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Early detection of diabetic retinopathy in fundus images using deep learning

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Abstract

Diabetic retinopathy causes the retinal blood vessels to deteriorate, resulting in significant eye issues. Automated DR diagnosis frameworks are vital for the early identification and detection of various eye-related diseases, allowing ophthalmic experts to provide a second opinion for effective treatment. Deep learning algorithms have emerged as an upgrade over traditional approaches that rely on handmade feature extraction. DR detection can be classified into four stages: non-retinopathy, mild, moderate, and severe. Fundus image-based DR screening procedures are widely used due to their ease of use, appropriate acquisition, and improved visibility of lesions. The rise in diabetes patients has increased the need for advanced skilled ophthalmologists to initiate the implementation of automatic DR diagnosis systems. The signs of possible DR are not visible to the human eye; thus, a system for automatic early detection of DR is the most important necessity for investigating the characteristics and pattern of DR.

Keywords: Diabetic Retinopathy, VGG19, fundus images, neural network

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1. Introduction

Diabetic retinopathy (DR) is the major cause of vision loss among diabetics, affecting millions globally. Early detection and precise grading of DR are critical for timely treatment and preventing vision loss. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in automating DR grading from retinal fundus images. CNNs excel at learning hierarchical representations straight from raw visual data, allowing the extraction of complex features indicating DR severity [1]. In the context of DR grading, CNNs are trained on large datasets of annotated retinal images, learning to classify them into different severity levels ranging from mild non-proliferative DR to severe proliferative DR. The CNN-based approach offers several advantages, including scalability, efficiency, and consistency in grading, compared to traditional manual grading methods, which can be subjective, time-consuming, and prone to inter-observer variability [2]. By leveraging CNNs, automated DR grading systems have the potential to enhance access to timely screening, improve patient outcomes, and alleviate the burden on healthcare resources. However, challenges such as dataset bias, model interpretability, and generalizability to diverse populations remain areas of active research in the field. Overall, CNN-based approaches hold great promise for revolutionizing the diagnosis and management of DR, paving the way for more accessible and effective healthcare solutions for individuals living with diabetes. Diabetic retinopathy (DR) is a sight-threatening complication of diabetes mellitus, impacting millions of people globally. Early detection and accurate grading of DR are crucial for timely treatment and preventing vision loss. In recent years, pretrained Convolutional Neural Network (CNN) models have emerged as powerful tools for automating DR grading from retinal fundus images [3]. These pretrained models are pre-trained on large-scale image datasets for generic tasks like object recognition or scene classification. Leveraging transfer learning, pretrained CNN models are fine-tuned on DR-specific datasets, adapting their learned representations to the task of DR grading. This approach offers several advantages, including reduced training time, improved generalization, and the ability to learn complex features indicative of DR severity. Figure 1 shows microvascular structure of eye with diabetic retinopathy symptoms.

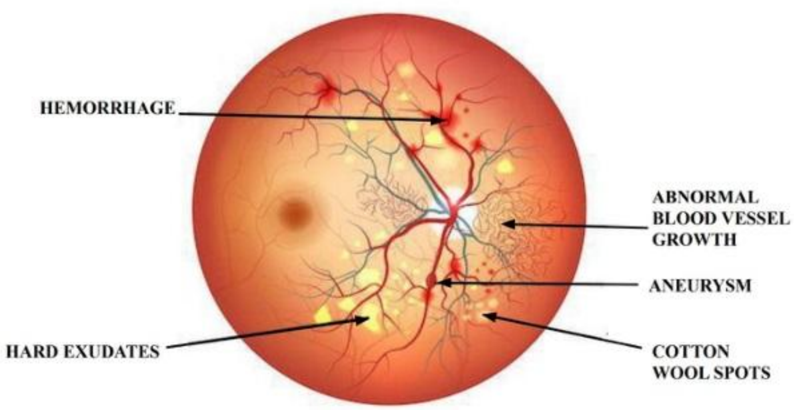

Fig.1. Microvascular complications of diabetic retinopathy [4]

2. Related Work

A diabetic retinopathy (DR) grading system utilizing Convolutional Neural Networks (CNNs) has been proposed in various research papers. These systems aim to automate the grading process, enhancing efficiency and accuracy in detecting DR severity levels. Different approaches have been explored, such as customizing CNN models based on fundus image lesions [5], utilizing multi-task learning for patch-level lesion classification and DR severity assessment [6], and incorporating deep attentive CNNs for fine-grained DR grading and lesion discovery [7]. These methods leverage advanced techniques like k-medoid clustering, principal component analysis, global attention mechanisms, and learnable connected modules to improve classification performance and handle the complexities of DR lesions. CNN models are tailored to the structural patterns of fundus images, optimizing the recognition of DR-relevant features, and outperforming widely used pre-trained models like ResNet152 and DenseNet121 in terms of accuracy while using fewer parameters [8]. By incorporating techniques like principal component analysis and k-medoid clustering, these CNN models can automatically grade DR severity into categories like No-DR, Mild NPDR, Moderate, Severe, and Proliferative DR with high accuracy, sensitivity, and specificity. Transfer learning, a technique where pretrained models are fine-tuned on DR-specific datasets, has been widely adopted to adapt pretrained CNNs to the task of DR grading [9]. pretrained CNN models offer scalability and efficiency in DR grading, enabling rapid analysis of large volumes of retinal images with minimal human intervention. This scalability is particularly beneficial in resource-constrained healthcare settings, where access to specialized ophthalmic expertise may be limited.

3. The Proposed Work

The use of pretrained CNN models for DR grading has gained traction due to their ability to leverage knowledge learned from large-scale image datasets for generic tasks, such as ImageNet classification. Transfer learning, a technique where pretrained models are fine-tuned on DR-specific datasets, has been widely adopted to adapt pretrained CNNs to the task of DR grading. Several studies have demonstrated the effectiveness of pretrained CNNs in accurately classifying retinal images into different DR severity levels, ranging from mild non-proliferative DR to severe proliferative DR [10]. Pretrained models like VGG16, VGG19, MobileNet and AlexNet have potential to extract features from fundus images because these pretrained models are trained on large datasets and capable of identifying different shapes and curves in the image [11].

3.1 Acquisition of dataset and preprocessing

The acquisition of a dataset and preprocessing are critical steps in developing an automated system for diabetic retinopathy (DR) grading using pretrained Convolutional Neural Network (CNN) models. The dataset must be carefully curated to include a diverse range of retinal fundus images annotated with DR grades [12]. This involves sourcing images from various sources, including medical databases, research institutions, and clinical settings, while ensuring representative coverage of different DR severity levels. Once collected, the dataset undergoes preprocessing to enhance image quality, normalize intensity, and standardize resolution [13]. Techniques such as contrast enhancement, histogram equalization, and resizing are applied to ensure consistency across images and facilitate effective model training. Additionally, data augmentation methods such as rotation, flipping, and zooming may be employed to increase dataset variability and improve model generalization [14][15]. Overall, the acquisition and preprocessing of the dataset lays the foundation for robust and reliable DR grading using pretrained CNN models, enabling accurate diagnosis and management of this sight-threatening condition [16].

We have acquired dataset from Kaggle [17]. It has 1000 images classified into 39 different categories. We only used Normal and DR1 and DR2 images to train and test the model. We resized images into 224 x 224 to make the input compatible with the proposed model.

Fig.2. Sample fundus images Label 0 (Non-DR), Label 1 (DR)

3.2 The Proposed model

The layered architecture of the proposed model is shown in Figure 2. The whole model is divided into 2 modules namely Feature extraction and Classification. We used VGG19 pretrained model for feature extraction by eliminating the fully connected layers. We stacked new classification layers on VGG19 to classify a fundus image into non-diabetic retinopathy (0) and diabetic retinopathy (1) classes.

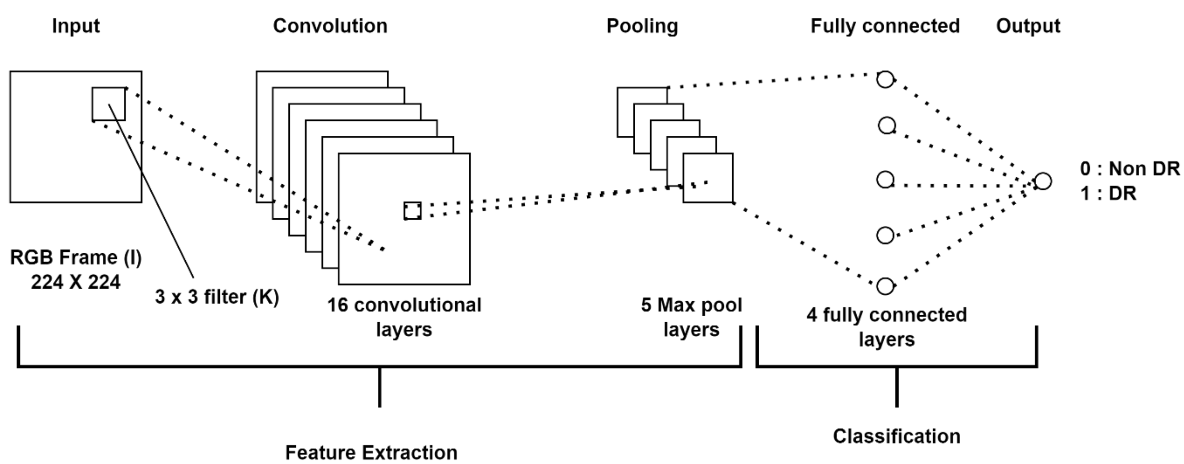

Fig.3. The proposed layered architecture of the model

Here below is the implemented model in python. Figure shows the layer wise output shape and number of parameters-

Table 1. Layered architecture of proposed model implemented in python.

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(None, 7, 7, 512)	20024384
flatten_2 (Flatten)	(None, 25088)	0
dropout_6 (Dropout)	(None, 25088)	0
dense_8 (Dense)	(None, 1024)	25691136
dropout_7 (Dropout)	(None, 1024)	0

```
 dense_9 (Dense)             (None, 1024)              1049600

 dropout_8 (Dropout)         (None, 1024)              0

 dense_10 (Dense)            (None, 512)               524800

 dense_11 (Dense)            (None, 1)                 513

=================================================================
Total params: 47290433 (180.40 MB)
Trainable params: 27266049 (104.01 MB)
Non-trainable params: 20024384 (76.39 MB)
_________________________________________________________________
```

3.3 Result and Discussion

The proposed model performed well with accuracy of **81.03%**. Overall, we have used 144 fundus images to train and test the model. Out of 144 images; 86 images are used for training and the remaining images are used to test the model. We have calculated accuracy indicators such as accuracy, precision, recall, specificity and F1 score for the proposed model. The accuracy of the model is calculated by using below mentioned formula-

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{.......1 [18]}$$

Here TP, TN, FP, and FN stand for True positive, True negative, False positive and False negative respectively.

Figure shows confusion matrix of the proposed model. We used 58 images to test the model. The model is predicting 47 samples with correct labels and 11 samples with incorrect labels.

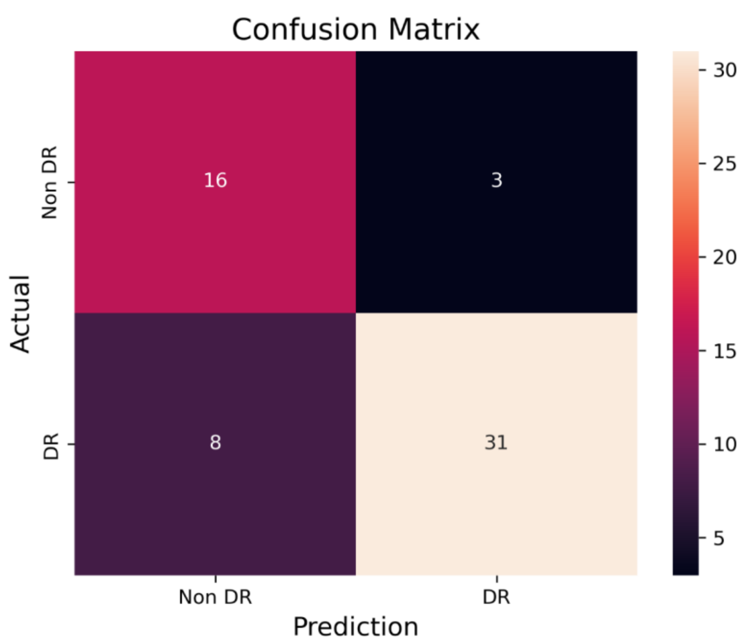

Fig.4. Confusion matrix

Figures 6, 7 and 8 shows Training accuracy vs Validation accuracy, Training loss vs Validation loss and Receiver operating characteristics (RoC) and Area under the curve (AUC) value respectively. The proposed model is trained for 10 epochs.

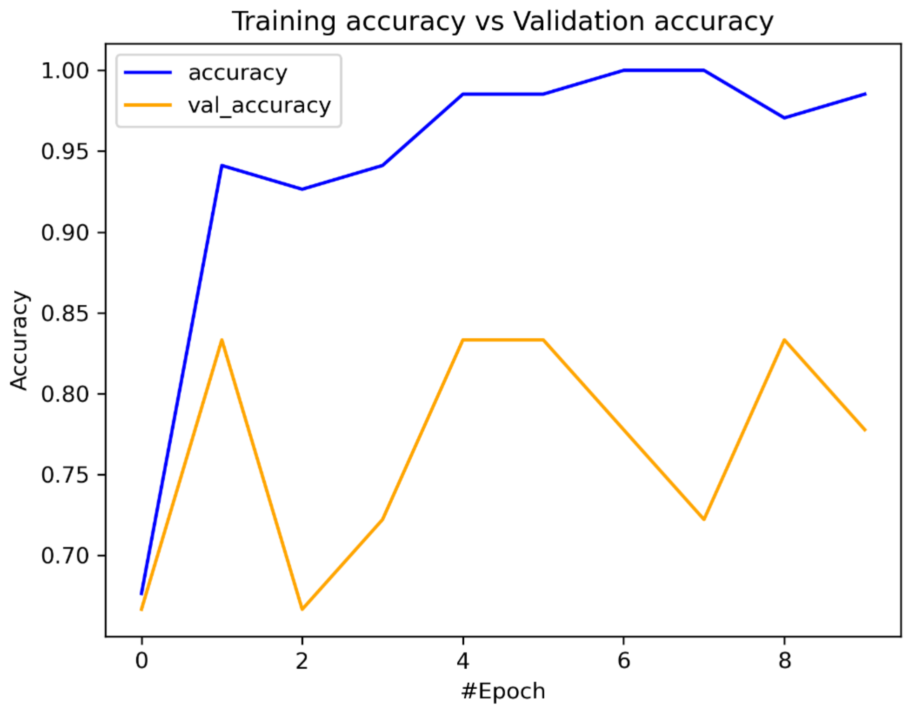

Fig.5. Training accuracy vs Validation accuracy

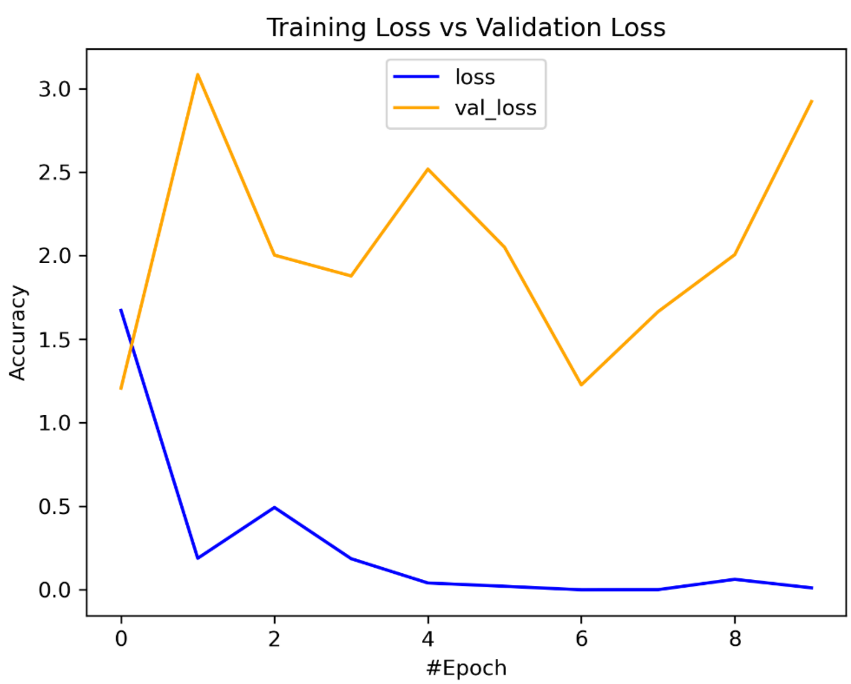

Fig.6. Training loss vs Validation loss

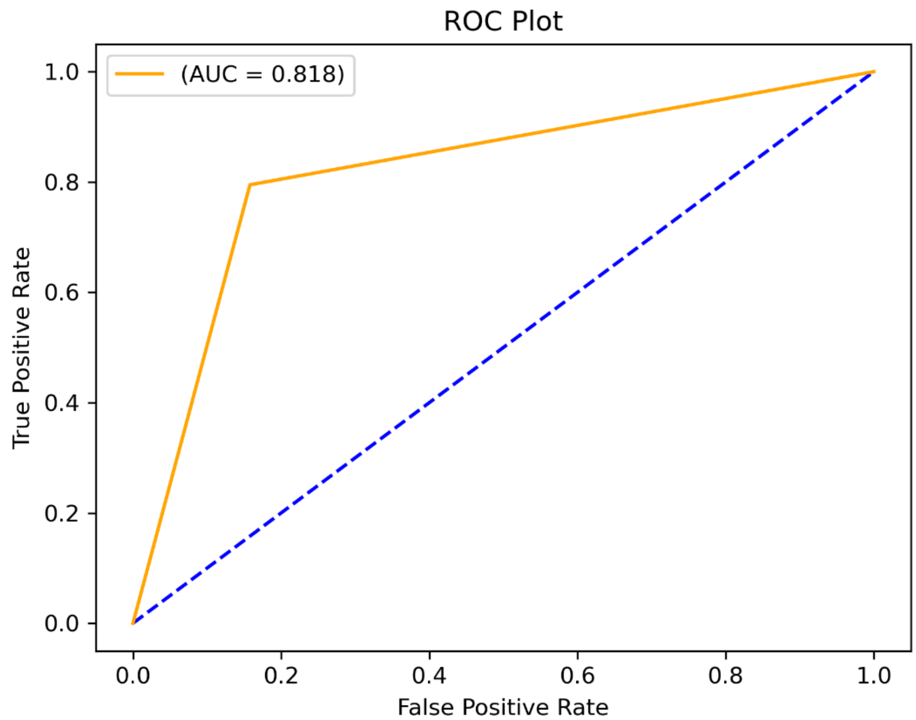

Fig.7. RoC curve and AUC value

Figure 8 shows value of Precision, Recall and F1 score for the proposed model. precision quantifies the accuracy of the positive predictions made by the model. It is calculated as the ratio of true positive predictions to the sum of true positive and false positive predictions [19][20][21].

$$Precision = \frac{TP}{TP + FP} \qquad \text{.......2 [22]}$$

Recall quantifies the model's ability to capture all positive instances while minimizing false negatives. It is calculated as the ratio of true positive predictions to the sum of true positive predictions and false negative predictions [23][24].

$$Recall/Sensitivity = \frac{TP}{TP + FN} \qquad \text{.......3 [25]}$$

The F1 score is a commonly used performance metric in classification tasks that provides a balance between precision and recall. It is the harmonic mean of precision and recall and is calculated using the following formula:

$$F1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad \text{.......4 [26]}$$

The F1 score ranges from 0 to 1, with higher values indicating better model performance.

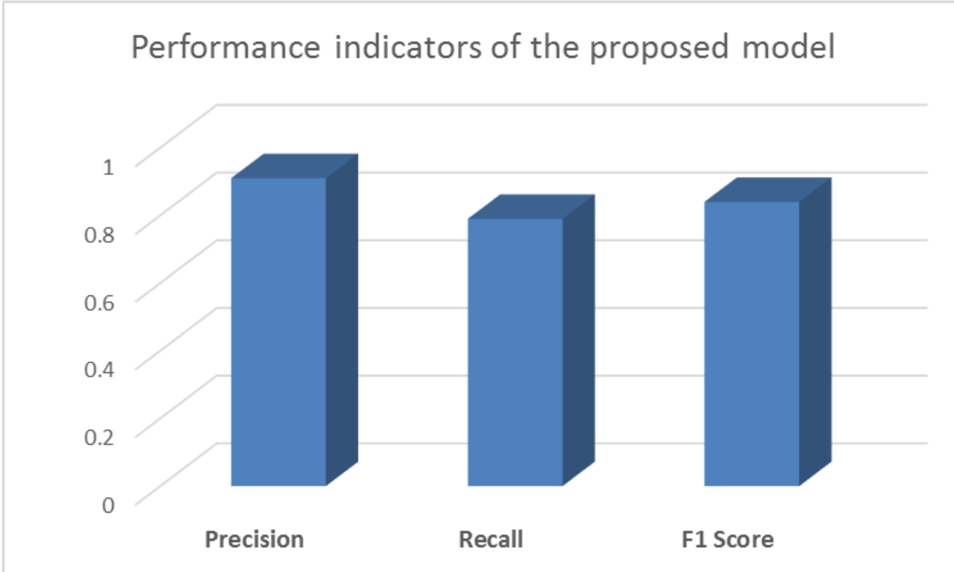

Fig.8. Precision, Recall and F1 score of the proposed model.

4. Conclusion

In conclusion, the utilization of pretrained Convolutional Neural Network (CNN) models presents a significant advancement in the field of diabetic retinopathy (DR) grading. These models offer a powerful tool for automating the process of grading retinal fundus images, which is crucial for early detection and effective management of DR, a leading cause of vision loss worldwide. Through transfer learning, pretrained CNNs leverage knowledge learned from large-scale image datasets to adapt to the task of DR grading, capturing complex features indicative of DR severity with high accuracy and efficiency. The scalability and efficiency of pretrained CNN models enable rapid analysis of large volumes of retinal images, providing a valuable resource for healthcare providers, particularly in resource-constrained settings. Despite the promising results, challenges such as domain adaptation, dataset bias, and model interpretability remain areas of ongoing research. Addressing these challenges will be crucial for realizing the full potential of pretrained CNN models in improving the diagnosis and management of diabetic retinopathy. Overall, pretrained CNN models represent a promising approach for automating DR grading, ultimately leading to better patient outcomes and more accessible eye care services for individuals with diabetes.

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