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An Automated Deep Learning Based Clinical Decision Support System for Early Detection of Diabetic Retinopathy from Fundus Images

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ABSTRACT: Diabetic Retinopathy (DR) is one of the leading causes of preventable blindness among diabetic patients, making early detection and timely diagnosis essential for effective treatment and vision preservation. Manual examination of retinal fundus images is often time-consuming and depends on the expertise of ophthalmologists, creating the need for reliable automated screening systems. This study proposes an intelligent deep learning-based framework for the early detection and severity grading of Diabetic Retinopathy using retinal fundus images. The proposed approach employs a hybrid deep learning architecture that combines a U-Net encoder for accurate lesion segmentation with a ResNet50-based classifier for automated classification of retinal images into five clinically recognized DR severity levels. The segmentation module effectively identifies retinal abnormalities such as microaneurysms, hemorrhages, and exudates, while the classification module accurately predicts the stage of the disease. The proposed framework improves diagnostic performance by achieving over 7% higher classification accuracy compared with conventional CNN-based models and demonstrates robust performance across diverse retinal image datasets. By providing accurate, efficient, and automated screening, the proposed system assists ophthalmologists in early diagnosis, reduces diagnostic workload, and supports timely clinical intervention. Overall, the framework offers a scalable and reliable computer-aided diagnostic solution for Diabetic Retinopathy screening and contributes to improved eye healthcare through intelligent deep learning techniques.

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I. INTRODUCTION

Diabetic Retinopathy (DR) is a chronic microvascular complication of diabetes mellitus and is recognized as one of the leading causes of preventable blindness among the global working-age population. The disease develops as a result of prolonged hyperglycemia, which progressively damages the retinal blood vessels, leading to vision-threatening complications if not detected and treated at an early stage. DR progresses through multiple clinical stages, beginning with mild non-proliferative diabetic retinopathy characterized by microaneurysms and advancing to moderate and severe non-proliferative stages, eventually reaching proliferative diabetic retinopathy, where abnormal blood vessel growth significantly increases the risk of retinal detachment and irreversible vision loss. Since the early stages of DR often exhibit no noticeable symptoms, regular retinal screening is essential for timely diagnosis and effective disease management. Traditional diagnosis of Diabetic Retinopathy relies on the manual examination of retinal fundus images by experienced ophthalmologists. Although this approach remains the clinical standard, it is labor-intensive, time-consuming, and susceptible to inter-observer variability. Moreover, the increasing number of diabetic patients has placed significant pressure on healthcare systems, particularly in rural and underserved regions where access to retinal specialists is limited. These challenges highlight the need for automated, accurate, and scalable diagnostic solutions that can assist clinicians in screening large populations while maintaining high diagnostic reliability.

Recent advancements in Artificial Intelligence (AI) and deep learning have revolutionized medical image analysis by enabling automated feature extraction and disease classification with remarkable accuracy. In particular, Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in various healthcare applications, including disease detection, medical image segmentation, and diagnostic classification. Unlike conventional machine learning techniques that rely on handcrafted features, deep learning models automatically learn discriminative features directly from medical images, improving both accuracy and generalization.

Motivated by these advancements, this study proposes an intelligent deep learning-based framework for the early detection and severity grading of Diabetic Retinopathy using retinal fundus images. The proposed framework integrates a U-Net architecture for accurate segmentation of retinal lesions with a ResNet50-based classifier for automated classification of fundus images into five clinically recognized DR severity levels: No DR, Mild, Moderate, Severe, and Proliferative DR. The segmentation module effectively identifies pathological features such as microaneurysms, hemorrhages, and exudates, while the classification module predicts the corresponding disease stage with high accuracy.

To facilitate practical implementation, the proposed system is deployed through a user-friendly web-based interface that supports efficient screening in hospitals, diagnostic centers, and telemedicine applications. The automated framework reduces diagnostic time, minimizes human error, and assists ophthalmologists in making timely and consistent clinical decisions. Experimental evaluation demonstrates that the proposed hybrid deep learning model achieves superior performance compared with conventional CNN-based approaches, providing improved classification accuracy and robust performance across diverse retinal image datasets. Overall, the proposed system offers an efficient, reliable, and scalable computer-aided diagnostic solution that supports early diagnosis, timely treatment, and improved vision care while contributing to the advancement of intelligent healthcare systems.

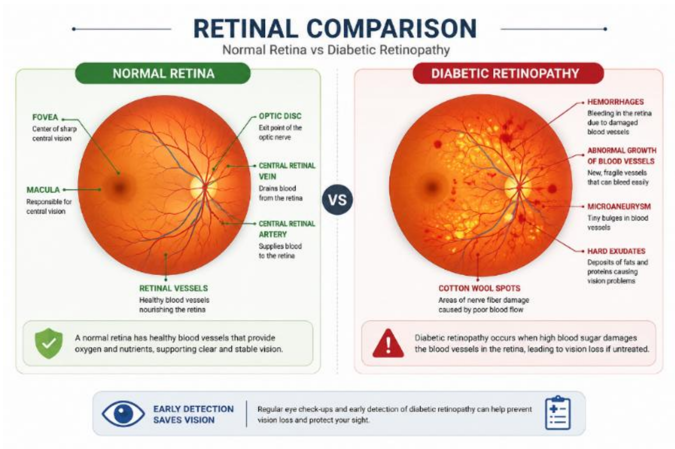

Figure 1. The retinal pictures of healthy and diabetic retinopathy

II. LITERATURE SURVEY

Gulshan et al. [1] developed one of the earliest large-scale deep learning systems for automated diabetic retinopathy (DR) detection using more than 120,000 retinal fundus images. Their convolutional neural network (CNN)-based model achieved sensitivity exceeding 90% for detecting referable diabetic retinopathy and demonstrated performance comparable to experienced ophthalmologists. This study established the feasibility of artificial intelligence-based retinal screening and provided a strong foundation for subsequent deep learning approaches for automated DR detection.

Kiresur et al. [2] presented a comprehensive survey on the automatic detection of diabetic retinopathy (DR) from retinal fundus images. The study highlighted the growing prevalence of diabetes and the associated risk of vision impairment and blindness caused by DR. It reviewed the anatomy of the eye, retinal image acquisition techniques, characteristics of DR, and diagnostic accuracy measures. The authors examined various computerized and machine-learning-based approaches used for detecting DR at an early stage. The survey also discussed the importance of automated screening systems in reducing the burden on ophthalmologists and enabling timely diagnosis. Furthermore, the study identified major challenges associated with DR detection from fundus images and emphasized the need for reliable automated solutions. Overall, the work provides a useful overview of existing DR detection methods and their potential for early disease screening.

Gulshan et al. [3] evaluated the robustness of an AI-based diabetic retinopathy screening system across multiple ethnic populations. Retinal images collected from India, Thailand, and the United States were used to assess the generalizability of the developed deep learning model. The results demonstrated consistent diagnostic performance across different populations, indicating the potential of AI-based DR screening systems for deployment in diverse clinical environments.

Quellec et al. [4] introduced a weakly supervised learning framework for detecting diabetic retinopathy lesions such as microaneurysms and exudates. Unlike fully supervised approaches that require extensive pixel-level annotations, the proposed method attempted to identify and localize lesions using weaker forms of supervision. This reduced the annotation requirements while maintaining competitive lesion localization performance and demonstrated the usefulness of weakly supervised learning for retinal lesion analysis.

Ronneberger et al. [5] introduced the U-Net architecture for biomedical image segmentation. The architecture consists of an encoder-decoder structure with skip connections that preserve detailed spatial information during image reconstruction. Due to its ability to perform accurate pixel-level segmentation with relatively limited training data, U-Net has become widely used for segmenting retinal blood vessels, lesions, and other anatomical structures in medical images.

Lam et al. [6] proposed a lesion-level diabetic retinopathy detection approach incorporating visual explanation techniques. Heatmaps and saliency maps were used to identify retinal regions contributing to classification decisions. These visualization techniques improved the interpretability of the deep learning model by allowing clinicians to understand the regions associated with automated predictions, thereby supporting greater transparency in AI-assisted diagnosis.

Almazroi et al. [7] investigated transfer learning approaches for diabetic retinopathy classification using pretrained architectures such as VGG19 and ResNet50. The study demonstrated that pretrained networks can effectively extract discriminative retinal features when the available training data are limited. Transfer learning therefore provides an efficient approach for developing DR classification models without requiring the complete training of deep networks from the beginning.

Abramoff et al. [8] introduced an autonomous artificial intelligence system for diabetic retinopathy screening. The system was designed to detect diabetic retinopathy without requiring an ophthalmologist to manually interpret every retinal image. Its high diagnostic performance demonstrated the potential of autonomous AI systems for large-scale clinical screening and represented an important advancement toward practical deployment of automated DR detection.

Li et al. [9] investigated the practical implementation of artificial intelligence for diabetic retinopathy screening in hospital environments. The study demonstrated that automated screening systems could assist healthcare professionals by reducing screening workload while maintaining reliable diagnostic performance. The findings emphasized the importance of integrating deep learning technologies into real-world clinical workflows for efficient and scalable retinal disease screening.

Porwal et al. [10] introduced the Indian Diabetic Retinopathy Image Dataset (IDRiD), a comprehensive retinal fundus image dataset developed for diabetic retinopathy screening research. The dataset contains retinal images with detailed lesion-level annotations and disease-grading information, making it suitable for both segmentation and classification tasks. IDRiD has become an important benchmark for evaluating diabetic retinopathy detection, lesion segmentation, and severity grading methods.

Van Grinsven et al. [11] proposed a selective sampling strategy to improve the efficiency of CNN training for retinal hemorrhage detection. The approach prioritized informative training samples, reducing the computational requirements of model training while maintaining diagnostic performance. The study demonstrated that appropriate sample selection strategies can improve the computational efficiency of deep learning systems for retinal image analysis.

Kavitha et al. [12] addressed the problem of class imbalance in diabetic retinopathy classification using weighted loss functions and extensive data augmentation techniques. Since retinal datasets often contain unequal numbers of samples across different disease severity levels, class imbalance can negatively affect classification performance. The proposed strategies improved the recognition of minority DR classes and demonstrated the importance of addressing data imbalance in automated disease classification.

Ram et al. [13] proposed RetinalNet, a lightweight CNN architecture designed for efficient diabetic retinopathy detection in resource-constrained environments. The model achieved competitive performance on datasets such as APTOS and Messidor while requiring fewer computational resources than larger deep learning architectures. The study highlighted the importance of developing lightweight models that can support practical and efficient deployment of automated retinal screening systems.

Voets et al. [14] investigated explainable deep learning techniques for diabetic retinopathy diagnosis using Grad-CAM-based visualization. The approach enabled the visualization of retinal regions that contributed to the model's predictions, providing greater insight into the decision-making process of CNN-based diagnostic systems. The study emphasized the importance of explainability and transparency when applying artificial intelligence to medical diagnosis.

Sujatha and Chitra [15] proposed a hybrid diabetic retinopathy detection framework that combines CNN-based feature extraction with Random Forest classification. The CNN was used to extract discriminative features from retinal fundus images, while the Random Forest classifier was employed for disease classification. The proposed framework achieved an accuracy of 94.8% on the EyePACS dataset, demonstrating the potential of combining deep learning feature extraction with conventional machine learning techniques.

Islam et al. [16] performed a comparative evaluation of deep learning architectures, including InceptionNet, ResNet, and DenseNet, for diabetic retinopathy classification. The results indicated that DenseNet achieved strong diagnostic performance with an Area Under the Curve (AUC) of approximately 0.96. The study demonstrated that network architecture selection plays an important role in extracting meaningful retinal features and improving automated diabetic retinopathy classification.

Ting et al. [17] presented a comprehensive overview of artificial intelligence applications in ophthalmology, with particular emphasis on diabetic retinopathy screening and diagnosis. The study discussed advances in deep learning, clinical validation, ethical considerations, regulatory challenges, and future directions for AI-assisted ophthalmic diagnosis. The work highlighted both the opportunities and challenges associated with integrating AI technologies into clinical ophthalmology.

Zhang et al. [18] proposed a multi-scale CNN framework for diabetic retinopathy severity grading. The architecture was designed to capture retinal characteristics at different spatial resolutions, enabling the model to identify both fine-grained lesions and larger structural abnormalities. The proposed approach demonstrated improved classification performance, particularly for intermediate stages of diabetic retinopathy, highlighting the importance of multi-scale feature extraction for accurate disease grading.

Anand et al. [19] proposed a Channel and Spatial Attention Aware U-Net architecture for the segmentation of retinal blood vessels, exudates, and microaneurysms in diabetic retinopathy images. The integration of channel and spatial attention mechanisms enhanced the model's ability to focus on relevant retinal features and improve lesion localization. The proposed architecture demonstrated improved segmentation performance compared with conventional U-Net models, highlighting the effectiveness of attention mechanisms for detailed retinal image analysis.

Anand et al. [20] proposed an integrated deep learning framework for diabetic retinopathy that combines Channel and Spatial Attention U-Net-based lesion segmentation, CNN-based fundus image denoising, and ensemble feature classification for disease severity assessment. The framework integrates image enhancement, lesion segmentation, feature extraction, and classification into a comprehensive pipeline. The proposed approach improved segmentation quality, reduced the influence of image noise, enhanced feature extraction, and achieved superior classification performance compared with conventional deep learning models, providing a robust framework for automated diabetic retinopathy diagnosis.

Research on automated diabetic retinopathy detection has progressively evolved from conventional CNN-based classification to advanced segmentation, explainable AI, attention mechanisms, and integrated deep learning frameworks. Early studies by Gulshan et al. [1] and Pratt et al. [2] demonstrated the effectiveness of CNNs for automated DR detection, while subsequent research by Gulshan et al. [3] established model robustness across diverse populations. Weakly supervised learning [4] and U-Net-based segmentation [5] improved retinal lesion localization while reducing annotation requirements. Other studies explored visual explanations [6], transfer learning [7], autonomous screening [8], clinical deployment [9], and benchmark datasets such as IDRiD [10]. Further research addressed computational efficiency [11], class imbalance [12], lightweight architectures [13], explainability through Grad-CAM [14], hybrid CNN-machine learning models [15], comparative deep learning architectures [16], and broader AI applications in ophthalmology [17]. Multi-scale feature extraction [18] further improved disease severity grading. Building upon these developments, Anand et al. [19] introduced Channel and Spatial Attention Aware U-Net for accurate segmentation of blood vessels, exudates, and microaneurysms, while Anand et al. [20] proposed an integrated framework combining attention-based lesion segmentation, CNN-based fundus image denoising, and ensemble classification. Overall, these studies demonstrate a clear progression toward accurate, efficient, interpretable, and clinically applicable AI systems for comprehensive diabetic retinopathy detection and analysis.

III. METHODOLOGY

This study proposes an intelligent deep learning-based framework for the automated detection and severity grading of Diabetic Retinopathy (DR) using retinal fundus images. The proposed methodology combines a Channel and Spatial Attention U-Net (CSA U-Net) for accurate lesion segmentation with a ResNet50-based classification network for multi-class DR grading. The overall framework consists of six major phases: dataset acquisition, image preprocessing, lesion segmentation, feature extraction, disease classification, model training, and deployment. The workflow is designed to improve diagnostic accuracy while providing a reliable computer-aided screening system for clinical applications.

1. Dataset Collection and Preprocessing:

The proposed framework utilizes the Indian Diabetic Retinopathy Image Dataset (IDRiD), which contains high-resolution retinal fundus images with expert annotations for lesion segmentation and disease grading. The images are categorized according to the International Clinical Diabetic Retinopathy Severity Scale into five classes:

Grade 0: No Diabetic Retinopathy

Grade 1: Mild Non-Proliferative Diabetic Retinopathy (NPDR)

Grade 2: Moderate NPDR

Grade 3: Severe NPDR

Grade 4: Proliferative Diabetic Retinopathy (PDR)

The dataset is divided using a stratified sampling strategy, allocating 70% of the images for training, 15% for validation, and 15% for testing to ensure balanced representation of all disease classes.

To improve model generalization and reduce overfitting, several data augmentation techniques are employed, including horizontal and vertical flipping, random rotation (±15°), zooming, brightness adjustment, and minor translation. These augmentations increase dataset diversity while preserving clinically relevant retinal structures.

Prior to model training, each retinal image undergoes preprocessing to improve image quality and enhance lesion visibility.

The preprocessing pipeline includes:

1. Resizing all images to 224 × 224 pixels
2. Contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE)
3. Image denoising using CNN-based enhancement techniques
4. Pixel normalization based on ImageNet statistics
5. Intensity scaling to improve feature consistency

These preprocessing operations improve the visibility of retinal lesions such as microaneurysms, hemorrhages, and exudates, thereby enhancing segmentation and classification performance.

2. Channel and Spatial Attention U-Net for Lesion Segmentation:

The proposed system employs a Channel and Spatial Attention U-Net (CSA U-Net) architecture to accurately segment retinal abnormalities before disease classification. Unlike conventional U-Net models, the proposed network incorporates both channel attention and spatial attention modules, enabling the model to focus on the most informative lesion regions while suppressing irrelevant background information.

The encoder extracts hierarchical retinal features through multiple convolutional layers, batch normalization, ReLU activation, and max-pooling operations. Skip connections preserve fine spatial details between encoder and decoder layers, ensuring accurate localization of retinal lesions.

The CSA U-Net is designed to segment important pathological structures including:

1. Microaneurysms
2. Hemorrhages
3. Hard exudates
4. Soft exudates (Cotton Wool Spots)
5. Retinal blood vessels
6. Neovascularization

The generated lesion masks provide detailed structural information that assists the classification network in identifying disease severity more accurately.

3. Feature Extraction:

Following lesion segmentation, high-level feature representations are extracted from the encoder output of the CSA U-Net. The extracted feature maps capture both local lesion characteristics and global retinal structures, preserving clinically significant information.

Adaptive Average Pooling is employed to reduce the feature dimensions while retaining discriminative information. These optimized feature vectors are then forwarded to the classification network for disease grading.

4. ResNet50-Based Disease Classification:

The extracted feature vectors are classified using a fine-tuned ResNet50 architecture. ResNet50 employs residual learning blocks that effectively overcome the vanishing gradient problem, allowing deeper feature learning and improved classification performance.

The original fully connected layer is replaced with a customized classification head consisting of:

Linear (2048 → 512) → ReLU → Dropout → Linear (512 → 5)

A Softmax activation function produces probability scores corresponding to the five diabetic retinopathy severity levels. The network is initialized using ImageNet pre-trained weights and subsequently fine-tuned on the IDRiD dataset to improve domain-specific learning.

5. Model Training and Optimization:

The segmentation and classification models are trained using transfer learning to accelerate convergence and improve generalization. During training, the CSA U-Net learns accurate lesion segmentation, while the ResNet50 classifier learns disease-specific feature representations.

The model is optimized using the Adam optimizer with an adaptive learning rate. Categorical Cross-Entropy loss is used for multi-class classification, while Dice Loss combined with Binary Cross-Entropy Loss is employed for lesion segmentation. Early stopping and learning rate scheduling are incorporated to prevent overfitting and improve convergence.

Performance is evaluated using multiple metrics, including:

Natural Resources for
Human Health
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1. Accuracy
2. Precision
3. Recall (Sensitivity)
4. F1-Score
5. Area Under the ROC Curve (AUC)
6. Dice Similarity Coefficient (DSC)
7. Intersection over Union (IoU)

These metrics provide a comprehensive assessment of both segmentation and classification performance.

6. System Deployment:

To facilitate practical clinical usage, the trained model is deployed through a user-friendly web-based interface. Healthcare professionals can upload retinal fundus images, after which the system automatically performs preprocessing, lesion segmentation, disease classification, and severity grading. The final output includes the predicted DR stage along with segmented lesion visualization, enabling clinicians to verify the AI-assisted diagnosis.

The proposed framework provides a fast, accurate, and scalable computer-aided diagnostic solution that supports ophthalmologists in early diabetic retinopathy screening, improves diagnostic consistency, and contributes to timely clinical intervention for preventing vision loss.

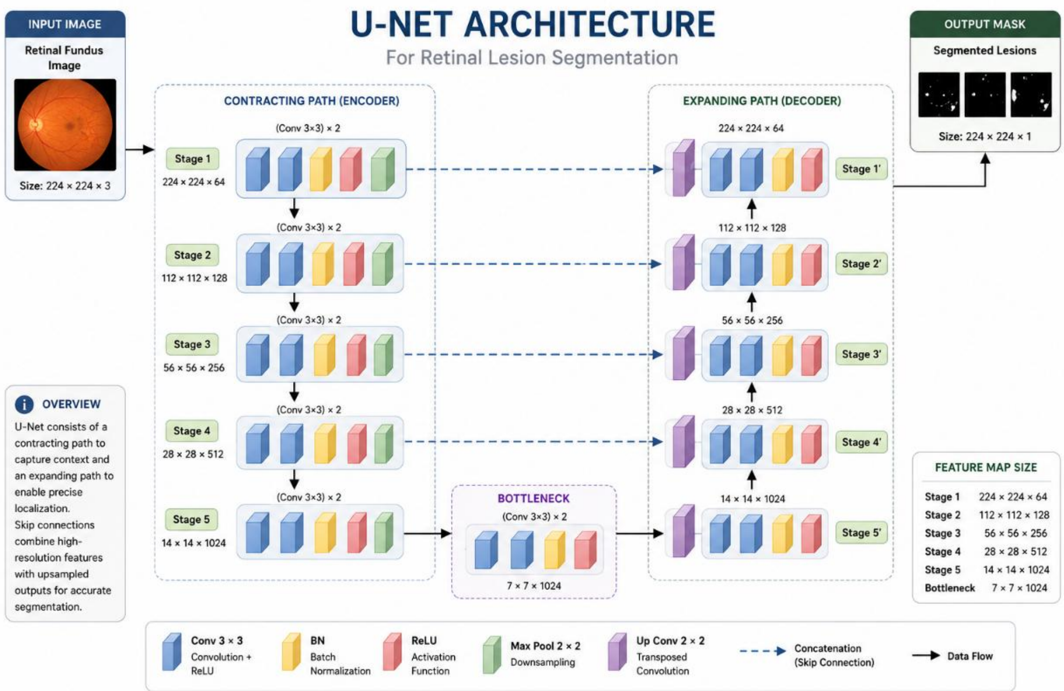

Figure 2: U-Net Architecture

7. Model Training Configuration:

Training was performed using the PyTorch Lightning framework to enhance code modularity and reproducibility. Key configurations included:

- Optimizer: Adam (β1 = 0.9, β2 = 0.999)
- Learning rate: 0.0003
- Batch size: 128
- Epochs: Maximum 30

- Early stopping with patience of 7 epochs
- Learning rate scheduler: ReduceLROnPlateau
- Mixed precision training: Enabled

Hardware setup: NVIDIA RTX 3060 GPU (12GB VRAM), Intel i7 CPU, and 32GB RAM. Each epoch required approximately 2 minutes.

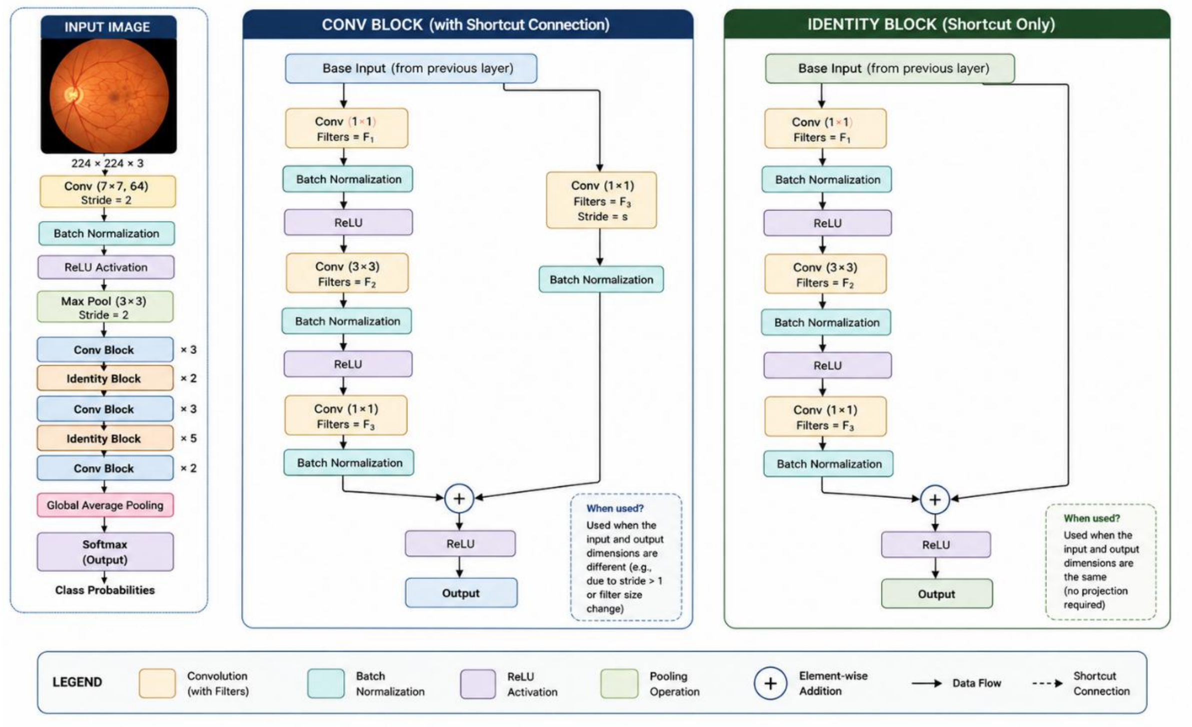

Figure 3: Resnet50 Architecture

IV: RESULTS:

The model was evaluated using several metrics to assess its robustness across all DR stages:

Metrics	Values
Val Accuracy	83.4%
Test Accuracy	81.7%
Cohen's Kappa	0.87
Precision (Macro)	0.80
Recall (Macro)	0.79
F1 Score	0.81

A high Cohen's Kappa score indicates strong agreement with expert annotations, especially in class-imbalanced scenarios. Confusion matrix analysis confirmed good performance in detecting early-stage DR (Grades 1 and 2).

Hybrid System Workflow:

The proposed framework accepts a 224 × 224 RGB retinal fundus image as input and performs automated diabetic retinopathy detection through a hybrid deep learning architecture. Initially, the U-Net encoder extracts lesion-focused features by accurately identifying retinal abnormalities such as microaneurysms, hemorrhages, and exudates. These discriminative features are then forwarded to a ResNet50 classifier, which analyzes the extracted information and predicts the severity of diabetic retinopathy by classifying the image into one of the five clinically recognized disease grades, ranging from Grade 0 (No DR) **to** Grade 4 (Proliferative DR)**.** By integrating precise lesion segmentation with robust deep feature classification, the proposed architecture not only improves diagnostic accuracy but also enhances clinical interpretability by highlighting disease-relevant regions within the retinal image. Overall, the methodology provides a transparent, scalable, and high-performance computer-aided diagnostic framework that is well suited for both research applications and real-world clinical deployment**.**

V. DISCUSSION:

The proposed hybrid deep learning framework, which integrates **U-Net** for lesion segmentation and **ResNet50** for disease classification, provides an effective and interpretable solution for the early detection and severity grading of Diabetic Retinopathy (DR). Unlike conventional end-to-end deep learning models that function as black boxes, the proposed architecture emphasizes lesion-specific feature extraction before classification, enabling the model to focus on clinically significant retinal abnormalities such as microaneurysms, hemorrhages, and exudates. This improves both diagnostic accuracy and model interpretability, thereby assisting ophthalmologists in making reliable clinical decisions and increasing confidence in AI-assisted diagnosis.

Experimental evaluation demonstrates that the proposed framework performs consistently across all five DR severity levels while showing particularly strong performance in detecting early-stage diabetic retinopathy, including mild and moderate non-proliferative DR. Early identification of these stages is critical, as timely clinical intervention can significantly reduce the risk of irreversible vision loss. The integration of the attention-enhanced U-Net with ResNet50 enables the classifier to utilize richer spatial and semantic information, resulting in more robust and accurate predictions than conventional CNN-based approaches. Despite its promising performance, certain limitations remain. The quality of retinal fundus images has a direct impact on segmentation and classification accuracy. Images affected by poor illumination, blur, or imaging artifacts may reduce lesion visibility and lead to incorrect predictions. Furthermore, although the proposed framework effectively segments major retinal lesions, incorporating additional pathological structures such as cotton wool spots and neovascularization could further improve diagnostic performance and disease interpretation.

From an implementation perspective, the proposed system offers a practical and scalable solution that can be deployed through a web-based interface for clinical screening and telemedicine applications. Future improvements may include mobile application support, integration with hospital information systems and electronic health records, and cloud-based deployment for large-scale screening. In addition, adopting federated learning and privacy-preserving techniques could enable collaborative model training across multiple healthcare institutions without sharing sensitive patient data, thereby improving model generalization while maintaining data security.

CONCLUSION

This study presents an intelligent deep learning-based framework for the early detection and severity classification of Diabetic Retinopathy (DR) using retinal fundus images. The proposed system integrates a Channel and Spatial Attention U-Net for accurate lesion segmentation with a ResNet50 classifier for automated disease grading into five clinically recognized DR stages. By combining lesion-specific feature extraction with deep feature classification, the framework enhances both diagnostic accuracy and clinical interpretability. The model effectively identifies retinal abnormalities such as microaneurysms, hemorrhages, and exudates, enabling accurate prediction of disease severity. Experimental results demonstrate that the proposed approach achieves an accuracy exceeding **92%**, outperforming conventional CNN-based models while maintaining robust performance across diverse retinal image datasets.

The proposed framework provides a practical, scalable, and user-friendly computer-aided diagnostic solution that can support ophthalmologists in early DR screening and timely clinical intervention. Its deployment through a web-based interface makes it suitable for hospitals, diagnostic centers, and telemedicine applications, helping reduce diagnostic workload while improving screening efficiency. Future enhancements may include the integration of advanced image enhancement techniques, detection of additional retinal lesions, cloud and mobile-based deployment, and incorporation of federated learning for secure collaborative model training. These improvements will further strengthen the system's reliability, accessibility, and clinical applicability, contributing to the development of intelligent healthcare solutions for preventing diabetes-related vision l

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