IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Exploring Deep Learning Architectures for Retinal Image Analysis in Diabetic Retinopathy

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Abstract— *Diabetes Mellitus is a metabolic disease chronic in nature involving millions across the globe and may lead to complications that are critical in nature like Diabetic Retinopathy (DR), an illness which causes permanent vision impairment. Prompt detection and precise DR classification are indispensable for effective therapy and prevention of blindness. Manual techniques employed till now for DR are tedious, with potential for variability, so motivating the implementation of computer-assisted techniques in medical imaging. This work provides an extensive review of the recent developments in the era of deep learning, including Convolutional Neural Networks (CNNs), for detecting and classifying DR from retinal fundus images. We review publicly accessible datasets and discuss a range of deep learning models applied in this area. The primary contributions of this study are: (1) providing state-of-the-art deep learning methods for DR diagnosis,*
(2) comparing their performance on standard datasets, and (3) outlining current shortcomings and possible directions for future work in automated retinal image analysis.

Keywords— *Deep Learning , Image Classification, Diabetic Retinopathy , Convolution Neural Network , Deep Neural etwork.*

I. INTRODUCTION

Diabetic Retinopathy (DR) represents a significant ocular complication stemming from Diabetes Mellitus (DM). The global burden of diabetes is substantial and growing; the World Health Organization projects that the number of individuals living with diabetes could climb from 420 million to as many as 578 million by the year 2030. Diabetes primarily manifests in two forms: Type 1, an autoimmune condition often diagnosed early in life, and Type 2, which is strongly linked to lifestyle factors and typically develops over many years. Both types impair the body's insulin mechanism, hindering the proper uptake of glucose and leading to chronically elevated blood sugar levels.

DR itself is a microvascular consequence of DM, specifically affecting the blood vessels within the retina. This impairment can obstruct blood flow, prompting the retina to generate new, often fragile, blood vessels in an attempt to compensate. The resulting abnormal vascular structure underlies the complications associated with DR, which can progressively worsen and potentially cause complete vision loss [2–4]. Therefore, timely and consistent screening is essential to identify DR in its prior levels and prevent severe outcomes [5, 6].

DR is categorised into two levels: proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR). NPDR typically involves leakage and swelling (macular edema) in the tiny retinal blood vessels, often causing mild vision disturbances. PDR is considered the more advanced and dangerous stage, marked due to born of abnormal new blood vessels (neovascularization) on the retinal surface. These new vessels are weak and can rupture, leading to hemorrhages, significant vision loss, and potentially eye pain. Several factors increase the risk of developing DR, including having either Type 1 or Type 2 diabetes, Hispanic or African ancestry, increased cholesterol levels (hypercholesterolemia), high blood pressure (hypertension), pregnancy, and a family history of the condition. Patients may experience symptoms such as blurry vision, seeing floaters or spots, developing blind spots in their central visual field, and experiencing diminished night vision.

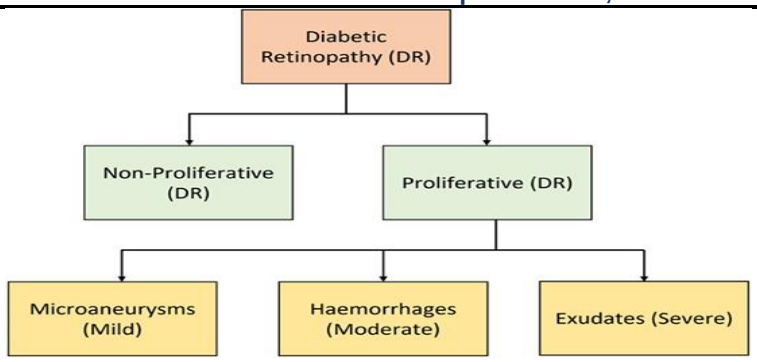

Fig. 1 Various stages of DR

Diagnosing DR often involves various imaging techniques, such as fundus photography, Optical Coherence Tomography (OCT), OCT-Angiography (OCT-A), Fluorescein Angiography (FA), and Scanning Laser Ophthalmoscopy (SLO) [7]. Fundus photographs provide two-dimensional images of the retina's interior, revealing key structures like the macula, fovea, optic nerve, and the network of blood vessels. These images can be obtained either through a mydriatic method, requiring pupil dilation via eye drops, or a non-mydriatic technique that avoids dilation.

While electro-retinography can measure the retina's electrical responses, clinical DR diagnosis heavily relies on ophthalmologists conducting non-invasive examinations of retinal fundus images. They meticulously search for characteristic lesions that indicate the presence and severity of DR. However, this manual evaluation process is demanding, requires significant expertise, and can be very time-consuming [11]. Furthermore, the number of available ophthalmologists often struggles to keep pace with the increasing population requiring DR screening. In response to these limitations, considerable research effort has focused on developing automated diagnostic tools [12, 13]. Many of these emerging automated systems utilize technologies based on Machine Learning (ML) and Deep Learning (DL) to analyze retinal images [14–17].

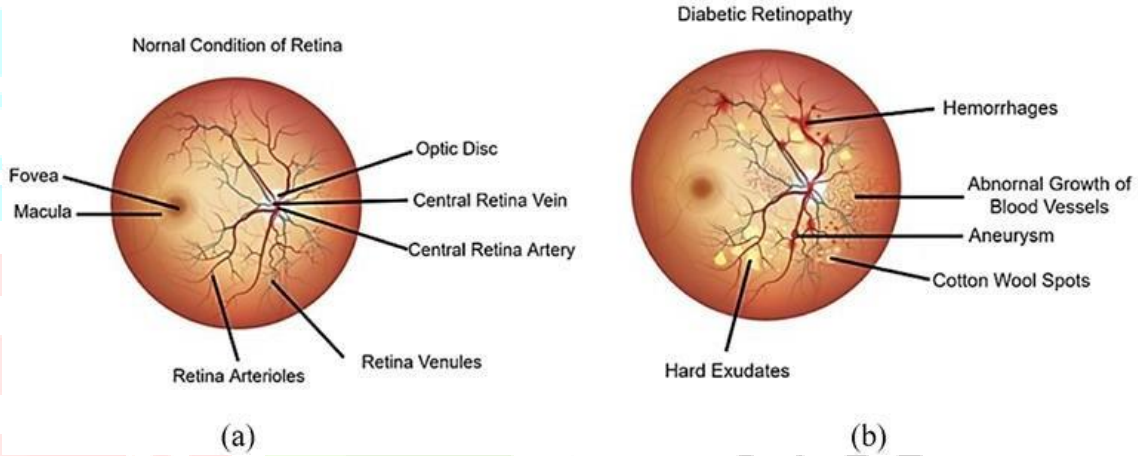

Fig. 2 a) Normal Retina b) Diabetic Retina

II. LITERATURE REVIEW

This work provides a hybrid solution for diabetic retinopathy (DR) detection using machine learning classifiers and deep feature extraction. Decision Trees, Random Forests, and SVMs' predictions are stacked using features extracted from MobileNetV2, DenseNet121, and Inception-ResNetV2. Hyperparameter optimization improves performance on the APTOS 2019 dataset, with preprocessing methods improving accuracy. The model performs 95.50% multi-class and 98.36% binary classification, and the best feature extractor is identified as DenseNet121. As a better alternative than single classifiers, the study highlights dataset bias, sample size limitation, and computational constraint but recommends further testing to ensure practicality in real-world applications.[1]

This research suggests a hybrid deep learning scheme for detecting diabetic retinopathy (DR) using GoogleNet and ResNet along with an adaptive particle swarm optimizer (APSO) for feature extraction. Machine learning classifiers such as Random Forest, SVM, Decision Tree, and Linear Regression classify DR severity based on the EyePACS dataset (35,126 images). Preprocessing operations such as resizing, green channel extraction, and data augmentation improve accuracy, and 94% overall accuracy is obtained. SVM has the best precision (97%) and F1 score (96%). Although outperforming current state-of-the-art methods, the research identifies areas of limitation in dataset generalizability, computational resource demand, and model explainability, not having temporal progression analysis for tracking DR.[2]

The EviRed project will create an AI system for the prediction of diabetic retinopathy (DR) progression based on imaging and systemic health information from 5000 French diabetic patients over two years. Retinal images from widefield photography, OCT, and OCTA will be utilized, with primary metrics being sensitivity, specificity, and AUC (aiming for >85%). Though encouraging, the limited focus on French patients, sole use of the EyePACS dataset, and absence of temporal analysis and computation resource information can potentially restrict applicability and clinician use.[3]

This work uses CNNs for computer-aided diabetic retinopathy (DR) detection and classification from two retinal image datasets (3,662 and 35,126 images). The model has 96.93% training and 95.08% validation accuracy for binary classification, with 95.65% test accuracy. For multi-class classification, it has 93.06% training and 81.12% validation accuracy, with 80.48% test accuracy. Performance is compromised by scarce severe-class data and dataset variability, affecting real-world generalizability.[4]

This research formulates a diabetic retinopathy (DR) risk estimation model through the use of CatBoost, supplemented with SHAP for explainability. Preprocessing involves missing value handling, outliers, and feature selection. CatBoost performs better than SVM, RF, XGBoost, and GBT with an accuracy of 82.50%. SHAP analysis reveals the most important biomarkers associated with DR. Although high predictive effectiveness and robustness against noise are achieved, drawbacks are the limited sample size and requirement for future clinical validation. [5]

This paper introduces a new DCNN for diabetic retinopathy (DR) detection, incorporating Long-Range units to learn global dependencies in retinal images. Based on Inception V3, the model is fine-tuned on Messidor and EyePACS datasets, with AUCs of 98.1% and 96.7% on Messidor and 83.6% multi-class accuracy on EyePACS. It surpasses state-of-the-art approaches in sensitivity and precision but is limited by dataset size, class imbalance, and computational efficiency.[6]

This paper presents DRNet13, a deep neural network for the detection of diabetic retinopathy (DR), incorporating higher layers for improved feature extraction. Employing a 7,500-image dataset from Aravind Eye Hospital, the model is preprocessed and augmented to yield 96% test accuracy with high precision and AUC values. It outperforms 15 pre-trained models, with DRNet13 providing better efficiency but in need of further verification for more general clinical use.[7]

This research utilizes transfer learning for detection of diabetic retinopathy (DR) employing VGG16 and VGG19 for feature extraction and Logistic Regression for classification. The models are trained on the IDRiD dataset (282 images) with high accuracy—90.4% for VGG16 and 89.4% for VGG19—compared to other classifiers. Withstanding robust performance, the drawbacks are small dataset size, image quality sensitivity, and high computational costs, and more validation is needed on large datasets for clinical practice. [8]

This paper introduces a Hybrid Diabetic Retinopathy Neural Network (DRNN) of ResNet-152 and DenseNet- 121 for detection of DR at an early stage based on fundus images. The model, having been trained on a Kaggle dataset (2750 images), attains 99.86% training and 96.91% validation accuracy, surpassing CNN, RNN, DBN, and GoogleNet. Although having strong performance, dataset diversity and computational requirements are challenges. Future development will improve accuracy and incorporate clinical data to facilitate better diagnosis.[9]

This work compares two deep learning models for diabetic retinopathy (DR) detection: a hybrid model of VGG16-XGBoost and DenseNet 121. Both models were trained using the APTOS 2019 dataset (3662 images). DenseNet 121 was found to be more accurate (97.30%) than the hybrid model (79.50%). Although high accuracy is demonstrated, dataset imbalance and high computational requirements are concerns. Future work will involve optimization of preprocessing, improving model stability, and creation of real-time automated DR detection systems for use in clinics.[10]

This research compares original and segmented retinal images for diabetic retinopathy (DR) diagnosis with Inception v3 and DenseNet-121. Classified on the APTOS dataset (5590 images), original images obtained better accuracies (80% and 83%) compared to segmented ones (72% and 69%). Original images were more effective, though there are constraints on information loss in segmentation, dataset variability, and a high demand for computation. Future research must incorporate temporal data, high-resolution segmentation, and lesion-based classification for better accuracy.[11]

This work introduces a tailored CNN method for diabetic retinopathy (DR) screening via k-medoid clustering, PCA, and inter/intra-class variation analysis. Tested on the KSU-DR, EyePACS, and APTOS2019 datasets, the DeepPCANet models performed better than pre-trained networks, with DeepPCANet-4 attaining 98.21% accuracy on APTOS2019. Although impressive, limitations exist in dataset specificity, sensitivity to image quality, and high computational requirements. Future work will increase model generalizability, solve poor- quality image issues, and optimize AutoML for clinical use.[12]

This paper introduces the DS-KL approach for diabetic retinopathy (DR) detection at an early stage, integrating knowledge learning and pixel-boundary segmentation to accurately classify exudates. Tested on DIARETDB1 and IDRiD datasets, it obtained 97.67% accuracy and surpassed CNN models such as AlexNet and ResNet-50. Issues are dataset generalizability, computational complexity, and variations in image quality. Future research will address wider validation, efficiency enhancement, and enhanced adaptability for clinical applications.[13]

This research uses the Harris Hawks Optimization (HHO) algorithm to increase a deep learning model for detecting diabetic retinopathy (DR), incorporating PCA as a feature extraction method. Tested on the Debrecen dataset, the model attained 97% accuracy, precision, and recall, which is better than KNN, SVM, and XGBoost. Challenges faced are generalizability of the dataset and high computational complexity. Future work will involve broader validation, improving efficiency, and advanced feature extraction for better detection.[14]

This work proposes a deep learning scheme with an RNN for prediction of early diabetic retinopathy (DR) from fundus images based on sophisticated preprocessing, employing cutting-edge techniques. Compared to methods employing hazard variables on EyePACS and Messidor-2 data, it delivered AUC values of 0.79 and 0.70. Main issues are dataset specificity and elevated computational requirements. Further work shall target increased generalizability, optimization, and real-time DR

detection at affordable cost for the purpose of early diagnosis and treatment.[15]

This paper offers a machine learning idea for diabetic retinopathy (DR) detection from fundus images through preprocessing, segmentation, and feature extraction through GLCM. Fuzzy classifier (85% accuracy) and CNN (90% accuracy) are used for classification, with the latter performing better. Limitations are specificity of the dataset, computational complexity, and dependency on manual feature extraction. Future research will involve extensive validation and real-time application for enhanced clinical relevance.[16]

This paper introduces an integrated multi-scale shallow CNN for detection of diabetic retinopathy, addressing dataset limitation and overfitting issues. The model enhances classification accuracy by 3% on small datasets and 3%–9% on large datasets and decreases training time based on the Kaggle DR dataset (35,126 images). Drawbacks are dataset dependency, computational requirements, and model complexity. Subsequent work will optimize integration techniques, improve sampling methods, and test performance on varied datasets towards clinical usability.[17]

This article introduces the "Diabetic Retinopathy – Segmentation and Grading Challenge" on the IDRiD dataset (516 retinal images with annotations) to improve DR diagnosis. With 148 submissions by 37 teams, leading models combined clinical information, augmentation, and ensembles for better accuracy. There are challenges in generalizability, computational cost, and lesion complexity. Future work will further improve the robustness, efficiency, and clinical usability of models.[18]

This article emphasizes teleophthalmology's use in the management of diabetic retinopathy (DR) in the context of COVID-19, facilitating remote screening and monitoring and minimizing infection risk. Indian and Italian studies illustrate high accuracy with non-mydriatic and retinal cameras. Limitations are the absence of national screening programs and long-term evidence of telemedicine's efficacy. In the future, telemedicine needs to be extended, made more accessible, and its cost-effectiveness assessed for DR management beyond the pandemic.[19]

TABLE I
AVAILABLE DL ARCHITECTURES IN DR DETECTION

DL (CNN) Models	Advantages	Limitations
AlexNet	ReLU activation function; Overlap pooling;	Larger number of parameters (60 million);
	Data augmentation and Dropout to avoid overfitting;	Be appropriate for handling basic and small data issues on average hardware; Basic and small data issues
GoogLeNet (Inception V1)	Inception model to extract features at different scales to increase the 1×1 convolutional kernels for dimensionality reduction reduces the computational complexity; Global average pooling layer instead of FC layers	Larger number of parameters (5 million); Heterogeneous topology between the inception blocks; Representational bottleneck
VGGNet	Same small-sized kernels to increase the depth of the network to improve the final performance	Larger number of parameters (138-180 million); High computational cost
Inception V4	Reduction block for pooling data	
Inception V3	Factorization using 1×n and n×1 convolutional kernels instead of n×n kernels to diminish representational bottleneck; RMSProp optimizer to accelerate the training	
Inception ResNet	Inception V3 or V4 combines with residual connection to improve computational efficiency	Accuracy is not significantly improved
ResNet	Residual block with a shortcut connection to reduce parameters and accelerate training convergence	High computational cost and requires more powerful hardware support;

III. CONCLUSIONS

Integrative deep learning methods are highly promising for improving the detection and classification of diabetic retinopathy. By combining the advantages of multiple models, datasets, and methods, these methods can offer efficient, accurate, and scalable solutions to DR screening and diagnosis. Despite the challenges, research and development in deep learning, data augmentation, transfer learning, and model interpretability provide highly promising opportunities for innovation. Dealing with ethical issues, encouraging teamwork, and putting patient- centeredness first are necessary to guarantee successful adoption of these technologies into clinical settings. Through further work, integrative deep learning methods have the ability to greatly improve the prior detection and treatment of diabetic retinopathy and thereby diminish the case load of vision loss due to this disease.

ACKNOWLEDGEMENT

The authors appreciate the supports from Medicaps University, India for the research and preparation of the manuscript.

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