

Detection and Classification of Neovascularization in Proliferative Diabetic Retinopathy Using Deep Learning

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ABSTRACT

Proliferative Diabetic Retinopathy (PDR) is a severe retinal disorder that poses a substantial risk to diabetic patients. Among the various complications associated with PDR, neovascularization stands out as a critical condition characterized by the abnormal growth of blood vessels on the retina. If left undetected and untreated in its early stages, neovascularization can lead to severe vision loss and even blindness. This paper explores the potential of utilizing fundus images, which provide a detailed view of the eye's posterior, for the early detection and classification of neovascularization. Given the intricate and random growth pattern and small size of neovascularization, conventional image processing techniques face challenges in accurate detection. In response to the inherent challenges associated with the precise detection and classification of neovascularization in fundus images, this study endeavors to harness the capabilities of deep learning methodologies. Deep learning has demonstrated exceptional proficiency in the automated extraction of pertinent features from complex objects characterized by intricate attributes. Specifically, the present investigation introduces a novel system, leveraging the prowess of pre-trained deep neural networks that have garnered prominence within the field. The ensemble of pre-eminent neural architectures encompasses Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19, collectively representing a comprehensive spectrum of deep learning models.

Keywords: CNN, Deep Learning, Neovascularization, Fundus Images, Pre-trained Networks, Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19.

Introduction

Proliferative Diabetic Retinopathy (PDR) represents a grave and debilitating complication stemming from diabetes mellitus, distinguished by the aberrant proliferation of blood vessels within the retinal region. Within the context of this ailment, neovascularization stands out as a particularly grave concern. Neovascularization encompasses an anomalous and unrestrained growth of blood vessels, giving rise to hemorrhages, fibrotic tissue formation, and ultimately culminating in the potential for vision impairment or complete blindness if expeditious intervention is not undertaken [1]. The early detection and precise classification of neovascularization hold paramount significance, as they serve as pivotal prerequisites for the timely implementation of therapeutic measures designed to ameliorate and forestall further deterioration of visual acuity.

Fundus images, which afford an exhaustive and intricate view of the intricate vascular network adorning the retina, assume a position of immense significance in the diagnostic landscape of various retinal pathologies, with neovascularization being of no exception. These images, obtained through ophthalmic imaging techniques, furnish invaluable insights for the identification and assessment of retinal disorders, with a particular focus on the intricate realm of neovascularization. However, its small size and irregular growth pattern pose challenges for conventional image processing techniques. To overcome these limitations, deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a promising approach. CNNs excel at automatically extracting intricate patterns from complex visual data [2], making them well-suited for neovascularization detection.

This study introduces a neovascularization detection and classification system grounded in deep learning techniques. We evaluate several pre-trained CNN architectures, including Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19, to identify the most effective model for detecting neovascularization in fundus images. The selected CNN will form the cornerstone of the neovascularization detection and classification model.

Neovascularization in Proliferative Diabetic Retinopathy is a critical condition that can lead to severe vision loss and blindness. This paper underscores the potential of deep learning, specifically CNNs, to automate the detection and classification of neovascularization using fundus images. The choice of the optimal CNN architecture is pivotal for developing an accurate and reliable model for clinical use. Early detection, facilitated by such models, can significantly enhance PDR management and improve the quality of life for diabetic patients.

Literature Survey

Numerous studies propose varied image processing techniques for Neovascularization detection in fundus images. However, detecting it remains challenging due to its abnormal, small-sized, and randomly growing pattern. Deep learning methods are increasingly popular in Biomedical Image Processing, offering potential for training CNN models for Neovascularization detection and classification. Some of the latest works are described in Table I below:

1) Existing methods, combining image processing and machine learning, exhibit preferable Neovascularization detection accuracy but are constrained. Detecting the abnormal growth pattern is essential for precise classification.

2) Current image processing techniques are suitable for Neovascularization detection based on training data, yet challenges persist due to varying growth patterns among patients. Detecting the abnormal and small growth pattern requires a mechanism capable of learning vessel behavior for proper classification.

3) Enhancing existing systems with deep learning for feature extraction and classification is promising. Deep learning models can learn random blood vessel growth patterns and classify Neovascularization by training on diverse datasets, acting as a base for detection and classification systems.

TABLE I. TABLE I. RECENT LITERATURE ON PROLIFERATIVE DIABETIC RETINOPATHY DETECTION

Ref.	Contributions	Results	Methods Used
[6]	- Proposed deep learning approach using MobileNetV2 model - Achieved 85.28% accuracy for DR classification, but High-performance models require	- Achieved 85.28% accuracy for DR classification	- Deep learning approach using MobileNetV2 model

	powerful computing resources and large amounts of data. - The proposed method achieves an accuracy of 85.28% for DR classification		
[7]	- Detection and classification of diabetic retinopathy - Use of deep learning techniques for feature extraction	- Accuracy of 0.47% in testing	- Deep learning techniques - ResNet-50 architecture for feature extraction
[8]	- Use of deep learning algorithms for neovascularization detection - MobileNet performed the best for predicting results	- MobileNet performed the best in detecting neovascularization. - MobileNet was used to build the model for predicting results from user-uploaded images.	- Deep learning algorithms (MobileNet, CNN with SVM, AlexNet, GoogleNet, ResNet, ResNet18, and ResNet and GoogleNet models) - Machine learning models for HOG feature extraction (Random Forest, Decision Tree, Gradient Boosting, Support Vector Classifier, and Voting Classifier)
[9]	- Proposed two deep learning architectures for DR detection and classification - Achieved high accuracy with DenseNet 121 model	- Hybrid network achieved 79.50% accuracy. - DenseNet 121 model achieved 97.30% accuracy.	- Hybrid network combining VGG16 and XGBoost Classifier - DenseNet 121 network
[10]	- Proposes a novel approach for automatic detection of diabetic retinopathy using fundus images - Compares CNNs and ResNet architecture for analyzing and classifying fundus images based on severity of DR	- Proposed approach provides promising solution for DR detection and classification.	- Comparative study of Convolutional Neural Networks (CNNs) - Comparative study of the ResNet architecture
[11]		- Image segmentation using UNet - Automisation using Convolutional Neural Networks and VGG16	- Automated detection, grading, and segmentation of Diabetic Retinopathy. - Improvement of image segmentation using UNet.
[12]	- Object recognition algorithms for detecting diabetic retinopathy - Trained CNN models for feature extraction and classification	- Maximum accuracy of 87% for multi-class classification - Maximum	- Convolutional Neural Network (CNN) models - ResNet-18, GoogLeNet, VggNet-19, and AlexNet

		accuracy of 98% for binary classification	
[13]	- Development of a deep learning model for diabetic retinopathy detection - Integration of the model with a web application for user interaction	- Development of a deep learning model for diabetic retinopathy detection - Integration with a web application for user interaction	- Deep learning techniques - Filtering techniques
[14]	- Deep learning-empowered diabetic retinopathy detection and classification model - Use of Contrast Limited Adaptive Histogram Equalization (CLAHE) technique for image enhancement	- DL-DRDC technique showed better DR diagnostic efficiency - Results examined using a benchmark MESSIDOR dataset	- Contrast Limited Adaptive Histogram Equalization (CLAHE) technique - Deep learning-based Efficient Net-based feature extractor
[15]	- Proposed a two-stage approach for automated DR classification - Achieved state-of-the-art performance on multiple datasets	- Average accuracy on EyePACS-1: 97.92% - Average accuracy on Messidor-2: 94.59% - Average accuracy on DIARETDBo: 93.52%	- Two-stage approach with U-Net models for segmentation - Hybrid CNN-SVD model for feature extraction and classification

M.C.S. Tang et al. [3] proposed a deep learning neural network in "A Deep Learning Approach for Neovascularization Detection Using Transfer Learning." Transfer learning, evaluated with AlexNet, GoogLeNet, ResNet18, and ResNet50, is employed to build the Neovascularization detection system, combining ResNet18 and GoogLeNet pre-trained models.

S.C. Munasingha et al. [4] introduced "A Novel Method for Detecting Neovascularization Regions in Digital Fundus Photographs," incorporating image processing and machine learning to segment Neovascularization regions, aiding in its detection.

H. Huang et al. [5] presented "An Efficient Deep Learning Network for Automatic Neovascularization Detection in Color Fundus Images" using Feature Pyramid Network and Vovnet. The model, evaluated with real-time fundus images, demonstrated reduced training/test times and high accuracy compared to Mask R-CNN.

Methodology

The proposed Neovascularization detection and classification network is developed using deep learning and transfer learning methodologies. Prominent pre-trained neural networks are subjected to rigorous

evaluation on both training and validation datasets comprising fundus images. The selection process culminates in the identification of the model boasting the highest accuracy, serving as the cornerstone upon which the proposed network is constructed. This network, in turn, undertakes two primary objectives: Detection and Classification.

A. Detection:

In the initial detection phase, the neural network model embarks on a comprehensive training regimen with the sole purpose of meticulously discerning Neovascularization within fundus images. This undertaking is inherently intricate, primarily attributed to the erratic and stochastic growth patterns exhibited by blood vessels afflicted by Neovascularization. The model must cultivate the prowess to adeptly apprehend the subtle nuances characterizing these irregularly proliferating blood vessels, ultimately enabling it to yield precise identifications of Neovascularization presence. This multifaceted phase represents a fusion of image processing methodologies and feature extraction techniques harmoniously interwoven with the intricate fabric of neural networks. This concerted effort markedly augments the precision and accuracy of Neovascularization detection within fundus images. The successful culmination of the detection stage serves as the bedrock upon which the subsequent classification task is predicated, wherein the objective revolves around ascertaining the stage and condition of Neovascularization manifesting in the patient's ocular domain.

B. Classification:

The subsequent classification phase of the proposed system equips the model with the capability to prognosticate the condition of Neovascularization delineated within fundus images. It is incumbent upon this phase to wield the capacity to detect and categorize Neovascularization with utmost precision, as the ramifications of undetected and unclassified cases can potentially culminate in permanent vision impairment and loss. The vital significance attributed to the detection and classification of Neovascularization underscores their pivotal roles, as they represent the critical junctures that facilitate timely interventions and therapeutic measures aimed at averting deleterious consequences.

Neovascularization, if left untreated, can result in permanent vision loss, emphasizing the importance of early detection. Diabetic Retinopathy encompasses five stages: Healthy/Normal, Mild, Moderate, Severe, and Proliferative. The presence of Neovascularization is initially identified in the Detection stage, and subsequently, the Classification stage assesses its condition based on the growth patterns of abnormal blood vessels on the retina. This classification process ensures that patients receive appropriate and timely treatment for their diagnosed condition, as revealed through their fundus images. The model must proficiently learn and discern the random growth patterns associated with these five stages to accurately determine the condition of the detected Neovascularization in the retina.

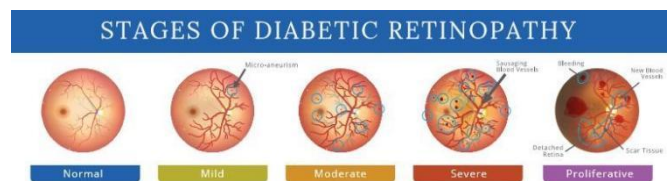


Fig. 1. Stages of Neovascularization

B. SYSTEM ARCHITECTURE:

System architecture refers to the high-level design or blueprint of the entire conceptual model of the proposed system. It provides a structural overview of how the system is built and organized. The proposed system is built on top of the pre-trained neural networks using transfer learning approaches. The underlying architecture for implementing the proposed system is given below.

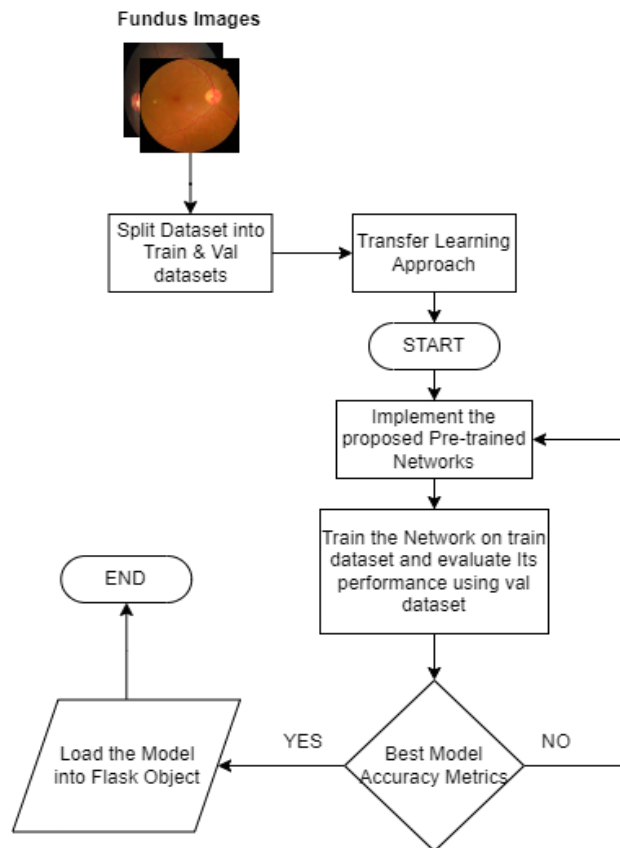


Fig. 2. System Flow Process

C. Working Principle:

The fundus image dataset is categorized into five stages, namely Healthy, Mild, Moderate, Proliferate, and Severe. To facilitate model training, ground truth annotations for the fundus images are generated as part of the image processing techniques. This dataset is subsequently divided into training and validation sets, enabling the evaluation of the model's performance throughout its training process.

The proposed network is meticulously crafted using a transfer learning methodology, representing a pivotal approach in the field of deep learning. Initially, pre-trained neural networks are harnessed and judiciously loaded, ushering in the commencement of an intricate fine-tuning process, meticulously tailored to leverage the training and validation datasets. This meticulous process of fine-tuning culminates in the selection of a neural network model distinguished by its outstanding performance metrics. This chosen model ascends to the venerated status of being the foundational cornerstone upon which the proposed system is meticulously erected, with its overarching mission singularly focused on the discerning and categorization of Neovascularization within the intricate tapestry of fundus images.

The primary pre-trained networks constitute an illustrious cohort, comprising the eminent likes of Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19 networks. This distinguished ensemble serves as the bedrock upon which the system's architecture thrives, exerting a pivotal influence in fortifying the model's innate robustness and elevating its acumen for accurate Neovascularization detection and classification.

Upon reaching the zenith of development and optimization, the resultant model is seamlessly and harmoniously interwoven into a user-friendly interface, meticulously constructed atop the Flask framework. This interface stands as a beacon of accessibility and convenience, beckoning both patients and users to partake in an interactive communion with the system. Its paramount function lies in expeditiously accommodating the facile uploading of fundus images by individuals, a pivotal step that inaugurates a comprehensive assessment of their ocular condition. In this virtuous synergy of technological sophistication and user-centric design, individuals are empowered to embark on a streamlined journey of Neovascularization detection and classification, redefining the landscape of medical diagnostics.

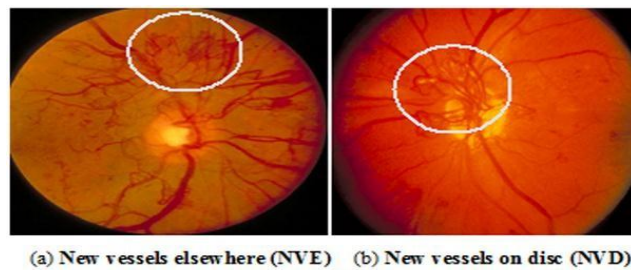


Fig. 3. Ground Truth Images

1) *Model Training:*

In the rigorous evaluation of neovascularization detection algorithms or systems, ground truth images assume an indispensable role as the linchpin upon which the assessment of automated image analysis methods hinges. These ground truth images serve as the quintessential reference points against which the efficacy of various automated techniques, encompassing segmentation and classification algorithms, is meticulously gauged [16]. Their paramount significance lies in their capacity to facilitate a comprehensive evaluation encompassing critical metrics such as accuracy, sensitivity, specificity, and an array of other performance indicators. Through a meticulous comparative analysis of the outcomes yielded by these automated methods when juxtaposed with the ground truth images, the veracity and robustness of neovascularization detection can be subjected to a stringent and methodical examination.

Within the intricate tapestry of this multifaceted process lies the pivotal domain of feature extraction. This pivotal facet entails the judicious extraction of pertinent attributes from segmented blood vessels, each attribute akin to a unique piece of a diagnostic puzzle. These extracted attributes, spanning a diverse spectrum of characteristics, encompass vital parameters such as vessel diameter, the tortuosity of vessels, intricate branching patterns, alongside nuanced features encompassing shape, intensity, and texture [16]. Each of these attributes, when meticulously scrutinized and meticulously analyzed, assumes a pivotal role in the profound quest to demarcate the fine line that separates normalcy from abnormality within the intricate realm of retinal blood vessels. It is these attributes, akin to the subtle brushstrokes of a masterful painting, that collectively contribute significantly to the discernment and grading of Neovascularization severity in the eyes of afflicted patients. In their multifaceted capacity, they serve as the discerning instruments that illuminate the path towards early intervention, effective treatment, and ultimately, the preservation of precious sight..

Classification techniques are subsequently applied within neural network models to categorize segmented blood vessels into five classes, representing different stages of diabetic retinopathy [17]. Convolutional Neural Networks (CNNs) are employed for this classification task. These neural networks undergo training on labeled datasets, enabling them to learn and recognize patterns, growth patterns, and distinctive features associated with both healthy and abnormal blood vessels. Consequently, the trained CNNs can make accurate predictions when presented with new fundus images, contributing to the effective diagnosis and classification of diabetic retinopathy stages.

Transfer learning, a machine learning technique, plays a critical role in the proposed system. It leverages knowledge acquired from one task or domain to enhance the performance of another related task or domain. In this approach, a pre-trained model serves as a fixed feature extractor, utilizing the layers of the model to extract relevant features from the input data. These features are then fed into a separate classifier or model tailored for the target task. Transfer learning harnesses the learned representations and features from the pre-trained model, which may encompass generic patterns or high-level features that can be transferred to the target task. The deep architecture of the pre-trained neural network models facilitates the learning of features from the datasets and the understanding of the behavior of blood vessel growth patterns. However, selecting the appropriate pre-trained model, considering domain and task similarity, and rigorously evaluating the transferred model's performance are crucial steps to ensure its effectiveness for the specific target task.

Testing And Results

The pre-trained neural networks are fine-tuned on the fundus image dataset, which is partitioned into separate training and validation datasets. Each pre-trained network undergoes training using these datasets. The validation dataset serves as a critical tool for assessing the model's performance metrics and accuracy in the detection and classification of Neovascularization within fundus images. The selection of the most accurate model is contingent on the excellence of its performance metrics.

Specifically, the pre-trained networks are trained on a dataset comprising over 3000+ training images and validated using a separate set of 300+ images for validation purposes. The choice of the pre-trained network architecture is made based on its performance in achieving the highest accuracy metrics under optimal conditions and with minimal training time. This rigorous testing phase evaluates the accuracy of each pre-trained network, ultimately leading to the selection of the most suitable model architecture for the construction of the proposed system.

Table II and Figure 4 present accuracy metrics for various pre-trained deep learning models employed in the task of Neovascularization detection and classification in fundus images. Inception ResNetV2 exhibited the highest accuracy at 86%, indicating its strong performance in accurately identifying and classifying Neovascularization cases. DenseNet followed with an accuracy of 74%, demonstrating a commendable performance, while ResNet50, ResNet18, AlexNet, and VGG19 achieved accuracies of 72%, 71%, 72%, and 72%, respectively. These metrics offer valuable insights into the effectiveness of each pre-trained model in recognizing Neovascularization patterns in fundus images, aiding researchers and developers in choosing an appropriate model based on factors like accuracy, computational efficiency, and model complexity for their specific application in Neovascularization detection and classification.

TABLE II. PERFORMANCE OF NEURAL NETWORKS

PRE-TRAINED MODEL	MODEL ACCURACY
Inception ResNetV2	86%
DenseNet	74%
ResNet50	72%
ResNet18	71%
AlexNet	72%
VGG19	72%

From the model training and validation, the Inception ResNetV2 model has better accuracy of prediction when compared to other CNN Models. This forms the base for developing the proposed system and the proposed model is loaded into a Python Flask object to create a web interface for the users to upload fundus images and classify its stage. Figure 5 shows the output of the system.

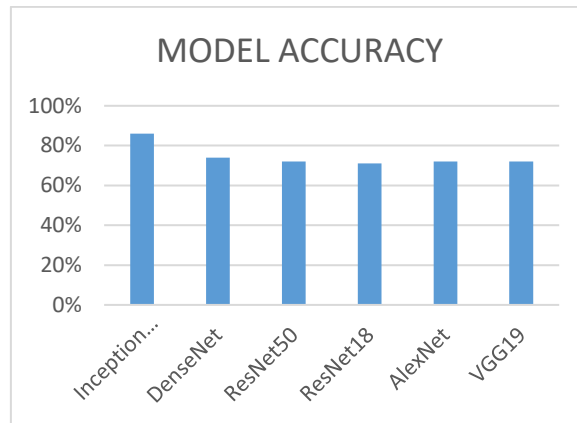


Fig. 4. Models' accuracy



Fig. 5. Prediction Result on New Image.

Conclusion

The application of deep learning techniques for Neovascularization detection and classification in diabetic retinopathy using fundus images represents a significant advancement in the field of ophthalmology. By harnessing the power of pre-trained models and deep learning methodologies, substantial progress has been made in automating the crucial task of Neovascularization detection, a key feature in various retinal diseases, including diabetic retinopathy. Transfer learning has emerged as a particularly effective strategy for addressing the challenges associated with limited annotated medical imaging data, mitigating the need for extensive datasets that can be difficult to obtain in the medical domain. The incorporation of transfer learning, particularly with pre-trained convolutional neural networks (CNNs) trained on unrelated large datasets, represents a significant advancement in the field of Neovascularization detection from fundus images. Transfer learning empowers the extraction of meaningful features from these images, even when working with limited datasets, leading to the development of highly accurate and robust Neovascularization detection models. The integration of transfer learning with deep learning approaches further elevates the accuracy and resilience of these models. Through the process of fine-tuning pre-trained Convolutional Neural Networks (CNNs) with domain-specific data, these models undergo a transformation that aligns them with the unique characteristics inherent to fundus images. This adaptation significantly bolsters the performance of

Neovascularization detection, marking a significant milestone in the quest for accurate and reliable diagnostic tools.

An exhaustive evaluation of six pre-trained CNN models, encompassing the likes of Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19, was meticulously conducted to ascertain the optimal architectural framework for the Neovascularization detection model employing transfer learning. This rigorous assessment unequivocally underscored the ascendancy of the transfer learning approach, with the Inception ResNetV2 model emerging as the pinnacle choice to serve as the cornerstone for the envisioned system. In subsequent stages, this model was subjected to rigorous training and seamlessly integrated into a Flask-based interface. This integration streamlined the intricate process of classifying fundus images, culminating in the categorization of these images into five discrete Neovascularization conditions. This groundbreaking development stands as a beacon of hope in the realm of diabetic retinopathy and other retinal disorders, offering the potential to revolutionize patient care and clinical outcomes.

The future prospects of this pioneering endeavor encompass a multitude of promising avenues for enhancement. Expansion of datasets through the incorporation of real-time patient fundus images promises to augment the accuracy of the detection models significantly. Furthermore, the utilization of GPU acceleration holds the potential to expedite model training, allowing for more efficient and expeditious diagnostic processes. The integration of these detection models into user-friendly websites and IoT devices opens the door to accessible and real-time diagnostic tools, poised to benefit both patients and healthcare providers. As research continues to advance, coupled with stringent validation practices, these approaches are poised to play an increasingly prominent role in clinical practice, thereby elevating the standard of care for patients afflicted with retinal diseases.

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