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Exploring the Intersection of AI and Diabetes: Insights through Non-invasive Technique Using Retina

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Abstract— Diabetes mellitus, a major threat to global health, can have serious complications, like diabetic retinopathy, the primary cause of blindness in people of working age. Novel developments in artificial intelligence (AI) present encouraging prospects for the timely identification, diagnosis, and treatment of diabetic retinopathy via retinal imaging. The focus of this research is on how deep learning models and machine learning algorithms are revolutionizing retinal screening procedures as it examines the relationship between AI and diabetes management. Artificial intelligence (AI) algorithms are able to recognize small changes in retinal structures with great accuracy, frequently outperforming human specialists, by evaluating large databases of retinal images. This paper explores the application of a customized VGG model, which is fine-tuned to classify diabetic retinopathy images into five severity levels with an accuracy of 93.75%. The customised VGG model is benchmarked against existing AI frameworks, including VGG 16 and VGG 19 to validate its performance. Due to the ability to intervene promptly, these advancements not only improve treatment outcomes but also aid in early detection. Moreover, the examination of AI integration into clinical practice looks at issues including data protection, ethical constraints, and the requirement for ongoing learning to keep up with changing medical knowledge. The research highlights how AI has the potential to transform diabetes treatment and lessen the prevalence of visual loss worldwide in its conclusion.

***Keywords*— Diabetes mellitus, Diabetic retinopathy, Artificial intelligence (AI) in healthcare, Retinal imaging, Deep learning models, Machine learning algorithms, AI in diabetes management, Retinal screening, AI in early detection, AI in clinical practice, Ethical considerations in AI, Data protection in AI healthcare, AI for visual loss prevention, AI-based retinal diagnosis, AI revolution in diabetes care**

1. INTRODUCTION

A. *Diabetes and Its Global Impact*

The Global Burden of Diseases (GBD), Injuries, and Risk Factors Study provides the most comprehensive and up-to-date analytical framework for understanding the global impact of diabetes. Drawing on this resource, researchers have developed detailed, location-specific, age-specific, and gender-specific estimates of diabetes prevalence and burden spanning from 1990 to 2021. Additionally, the study offers insights into the proportions of type 1 and type 2 diabetes cases in 2021, identifies risk factors contributing to the type 2 diabetes burden, and projects diabetes prevalence trends through 2050.

Diabetes has emerged as a significant global health crisis, profoundly affecting individuals, families, and healthcare systems worldwide. According to the International Diabetes Federation (IDF) Diabetes Atlas 2021, approximately 10.5% of adults aged 20 to 79 are living with diabetes. Alarmingly, nearly half of these individuals remain undiagnosed, underscoring the critical need for improved screening and awareness programs.

B. *Diabetes Mellitus (DM): A Chronic Health Challenge*

Diabetes mellitus (DM) is a chronic metabolic disorder characterized by persistently elevated blood glucose levels. This condition poses significant health risks, leading to various acute and long-term complications. Among these are cardiovascular disease, diabetic neuropathy, nephropathy, and retinopathy, with Diabetic Retinopathy (DR) standing out as a leading cause of vision impairment and blindness among adults globally.

C. *Diabetic Retinopathy: A Window into Vascular Health*

Diabetic Retinopathy (DR) is a microvascular complication of diabetes caused by prolonged hyperglycemia, leading to damage in the retinal blood vessels. It is categorized by the presence of hallmark lesions, including microaneurysms, hemorrhages, hard exudates, and neovascularization. The timely detection and management of DR are crucial to preventing severe vision loss, making routine retinal examinations a cornerstone of diabetes care.

The retina offers a unique and accessible view of the vascular system, acting as a "window" into an individual's systemic health. Pathological changes in the retinal microvasculature due to DR can be identified through non-invasive retinal imaging techniques such as:

- Fundus photography: Provides a two-dimensional image of the retina.
- Optical coherence tomography (OCT): Captures cross-sectional images of the retina, revealing its layers and structural abnormalities.
- Fluorescein angiography: Highlights the vascular changes in the retina through the use of fluorescent dye.

These imaging modalities enable clinicians to detect and assess DR progression, offering critical insights for treatment planning.

D. *Artificial Intelligence (AI) in Diabetic Retinopathy Detection*

In recent years, Artificial Intelligence (AI), particularly deep learning algorithms, has revolutionized the field of DR detection and management. Deep learning, a subfield of AI, leverages artificial neural networks to recognize complex data patterns. Convolutional Neural Networks (CNNs), a key architecture in deep learning, have been extensively trained on large datasets of annotated retinal images to automatically detect and classify DR severity levels.

These AI-driven systems excel in:

- Analyzing large datasets: AI systems process vast amounts of data efficiently, identifying patterns that might elude human observers.
- Ensuring diagnostic consistency: AI reduces variability in assessments, ensuring objective and reliable results.
- Enhancing accessibility: By automating diagnosis, AI bridges gaps in regions with limited access to trained ophthalmologists.

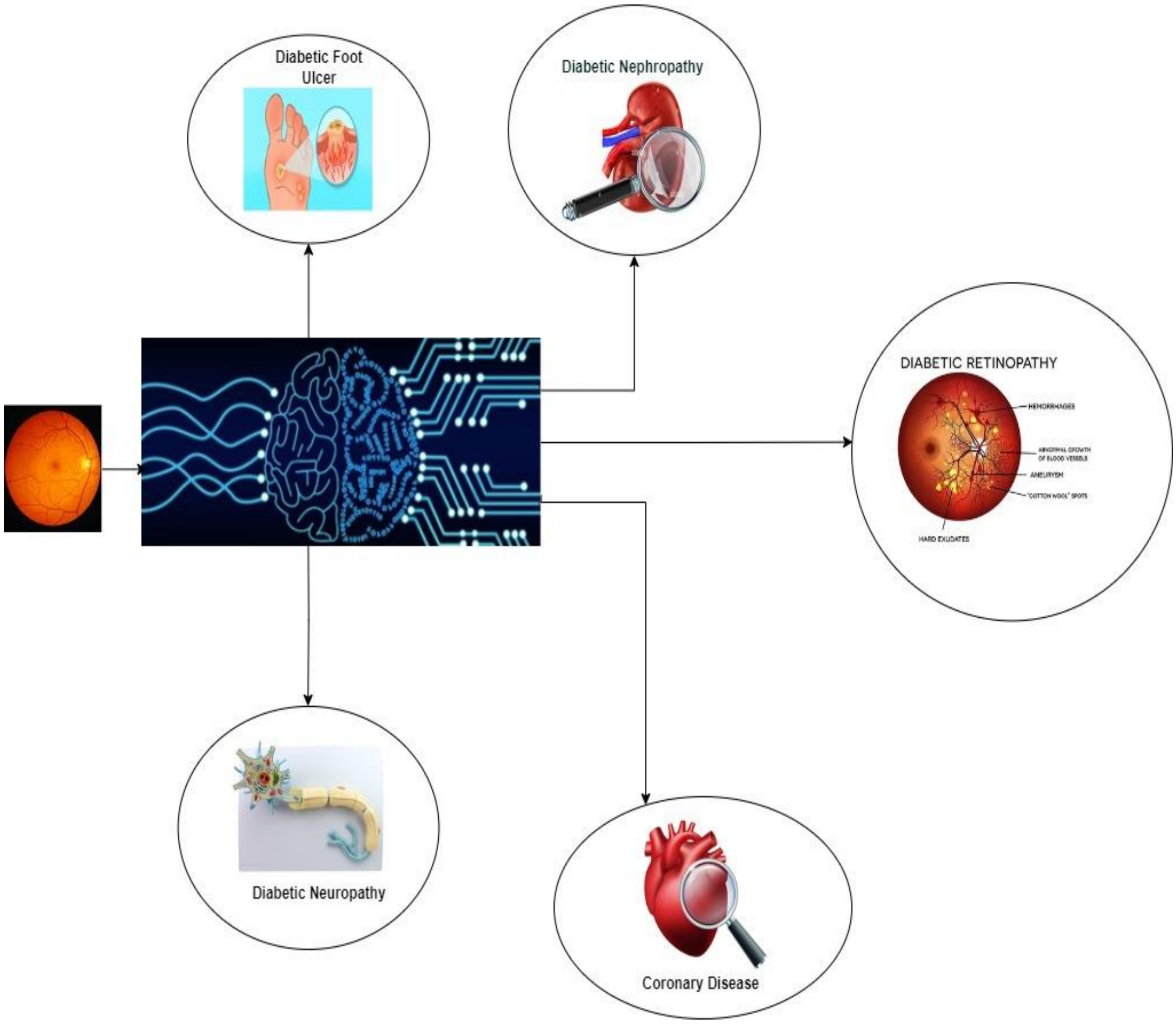

Figure 1 illustrates an advanced AI-driven diagnostic system capable of detecting various diabetes-related complications—including retinopathy, neuropathy, nephropathy, coronary disease, and diabetic foot ulcers—through the analysis of retinal images.

E. The Benefits of AI-Powered DR Screening

The integration of AI into DR screening offers transformative benefits:

- Cost-effectiveness: AI reduces reliance on expensive equipment and specialized personnel.
- Speed and efficiency: AI systems process retinal images rapidly, enabling high-throughput screenings.
- Scalability: AI technology can be deployed in remote or underserved areas, enhancing healthcare access.
- Prevention of complications: Early detection and intervention minimize the risk of severe outcomes, reducing future healthcare costs.

This scalable and non-invasive approach is reshaping diabetes care by delivering timely and accurate DR screening, particularly in regions with resource constraints. With fewer complications and a reduced need for specialist referrals, AI-powered systems promise to make diabetes-related vision care more accessible, affordable, and effective.

2. LITERATURE REVIEW

A. *Advancing AI Applications in Diabetes and Related Complications*

R. Poplin et al.[4] (2018) published a groundbreaking study in *Nature Biomedical Engineering* demonstrating how deep learning can predict cardiovascular risk factors using retinal fundus photographs. By employing the Inception V3 architecture, the study extracted and quantified multiple cardiovascular risk factors from retinal images. This approach revealed how retinal imaging could offer insights beyond ophthalmologic health, marking a significant step toward AI-driven systemic disease prediction.

Benson et al. [5] investigated the application of CNN VGG16 for assessing the risk of Diabetic Peripheral Neuropathy (DPN) through retinal imaging. By analyzing digital fundus photographs, this approach demonstrated the potential of machine learning in identifying early signs of DPN, enhancing early detection and improving patient outcomes.

Cervera et al. [6] expanded on this concept by leveraging multiple deep learning architectures, including SqueezeNet, Inception, and DenseNet, to analyze color fundus photographs for the detection of Peripheral Neuropathy (PN). The automated analysis improved diagnostic accuracy, reducing the need for manual evaluation and paving the way for scalable and efficient screening methods.

Shaomin et al. [7] took a novel approach by integrating AI and traditional clinical factors for diagnosing Diabetic Kidney Disease (DKD) in type 2 diabetes patients. Using Synthetic Minority Oversampling Technique (SMOTE), the model combined retinal vascular parameters with clinical data to enhance diagnostic precision. This study demonstrated how multi-modal data integration could elevate the diagnostic power of AI systems.

Shankar et al. [8] proposed an Extreme Learning Machine (ELM) model for predicting Diabetic Foot Ulcers (DFU). This method outperformed traditional algorithms like KNN, SVM, and ANN, achieving a remarkable 96.15% accuracy. The high efficiency of ELM highlights its potential for rapid, reliable, and cost-effective DFU prediction, making it an attractive option for clinical implementation.

Goyal et al. [9] explored AI's role in detecting ischemia and infection in DFUs. By introducing a new dataset and testing both traditional and deep learning methods, the Ensemble CNN model achieved the highest accuracy. This advancement emphasizes the potential of AI in remote monitoring and early intervention for diabetic foot complications.

Benson J et al. [10] revisited DPN risk assessment using CNN-VGG16, achieving an impressive 89% accuracy. Their method demonstrated the feasibility of integrating routine retinal screenings for early DPN detection, potentially standardizing care and improving patient outcomes.

B. *Microvascular Analysis for Enhanced Diagnostics*

The measurement of retinal microvascular parameters such as Central Retinal Arteriolar Equivalent (CRAE), Central Retinal Venular Equivalent (CRVE), Arteriovenous Ratio (AVR), and fractal dimensions has opened new avenues in systemic disease diagnostics. Using advanced tools like VAMPIRE version 3.1.4, researchers analyzed these parameters in an annular zone around the optic disc, offering detailed insights into vascular health. Such measurements are crucial for understanding complications like cardiovascular disease and kidney dysfunction in diabetic patients.

C. *Innovative AI Models in Diabetic Complication Detection*

Cervera et al. [11] further validated a deep learning system combining SqueezeNet, Inception, and DenseNet architectures for detecting Diabetic Neuropathy (DN). Achieving an AUC of 0.8013, this system demonstrated the potential for incorporating DN detection into routine diabetic retinopathy (DR) screenings, enhancing early diagnosis and patient education.

Sabanayagam et al. [12] developed a ConDenseNet-based deep learning algorithm for detecting Chronic Kidney Disease (CKD) from retinal images. With AUCs ranging from 0.733 to 0.938 across multiple datasets, the study showcased the utility of retinal photography as a supplementary tool for CKD screening, particularly in community settings.

Zhang et al. [13] advanced AI applications further by utilizing ResNet-50 to identify CKD and type 2 diabetes from fundus images. The deep learning model achieved high AUCs of 0.85–0.93, validating its effectiveness across diverse datasets, including images captured via smartphones. Such adaptability highlights the potential for deploying these models in resource-limited settings, where traditional diagnostic tools may be inaccessible.

Mueller et al. [14] demonstrated the potential of deep learning for detecting Peripheral Arterial Disease (PAD) using color fundus photography. Their attention-based model achieved an ROC AUC of 0.890, with its interpretability highlighting retinal features like the optic disc and temporal arcades. This study underlines the value of AI in diagnosing systemic vascular diseases through retinal analysis.

Yatam et al. [15] utilized the VGG-16 architecture to detect diabetic retinopathy from retinal images, aiming to automate the diagnostic process. Their model achieved strong results, further emphasizing the role of deep learning in improving the accuracy and efficiency of DR detection.

D. Gaps in AI for Diabetic Retinopathy

Despite extensive research into AI’s applications for systemic complications of diabetes, significant gaps remain in its utilization for Diabetic Retinopathy (DR). As DR is a leading cause of blindness, AI-driven solutions could revolutionize its early detection, diagnosis, and management. However, current challenges include:

- Scalability: Real-world applications of AI tools, especially in low-resource settings, are limited.
- Clinical Integration: Few studies address how AI can be seamlessly integrated into clinical workflows for large-scale screenings.
- Ethical Concerns: Issues like data privacy, algorithmic bias, and the need for continuous learning remain underexplored.
- Patient Engagement: AI tools need to focus more on patient education and empowering individuals to take proactive measures.

E. Future Directions and Opportunities

To bridge these gaps, future research should focus on:

- Improved Datasets: Diverse, high-quality datasets are essential for training models that generalize well across populations.
- Hybrid Approaches: Combining deep learning with traditional clinical parameters may enhance diagnostic precision.
- Resource Adaptability: Models optimized for use with low-cost devices, such as smartphone-based fundus cameras, can extend access to underserved regions.
- Transparent AI: Building interpretable models will enhance trust and adoption among healthcare professionals.
- Policy Development: Establishing ethical frameworks for data use and addressing algorithmic biases will be critical for equitable deployment.

AI holds immense potential to transform DR care by improving early detection, reducing vision loss, and lowering healthcare costs. By addressing the existing gaps and challenges, researchers and practitioners can harness the full power of AI to combat the growing burden of diabetic complications.

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3. METHODOLOGY USED

A. *Retinal Images Analysis Using AI*

AI is starting to gain traction as a novel approach to ophthalmological data analysis, with the goal of revealing novel pathogenic and clinical insights into retinal illnesses. Age-related macular degeneration, myopia, and diabetic retinopathy are among the most common retinal illnesses for which AI-based algorithms are used.AI is an effective tool for boosting the volume of information obtained in research and therapeutic settings. Nonetheless, there are still a lot of problems that need to be solved, such as the necessity for extremely big databases and the ensuing high demand for resources and technology. Furthermore, a number of ethical concerns need to be discussed, and regulations governing the application of AI algorithms and ensuring the accuracy of the data analysis are required.

Retina image analysis using artificial intelligence (AI) involves applying machine learning and deep learning techniques to interpret and analyze images of the retina.

Artificial intelligence in the detection, diagnosis, and monitoring of retinal diseases, including macular degeneration, chorioretinopathy, diabetic retinopathy, and macular edema. The methodologies employed in these models are discussed, their effectiveness in research and clinical contexts is assessed, and future directions and problems in the application of artificial intelligence to retinal disorders are highlighted in this work.

B. *Diabetic Retinopathy screening*

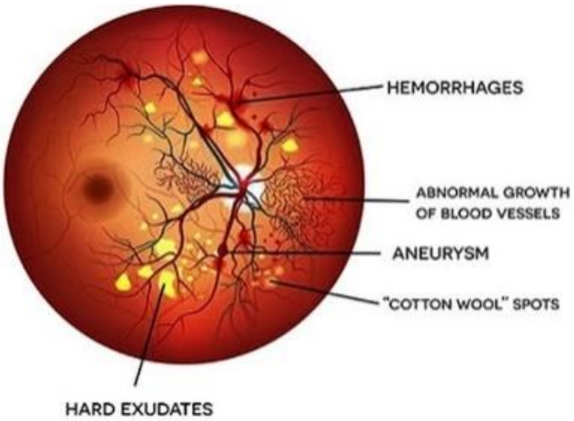


Figure 2 -Diabetic Retinopathy

Diabetic retinopathy (DR) is a major cause of vision loss among individuals with diabetes, affecting about one-third of diabetic patients worldwide. If untreated, DR can lead to blindness or severe vision impairment as it progressively damages the retina's blood vessels. Effective screening is crucial for managing this condition, as it enables early detection and timely intervention to prevent irreversible vision loss. Figure 2 shows common signs of diabetic retinopathy in the retina, including hemorrhages, abnormal blood vessel growth, aneurysms, "cotton wool" spots, and hard exudates. Figure 3 shows the DR is categorized into four stages:

Mild: Microaneurysms develop, causing small, balloon-like swellings in the retina's tiny blood vessels.

Moderate: The retinal blood vessels become obstructed, leading to hemorrhages within the retina.

Severe: Increased blockage of retinal blood vessels results in insufficient blood supply to various retina areas, with a significant rise in retinal hemorrhage.

Proliferative DR: New, abnormal blood vessels form on the retina's surface. These fragile vessels are prone to bleeding and can fill the eye with dangerous hemorrhages. They may also evolve into connective tissue, causing the retina to shrink and detach, ultimately resulting in blindness.

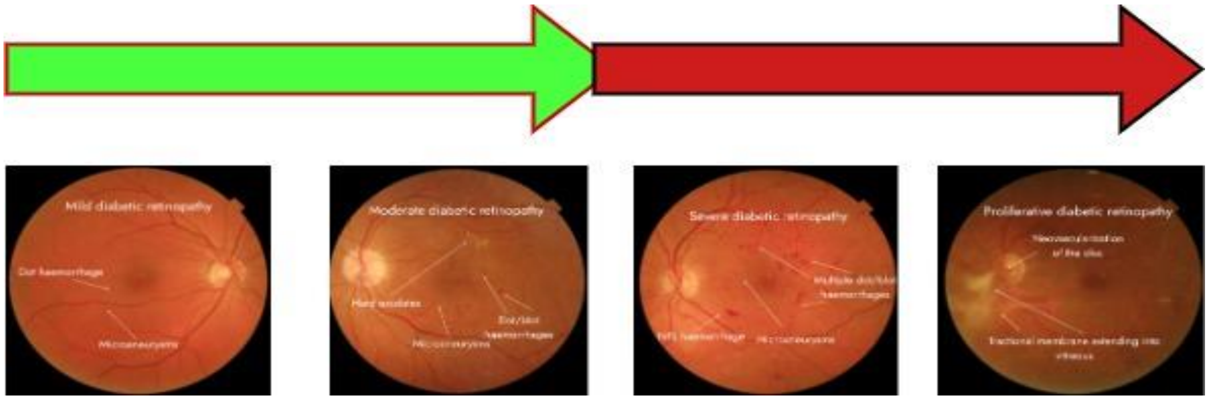


Figure 3 -Mild, Moderate, Severe, Proliferative DR

C. Feature of Diabetics Retinopathy Retina Images

Figure 4 provides visual indicators of diabetic retinopathy, highlighting key retinal changes. Focal and Generalized A-V (Arteriovenous) Changes: Specific and widespread alterations in retinal blood vessels due to diabetes.Arteriolosclerosis: Thickening of small retinal arteries, restricting blood flow.Flame-shaped Retinal Hemorrhages: Flame-like bleeding patterns on the retina, indicating vessel damage.Cotton-wool Spots: White, fluffy lesions caused by localized nerve fiber damage due to poor blood supply.Disc Edema: Swelling around the optic disc, often due to increased intracranial or ocular pressure.Macular Star: A star-shaped pattern of deposits around the macula due to leaking blood vessels.

These features are commonly used to assess the severity of diabetic retinopathy and guide treatment decisions.

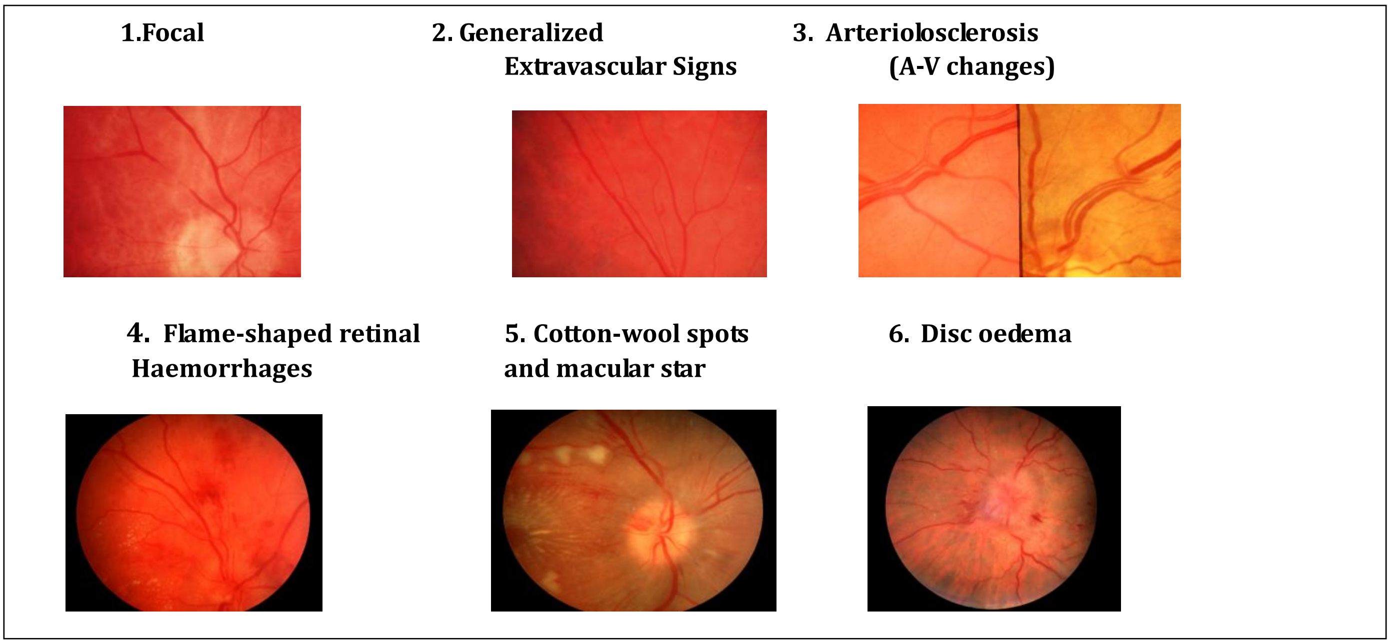


Figure 4-Feature of DR

D. Description of the DR dataset

The dataset is structured to support the development and evaluation of machine learning models. It comprises a total of 769 data instances, which are divided into two subsets: a training set and a testing set. The training set consists of 613 data points, representing approximately 80% of the total data, and is primarily used for model training and learning patterns from the data. The testing set includes the remaining 156 data points, which account for about 20% of the dataset.

The fundus photography technique was used to capture these photographs. The only method for identifying any anomalies in the eye is fundus photography. These pictures were taken under a variety of imaging conditions. The collection of these photos served as the basis for both the model's testing and training. As indicated in Table I, each image in the dataset has been given an integral value by a professionally educated doctor based on the severity of the disease, ranging from 0 to 4. Figure 5 shows the sample images from the dataset.

TABLE I DIABETIC RETINOPATHY SEVERITY RANGE

Range	Severity
0	No DR
1	Mild DR
2	Moderate DR
3	Sever DR
4	Proliferative DR

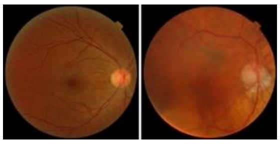
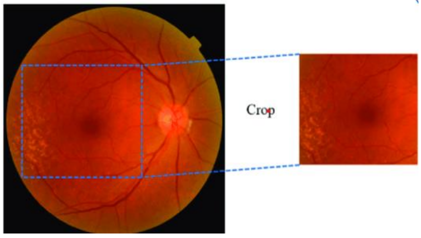


Figure 5 Images from Dataset

F. Data Image Pre-Processing (Augmentation &Resize)

Resize: Standardize the input images by resizing them to a consistent size required by the CNN models (e.g., 224x224 pixels).
Augmentation: Enhance the training dataset by applying transformations such as flipping, rotating, zooming, and adjusting brightness. This helps to improve model robustness and prevent overfitting by simulating a variety of image conditions.



G. Block Diagram

Figure 7 illustrates the diabetic retinopathy screening. from system depicted as remote servers and databases, processes retinal image data captured by a retinal imaging device, such as a fundus camera or OCT scanner. AI algorithms analyze the images within the dataset generating diagnostic results like risk scores for diabetic retinopathy. These results are accessible to healthcare providers through interfaces on computers or mobile devices, ensuring prompt patient care. Patient data privacy measures safeguard sensitive information, including encryption and secure transmission protocols. Additionally, a feedback loop may exist, where diagnostic results contribute to the continuous improvement of AI algorithms over time.

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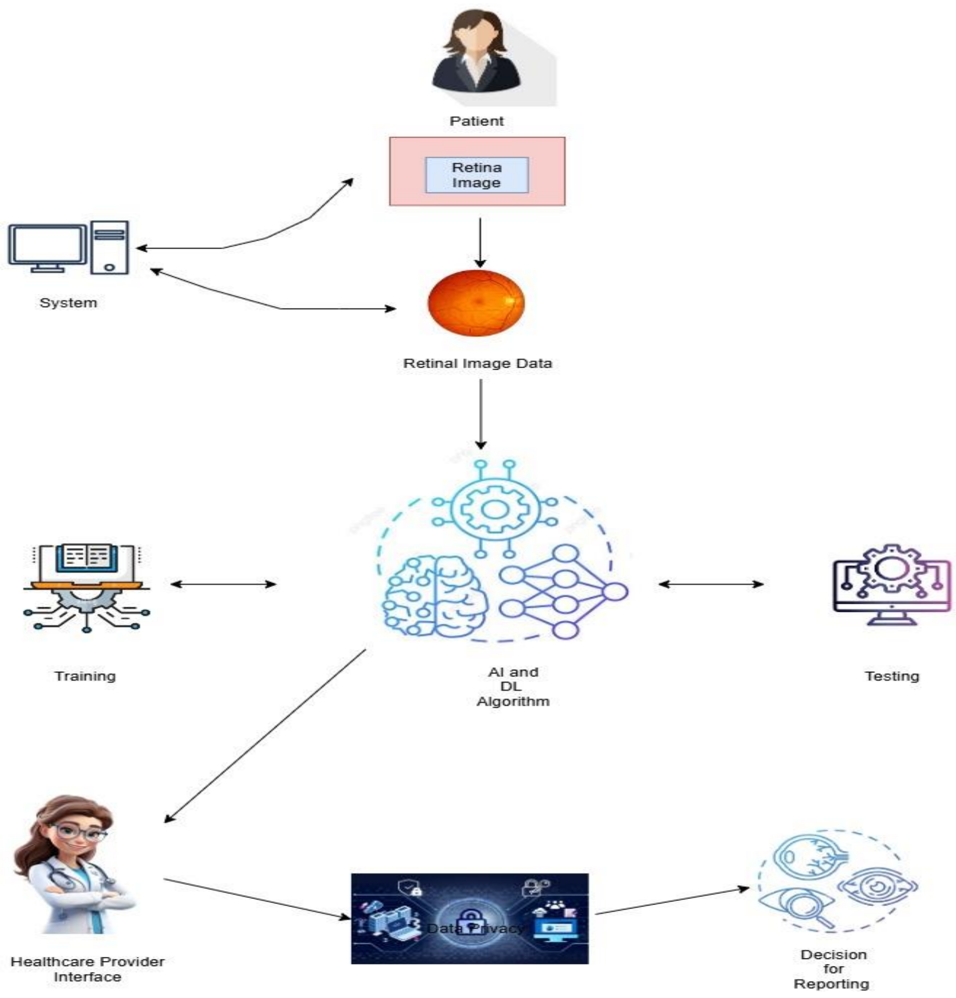

Figure 7-Proposed Method Work Flow

This image illustrates a workflow for using AI and deep learning (DL) algorithms in analyzing retinal images for healthcare applications. Here's a breakdown of the process depicted:

1. Patient and Retinal Image Capture:

The process begins with the patient, whose retina image is captured using specialized imaging systems. The captured image is then transferred to a system for processing.

2. Retinal Image Data Handling:

The captured retinal image data undergoes preprocessing and is fed into a customised VGG.

3. Training and Testing:

The AI and DL models are trained on a dataset of retinal images to learn patterns associated with different conditions. Testing is performed to validate the model's accuracy and reliability.

4. Decision and Reporting:

Decisions are made regarding potential conditions, such as identifying retinal abnormalities, based on the algorithm's analysis. These results are prepared for reporting.

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5. Healthcare Provider Interface:

The insights generated by the AI and DL algorithms are presented to healthcare providers through an interface for further interpretation.

6. Data Privacy:

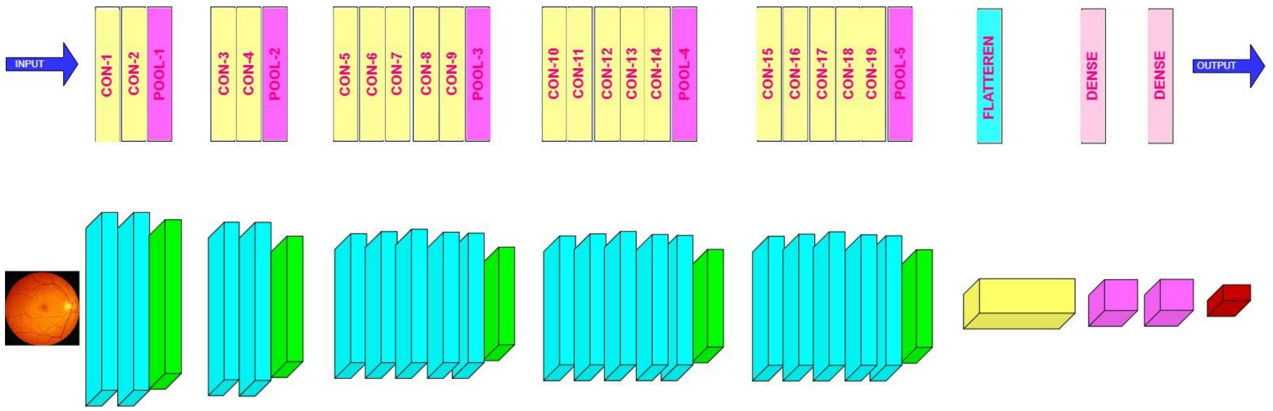
The workflow ensures data privacy, highlighting the secure handling of sensitive patient data throughout the process.

This system streamlines the analysis of retinal images, supporting healthcare professionals in making more accurate and timely diagnoses.

H. *Customised VGG*

A customized VGG (Visual Geometry Group) model is a modified version of the standard VGG neural network architecture was introduced in this paper , tailored to specific tasks by altering its layers, filters, or parameters, often used to improve performance on unique datasets or specialized image classification problems. Figure 6 shows the customised VGG neural network.

Here is an overview of the VGG architecture:
Convolutional Layers:
Conv1: 64 filters, kernel size 3x3, stride 1, padding 1
Conv2: 64 filters, kernel size 3x3, stride 1, padding 1
Max Pooling: kernel size 2x2, stride 2
Conv3: 128 filters, kernel size 3x3, stride 1, padding 1
Conv4: 128 filters, kernel size 3x3, stride 1, padding 1
Max Pooling: kernel size 2x2, stride 2
Conv5: 256 filters, kernel size 3x3, stride 1, padding 1
Conv6: 256 filters, kernel size 3x3, stride 1, padding 1
Conv7: 256 filters, kernel size 3x3, stride 1, padding 1
Max Pooling: kernel size 2x2, stride 2
Conv8: 512 filters, kernel size 3x3, stride 1, padding 1
Conv9: 512 filters, kernel size 3x3, stride 1, padding 1
Conv10: 512 filters, kernel size 3x3, stride 1, padding 1
Max Pooling: kernel size 2x2, stride 2
Fully Connected Layers:
FC11: 4096 neurons
FC12: 4096 neurons
FC13: 1000 neurons (for 1000-class classification)



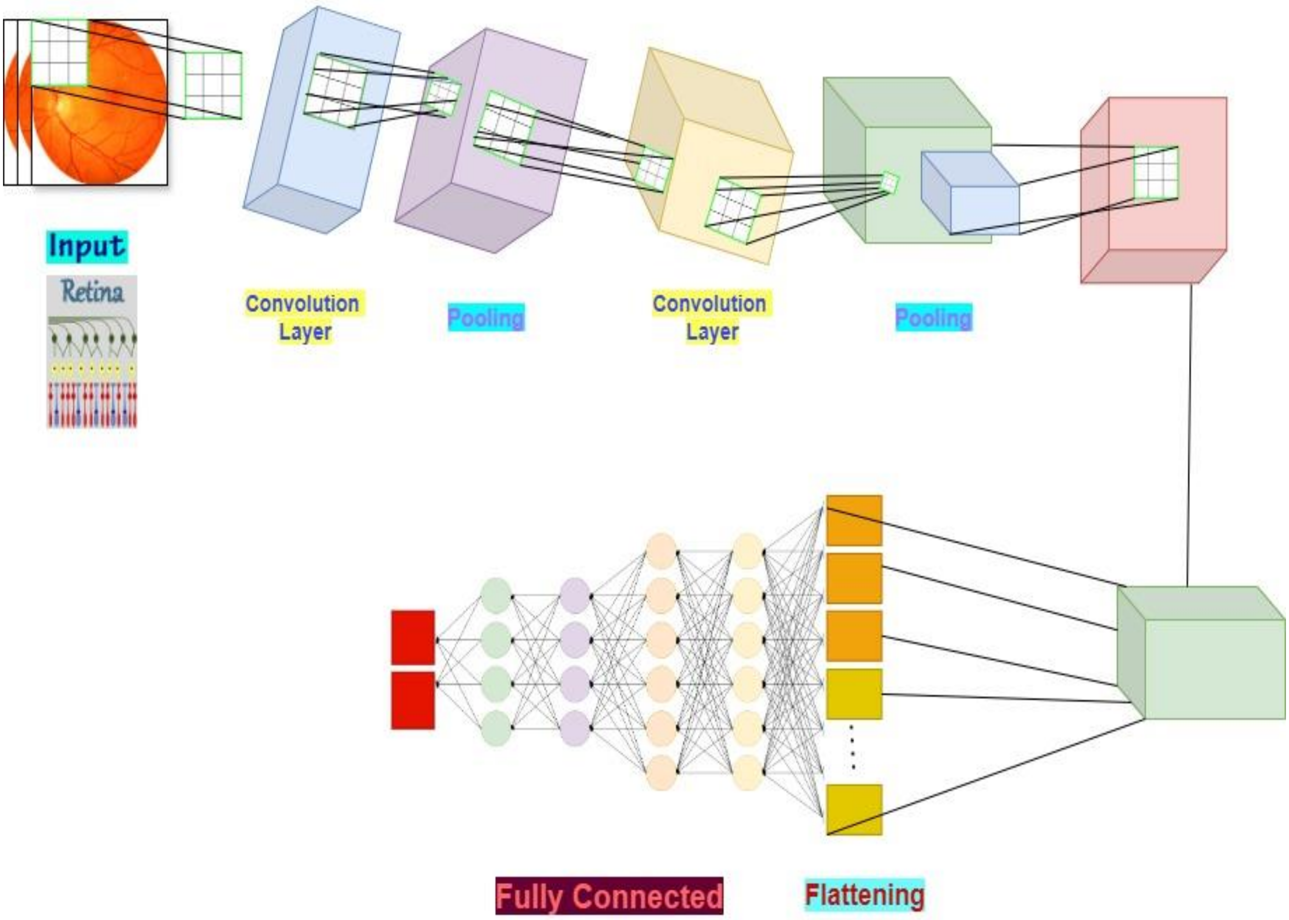


Figure 6-Customised VGG Model Architecture

I. *Model Training*

We trained the model for 30 epochs, with each epoch representing one complete pass through the training dataset in convolutional neural networks. Typically, neural network training requires multiple epochs to achieve good performance. The ADAM optimizer was used during training. Optimizers help fine-tune the neural network's parameters, like the learning rate and weights, to reduce loss. ADAM is considered one of the most efficient optimizers, as it speeds up the training process significantly. The model was trained with a Cross Entropy loss function, a Softmax activation layer, and a batch size of 32. We used a learning rate of 0.001, which is ADAM's default setting.

J. *Data testing*

We evaluated our model on a fresh dataset of 769 retinal images, separate from the 613 images used for training. During testing, image preprocessing and feature extraction were performed. The model classified the images based on the severity of Diabetic Retinopathy, assigning a label from 0 to 4 (as outlined in Table-I). Our model achieved an accuracy of 93.75 Over the course of 30 epochs, there was a loss of 1.83%.

We used it to customised the VGG pretrained model, train, and test our model.

4. Result and Discussion

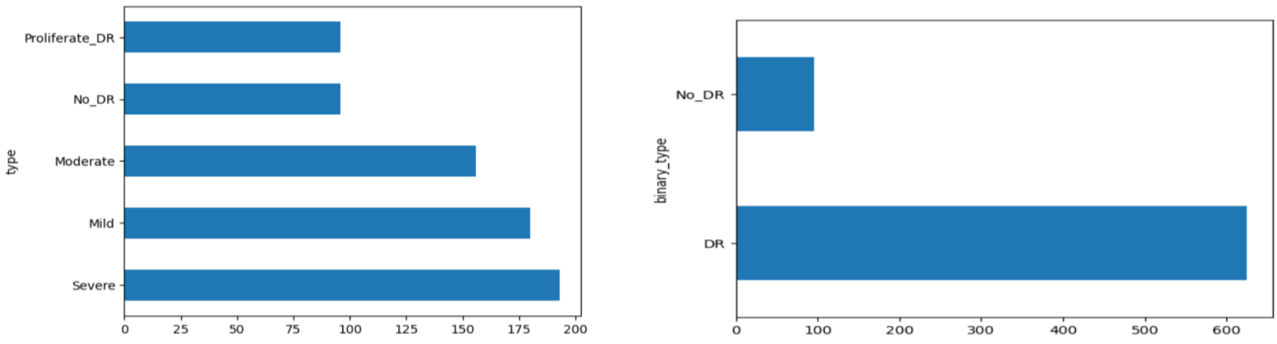
Applied experiments for the detection of diabetic retinopathy with the models discussed in the study. It was made using the Python language with Jupyter Notebook in Google Colaboratory (CoLab).

The model was able to detect the severity of Diabetic Retinopathy of the input images and labelled them according to it on a scale of 0-4. The details of the model and the results achieved are given in Table II

TABLE II – PERFORMANCE METRICS

Training data	613
Testing data	156
optimizer	ADAM
Epoch	30
Accuracy	93.75
Loss	1.83

Datasets are classified into 5 classes and also split into two folders one as training and another as testing images segregate those images into two folders NO DR and DR retina images shown in Figure 8



	id_code	diagnosis	binary_type	type
0	0024cdab0c1e	1	DR	Mild
1	00cb6555d108	1	DR	Mild
2	0124dffecf29	1	DR	Mild
3	01b3aed3ed4c	1	DR	Mild
4	0369f3efe69b	1	DR	Mild

```
Found 613 images belonging to 5 classes.
Found 156 images belonging to 5 classes.
```

Figure 8 -Dataset Classification by Classes

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.9375 - loss: 1.8338 - val_accuracy: 0.5000 - val_loss: 11.2013
```

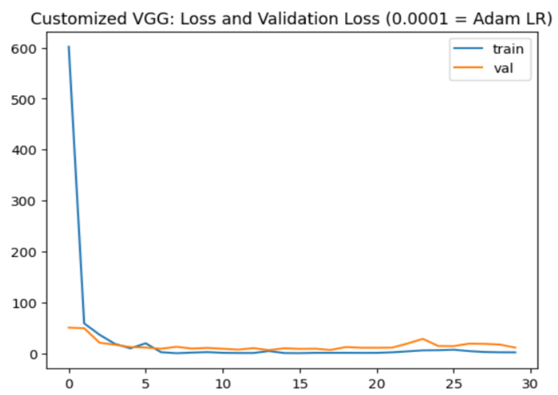


Figure 9 - Accuracy of Customised VGG

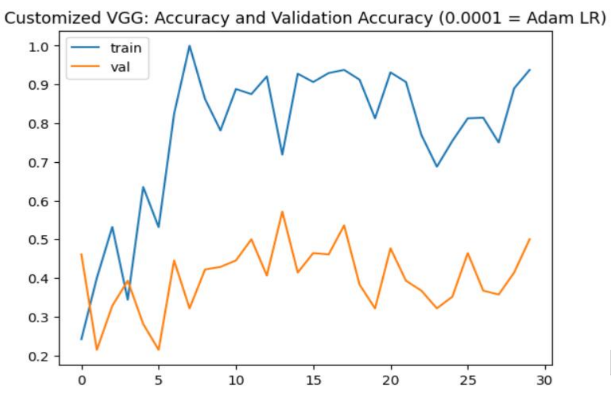


Figure 10-Loss of Customised VGG

Figure 9, 10 shows the training performance of accuracy (93.75%) and loss (11%), and Figure 11 shows the confusion matrix for DR from the dataset. Figure 12 shows the training, testing, and total parameters performed in customised VGG

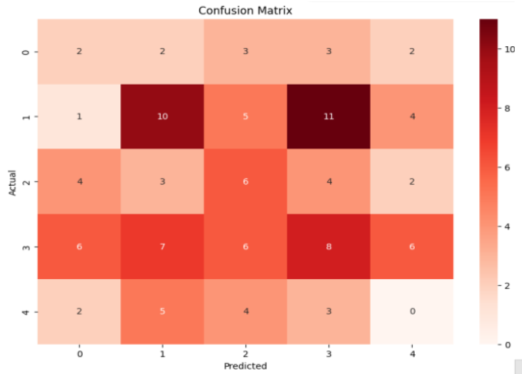
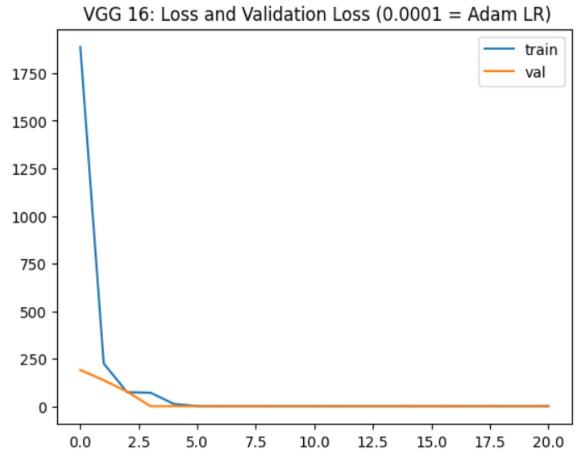


Figure 11-Confusion matrix

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 224, 224, 1)	0
conv2d (Conv2D)	(None, 222, 222, 64)	640
conv2d_1 (Conv2D)	(None, 220, 220, 64)	36,928
max_pooling2d (MaxPooling2D)	(None, 110, 110, 64)	0
conv2d_2 (Conv2D)	(None, 108, 108, 128)	73,856
conv2d_3 (Conv2D)	(None, 106, 106, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 53, 53, 128)	0
conv2d_4 (Conv2D)	(None, 51, 51, 256)	295,168
conv2d_5 (Conv2D)	(None, 49, 49, 256)	590,080
conv2d_6 (Conv2D)	(None, 47, 47, 256)	590,080
conv2d_7 (Conv2D)	(None, 45, 45, 256)	590,080
conv2d_8 (Conv2D)	(None, 43, 43, 256)	590,080
max_pooling2d_2 (MaxPooling2D)	(None, 21, 21, 256)	0
conv2d_9 (Conv2D)	(None, 19, 19, 256)	590,080
conv2d_10 (Conv2D)	(None, 17, 17, 256)	590,080
conv2d_11 (Conv2D)	(None, 15, 15, 256)	590,080
conv2d_12 (Conv2D)	(None, 13, 13, 256)	590,080
conv2d_13 (Conv2D)	(None, 11, 11, 256)	590,080
max_pooling2d_3 (MaxPooling2D)	(None, 5, 5, 256)	0
conv2d_14 (Conv2D)	(None, 3, 3, 512)	1,180,160
conv2d_15 (Conv2D)	(None, 1, 1, 512)	2,359,808
conv2d_16 (Conv2D)	(None, 1, 1, 512)	2,359,808
conv2d_17 (Conv2D)	(None, 1, 1, 512)	2,359,808
conv2d_18 (Conv2D)	(None, 1, 1, 512)	2,359,808
max_pooling2d_4 (MaxPooling2D)	(None, 0, 0, 512)	0
flatten (Flatten)	(None, 0)	0
dense (Dense)	(None, 4096)	4,096
dense_1 (Dense)	(None, 4096)	16,781,312
dense_2 (Dense)	(None, 1000)	4,097,000

Total params: 37,366,696 (142.54 MB)
Trainable params: 37,366,696 (142.54 MB)
Non-trainable params: 0 (0.00 B)

Figure 12 – Architecture Model Summary



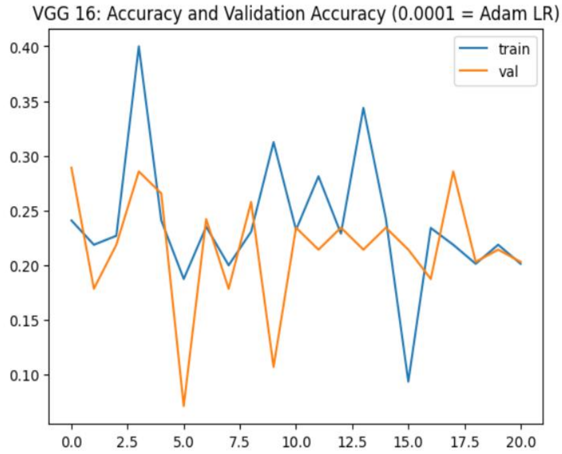
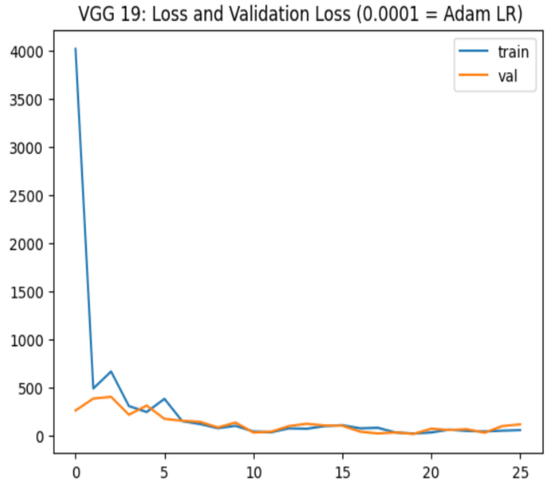


Figure 13 -Accuracy for VGG 16

Figure 14-Loss for VGG 16

Figures 13 and 14 shows the accuracy and Loss for the VGG 16 architecture and Figures 15 and 16 shows the Accuracy and Loss for the VGG 19 .



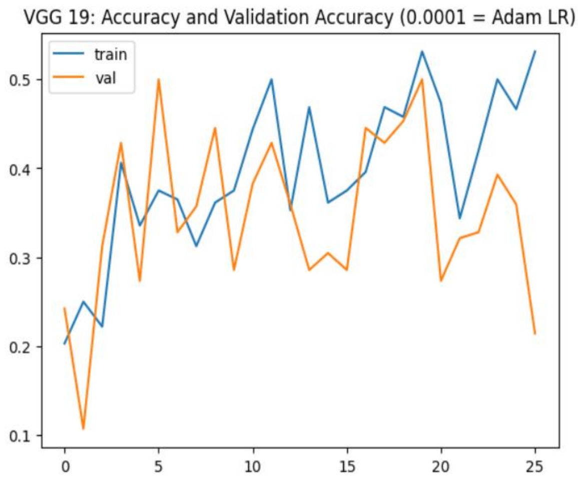


Figure 15 -Accuracy for VGG 19

Figure 16– Loss for VGG 19

Table III shows the Parameter Comparison for VGG 16, VGG 19 and Customised VGG and Table IV shows Comparison for table architecture layer for VGG 16, 19 and Customised VGG.

TABLE III PARAMETER COMPARISON FOR VGG 16, VGG 19 AND CUSTOMISED VGG

Layer Group	**VGG 16**	**VGG19**	**Customised VGG**
Conv1 Block	38,720	38,720	37,576
Conv2 Block	221,440	221,440	221,440
Conv3 Block	1,475,584	2,065,664	2,065,664
Conv4 Block	7,079,936	9,439,232	11,799,528
Conv5 Block	7,079,936	9,439,232	11,799,528
FC Layers	123,643,856	123,643,856	123,643,856
Total	138,357,544	143,667,240	147,366,696

TABLE IV ARCHITECTURE LAYERS DESCRIPTION FOR VGG 16,19 AND CUSTOMISED VGG.

Block	VGG16	VGG 19	Customised VGG
Block1	Conv1_1, Conv1_2, MaxPool	Conv1_1, Conv1_2, MaxPool	Conv1_1, Conv1_2, MaxPool
Block 2	Conv2_1, Conv2_2, MaxPool	Conv2_1, Conv2_2, MaxPool	Conv2_1, Conv2_2, MaxPool
Block 3	Conv3_1,Conv3_2, Conv3_3,MaxPool	Conv3_1,Conv3_2, Conv3_3,Conv3_4, MaxPool	Conv3_1,Conv3_2, Conv3_3,Conv3_4, Conv3_5,MaxPool
Block 4	Conv4_1,Conv4_2, Conv4_3,MaxPool	Conv4_1,Conv4_2, Conv4_3,Conv4_4, MaxPool	Conv4_1,Conv4_2, Conv4_3,Conv4_4, Conv4_5,MaxPool
Block 5	Conv5_1,Conv5_2, Conv5_3,MaxPool	Conv5_1,Conv5_2, Conv5_3,Conv5_4, MaxPool	Conv5_1,Conv5_2, Conv5_3,Conv5_4, Conv5_5,MaxPool
FC Layer	FC1,FC2	FC1,FC2	FC1,FC2,FC3

5. CONCLUSION AND FUTURE WORK

The integration of artificial intelligence into diabetic retinopathy management has the potential to significantly transform diabetes care and reduce the global burden of vision loss. AI's ability to enhance early detection and provide more precise diagnosis empowers healthcare providers to implement timely interventions, ultimately improving patient outcomes. As AI technology continues to evolve, its role in routine clinical practice will likely expand, leading to more personalized and efficient care.

Looking to the future, ongoing research is crucial to addressing the challenges of AI implementation, including data security, ethical considerations, and the need for continuous training of AI models. Collaboration between AI developers, healthcare professionals, and policymakers will be key to ensuring that AI-driven innovations are both effective and accessible to all patients. With sustained efforts, AI has the potential to play a pivotal role in shaping the future of diabetes management, reducing complications, and improving quality of life for millions of individuals worldwide. As the global diabetes burden continues to grow, the integration of AI-driven solutions in diabetic care is expected to play a pivotal role in combating its complications. Further advancements in AI technology, combined with enhanced accessibility to retinal imaging, have the potential to bridge healthcare disparities and transform outcomes for millions of individuals worldwide.

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