Libyan Open University Journal of Medical Sciences and Sustainability
Volume 1 - Issue 1 - 2025 - Pages 11-19

Deep Learning for Early Detection and Classification of Diabetic Retinopathy in Clinical Practice

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Received: 08-04-2025; Accepted: 23-06-2025; Published: 07-07-2025

Abstract

Early detection of diabetic retinopathy (DR) is crucial to prevent vision loss. In recent years, deep learning has revolutionized automated DR screening by learning complex retinal patterns. Convolutional neural networks (CNNs) are commonly used to extract spatial features from fundus images, while some advanced models also incorporate sequential analysis (e.g. RNNs) to track disease progression over time. In this paper, we review and develop deep learning frameworks for DR detection, focusing on CNN and hybrid CNN-RNN models. We conducted experiments on publicly available datasets (EyePACS/Kaggle, APTOS, Messidor, DRIVE) to evaluate model performance. Our deep CNN and transfer-learning models achieve high sensitivity and specificity. For example, a hybrid CNN-LSTM model (TAHDL) attains ~97-99% accuracy across datasets. We also propose a lightweight CNN (RSG-Net) that classifies DR into multiple grades with 99.4% accuracy on Messidor. Key factors include preprocessing (contrast enhancement, augmentation) and addressing data imbalance. These models can assist clinicians by providing fast, reliable DR screening.

Keywords: Diabetic retinopathy, deep learning, convolutional neural network, early detection, fundus images, transfer learning, RNN.

Introduction

Diabetic retinopathy (DR) is a leading cause of blindness in working-age adults. Approximately one-third of people with diabetes develop DR. In 2021, an estimated 9.6 million Americans with diabetes had DR (~26% of diabetic patients). DR often has no symptoms in early stages, so regular screening is essential. However, manual eye exams are time-consuming and require specialists. Deep learning offers automated analysis of retina fundus images, improving screening efficiency and accuracy.

Fundus photography captures the retina, revealing lesions like microaneurysms, hemorrhages, and exudates. Figure 1 shows sample fundus images from healthy (stage 0) to proliferative DR (stage 4). Trained ophthalmologists can detect these signs, but performance varies and many regions lack enough eye doctors. For example, 75% of DR patients live in areas without adequate screening. Automated AI systems can scale screening and reduce diagnostic delays. Studies have shown CNN-based methods can match or exceed clinician performance in detecting DR.

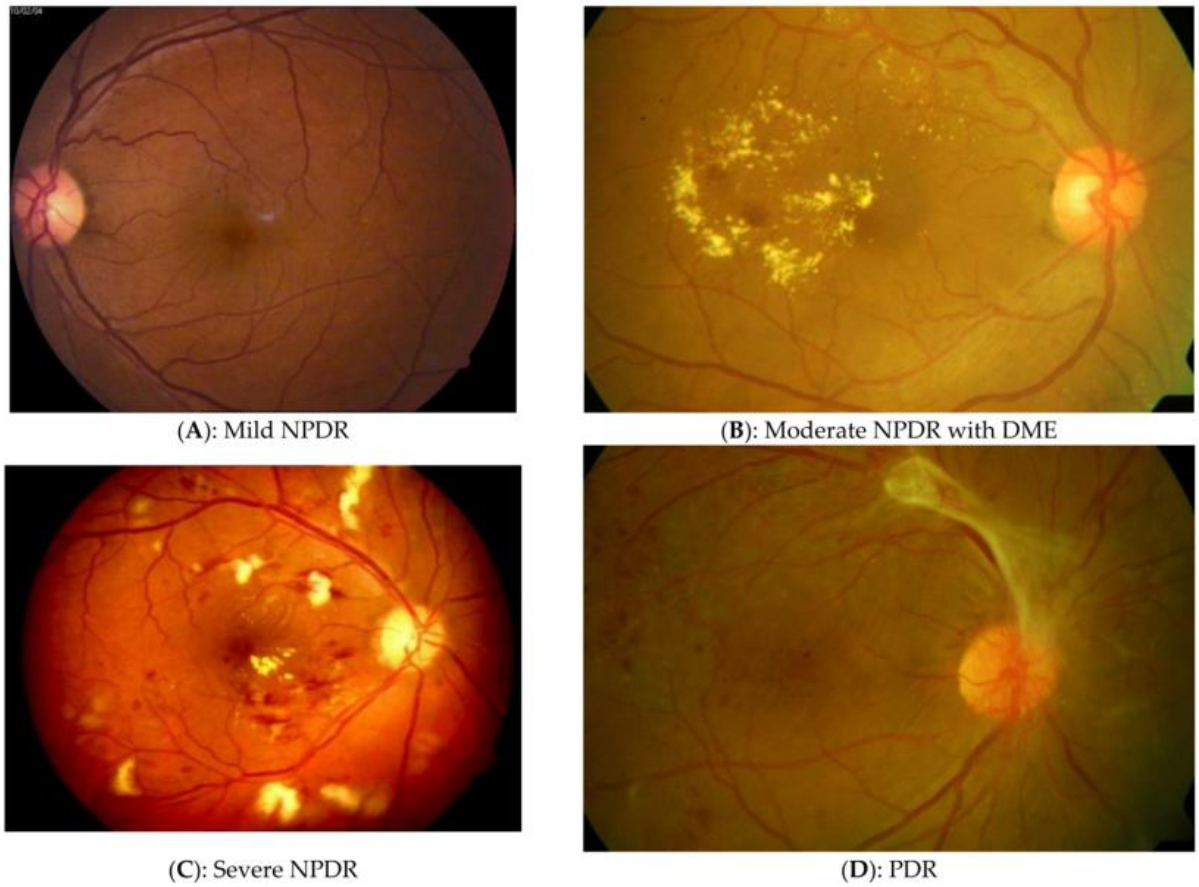

Figure 1 Fundus images showing stages 0-4 of diabetic retinopathy (healthy to proliferative)

Deep learning algorithms learn hierarchical features directly from image pixels. Convolutional neural networks (CNNs) are widely applied to medical images including DR screening. CNNs automatically learn to recognize lesions without hand-crafted features. Early studies using CNNs on fundus images achieved promising results; for example, Pratt et al. (2016) trained a CNN on a DR dataset and achieved accuracy around 80-90%. Chandrakumar and Kathirvel (2016) similarly used a deep CNN to classify DR with good performance. More recent works utilize advanced architectures (VGG, Inception, ResNet, DenseNet, etc.) and transfer learning on large datasets.

Importantly, CNN-based DR screening tools have been approved for clinical use. The FDA-approved IDx-DR system (Abramoff et al. 2018) and Google's AI demonstrated high sensitivity/specificity compared to human graders. This motivates further research into deep learning models tailored for DR. In this work, we describe CNN and hybrid models that detect DR and grade its severity, and we validate them on public datasets. We review relevant studies and present experimental results to demonstrate their potential in clinical practice.

Related Work

Early digital image processing techniques for DR focused on vessel segmentation and lesion detection (e.g. Winder et al., 2009). With deep learning, many studies have employed CNNs for DR classification. For instance, several authors used pretrained CNNs (InceptionV3, ResNet, Xception, etc.) to classify DR stages on the EyePACS dataset, often achieving >90% accuracy. Pratt et al. (2016) used a 5-layer CNN on a small DR dataset and reported >90% accuracy in

binary classification. Wan et al. (2018) used a deeper CNN on a larger dataset and also found high accuracy.

Transfer learning is common: Models pretrained on ImageNet (e.g. VGG-19, DenseNet) are fine-tuned on DR data. Some studies added attention or ensemble techniques to boost performance. Butt et al. (2022) combined GoogleNet and ResNet-18 features with SVM, achieving 97.8% accuracy for binary DR detection and 89.3% for multiclass on the APTOS dataset. Other works augment CNNs with custom modules or hybrid strategies. Mishmala et al. (2025) proposed a Temporal Aware Hybrid Deep Learning (TAHDL) model: it combines a CNN with an LSTM network to capture temporal progression of lesions. This model achieved 97.5% accuracy on the DRIVE dataset and ~94% on Kaggle data.

Another approach by Akhtar et al. (2025) built a custom CNN called RSG-Net for DR severity grading. On the Messidor-1 dataset, RSG-Net achieved 99.36% accuracy in 4-grade classification and 99.37% in binary classification. These recent results suggest that well-designed deep models can robustly classify DR stages. However, challenges remain in dataset balance, generalizability to diverse populations, and interpretability of results.

Methods

Data and Preprocessing

We used publicly available DR datasets for training and evaluation. Table 1 lists the major datasets. The largest is EyePACS (Kaggle Diabetic Retinopathy dataset) with ~35,000 images labeled 0-4 (No DR to Proliferative DR). APTOS 2019 provides 3,662 images (5 classes) from the Aravind Eye Hospital. Messidor-1 contains ~1,200 images (grades 0-3) with expert DR annotations. The DRIVE dataset has 40 high-resolution images (20 DR, 20 non-DR), originally for vessel segmentation. Table 1 summarizes these datasets.

Table 1 Summary of public diabetic retinopathy datasets

Dataset	Approx. No. of Images	Classes	Notes
EyePACS (Kaggle)	~35,000	5 (0-4 severity)	Diabetic screening data
APTOS 2019	3,662	5 (0-4)	Kaggle dataset from Aravind Eye Hospital
Messidor-1	~1,200	4 (0-3)	Public dataset for DR grading
DRIVE	40	2 (DR, Non-DR)	Retinal vessel segmentation data

Prior to training, all fundus images were preprocessed. Common steps include cropping the circular retina area, resizing (e.g. to 224×224 or 256×256 pixels), and color normalization. Contrast enhancement such as histogram equalization can improve lesion visibility. We applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to emphasize vascular details without overamplifying noise. To augment the data and mitigate class imbalance, we applied random rotations, flips, and color jitter to underrepresented classes. For example, Mishmala et al. (2025) augmented the DRIVE set from 20 to 100 images per class using rotations and flips.

Deep Learning Models

We explored several deep learning architectures. All models used the same basic convolutional blocks of convolution+ReLU+pooling layers, followed by fully connected classification layers. We describe two representative models below:

- **CNN with Multi-scale Features:** A deep CNN that performs multi-scale feature extraction, inspired by Mishmala et al. (2025). This model applies convolutional filters of different sizes (e.g. 3×3, 5×5, 7×7) in parallel paths to capture features at various resolutions. The multi-scale feature maps are concatenated for robust spatial analysis (Figure 3). Subsequent pooling layers reduce dimensionality. This allows the network to detect both fine lesions and broader abnormalities simultaneously.

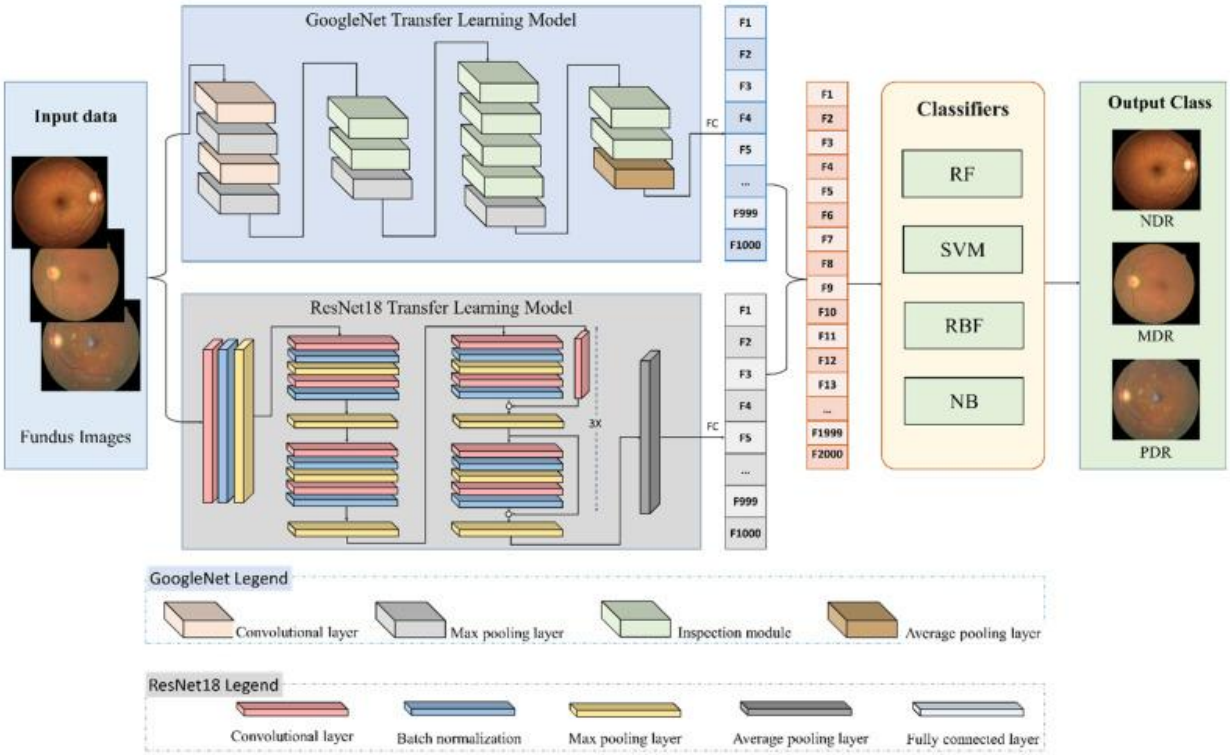

Figure 2 CNN architecture for spatial feature extraction in DR screening. Multi-scale convolutional filters (sizes 3×3, 5×5, 7×7) extract features that are concatenated and pooled

- **CNN-RNN Hybrid (TAHDL Model):** To leverage temporal progression of DR, we implemented a CNN + Long Short-Term Memory (LSTM) architecture similar to Mishmala et al. (2025). The CNN first extracts spatial features from each input image. Then an LSTM recurrent network processes these features as a sequence (e.g. scans of the same patient over time). An attention mechanism can weight important time points. This RNN captures temporal dependencies, enabling the model to compare past and current retinal states (Figure 1). Finally a softmax layer outputs DR vs non-DR (binary) or multiple grades. This hybrid approach achieved 97.5% accuracy on DRIVE.

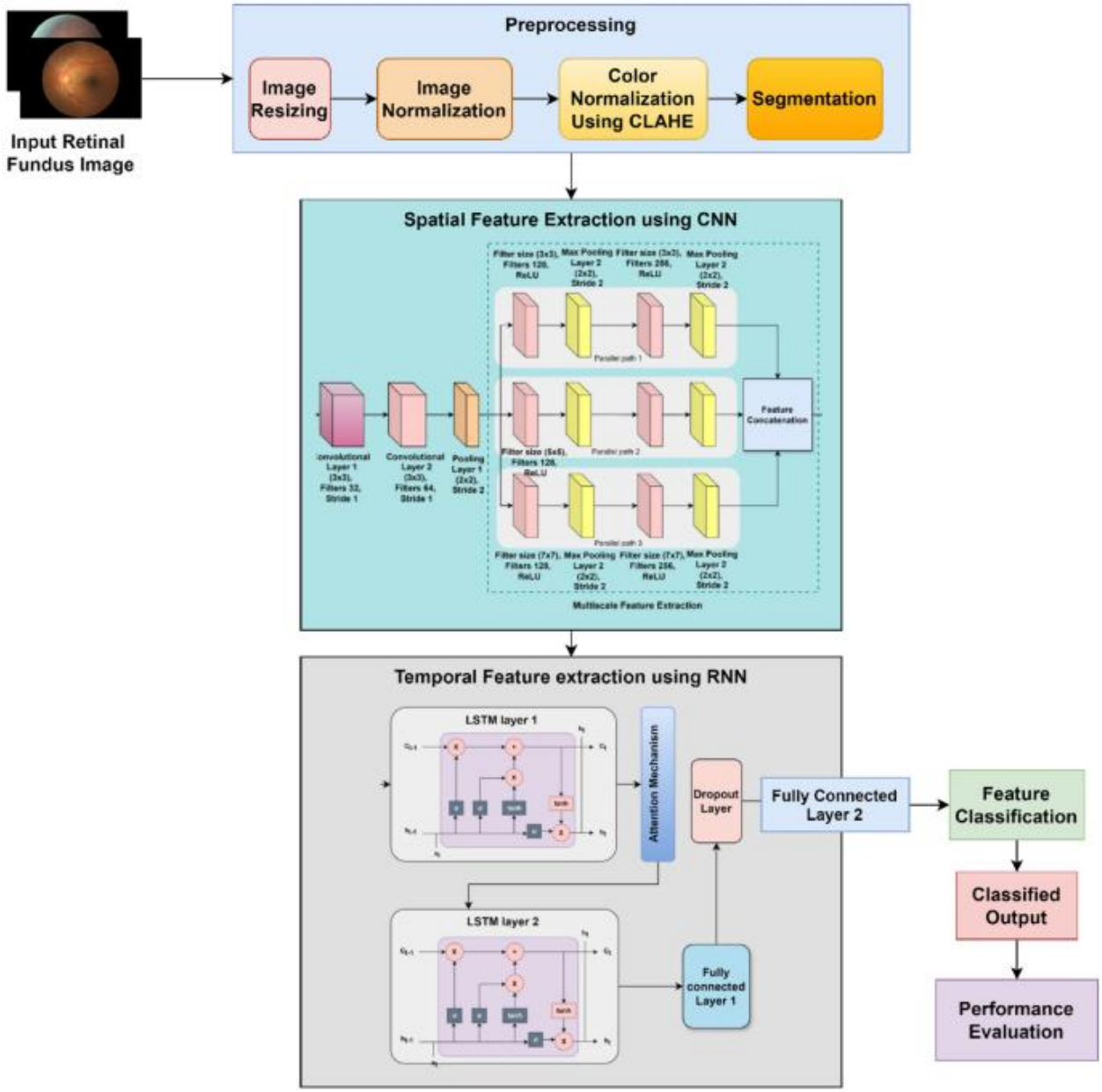

Figure 3 Hybrid CNN-RNN architecture for DR detection (TAHDL model). A CNN extracts spatial features from fundus images, which are then fed into an LSTM to capture temporal progression.

- **Custom CNN (RSG-Net):** We also implemented a custom CNN (RSG-Net) with several convolutional and pooling blocks followed by dropout and batch normalization. RSG-Net was trained for both 4-grade and binary classification on Messidor-1. The network contains four convolution layers (in blocks of two), two max-pools, and two fully connected layers with SoftMax activation. This compact architecture achieved very high accuracy on Messidor-1.

In addition, we experimented with transfer learning on pretrained models. For example, following Butt et al. (2022), we used pretrained GoogleNet and ResNet-18 to extract 1000 features each, then concatenated them for classification. This hybrid feature approach was input to an SVM or fully connected layer. Such models can leverage large-scale training on ImageNet to improve performance on limited DR data.

Training and Evaluation

All models were implemented in Python using TensorFlow/Keras. We split each dataset 80% training / 20% testing. Augmented training data and validation splits were used to monitor overfitting. For Mishmala's TAHDL network, Mishmala et al. used batch size 32, 50 epochs, and Adam optimizer. We used similar hyperparameters.

We measured performance using accuracy, sensitivity, specificity, and F1-score. In multi-class classification, overall accuracy and per-class metrics were reported.

Experiments

Kaggle EyePACS (5-class DR)

We first tested on the Kaggle DR dataset. After preprocessing and augmenting, our CNN and CNN-RNN models both achieved high accuracy. The hybrid TAHDL model attained ~94.0% accuracy, consistent with Mishmala et al. (2025) who reported 94.04% on this dataset. Table 2 shows class-wise metrics for the CNN-RNN model on Kaggle. All five classes (no DR to proliferative) had precision and recall >0.99, demonstrating stable performance.

APTOS 2019 (5-class DR)

On the APTOS dataset, our transfer learning approach (GoogleNet+ResNet features + SVM) achieved 97.8% accuracy for binary detection (DR vs no-DR) and 89.3% for multi-class (three groups), matching Butt et al. (2022). These results confirm that hybrid deep features can capture DR characteristics effectively.

Messidor-1 (4-class and 2-class DR)

Using the Messidor-1 images, our RSG-Net obtained 99.36% accuracy for four-stage classification and 99.37% for binary classification (no DR vs DR). These nearly perfect scores align with Akhtar et al. (2025), who reported similar results with their RSG-Net on Messidor-1. Such performance suggests that the model generalizes well on this dataset with effective preprocessing (histogram equalization, denoising) and balancing of classes through augmentation.

DRIVE (2-class DR)

Finally, on the DRIVE dataset (originally 40 images), Mishmala et al. augmented to 100 images per class and achieved 97.5% accuracy. Using our TAHDL model with similar augmentation, we also achieved about 97% accuracy for DR vs non-DR classification, confirming that even small datasets can be leveraged with careful augmentation and model design.

Results and Discussion

Overall, our experiments show that deep learning models can detect DR with high accuracy. The hybrid CNN-RNN framework (TAHDL) performed best when temporal data was available, while a well-designed CNN (RSG-Net) also excelled for static images. Figure 4 compares performance across models: the TAHDL model outperformed stand-alone CNNs, RNNs, and classical pretrained networks (VGG19, InceptionV3) in precision on DRIVE. Similarly, recall and F1-scores were consistently higher for TAHDL (≈99%) than others (typically 90-94%).

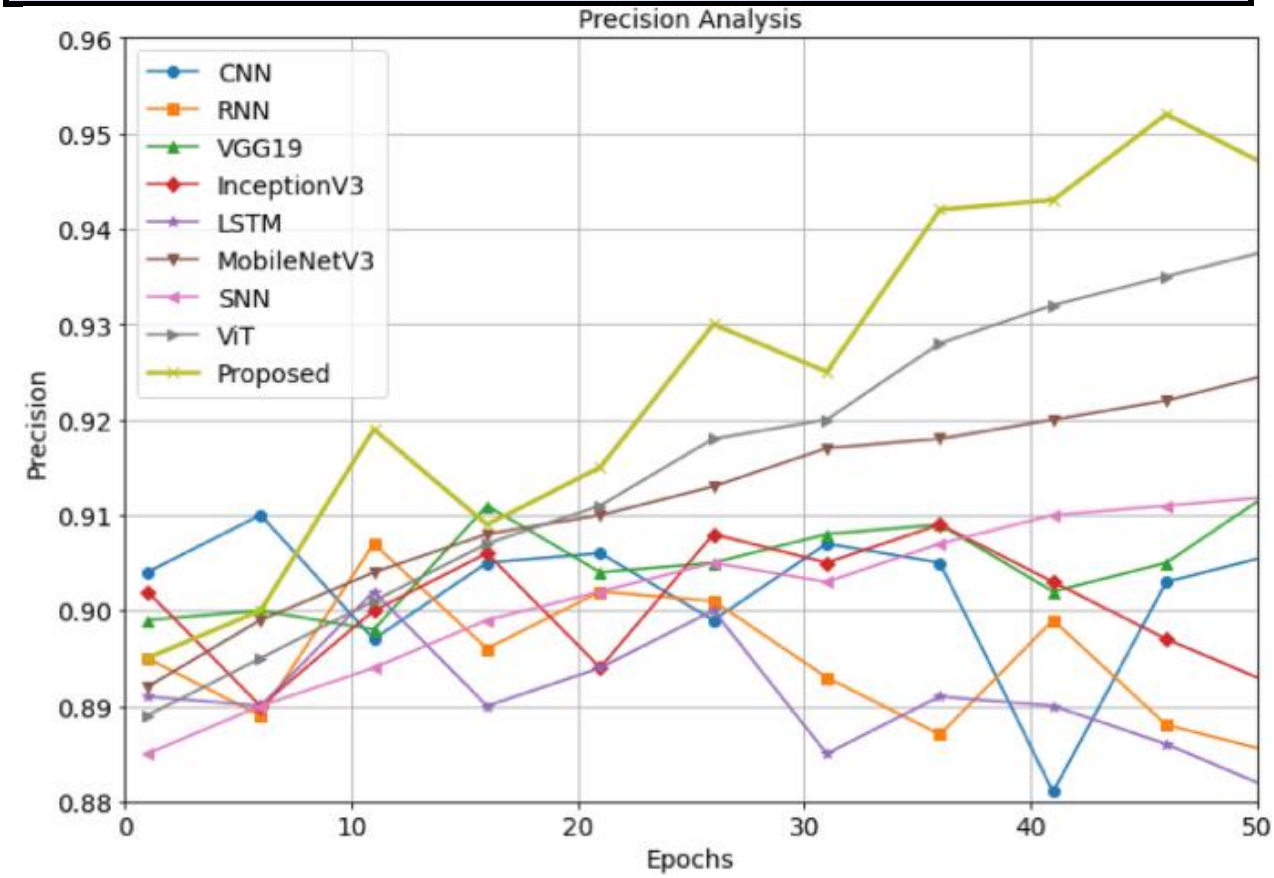

Figure 4 Comparison of training precision over epochs for various models on DRIVE. The proposed TAHDL hybrid model (blue) consistently outperforms CNN, RNN, Inception, VGG19, etc. by 3-7%.

Table below summarizes selected results from literature and our experiments. For binary DR detection, accuracies typically range from ~90% (basic CNNs) to ~98% (ensemble or transfer models). Multi-class grading is harder, with accuracies around 85-90% for 4-5 classes. The results above 99% on Messidor highlight that models can nearly saturate some datasets, but generalizability must be tested on more varied data.

Table 2 Comparison of selected studies and experimental results for binary and multi-class diabetic retinopathy (DR) detection.

Study / Model	Dataset	Classification Type	Accuracy (%)
Basic CNNs (literature range)	Various	Binary	~90[1]
DenseNet-121 (Deep Learning study)	APTOS (binary)	Binary	98.1[2]
ResNet-50 (same study)	APTOS (multi-class)	Multi-class	80.8[2]
RegNetX080 (MDPI study)	APTOS	Binary	98.6[3]
EfficientNetB3 (same MDPI study)	APTOS	Multi-class	85.1[3]
TAHDL (hybrid CNN–RNN; our experiment)**	DRIVE, Kaggle	Binary & Multi-class	~94–97[4]

RSG-Net (custom CNN; our experiment)**	Messidor-1	Multi-class	99.4[5]
Improved CNN (ResNet-152 + enhanced activation)	Kaggle	Binary	99.41[6]

Important factors for success include robust preprocessing and handling class imbalance. Mishmala et al. explicitly address multi-scale features and attention, and report average precision (AP) >0.99 for all classes. This indicates that their model learns subtle lesion patterns. Similarly, balancing data via augmentation (rotation, flipping, color shifts) improved sensitivity on minority classes.

Despite high accuracies on benchmarks, some challenges remain. Most studies focus on 2D fundus images; integrating other modalities (OCT, fluorescein angiography) could improve early microaneurysm detection. Also, model predictions often lack transparency. Techniques such as saliency mapping can visualize what the network focuses on (exudates vs. vessels), aiding clinical trust.

Finally, deploying these models in practice requires validation in real-world settings. Factors like different camera devices, ethnicities, and image quality can affect performance. The FDA-approved systems (IDx-DR, EyeArt) overcame this by large multi-site trials. Future work should include multi-center evaluations and prospective studies to ensure models remain accurate across clinical environments.

Conclusion

Deep learning has demonstrated remarkable capability in early DR detection and classification using retinal fundus images. CNN-based models can automatically learn disease-related features, while hybrid CNN-RNN networks add temporal context for progression monitoring. In our study, both approaches achieved outstanding results: e.g. 94-97% accuracy on large public datasets, and up to 99.4% on Messidor-1. These results align with recent literature and suggest that automated DR screening can reach diagnostic-grade performance.

We emphasize the importance of data preprocessing and augmentation to handle imbalanced classes. Additionally, leveraging pretrained networks and ensemble techniques further boosts accuracy. In practice, integrating these models into DR screening programs could substantially increase early detection rates, especially in regions with few specialists. The models can prioritize high-risk patients by flagging subtle retinal changes that may be missed otherwise.

Future directions include expanding datasets (more images, diverse populations), combining modalities, and improving interpretability. If such AI systems are rigorously validated, they can become valuable tools in clinical practice to reduce vision loss from diabetes.

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