International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Deep Learning for Early Detection of Diabetic Retinopathy: A Colour Fundus Image-based Approach with VGG16 and VGG19

Anand Ratnakar
M.Tech Robotics And Artificial Intelligence, Dept. of Manufacturing Engineering and Industrial Management, COEP Technological University Pune, India.

ABSTRACT -

Diabetic retinopathy (DR) is a prevalent complication of diabetes, posing a significant threat to vision. Early detection and intervention are critical to prevent vision loss. However, manual screening of retinal images for DR is time-consuming and susceptible to human error. This study investigates the application of deep learning models, specifically VGG16 and VGG19, for automated DR diagnosis in Colour Fundus images. We evaluate their performance in classifying images as either Diabetic Retinopathy or No Diabetic Retinopathy. Our results demonstrate high testing accuracy with VGG16 achieving 93.96%, suggesting a promising approach for automated DR screening and aiding healthcare professionals in early and accurate diagnosis.

Keywords : Convolutional Neural Network, Diabetic Retinopathy, Visual Geometry Group 16 (VGG16), Visual Geometry Group 19 (VGG19), Transfer Learning, Deep Learning.

1. INTRODUCTION

Diabetes is a chronic condition affecting millions globally, and diabetic retinopathy (DR) is one of its leading complications. Characterized by damage to the blood vessels in the retina, DR can gradually lead to vision loss and blindness if left untreated. Early detection and timely intervention are crucial for preserving vision. However, traditional methods of DR screening rely on manual interpretation of retinal images by ophthalmologists. This approach is often time-consuming, subjective, and prone to human error.

The increasing prevalence of diabetes and limited availability of ophthalmologists further challenge timely screening and diagnosis. Therefore, there is a pressing need for automated and accurate tools to assist healthcare professionals in DR detection and facilitate early intervention.

This research explores the potential of deep learning models for automated DR diagnosis using Colour Fundus images. Deep learning has revolutionized various image recognition tasks, and its application in medical image analysis holds tremendous promise. Here, we investigate the performance of VGG16 and VGG19 architectures in classifying Colour Fundus images into Diabetic Retinopathy and No Diabetic Retinopathy categories.

2. LITERATURE REVIEW

2.1. Limitations of Manual Diabetic Retinopathy (DR) Screening:

While manual screening of retinal images by ophthalmologists remains the gold standard for DR diagnosis, it faces significant limitations:

- **Subjectivity and Variability:** Ophthalmologists' interpretations can be subjective, leading to inconsistencies and potential misdiagnoses, particularly for early-stage DR.

- **Time-consuming Process:** Manual screening of large datasets is a slow and laborious process, hindering efficient screening programs.
- **Limited Specialist Availability:** The growing prevalence of diabetes creates a strain on ophthalmic resources, limiting access to timely DR screening, especially in remote areas.

These limitations highlight the urgent need for automated and objective methods for DR detection.

2.2. Machine Learning and Deep Learning for DR Detection:

Machine learning and deep learning offer promising alternatives to traditional manual screening approaches.

- **Machine Learning with Feature Engineering:** Early research explored machine learning algorithms like K-nearest neighbors (KNN) and support vector machines (SVM) for automated DR detection. However, these methods require manually extracting features from retinal images, a complex and expertise-dependent process that significantly impacts performance. Additionally, hand-crafted features may not capture the most critical aspects of retinal images for accurate DR classification.
- **Deep Learning for Feature Learning:** Deep learning, particularly convolutional neural networks (CNNs), addresses the feature engineering challenge by automatically learning relevant features directly from retinal images. This capability makes CNNs well-suited for DR detection tasks, as they can learn intricate patterns and relationships within the image data.

2.3. Deep Learning Architectures for DR Detection:

Several deep learning architectures have been investigated for DR detection, with CNNs demonstrating remarkable success.

- **Pre-trained CNN Models:** Leveraging pre-trained CNN models like VGG16 and VGG19 has become a popular approach. These models are trained on vast image datasets and then fine-tuned for specific tasks like DR classification. Studies have shown promising results using these models, achieving good performance in DR diagnosis.
- **Transfer Learning:** Transfer learning is a technique where a pre-trained CNN model's weights are used as a starting point for a new task. This approach leverages the learned features from the pre-trained model and fine-tunes them for DR classification, improving efficiency and potentially achieving higher accuracy than training a model from scratch.

3. METHODOLOGY

3.1 Dataset

This dataset consists of a large collection of high-resolution retinal images captured under various imaging conditions. A medical professional has assessed the presence of Diabetic Retinopathy in each image and assigned a rating on a scale ranging between 0 and 1, which corresponds to the following categories:

- Diabetic Retinopathy ---> **0**
- No Diabetic Retinopathy ---> **1**

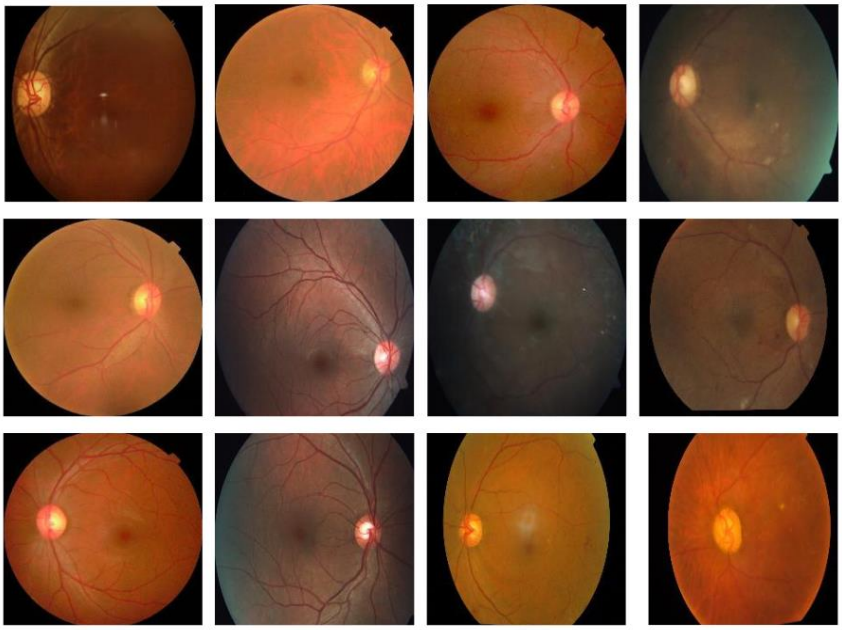

Figure 1. Diabetic Retinopathy Dataset.

3.1.1. Number of Classes: 2 (Diabetic Retinopathy and No Diabetic Retinopathy).

3.1.2. Data Split: Training set (2076 images), Validation set (762 images)..

3.1.3. Image Format: Colour Fundus ImageS (RGB) with varying resolutions.

3.2. Proposed Approach

Our research builds upon the existing body of knowledge in machine learning and deep learning for diabetic retinopathy (DR) detection. By acknowledging this established research, we contextualize our work and position it as an extension of current efforts in this field.

3.2.1. Application of Pre-trained CNN Architectures:

We propose investigating the use of VGG16 and VGG19, both prominent pre-trained convolutional neural network (CNN) architectures, for automated DR diagnosis in Colour Fundus images. This approach leverages the power of pre-trained models to potentially achieve accurate DR classification without the need for extensive training from scratch.

3.2.2. Focus on Binary Classification:

Our investigation focuses on a binary classification task. The models will be trained to classify Colour Fundus images into two distinct categories: Diabetic Retinopathy or No Diabetic Retinopathy. This clear definition of the task allows for focused evaluation of model performance in accurately differentiating between these two classes.

3.2.3. Comparative Analysis of VGG16 and VGG19:

A crucial aspect of our research is the comparative analysis of VGG16 and VGG19 performance. We will evaluate and compare their accuracy in DR classification using Colour Fundus images. This evaluation will help us identify which pre-trained CNN architecture achieves superior performance in this specific task. This knowledge will be instrumental in the development of reliable automated DR screening tools.

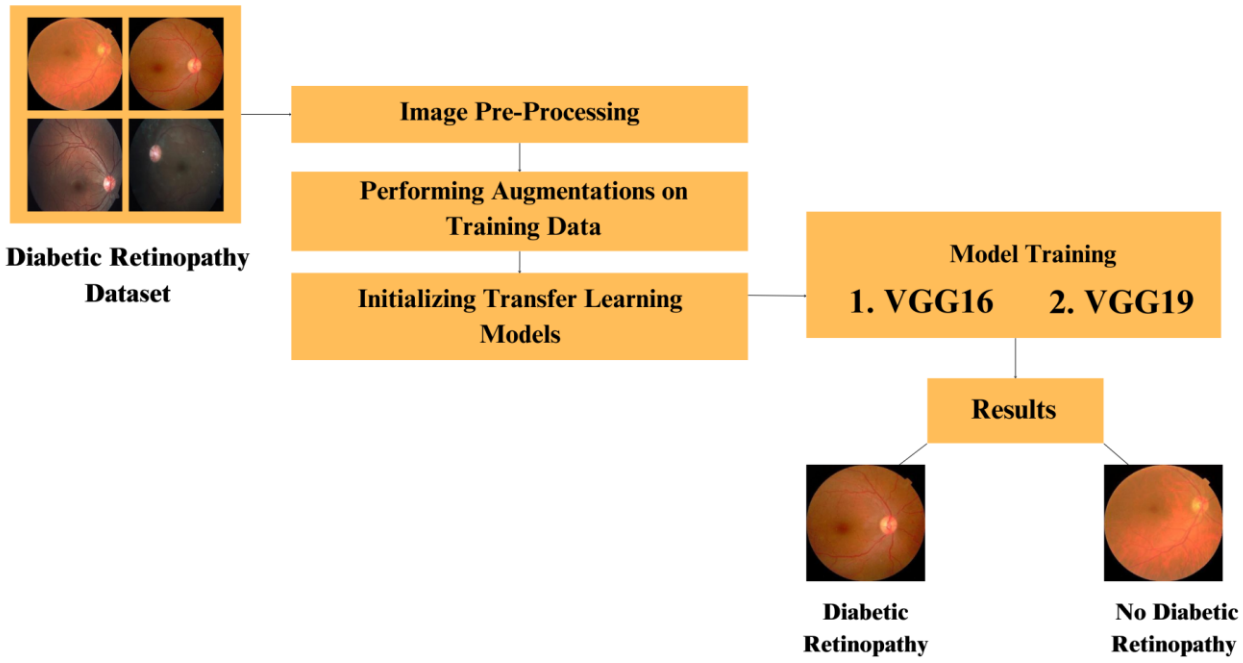

Figure 2. Flowchart of the proposed work.

3.3. Proposed Pre-Trained Models

This research investigates the suitability of pre-trained convolutional neural networks (CNNs) for automated diabetic retinopathy (DR) diagnosis using Colour Fundus images. Two prominent architectures, VGG16 and VGG19, are evaluated for their potential in this task.

3.3.1. Visual Geometry Group 16 (VGG16):

VGG16 offers a compelling choice for DR classification due to its balanced architecture (16 layers). This balance translates to:

- **Efficient Feature Extraction:** Pre-trained on the massive ImageNet dataset, VGG16's weights provide a strong foundation for feature extraction in the domain of medical images. These pre-learned features can be effectively fine-tuned for DR classification from Colour Fundus images.
- **Focus on Critical Visual Patterns:** VGG16's convolutional layers have the capability to automatically learn crucial visual patterns from Colour Fundus images. These patterns might differentiate between healthy and DR-affected retinas, aiding in accurate classification.
- **Alignment with Research Goal:** VGG16 is inherently suited for binary classification tasks, perfectly aligning with our research objective of classifying images as either Diabetic Retinopathy or No Diabetic Retinopathy.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 32, 32, 3)]	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv2 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv3 (Conv2D)	(None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 500)	256500
dropout (Dropout)	(None, 500)	0
dense_1 (Dense)	(None, 600)	300600
dropout_1 (Dropout)	(None, 600)	0
dense_2 (Dense)	(None, 400)	240400
dense_3 (Dense)	(None, 2)	802

Total params: 15512990 (59.18 MB)
Trainable params: 798302 (3.05 MB)
Non-trainable params: 14714688 (56.13 MB)

Figure 3. Configuration of VGG16 Model.

3.3.2. Visual Geometry Group 19 (VGG19):

VGG19 presents an alternative approach with its deeper architecture (19 convolutional layers). This increased depth allows for:

- **Potentially Richer Feature Learning:** VGG19's additional layers might enable it to learn more intricate and specific features from Colour Fundus images compared to VGG16. These richer features could potentially lead to more accurate DR classification.
- **Computational Cost Consideration:** While the potential for enhanced accuracy with VGG19 is promising, it's crucial to evaluate the trade-off. The deeper architecture might come at the cost of increased computational resources required for training and running the model.

A core aspect of this research involves a comparative analysis of VGG16 and VGG19 performance. This evaluation will determine if the potential benefits of VGG19's deeper learning outweigh the computational cost, ultimately identifying the optimal pre-trained CNN architecture for automated DR diagnosis using Colour Fundus images.

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 32, 32, 3)]	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv4 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv4 (Conv2D)	(None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv2 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv3 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv4 (Conv2D)	(None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0
flatten_2 (Flatten)	(None, 512)	0
dense_8 (Dense)	(None, 500)	256500
dropout_4 (Dropout)	(None, 500)	0
dense_9 (Dense)	(None, 600)	300600
dropout_5 (Dropout)	(None, 600)	0
dense_10 (Dense)	(None, 400)	240400
dense_11 (Dense)	(None, 2)	802

Total params: 20822686 (79.43 MB)
Trainable params: 798302 (3.05 MB)
Non-trainable params: 20024384 (76.39 MB)

Figure 4. Configuration of VGG19 Model.

4. EXPERIMENTS AND RESULTS

The Two Pre-trained models, VGG16 and VGG19 are implemented in Python 3.11.4: Jupyter Notebook , Here we detail the experimental setup and the results.

4.1. VGG16 Model :

Title	Results
Loss	0.1783
Accuracy	93.96%
No. of Parameters (Total)	15.51299 M
No. of Parameters (Trainable)	0.798302 M

Table 1. Performance Analysis for VGG16 Model.

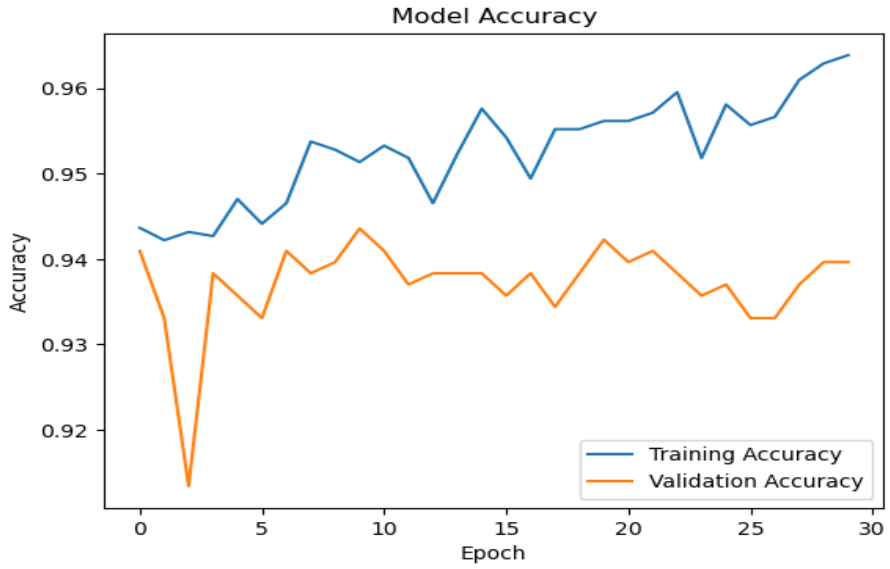

Figure 5. Comparison between training accuracy and validation accuracy for VGG16 Model.

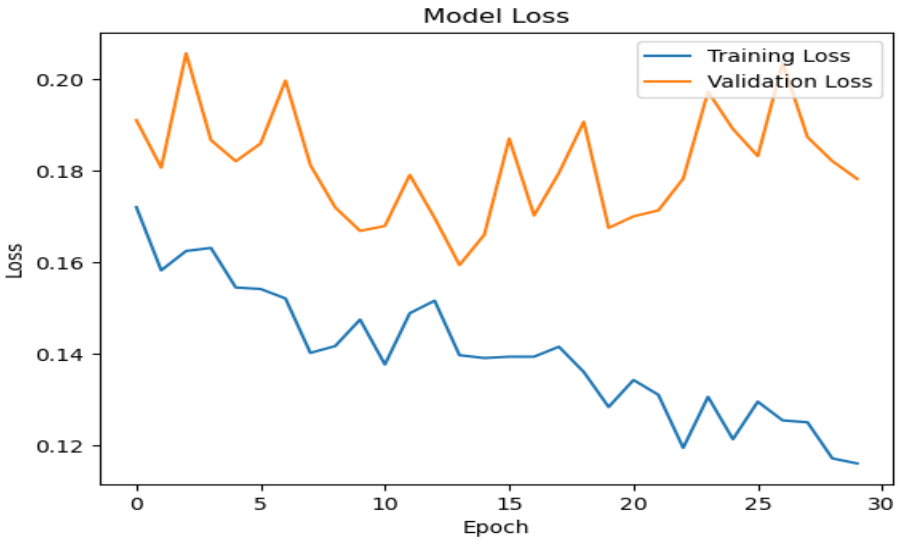

Figure 6. Comparison between training loss and validation loss for VGG16 Model.

4.2. VGG19 Model :

Title	Results
Loss	0.2318
Accuracy	91.99%
No. of Parameters (Total)	20.822686 M
No. of Parameters (Trainable)	0.798302 M

Table 2. Performance Analysis for VGG19 Model.

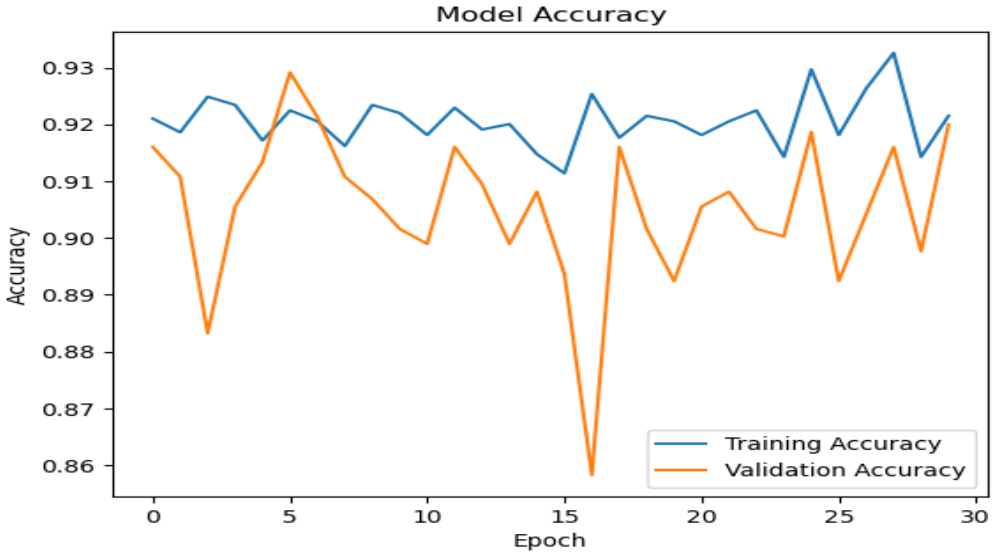

Figure 7. Comparison between training accuracy and validation accuracy for VGG19 Model.

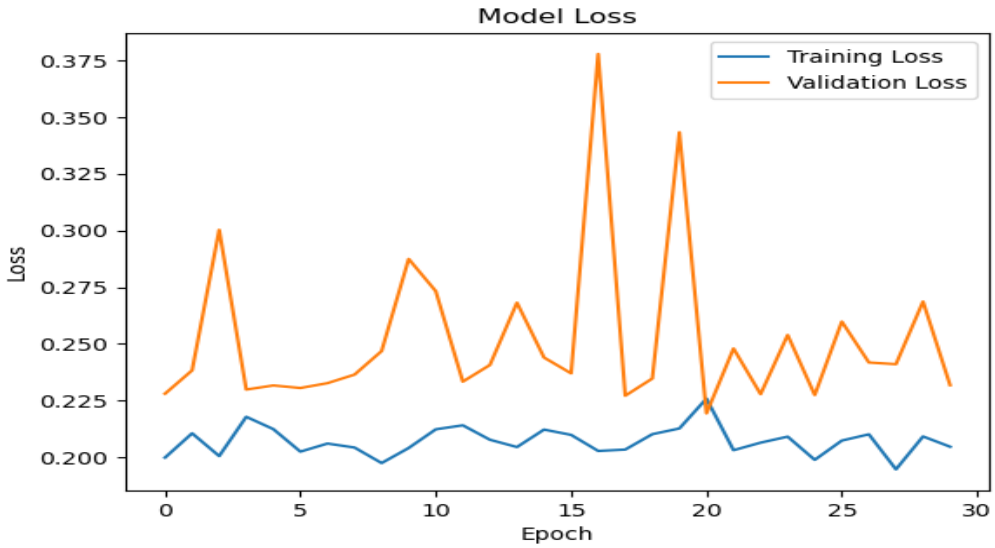

Figure 8. Comparison between training loss and validation loss for VGG19 Model.

Pre-Trained Models	Loss	Accuracy	No. of Parameters (Total)	No. of Parameters (Trainable)
VGG16	0.1783	93.96%	15.51299 M	0.798302 M
VGG19	0.2318	91.99%	20.822686 M	0.798302 M

Table 3. Comparison Between Pre-Trained Models used in Proposed Work.

5. CONCLUSION

This research investigated the potential of pre-trained convolutional neural networks (CNNs) for automated diabetic retinopathy (DR) diagnosis using Colour Fundus images. We evaluated the performance of VGG16 and VGG19 architectures in classifying these images for DR detection. Our analysis revealed that VGG16 achieved a superior accuracy of 93.96% in classifying DR compared to VGG19, which achieved an accuracy of 91.99%. This finding suggests that pre-trained CNNs, particularly VGG16 in this case, hold significant promise for automated DR diagnosis. By leveraging this approach, we can develop reliable automated screening tools, potentially leading to improved efficiency, wider accessibility for DR screening, and ultimately earlier intervention for patients.

REFERENCES

[1] Mujeeb Rahman KK, Nasor M, Imran A. Automatic Screening of Diabetic Retinopathy Using Fundus Images and Machine Learning Algorithms. *Diagnostics*. 2022; 12(9):2262. https://doi.org/10.3390/diagnostics12092262

[2] S.A, Sivakumar & B., Maruthi Shankar & Naveen, R.. (2019). Diabetic Retinopathy Detection using Image Processing. International Journal of Engineering and Advanced Technology. 8. 937-941. 10.35940/ijeat.F1179.0886S19.

[3] Malhi, A., Grewal, R. & Pannu, H.S. Detection and diabetic retinopathy grading using digital retinal images. *Int J Intell Robot Appl* **7**, 426–458 (2023). https://doi.org/10.1007/s41315-022-00269-5

[4] Akter, M., Uddin, M. S., Khan, M. H.: Morphology-based exudates detection from color fundus images in diabetic retinopathy. In: 2014 International Conference on Electrical Engineering and Information & Communication Technology, IEEE, pp. 1–4, (2014)

[5] Aleem, S., Sheng, B., Li, P., Yang, P., Feng, D.D.: Fast and accurate retinal identification system: using retinal blood vasculature landmarks. IEEE Trans. Indus. Inform. **15**(7), 4099–4110 (2018)

[6] Carrera, E. V., González, A., Carrera, R.: Automated detection of diabetic retinopathy using svm. In: 2017 IEEE XXIV International Conference on Electronics, Electrical Engineering and Computing (INTERCON), IEEE, pp. 1–4 (2017)

[7] Choudhury, S., Bandyopadhyay, S., Latib, S., Kole, D., Giri, C.: Fuzzy c means based feature extraction and classification of diabetic retinopathy using support vector machines. In: 2016 International Conference on Communication and Signal Processing (ICCSP), IEEE, pp. 1520–1525 (2016)
[8] Gurudath, N., Celenk, M., Riley, H. B.: Machine learning identification of diabetic retinopathy from fundus images. In: 2014 IEEE Signal Processing in Medicine and Biology Symposium (SPMB), IEEE, pp. 1–7 (2014)

[9] Pal, R., Poray, J., Sen, M.: Application of machine learning algorithms on diabetic retinopathy. In: 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), IEEE, pp. 2046–2051 (2017)

[10] Ravishankar, S., Jain, A., Mittal, A.: Automated feature extraction for early detection of diabetic retinopathy in fundus images. In: 2009 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 210–217 (2009)

[11] Xu, K., Feng, D., Mi, H.: Deep convolutional neural network-based early automated detection of diabetic retinopathy using fundus image. Molecules **22**(12), 2054 (2017)

[12] Yadav, J., Sharma, M., Saxena, V.: Diabetic retinopathy detection using feedforward neural network. In: 2017 Tenth International Conference on Contemporary Computing (IC3), IEEE, pp. 1–3 (2017)

[13] Yalçin, N., Alver, S., Uluhatun, N.: Classification of retinal images with deep learning for early detection of diabetic retinopathy disease. In: 2018 26th Signal Processing and Communications Applications Conference (SIU), IEEE, pp. 1–4 (2018)

[14] Yu, S., Xiao, D., Kanagasingam, Y.: Exudate detection for diabetic retinopathy with convolutional neural networks. In: 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, pp. 1744–1747 (2017)

.

[15] Padmanayana, & Kadan, Anoop. (2022). Binary Classification of DR-Diabetic Retinopathy using CNN with Fundus Colour Images. Materials Today: Proceedings. 58. 10.1016/j.matpr.2022.01.466.

[16] Das D, Biswas SK, Bandyopadhyay S. Detection of Diabetic Retinopathy using Convolutional Neural Networks for Feature Extraction and Classification (DRFEC). Multimed Tools Appl. 2022 Nov 29:1-59. doi: 10.1007/s11042-022-14165-4. Epub ahead of print. PMID: 36467440; PMCID: PMC9708148.

[17] Dataset - https://www.kaggle.com/datasets/pkdarabi/diagnosis-of-diabetic-retinopathy