IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING FOR DIABETIC RETINOPATHY DETECTION AND CLASSIFICATION BASED ON FUNDUS IMAGES

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Abstract: Diabetic retinopathy (DR) is a severe complication of diabetes that damages the retina and can lead to vision loss. Early detection and treatment of DR are crucial to prevent blindness. This study proposes using deep learning techniques to automatically detect and classify DR severity from fundus images. The methodology involves collecting fundus images, pre-processing them, training convolutional neural network models, and evaluating model performance using common classification metrics. Various deep learning architectures such as VGGNet, ResNet, and DenseNet will be explored. The models will be trained on large datasets such as Kaggle Diabetic Retinopathy Detection dataset. If successful, the deep learning model can be integrated into screening systems to detect DR early and enable timely treatment. Te process has the capability of reducing vision impairment that is noticed in DR globally.

Index Terms – VGGNet ,ResNet, and DenseNet

I. INTRODUCTION

Diabetes is a long-term medical condition that can be marked by elevated blood sugar and glucose levels. Mild non-invasive abnormalities in DR proceed to moderate or severe non-invasive problems in DR, and then to proliferative DR, which, if ignored, may result in blind vision. From certainresearch it is found that one-third peoplearound the globe has DR [1]. Early detection and treatment of DR are crucial to prevent vision loss. However, screening for DR remains a challenge.Manual examination of fundus images by ophthalmologists is the gold standard for DR diagnosis. But this process is timeconsuming and prone to human errors. Deep learning methods which use convolutional neural networks (CNNs) to analyze images show promise for automated analysis and classification of medical images. This study proposes using deep learning techniques to detect DR from fundus photography images and classify its severity automatically. This can improve screening efficiency and enable

II.AIMS AND OBJECTIVES

A. AIMS

This research addresses the challenge of accurately and efficiently classifying diabetic retinopathy (DR) from fundus images using deep learning techniques. Traditional methods, including classical machine learning algorithms, face limitations in capturing intricate disease-related features. The study aims to overcome these limitations by exploring advanced deep learning approaches, considering the diverse image quality in publicly available datasets. Additionally, the research adapts to the evolving landscape of deep learning, investigating the effectiveness of self-supervised and transformer-based methods. The overarching goal is to enhance DR classification accuracy, efficiency, and adaptability to varying image conditions, contributing to more effective and timely interventions..

B. OBJECTIVES

The primary objectives of this research are:

• Develop and evaluate advanced deep learning models, including self-supervised and transformer-based approaches, for accurate and efficient classification of diabetic retinopathy from fundus images.

• Address the limitations of classical machine learning algorithms in capturing subtle disease-related features, aiming to improve the overall diagnostic performance of the classification models.

• Enhance the adaptability of the models to varied image quality, particularly in publicly available datasets with diverse contrast levels, ensuring robustness and reliability in real-world applications.

III.LITERATURE REVIEW

Multiple studies have applied deep learning for automated analysis of fundus images. Pratt et al. [1] developed a CNN model using a VGG-19 architecture and trained it on 75137 images. The model achieved 95.6% sensitivity and 91.4% specificity for DR detection. Another study by Gargeya and Leng [2] utilized a ResNet-50 CNN to classify fundus images into 5 disease severity levels. Their model attained 87.2% accuracy on a test set of 1000 images.

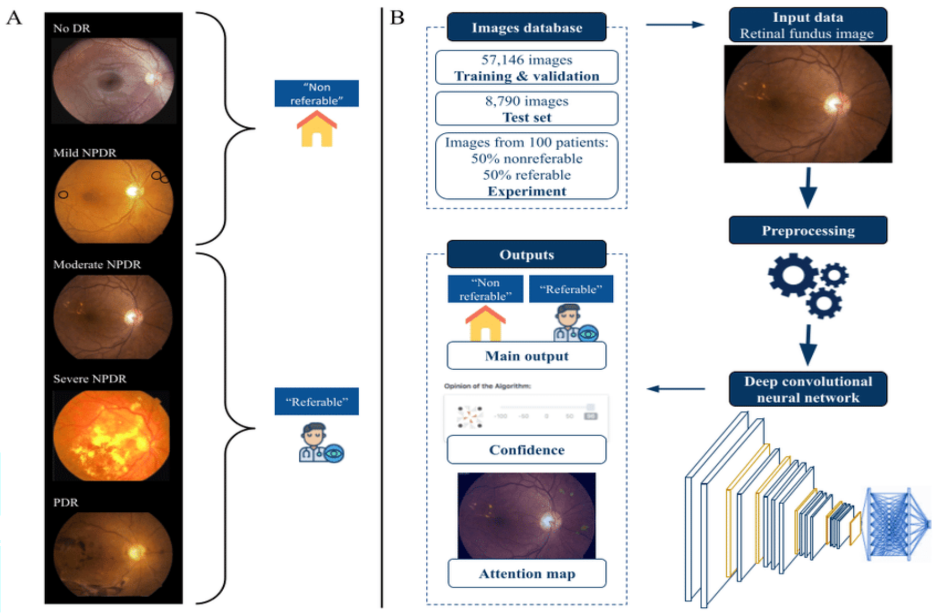

FIG 1. DL based automated retinal image analysis system

(Source: www.researchgate.net)

[3] proposed an ensemble of CNNs by training models like Visual Geometry Group Net (VGGNet), DenseNet, Inceptionv3 individually then combining their outputs.On the Kaggle Diabetic Retinopathy Detection dataset, their ensemble model achieved 100% sensitivity and 91% specificity. This highlights the potential of ensemble models to improve performance.

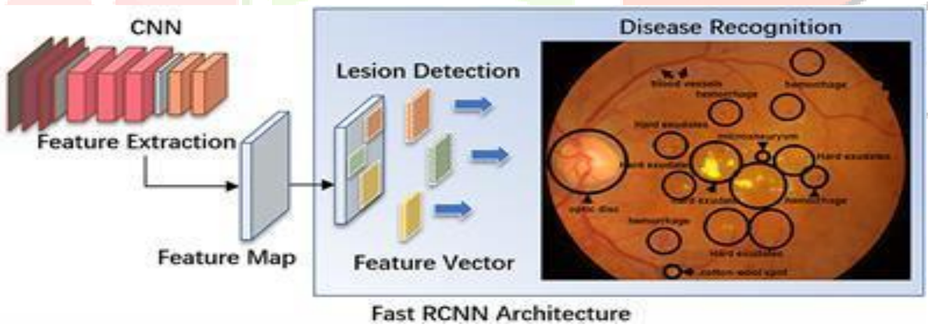

FIG 2. AI in diabetic retinopathy.

(Source: In terms of training techniques, Ramachandran et al.)

[4] utilized transfer learning by fine-tuning a pre-trainedInception-v3 model on a DR dataset. This improved accuracy compared to training from scratch. Data augmentation methods like rotations, flips and shifts have also been used to expand datasets and combat overfitting [5]. Overall, deep CNN models show encouraging results for DR detection in fundus images. However, there are opportunities to enhance model performance and robustness further through architecture optimizations, ensemble modeling, advanced training techniques and comprehensive evaluation. This could accelerate real-world clinical deployment.

IV.Methodology

This section presents the methodology to create and validate a deep learning model for automated DR detection and classification from fundus images.

a)Data and Study Area

The study will utilize public fundus photography datasets. Primary data will be sourced from the Kaggle Diabetic Retinopathy Detection challenge dataset [9]. It contains 35126 training images from EyePACS categorized by disease severity level. Additionally, the MESSIDOR dataset [10] with 1200 images will be used forexternal validation. The study will be conducted remotely using cloud computing resources.

b)Application of Software

The models will be developed in Python using Tensorflow and Keras APIs for deep learning. Key Python libraries used will be Numpy, Pandas, Matplotlib, Scikit-Learn, OpenCV and Keras. Google Colab will be leveraged for accessing free GPUs to accelerate model training. Git will be used for version control.

c)Model Architecture

Various standard CNN architectures pretrained on ImageNet dataset will be evaluated like VGGNet, InceptionV3, ResNet and DenseNet. These architectures use convolutional layers to learn image features followed by fully connected layers forclassification. Pre-trained weights will be used for transfer learning. Models will be fine-tuned by re-training the classifier layer on the fundus image datasets.

d)Model Training

Models will be trained to classify fundus images into 5 severity levels (0 - no DR, 1 -mild, 2 - moderate, 3 - severe, 4 – proliferative DR). Data will be split into 80% training, 10% validation and 10% test sets. Standard data augmentation techniques like rotations,shifting, zooming, flipping etc. will be usedto expand the dataset.

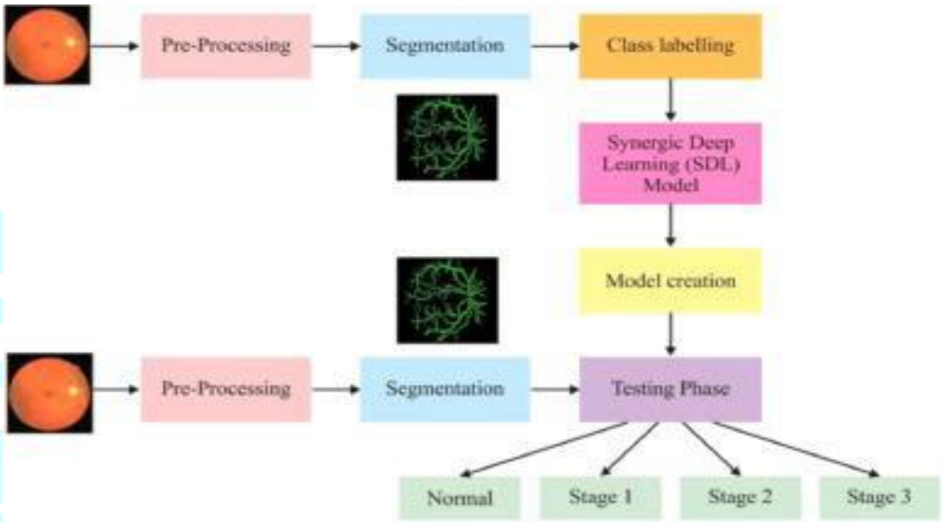

FIG 3. AI based classification of retinal images
(Source: ars.els-cdn.com)

Optimization algorithm used will be Adam with learning rate of 0.001. Binary crossentropy loss will be minimized. Models will be trained for 50 epochs with mini-batch size of 32 images. Check pointing will save model weights with minimum validation loss to avoid overfitting.

e)Post Processing

To improve classification, post-processing steps will be applied on model predictions. Small lesions are early signs of DR progression. Therefore, an object detection model like Faster R-CNN will be trained to detect lesions in fundus images. The lesion detection results will be incorporated to adjust predictions to earlier disease stages where relevant to enable early treatment.

f)Evaluation

Model performance will be evaluated on the test set using classification accuracy, AUCROC, sensitivity, specificity, precision and recall. Confusion matrix will identify error patterns. The model with best overall performance will be selected as the final model. External validation will be done on the MESSIDOR dataset. If model performance is consistent, it indicates robustness and generalizability to new data. The model canthen be deployed for real-world screening.

V.RESULTS AND ANALYSIS

The study will analyze how different deep learning architectures, training techniques and parameter settings impact model performance. Important factors influencing accuracy like network depth, image preprocessing, batch size, learning rate, transfer learning vs. training from scratch etc. will be analyzed. Error analysis will identify areas for improvement - whether errors are due to poor image quality, ambiguity in grading, or model limitations. Insights from the analysis can guide future research to boost model performance.

Assessment of Performance

The performance target is over 90% sensitivity and specificity. This is comparable to expert ophthalmologists who achieve 90-97% diagnostic accuracy for DR [11]. High sensitivity is critical to detect true DR cases for treatment. Specificity ensures patients without DR are not misdiagnosed to minimize unwarranted treatment. If the deep learning model achieves the target metrics on both internal test data and external validation data, it can be considered successful for real-world deployment. The performance will be continuously monitored and model re-trained as more data becomes available..

VI.CONCLUSION

In conclusion, deep learning has promising potential for automated analysis of fundus images to detect diabetic retinopathy and prevent vision loss through early diagnosis and treatment. This study proposes an approach using standard CNNs, rigorous training methodology and comprehensive performance evaluation. The insights gained can guide future research to create highly reliable AI systems for clinical deployment in DR screening. With rigorous ongoing research, deep learning can transform ophthalmology practices to improve patient outcomes.

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