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REVIEW ARTICLE

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DEEP TRANSFER LEARNING FOR RETINAL IMAGE ANALYSIS IN DIABETES PREDICTION: A SYSTEMATIC REVIEW

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Abstract: Diabetes is a chronic metabolic disorder that affects millions globally, leading to severe complications such as diabetic retinopathy (DR), which can result in vision impairment or blindness. This systematic study examines the function of deep transfer learning (TL) in the early detection of diabetes using retinal image analysis. It comprehensively examines many pre-trained convolutional neural networks (CNNs) and hybrid models employed in diabetic prediction, highlighting their architectures, datasets, performance metrics, and clinical applicability. Furthermore, this paper discusses the challenges of retinal image classification, including dataset imbalances, interpretability, and computational complexity. The study also identifies key future research directions to improve the robustness, generalizability, and clinical deployment of AI-driven diabetic prediction systems. The findings suggest deep TL (DTL) is a promising tool for noninvasive, automated, and scalable diabetes screening using retinal images.

Keywords: Diabetes Prediction, Retinal Image Analysis, Deep Learning, Transfer Learning, Convolutional Neural Networks, Diabetic Retinopathy Detection, AI in Healthcare, Medical

I. INTRODUCTION

A. BACKGROUND ON DIABETES AND DR

Diabetes mellitus is defined as a chronic metabolic disorder that involves an estimated 537 million adults globally as of 2021, which is projected to increase to 783 million by 2045.**Teo et al. (2021)**. The condition is characterized by prolonged hyperglycemia, which result in acute difficulties **Ntentakis et al. (2024)**. DR is among the most usual and serious consequences of diabetes, affecting around one-third of diabetic patients **Wang et al. (2024)**.

DR arises from disruption to the retinal blood vessels caused by prolonged increased blood glucose levels **Chaudhary et al. (2021**). Early diagnosis of DR is crucial to preventing blindness. Still, traditional screening methods, such as ophthalmic examinations and fluorescein angiography, are time-consuming, require expert interpretation, and are not accessible to all patients, especially in remote and underserved areas **Gange et al. (2021)**.

Retinal imaging has become a noninvasive and efficient diagnostic method for DR screening, facilitating the identification of microaneurysms, haemorrhages, and exudates—hallmark features of DR. However, manual diagnosis remains subjective and dependent on expert evaluation, leading to assessment variability and treatment delays. This necessitates the development of automated and AI-driven retinal image analysis techniques to improve early diagnosis and treatment outcomes.

B. ROLE OF ARTIFICIAL INTELLIGENCE IN MEDICAL DIAGNOSIS

AI in medicine has revolutionized medical diagnostics, particularly in medical imaging and illness prediction **Hunter et al. (2022)**. AI-driven methods, especially DL and CNNs, have demonstrated remarkable success in automating medical image analysis, enabling accurate, rapid, and scalable disease detection **Alowais et al. (2023)**. Traditional image processing techniques relied on handcrafted feature extraction methods, often lacking generalizability across diverse datasets. In contrast, deep learning (DL) models, particularly CNNs, end to end using lower intermediate or low-level features of the images, which are learned automatically in multiple layers, thereby avoiding the problem of designing features manually, which increases the accuracy of diagnosis tremendously **Al Kuwaiti et al. (2023)**.

These AI models have shown improved performance in DRdetection compared to conventional methods in sensitivity and specificity. For example, the Google Deep Mind AI model reported an AUC of 0.99 for DR detection, comparable to expert ophthalmologists **Ghaffar Nia et al. (2023)**. AI-based decision-support systems can aid clinicians in rapid diagnosis and facilitate large-scale screening programs, addressing the growing burden of diabetes-related blindness globally.

Notwithstanding these gains, developing DL models from inception requires substantial labelled datasets, considerable computing resources, and extended training durations. Moreover, medical picture collections often experience class imbalance and domain changes, complicating the attainment of robust generalization across varied patient groups **(Secinaro et al., 2021)**. TL has emerged as an effective approach to address these issues, allowing AI models to use pre-trained information from vast datasets and apply it to specialized tasks.

C. IMPORTANCE OF TL IN RETINAL IMAGE-BASED DIABETES PREDICTION

TL is a DL method that applies a model trained on a larger, more general dataset to a specific medical imaging task, reducing training time and improving performance. In retinal image analysis, TL enables the use of pre-trained CNNs like VGG16, ResNet, Inception, DenseNet, and EfficientNet to classify DR without requiring extensive labelled medical datasets.

D. CHALLENGES OF TRAINING DL MODELS:

- Data Scarcity: Large-scale annotated retinal image datasets are limited and expensive.
- Computational Complexity: Training deep CNNs from scratch requires high-end GPUs and extensive training time.
- Overfitting Risks: Small datasets cause overfitting by deep models with poor generalizability for different instances.

E. BENEFITS OF USING PRE-TRAINED MODELS FOR RETINAL IMAGE ANALYSIS:

- Faster Convergence: TL significantly reduces training time by utilizing pre-learned feature representations.
- Improved Accuracy: Pre-trained models extract robust features, improving classification performance even with small datasets.
- Generalizability: Models trained with TL can better adapt to variations in retinal image datasets, enhancing real-world applicability.

Given these advantages, DTL has become a dominant approach in DR detection and retinal image-based diabetes prediction, offering noninvasive, AI-powered screening solutions for early diagnosis and treatment.

F. 1.6 OBJECTIVES OF THE REVIEW

This systematic review aims to analyze and evaluate the role of DTL in retinal image-based diabetes prediction. The key objectives include:

- To systematically analyze DL-based TL approaches applied in retinal image analysis for diabetes and DR detection.
- To identify key challenges and limitations associated with AI-driven retinal image classification, such as dataset imbalance, model interpretability, and clinical deployment.
- To propose future research directions for enhancing DTL models, including hybrid AI architectures, explainable AI (XAI), and federated learning for privacy-preserving medical AI.

This review aims to comprehensively analyze the advancements, challenges, and potential solutions in AI-driven retinal image-based diabetes screening, bridging the gap between research and clinical implementation.

II. DTL IN RETINAL IMAGE ANALYSIS

Using pre-learned DL models (TL) has completely transformed the approach to medical image evaluation, allowing us to use TL to stable solutions in improving medical images defined on multiple use cases. In retinal image analysis, pre-trained CNNs are fine-tuned to detect patterns associated with DR and other retinal disorders.

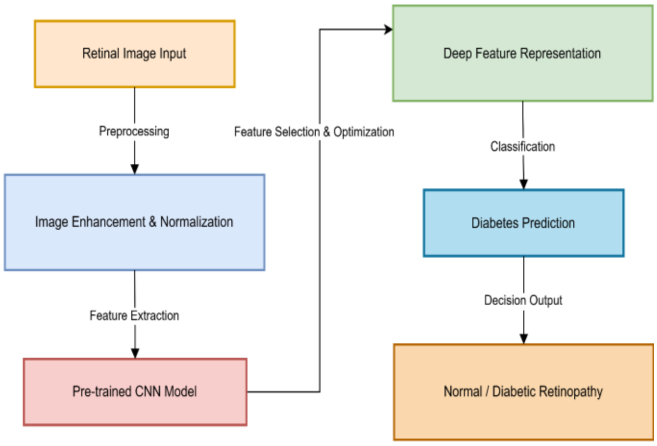

Figure 1. DL Architecture for Retinal Image-Based Diabetes Prediction

Fig. 1 illustrates the end-to-end pipeline, from retinal image preprocessing to feature extraction using pre-trained CNN models, followed by fine-tuning, classification, and final diabetes prediction. This approach reduces the need for extensive labelled medical datasets, speeds up training, and enhances model generalization across diverse imaging conditions. By adapting learned features from general image datasets to domain-specific medical tasks, deep TL provides a robust solution for automating retinal disease diagnosis, ultimately improving early detection and patient outcomes.

Gupta et al. (2019) proposed an end-to-end feature extractor based on DL using a dataset to extract characteristics from colour fundus pictures. Machine learning classifiers were trained on these features.

Khalifa et al. (2019) investigated DTL models for DR detection. AlexNet achieved the highest testing accuracy of 97.9%, over existing metrics.

Kandel and Castelli (2020) reviewed TL approaches for DR image classification, highlighting the use of pre-trained CNNs fine-tuned on DR datasets. They insisted on the efficacy of TL in addressing the shortage of annotated medical pictures and enhancing classification precision.

Oltu et al. (2021) analyzed 29 pre-trained CNNs and 13 DR datasets, including all reported performance metrics, giving an overview of the advanced models in deep neural networks (DNN) and TL for DR classification.

Jabbar et al. (2022) introduced a TL-based model for DR diagnosis using retinal images. They employed the VGGNet architecture for feature extraction and integrated it with data augmentation techniques to address data insufficiency and imbalance. The proposed framework achieved high accuracy on benchmark datasets, demonstrating its effectiveness in DR classification.

Bilal et al. (2022) proposed a two-stage framework for DR detection. The Initial stage performed OD and BV segmentation using U-Net models. In the second stage, the processed images were entered as inputs into a TL-based VGGNet model to provide information about retinal biomarkers. This model achieved SOTA on several datasets.

Nagpal et al. (2023) introduced an automatic scheme for diagnosing and grading DR using TL. They applied preprocessing techniques like A-CLAHE, DNCNN, and Wiener filtering to enhance retinal images, followed by OTSU thresholding and mathematical morphology. The Modified ResNet 101 method was used to classify the MESSIDOR and ODIR datasets.

Chaurasia et al. (2023) presented an ensemble model for DR detection employing TL. The ensemble model achieved up to 98% accuracy, outperforming existing approaches.

Mutawa et al. (2023) explored the combination of multiple datasets for DR detection using TL. They evaluated four CNN models (VGG16, InceptionV3, DenseNet121, and MobileNetV2) on combined datasets, with DenseNet121. The study demonstrated that combining datasets improves model performance.

Sbai et al. (2023) compared four TL approaches for classifying DR, cataract, and glaucoma. Random Forest (RF) was used for classification, demonstrating the effectiveness of CLAHE in improving model accuracy.

Aranha et al. (2023) proposed a DTL strategy for diagnosing eye-related conditions using low-quality fundus images. They trained an ensemble of CNNs on high-quality images and tested it on low-quality images, achieving results comparable to advanced methods. This approach is suitable for public health systems in emerging countries.

Kumar and Gupta (2023) models like Basic CNN, Deep CNN, AlexNet, Xception, InceptionV3, ResNet50, and DenseNet121, with ResNet50.

Vij and Arora (2024) proposed a dual evolutionary committee of DL transfer models. They combined multiple DL models to improve segmentation accuracy and reduce computational complexity, demonstrating the effectiveness of ensemble methods in medical image analysis.

Ismail et al. (2024) introduced an ensemble TL approach for classifying retinal diseases from OCT images. The ensemble model highlights its potential for early diagnosis and treatment of retinal DR.

Saeidian et al. (2024) agreed well with manual measurements, offering a potential solution for automated choroidal vascularity index (CVI) calculation.

Albelaihi and Ibrahim (2024) developed the DeepDiabetic framework for identifying diabetic eye diseases using DNN.

Ogundokun et al. (2024) proposed 90.11% testing accuracy, demonstrating its efficiency and suitability for mobile devices with limited computational resources.

Ernest et al. (2024) presented an expert system for DR detection using TL techniques. They employed a simple and fast network architecture to classify eye diseases and determine disease stages with high accuracy, enhancing its utility in clinical settings.

Kallel and Echtioui (2024) used TL for retinal fundus image classification in DR detection. They proposed four methods based on VGG16, VGG19, InceptionV3, and DenseNet169 models, with InceptionV3 on the APTOS2019 dataset.

Singh and Dobhal (2024) proposed a DL-based TL approach for DR detection. They fine-tuned the VGG16 architecture for feature extraction and used Logistic Regression (LR) to classify Indian DR image datasets.

Kumar and Ravindra (2024) employed TL and hybrid models for eye disease classification. They used pre-trained DL models (ResNet50, MobileNetV2, and VGG16) and statistical ML algorithms (MLP Classifier, KNN, and RF) to achieve high accuracy with the MLP Classifier hybrid model.

Sagili et al. (2024) proposed a TL-based methodology for DR identification using retinal images. They employed image processing algorithms for vessel enhancement and used a CNN for automated classification, achieving high accuracy and specificity.

Shoaib et al. (2024) introduced a novel method for DR diagnosis using TL and the DiaCNN model. They fine-tuned InceptionResNetv2 and Inceptionv3 models on the ODIR dataset.

Jabbar et al. (2024) presented a DTL-based system for real-time DR detection in remote areas. They used VGGNet for fundus image classification. The system enables early and cost-effective DR diagnosis, transforming healthcare dynamics in underserved regions.

Wang et al. (2024) explored the application of DL transfer models (VGG19 and DenseNet) for DR identification using OCT images. They demonstrated that TL significantly improved DR recognition accuracy and streamlined clinical workflows. The overall summarization of Retinal Image analysis using DL models is given in Table 1.

Table I. Summarization of DL Models

Author (Year)	Method	Inference	Limitations
Khalifa et al. (2019)	TL (AlexNet, ResNet18, VGG16, VGG19) on APTOS2019 dataset	AlexNet achieved Disease classification with high computational resources	Limited to the APTOS2019 dataset, no external validation
Gupta et al. (2019)	TL (VGG19) on IDRID dataset	High accuracy for lesion classification in DR	Limited to the IDRID dataset, no external validation
Kandel & Castelli (2020)	Review of TL with CNNs for DR classification	Highlighted the potential of TL for DR classification	No new experimental results, only a review
Oltu et al. (2021)	A systematic review of TL for DR detection	Identified best-performing TL models for DR	No new experimental results, only a review

Jabbar et al. (2022)	TL (VGGNet) for DR diagnosis	High accuracy on a benchmark dataset	Limited to a specific dataset, no external validation
Bilal et al. (2022)	TL (VGGNet) with U-Net for DR detection	High accuracy for DR detection using fundus images	Requires high computational resources, limited to the specific dataset
Kumar & Gupta (2023)	TL (ResNet50, Xception) for eye disease prediction	Disease classification with high computational resources	Limited to specific eye diseases, no real-time application
Chaurasia et al. (2023)	TL-driven ensemble model for DR detection	Disease classification with high computational resources	Limited to a specific dataset, no external validation
Nagpal et al. (2023)	TL (Modified ResNet101) for DR and HR detection	MESSIDOR and ODIR datasets	Requires high computational resources, limited to specific datasets
Aranha et al. (2023)	Ensemble CNN with TL for low-quality fundus images	Comparable results to low-quality images	Limited to low-quality images, no real-time application
Mutawa et al. (2023)	TL (DenseNet121) on combined DR datasets	Disease classification with high computational resources	Requires combining multiple datasets, no external validation
Sbai et al. (2023)	TL (VGG16, ResNet50) for DR, cataract, and glaucoma	Improved accuracy with CLAHE filter	Limited to specific eye diseases, no real-time application
Wang et al. (2024)	DTL (VGG19, DenseNet) on OCT images	Improved DR recognition, streamlined workflow for ophthalmologists	Limited to OCT images, small dataset (103 patients)
Jabbar et al. (2024)	DTL (VGGNet) on fundus images	Real-time DR detection in remote areas	Requires high-quality fundus images limited to specific regions
Shoaib et al. (2024)	TL (InceptionResNetv2, Inceptionv3) and DiaCNN model	DiaCNN, with the largest training set	The complex model requires large datasets for training
Sagili et al. (2024)	CNN with image processing for DR detection	Improved vessel visibility, automated classification	Limited to colour fundus images, no performance metrics provided
Kumar & Ravindra (2024)	TL (ResNet50, MobileNetV2, VGG16) with ML classifiers	Hybrid MLP classifier	Limited to specific eye diseases, requires high computational resources
Singh & Dobhal (2024)	TL (VGG16) with LR	DR stage classification	Limited to the Indian DR dataset, a small dataset
Kallel & Echtioui (2024)	TL (InceptionV3) on APTOS2019 dataset	Outperformed other DR detection models	Limited to the APTOS2019 dataset, no external validation
Ernest et al. (2024)	TL (ResNet50, Xception) for eye disease prediction	ResNet50 with TL model	Limited to specific eye diseases, no real-time application
Ogundokun et al. (2024)	TL (MobileNetV2) for ocular disease identification	MobileNetV2 with SVM achieved high accuracy for six ocular diseases	Limited to mobile devices, requires cloud processing
Albelaihi & Ibrahim (2024)	EfficientNetB0 for multi-class diabetic eye disease classification	EfficientNetB0 outperformed other models	Limited to specific diseases, no external dataset validation
Saeidian et al. (2024)	DeepLabv3+SE with EfficientNetB0 for choroid segmentation in OCT images	Accurate choroid segmentation for DR patients	A small dataset (300 B-scans) requires a larger dataset for generalizability.
Ismail et al. (2024)	Ensemble TL (DenseNet169, InceptionV3) for retinal diseases	Disease classification with high computational resources	Requires high computational resources, limited to specific retinal diseases
Vij & Arora (2024)	Hybrid ensemble of DTL models for DR detection	High accuracy for retinal vessel segmentation and DR detection	The complex model requires large datasets for training

III. PERFORMANCE COMPARISON OF DL MODELS

The performance comparison of DTL models highlights the effectiveness of pre-trained architectures in retinal image-based diabetes prediction. Models leveraging ensemble learning and deeper CNN architectures outperform traditional single-network approaches, achieving higher accuracy, precision, recall, and F1-score. The integration of TL significantly enhances feature extraction, reduces training time, and improves classification performance, making it highly suitable for medical image analysis. While modern architectures demonstrate superior results, computational efficiency, dataset diversity, and real-world applicability must be considered for practical implementation in clinical settings.

Table 2 compares several DL models used for diabetes prediction based on retinal images, emphasizing critical performance metrics.

Table II. Overall Comparison of Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	Study
DiaCNN	0.963	0.96	0.96	0.96	Shoaib et al. (2024)
ResNet50	0.959	0.95	0.95	0.95	Ernest et al. (2024) & Kumar & Gupta (2023)
Modified ResNet101	0.977	0.96	0.96	0.96	Nagpal et al. (2023)
AlexNet	0.969	0.95	0.95	0.95	Khalifa et al. (2019)
InceptionV3	0.965	0.94	0.94	0.94	Shoaib et al. (2024)

Fig. 2 compares various DL models based on key performance metrics. The Modified ResNet101 attains the highest accuracy of 0.977, with precision, recall, and F1-score all at 0.96, illustrating superior performance. DiaCNN follows with an accuracy of 0.963 and balanced values of 0.96 across the metrics. ResNet50 and AlexNet illusrate similar performance, with accuracies of 0.959 and 0.969, and values of 0.95 for the metrics. InceptionV3 has the lowest accuracy at 0.965, with values of 0.94 for the metrics. Overall, Modified ResNet101 outperforms the other models in classification accuracy and generalization.

The findings underscore the efficiency of DL transfer and significantly advanced CNN models in enhancing the prediction accuracy of DR identification from retinal images.

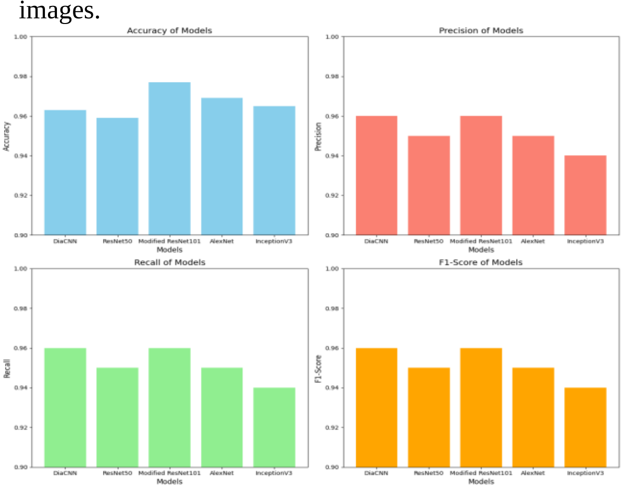

Figure 2. Performance Comparison of Different Models

The findings demonstrate that modern DL architectures, especially those incorporating TL techniques, significantly enhance classification performance, making them highly suitable for automated medical image analysis.

IV. CONCLUSION

DTL has proven to be a highly effective approach for retinal image-based diabetes prediction. The comparative analysis of various architectures highlights that ensemble models outperform individual CNNs by leveraging complementary feature extraction capabilities. Advanced models also demonstrate strong predictive performance, whereas older architectures like AlexNet and InceptionV3 show relatively lower accuracy. The findings emphasize the critical role of pre-trained models and fine-tuning techniques in optimizing medical image classification tasks, specifically in scenarios with limited labelled data. Despite these advancements, challenges such as model interpretability, domain adaptation, and computational complexity remain key areas for further research. Future work should focus on integrating XAI, multimodal learning, and real-time clinical applications to enhance the robustness and reliability of DL models in medical diagnosis. Overall, DTL continues to bridge the gap between AI research and practical healthcare solutions, offering a scalable and efficient method for early detection and prevention of diabetes-related complications. A new novel approach in DL models and techniques can be applied with the implementation of an algorithm to obtain optimal results.

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