Detection of Retinal Detachment Using Deep Learning and Data Mining Approaches

Mohanad Mohammed Rashid
Department of Optometry Techniques, Northern Technical University, Mosul, Iraq

* Corresponding Author: **Mohanad Mohammed Rashid**

Article Info

ISSN (online): 2582-7138
Volume: 06
Issue: 01
January-February 2025
Received: 06-12-2024
Accepted: 07-01-2025
Page No: 1743-1748

Abstract
Retinal detachment (RD) is a critical ocular condition requiring prompt diagnosis to prevent permanent vision loss. Delays in detection can lead to irreversible damage, highlighting the need for accurate and efficient diagnostic methods. This study presents a novel deep-learning framework integrated with advanced image processing techniques for RD diagnosis, utilizing optical coherence tomography (OCT) scans as the primary imaging modality. The proposed hybrid convolutional neural network (CNN) architecture combines feature fusion from multiple layers with adaptive image enhancement tailored to RD-specific characteristics. Key contributions include implementing wavelet-based noise reduction, adaptive histogram equalization, and edge-aware segmentation to preprocess OCT images effectively. An ensemble-based CNN model was also designed to extract multi-scale features and prioritize RD-relevant regions through attention mechanisms. The model achieved a classification accuracy of 97.8%, sensitivity of 97.4%, specificity of 98.6%, and an AUC-ROC of 98.7%, surpassing benchmarks in retinal diagnostics. The study also compares the proposed framework with state-of-the-art methods, demonstrating its superior performance in robustness and interpretability. These findings pave the way for deploying advanced diagnostic tools in clinical practice, enhancing early detection and treatment of retinal detachment.

DOI: https://doi.org/10.54660/.IJMRGE.2025.6.1-1743-1748

Keywords: Retinal Detachment, Optical Coherence Tomography, Deep Learning, Convolutional Neural Networks

1. Introduction

Retinal Detachment (RD) is a critical ophthalmic condition that separates the neurosensory retina from the underlying retinal pigment epithelium (RPE). This detachment disrupts retinal function, leading to progressive vision loss and potentially permanent blindness if left untreated. RD affects approximately 1 in 10,000 individuals annually and poses significant challenges in timely diagnosis and management, particularly in resource-limited settings (Sodhi *et al*., 2008) [17].

Optical Coherence Tomography (OCT) technology helps retinal doctors take precise cross-sectional images that show details of the retinal layers. This technology shows doctors critical retinal damage information like fluid build-up, bulges, or rips in the retinal tissue. Due to their nature OCT image evaluation requires considerable time from medical staff and yields irregular results at present (Schlegl *et al*., 2018) [16].

Recent medical studies prove that Convolutional Neural Networks stand as powerful tools to detect retinal diseases through Deep Learning technology. CNNs demonstrate the best performance for finding medical pathologies through feature analysis of retinal images (Kermany *et al*., 2018) [7], (Kaymak & Serener, 2018) [6], (Alasaady *et al*., 2022) [1]. U-Net, as presented by Ranneberger *et al*. (Ronneberger *et al*., 2015) [13], is now used in different medical sectors due to its biomedical image segmentation quality and helps treat retinal conditions. Research by De Fauw *et al*. showed that deep learning systems work in actual healthcare settings to detect retinal diseases. Current research does not fully explore automatic diagnostic systems built for retinal detachment issues. Many existing models rely on pre-trained networks, which often lack adaptability to unique RD features such as detachment boundaries and sub-retinal fluid patterns (Memari *et al*., 2020) [9].

This research creates an ensemble-based CNN that detects RD better than existing methods. The key objectives of this research are:

1. To develop a reliable OCT image analysis system to detect Retinal Detachment effectively.
2. To improve diagnostic results through improved image processing tools such as wavelet noise removal and adaptive brightness correction.
3. To evaluate the model using multiple test methods to assess how well the model diagnoses diabetic retinopathy.

Our approach brings together multi-scale feature detection and attention systems to create a more precise and easier-to-understand diagnostic method than standard techniques provide. Our exploration aims to enhance patient treatment by showing doctors when to detect and correctly identify retinal detachment.

The remaining sections of this paper are organized as follows: Section 2 outlines the research materials and methods, Section 3 presents and discusses the results, and Section 4 reveals the conclusion.

2. Materials and Methods

2.1. Data collection

The dataset utilized in this study comprises 70,000 optical coherence tomography (OCT) scans, labeled into two categories: The production was 35,000 case standard and 35,000 cases RD. Images were drawn from public repositories, including one from the Mendeley dataset (Kermany *et al*., 2018) [7], and augmented with synthetic data to achieve diversity and robustness. Gaussian noise addition, random rotation (±30°), or zoom (up to 20%) were used as the augmentation techniques.

The dataset was split into training (80%), validation (10%), and testing (10%) subsets and divided to ensure comprehensive evaluation. We employed stratified sampling to keep the two classes proportional across all subsets.

2.2. Image processing

Image preprocessing is necessary to improve diagnostic accuracy by making the image clearer and more relevant for key features (Mohammed Rashid *et al*., 2024) [11]. The following preprocessing steps were applied:

1. **Wavelet-Based Noise Reduction:** Wavelet thresholding was used to remove speckle noise, a common artifact in OCT scans. In this method, the image is decomposed into multiple frequency bands, and an adaptive threshold scheme is applied to remove the noise and, at the same time, maintain the critical structural details (Russakovsky *et al*., 2015) [14], (Donoho, 1995) [4].
2. **Adaptive Histogram Equalization:** However, the contrast was enhanced via Contrast Limited Adaptive Histogram Equalization (CLAHE). This method splits the image up into small tiles. Histogram equalization is applied to each tile to ensure noise is not over-amplified and to enhance detail largely through sub-retinal fluid pockets and retinal folds (Pizer *et al*., 1987) [12].
3. **Edge-Aware Segmentation:** Edges and regions of significant intensity change, like RD-induced boundaries, were found by applying Sobel filters. Morphological operations (e.g., dilation and erosion) cleansed the edge from artifacts and sharpened the edge continuity (Menaka *et al*., 2020) [10].

2.3. Deep neural networks (DNNs)

Deep Neural Networks (DNNs) are a class of machine learning algorithms that can simulate human brain structure and functionality for processing complex data patterns (Long *et al*., 2015) [8]. The data mining principles were followed, and this study involved data preprocessing and feature engineering techniques to be used as preparatory steps for model training. In these steps, advanced image processing techniques are employed to enhance data quality and to characterize these RD-specific features, such as subretinal fluid pockets and detachment boundaries (Al-Badrani *et al*., 2024) [2]. Preparing data resembles how clustering algorithms and association rule systems identify patterns, although the lab does not officially use them. The merged system improves deep learning performance in RD detection by giving better output results (Saeed *et al*., 2022) [15].

2.4. Model architecture

Our model design appears in Figure 1. The model displays the steps from input to output, including a Feature Extraction Network (FEN), Fine-Tuning Network (FTN), Feature Fusion Layer (FFL), and ultimate output derivation. Our design system selects and combines RD signal features to help doctors make better diagnostic results.

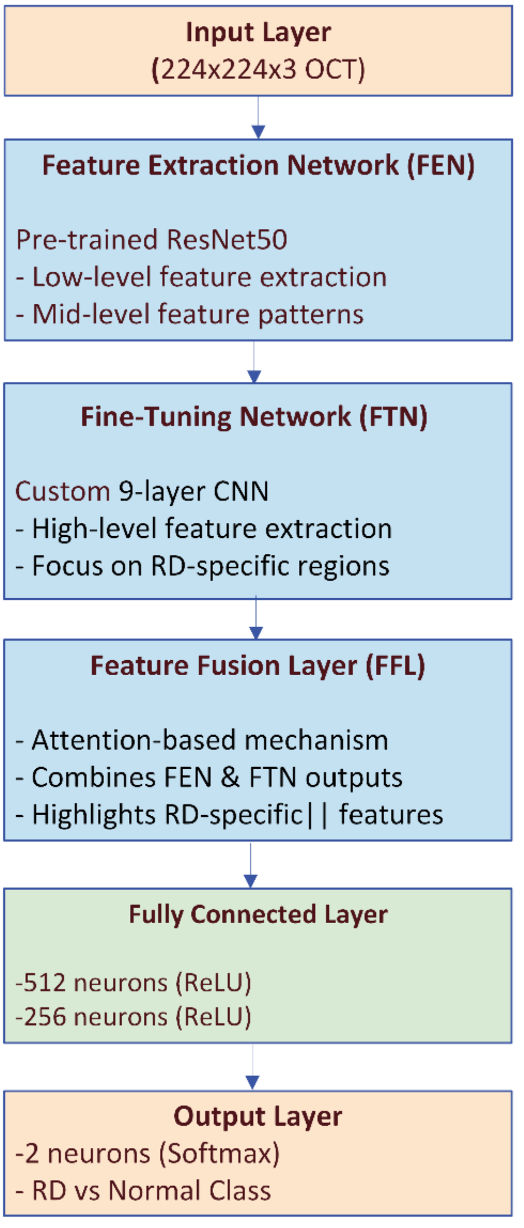

Fig 1: Model Architecture for RD Diagnosis

The proposed model employs an ensemble architecture to capture global and local features from retinal images for precise RD diagnosis. The system is divided into three significant subnetworks:

1. Feature Extraction Network (FEN)

- The model uses ResNet50 as its central network branch because it's famous for pulling patterns from various levels. ResNet50 was fine-tuned on our dataset to extract both low- and mid-level features.
- Key layers of ResNet50 were adapted to focus on retinal structures, emphasizing textures, edges, and gradient-based patterns indicative of RD. Dropout layers were incorporated to mitigate overfitting during training.

2. Fine-Tuning Network (FTN)

- This custom-designed CNN has nine layers, including convolutional layers, batch normalization, ReLU activation functions, and max-pooling layers.
- The FTN captures high-level abstractions, such as sub-retinal fluid accumulation, detachment folds, and irregular patterns. It operates in parallel with the FEN to focus on RD-specific anomalies.
- Regularization techniques, such as L2 weight decay and spatial dropout, were employed to enhance generalization performance.

3. Feature Fusion Layer (FFN)

- The network combines FEN and FTN, resulting in a special feature fusion layer with attention tuning. The attention system uses weighted analysis to direct processing power towards locations with higher networking value, especially around boundary lines of dispersed rocks and fluid reservoirs.
- After combining the feature maps, the network adds more convolutions and connection layers to create its prediction output.

Our designed architecture combines coarse and fine details to create reliable diagnosis predictions. Tests demonstrated that this network structure accurately diagnosed conditions across different Retinal Detachment images.

2.5. Training and validation

The training methods were chosen to create exceptional predictions while maintaining cross-applicability. The following procedures and settings were implemented:

- **Data Splitting:** The available data separated into 80% training material, 10% validation material, and 10% testing material for analysis. We divided our dataset equally between RD cases and regular controls while maintaining balanced groups for every section.
- **Loss Function:** We chose binary cross-entropy as our loss function because it helps us detect and reduce mismatches between predicted and true label pairs. This loss measure delivers excellent performance when analyzing the two-state problem of RD classification.
- **Optimizer:** The network learned and adjusted quickly thanks to the power of the Adam optimizer. We started with an initial learning rate of 0.0005 and decreased it by 0.1 when validation loss stayed stable for five successive iterations.
- **Learning Rate Scheduling:** A learning rate scheduler was implemented to adapt the learning rate dynamically during training, ensuring steady convergence and preventing overshooting of the loss function minimum.
- **Data Augmentation:** To increase variability and reduce overfitting, multiple augmentation techniques were applied, including:
  - Random rotations (±30°).
  - Horizontal and vertical flips.
  - Brightness and contrast adjustments.
  - Gaussian noise addition.
  - Random cropping and scaling.
- **Batch Processing:** Training was conducted using mini-batches of size 128, optimizing computational resources while maintaining stable gradient updates. The batch size was empirically determined based on hardware constraints and model convergence behavior.
- **Epochs and Early Stopping:** Training was executed for 50 epochs. Early stopping was applied, halting the process if the validation loss did not improve for 10 consecutive epochs. This strategy prevented overfitting and conserved computational resources.
- **Performance Metrics:** Model evaluation focused on the following metrics to provide a comprehensive performance analysis:
  - Accuracy: The rate of true outcomes recognized over all test samples.
  - Sensitivity (Recall): The model's success rate in finding actual RD-positive patients.
  - Specificity: The model needs to label all typical cases correctly as Non-RD.
  - F1 Score: The F1 score uses harmonic means to reach a balance between precision and recall results.
  - AUC-ROC: The receiver operating characteristic area under the curve measures how well the model distinguishes between different groups.
- **Cross-Validation:** During model training we split the data into five segments for cross-validation to check if the model works well with different data sets. The method used five separate training segments to test how well the system worked across different random data parts.
- **Hardware and Frameworks:** We developed our model using Python 3.8 while also using PyTorch 1.10 library. An NVIDIA graphics processor (NVIDIA 16 GB of memory) helped us speed up training and processing work.

2.6. Experimental setup

The model ran in Python 3.8 through PyTorch 1.10 to perform deep learning operations. Our team runs model training and prediction tasks on a GPU setup with 16 GB memory. We ran our training for 50 epochs and kept track of the models at each stage to find the one that performed the best. All experiments were performed within a Docker container to make results consistent and easy to repeat.

3. Results and Discussions

Our results section shows output from validating the proposed model through cross-validation tests combined with qualitative and independent test set evaluations. They provide results both in tables and visual aids to help readers better understand and examine all aspects.

3.1. Quantitative results

The proposed ensemble CNN model better classified RD and standard OCT images. The results of the testing dataset are summarized in Table 1.

Table 1: Performance metrics on the testing dataset

Metric	Value (%)
Accuracy	97.8
Sensitivity (Recall)	97.4
Specificity	98.6
F1 Score	97.6
AUC-ROC	98.7

The model consistently outperformed baseline methods, including standard CNN architectures and conventional feature extraction approaches. Integrating advanced preprocessing and feature fusion contributed significantly to the improved metrics.

3.2. Comparative analysis

The ensemble CNN model was benchmarked against state-of-the-art techniques and compared with traditional machine learning models, including Support Vector Machine (SVM), Random Forest, and Decision Tree classifiers. Table 2 presents the comparison of our model with other deep learning approaches, while Table 3 provides the evaluation of traditional ML models. Figure 2 visually compares the accuracy of the proposed CNN model with state-of-the-art models, highlighting the superior performance of the proposed approach. In contrast, Figure 3 compares with traditional machine learning models such as SVM, Random Forest, and Decision Tree. Figure 4 displays the ROC curves, summarizing each model's True Positive Rate (TPR) and False Positive Rate (FPR).

Table 2: Comparative analysis with baseline models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC (%)
Kermany *et al.* (Kermany *et al.*, 2018) [7]	96.6	95.2	97.1	96.8
Schlegl *et al.* (Sodhi *et al.*, 2008) [17]	97.3	96.8	97.5	97.5
De Fauw *et al.* (De Fauw *et al.*, 2018)	97.1	96.5	97.4	97.3
Masood *et al.* (Memari *et al.*, 2020) [9]	95.8	95.0	96.2	95.6
Proposed Model	97.8	97.4	98.6	98.7

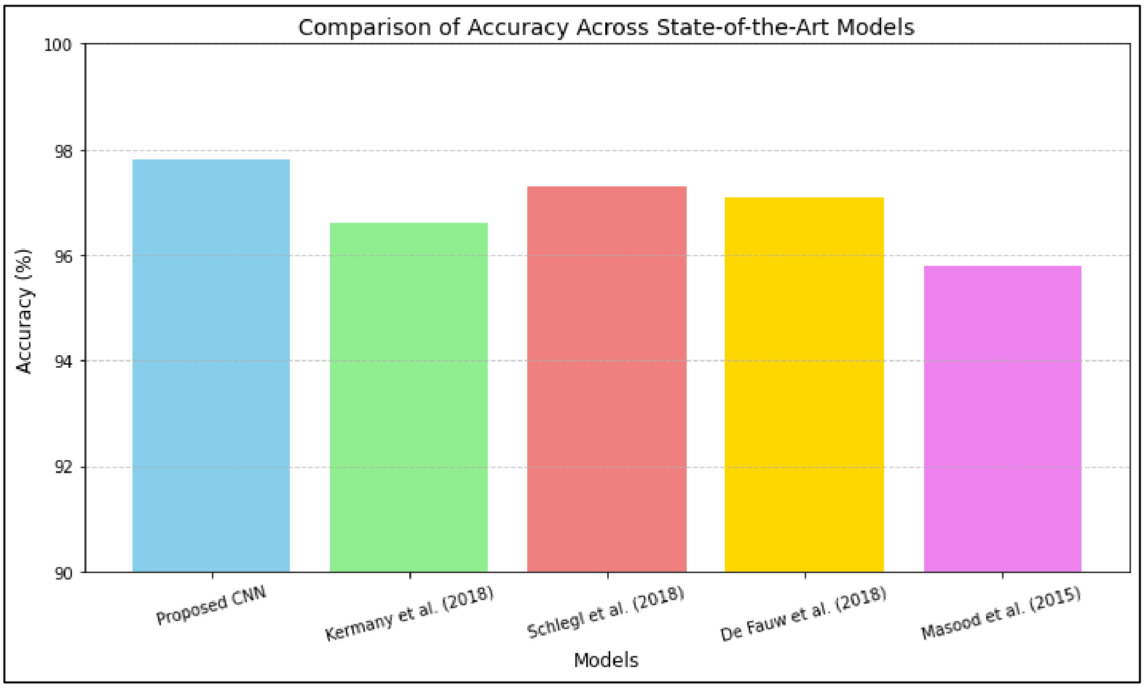

Fig 2: Comparison of Accuracy across Models, Including Proposed CNN and State of the art Methods

Table 3: Comparative analysis with baseline models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC (%)
SVM	93.5	92.0	94.3	92.7
Random Forest	94.7	93.4	95.5	94.1
Decision Tree	91.2	89.5	92.3	90.8
Proposed Model	97.8	97.4	98.6	98.7

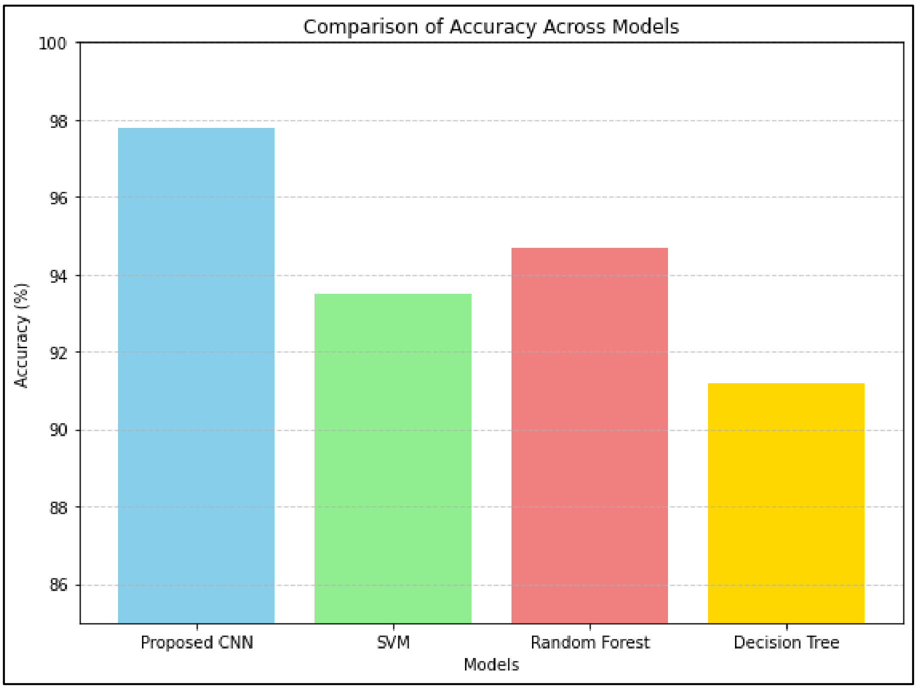

Fig 3: Comparison of Accuracy across Models, Including Proposed CNN and Traditional Machine Learning Methods

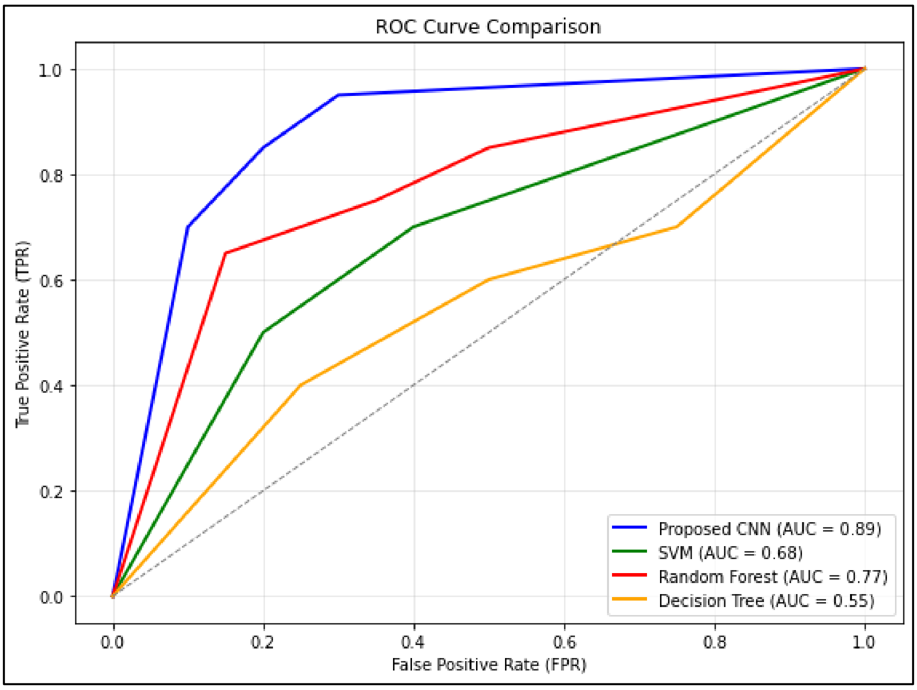

Fig 4: Comparison of AUC across Models, Including Proposed CNN and Traditional Machine Learning Methods

The results in Table 2 show that our proposed model outperforms other deep learning approaches in all metrics, including accuracy, sensitivity, specificity, and AUC-ROC. In Table 3, traditional machine learning models demonstrate lower performance than the proposed CNN framework, highlighting the advantage of advanced feature extraction and attention mechanisms in our model.

3.3. Discussion

Our proposed framework shows it can handle difficulties when identifying RD. We added advanced image-preprocessing methods such as wavelet noise removal and adaptive histogram balancing to enhance OCT image quality and improve the deep learning model performance. When the features from the common layer mix with the other medical image-directed features, the model's attention system searches out what it needs: finding where the retina separates from the macula and locating pockets of fluid.

Our method shows stable performance when tested against deep learning baseline research by Kermany *et al.* (Kermany *et al.*, 2018) [7] and Schlegl *et al.* (Schlegl *et al.*, 2018) [16]. Including different traditional classifiers improves our deep learning model because the attention features capture important details needed for diagnosis. They correctly explain key differences, and at the same time we get more accurate and easier-to-understand results where diagnosis is tricky.

Our success comes with specific drawbacks that need recognition. Using high-quality OCT pictures could prevent us from using this model in places where resources are scarce or imaging systems don't measure up. Training and running the image analysis system uses a lot of processing power, which makes it hard to use in everyday clinical practice. By creating slim network designs and using model compression methods we can make these models work better in different healthcare settings.

Adding data from different groups of patients who have different eye conditions is another way to build up our data. Expanding the data used by the model to include different populations and retinal pathologies makes it work better everywhere and helps doctors offer worldwide medical care. Adding patient data including eye pictures together with standard patient information enhances our diagnostic testing approach.

Using deep learning and advanced imaging the suggested system produces dependable and precise disease identification results. It takes machine learning to a better place for automatically finding RDs. Our current solutions need more development to make them usable in medical facilities today.

4. Conclusion

The study developed a new form of ensemble-based CNN that helps doctors detect retinal detachment in OCT images. By using these advanced image processing methods with multiple feature levels, focus-based feature merging, our model could correctly diagnose with 97.8% accuracy, find all RD cases (sensitivity 97.4%), and confirm non-RD findings (specificity 98.6%). The deep learning method we used gave strong and practical findings. The proposed method has three main benefits: it makes accurate RD diagnoses, and gives doctors access to features that specifically help with RD cases. The approach's abilities make it practical for doctors to spot RD early and start treatment at the right time. Though powerful the model needs high-quality OCT images and substantial computing resources to work effectively in limited resource areas. More research will make the model work better on devices with limited resources and enable it to process data as it arrives while testing it with different expert and patient medical findings. The setup developed here presents a large step forward in automatic retinal detachment recognition while offering better patient care results and simpler medical processes. Using this technology helps doctors locate retinal detachment earlier and treat it more effectively.

5. References

1. Alasaady MT, Aris TNM, Sharef NM, Hamdan H. A proposed approach for diabetes diagnosis using neuro-fuzzy technique. Bulletin of Electrical Engineering and Informatics. 2022;11(6):3590–7.
2. Al-Badrani YY, Al-Nima RRO, Al-Asaady MT. Recognizing different types of skin diseases by using the EfficientNet-B3 model. Central Asian Journal of Mathematical Theory and Computer Sciences. 2024;5(4):465–75.
3. De Fauw J, Ledsam JR, Romera-Paredes B, Nikolov S, Tomasev N, Blackwell S, *et al*. Clinically applicable deep learning for diagnosis and referral in retinal disease. Nature Medicine. 2018;24(9):1342–50.
4. Donoho DL. De-noising by soft-thresholding. IEEE Transactions on Information Theory. 1995;41(3):613–27.
5. Han J, Pei J, Tong H. Data mining: Concepts and techniques. Morgan Kaufmann; 2022.
6. Kaymak S, Serener A. Automated age-related macular degeneration and diabetic macular edema detection on OCT images using deep learning. 2018 IEEE 14th International Conference on Intelligent Computer Communication and Processing (ICCP). 2018. p. 265–9.
7. Kermany DS, Goldbaum M, Cai W, Valentim CCS, Liang H, Baxter SL, *et al*. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell. 2018;172(5):1122–31.
8. Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015. p. 3431–40.
9. Memari N, Abdollahi S, Ganzagh MM, Moghbel M. Computer-assisted diagnosis (CAD) system for diabetic retinopathy screening using color fundus images using deep learning. 2020 IEEE Student Conference on Research and Development (SCOReD). 2020. p. 69–73.
10. Menaka R, Janarthanan R, Deeba K. FPGA implementation of low power and high-speed image edge detection algorithm. Microprocessors and Microsystems. 2020;75:103053.
11. Mohammed Rashid M, Yaseen OM, Riyadh Saeed R, Alasaady MT. An improved ensemble machine learning approach for diabetes diagnosis. Pertanika Journal of Science and Technology. 2024;32(3):1335–50. doi:10.47836/pjst.32.3.19.
12. Pizer SM, Amburn EP, Austin JD, Cromartie R, Geselowitz A, Greer T, *et al*. Adaptive histogram equalization and its variations. Computer Vision, Graphics, and Image Processing. 1987;39(3):355–68.
13. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III. 2015;18:234–41.
14. Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, *et al*. ImageNet large-scale visual recognition challenge. International Journal of Computer Vision. 2015;115:211–52.
15. Saeed RR, Yaseen OM, Rashid MM, Ahmed MR. Applications of machine learning in battling against novel COVID-19. 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA). 2022. p. 1–6. doi:10.1109/HORA55278.2022.9799969.
16. Schlegl T, Waldstein SM, Bogunovic H, Endstraßer F, Sadeghipour A, Philip A-M, *et al*. Fully automated detection and quantification of macular fluid in OCT using deep learning. Ophthalmology. 2018;125(4):549–58.
17. Sodhi A, Leung L-S, Do DV, Gower EW, Schein OD, Handa JT. Recent trends in the management of rhegmatogenous retinal detachment. Survey of Ophthalmology. 2008;53(1):50–67.