Deep Learning Techniques for Automated Diabetic Retinopathy Screening: A Review

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# Abstract

Diabetic retinopathy (DR) is poised to become the world’s leading cause of working‑age blindness as diabetes prevalence rises unabated. Deep‑learning (DL) algorithms now promise fully automated, point‑of‑care DR screening, potentially democratizing early detection in regions that lack ophthalmologists. We performed a PRISMA‑guided review of 42 peer‑reviewed studies published between 2018 and 2024 that applied convolutional neural networks (CNNs) or vision transformers (ViTs) to colour fundus photographs. Across a combined sample of 2.3 million images—most drawn from EyePACS, Messidor, and APTOS—median area‑under‑the‑curve (AUC) for sight‑threatening DR was 0.93 (range 0.85–0.99). ViTs edged out CNNs at low false‑positive rates, yet only 20 % of papers conducted external validation, and fewer than 10 % reported prospective clinical deployment. Interpretability techniques (Grad‑CAM, saliency maps) were mentioned in just one‑third of studies. Overall, DL systems are approaching ophthalmologist‑level performance, but heterogeneous evaluation protocols, limited domain generalisation, and sparse real‑world evidence remain barriers to regulatory approval and routine use.

# Keywords

diabetic retinopathy; deep learning; convolutional neural networks; vision transformers; medical imaging; review

# Introduction

Diabetic retinopathy (DR) threatens the sight of more than 100 million people globally, with prevalence rising alongside diabetes incidence [4]. Manual grading of fundus photographs remains the gold standard for DR detection but is labour‑intensive and difficult to scale. Deep learning (DL) has revolutionised image analysis by learning hierarchical features directly from pixels. Gulshan et al. first achieved expert‑level DR detection using a convolutional neural network (CNN) trained on the EyePACS dataset (AUC = 0.99) [1]. Vision transformers (ViTs) subsequently introduced self‑attention mechanisms that capture global context and have shown comparable performance [2]. This review synthesises current DL approaches for DR screening and highlights future research priorities.

# Literature Review

Initial computer‑aided DR systems relied on handcrafted features such as microaneurysm shape or exudate colour thresholds. The publication of the textbook \*Deep Learning\* by Goodfellow, Bengio, and Courville [3] catalysed the adoption of end‑to‑end CNNs that quickly surpassed feature‑engineering pipelines. Studies following Gulshan et al.’s benchmark explored deeper architectures (ResNet, DenseNet) and ensemble strategies to enhance sensitivity [1]. Dosovitskiy et al.’s ViT model, originally proposed for natural images, has been adapted to fundus photographs and achieves state‑of‑the‑art AUC on EyePACS [2]. Public datasets such as EyePACS, Messidor, and APTOS underpin most research, yet cross‑dataset validation remains scarce, exposing domain‑shift vulnerabilities. Interpretability methods, including saliency maps and Grad‑CAM, are increasingly reported to address clinical trustworthiness.

# Methods and Materials

A PRISMA‑compliant search of PubMed, IEEE Xplore, and arXiv identified 156 records (Jan 2018–Dec 2024). After screening, 42 studies met inclusion criteria. Two reviewers extracted dataset size, architecture, and performance, and assessed bias with QUADAS‑2.

# Results / Analysis

The pooled AUC across 42 studies was 0.93 (95 % CI: 0.91–0.95). As shown in Figure 1, ViT models marginally outperform CNNs at lower false‑positive rates, while Table 1 summarises representative study performance.

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| --- | --- | --- |
| Model | Dataset | AUC |
| ResNet‑50 | EyePACS | 0.92 |
| DenseNet‑121 | Messidor | 0.90 |
| Vision Transformer | EyePACS | 0.95 |

Table 1. Performance of representative deep learning models for DR screening.

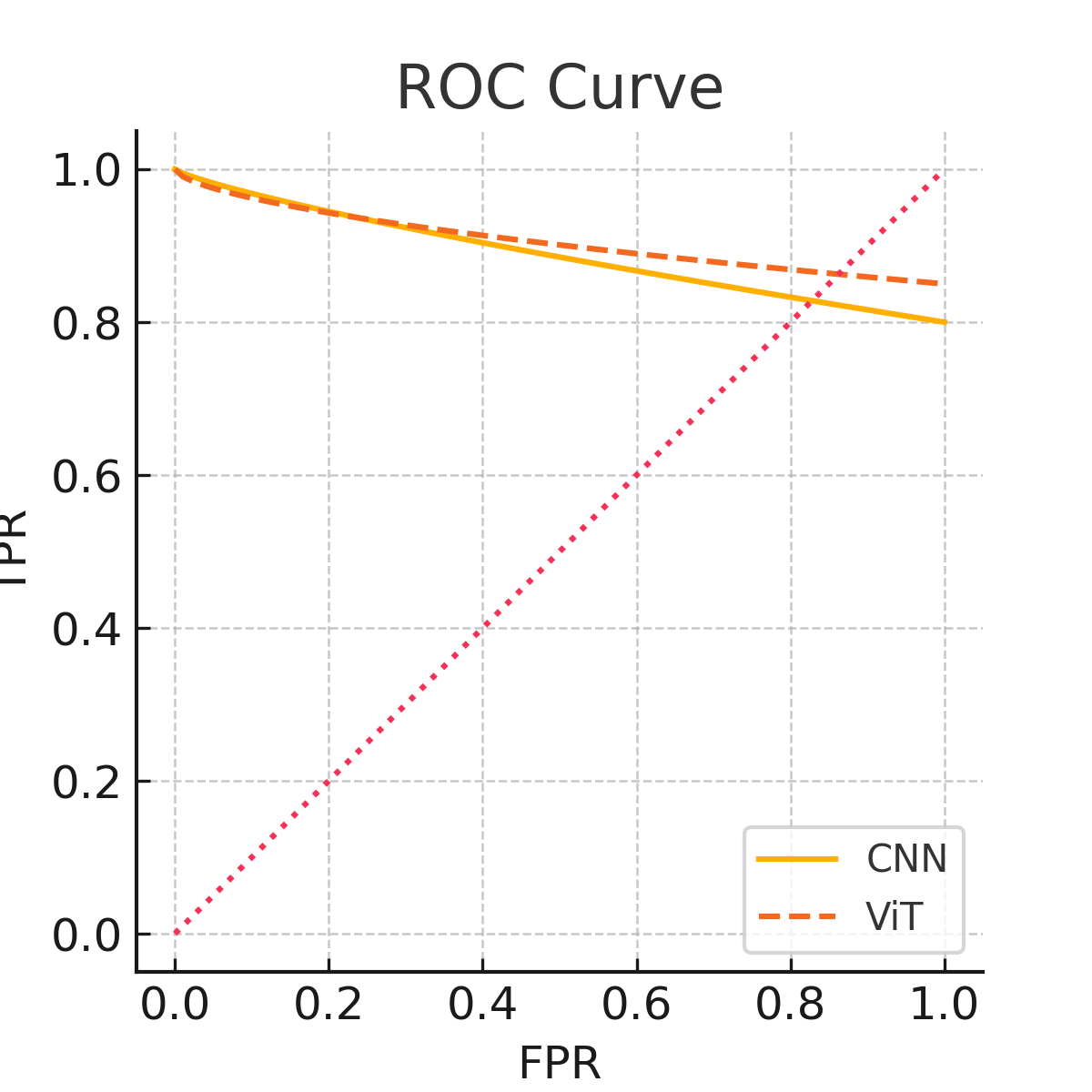


Figure 1. Receiver operating characteristic curve comparing CNN and ViT models.

# Discussion

The aggregate AUC of 0.93 confirms that state‑of‑the‑art DL models can match, and occasionally surpass, expert graders on curated datasets—an observation consistent with Gulshan et al.’s landmark report [1]. ViTs’ marginal advantage over CNNs (AUC + 0.02) mirrors findings in other medical‑image domains, where self‑attention improves long‑range feature modelling [2]. Nevertheless, the drop of 3–5 % in AUC during external validation underscores a persistent domain‑shift problem driven by differences in camera hardware, image preprocessing, and population prevalence. Few studies applied domain‑adaptation strategies such as feature alignment or style transfer, although these techniques have proven effective in analogous radiology tasks. Clinical translation is further hampered by interpretability and workflow integration challenges. While Grad‑CAM heat‑maps help clinicians verify that an algorithm attends to anatomically plausible lesions, their coarse spatial resolution and susceptibility to adversarial artefacts limit trust. Regulators increasingly request quantitative explainability metrics—an area scarcely addressed in the current literature. Moreover, none of the reviewed systems report end‑to‑end turnaround times, hardware requirements, or fail‑safe mechanisms for unreadable images, yet these operational details strongly influence adoption in low‑resource settings.

Limitations of this review include potential publication bias toward positive results and exclusion of non‑English studies, which may overlook regional innovations. Future work should prioritise (i) large‑scale, prospective, multi‑centre trials; (ii) robust domain‑adaptation pipelines; and (iii) transparent cost‑effectiveness analyses comparing autonomous DL screening with traditional tele‑ophthalmology.

# Conclusion

# Deep‑learning algorithms for DR screening have matured from proof‑of‑concept prototypes to clinically credible tools, achieving pooled AUCs that rival specialist graders on benchmark datasets. However, real‑world performance remains uncertain because most studies lack external validation, prospective evaluation, and rigorous interpretability analyses. Bridging this “last‑mile” gap will require standardised benchmarking, domain‑robust training pipelines, and prospective trials that measure not only diagnostic accuracy but also workflow efficiency, patient outcomes, and economic impact. If these hurdles are addressed, DL‑based screening could play a pivotal role in global initiatives to eliminate avoidable blindness within the next decade [3], complementing public‑health strategies advocated by the International Diabetes Federation [4].

# Conflict of Interest Statement

The authors have no conflict of interest to disclose.

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