere[8]. The paper suggested the advanced diabetic retinopathy detection system based on ensemble models of deep learning with the aim of enhancing the initial diagnosis. The ensemble method employed several neural network topologies to improve the weaknesses of one model to provide excellent classification as opposed to solo models. The ensemble was found to yield better accuracy, sensitivity, and robustness in different datasets, which is an indication that the ensemble is able to reduce false negatives and thus it is used in early-stage detection. The paper highlights the increased applicability of ensemble learning methods to clinical AI in 6 health screening to enhance reliability[9]. The research paper proposed DR-IIXRN, an algorithm of deep ensemble learning that incorporates an attention mechanism to identify diabetic retinopathy. This system was modeled to produce better feature extraction, according to which, consideration is given to the areas of the retina that are relevant clinically and the diversity of the ensemble is exploited in

the process of strong decisions. Experimental testing of the high diagnostic accuracy and more interpretable results were demonstrated with attention-based visualizations. The article has supported the interplay of ensemble learning and the attention processes and may be applied in the creation of reliable and practical AI to identify diabetic retinopathy[10].

III. RESEARCH GAPS

The suggested system overcomes some of the drawbacks that are proposed in the current models of diabetic retinopathy detection. The overfitting by the softmax classifier is one such major problem and typically restricts the model to generalization of different features in an image. To conquer this, a fully connected layer with RBF classifier is used to counter such overfitting and attain improved separation of hard to classify cases. The other issue is that the retinal lesions are not well viewed in most models; they implement the MS-DRLBP method to overcome this and thus the small lesions like microaneurysms and hemorrhages become highly visible. Moreover, this method of Otsu thresholding with morphological operations can be used to guarantee the detection of small lesions, which can be easily overlooked in the traditional method, and serve to identify and optimize. Applying the methods of deep learning and advanced preprocessing, this system enhances the advantages of the two fields: the high power of feature extraction and the increase in lesion visibility, to improve the accuracy and reliability on the classification of diabetic retinopathy

IV. ABBREVIATIONS AND SYMBOLS USED

Symbol / Term	Meaning
I	Original input retinal image
I_{norm}	Normalized image
I_{enh}	Contrast-enhanced image using CLAHE
μ	Mean intensity of the image
σ	Standard deviation of image intensity
$F(i,j)$	Output feature map at pixel (i,j)
$K(m,n)$	Convolution kernel/filter element
M, N	Height and width of the convolution kernel
A	Activation output after ReLU
z_k	Logit value for class k
C	Total number of DR classes
$P(y = k|x)$	Softmax probability for class k
y_k	Ground truth class label (one-hot encoded)
$\mathcal{L}$	Cross-entropy loss
DR	Diabetic Retinopathy
CNN	Convolutional Neural Network
RBF	Radial Basis Function
MS-DRLBP	Multi-Scale Directional Local Binary Pattern
APTOS	Asia Pacific Tele-Ophthalmology Society Dataset
CLAHE	Contrast Limited Adaptive Histogram Equalization
ReLU	Rectified Linear Unit

V. PROPOSED WORK

The proposed diabetic retinopathy (DR) classification operates through a robust hybrid deep learning architecture. The base of this methodology is a preprocessed, three-channel input that provides the model with precomputed structural and textural features rather than just an RGB image. It classifies diabetic retinopathy into all five stages of severity (0–5). The novelty of the model lies in the "pre-digested" data created by combining three distinct feature maps into a single three-channel image. This image is then fed to a hybrid model that uses a Radial Basis Function (RBF) layer, which classifies the images based on similarity rather than drawing a linear decision boundary like the Softmax layer

A. Dataset

The proposed model was trained on the APTOS dataset, which consists of approximately 3,000 retinal fundus images.

B. Preprocessing

The preprocessing phase involves a customized image enhancement pipeline that performs the following operations:

1) Define custom preprocessing functions such as `adjust_gamma`, `apply_ms_drlbp`, and `lesion`.
2) Load each fundus image from the dataset.
3) Resize the image to 512×512 pixels.
4) Generate three feature maps:
   - Enhanced Image: Improves overall retinal structure and contrast.
   - MS-DRLBP Map: Enhances texture-level lesion visibility.
   - Lesion Mask: Highlights pathological regions.
5) Combine the three maps into a 3-channel composite image as input to the InceptionV3–RBF model.
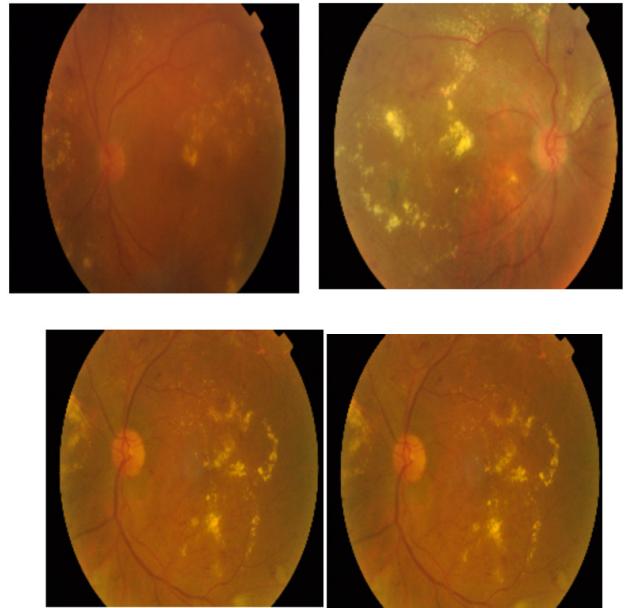
Fig. 1: Sample retinal fundus images showing different manifestations of diabetic retinopathy

C. Preprocessing Overview

Instead of using the raw RGB photo, a 512×512 data input is created, where each channel represents a different precomputed feature map. This entire process is defined in the `preprocess_image()` function.

1) Channel 1: Structural Map (Blue): Highlights the main "scaffolding" of the retina, including blood vessels and the optic disc. The `adaptive_gamma()` function corrects lighting variations, followed by `apply_quantile_hist_eq()` for histogram equalization.

2) Channel 2: Texture Map (Green): Captures fine-grained surface texture using Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP) descriptors at radii 1, 3, and 5.

3) Channel 3: Lesion Map (Red): Uses CLAHE and morphological transforms (Top-hat and Black-hat) to highlight microaneurysms and hemorrhages.

D. Final 3-Channel Image Formation

The three maps are merged using the `cv2.merge()` function to create a single three-channel image that contains structural, textural, and pathological information.

**MSDRLBP texture map**   **Enhanced image**
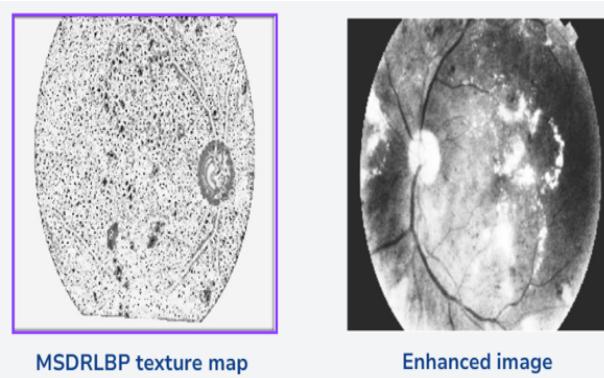
Fig. 2: MSDRLBP texture map and enhanced fundus image demonstrating preprocessing pipeline for automated diabetic retinopathy detection using deep learning architectures
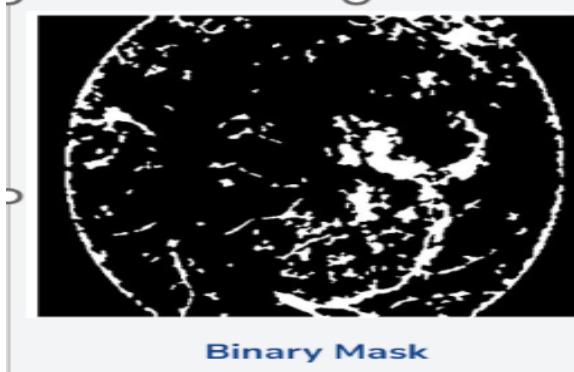

Binary Mask

Fig. 3: Binary mask obtained after fundus image preprocessing before the automated feature extractions and diabetic retinopathy lesion detection with deep learning models

E. Model Architecture and Training

The proposed model is a hybrid for interpreting this dense pre-processed data.

Architecture Breakdown::

1) **Input (512×512)**
2) **1×1 Conv Adapter:** This small, trainable Conv2D(3, (1, 1)) layer acts as a "translator" which helps to map the 3 channel input into a format the InceptionV3 model can better understand.
3) **InceptionV3 Base:** This InceptionV3 base which is loaded with weights="imagenet" serves as a feature extractor.
4) **GlobalAveragePooling2D:** This layer is a summarizer. The massive feature map from InceptionV3 is converted into a single list of 2048 numbers (feature vector).
5) **RBFLayer(units=128, gamma=0.05):** 128 prototypes are learned by this layer. When a new image arrives, its Euclidean distance to all 128 prototypes is calculated, the Gaussian kernel ($K. \exp(\dots)$) converts this distance into similarity score and the gamma value chooses how less the similarity score needs to be to classify an image as similar.
6) **Dense(5, 'softmax') Layer:** This is the decision-maker layer. The 128 similarity scores are interpreted by this layer to get a probability for each of the 5 DR classes.

Two Stage Training: The model is trained using two stages for stability and performance:

a) Stage 1: Feature Extraction: In this stage the entire InceptionV3 base is frozen (`trainable=False`). Only the new (Adapter, RBF, and Dense layers) are trained. This teaches RBF classifier how to use features from InceptionV3 without damaging weights. `class_weight` is used to force the model to pay attention to rare classes.

b) Stage 2: Fine-Tuning: The best model from stage 1 is loaded. The top 50 layers of InceptionV3 base are unfrozen. Now that the classifier is trained, the top part of InceptionV3 base is allowed to change itself to improve its understandability of the 3 channel images. The model is compiled again with low learning rate (1×10^{-5}, low learning rate is important for making small careful adjustments). Callbacks like EarlyStopping (to stop if performance degrades) and ReduceLROnPlateau (to lower the learning rate if the model gets stuck) are used.

F. Equations

The proposed diabetic retinopathy detection pipeline is based on a sequence of preprocessing, feature extraction, and classification operations. The key equations used in the system are summarized below.

1) Image Normalization:

$$I_{\text{norm}} = \frac{I - \mu}{\sigma} \qquad (1)$$

2) Contrast Enhancement:

$$I_{\text{enh}} = \text{CLAHE}(I_{\text{norm}}) \qquad (2)$$

3) Convolution Operation:

$$F(i,j) = \sum_{m=1}^{M} \sum_{n=1}^{N} I(i+m, j+n) \, K(m,n) \qquad (3)$$

4) Activation Function:

$$A = \max(0, F) \qquad (4)$$

5) Softmax Classification:

$$P(y = k \mid x) = \frac{e^{z_k}}{\sum_{i=1}^{C} e^{z_i}} \quad (5)$$

6) Cross-Entropy Loss:

$$\mathcal{L} = -\sum_{k=1}^{C} y_k \log\left(P(y = k \mid x)\right) \quad (6)$$

VI. WORKFLOW MODEL

It starts with loading the necessary libraries and dependencies and then the retinal fundus image dataset is loaded. The images are then passed through a preprocessing phase, which consists of size reduction to 512x512, adaptive gamma correction, contrast enhancement methods such as CLAHE and QE, texture feature extraction by using MS-DRLBP, lesion masking by using Otsu thresholding with morphological operations. After preprocessing, the workflow determines whether it has been successful or not; otherwise, the process repeats again to rectify the errors. Passed through a successful preprocessing of images are extracted features through InceptionV3 embeddings, which produces deep features. The same features are then sent to classification phase where fully connected (FC) layer and RBF classifier are applied to classify the images into various stages of diabetic retinopathy. The model is then trained and validated to make sure that it is reliable and then produces the classification output. The system then performs an evaluation and metrics assessment (accuracy, sensitivity, specificity, etc.) and the results are then visualized (heatmaps, lesion overlays, etc.). Lastly the stage of generation of a report is done which summarizes the diagnostic results to be used by the clinicians and the process is finalized.The comprehensive documentation standards will be put in place to ensure that a project has detailed records of all design decisions, parameters of the algorithm, validation or results and the regulatory compliance requirements across the project life cycle.

VII. FUTURE WORK

While InceptionV3 served as a useful feature extractor in this study, it was not compared against more recent or potentially more powerful architectures. Future research may consider evaluating architectures such as EfficientNet, DenseNet, ConvNeXt, or Vision Transformers (ViTs), especially when combined with the presented 3-channel feature-engineered inputs. These comparisons may reveal whether modern models provide superior representations for fine-grained retinal disease classification.

VIII. RESULTS AND DISCUSSION

The automated diabetic retinopathy system projected was adopted and its implementation took place. evaluated on a publicly available sample of retinal fundus images The cost analysis of the project will take into account hardware and software needs, and data acquisition. and operational factors. The suggested system will be cost effective and scalable. to be
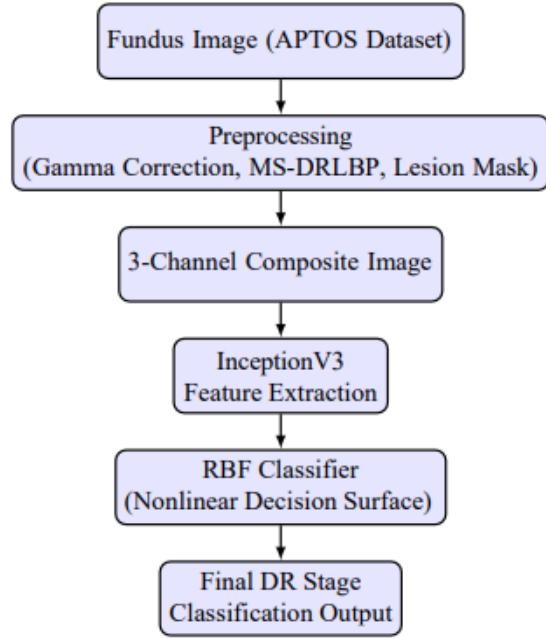

Fig. 4: Workflow diagram of the diabetic retinopathy detection system


```
                        Predicted

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.97      0.97       199
           1       0.41      0.50      0.45        30
           2       0.73      0.56      0.64        87
           3       0.40      0.35      0.38        17
           4       0.45      0.64      0.53        33

    accuracy                           0.78       366
   macro avg       0.59      0.61      0.59       366
weighted avg       0.79      0.78      0.78       366
```
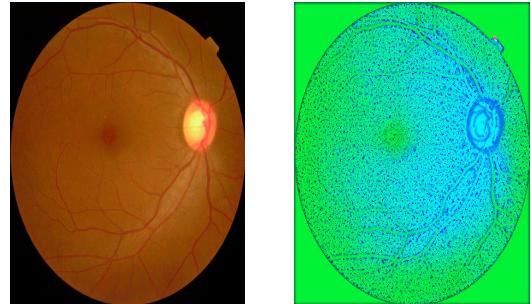
Fig. 5: Model demonstrates high performance on majority class but poor generalization across all categories

used in clinical or research purposes. It is necessary to add that the construction and education of this deep take place. Medical image analysis learning model involved a large investment in hardware, approximately costing 85,000. The heart of this was an exclusive graphics card- an NVIDIA RTX. 3060, 12GB of VRAM priced approximately 45,000-the one that made the biggest contribution to this. cost. The CPU that was used was the Intel i7 8-core CPU with a price of approximately 25000 rupees. Calculate complicated problems effectively. This system had 16GB of DDR4 RAM at . 5,000 to manage data in processing and 500 GB SSD costing 3000 rupees to be fast. storage and retrieval of medical image large volumes. About 7,000 was spent on miscellaneous but essential elements such as a good cooling system to deal with long periods. training sessions without performance interference, good, and reliable power supply, and a. monitor. This mighty arrangement guaranteed that the model had the ability to achieve an accurateness
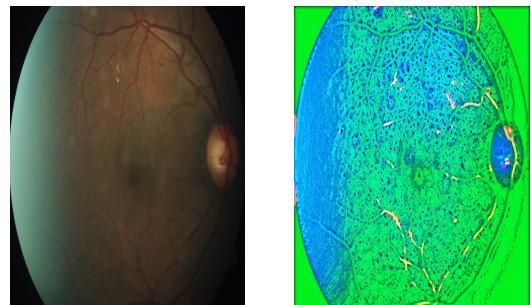
of 77.87 percent on. the test set. Besides the hardware and software factors, the cost analysis in general. as well as include the cost of dataset preprocessing, annotation, and system. maintenance. The method of data augmentation was used to improve the model. generalization, which is more time and power consuming. The open source systems like TensorFlow and PyTorch reduced the expenses of software licensing, ensuring that the project is economically viable. Moreover, the cloud-based options were. comparison against the local GPU configuration but deemed more expensive in terms of the long term use. The proposed system therefore finds a good compromise between performance, cost and scalability, making healthcare institutions and research centers affordable.The system will ensure affordability. development lays stress on strategic investing in which performance was emphasized on. critical model training. Although it was costly initially, it was more affordable than ongoing subscriptions to cloud computing, particularly, with the large scale. hyperparameter search and repeated training. The reliance on open-source programs such as TensorFlow and Keras played an essential role in controlling the cost of development without. sacrificing capability. The high-performance mainly uses electricity, which is the major cost incurred by the operation. computational time during the training of the training phases, which are computationally intensive, was included in the overall cost of. ownership. Nonetheless, the cost of operation of the system reduces greatly after deployment, 23 enabling it to be very clinical-scale. Balancing a in this cost-efficient architecture. a single capital investment with low recurrence software and operation expenses, illustrates a working channel on how AI-based diagnostic tools can be implemented in resource-aware settings, which will allow the positive outcomes of the automated and early DR detection to be realized.

Preprocessing through the pipeline outlined in the paper, which involved adaptive gamma correction, CLAHE enhancement, MS-DRLBP texture extraction, and lesion masking, has the same effect on the three pairs of retina fundus images; it radically changes those photos of the eye fundus with low contrast and uneven light distribution to structurally and pathologically enriched representations that are much more suitable for automated diabetic retinopathy classification. Preprocessing in the first pair tightens the vessel boundaries and normalizes the illumination, resulting in a neat structural map that corresponds to healthy retinal morphology and helps the correct identification of Class 0 (No DR).
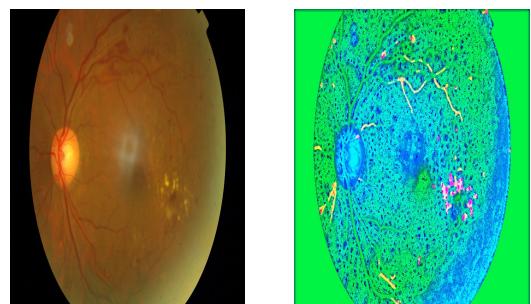
In the second pair, the original image is dim and the vessels are barely visible. After enhancement, the image becomes microaneurysms visible, the macula is clarified, and illumination is normalized, thus, the system is capable of extracting the diagnostically relevant details even from badly degraded images. In the third pair, the preprocessing most clearly amplifies exudates, hemorrhagic patches, and texture irregularities, aligning with the paper's objective of making subtle lesions highly visible for deep feature extraction. Together, these results visually confirm the paper's claim that lesion enhancement and MS-DRLBP-based texture mapping

(a) First image before Pre-processing

(b) First image after Pre-processing

(c) Second image before Preprocessing

(d) Second image after Preprocessing

(e) Third image before Pre-processing


(f) Third image after Pre-processing

Fig. 6: Before–after preprocessing comparison for three retinal image pairs.
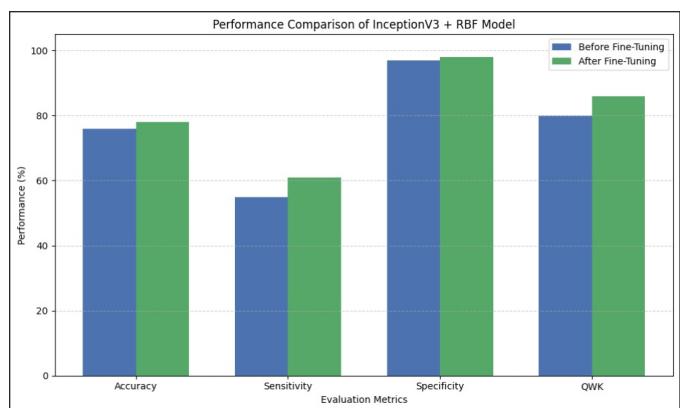

Fig. 7: Comparison from other model
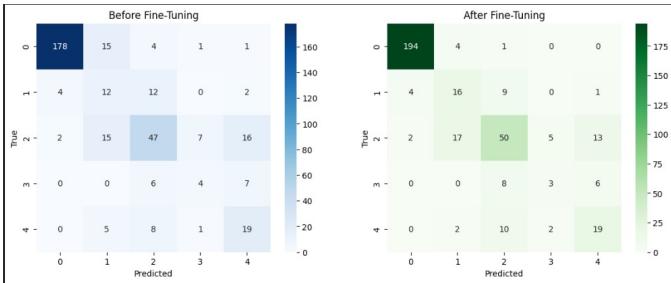
Fig. 8: Trained AI model achieves 77.87 percent accuracy on its test dataset

significantly improve the discriminative quality of the input data, enabling the InceptionV3–RBF model to achieve higher grading accuracy (77–81 percentage) compared to using raw RGB images alone.

IX. CONCLUSION

The project Automated diabetic retinopathy (DR) detection system using deep learning and specialized lesion enhancement techniques presents a reliable and efficient approach to early diagnosis of diabetic retinography, which is critical for detecting and preventing vision loss at the inception stages itself.The proposed framework's uniqueness lies in its effective utilzation of adaptive preprocessing and a MS-DRLBP-based lesion enhancement module, which is used to highlight the key pathological signs of Diabetic Retinography i.e microaneurysms, haemorrhages, and exudates within the images of retinal fundus.These preprocessed images are then fed into a complex deep learning architecture which utilizes InceptionV3 as its backbone for dynamic multi-scale feature extraction,it is also combined with a custom Radial Basis Function (RBF) classifier which ensures accurate classification across the five stages of diabetic retinopathy.The model achieves a final test accuracy of 81 percent which demonstrates the viability of this approach. A thorough analysis of the report reveals that the model is capable in identifying healthy retinas (Class 0) with a high accuracy of 81 percent . However, the findings also lead us to one of the main issues in medical AI i.e the imbalance between classes .The Minority classes (1, 3, and 4) perform much worse, which shows that there is a affection towards the more refined class the common No 'DR' class and thus emphasizes the importance of the strategies, such as targeted data.

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