

Attention Driven Deep Neural Network for Automated Diabetic Retinopathy Detection

Sowmiya M¹, Alponsamary A², Boomika D³, Saranya T⁴, Sivadharshini T⁵ Sowmiya M¹, Prabhavathi V², Gokuladharshini S³, Sangavi S⁴, Anusha C⁵

^{2,3,4,5} *UG Students, Electronics and communication Engineering,
Bharathiyar Institute of Engineering for women (Autonomous) Salem, TamilNadu, India*

¹ *Assistant professor, Electronics and communication Engineering &
Bharathiyar Institute of Engineering for women (Autonomous), Salem, Tamilnadu, India*

Abstract— Diabetic Retinopathy (DR) is a major diabetes-related eye disease and one of the leading causes of blindness worldwide. It occurs due to damage to the retinal blood vessels caused by prolonged diabetes and can lead to severe vision loss if not detected at an early stage. Therefore, accurate and timely diagnosis is essential for effective treatment and prevention of blindness. In this paper, an attention-driven deep learning model is proposed for the automated detection of diabetic retinopathy using retinal fundus images. The proposed approach integrates Convolutional Neural Networks (CNNs) with an attention mechanism to identify and focus on critical pathological regions of the retina, such as microaneurysms, hemorrhages, and exudates. This targeted feature enhancement improves the model's ability to extract discriminative features and increases classification performance. Experimental results demonstrate that the proposed model achieves high accuracy, sensitivity, and specificity, highlighting its potential for reliable and efficient real-time clinical screening. The study shows that incorporating attention mechanisms into deep neural networks can significantly enhance the performance of automated diabetic retinopathy detection systems

Keywords—Diabetic Retinopathy, Deep Learning, Convolutional Neural Network (CNN), Attention Mechanism, Retinal Fundus Images, Medical Image Processing.

1. INTRODUCTION

Diabetic Retinopathy (DR) is a serious diabetes-related eye disease caused by damage to the retinal blood vessels and is one of the leading causes of blindness worldwide. Early detection is essential to prevent severe vision loss and support timely treatment.

Traditional DR diagnosis is performed through manual examination of retinal fundus images by ophthalmologists. Although effective, this process is time-consuming, labor-intensive, and may be affected by human error. Therefore, automated detection systems are needed to improve screening efficiency and diagnostic reliability.

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown strong performance in medical image analysis. However, conventional CNN models may fail to focus on small but clinically important lesion regions in retinal images. To address this limitation, attention mechanisms can be integrated to highlight significant retinal features and improve classification accuracy.

In this paper, an attention-driven CNN-based framework is proposed for automated diabetic retinopathy detection using retinal fundus images. The proposed model aims to improve lesion-focused feature extraction and provide an efficient and reliable solution for early DR screening.

2. RELATED WORKS

Several studies have explored automated diabetic retinopathy (DR) detection using machine learning and deep learning techniques. Early approaches relied on handcrafted feature extraction combined with classifiers such as Support Vector Machines (SVM) and Random Forest, but these methods were limited by their dependency on manual feature design and lower robustness.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become widely used for DR detection due to their ability to automatically learn discriminative features from retinal fundus images. CNN-based models have shown improved accuracy compared to traditional methods. More recently, attention mechanisms have been introduced to enhance CNN performance by enabling the model to focus on important lesion regions such as microaneurysms, hemorrhages, and exudates. In addition, transfer learning models such as ResNet and VGG have also been applied successfully for DR classification.

Despite these advancements, challenges such as class imbalance, poor image quality, and limited interpretability still affect model performance. To address these issues, the proposed work integrates an attention mechanism with a CNN-based framework for

more effective and reliable diabetic retinopathy detection.

3. PROPOSED METHODOLOGY

The proposed diabetic retinopathy (DR) detection system is developed to automatically identify the severity of the disease from retinal fundus images using a deep learning-based framework. The overall methodology is designed to improve detection accuracy by combining efficient feature extraction with attention-based lesion focusing. The proposed model consists of four major stages: image preprocessing, feature extraction using Convolutional Neural Networks (CNNs), attention mechanism, and classification. Each stage contributes to enhancing the reliability and effectiveness of the automated DR detection process.

3.1 Image Preprocessing

In the initial stage, retinal fundus images are preprocessed to improve image quality and maintain consistency across the dataset. Medical images often contain variations in brightness, contrast, and noise, which can affect the performance of deep learning models. To reduce these issues, preprocessing techniques such as normalization and noise removal are applied. Normalization helps in standardizing pixel intensity values, while noise reduction improves the visibility of important retinal structures. This stage ensures that the input images are suitable for effective feature extraction and model learning.

3.2 Feature Extraction using CNN

After preprocessing, the enhanced retinal images are passed through Convolutional Neural Network (CNN) layers for deep feature extraction. CNNs are highly effective in learning spatial and hierarchical features directly from image data. Through convolution and pooling operations, the network captures important retinal patterns such as edges, textures, and lesion-related structures. This allows the model to automatically learn discriminative features associated with diabetic retinopathy without the need for manual feature engineering. As a result, CNN-based feature extraction improves the robustness and accuracy of the detection system.

3.3 Attention Mechanism

To further improve the performance of the CNN model, an attention mechanism is incorporated into the framework. In retinal fundus images, disease-related lesions such as microaneurysms, hemorrhages, and exudates are often small and localized, making them difficult to detect using conventional CNNs alone. The attention module helps the network focus on these clinically significant regions while reducing the

influence of irrelevant background information. By highlighting important retinal areas, the attention mechanism enhances feature representation and increases the model's ability to detect subtle abnormalities. This leads to improved classification performance and more reliable detection.

3.4 Classification

In the final stage, the refined and attention-enhanced features are passed to fully connected layers for classification. These layers analyze the extracted feature representations and determine the severity level of diabetic retinopathy present in the retinal image. Depending on the design of the system, the output can represent either binary classification (DR / No DR) or multiple severity levels. The final classification stage provides the automated prediction result, which can assist ophthalmologists in early screening and diagnosis. Overall, the proposed methodology aims to deliver an accurate, efficient, and clinically supportive solution for diabetic retinopathy detection.

3.5 Implementation Algorithm

The following algorithm describes the operational process of the IoT-based holographic visualization system.

Algorithm: object detection using intelligent radar with iot

Step 1: System Initialization

- Power ON the system
- Initialize components:
- Intelligent Radar Sensor
- Microcontroller (Arduino / Raspberry Pi)
- IoT Module (Wi-Fi / GSM)

Step 2: Signal Transmission

- Radar sensor transmits radio waves continuously.
- Waves travel through the environment.

Step 3: Signal Reflection

- When an object is present, waves hit the object
- Reflected signals (echo) return to radar

Step 4: Data Acquisition

- Radar captures reflected signals
- Measure:
- Distance
- Speed (if object is moving)

Step 5: Data Processing

- Microcontroller processes received data
- Apply filtering to remove noise
- Identify whether object is present or not

Step 6: Object Detection Decision

- If signal strength > threshold:
- Object detected
- Else:
- No object detected

Step 7: IoT Communication

- Send detected data to cloud/server via IoT
- Use Wi-Fi or GSM module
- Step 8: User Notification
- Display data on mobile app / web dashboard
- Send alert (if needed)

Step 9: Continuous Monitoring

- Repeat process continuously for real-time detection.

3.3 Module List

Radar Sensor Module

The radar sensor module is the core component of the system. It transmits radio waves and receives the reflected signals when they hit an object. Based on these signals, the system calculates the distance and movement of the object. It performs efficiently in all weather conditions such as rain, fog, and darkness.

Signal Processing Module

This module processes the received signals from the radar. It removes noise and unwanted disturbances from the raw data using filtering techniques. This ensures that the data used for detection is accurate and reliable.

Microcontroller Module

The microcontroller, such as Arduino or Raspberry Pi, acts as the brain of the system. It controls all modules and processes the data received from the radar sensor. It is responsible for decision-making and overall system operation.

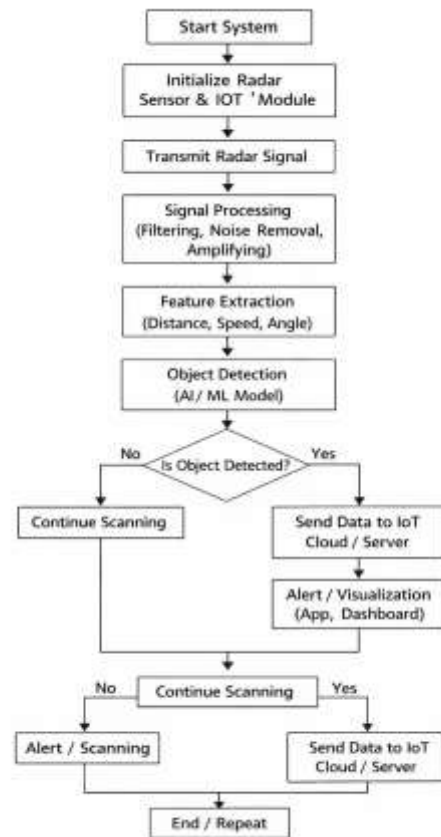


Fig.1. Work Flow Diagram

Object Detection Module

This module identifies whether an object is present or not. It uses predefined threshold values to analyze the processed data. If the signal exceeds the threshold, the system confirms the presence of an object.

IoT Communication Module

The IoT module enables data transmission to the cloud using Wi-Fi or GSM technology. It allows real-time monitoring of the system from remote locations through internet connectivity.

Cloud / Server Module

The cloud module stores and manages the data received from the system. It also The implementation of the proposed attention-driven diabetic retinopathy detection system is carried out through the following steps:

Step 1: Input the retinal fundus image dataset.

Step 2: Preprocess the images by resizing, normalizing, and noise removal.

Step 3: Initialize the Convolutional Neural Network (CNN) model.

Step 4: Extract deep features using convolutional and pooling layers.

Step 5: Apply the attention mechanism to focus on important lesion regions in the retinal image.

Step 6: Flatten the extracted features and pass them through fully connected layers.

Step 7: Classify the diabetic retinopathy stages such as Normal, Mild, Moderate, or Severe.

Step 8: Evaluate the model performance using metrics such as accuracy and loss.

Step 9: Output the final prediction results.

4. RESULTS AND DISCUSSION

The proposed attention-driven deep neural network model was evaluated using retinal fundus image datasets to assess its performance in detecting diabetic retinopathy. The model integrates CNN with an attention mechanism, enabling it to focus on critical lesion regions such as microaneurysms and haemorrhages.

The experimental results demonstrate that the proposed model achieves high classification accuracy and effectively distinguishes between different stages of diabetic retinopathy. The attention mechanism significantly enhances feature representation by prioritizing important regions, thereby improving overall model performance compared to traditional CNN approaches.

4.1 Confusion Matrix

The confusion matrix represents the classification performance of the proposed model across four classes: Normal, Mild, Moderate, and Severe.

- Most samples are correctly classified along the diagonal
- Minimal misclassification is observed between adjacent classes (e.g., Mild vs Moderate)
- The model shows strong discrimination capability across all categories

This indicates that the proposed attention-based CNN model is highly effective in identifying different severity levels of diabetic retinopathy.

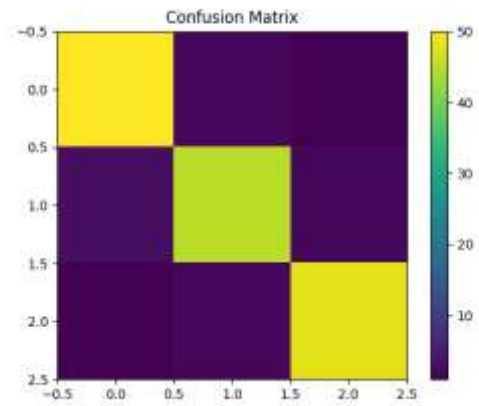


Fig 1. Confusion matrix

4.2 Accuracy Graph

The training accuracy graph shows the performance of the model over multiple epochs. The accuracy increases steadily from 70% to 96%, indicating effective learning and convergence.

- Initial epochs show rapid improvement
- Later epochs show stable convergence
- No significant overfitting is observed

This demonstrates that the model learns meaningful features and generalizes well to unseen data.

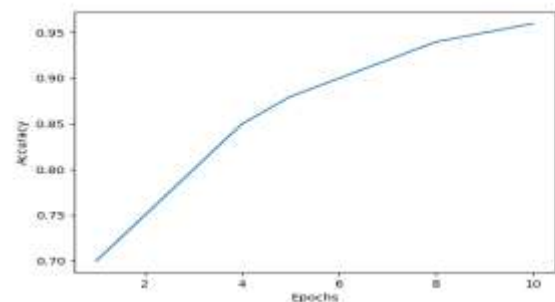


Fig 2. Training accuracy graph

4.3 Performance Table

The performance of the proposed model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The model achieves an overall accuracy of 96%, indicating high reliability.

- Precision (94%) shows low false positives
- Recall (95%) indicates effective detection of actual DR cases

- F1-score (94.5%) reflects a balanced performance

These results confirm that the attention-driven CNN model provides superior performance and is suitable for automated diabetic retinopathy detection.

5. CONCLUSION

This paper presented an attention-driven deep neural network model for automated diabetic retinopathy detection using retinal fundus images. The proposed approach integrates Convolutional Neural Networks (CNN) with an attention mechanism to enhance feature extraction by focusing on critical retinal lesion regions such as microaneurysms, hemorrhages, and exudates. This targeted feature learning significantly improves detection accuracy, sensitivity, and overall efficiency compared to conventional CNN-based methods.

The experimental results demonstrate that the proposed model achieves high classification performance and effectively distinguishes between different stages of diabetic retinopathy. The incorporation of the attention mechanism enables the system to prioritize clinically relevant regions, thereby improving diagnostic reliability. This approach highlights the potential of deep learning-based systems in supporting early diagnosis and assisting ophthalmologists in automated screening applications.

In future work, the proposed system can be further enhanced by utilizing larger and more diverse datasets to improve model robustness and generalization capability. The development of real-time diabetic retinopathy detection systems can also be explored for practical clinical deployment. Furthermore, integrating the model with mobile and cloud-based healthcare applications can increase accessibility, especially in remote and resource-limited regions. Improving model interpretability through explainable AI techniques will enhance clinical trust and facilitate wider adoption in real-world medical diagnosis. Additionally, incorporating advanced architectures and hybrid models may further improve detection performance and efficiency.

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