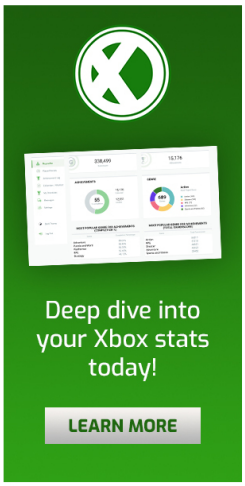
Experience the best with our premium plans – unlock exclusive features now!

Trusted GPT-5, ChatGPT and AI Detector tool by ZeroGPT

ZeroGPT the most Advanced and Reliable Chat GPT, GPT5 & AI Content Detector




```
DR-RAM: Diabetic Retinopathy Detection Using
Recurrent Attention and Reinforcement Learning
National University of Technology (NUTECH)
Group Members:
Ahad Imran (F23607034)
Zain-Ul-Abidin (F23607031)
Hamza Abdul Karim (F23607046)
Imaan Aftab (F23607041)
Subject:Reinforcement Learning (CS480)
Submitted to:Lec. Asif Mehmood
Code Repository:GitHub
Kaggle Notebook:Kaggle
December 2025
Abstract
```

Detect Text | Upload File | 14,999/15,000 Characters
Check 350,000 characters, Upgrade Here

Your File Content is Most Likely Human written

15.75% AI GPT*

DR-RAM: Diabetic Retinopathy Detection Using
Recurrent Attention and Reinforcement Learning
National University of Technology (NUTECH)
Group Members:
Ahad Imran (F23607034)
Zain-Ul-Abidin (F23607031)
Hamza Abdul Karim (F23607046)
Imaan Aftab (F23607041)
Subject:Reinforcement Learning (CS480)
Submitted to:Lec. Asif Mehmood
Code Repository:GitHub
Kaggle Notebook:Kaggle
December 2025
Abstract

Diabetic Retinopathy (DR) is a leading cause of preventable blindness, affecting millions of diabetic patients globally. Current Computer-Aided Diagnosis (CAD) systems rely on passive Convolutional Neural Networks (CNNs) that process entire high-resolution fundus images, resulting in computational inefficiency and limited interpretability. This paper introduces the Diabetic Retinopathy Recurrent Attention Model (DR-RAM), a novel framework that reformulates DR detection as a sequential decision-making problem with attention mechanisms inspired by Reinforcement Learning principles. Using recurrent glimpse-based processing, DR-RAM learns to sequentially attend to diagnostically relevant regions—such as the optic disc, macula, and vascular arcades—mimicking the active visual search behavior of expert ophthalmologists. Experiments on the APTOS 2019 dataset demonstrate that DR-RAM achieves a Quadratic Weighted Kappa score of0.8914 and accuracy of82.13%, outperforming the EfficientNet-B0 baseline (Kappa: 0.8702, Accuracy: 79.81%) while providing explicit glimpse trajectories that enhance clinical interpretability. The complete implementation is available on GitHub and Kaggle.

1 1 Introduction

1.1 Background

Diabetic Retinopathy (DR) is a microvascular complication of diabetes mellitus that progressively damages the retina, potentially leading to irreversible vision loss. The International Diabetes Federation estimates that over 537 million adults have diabetes, with approximately one-third at risk of developing DR [2]. The condition progresses through distinct stages—from mild Non-Proliferative DR (NPDR) characterized by microaneurysms, to sight-threatening Proliferative DR (PDR) involving neovascularization and potential retinal detachment.

Early detection through regular fundus screening is critical for preventing vision loss. However, the global shortage of trained ophthalmologists, particularly in developing nations, creates a significant bottleneck in DR screening programs. This disparity has motivated substantial research into automated Computer-Aided Diagnosis (CAD) systems powered by Deep Learning.

1.2 Problem Statement and Research Gap

Our comprehensive literature review of 30 recent studies (2020–2024) revealed that the current state-of-the-art in DR detection is dominated by supervised CNN architectures, including ResNet, DenseNet, and EfficientNet variants [1]. While these models achieve impressive accuracy metrics (often exceeding 95% on benchmark datasets), they suffer from three fundamental limitations:

1.Computational Waste:Standard CNNs process every pixel of high-resolution fundus images (often 2000×1500 pixels) uniformly, expending significant computational resources on healthy background tissue that carries no diagnostic value.

2.Resolution Trade-offs:To fit GPU memory constraints, images are typically down-sampled to 224×224 or 299×299 pixels, potentially destroying subtle lesions such as microaneurysms that are only a few pixels in diameter.
3.The "Black Box" Problem:Passive CNNs lack inherent interpretability. While post-hoc methods like Grad-CAM exist, they do not reveal the actual decision-making process—only statistical correlations.
1.3 Proposed Solution and Contributions
This paper addresses the identified gap by proposing theDiabetic Retinopathy Recurrent Attention Model (DR-RAM). Rather than treating diagnosis as a static image-to-label mapping, DR-RAM is anactive agentthat learnswhereto look in a retinal image through attention mechanisms inspired by Reinforcement Learning. Our key contributions are:
2 • A novel formulation of DR detection as a sequential attention problem with recurrent state aggregation.
• A multi-scale glimpse sensor that mimics human foveal and peripheral vision.
• Experimental validation demonstrating superior accuracy compared to EfficientNet-B0 baseline with enhanced interpretability through visualizable attention trajectories.
• Open-source implementation available on GitHub and Kaggle for reproducibility.
2 Proposed Method
2.1 Problem Formulation: Sequential Attention for DR
We formulate DR diagnosis as a sequential decision-making problem where an agent interacts with a retinal image environment overTtime steps. At each stept, the agent:
1. Receives a partial observationx t(a "glimpse" extracted from locationl t−1).
2. Updates its internal belief stateh tusing a recurrent network.
3. Selects the next locationl tto observe.
4. At the final stepT, outputs a classification decision.
The objective is to maximize classification accuracy while learning efficient attention patterns:
J(θ) =E"
LCE(y,ˆy)+λT
∑
t=1Lattn(lt)#
(1)
whereL CEis the cross-entropy loss andL attnencourages meaningful attention patterns.
2.2 Architecture Overview
The DR-RAM architecture consists of four interconnected neural network modules, as illustrated in Figure 1:
3 Figure 1: DR-RAM System Architecture showing the Glimpse Sensor, Glimpse Network (CNN), Core Network (GRU), Location Network (Attention Policy), and Classification Network.
2.2.1 Glimpse Sensor
The glimpse sensor extracts multi-resolution patches centered at locationl t∈[−1,1]2. We use k=3 scales, where each subsequent scale doubles the receptive field but maintains the same output resolution (64×64). This design mimics human vision, where foveal regions provide high acuity while peripheral regions provide contextual information.
4 2.2.2 Glimpse Network
A lightweight CNN processes the concatenated multi-scale patches into a feature vectorg t∈ R512. The network combines this with location information via:
gt=fg(ρ(x t),lt−1)(2)
2.2.3 Core Network (GRU)
A Gated Recurrent Unit (GRU) maintains the internal stateh t, integrating information across glimpses:
ht=GRU(g t,ht−1)(3)
2.2.4 Location and Classification Networks
The location network outputs parameters for the next attention location:
lt=tanh(f l(ht))(4)
The classification network outputs the final DR grade probabilities using a softmax layer.
2.3 Training Procedure
The model is trained end-to-end using:
•Multi-step supervision:Classification loss computed at each glimpse step with increasing weights for later steps.
•AdamW optimizerwith learning rate 3×10−4and weight decay 10−4.
•Cosine annealinglearning rate schedule.
•Label smoothing(ε=0.1) for regularization.
•Weighted random samplingto address class imbalance.
3 Experiments
3.1 Dataset
We use theAPTOS 2019 Blindness Detection Dataset[3] from Kaggle, containing 3,662 retinal fundus photographs graded on a 5-point scale:
• 0: No DR (1,805 images, 49.3%)
5 • 1: Mild NPDR (370 images, 10.1%)
• 2: Moderate NPDR (999 images, 27.3%)
• 3: Severe NPDR (193 images, 5.3%)
• 4: Proliferative DR (295 images, 8.1%)
The dataset exhibits significant class imbalance, which we address using weighted random sampling during training.
3.2 Preprocessing Pipeline
Following established practices [6], we apply:
1.Black Border Cropping:Remove black borders to isolate the retinal region using grayscale thresholding.
2.Ben Graham's Preprocessing:I new=4I−4·Gaussian(I,σ=10) +128 to normalize illumination and enhance vessel contrast.
3.Resizing:Images resized to 380×380 for the environment, with glimpses of 64×64.
3.3 Training Configuration
Table 1: Training Hyperparameters
Hyperparameter Value
Train/Validation Split 80%/20% (2,929 / 733 images)
Batch Size 32

Epochs 15
Optimizer AdamW
Learning Rate 3×10−4
Weight Decay 10−4
Number of Glimpses 6
Hidden Size 512

Deep dive into your Xbox stats today!
LEARN MORE

```
DR-RAM: Diabetic Retinopathy Detection Using
Recurrent Attention and Reinforcement Learning
National University of Technology (NUTECH)
Group Members:
Ahad Imran (F23607034)
Zain-Ul-Abidin (F23607031)
Hamza Abdul Karim (F23607046)
Imaan Aftab (F23607041)
Subject:Reinforcement Learning (CS480)
Submitted to:Lec. Asif Mehmood
Code Repository:GitHub
Kaggle Notebook:Kaggle
December 2025
Abstract
```

Detect Text Upload File 14,999/15,000 Characters
Check 350,000 characters, Upgrade Here

Your File Content is Most Likely Human written

• All metrics show consistent improvement with DR-RAM.
4.2 Confusion Matrix Analysis
Figure 2 shows the confusion matrix for DR-RAM predictions on the validation set.
7 Figure 2: Confusion Matrix for DR-RAM on the APTOS 2019 Validation Set. The model shows strong performance on No DR (0) and Moderate NPDR (2), with expected confusion between adjacent severity levels.
Key observations:
• Strong performance on majority classes (No DR and Moderate NPDR)
• Mild NPDR (class 1) shows highest confusion with No DR (class 0), consistent with subtle clinical differences
• Most misclassifications occur between adjacent severity levels, which is clinically expected
4.3 Model Comparison Visualization
Figure 3 presents a visual comparison of DR-RAM against the baseline across all evaluation metrics.
8 Figure 3: Performance comparison between DR-RAM and EfficientNet-B0 across all metrics. DR-RAM consistently outperforms the baseline, with the largest improvement in Quadratic Weighted Kappa.
4.4 Glimpse Trajectory Visualization
Figure 4 demonstrates DR-RAM's learned attention patterns, providing interpretability absent in standard CNN approaches.
9 Figure 4: Glimpse trajectory visualization showing the sequential attention pattern learned by DR-RAM. Numbers indicate the order of glimpses (1-6), demonstrating the model's strategy of examining different retinal regions to accumulate diagnostic evidence.
1.Initial Orientation:Begins near the image center
2.Anatomical Landmark Detection:Moves towards the optic disc
3.Vascular Examination:Traverses vascular arcades where lesions commonly appear
4.Lesion Investigation:Focuses on suspicious regions
5.Confirmation:Final glimpses verify findings before classification
10 5 Discussion
5.1 Why DR-RAM Outperforms Standard CNNs
The superior performance of DR-RAM can be attributed to:
1.Focused Processing:By attending to specific regions sequentially, the model allocates computational resources to diagnostically relevant areas.
2.Multi-scale Integration:The glimpse sensor's multi-resolution design captures both fine details (microaneurysms) and broader context (vascular patterns).
3.Temporal Aggregation:The GRU-based core network effectively integrates information across multiple glimpses.
5.2 Clinical Interpretability
Unlike traditional CNNs, DR-RAM's glimpse trajectories offer:
•Explicit Reasoning:The sequence shows exactly where the model looked
•Alignment with Clinical Practice:Patterns mirror ophthalmologist examination behavior
•Error Analysis:Failed predictions can be debugged by examining attention
6 Conclusion
6.1 Summary of Findings
This paper introduced DR-RAM, achieving:
1.Superior Performance:Kappa of0.8914vs baseline 0.8702 (+2.12%)
2.Interpretability:Explicit, visualizable glimpse trajectories
3.Reproducibility:Open-source code on GitHub and Kaggle
6.2 Limitations
• Fixed number of 6 glimpses; adaptive stopping could improve efficiency
• Validation limited to APTOS 2019 dataset
• Low GPU utilization indicates room for optimization
11 6.3 Future Work
• Implement explicit RL training (REINFORCE, PPO) for location policy

• Adaptive stopping based on confidence
• Multi-dataset validation (Messidor-2, EyePACS)
• Clinical deployment trials

Code Availability

The complete implementation, trained models, and experimental notebooks are available at:
•GitHub:https://github.com/Ahad690/DR-RAM-Diabetic-Retinopathy-Detection
•Kaggle:https://www.kaggle.com/code/mahad69/dr-ram-diabetic-retinopathy-reinforcement-learning

References

[1] A. Imran, Z. Abidin, H. A. Karim, and I. Aftab, "Literature Review: Deep Learning Approaches in Diabetic Retinopathy," Assignment 01-02, CS480 Reinforcement Learning, NUCES, 2025.

[2] International Diabetes Federation, "IDF Diabetes Atlas, 10th Edition," 2021. [Online]. Available:https://diabetesatlas.org/

[3] Asia Pacific Tele-Ophthalmology Society, "APTOS 2019 Blindness Detection," Kaggle, 2019. [Online]. Available:https://www.kaggle.com/competitions/aptos2019-blindness-detection

[4] M. Tan and Q. V . Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," inProc. ICML, 2019, pp. 6105–6114. [Online]. Available:https://arxiv.org/abs/1905.11946

[5] V . Mnih, N. Heess, A. Graves, and K. Kavukcuoglu, "Recurrent Models of Visual Attention," inNeurIPS, 2014, pp. 2204–2212. [Online]. Available:https://arxiv.org/abs/1406.6247

[6] G. Alwakid, W. Gouda, and M. Humayun, "Deep learning-based prediction of diabetic retinopathy using CLAHE and ESRGAN,"Healthcare, vol. 11, no. 6, p. 863, 2023. [Online]. Available:https://www.mdpi.com/2227-9032/11/6/863

12 [7] R. Al-ahmadi, H. Al-ghamdi, and L. Hsairi, "Classification of Diabetic Retinopathy by Deep Learning,"Int. J. Online Biomed. Eng., vol. 20, no. 1, 2024. [Online]. Available: https://online-journals.org/index.php/i-joe/article/view/45775

[8] L. Daiet al., "A deep learning system for detecting diabetic retinopathy across the disease spectrum,"Nature Communications, vol. 12, p. 3242, 2021. [Online]. Available:https://www.nature.com/articles/s41467-021-23458-5

[9] V . Gulshanet al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy,"JAMA, vol. 316, no. 22, pp. 2402–2410, 2016. [Online]. Available:https://jamanetwork.com/journals/jama/fullarticle/2588763

[10] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. CVPR, 2016, pp. 770–778. [Online]. Available:https://arxiv.org/abs/1512.03385

[11] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," inProc. CVPR, 2017, pp. 4700–4708. [Online]. Available: https://arxiv.org/abs/1608.06993

[12] K. Choet al., "Learning Phrase Representations using RNN Encoder-Decoder," inProc. EMNLP, 2014, pp. 1724–1734. [Online]. Available:https://arxiv.org/abs/1406.

[13] I. Loshchilov and

Using AI Text?
It Can Be Detected

Make it Human →

Highlighted text is suspected to be most likely generated by AI*
14,999 Characters
1,792 Words

Export to PDF

Upgrade to Premium plans here

Instructions for Educators and Evaluators

Simple and Credible Open AI, Grok, DeepSeek, and Gemini Detector Tool for Free

Millions of Users Trust ZeroGPT, See what sets ZeroGPT apart

Highlighted Sentences

Every sentence written by AI is highlighted, with a gauge showing the percentage of AI inside the text

Multiple Features

Enjoy our Top-notch Plagiarism Checker, Paraphraser, Summarizer, Grammar checker, Translator, Writing Assistant...

High Accuracy Model

Advanced and premium model, trained on all languages and multiple LLM models to provide highly accurate results

Generated Report

Automatically generated .pdf reports for every detection, used as a proof of AI-Free plagiarism

Support All Languages

Support all the languages with the highest accuracy rate of detection

Batch Files Upload

Simply upload multiple files at once, and they will get checked automatically in the dashboard

Get Premium Features

Unlock growth potential with our API
Our API is available for the AI Detector, Plagiarism Checker, Paraphraser, Summarizer, Grammar and Spell Checker, Chatbot & Translator.
Our team has developed a user-friendly API for organizations. Get API access

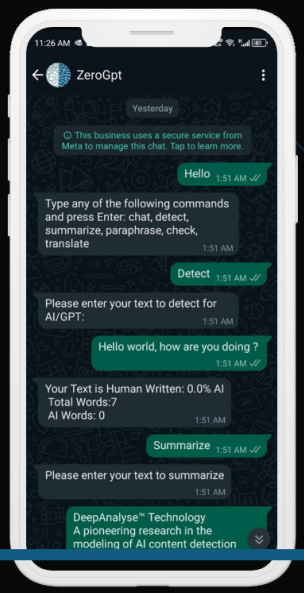
DeepAnalyse™ Technology

A pioneering research in the modeling of AI content detection

Our AI detection model includes several components that analyze text to determine its origin and if it was written by AI. We use a multi-stage methodology designed to optimize accuracy while minimizing false positives and negatives. From the macro level to the micro one, this is how DeepAnalyse™ Technology works. Our model specializes in identifying AI generated content like Chat GPT, GPT 3, GPT 4, GPT5, Gemini, Grok, Perplexity AI, Claude, DeepSeek, LLaMa models ... Finally, we employ a comprehensive deep learning methodology, trained on extensive text collections from the internet, educational datasets, and our proprietary synthetic AI datasets produced using various language models.

Use ZeroGPT in Whatsapp and Telegram

ZeroGPT is now available on WhatsApp and Telegram. Chat With ZeroGPT: Advanced ChatBot, Detect AI, Summarize, Paraphrase, Translate and Check for Grammar Errors... all these features available inside WhatsApp and Telegram.



WhatsApp

Register your WhatsApp's number in the Dashboard (section "Social Settings") and start using all the features of ZeroGPT inside WhatsApp using the phone number **+1 (206) 372-5474**

Telegram

Register the telegram code inside your Dashboard (section "Social Settings") and start using all the features of ZeroGPT inside Telegram using the telegram bot **zerogpt_official_bot**

Get Your MAX / EXPERT Subscription

Explore More Tools to Enhance Your Writing Skills

Fix grammar and spelling mistakes, detect AI plagiarism, check for plagiarism, generate citations, advanced word counter, powerful summarizer and paraphraser

- AI Humanizer
- Plagiarism Checker
- AI Grammar Checker
- AI Summarization Tool
- AI Paraphrasing Tool
- AI Translator
- Dictionary
- Word Counter Tool
- Citation Generator
- Advanced AI ChatBot
- AI Email Helper

Your questions, answered

How Does ZeroGPT AI Detector work?

What is the accuracy rate of ZeroGPT?

Who Benefits from ZeroGPT's AI content detector?

Will my text get plagiarized or be available online, if I check it on ZeroGPT?

How can I integrate ZeroGPT tool in my organization or website on a large scale?

Does ZeroGPT work with different languages?

How can I cite the AI detector?

Check Our Blog created with the help of AI

5 Mind Blowing Technologies we'll see in 2024
10 Ridiculous Technologies That Will Actually Make Your Life Better

2025 Copyright © ZeroGPT.com

More about

- Pricing
- API
- FAQ
- Our policy
- Terms of use

Features

- AI Detector
- AI Humanizer
- AI ZeroChat-4 & 5
- AI Plagiarism Checker
- AI Summarizer
- AI Paraphraser
- AI Grammar Checker
- AI Translator
- Dictionary
- Word Counter
- Dictionary
- AI Email Helper

Question / Business Inquiry

You can email us at

support@zerogpt.com

Our support team is spread across the globe to give you answers fast