chemistry proceedings

MDPI

Proceeding Paper

Explainability of Diabetic Retinopathy Detection & Classification with Deep Learning Hybrid Architecture: AlterNet-K & ResNet-101 †

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† Presented at the 29th International Electronic Conference on Synthetic Organic Chemistry (ECSOC-29); Available online: https://sciforum.net/event/ecsoc-29.

Abstract

Diabetic Retinopathy (DR), an eye disease that threaten cause of irreversible blindness. It always challenging to detect and diagnose on time. There are many ophthalmic invasive procedures exists in medical science for diagnosis of oculi (eyes). The one and all are required highly skilled medical practitioners with operational knowledge of diagnosing the sensitive organs like retina and its tiny vessels, due to dearth of retinal specialist, eye's organs sensitivity and complexity of retinal therapy the invasive procedure is time consuming, costly and have slow progress. The fundus images are the visual information of the rear part of the retina. The progression of lesions around the retinal tissue's surface, the electric signals not able to reach at visual cortex, then blurry vision or the vision loss experienced by the patients. The older methods of retinal fundus images for diagnosing lesions and symptoms of DR takes time, that causes delay in treatment and hence reducing the chance of success. Therefore, for the early diagnosis using fundus or retinal images can save the required efforts and time of doctors and patients both. Artificial Intelligence (AI) techniques have the capability to learn the tissues structure of eye's anatomy and to give the analysis about disease through the retinal fundus images. Firstly, apply the image preprocessing techniques followed by segmentation, filtering then classify the disease using the Artificial intelligence-based model. The proposed model should be trained over balanced dataset of DR images for prediction of accurate results followed by explain the decisions that diagnosed by model is correctly classified or not using Explainable AI (XAI) algorithm. The rapid growth and better outcome of machine learning and deep learning algorithms are the reason to adopt it and enhance the early diagnosis and treatments of the patients.

Keywords: diabetes complications; diabetic retinopathy; artificial intelligence; automated retinopathy detection; AlterNet-K; deep-learning technique; explainability; LIME; fundus images classification

Academic Editor(s): Name

Published: date

Citation: Gupta, L.; Gupta, R.; Agarwal, P.; Praveen, S. Explainability of Diabetic Retinopathy Detection & Classification with Deep Learning Hybrid Architecture: AlterNet-K & ResNet-101. *Chem. Proc.* **2025**, *volume number*, x. https://doi.org/10.3390/xxxxx

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1. Introduction

Diabetes Mellitus (DM) is the most popular chronic metabolic disorder. Diabetes mellitus occurs due to the situation of extra glucose circulation in blood plasma, called hyperglycemia in medical acronyms. It refers to non-manageable glucose amount due to imbalance secretion of insulins by the organ called as pancreas. The diabetes leads to various types of complications in the form of microvascular and macrovascular diseases for example, neuropathy, nephropathy, retinopathy, cardio-vascular diseases [1]. Hyperglycemia is a primary biomarker that leads due to imbalance in metabolism of carbohydrates, proteins, and lipids also [2,3]. The significant classification of diabetes found in the forms of type 1 and type 2 as per their management strategy. Type 1 diabetes is immune radiated and it occurs suddenly most of the time, its reason is not known that is idiopathic disease, while type 2 diabetes is related to insulin deficiency or insulin secretion and resistance, sometime patient requires dosage of extra insulins for balancing the amount of glucose in the body [2]. Diabetic Retinopathy (DR) is a microvascular eyes disorder that affects retinal vessels and various types of cells, neural and glial tissue in retina that leads to vision loss or permanent blindness [4]. As DR is asymptomatic and irreversible in some cases. The occurrence of DR is typically, more in type 1 diabetic patients in respect of type 2 [9], with 77.3% for type 1 and 25.2% for type 2 respectively [5,7]. DR found among the working age populations of 20 to 65 years [6]. The diabetic macular edema (DME) is more probable in type 2 diabetic patients in which the swelling becomes at retina. There are major factors responsible for growing of DR in oculi are hypertension, chronic diabetes with poor hyperglycemia, dyslipidemia (case of high cholesterol and lipids in vessels) and genetic factors as well [7].

The chemical compound Advanced Glycation End products (AGEs) are made when sugar interacts with proteins or fats in the bloodstream, the association of high levels of AGEs have been linked to diabetic retinopathy [8,9]. The Organic chemical agents such as glucose, sorbitol, AGEs, and oxidized lipids are all part of a biochemical cascade triggered due to high blood sugar. These chemical molecules damage retinal blood vessels, promote inflammation, and cause the characteristic bleeding and vision loss seen in diabetic retinopathy.

Nowadays, there are many organic chemical compounds like pesticides, herbicides used for inhibits insects in agriculture plants that exploits health specially to retina damage [10]. There are some changes would be occurred while the formation or growth of retinopathy disorder occur due to formation of the new blood vessels at retinal surface that start to cover up the surface of retina, called as neovascularization, ischemia leakages [11], lipid-proteins at retinal surface due to poor maintenance of lipid profiles in vessels that causes the different tiny spots and covered the retinal area of vision that leads to vision impairments.

In few research study reports related to DR, the authors explained that the proportionality among DR and Diabetic Kidney functional diseases and cardiovascular diseases [12]. Another complications happen in oculi due to DR are pericyte loss, capillary occlusion, basement membrane thickening, vascular shunting and vitreous hemorrhages [13], these factors break the blood retinal barrier in DR [14].

2. Related Works

In this section, we are looking literatures about major research works done for diagnosing diabetic retinopathy using machine learning models and some deep learning architectures. Deep learning techniques for Diabetic Retinopathy detection and classification explores a diverse range of approaches, each with its unique advantages and disadvantages. While some methods such as [15] focus on developing deep radiomic sequencer

designed specifically for diabetic retinopathy diagnosis, others like [16], explore the benefits of transfer learning and semi-supervised learning techniques. Additionally, studies highlight the effectiveness of combining transfer learning techniques with data augmentation techniques to improve model performance. Instead of such advancements, challenges such as dataset diversity, model generalizability, and scalability to real-world clinical setups remain exist. Many different techniques have been proposed for the diabetic retinopathy detection and classification from colored fundus images over the years. While machine learning approaches focused on extracting features and using classifiers like Support Vector Machines, Naive Bayes, Fuzzy logic or K-Nearest Neighbor's, deep learning approaches have achieved state-of-the-art results by utilizing convolutional neural networks (CNNs) but all methods are of black box nature, they do not provide any explanations and interpretations for classification or misclassification. So that, further research efforts in this regard are needed to address these challenges and advance the field towards more sturdy and widely applicable solutions for Diabetic retinopathy detection.

These are some deep learning models for diabetic retinopathy detection and classification:

Table 1.

Model	Metrics	Classification Methods	Explainability
Kumar, Devinder et al. [15]	Accuracy—73.2%	Deep Radiomic Sequencer	No
Gangwar et al. [16]	Accuracy for Messidor 1 and APTOS datasets are 72.33%, 82.18% respectively.	Inception ResNet-V2	No
Uddin, et al. [17]	accuracy is only 75% and ROC curve performance is 83%	Logistic regression	No
Zhen, et al. [18]	Accuracy is 75.5%	DenseNet	No
Proposed Model	**Accuracy is 92.47%**	**Hybrid method: ResNet—101 & AlterNet—k**	**Yes**

In above listed deep learning techniques, AlterNet-K overperforms than other models.

3. Methodology

In this section, we are discussing about the different datasets of Diabetic retinopathy disease, usually these are called retinal images or fundus images dataset.

A. Datasets

B. Proposed Model

A. Datasets:

For experiments using machine learning models in diagnosis of Diabetic Retinopathy, there are standard datasets available publicly: ATPOS, ARIA, CHASE-DB1, DIARETDB0, DiaretDB1, Kaggle—Diabetic Retinopathy 224 × 224, EyePacks, E-Ophtha, Messidor,INDIAN DIABETIC RETINOPATHY IMAGE DATASET (IDRID).

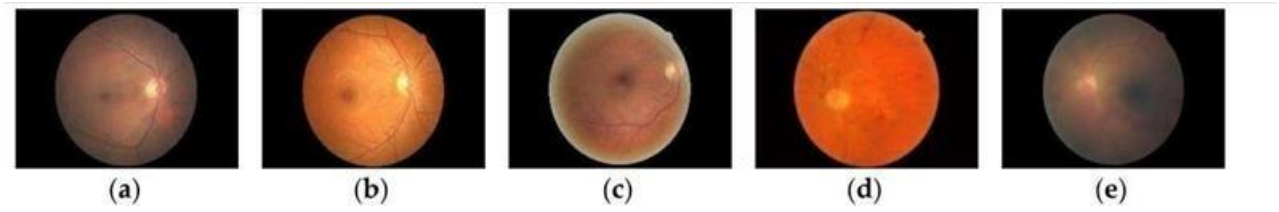


Figure 1. Fundus Images are describing the different grading of DR [16].

According to International clinical Diabetic Retinopathy Disease Severity Scale (ICDRDSS), the stages of DR grading divided as following. These datasets contain fundus images with different stages of Diabetic Retinopathy–

(a) Grade 0 (Healthy eye)—It represents no abnormalities in eyes, i.e., no symptoms of diabetic retinopathy shown in these fundus images.

(b) Grade 1 (Mild DR)—This grading represents the mild stage of DR, mostly occurred in type 2 diabetic patients at initial stages but there is no vision loss happen at this stage. The microaneurysms found in this stage.

(c) Grade 2 (Moderate DR)—This grading stage represents starting stage of DR when treatment is important and disease can be reversible if detected timely.

(d) Grade 3 (Severe DR)—In this stage, mostly patients feels complications in their vision. The new vessels formation at retinal vasculature covered the retina. If treatment of DR has not started then loss of vision is highly expected [26,27].

(e) Grade 4 (PDR)—This level is the advance and worst stage of DR, when the entire retina covered by new vessels and hemorrhages spots. In few cases, the macula of the retina becomes affected, that causes *Maculopathy*.

Tariq, Maria et al. [19] discussed about the stages of DR sign for disease classification. The grading of retinal images decided based on lesions shapes and symptoms of the tiny spots available around the retina. The worst case of PDR is referred as diabetic maculopathy, in which macula (central vision point of eye) is damaged completely [20].

B. Proposed Model AlterNet—K

AlterNet is a type of hybrid model that takes convolutional layers (conv) from Convolution Neural Networks (CNNs) and Multi-Scale Attention (MSAs) blocks from Vision Transformers by "alternately replacing convolutional blocks with MSA blocks from the end of a baseline CNN model". If the performance of the model hasn't improved, an additional convolutional block "located at the end of an earlier stage" is replaced with an MSA block, and "more heads and higher hidden dimensions for MSA blocks" are used in later stages [21].

The aim of the research is to address the critical issues by proposing a deep learning-oriented approach for diabetic retinopathy detection with the capability and learning of AlterNet—k architecture. The flow diagram for proposed model is given below.

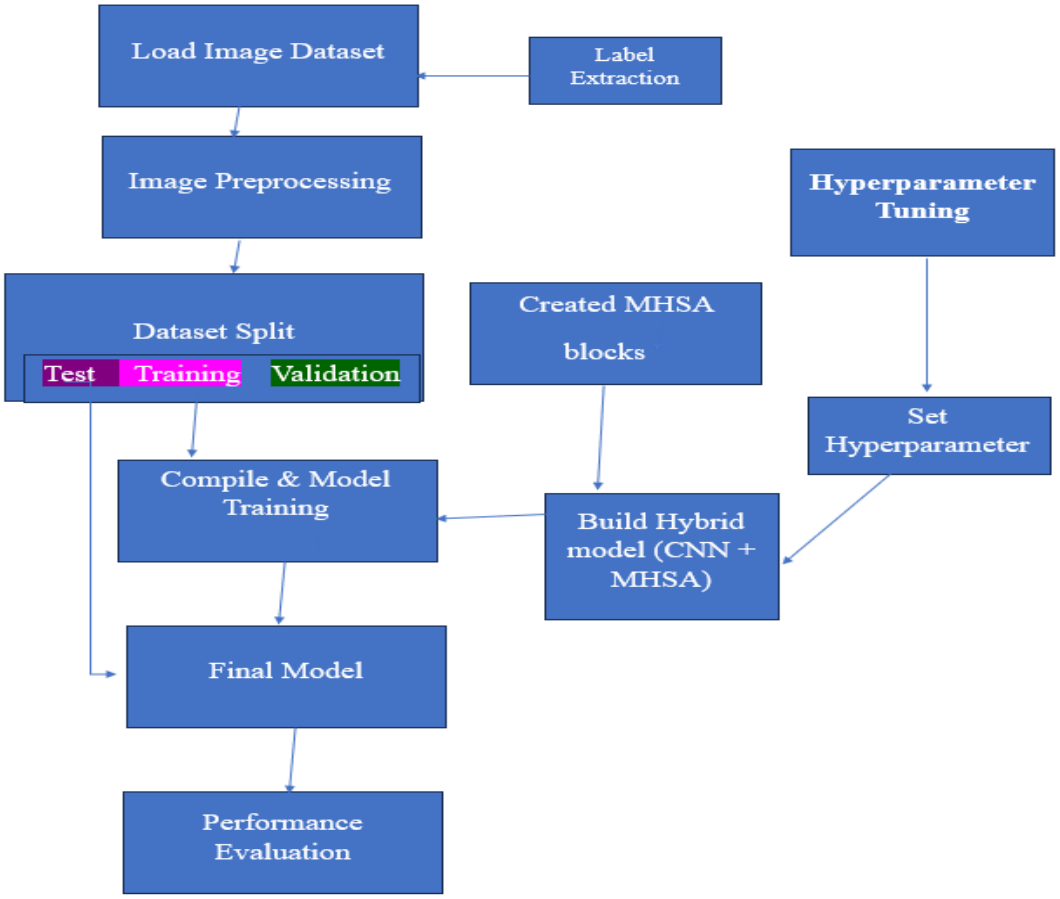


Figure 2. Flow Diagram for proposed Model.

The detailed diagram for AlterNet architecture is given as below:

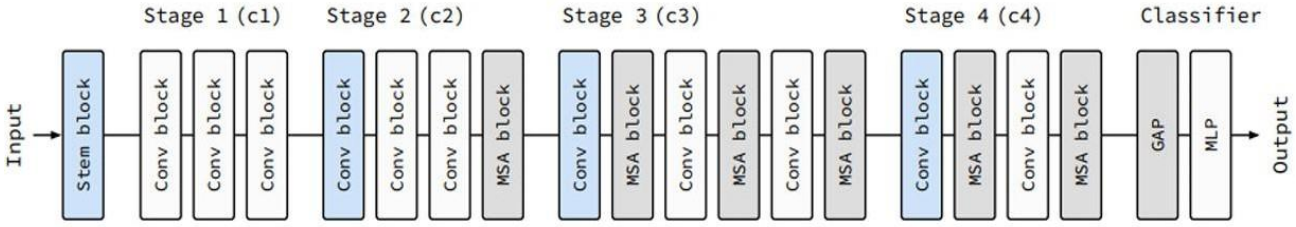


Figure 3. AlterNet Architecture [25].

The proposed work follows the workflow of involved layers in experiment. The dataset source is from Kaggle with 3662 retinal images.

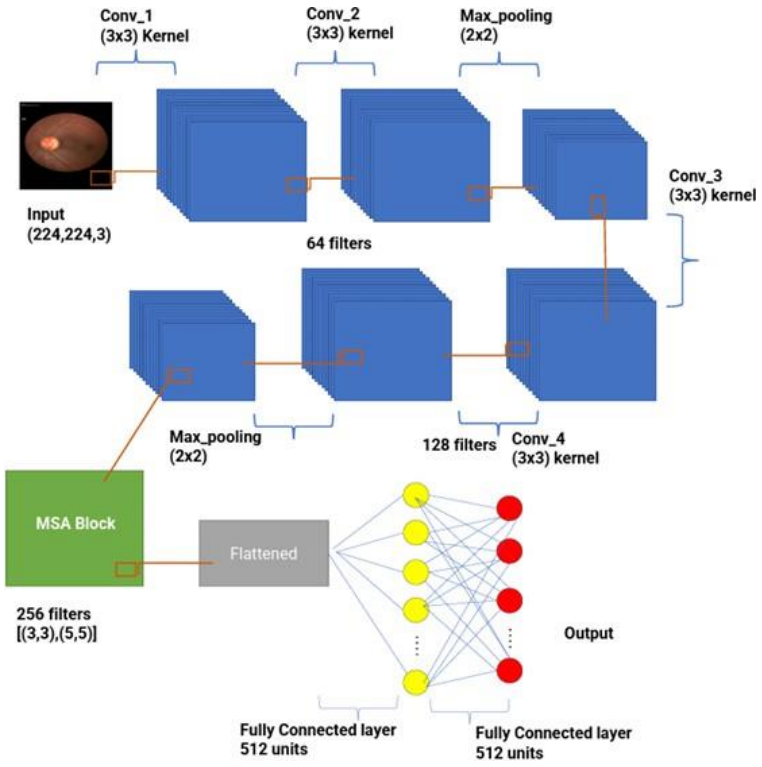


Figure 4. Methodology of AlterNet—K Model [25].

4. Results & Descriptions

In proposed model, we implement the AlterNet-K model for Diabetic Retinopathy detection and classification followed the architecture as shown in figure in Section 3. The work was started with preprocessing, data augmentation followed by split the dataset into training and validation subsets. The model includes convolutional layers, max pooling, an MSA (Multi-Scale Attention) block, and fully connected layers. We used TensorFlow and Karas for the implementation.

With the aim of avoid the model from overfitting, add *batch normalization*, and *drop out layers*. For hidden convolution layers, use the *relu* activation function, at last output layer, SoftMax activation function used. The model was trained for 50 epochs. After complete the model training, the graph among training loss, validation loss and number of epochs as shown below:

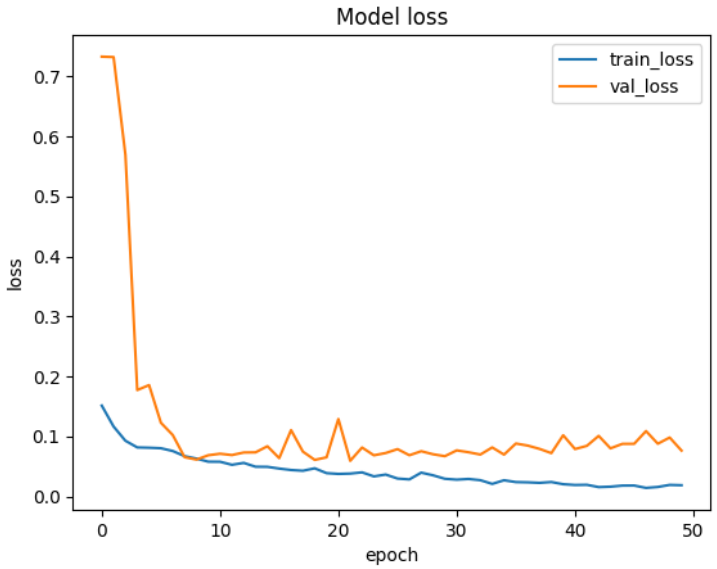


Figure 5. Loss vs. Epochs.

The graph among training accuracy, validation accuracy and number of epochs as shown below:

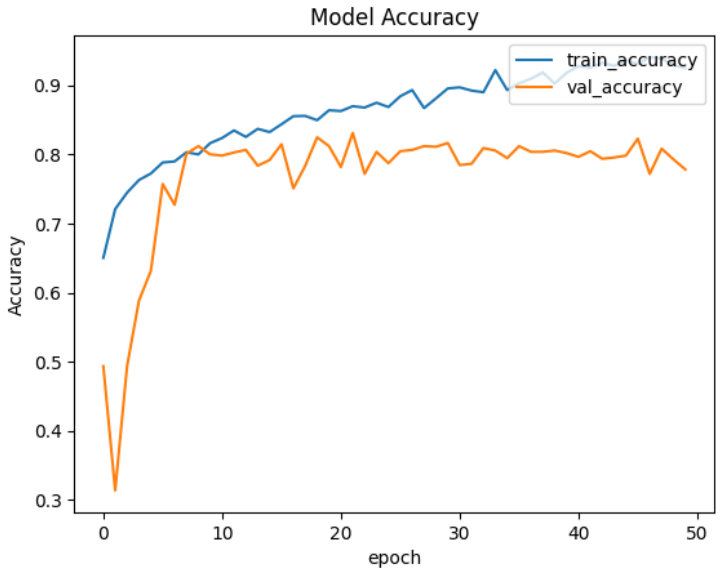
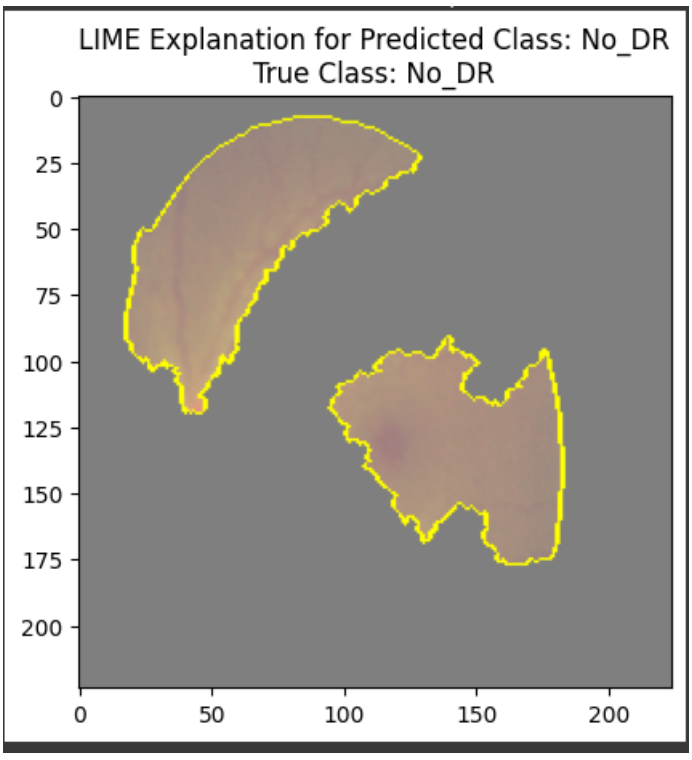
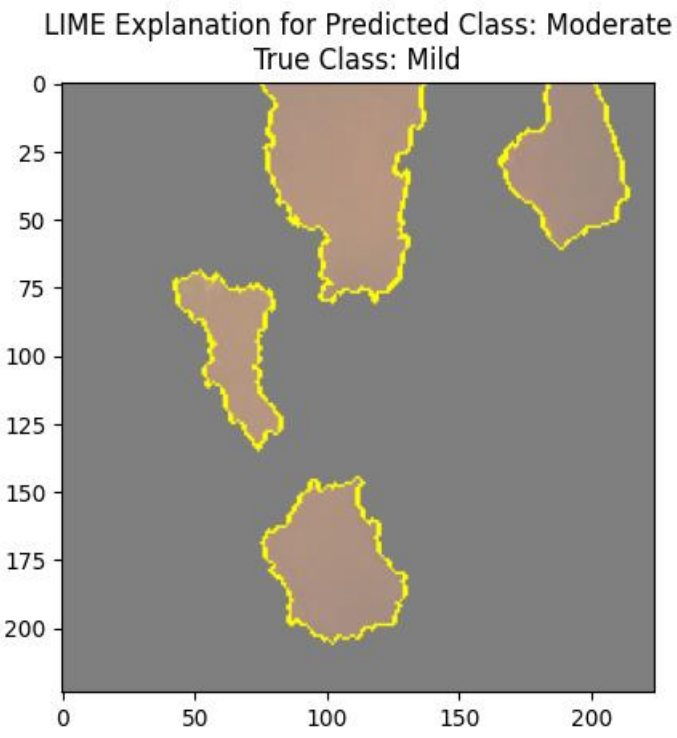


Figure 6. Accuracy vs. Epochs.



(**a**)



(**b**)

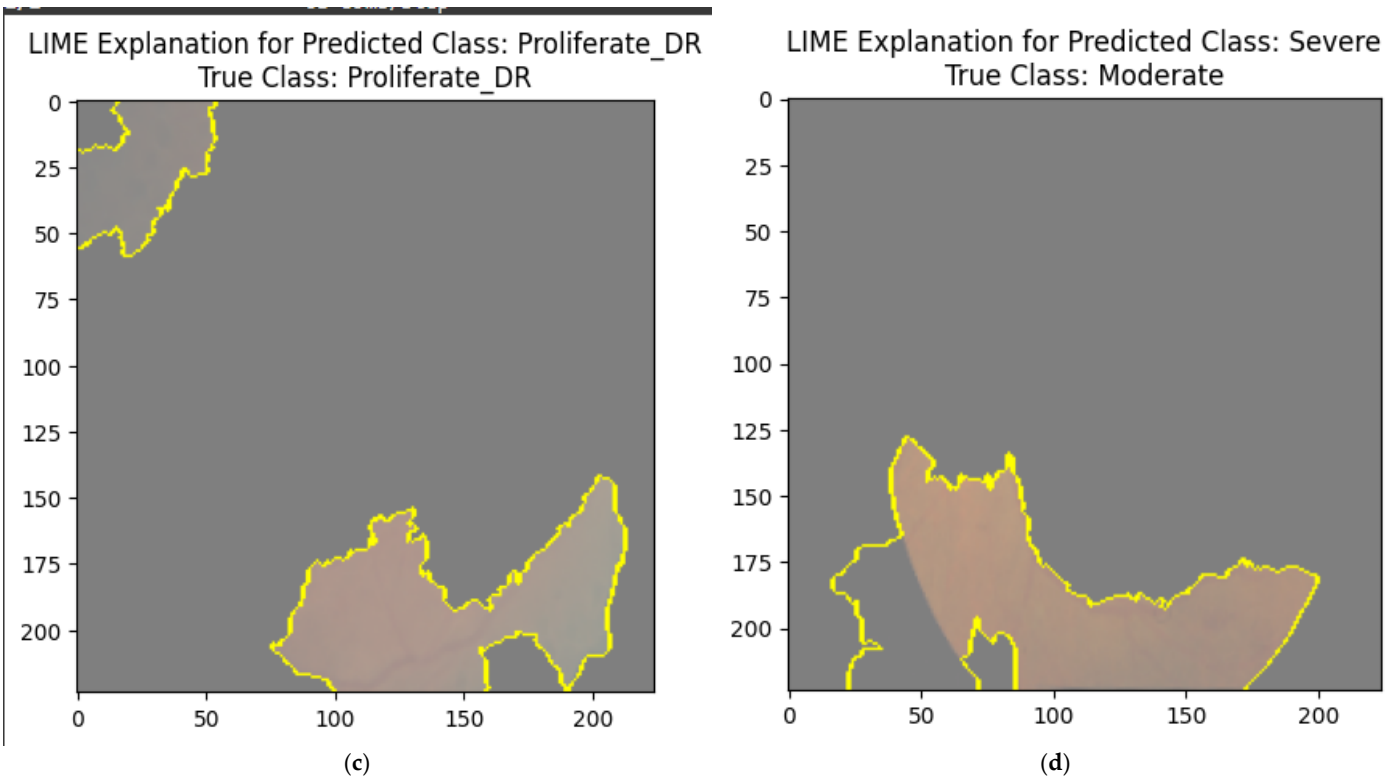


Figure 7. LIME Explanation of DR images (**a**) For Healthy Image (**b**) For Moderate Image (**c**) Proliferative DR (**d**) Severe.

In above DR images, LIME explains a single image prediction performed by our hybrid model (AlterNet-K & ResNet-101) [25]. It highlights which regions (super pixels) of the input image contributed most to the model's predicted class.

Highlighted regions (outlined in yellow) represent most influential image areas for the model's decision and Gray background represent regions the model found less important or irrelevant.

Each image shows-

A. Predicted Class (what the model decided)

B. True Class (the correct label from your dataset)

The model correctly identifies the eye as healthy images (No DR). The yellow-highlighted regions likely correspond to the **retinal background and vessels**, which the model associates with non-diseased eyes. Smooth, uniform regions without bright lesions or haemorrhages are important features here. The model slightly overestimates severity (predicts Moderate instead of Mild). The yellow areas may correspond to **small lesions or early microaneurysms**—LIME shows these as features the model found important. This suggests the model is sensitive to small bright or dark spots but may be confused about their severity.

The model correctly identifies **severe proliferative DR**. Yellow-highlighted regions indicate **active lesions**, possibly exudates or neovascular formations. These regions strongly influenced the model's decision, showing that it focuses on the disease-specific patterns. The model sees the lesions as more severe than they are actually. The yellow contours highlight **large lesion-like patterns**, perhaps due to contrast or uneven lighting.

The model may be confusing **moderate DR lesions** (haemorrhages or exudates) with **proliferative-like features**, indicating for improvement in fine-grained severity discrimination.

5. Conclusions and Future Directions

The imaging of retina helps in diagnosis of early DR by using different methods of Artificial intelligence including Machine learning, Deep learning with image and digital filter processing algorithms.

The right, clear imaging of retina can be able to predict the DR at primary proliferative stage of diabetic macular edema, which can be easily treatable without surgery and the possibility of vision loss is to be reduced [23]. The image processing techniques used for feature extraction, preprocessing of undesired pixels and parts of images, followed by applying the segmentation and filters to enhance the image quality. Then, filtered image required to be trained using machine learning models that make it able to test the further images and classify the result according to class labels [24]. The classification algorithms used to assign a label or class category to the image data on behalf of the set of lesions. The prediction of classification algorithms performed over the different classes.

The novel proposed model implemented for Diabetic Retinopathy (DR) detection and classification. The model integrates convolutional layers for feature extraction and max pooling layers for removing unnecessary features. The Multi-Scale Attention (MSA) Block enhances feature learning by applying different receptive field sizes. The fully connected layers ensure the final classification.

Although this proposed model is novel in detection diabetic retinopathy disease, the work has scope to optimized further with hyperparameter tuning, data augmentation and scaled up with other datasets also. The different explainable AI techniques can also be used for showing the explainability and interpretability-based decisions regarding the classified results. The same work can be applied for O**ptical Coherence Tomography** (OCT) images also.

Author Contributions:

Funding:

Institutional Review Board Statement:

Informed Consent Statement:

Data Availability Statement:

Conflicts of Interest:

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