International Journal of Advanced Computer Technology
ISSN: 2319-7900 www.ijact.org Volume 14, Issue 1, February 2025

Automated Diabetic Retinopathy Detection Using Deep Learning: A Comparative Analysis of VGG-16 and ResNet50

Ankit Sharma, Parv Wadhwa, Saksham Arora
School of Computer Sciences and Technology
Bennett University Greater Noida
e22cseu0352@bennett.edu.in, e22cseu0561@bennett.edu.in, e22cseu0360@bennett.edu.in

Abstract—Diabetic retinopathy (DR) is a leading cause of blindness worldwide, primarily affecting individuals with prolonged diabetes. Early detection is crucial for preventing severe vision loss, yet conventional diagnostic methods are time-intensive and require specialized expertise. This study proposes a deep learning-based automated DR classification system utilizing convolutional neural networks (CNNs), specifically VGG-16 and ResNet50 architectures. The model classifies DR into five categories: normal, mild, moderate, severe, and proliferative DR. A dataset of retinal fundus images was preprocessed and analyzed using these CNN models, with performance evaluated based on classification accuracy. The VGG-16 model achieved an accuracy of 79.99%, outperforming ResNet50, which attained 70%. The findings highlight the effectiveness of deep learning in automated DR screening, demonstrating its potential for enhancing early diagnosis and patient care. Further improvements, such as advanced preprocessing, data augmentation, and hybrid modelling, can refine the accuracy and clinical applicability of AI-driven diagnostic tools.

Keywords— Diabetic Retinopathy, Deep Learning, Convolutional Neural Networks, VGG-16, Resnet50, Retinal Image Analysis.

Introduction

Diabetic Retinopathy (DR) is a severe complication of diabetes that affects the blood vessels in the retina, the light-sensitive tissue at the back of the eye. Left untreated, DR can progress from mild visual impairment to complete blindness. The condition is particularly prevalent among individuals with Type 1 and Type 2 diabetes, especially those with prolonged high blood sugar levels. Despite its severity, DR often remains undiagnosed in its early stages due to a lack of noticeable symptoms. Early detection of DR is critical to preventing severe vision loss. Regular eye screenings allow for timely interventions, reducing the risk of irreversible damage. However, traditional diagnostic methods, such as dilated eye exams and fundus photography, are resource-intensive and often inaccessible in rural or underdeveloped areas. Automated detection systems leveraging artificial intelligence (AI) and deep learning offer a promising solution to this challenge by enabling fast, accurate, and cost-effective screening. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable potential in medical image analysis, especially for detecting diabetic retinopathy (DR). CNN models can efficiently process retinal fundus images and identify key features associated with different severity levels of DR, ranging from No DR to Mild, Moderate, Severe, and Proliferative DR. Advanced CNN architectures, such as VGG-16 and ResNet50, are capable of automatically learning hierarchical features from retinal images, reducing the need for manual feature extraction. However, despite their effectiveness, challenges such as dataset limitations and model generalization remain critical areas for further improvement.

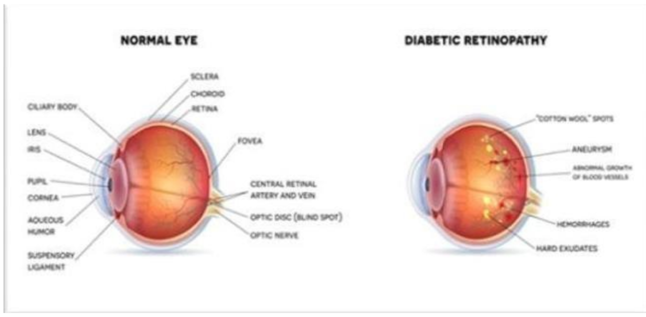

Fig:1 shows normal and diabetic eyes.

Figure 1 shows normal and diabetic eyes, highlighting the differences in retinal structure that aid in identifying DR. The primary objective of this research is to develop an efficient deep learning-based system for automated diabetic retinopathy (DR) classification, enabling early detection and improving patient outcomes. This study focuses on comparing the performance of VGG-16 and ResNet50 models for DR classification, developing a novel blood vessel segmentation technique to enhance classification accuracy, and employing data augmentation methods to address dataset limitations. Additionally, advanced preprocessing techniques are applied to optimize model performance, increasing accuracy while reducing false classifications. By leveraging CNN-based architectures and image enhancement techniques, this study aims to contribute to the development of scalable, AI-driven diagnostic solutions that can be implemented in both clinical and remote healthcare settings, ultimately reducing the prevalence of diabetes-induced blindness worldwide.

Literature Review

Ophthalmologists or optometrists primarily perform traditional diabetic retinopathy detection through comprehensive eye examinations. These methods have been the standard approach for diagnosing DR and assessing its severity.

2.1. Visual Acuity Test

A visual acuity test is one of the initial steps in diagnosing DR. This test measures the patient's ability to see clearly at various distances, helping detect early vision impairment. Changes in visual acuity may indicate retinal damage caused by DR, prompting further diagnostic evaluation.

2. Pupil Dilation and Fundus Examination

Eye specialists perform pupil dilation using eye drops to thoroughly examine the retina, allowing for a detailed inspection of the retinal blood vessels, macula, and optic nerve. A fundus examination is then conducted using an ophthalmoscope or a specialized fundus camera to capture high-resolution images of the retina. These images help in identifying key indicators of diabetic retinopathy (DR), such as microaneurysms, which are small bulges in retinal blood vessels, and haemorrhages, which appear as bleeding spots caused by vessel rupture. Additionally, oedema, or swelling in the macula, can lead to vision distortion. At the same time, neovascularization, the formation of abnormal new blood vessels, signals advanced stages of DR. Despite their effectiveness, traditional diagnostic methods are time-consuming, require specialized expertise, and are often inaccessible in rural or underserved regions. The increasing demand for more efficient, scalable, and accessible solutions has driven the development of AI-assisted DR detection techniques, which leverage deep learning models to automate the screening process, improving early diagnosis and patient outcomes.

B. Modern DR Detection Approaches

With advancements in medical imaging and AI, modern approaches to DR detection aim to enhance diagnostic accuracy, reduce human error, and increase accessibility. Two key innovations in this domain include telemedicine and AI-assisted diagnosis.

1. Telemedicine and AI-assisted diagnosis

Telemedicine has revolutionized DR detection by enabling remote screening and diagnosis. Patients can have their retinal images captured using a fundus camera at local healthcare centres, and these images can then be transmitted to specialists for evaluation. Telemedicine bridges the gap between patients and ophthalmologists, particularly in areas with limited access to eye care facilities. AI-assisted diagnosis further enhances the effectiveness of telemedicine. AI algorithms can analyze retinal images automatically, detecting DR-related abnormalities without requiring an ophthalmologist to review every image manually. This significantly reduces the workload of specialists while improving early detection rates.

2. Benefits of AI in DR Screening

AI-driven diabetic retinopathy (DR) detection systems offer several significant advantages, making them a transformative tool in modern ophthalmology. Increased efficiency is one of the key benefits, as automated screening enables faster and more accurate DR detection compared to traditional manual assessments. Additionally, scalability allows AI models to be integrated into telemedicine networks, making DR screening accessible even in remote and underserved regions where specialized ophthalmologists may not be available. Another major advantage is early intervention, as AI can detect subtle retinal abnormalities at an early stage, allowing for timely medical treatment and reducing the risk of severe vision loss. Moreover, AI-driven screening contributes to cost reduction by minimizing the need for frequent in-person ophthalmology visits, lowering healthcare costs for both patients and medical institutions. These advancements have positioned AI as a game-changer in DR detection, leading to the widespread adoption of deep learning models for automated image classification, ultimately improving diagnostic accuracy and patient outcomes.

C. AI-Based DR Detection

Artificial intelligence, particularly deep learning-based approaches, has emerged as a powerful tool for DR detection. Convolutional Neural Networks (CNNs) are widely used for analyzing retinal fundus images, allowing for automated classification of DR severity levels. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in medical image analysis due to their ability to extract and learn hierarchical features from images automatically. In diabetic retinopathy (DR) detection, CNNs process retinal fundus images and classify them into five categories: No DR (healthy retina), Mild DR (early-stage damage with microaneurysms), Moderate DR (increased haemorrhages and vascular changes), Severe DR (significant retinal damage and neovascularization), and Proliferative DR (advanced stage with abnormal vessel growth and high risk of vision loss). Popular CNN architectures such as VGG-16 and ResNet50 have been extensively utilized for DR classification. These models are pre-trained on large-scale image datasets and later fine-tuned to recognize DR-specific retinal features with high accuracy. The VGG-16 model is a deep CNN architecture with 16 layers. It is known for its simple yet effective design, making it widely used in medical imaging tasks.

On the other hand, ResNet50 is a 50-layer deep residual network designed to learn complex visual patterns while addressing the vanishing gradient problem in deep networks. Studies indicate that CNN-based models can match or even surpass human-level accuracy in DR detection, making them highly viable for real-world clinical applications, particularly in automated screening and early diagnosis. One of the biggest challenges in AI-based diabetic retinopathy (DR) detection is the limited availability of labelled retinal images for training deep learning models. To overcome this, transfer learning is commonly employed, where pre-trained convolutional neural network (CNN) models are fine-tuned on DR-specific datasets. This approach allows AI models to leverage prior knowledge from large medical imaging datasets, enhancing classification accuracy while requiring fewer training images. Recent studies have demonstrated that AI models can achieve remarkable accuracy in DR detection, with sensitivity rates as high as 91.7% and specificity rates of 98.5%. However, despite these advancements, AI-based DR detection systems still face several challenges. Data quality issues, such as variability in retinal image quality, can significantly impact model performance.

Additionally, biases in training data may lead AI models to underperform in certain demographics if the datasets are not sufficiently diverse. Another challenge is the interpretability of deep learning models, which often function as "black boxes," making it difficult to understand their decision-making processes. While AI-driven DR screening shows great promise, these challenges emphasize the need for AI to be used in combination with traditional diagnostic techniques to ensure both reliability and accuracy.

The detection of diabetic retinopathy has evolved from traditional ophthalmic examinations to AI-assisted screening techniques, significantly improving the accuracy and accessibility of DR diagnosis. Telemedicine and deep learning models, particularly CNN architectures like VGG-16 and ResNet50, have demonstrated remarkable potential in automating DR classification. Furthermore, transfer learning has helped overcome dataset limitations, enhancing the generalizability of AI models. Despite its advantages, AI-based DR detection is not without limitations. Issues related to data quality, bias, and model interpretability need to be addressed before widespread clinical adoption. Nonetheless, integrating AI with traditional diagnostic methods offers a comprehensive and scalable solution for early DR detection, ultimately reducing diabetes-related blindness worldwide.

Methodology and Materials

A. Deep Learning for Image Classification

Although artificial neural networks have already been extensively utilized in medical imaging, a particular kind of neural network called a "Deep Network," particularly CNN (Convolutional Neural Networks), yields remarkable results in terms of categorization and extraction. CNNs have proven highly effective in recognizing handwritten characters and various complex patterns in images. CNNs eliminate the necessity for a time-consuming manual feature extraction process by automatically identifying important patterns. These networks consist of multiple layers responsible for extracting low-level and high-level features. The first layers focus on detecting edges and textures, while deeper layers learn more abstract representations. CNNs employ specific techniques to enhance their robustness and accuracy. Dropout, for instance, allows deep networks to produce accurate results even when some functionality is absent from the test data. This method prevents overfitting by randomly deactivating a fraction of neurons during training. Another essential component is the Rectified Linear Unit (ReLU), a transfer function that prevents training saturation and enhances convergence speed. ReLU introduces non-linearity by setting all negative values to zero, ensuring that the network learns more complex patterns efficiently.

B. Model Selection

VGG-16 Architecture:- VGG-16 is a popular convolutional neural network variant known for its deep architecture, consisting of 16 layers, including 13 convolutional layers and three fully connected layers. The model requires learning 16 weight parameters and assigns an image of size 224x224 pixels to one of 1000 predefined classes. The output is a probability vector of size 1000, representing the likelihood of the image belonging to each class. The VGG-16 architecture is illustrated in Figure 2. This model utilizes 3x3 pixel filters with a stride of 1-pixel increments. Zero-padding is applied to maintain equal input and output dimensions. A ReLU activation layer follows each convolutional layer to enhance non-linearity. The last fully connected layers generate a 4096-dimensional vector, followed by a SoftMax activation function to classify the image.

ResNet50 Architecture:- The Residual Network (ResNet50) won the 2015 ImageNet Large Scale Visual Recognition Competition (ILSVRC). ResNet50 is a deep network comprising 50 layers with approximately 25.6 million parameters. It features a convolutional layer, identity blocks, and a fully connected layer. ResNet50 introduces the concept of residual learning, where the identity block ensures that the input signal is directly passed to deeper layers, preventing vanishing gradient issues. The output of a residual block is the sum of the input signal and the transformed signal from internal layers. The architecture of ResNet50 is shown in Figure 3.

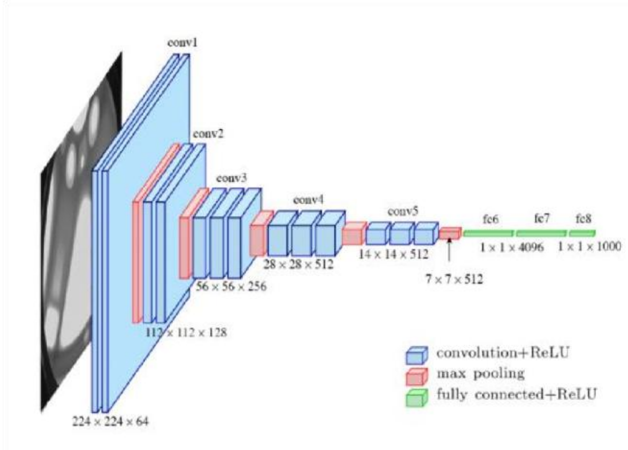

Fig. 2 Architecture of the VGG-16 Model.

C. Data Collection and Processing

The Fundus Image Dataset (EyePACS) is used in this research with a background camera, a specialized optical instrument combining a low-power microscope and a camera, to capture fundus images of the retina. This device simultaneously illuminates and scans the retina, producing high-resolution images of the macula, optic disc, and posterior pole. The dataset used in this study is sourced from EyePACS, a free platform for diabetic retinopathy screening.

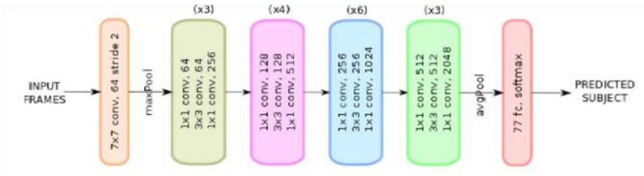

Fig. 3 Architecture of the ResNet50 Model.

The dataset comprises 35,126 retinal images captured under varying imaging conditions. Each subject has left and right eye images labelled accordingly (e.g., "1_left.png" represents the left eye of patient 1). Each image is resized to 224x224 pixels, and a clinician assigns a score from 0 to 4, indicating the severity of diabetic retinopathy. The distribution of images across different severity levels is shown in Table 1. The images undergo several preprocessing steps to enhance model performance and ensure consistency before training. Normalization is applied by scaling pixel values to a range of 0 to 1, which improves numerical stability and accelerates convergence during training. Additionally, image resizing is performed, where all images are adjusted to a uniform size of 224x224 pixels. This standardization ensures compatibility with deep learning architectures such as VGG-16 and ResNet50, allowing for efficient feature extraction and classification.

Table 1. Distribution of Images by Class and Stage, with Corresponding Size in Percentage.

Class	Stage	# Images	Size (%)
Normal Eyes	0	25,810	73
Mild DR	1	2,443	7
Moderate DR	2	5,292	15
Severe DR	3	873	2
Proliferative DR	4	708	2

D. Image Segmentation and Augmentation

Segmenting blood vessels in fundus images plays a crucial role in detecting diabetic retinopathy by highlighting key retinal structures. Techniques such as adaptive thresholding and morphological operations are employed to isolate blood vessel patterns, enabling more accurate classification and diagnosis. Additionally, various augmentation techniques are applied to enhance model generalization and improve robustness. Flipping, both horizontal and vertical, introduces variations in image orientation, while rotation randomly adjusts the images within a specific range to simulate different viewing angles. Blurring, particularly Gaussian blurring, is used to replicate varying focus levels, making the model more adaptable to diverse imaging conditions. These augmentation techniques collectively enhance model performance by increasing the diversity of training samples, reducing overfitting, and ensuring that convolutional neural networks (CNNs) generalize well to unseen data. These techniques improve model performance by increasing the diversity of training samples, reducing overfitting, and ensuring the CNNs generalize well to unseen data.

PROPOSED METHOD

A. System Workflow

The process of diagnosing Diabetic Retinopathy (DR) begins with acquiring a retinal image, specifically a fundus image, which serves as the primary input for analysis. Before proceeding with the detection, the image undergoes preprocessing to enhance its quality, including data-cleaning techniques aimed at removing extraneous details or noise. This improves the image's clarity and ensures accurate detection. Following preprocessing, the retinal image is segmented into significant regions, such as blood vessels or lesions, which are crucial for identifying DR. Blood vessels, in particular, play a key role in DR detection, making their isolation necessary for precise classification. While traditional segmentation methods like U-NET have been widely used in previous studies, the lack of pre-segmented retinal images in the dataset prompts this study to explore alternative approaches. These methods combine filters and transformations to achieve high-quality segmentation directly from the fundus images. This segmentation step enhances the model's focus on relevant areas, thereby improving classification accuracy. Once the images are segmented, they undergo augmentation through various techniques, such as flipping, rotation, zooming, blurring, and brightness adjustments. This augmentation significantly increases the dataset's size, aiding in better generalization during model training. As a result, the augmented dataset includes over 11,000 images for training, while the validation dataset remains at 2,794 images.

B. CNN Model Training

For model training, the ResNet50 architecture was chosen due to its efficiency in image classification tasks. ResNet50 comprises 48 convolutional layers and incorporates batch normalization to enhance stability during the training process. The model employs the SoftMax function for classification, ensuring an accurate probability distribution across different classes. The learning rate was set to 0.0005, with training conducted over 200 epochs to achieve optimal accuracy. To further improve performance, hyperparameter tuning was carried out, adjusting key parameters such as learning rate, batch size, and dropout rates. This optimization ensures that the model generalizes well to new images, ultimately enhancing the overall classification accuracy for detecting Diabetic Retinopathy (DR). The system workflow and model architecture are visually represented in the flowchart in Figure 4.

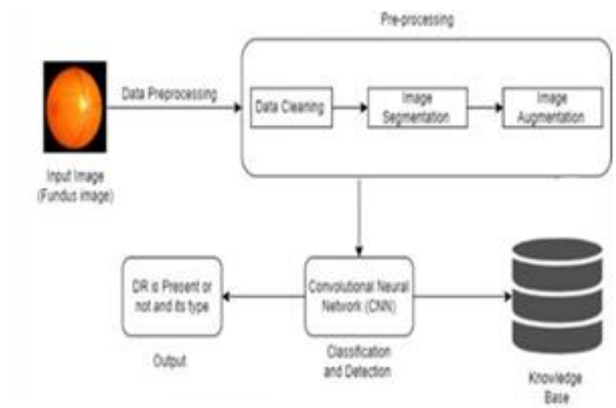

Fig. 4 Pipeline Process of the Proposed Model

Results and Discussion

The model processed all 2,794 images in just 210 seconds, showcasing its efficiency in handling large datasets. This rapid processing speed highlights the system's potential for real-time clinical and diagnostic applications. The model achieved an overall classification accuracy of 71.51%, as shown in Table 2, which demonstrates its capability to analyze intricate retinal features associated with different stages of diabetic retinopathy.

Table 2. Comparison of VGG-16 and ResNet50 Performance.

Models	Acc (%)	Pre (%)	Rec (%)
VGG-16	79.99	80	78
ResNet50	70	72	68

A. Performance of VGG-16

The results, as demonstrated in Figure 5, show the training and validation accuracy trends of the VGG-16 model, confirming its effectiveness in early diabetic retinopathy detection. Similarly, Figure 6 presents the training and validation loss curves, illustrating how the model's learning process stabilized over time.

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ISSN: 2319-7900 www.ijact.org Volume 14, Issue 1, February 2025

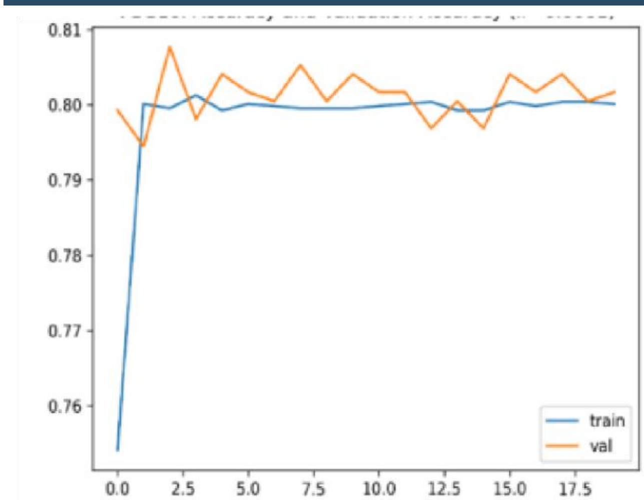

Fig. 5 Training and Validation Accuracy of the VGG-16 Model.

The model was trained on a balanced dataset consisting of 3,448 training images and 862 validation images, using the Categorical Cross-Entropy loss function and the ADAM optimizer. Through careful tuning, the model achieved its best performance with a learning rate of 0.0001 over 20 epochs, reaching an accuracy of 79.99%. While VGG-16 outperforms many conventional methods in classification accuracy, its high computational demands pose challenges for real-time deployment. Despite its effectiveness in detecting retinal patterns, the model requires substantial processing power, which may limit its practical application in clinical settings.

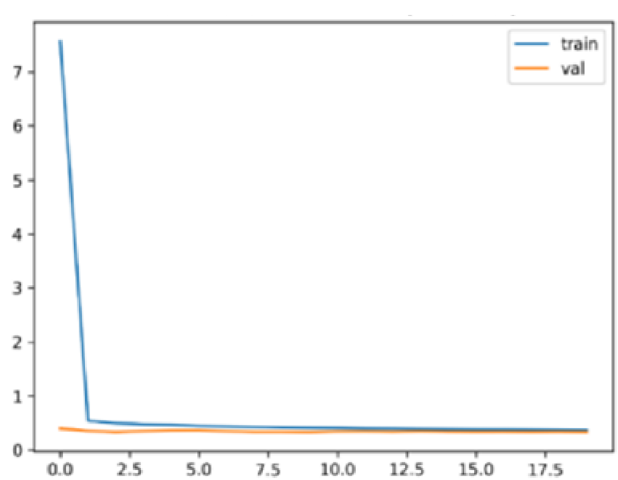

Fig. 6 Training and Validation Loss of the Model.

B. Performance of ResNet50

The accuracy and loss trends of the ResNet50 model over 15 epochs are illustrated in Figures 7 and 8, respectively. Figure 7 shows the training and validation accuracy trends, where the validation accuracy remains steady at approximately 70%, while the training accuracy stabilizes only after epoch 2. This indicates an initial learning phase before convergence. Figure 8 presents the training and validation loss curves, highlighting a sharp decline in loss from 5.5 in Epoch 1 to 1.52 in Epoch 2, reflecting improved learning efficiency and better feature extraction as training progresses. The confusion matrix analysis highlights the classification consistency of ResNet50. Although the model maintains stable validation accuracy, some misclassifications persist, suggesting potential areas for improvement. Fine-tuning hyperparameters, enhancing preprocessing techniques, or incorporating additional data augmentation methods could help mitigate these misclassifications and enhance overall model performance.

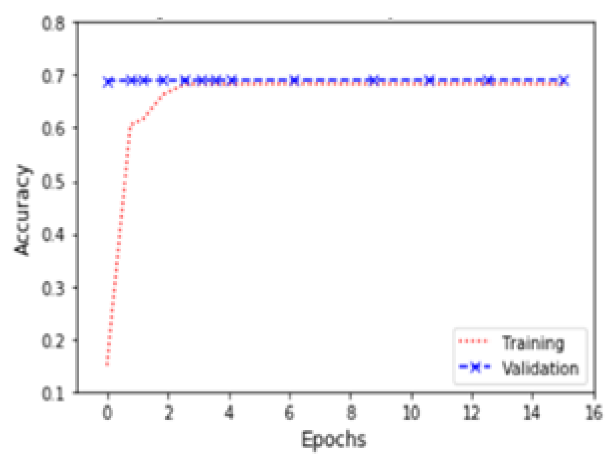

Fig. 7 Training and Validation Accuracy of the ResNet50 Model.

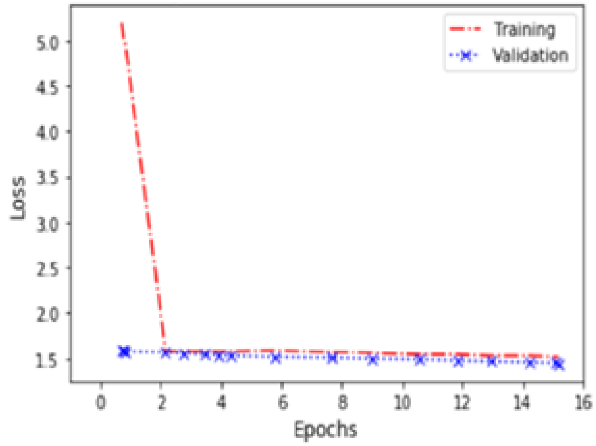

Fig. 8 Training and Validation Loss of the ResNet50 Model.

C. Comparison of Model Performance

When comparing the performance of VGG-16 and ResNet50, VGG-16 achieved a higher accuracy of 79.99%, as shown in Table 2, whereas ResNet50's validation accuracy remained at 70%. Despite this, ResNet50 demonstrated superior generalization capabilities due to its residual learning approach, which effectively mitigates vanishing gradient issues. This enables ResNet50 to maintain stable learning even in deeper architectures, making it more adaptable to complex feature extraction. While both models perform well in diabetic retinopathy classification, several improvements could further enhance their accuracy and robustness. Fine-tuning hyperparameters, expanding data augmentation techniques, and implementing ensemble modelling may help improve performance. Additionally, incorporating attention mechanisms or hybrid models could refine the classification process by focusing on critical retinal features, leading to more reliable and precise diabetic retinopathy detection.

Conclusion

Deep learning technologies like ResNet-50 and VGG-16 have revolutionized diabetic retinopathy (DR) diagnosis by enabling faster detection and improved accuracy compared to traditional methods. ResNet-50 achieved a classification accuracy of 70%, benefiting from its residual learning architecture, which effectively addresses issues such as overfitting and vanishing gradients. On the other hand, VGG-16, with enhancements like SMOTE for data balancing, achieved a higher accuracy of 79.99%, demonstrating the potential of deep learning models to produce reliable and clinically valuable results. Beyond aiding ophthalmologists in early DR severity assessment, these AI-driven systems open avenues for developing similar models for diagnosing other vision-related disorders. By integrating automated screening technologies, healthcare systems can enhance patient outcomes and prevent blindness through timely interventions. Future improvements, such as hyperparameter tuning, advanced augmentation techniques, and attention mechanisms, can further enhance model performance, making AI a cornerstone in medical diagnosis and healthcare innovation.

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