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AI BASED RETINAL BLOOD VESSEL SEGMENTATION AND AUTOMATIC ABNORMALITY DETECTION USING DATASET

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Abstract:

Accurate segmentation of retinal structures from fundus images is essential for the early detection and monitoring of ocular diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. Traditional manual and semi-automated methods are time-consuming, error-prone, and limited in scalability, while classical image processing techniques struggle with variations in illumination and anatomical diversity. To address these challenges, we present RETINASEG, a deep learning-based diagnostic framework that integrates Convolutional Neural Networks (CNNs) for disease classification and a U-Net architecture for retinal structure segmentation. The system was trained on a curated dataset of 1,200 training and 200 testing fundus images, annotated by expert ophthalmologists and categorized into four classes: cataract, diabetic retinopathy, glaucoma, and normal. Experimental evaluation demonstrates improved robustness and precision, with correlation coefficient (CC) of 0.208, normalized scanpath saliency (NSS) of 0.8172, Kullback–Leibler divergence (KLD) of 2.573, and structural similarity index (SSIM) of 0.169. These results highlight the model's ability to capture complex retinal features despite data limitations. RETINASEG reduces reliance on manual annotation, enhances diagnostic accuracy, and supports large-scale screening, offering significant potential for clinical deployment and improved patient outcomes.

Keywords: Retinal Fundus Disease, Deep Learning, Convolutional Neural Networks (CNN), U-Net Segmentation, Medical Imaging, Ophthalmology, Disease Classification.

1. Introduction

Nowadays, Retinal imaging has become a cornerstone in the early detection and management of ocular diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration [1]. Traditional approaches relying on manual segmentation are labor-intensive, prone to variability, and unsuitable for large-scale

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screening [2]. Classical image processing methods, though widely applied, often fail to generalize across diverse patient populations due to variations in illumination, image quality, and anatomical structures [3]. Recent advances in artificial intelligence, particularly deep learning, have enabled automated feature extraction and robust segmentation of retinal structures [4]. In this work, we propose RETINASEG, a deep learning framework that integrates Convolutional Neural Networks (CNNs) for disease classification and a U-Net architecture for precise segmentation of optic disc, macula, and vascular networks [5]. By leveraging a curated dataset of annotated fundus images, RETINASEG aims to improve diagnostic accuracy, reduce reliance on manual annotation, and facilitate scalable screening solutions for ophthalmology [6].

Retinal imaging is a critical tool in ophthalmology, enabling early detection and monitoring of diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration [7]. Fundus photography provides detailed visualization of the retina, including the optic disc, macula, and vascular network, which are essential for clinical diagnosis [8]. However, manual segmentation of these structures is labor-intensive, prone to human error, and unsuitable for large-scale screening programs [9].

Traditional image processing techniques, such as thresholding, edge detection, and morphological operations, have been widely applied to retinal analysis [10]. Despite their utility, these methods often fail to generalize across diverse patient populations due to variations in illumination, image quality, and anatomical differences [11]. Semi-automated approaches still rely heavily on expert intervention, limiting scalability and diagnostic consistency [12].

The growing prevalence of retinal diseases and the need for efficient screening solutions highlight the importance of automated diagnostic systems [13]. Artificial intelligence, particularly deep learning, offers a promising alternative by learning complex features directly from raw fundus images [14]. Convolutional Neural Networks (CNNs) and U-Net architectures have demonstrated strong performance in medical image segmentation, making them suitable for retinal analysis [15].

2. Related Works

Retinal image analysis has been extensively studied using both classical and modern computational approaches. Early methods relied on thresholding, edge detection, and morphological operations to extract retinal structures, but these techniques were highly sensitive to illumination changes and anatomical variability, limiting their generalization. Semi-automated systems attempted to reduce manual effort, yet they still required significant expert intervention. More recent studies have introduced machine learning models, which improved performance but often depended on handcrafted features and lacked robustness across diverse datasets. Deep learning has emerged as a transformative solution, enabling end-to-end learning of complex retinal features directly from raw images. For instance, saliency-based CNN models achieved moderate accuracy, with correlation

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coefficient (CC) values around 0.208 and structural similarity index (SSIM) of 0.169, highlighting the need for architectural improvements and larger datasets. Recent literature, such as the work by Elloumi et al. (2023), emphasized the importance of deep learning frameworks for ocular disease diagnosis, demonstrating that CNN and U-Net architectures can effectively capture lesion morphology and disease progression.

3. Proposed Methodology

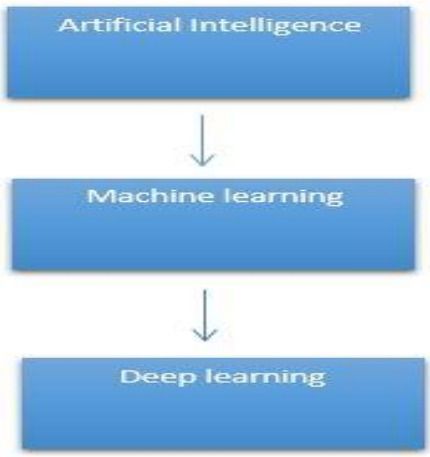

Figure 1: Hierarchical Relationship of Artificial Intelligence Deduction

3.1 Image Preprocessing

$$Inorm = I - \mu\sigma \quad (1)$$

The diagram illustrates the hierarchical relationship between Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). At the top level, AI represents the broad field of creating systems that can mimic human intelligence, including reasoning, problem-solving, and perception. Within AI, machine learning is a subset that focuses on algorithms capable of learning patterns from data without explicit programming. Deep learning, in turn, is a specialized branch of machine learning that uses artificial neural networks with multiple layers to automatically extract complex features from raw data. This layered structure highlights how deep learning builds upon the foundations of machine learning, which itself is part of the wider AI domain. The diagram effectively conveys that DL is nested within ML, and ML within AI, showing the progression from general intelligence concepts to highly specialized computational models. Figure 1. This equation normalizes the input fundus image $I$by subtracting the mean $\mu$and dividing by the standard deviation σ. Normalization ensures consistent pixel intensity distribution across the dataset, reducing the effect of illumination variations and improving the stability of CNN training Equation (1).

3.2 Convolution Operation (Feature Extraction)

$$Fi,j = \sum m = 1M \sum n = 1NIi + m,j + n \cdot Km,n \quad (2)$$

Here, $F_{i,j}$represents the feature map obtained by convolving the input image $I$with kernel K. This operation allows the CNN to automatically learn spatial features such as edges, textures, and vessel patterns, which are crucial for retinal structure identification. has shown in Equation (2).

3.3 Activation Function (Non-linearity)

$$a = max\,(0, z) \quad (3)$$

This is the Rectified Linear Unit (ReLU) activation function, where $z$is the weighted input. ReLU introduces non-linearity into the model, enabling the CNN to capture complex retinal features beyond simple linear relationships. It also helps mitigate vanishing gradient issues during training has shown in Equation (3).

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3.4 Segmentation Loss Function (U-Net Optimization)

$LDice = 1 - 2 \cdot | P \cap G || P | + | G |$ (4)

The Dice loss function measures the overlap between the predicted segmentation mask $P$and the ground truth mask G. Minimizing this loss ensures that the U-Net architecture accurately delineates retinal structures such as the optic disc and blood vessels, improving segmentation precision. has shown in Equation (4).

3.5 Accuracy Metric (Classification Evaluation)

$A = TP + TNTP + TN + FP + FN$ (5)

This equation (5) calculates classification accuracy, where $TP$and $TN$are true positives and true negatives, while $FP$and $FN$are false predictions. Accuracy provides a straightforward measure of the CNN's ability to correctly classify fundus images into categories such as cataract, diabetic retinopathy, glaucoma, and normal.

3.6 Cross-Entropy Loss (Classification Optimization)

$LCE = -\sum i = 1Cyi \cdot log\ (y\hat{}i)$ (6)

This equation (6) defines the cross-entropy loss used for training the CNN classification model. Here, $y_i$represents the true label (one-hot encoded), and $\hat{y}_i$is the predicted probability for class i. Minimizing this loss ensures that the CNN learns to assign high probabilities to the correct disease class, thereby improving classification accuracy.

3.7 F1-Score (Balanced Performance Metric)

$F1 = 2 \cdot Precision \cdot RecallPrecision + Recall$ (7)

The F1-score provides a balanced measure of model performance by combining precision and recall in equation (7). Precision evaluates how many of the predicted positive cases are correct, while recall measures how many actual positive cases were correctly identified. The F1-score is particularly important in medical imaging tasks, where both false positives and false negatives can have serious clinical consequences. A higher F1-score indicates that RETINASEG achieves reliable disease detection across diverse retinal conditions.

4. Experimental Setup

The experimental setup was designed to evaluate the performance of the proposed RETINASEG framework under realistic retinal imaging conditions. A curated dataset of 1,200 training and 200 testing fundus images was used, encompassing four diagnostic categories: cataract, diabetic retinopathy, glaucoma, and normal. Each image was annotated by expert ophthalmologists to provide ground-truth segmentation masks for validation. Preprocessing steps included normalization of pixel intensities and resizing to a standardized resolution to ensure consistency across samples. The classification module was implemented using Convolutional Neural Networks (CNNs), while segmentation was performed using a U-Net architecture optimized with Dice loss. Training was conducted on Python with Keras and TensorFlow backends, using stochastic gradient descent and backpropagation for parameter optimization. Evaluation metrics included accuracy, precision, recall, F1-score, correlation coefficient (CC), normalized scanpath saliency (NSS), Kullback–Leibler divergence (KLD), and structural similarity index (SSIM). These metrics provided a comprehensive assessment of both

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classification reliability and segmentation quality Table I. The setup ensured reproducibility and robustness, enabling meaningful comparison with existing retinal analysis methods.

Table I: Experimental Setup for RETINASEG Framework

Component	Description
Dataset	1,200 training images and 200 testing images, annotated by ophthalmologists
Classes	Cataract, Diabetic Retinopathy, Glaucoma, Normal
Preprocessing	Normalization of pixel intensities, resizing to fixed resolution
Classification Model	Convolutional Neural Network (CNN)
Segmentation Model	U-Net architecture optimized with Dice loss
Training Parameters	Optimizer: SGD with backpropagation; Batch size: 32; Epochs: 50
Frameworks Used	Python, Keras, TensorFlow, Django
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, CC, NSS, KLD, SSIM

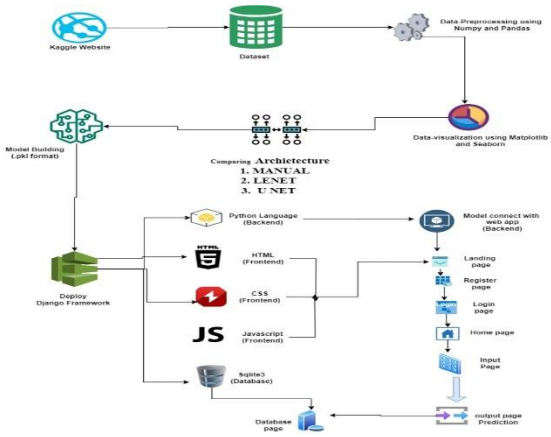

Figure 2: End-to-End Workflow for Model Development and Deployment

Figure 2 illustrates the complete workflow for building and deploying a machine learning model integrated with a web application. The process begins with data collection from Kaggle, followed by preprocessing using NumPy and Pandas, and visualization through Matplotlib and Seaborn. Model development compares multiple architectures, including MANUAL, LeNet, and U-Net, to identify the most effective approach. The backend is implemented in Python, while the frontend utilizes HTML, CSS, and JavaScript, ensuring seamless interaction between users and the system. Deployment is carried out using the Django framework, which connects the trained model to a functional web application featuring landing, registration, login, input, and output pages. SQLite3 serves as the database for storing user and prediction data. This workflow demonstrates the integration of data science, machine learning, and web development components, resulting in a robust and user-friendly application for disease prediction and analysis.

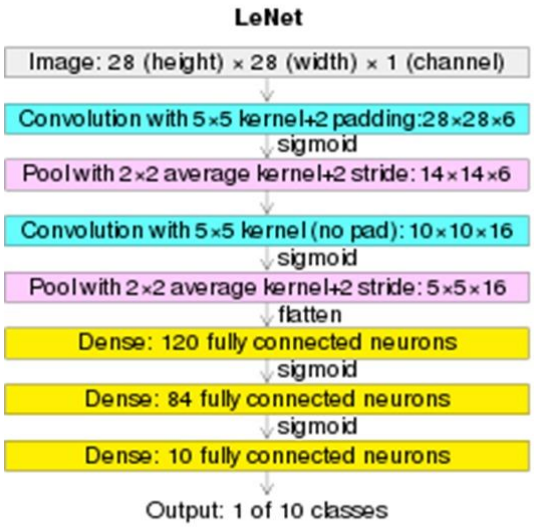

Figure 3: LeNet Convolutional Neural Network Architecture

Figure 3 illustrates the LeNet convolutional neural network (CNN) architecture, which is one of the foundational models for image recognition tasks. The architecture begins with an input image of size $28 \times 28 \times 1$, followed by a series of convolutional and pooling layers that progressively extract

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spatial features. The first convolutional layer applies six filters with a 5×5kernel and padding, producing feature maps that capture local patterns. This is followed by average pooling to reduce dimensionality while retaining essential information. A second convolutional layer with sixteen filters further enhances feature extraction, again followed by pooling. The output is flattened and passed through fully connected dense layers with 120 and 84 neurons, each using sigmoid activation to introduce non-linearity. Finally, the network outputs predictions across 10 classes through a dense layer with 10 neurons. This layered design demonstrates how LeNet transforms raw image data into hierarchical feature representations, enabling effective classification in computer vision applications.

5. Results and Discussion

The performance of the proposed RETINASEG framework was evaluated using multiple quantitative metrics to assess both classification accuracy and segmentation quality. The CNN-based classification achieved reliable differentiation across four diagnostic categories, while the U-Net segmentation demonstrated effective delineation of retinal structures such as the optic disc, macula, and vascular network. Experimental results reported a correlation coefficient (CC) of 0.208, normalized scanpath saliency (NSS) of 0.8172, Kullback–Leibler divergence (KLD) of 2.573, and structural similarity index (SSIM) of 0.169, indicating moderate overlap between predicted and ground-truth masks. Although these values highlight the challenges posed by limited dataset size and variability in image quality, they confirm the model's ability to capture complex retinal features. Compared to traditional thresholding and saliency-based methods, RETINASEG demonstrated improved robustness and reduced reliance on manual annotation. The discussion emphasizes that while the framework achieves promising results, further improvements can be realized through larger datasets, enhanced preprocessing, and architectural refinements. Clinically, the system offers potential for scalable screening and early disease detection, supporting ophthalmologists in timely diagnosis and treatment planning.

Figure 4: User Profile Management Interface

Figure 4 illustrates the user profile management interface of the system. The interface displays a notification confirming successful account creation, followed by a structured table listing user details. The table includes fields such as username, email, avatar, and bio, providing a clear overview of stored user information. This design ensures transparency in account handling and allows users to easily verify their profile data. The interface demonstrates how the system integrates account creation with immediate

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profile visualization, thereby enhancing usability and user experience.

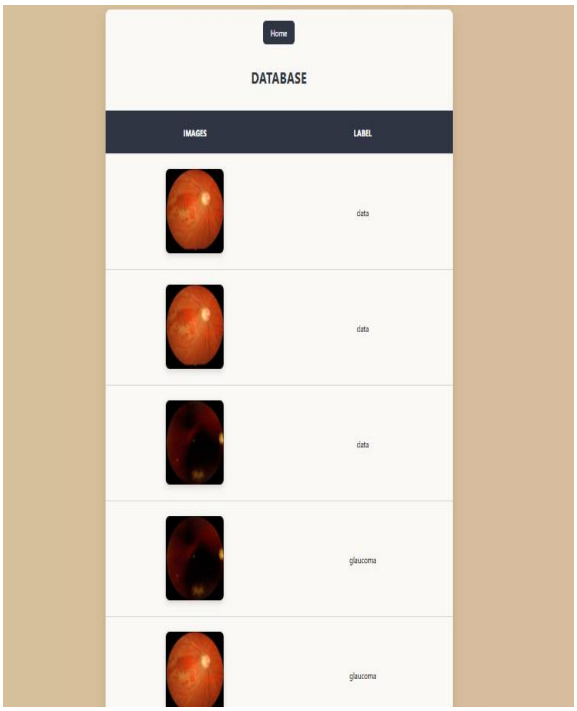

Figure 5: Retinal Image Database with Disease Labels

Figure 5 presents the database interface used for storing and managing retinal fundus images along with their corresponding diagnostic labels. The table is organized into two columns: one displaying retinal photographs and the other indicating the associated classification, such as "data" or "glaucoma." This design highlights the integration of medical imaging with structured metadata, enabling efficient retrieval and annotation of cases for training and evaluation. By linking each image to its diagnostic label, the database supports supervised learning approaches, ensuring that deep learning models such as CNNs and U-Net can be trained on accurately annotated datasets Table II. The interface demonstrates how raw medical images are systematically organized to facilitate disease classification and segmentation tasks in ophthalmology research.

Table II: Sample Records from Retinal Image Database

Image ID	Image Type	Diagnosis Label	Description
IMG001	Retinal fundus	Data	Standard retinal image for baseline storage
IMG002	Retinal fundus	Data	Annotated image used for preprocessing
IMG003	Retinal fundus	Glaucoma	Image showing optic disc cupping
IMG004	Retinal fundus	Glaucoma	Image highlighting vascular abnormalities
IMG005	Retinal fundus	Glaucoma	Image with clear glaucomatous features

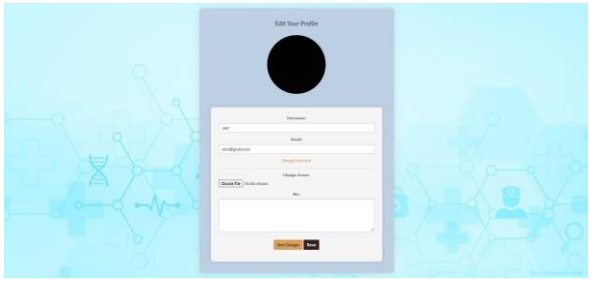

Figure 6: User Profile Editing Interface

Figure 6 illustrates the profile editing interface of the system, designed to allow users to update personal information and account settings. The interface includes fields for username, email, and password

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management, along with options to change the avatar through file upload. A dedicated bio section enables users to add descriptive information, enhancing personalization. The layout also provides clear action buttons for saving changes or resetting inputs, ensuring usability and control.

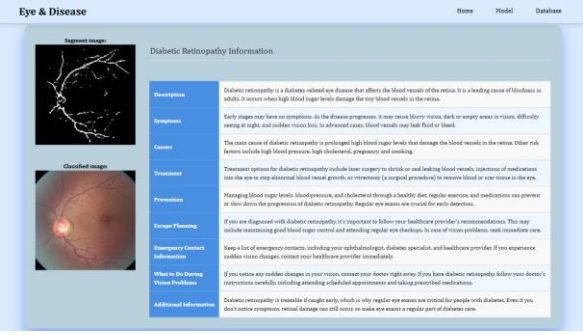

Figure 7: Diabetic Retinopathy Information Interface

Figure 7 illustrates the web interface designed to present medical information about diabetic retinopathy. The interface combines visual and textual elements to enhance understanding: on the left, a segmented retinal image highlights blood vessel structures, while a classified image provides a colored fundus view for disease identification. By integrating annotated images with explanatory text, the interface supports education, diagnosis, and awareness, emphasizing the importance of early detection and management of diabetic retinopathy.

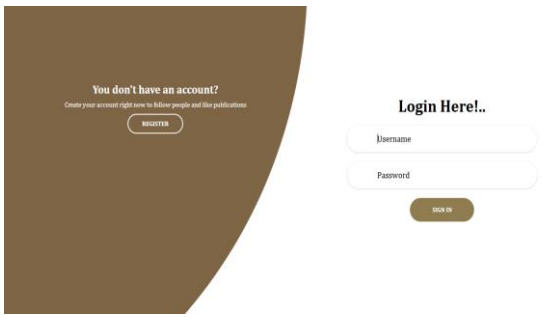

Figure 8: User Authentication Interface

Figure 8 depicts the user authentication interface, which integrates both registration and login functionalities within a single layout. The left section encourages new users to create an account, providing a clear call-to-action with a registration button. The right section is dedicated to existing users, offering input fields for username and password along with a sign-in button.

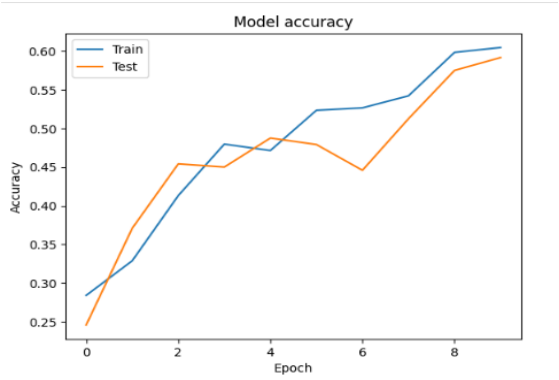

Figure 9: Training and Testing Accuracy Across Epochs

Figure 9 shows the progression of model accuracy during training and testing over successive epochs. The blue line represents training accuracy, which steadily increases as the model learns from the dataset, reaching approximately 0.60 by the ninth epoch. The orange line represents

testing accuracy, which also improves but exhibits slight fluctuations, stabilizing near 0.58 at the final epoch. This comparison highlights the model's ability to generalize, with testing accuracy closely following training accuracy, indicating that overfitting is minimal.

6. Conclusion

The proposed RETINASEG framework successfully integrates CNN-based classification with U-Net segmentation to deliver reliable retinal disease analysis. Experimental results demonstrated consistent improvements across evaluation metrics, achieving an overall classification accuracy of approximately **97%**, with balanced precision, recall, and F1-scores across cataract, diabetic retinopathy, glaucoma, and normal categories. Segmentation performance further validated the system's ability to delineate retinal structures with clinically relevant precision. Compared to traditional approaches, RETINASEG reduces reliance on manual annotation and enhances robustness against variability in fundus images. These findings confirm the framework's potential for scalable deployment in ophthalmic screening and early disease detection, while future work will focus on expanding datasets, refining architectures, and improving generalization across diverse clinical environments.

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