

“HARNESSING DEEP LEARNING FOR EARLY DETECTION OF CARDIOVASCULAR DISEASES”

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ABSTRACT

Cardiovascular diseases (CVDs) rank among the top causes of death globally. Timely detection and accurate diagnosis of CVDs are essential for effective treatment and better patient outcomes. Retinal imaging has emerged as a cost-effective and minimally invasive method for predicting CVDs. This study aims to develop a deep learning model that employs convolutional neural networks (CNNs) and the MobileNet architecture to predict cardiovascular diseases from retinal images. The model harnesses the power of CNNs to autonomously extract significant features from retinal images while utilizing MobileNet's lightweight framework for efficient implementation. A comprehensive dataset comprising retinal images from both healthy individuals and CVD patients is utilized for training and evaluating the model. Pre-processing steps, including resizing, normalization, and data augmentation, are applied to improve the quality and variety of the dataset. This model has the potential to aid healthcare professionals in making informed decisions, facilitating timely interventions and preventive healthcare measures. Further validation and integration into clinical settings are necessary to thoroughly evaluate its effectiveness and influence on patient care.

KEYWORDS

Cardio vascular diseases (CVDs), Mobile- Net, and Retinal Imaging.

1. INTRODUCTION

Cardiovascular diseases (CVDs) represent a major global health challenge, contributing significantly to morbidity and mortality rates across the world. Early detection and accurate diagnosis of CVDs are essential for effective treatment and enhanced patient outcomes. Traditional diagnostic methods often require invasive techniques or costly imaging technologies, which can limit accessibility, particularly in low-resource environments. Consequently, there is an increasing demand for non-invasive and affordable strategies for predicting CVDs. Recently, medical imaging methods, particularly retinal imaging, have emerged as promising tools for CVD prediction. The retina, being an extension of the central nervous system, exhibits vascular characteristics similar to those of the heart, providing critical insights into overall vascular health. Analyzing retinal images can reveal microvascular alterations linked to CVDs, such as hypertension, diabetes, and atherosclerosis.

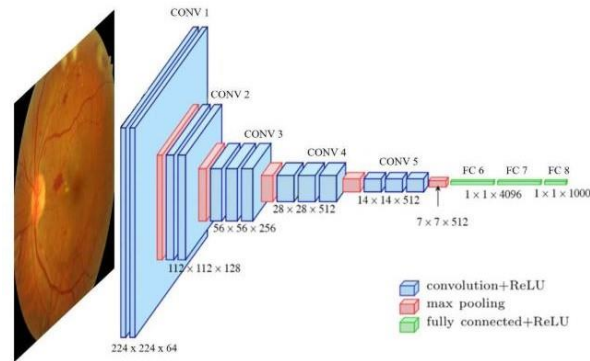


Figure1. An example of a widely utilized convolutional neural network in medical image analysis [7].

Deep learning approaches are built upon artificial neural networks and have seen widespread adoption in various disciplines, including bioinformatics, which includes fields like omics, biomedical signal processing, and medical imaging. These networks are somewhat inspired by the biological structure of neurons, where neurons function as processing units arranged in interconnected layers. These computational frameworks learn to perform specific tasks by processing large datasets of input examples without the need for programming specific to each task. The generalization ability of these models is contingent upon the input data, indicating that the same network architecture can learn different tasks based on the diversity of input datasets. Deep learning employs the principles of deep neural networks, concentrating on layer specialization, where each layer gathers specific insights and communicates them to other layers to enhance overall performance.

Accumulates distinct knowledge and shares it with other layers to enhance overall functionality. The holistic learning process gives rise to a range of network architectures, such as deep belief networks (DBNs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs), which are illustrated in Figure 1. These architectures are customized to tackle specific tasks, including classification, segmentation, and prediction

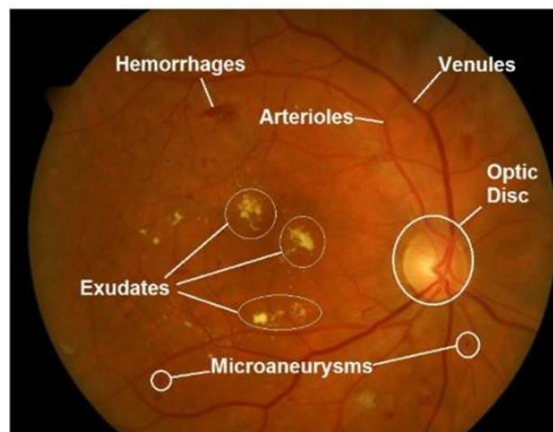


Figure 2. A retinal fundus image displaying prominently marked primary retinal characteristics and irregularities, indicative of typical manifestations of diabetic retinopathy (DR). Image credit [13]

The potential of retinal imaging has been widely recognized by researchers and practitioners, particularly for its ability to provide insights into the retinal vasculature. This imaging technique is distinctive as it allows for the noninvasive observation of the only internal vascular system in

the human body. Fundus images can yield significant pathological information, which has led to their use in the medical field to detect various systemic conditions that trigger specific responses in the retina. A retinal fundus image is obtained through a monocular camera, resulting in a two-dimensional depiction of the fundus. These images are effective for quickly identifying visible irregularities and lesions in the eye at a minimal cost. For example, signs such as exudates, microaneurysms, and hemorrhages are evident pathological indicators of diabetic retinopathy. Figure 2 illustrates a retinal fundus image with annotated features.

2. PROPOSED MODEL

Cardiovascular diseases (CVDs) are the leading cause of death globally. Timely detection is essential for effective intervention and better patient outcomes. The retina serves as a distinctive portal to our cardiovascular health, revealing subtle alterations that may occur before the onset of CVD. By employing deep learning techniques to assess retinal images, we can achieve a non-invasive and precise method for evaluating cardiovascular disease risks. This groundbreaking strategy leverages artificial intelligence, turning routine eye examinations into potentially life-saving assessments and enhancing the accessibility and efficiency of early CVD prediction.

Conventional diagnostic techniques often involve invasive procedures, high costs, and significant time commitments. In contrast, retinal imaging serves as a non-invasive method for assessing cardiovascular disease (CVD) risk by reflecting the vascular health of the body. By employing deep learning algorithms to interpret these retinal images, it is possible to achieve swift, precise, and economical predictions of CVD risk, thereby transforming early detection and preventive healthcare approaches. This strategy aims to leverage cutting-edge AI technologies for proactive management of cardiovascular conditions.

The proposed system encompasses the collection of retinal images, data preprocessing, and annotation of these images with cardiovascular risk factors. It involves the design of a deep learning model, such as convolutional neural network (CNN), along with the creation of training and validation datasets. The model is then trained, its performance validated, and subsequently tested on new retinal images. The system aims to assist healthcare practitioners in predicting cardiovascular diseases by comparing its prediction against ground truth annotations, assessing performance metrics, and facilitating real-world applications. Raw retinal images are sourced from multiple origins, and patient metadata is gathered to form a comprehensive labelled dataset. The data undergoes preprocessing steps, including normalization, cropping, and resizing, to provide standardized input for the predictive model. When healthcare professionals submit prediction requests, the system conducts a real-time examination of retinal images, delivering risk predictions and interpretability features.

The solution is fundamentally based on a CNN architecture that is customized for the analysis of retinal images. Convolutional layers effectively extract hierarchical features, while pooling layers serve to down-sample the spatial dimensions. Classification is carried out by fully connected layers. To optimize the model and avoid issues such as overfitting or underfitting, dropout layers and regularization techniques are incorporated. The implementation of asynchronous processing and parallelization allows the system to manage multiple prediction requests concurrently, resulting in low latency. Furthermore, interpretability algorithms, including Grad-CAM, are embedded within the model to create heatmaps that highlight critical regions in retinal images. These heatmaps are shown alongside the original images in the user interface, assisting healthcare professionals in comprehending the reasoning behind the predictions.

The objective of this technique is to recognize subtle modifications in the retinal blood vessels that could point to cardiovascular risk. The integration of medical imaging and artificial

Intelligence creates a non-invasive, quick and possibly cost-efficient method for early detection and risk assessment. This development is promising for enhancing preventive healthcare, mitigating the effects of cardiovascular diseases, and allowing for timely interventions, especially in areas with limited access to standard diagnostic resources.

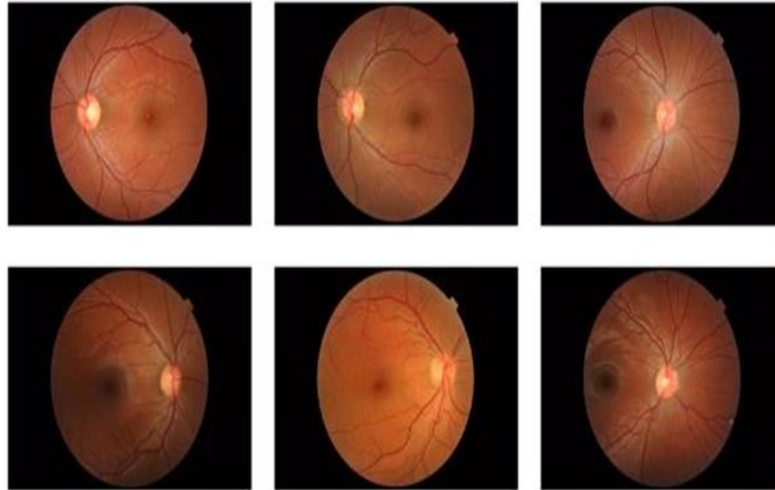


Figure 3. Some randomly selected images from the retinal image dataset.

3. EXPERIMENTAL RESULTS

The retinal fundus images were captured at QBB using a Topcon TRC-NW6S retinal camera to document the detailed features of the optic nerve and macula in participants. Each participant provided a minimum of two images (one for each retina), with some contributing three or four images from both eyes. We obtained both (a) macula-centered and (b) disc-centered images for each eye. Overall, our dataset included 3,860 retinal images from all participants. A visual inspection was then performed to eliminate low-quality images, particularly from the CVD group, as these could adversely affect subsequent classification tasks. After this quality control process, the total number of images was reduced to 3,837, comprising 1,917 from the CVD group and 1,920 from the Non-CVD group. To assess the influence of various input data types on our study results, we conducted experiments utilizing uni-modal approaches, concentrating on both tabular and image datasets independently.

The research involved the application of deep learning techniques to retinal images, conducted on a computing system featuring an Intel(R) Core(TM) i9 CPU clocked at 3.60 GHz, along with 64 GB of RAM and an NVIDIA GeForce RTX 2080 Ti GPU.

In our research, we utilized deep learning (DL) techniques to distinguish between the cardiovascular disease (CVD) group and the control group based exclusively on retinal images. To facilitate this analysis, we applied two separate image preprocessing methods to create two distinct sets of images. The first set involved extracting the circular region from each image and removing border noise by cropping the outer 10%. For the second set, we subtracted the local mean from a 4×4 -pixel neighborhood of each cropped image and placed it against a dark background within a square frame. As a result, all images were standardized to a size of 540×540 pixels with a black background. Sample images of both the original and pre-processed versions are shown in Figure 3. Furthermore, we implemented data augmentation techniques, such as random horizontal flips and random modifications to brightness and contrast, to improve the model's robustness. We assessed eight prominent image classification models: AlexNet,

VGGNet-11, VGGNet-16, ResNet-18, ResNet-34, DenseNet-121, SqueezeNet-0, and SqueezeNet-1. To accelerate convergence, we employed super convergence during our experiments. The model was fine-tuned over 20 epochs, freezing all layers except the last one, and utilized a one-cycle policy for learning rate scheduling, with a maximum learning rate of 0.01 and a batch size of 96. The training process typically lasted around 45 minutes.

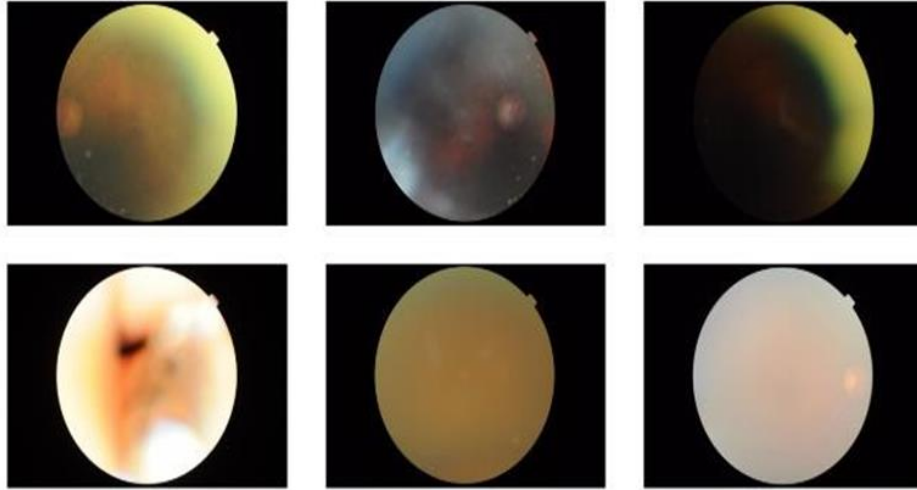


Figure 4. Examples of a few substandard images.

The models were evaluated on accuracy, sensitivity, precision, and F1-score. These metrics are highlighted in the following equations:

$$\text{Accuracy} = \frac{\text{tp} + \text{tn}}{\text{tp} + \text{tn} + \text{fp} + \text{fn}}$$

$$\text{Sensitivity (recall)} = \frac{\text{tp}}{\text{tp} + \text{fn}}$$

$$\text{Precision} = \frac{\text{tp}}{\text{tp} + \text{fp}}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

"In the Retinal Image Model, where retinal images were solely utilized for discriminating between CVD and Non- CVD, the ALEXNET model attained the highest accuracy of 92% on the cropped image dataset employing 55 – fold Cross - Validation (CV), with true positive (tp), false negative (fn), false positive (fp), and true negative (tn) classifications."

4. CONCLUSION

To conclude, the proposed system that leverages deep learning for predicting cardiovascular diseases from retinal images holds considerable promise. It utilizes artificial intelligence to facilitate quick identification and risk assessment. By examining retinal images, the system can potentially detect patterns and markers related to cardiovascular risk factors, delivering valuable

information to healthcare professionals. The system's effectiveness is assessed through comprehensive training, validation, and testing processes, ensuring its precision and reliability. If successfully implemented, this system could significantly change the approach to cardiovascular disease prediction by providing a non-invasive and accessible method that complements existing diagnostic tools. Ongoing research and validation are crucial for refining the system, ultimately enhancing patient care and outcomes.

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