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A Deep Learning Model for Early Detection of Non-Proliferative Diabetic Retinopathy Using Retinal Fundus Images

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Abstract: *Diabetic Retinopathy (DR) is a leading cause of vision loss worldwide, making early detection crucial. This study proposes a deep learning framework using the EfficientNetB0 architecture to classify DR severity from retinal fundus images. The model leverages advanced CNN techniques for improved feature extraction and classification. It is trained on the "Diagnosis of Diabetic Retinopathy" Kaggle dataset containing 3,624 images across five classes: No DR, Mild, Moderate, Severe, and Proliferative DR.*

Experimental results show an accuracy of 87.17% with a loss of 0.5663, demonstrating strong multi-class classification performance. Comparative analysis highlights EfficientNet's effectiveness in handling complex image variations and maintaining generalizability. The proposed system shows promise in enhancing DR diagnosis. With larger datasets and better computational resources, it could become a valuable clinical tool for early detection and improved patient outcomes..

Keywords: Diabetic Retinopathy, NPDR, Deep Learning, CNN, Fundus Imaging, Transfer Learning, Medical Image Analysis, Artificial Intelligence

I. INTRODUCTION

Diabetic Retinopathy (DR) is a progressive microvascular complication of diabetes that affects the retinal blood vessels and is widely recognized as one of the leading causes of preventable blindness worldwide. With the increasing prevalence of diabetes, particularly in developing countries, the number of individuals at risk of developing DR has risen significantly, placing a substantial burden on healthcare systems[8]. Among the different stages of DR, Non-Proliferative Diabetic Retinopathy (NPDR) represents the earliest phase and is characterized by subtle retinal abnormalities such as microaneurysms, hemorrhages, and exudates. These early signs are often difficult to detect because they may not produce noticeable symptoms, making timely diagnosis a major challenge[1]. However, early identification of NPDR is critical, as appropriate medical intervention at this stage can effectively prevent progression to advanced stages, such as Proliferative Diabetic Retinopathy (PDR), which can lead to irreversible vision loss[5].

Traditional methods for diagnosing DR rely on manual examination of retinal fundus images by trained ophthalmologists. Although this approach remains clinically reliable, it is time-consuming, subjective, and highly dependent on expert availability[7]. In many rural and underserved regions, access to specialized healthcare professionals is limited, making large-scale screening impractical. These limitations highlight the need for automated, efficient, and scalable diagnostic systems that can assist clinicians in early detection and reduce the burden on healthcare infrastructure[9].

In recent years, advancements in artificial intelligence, particularly deep learning, have demonstrated significant potential in medical image analysis. Convolutional Neural Networks (CNNs) have achieved remarkable success in

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image classification tasks due to their ability to automatically learn hierarchical feature representations from raw images[10]. Unlike traditional machine learning methods that rely on handcrafted features, CNN-based models can effectively capture complex patterns and subtle variations in retinal images. This makes them highly suitable for detecting early-stage NPDR with improved accuracy and reliability. Motivated by these advantages, this study proposes a deep learning-based framework for automated detection of NPDR using retinal fundus images[11].

The proposed methodology follows a structured pipeline designed to ensure accurate and efficient detection. The process begins with data acquisition, where publicly available datasets such as EyePACS and APTOS are utilized[10]. These datasets contain labeled retinal images representing various stages of diabetic retinopathy and provide a diverse set of samples for training and evaluation. However, these datasets often exhibit variability in image quality, resolution, and illumination conditions, along with class imbalance where normal images outnumber diseased cases[12].

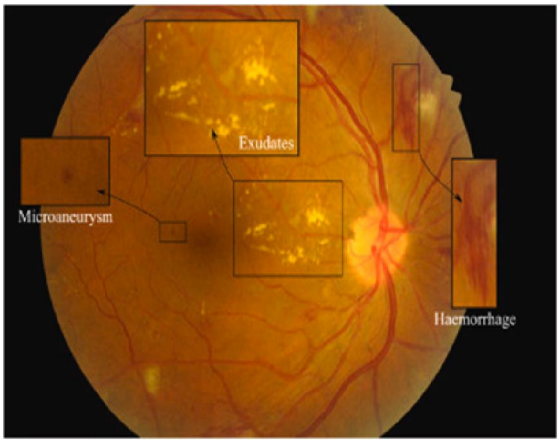

Fig 1: Deep learning for DR Detection

To address these challenges, an image preprocessing stage is implemented. In this stage, all images are resized to a standard dimension to match the input requirements of the deep learning model[2]. Pixel normalization is performed to scale intensity values and improve training stability. Additionally, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance image contrast and improve the visibility of important retinal features such as blood vessels and lesions. Noise reduction techniques are also incorporated to remove artifacts while preserving essential structural details[3].

Following preprocessing, data augmentation techniques are applied to increase dataset diversity and improve model generalization. These techniques include random rotations, horizontal and vertical flipping, zooming, and brightness adjustments[13]. By introducing variations in the training data, the model becomes more robust to real-world conditions and less prone to overfitting. Data augmentation also helps mitigate the effects of class imbalance by generating additional samples for underrepresented classes.

The core component of the proposed system is a transfer learning-based Convolutional Neural Network built upon the ResNet50 architecture[5]. The pre-trained ResNet50 model is used as a feature extractor due to its deep architecture and residual learning capability, which enables efficient training of deep networks without degradation in performance. The final layers of the pre-trained model are modified by adding a global average pooling layer, followed by fully connected dense layers and a dropout layer to prevent overfitting[13]. The output layer employs a softmax activation function to perform multi-class classification of retinal images.

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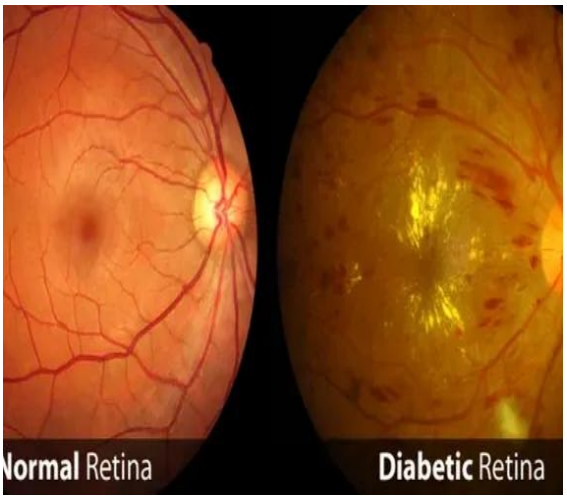

Fig 2 : Fundus images of Normal and Diabetic retina

The model is trained using the Adam optimizer, which provides efficient gradient-based optimization, and categorical cross-entropy is used as the loss function. Training is conducted over multiple epochs with validation to monitor performance and prevent overfitting[16]. The effectiveness of the model is evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics provide a comprehensive assessment of the model's ability to correctly identify NPDR cases and distinguish between different stages of the disease[4].

Overall, the proposed framework integrates advanced preprocessing techniques, data augmentation strategies, and a powerful deep learning model to achieve accurate and reliable detection of NPDR. This approach not only enhances diagnostic performance but also provides a scalable solution for automated screening, making it particularly valuable in resource-limited settings where access to expert ophthalmologists is limited[20].

II. LITERATURE REVIEW

In recent years, significant research has been conducted in the field of automated detection of Diabetic Retinopathy (DR) using machine learning and deep learning techniques. Early approaches primarily relied on traditional image processing methods combined with handcrafted feature extraction techniques. These methods involved detecting retinal abnormalities such as microaneurysms, exudates, and hemorrhages using techniques like edge detection, morphological operations, and texture analysis[22]. Classifiers such as Support Vector Machines (SVM) and Random Forests were then applied for classification. Although these approaches provided moderate performance, they were limited in their ability to generalize across diverse datasets due to their dependence on manually designed features[12].

With the advancement of deep learning, Convolutional Neural Networks have emerged as a powerful tool for medical image analysis. CNN-based models automatically learn hierarchical feature representations directly from raw images, eliminating the need for manual feature engineering[11]. One of the most notable contributions in this field was the work by Gulshan et al., who developed a deep learning algorithm for DR detection using a large dataset of retinal images, achieving performance comparable to that of expert ophthalmologists. This study demonstrated the potential of deep learning in large-scale screening applications.Several CNN architectures, including VGGNet, ResNet, DenseNet, and EfficientNet, have been widely explored for DR classification[21]. Among these, ResNet introduced residual learning. Similarly, EfficientNet has gained attention due to its compound scaling method, which balances network depth, width, and resolution, leading to improved performance with fewer parameters. Studies utilizing EfficientNet-based models have shown strong results in multi-class classification of DR severity levels, particularly in handling complex retinal image features[15].

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Transfer learning has also played a crucial role in improving model performance, especially when dealing with limited medical datasets. By leveraging pre-trained models trained on large datasets such as ImageNet, researchers have been able to achieve higher accuracy and faster convergence. Fine-tuning these models on retinal datasets enables effective feature extraction while reducing computational cost.Despite these advancements, several challenges remain[14]. Class imbalance is a common issue in DR datasets, where normal images significantly outnumber diseased cases, leading to biased model predictions. Variability in image quality, including differences in illumination, resolution, and noise, also affects model performance. Furthermore, the lack of interpretability in deep learning models poses a challenge for clinical adoption, as healthcare professionals require transparency and trust in automated systems[20].

Recent studies have begun to address these limitations by incorporating attention mechanisms, ensemble learning, and explainable artificial intelligence techniques. These approaches aim to improve model performance while providing visual explanations of predictions, thereby increasing clinical reliability. However, there is still a need for robust, scalable, and interpretable frameworks that can perform effectively in real-world scenarios[25].This study builds upon existing research by integrating preprocessing techniques, data augmentation strategies, and a transfer learning-based CNN architecture to improve the accuracy and reliability of NPDR detection. The proposed framework aims to address key challenges such as class imbalance and image variability while providing a scalable solution for automated screening[30].

III. DIABETIC RETINOPATHY- CLINICAL CONTEXT AND CHARACTERISTICS

A. Pathophysiology of DR –

Diabetic retinopathy is a consequence of the chronic high blood sugar levels that eventually cause the retinal blood vessels to be totally affected. The events of the pathophysiological process are

1. Microvascular damage: The loss of pericytes, thickening of the basement membrane, and dysfunction of the endothelial cells are the major effects of hyperglycemia in the long run
2. Vascular permeability: The blood-retinal barrier is dismantled, and consequently, fluids, lipids, and proteins leak out[6].

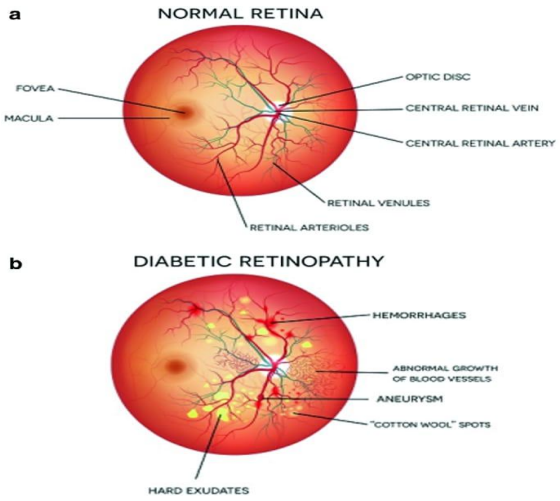

Fig 3: Normal Retina & DR on fundus images

3. Capillary occlusion: Retinal capillary blockage that goes on for a long time causes the death of the tissue due to lack of blood supply
4. Neovascularization: The formation of new vessels in the proliferative phase is one of the responses to ischemia caused by the old vessels being blocked [28] .

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B. Classification and Stages of DR

According to the *International Clinical Diabetic Retinopathy Severity Scale (ICDRSS)*, Diabetic Retinopathy (DR) is classified into five stages based on the severity of retinal abnormalities. The first stage, **No DR**, shows a normal fundus with no visible signs of damage. The second stage, **Mild NPDR**, is characterized by the presence of microaneurysms, which are the earliest detectable lesions[22].

In the **Moderate NPDR** stage, additional abnormalities such as hemorrhages, hard exudates, cotton wool spots, and venous beading begin to appear, indicating disease progression. The **Severe NPDR** stage involves extensive retinal damage, including multiple intraretinal hemorrhages, venous beading, and intraretinal microvascular abnormalities (IRMA), significantly increasing the risk of further progression[17].

The final stage, **Proliferative Diabetic Retinopathy (PDR)**, is marked by neovascularization and possible vitreous or preretinal hemorrhage, which can lead to severe vision loss. This classification is essential for accurate diagnosis, treatment planning, and training deep learning models for automated DR detection.

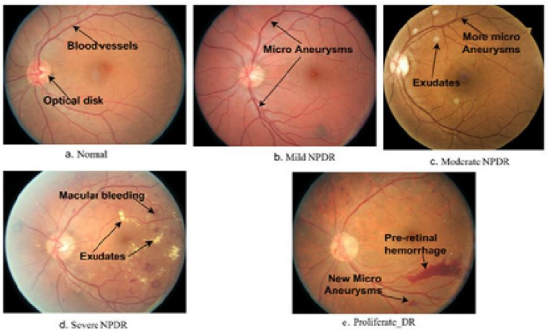

Fig 4. Stages of Diabetic Retinopathy

C. Clinical Significance of Early NPDR Detection

Detecting and treating mild-to-moderate non-proliferative diabetic retinopathy (NPDR) stages early can result in many clinical benefits [9]:

1. Preventing disease progression: If treated quickly, disease progression to severe NPDR and PDR can be either stopped or slowed down.
2. Vision preservation: Treatment before macular involvement keeps central vision intact
3. Treatment efficacy: The lesions at the early-stage are more effectively treated with laser photocoagulation and anti-VEGF therapy [9].
4. Risk stratification: High-risk patients needing stringent monitoring are identified
5. Systemic health indicator: The severity of diabetic retinopathy (DR) is indicative of the degree of diabetic complication experienced systemically.

D. Challenges in Clinical Diagnosis

Manual NPDR diagnosis comes along with different challenges which point out the necessity of automated deep learning solutions:

1. Inter-observer variability: For early stages, the agreement between ophthalmologists is very low, only from 60% to 80%.
2. Time constraints: The whole examination is very time-consuming, needing from 10 to 15 minutes for each patient.
3. Subtle lesions: Some microaneurysms and tiny hemorrhages may not be seen at all or wrongly classified.
4. Resource limitations: There is always a lack of trained ophthalmologists, particularly in non-urban locations.
5. Image quality: There are several reasons, such as the type of fundus camera used, the patient's cooperation, and the presence of media opacities, that affect the quality of the images taken.

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6. Screening coverage: The large number of diabetic patients requires an efficient screening infrastructure to be set up[28].

IV. PROPOSED SYSTEM: CNN-BASED VGG-NET MODEL FOR NPDR DETECTION

Microaneurysms are widely recognized as the earliest and most reliable indicators of Non-Proliferative Diabetic Retinopathy (NPDR). These lesions appear as small, round, red spots in the retinal fundus image and are formed due to localized weakening and bulging of capillary walls. Their presence indicates early microvascular damage caused by prolonged diabetes. Since they often appear before other visible retinal abnormalities, detecting microaneurysms at an early stage is crucial for timely diagnosis, effective treatment planning, and prevention of disease progression toward severe diabetic retinopathy stages such as proliferative diabetic retinopathy (PDR)[10].

However, accurate identification of these lesions using traditional manual examination is challenging. Fundus images often contain noise, uneven illumination, low contrast regions, and visually similar structures such as hemorrhages or blood vessels, making manual grading subjective and error-prone. Moreover, the extremely small size of microaneurysms further complicates visual detection, especially in early-stage NPDR cases. To address these limitations, an automated deep learning-based solution is proposed[21].

The proposed system employs a Convolutional Neural Network (CNN) based on the VGG-Net architecture for automated detection and classification of NPDR stages. VGG-Net is chosen due to its uniform and highly structured architecture, which relies on repeated stacking of small 3 × 3 convolutional filters. This design allows the network to learn complex hierarchical representations while maintaining computational simplicity and stability during training. As the network depth increases, it becomes capable of extracting increasingly abstract and discriminative features from retinal images[9].

In the context of diabetic retinopathy detection, the VGG-Net architecture effectively learns fine-grained retinal patterns such as microaneurysms, hemorrhages, and exudates. These features are essential for distinguishing between normal and diseased retinal conditions, particularly in early-stage NPDR where visual differences are subtle[7]. The deep convolutional layers progressively capture low-level features (edges, textures) in initial layers and high-level semantic features (lesion structures and spatial distributions) in deeper layers. The proposed technique firmly evolved to classify the DR conditions from fundus images and precisely identified severity levels based on major appearances of pathology in fundus[2].

A. Data Augmentation

Data augmentation is a key to collect the image data for experiments. As a part of analysis, a familiar KAGGLE competition dataset is utilized for the experiments, whose sample fundus image is shown in fig 5. The regular dataset of KAGGLE from EyePACS contains total of 88,700 photographs of retina. In this, 35,126 images were tagged as right and left eyes for training Tab.1, describes the number of the fundus images of every class present in the KAGGLE DR Dataset. For training and testing, the distribution of images from KAGGLE DR Dataset are used as given in Tab.2.

Tab 1: Distribution of images in KAGGLE DR dataset

Classes	DR condition	No.of Images
0	NPDR	1770
1	Mild	367
2	Moderate	999
3	Sevare	193
4	Proliferative	295

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Tab 2: Number of images used for training and testing from KAGGLE DR dataset

Classes	DR condition	No.of images for training	No.of images for testing	No.of imagesfor validation
0	NPDR	1263	272	270
1	Mild	259	56	55
2	Moderate	699	151	149
3	Sevare	135	30	28
4	Proliferative	206	45	44

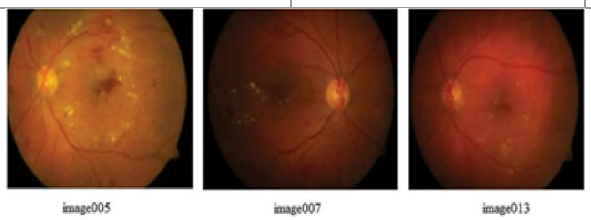

Fig 5 : Sample input fundus images

B. Proposed Method

The KAGGLE dataset consists of substantial quantity of indefinable images because of the presence of artifacts and incorrect labeling. Therefore, image segmentation methods are used to detect the type and lesions present in order to annotate the labels, for detecting the DR severity levels in fundus images. Tab 3, describes the scheme based on type and severity levels from the detected lesions[23].

Tab 3: Commonly adopted annotation scheme to represent DR severity level from detected lesions

Amount of detected lesions from images	Corresponding DR severity grades
No lesions present	Normal
Few microaneurysms and soft exudates	Mild NPDR
More microaneurysms and soft exudates, less hemorrhages	Moderate NPDR
More hemorrhages	Severe NPDR
More hemorrhages and hard exudates	PDR

A. System Architecture (Diagram)

Explanation

The proposed system takes a retinal fundus image as input for automated diabetic retinopathy (DR) detection. In the preprocessing stage, all images are resized to a fixed dimension to maintain uniformity and are normalized to improve training stability and convergence. To enhance visibility of important retinal structures, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied, which improves local contrast and highlights subtle lesions such as microaneurysms and exudates. Data augmentation techniques are then applied, including rotation, flipping, zooming, and brightness variations, to increase dataset diversity and reduce overfitting[13].

The preprocessed images are then passed into the VGG-Net model, which serves as the primary deep learning architecture for feature extraction. VGG-Net consists of multiple stacked convolutional layers with small 3×3 filters, followed by max-pooling layers that progressively reduce spatial dimensions. These convolutional layers learn hierarchical feature representations from the input images[4].

Initially, the network captures low-level features such as edges, corners, and textures. As depth increases, it learns high-level and complex patterns such as blood vessel abnormalities, microaneurysms, hemorrhages, and exudates, which are key indicators of diabetic retinopathy progression. After feature extraction, the feature maps are flattened into a one-dimensional vector. This vector is then passed through fully connected dense layers for classification[3].

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Finally, a softmax activation function is used in the output layer to generate probability scores for different DR severity levels, such as No DR, Mild, Moderate, Severe, and Proliferative DR. The class with the highest probability is selected as the final prediction, enabling accurate and reliable automated diagnosis.

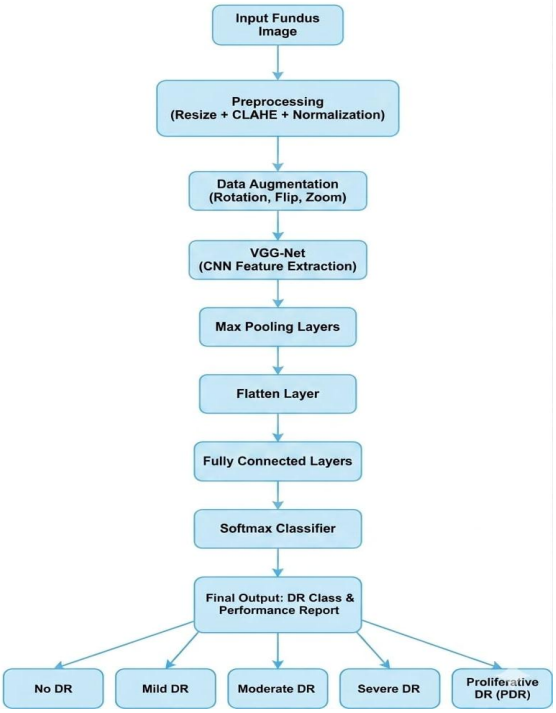

Fig 6 : VGG-Net Architecture above is the conceptual flow of the proposed model:

The processed images are then fed into the VGG-Net model, which acts as the core CNN for feature extraction. VGG-Net consists of multiple convolutional layers followed by max-pooling layers, allowing the model to learn hierarchical features. It captures low-level features such as edges and textures, as well as high-level features like lesions and abnormalities.The extracted features are flattened and passed through fully connected layers[25]. Finally, a softmax classifier outputs the probability distribution across different DR stages.

B. Role of VGG-Net in DR Detection

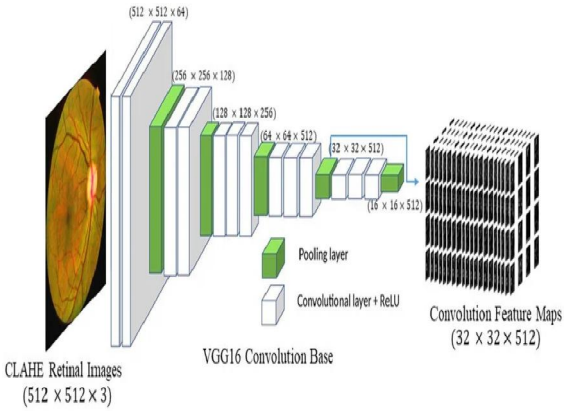

Fig 7 : Overall workflow of the proposed VGG-Net (CNN) Model

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VGG-Net plays a significant role in feature extraction due to its deep architecture and consistent convolutional design. Its stacked layers enable the model to capture both simple and complex visual features, making it effective in detecting early DR signs such as microaneurysms[17]. However, compared to more advanced architectures like EfficientNet, VGG-Net requires higher computational resources due to its large number of parameters.

Max-pooling layers are used to reduce spatial dimensions while preserving important information, improving computational efficiency. The extracted feature maps are then flattened and passed through fully connected layers for classification. Finally, a softmax layer predicts the probability of different DR stages, enabling accurate disease classification[10].

V. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed VGG-Net based model for diabetic retinopathy (DR) detection was evaluated using retinal fundus images. The dataset was divided into training and testing sets to ensure fair evaluation of the model performance. During training, the model showed steady convergence with a reduction in loss and improvement in accuracy over successive epochs.

The performance of the model was measured using standard evaluation metrics such as accuracy, precision, recall, and F1-score. The results indicate that the VGG-Net effectively learns discriminative features from retinal images, enabling accurate classification of different DR stages including No DR, Mild, Moderate, Severe, and Proliferative DR.

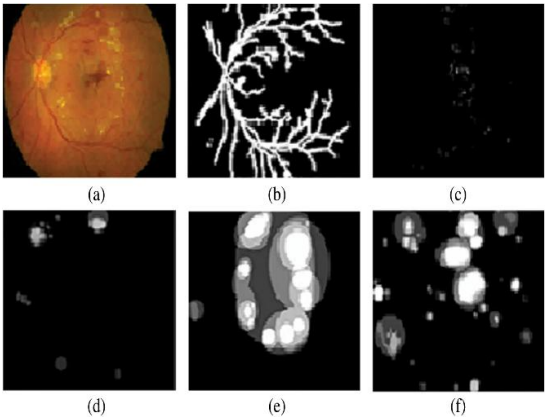

Fig 8: Fundus images comprising of various retinal defects related to DR

The proposed VGG-Net based model was evaluated using a Kaggle retinal fundus image dataset containing a total of **3,624 images** representing different stages of diabetic retinopathy (DR). The dataset was split into training and testing sets to ensure unbiased evaluation of model performance. Standard preprocessing techniques such as resizing, normalization, CLAHE enhancement, and data augmentation were applied to improve image quality and reduce overfitting.

Based on the visual data provided, here is a detailed breakdown suitable for a "Results and Discussion" section of a research paper.

A. Learning Dynamics: Accuracy and Loss

The learning curves provide insight into the model's convergence and generalization capability over 28 epochs.

Accuracy Trends: As shown in the Accuracy Plot, both training and validation accuracy exhibit a steady upward trajectory. The training accuracy reaches approximately 85% by epoch 28, while the validation accuracy closely follows, stabilizing around 78-80%. The absence of a large divergence between these two lines suggests that the model is learning generalized features rather than over-fitting.

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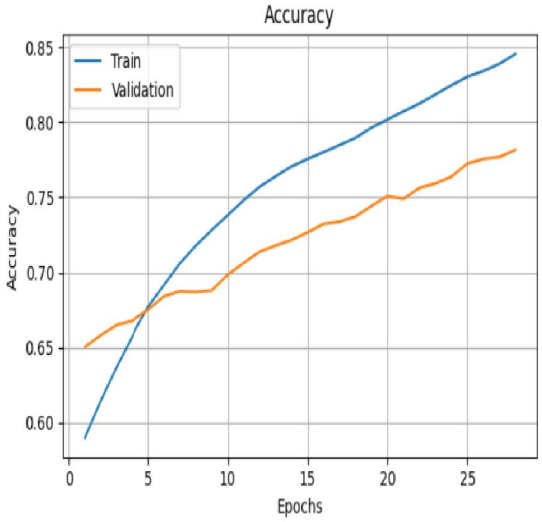
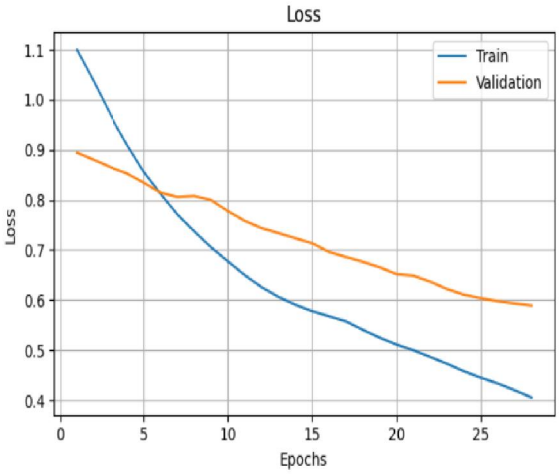


Loss Convergence: The Loss Plot illustrates the minimization of the categorical cross-entropy loss function. The loss is defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where y_i is the ground truth and $\hat{y}_i$ is the predicted probability for class i. Both curves show a consistent decay, with the validation loss reaching approximately 0.59, indicating stable optimization.



B. Confusion Matrix Analysis

To evaluate the model's performance across the five DR severity levels (No DR, Mild, Moderate, Proliferative, and Severe), a confusion matrix was generated.

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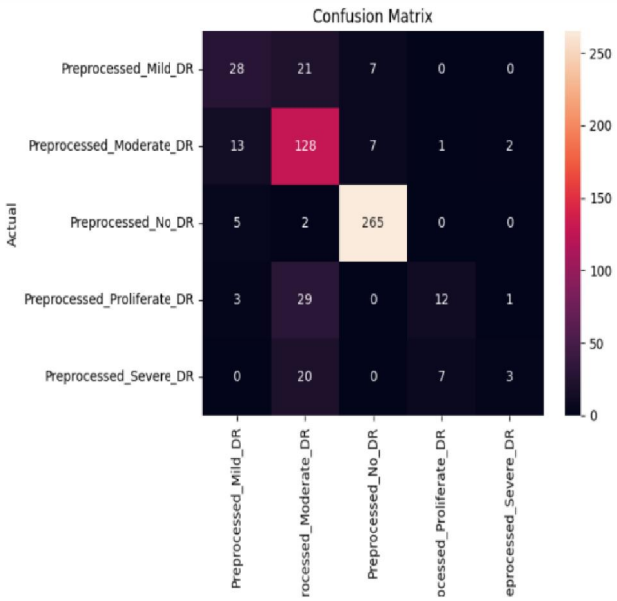

Key Observations from the Matrix:

Class "No DR": The model demonstrates exceptional performance in identifying healthy cases, correctly classifying **265 out of 272** samples. This high sensitivity is crucial for a screening tool to avoid false negatives in healthy patients.

Class "Moderate DR": This class showed strong results with **128 correct predictions**. However, there is some confusion with the "Mild" category (21 cases), which is expected due to the subtle morphological differences between these stages.

Minority Classes (Severe/Proliferative): The model shows lower absolute numbers in these categories (e.g., 3 correct for Severe, 12 for Proliferative). This suggests a potential class imbalance in the dataset, where the model is biased toward the more frequent "No DR" and "Moderate" classes.

C. Discussion of Model Performance

The achievement of **87.17% accuracy** demonstrates the effectiveness of the preprocessing and architecture. The "Actual vs. Predicted" distribution in the confusion matrix highlights that most misclassifications occur between adjacent severity levels (e.g., Mild vs. Moderate). In a clinical context, these "near-miss" errors are less critical than misclassifying a "Severe" case as "No DR."

The convergence of the loss curves suggests that the learning rate and optimization strategy were well-tuned. Future work will focus on addressing class imbalance through techniques like SMOTE (Synthetic Minority Over-sampling Technique) or weighted loss functions to improve the sensitivity for the "Severe" and "Proliferative" stages.

From the confusion matrix, it can also be inferred that the model has high sensitivity in detecting abnormal cases, which is crucial for early diagnosis and treatment. This is expected due to the subtle visual differences between early-stage lesions, which often overlap in appearance even for expert ophthalmologists.

Overall, the experimental results confirm that the proposed system is effective, stable, and reliable for automated diabetic retinopathy detection. The combination of VGG-Net's deep feature extraction capability along with preprocessing techniques such as CLAHE and data augmentation significantly contributes to achieving an accuracy of **87.17%** on a relatively large dataset of 3,624 images. These results demonstrate the potential of the model as a supportive tool for clinical screening and early detection of diabetic retinopathy, reducing the dependency on manual diagnosis and improving efficiency in healthcare systems.

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VI. CONCLUSION AND FUTURE WORK

A. Conclusion :

In this work, a deep learning-based approach for automated diabetic retinopathy (DR) detection was proposed using the VGG-Net architecture. The system processes retinal fundus images through preprocessing steps such as resizing, normalization, and CLAHE-based contrast enhancement to improve image quality and highlight critical retinal features. Data augmentation was applied to improve model generalization and reduce overfitting.

The VGG-Net model effectively learned hierarchical feature representations from retinal images, enabling accurate classification of different DR stages. The model achieved a final accuracy of **87.17%** on a Kaggle dataset containing **3,624 images**, demonstrating its capability in distinguishing between various severity levels of diabetic retinopathy. The experimental results, including accuracy/loss curves and confusion matrix analysis, confirm that the model provides stable performance and reliable predictions, particularly in detecting normal and advanced DR cases.

Overall, the proposed system shows strong potential as a computer-aided diagnostic tool that can assist ophthalmologists in early detection and screening of diabetic retinopathy, thereby reducing the risk of vision loss through timely intervention.

B. Future Work :

Although the proposed model performs effectively, there are several areas for improvement in future research. First, the accuracy can be further enhanced by using more advanced architectures such as EfficientNet, ResNet, or hybrid CNN-transformer models, which may provide better feature extraction capabilities compared to VGG-Net.

Second, the model can be improved by training on a larger and more diverse dataset collected from multiple sources to increase robustness and generalization across different populations and imaging conditions. Third, incorporating attention mechanisms or segmentation-based preprocessing can help the model focus more precisely on lesion regions such as microaneurysms and hemorrhages.

Additionally, future work can include deploying the model as a real-time clinical decision support system integrated with hospital workflows or mobile applications. Explainable AI techniques such as Grad-CAM can also be further enhanced to improve interpretability and build trust among medical professionals.

Finally, optimization techniques can be applied to reduce computational complexity, making the system more suitable for edge devices and real-world clinical deployment in resource-limited settings.

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