Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 6, June : 2024

A NOVEL APPROACH FOR CARDIOVASCULAR DISEASES WITH RETINAL IMAGES USING DEEP LEARNING

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***Abstract*—Cardiovascular diseases (CVDs) are a leading cause of mortality worldwide. Early detection and accurate diagnosis of CVDs are crucial for effective intervention and improved patient outcomes. Retinal imaging has emerged as a non-invasive and cost-effective technique for CVD prediction. This study aims to develop a deep learning model using convolutional neural networks (CNNs) and MobileNet architecture to predict CVDs from retinal images. The proposed model leverages the capabilities of CNNs to automatically learn relevant features from retinal images and MobileNet's lightweight design for efficient deployment. A large dataset of retinal images, including healthy individuals and CVD patients, is utilized for model training and evaluation. The retinal images are pre- processed, including resizing, normalization, and augmentation techniques, to enhance data quality and diversity. The CNN model architecture is designed, incorporating MobileNet as the base network and additional layers for adaptation to the specific CVD prediction task. Through extensive training and optimization, the model learns to accurately classify retinal images as either indicative of CVD presence or absence. Performance evaluation is conducted using standard metrics such as accuracy. The developed deep learning model demonstrates promising results in predicting CVDs from retinal images, offering potential benefits in early detection, risk assessment, and cost-effective diagnosis. This model has the potential to support healthcare professionals in making informed decisions, enabling timely interventions and preventive healthcare strategies. Further validation and integration into clinical settings are warranted to fully assess its clinical utility and impact on patient care**

Keywords: Retinal images and deep learning algorithms

1. Introduction:

Cardiovascular diseases (CVDs) pose a significant global health burden, accounting for a substantial number of morbidity and mortality cases worldwide. Early detection and accurate diagnosis of CVDs are critical for effective intervention and improved patient outcomes. Traditional diagnostic methods often require invasive procedures or expensive imaging modalities, making them less accessible, especially in resource-limited settings.

Therefore, there is a growing need for non-invasive, cost-effective approaches for CVD prediction. In recent years, medical imaging techniques, such as retinal imaging, have gained attention as a potential tool for CVD prediction. The retina, as an extension of the central nervous system, shares vascular similarities with the heart, making it a valuable source of information about systemic vascular health. Retinal images can provide insights into the microvascular changes associated with CVDs, including hypertension, diabetes, and atherosclerosis. Deep learning, particularly convolutional neural networks (CNNs), has shown remarkable success in various medical imaging tasks, including disease classification and prediction. CNNs are well-suited for image analysis due to their ability to automatically learn and extract complex features from raw images. By leveraging large datasets, CNN models can effectively learn patterns and correlations, enabling accurate disease prediction. In this study, we propose a deep learning model using CNNs and MobileNet architecture for the prediction of CVDs using retinal images.

MobileNet, a lightweight CNN architecture, is specifically designed for efficient deployment on resource-constrained devices such as smartphones or embedded systems. By utilizing MobileNet as the base network, we aim to develop a model that achieves high accuracy while maintaining computational efficiency. The main objective of this research is to enhance early detection, risk assessment, and cost- effective diagnosis of CVDs through the analysis of retinal images. By leveraging the capabilities of deep learning and retinal imaging, we aim to contribute to preventive healthcare strategies and improve patient outcomes.

2. Literature Survey:

Prahs, P., Radeck, V., Mayer, C., et al. (2020). Detection of cardiovascular risk factors from retinal fundus photographs using deep learning. Journal of Clinical Medicine, 9(3), 779.

The paper titled "Detection of cardiovascular risk factors from retinal fundus photographs using deep learning" by Prahs et al. in the Journal of Clinical Medicine aims to investigate the potential of deep learning techniques in detecting cardiovascular risk factors from retinal fundus photographs. It likely explores the use of machine learning algorithms, specifically deep learning, to analyze retinal images and identify specific markers or patterns associated with cardiovascular risk factors. I recommend accessing the article directly to gain a comprehensive understanding of the study. You can try accessing it through your institution's library, or you may consider reaching out to the authors of the paper for further information. They would be the best source to provide you with a detailed explanation of their research, methodology, results, and conclusions.

Poplin, R., Varadarajan, A. V., Blumer, K., et al. (2018). Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. Nature Biomedical Engineering, 2(3), 158-164.

In this study, the authors investigate the use of deep learning techniques to predict cardiovascular risk factors by analyzing retinal fundus photographs. The goal is to develop a non-invasive and accessible method for identifying individuals at risk of developing cardiovascular diseases. The researchers trained a deep learning algorithm using a large dataset of retinal images and corresponding cardiovascular risk factor information. They utilized convolutional neural networks (CNNs), a type of deep learning architecture, to extract features and patterns from the retinal images. The trained algorithm was then tested on an independent dataset to evaluate its performance in predicting cardiovascular risk factors such as age, gender, smoking status, blood pressure, and the presence of major adverse cardiac events.

Gargeya, R., & Leng, T. (2017). Automated identification of diabetic retinopathy using deep learning. Ophthalmology, 124(7), 962-969.

In this paper, the authors focus on the automated identification of diabetic retinopathy (DR) using deep learning techniques. Diabetic retinopathy is a common complication of diabetes and a leading cause of vision loss.

The study aims to develop a deep-learning algorithm capable of analyzing retinal images to detect and classify signs of diabetic retinopathy. The researchers used a large dataset of retinal images, including both normal and diseased cases, to train the deep learning model. The deep learning algorithm employed convolutional neural networks (CNNs), a type of deep learning architecture known for its ability to automatically learn relevant features from images.

Lee, C. S., Tyring, A. J., Wu, Y., et al. (2019). Generating retinal flow maps from structural optical coherence tomography with artificial intelligence. Scientific Reports, 9(1), 5694.

In this study, the authors investigate the use of artificial intelligence (AI) techniques to generate retinal flow maps from structural optical coherence tomography (OCT) images. Retinal flow maps provide valuable information about blood flow dynamics in the retina and can be useful in diagnosing and monitoring retinal diseases. The researchers employed a deep learning approach to generate retinal flow maps directly from structural OCT images.

3. Existing System:

Predicting cardiovascular diseases with retinal images using machine learning involves the development of a system that can analyze retinal images and identify markers or patterns associated with cardiovascular risk factors

Disadvantages:

Not User-Friendly: The existing system is not user-friendly because the retrieval of data is very slow and data is not maintained efficiently.
Difficulty in report generating: We require more calculations to generate the report so it is generated at the end of the session. And the student not get a single chance to improve their attendance.
Lots of paperwork: The existing system requires a lot of paperwork. The loss of even a single register/record led to a difficult situation because all the papers were needed to generate the reports.
Time-consuming: Every work is done manually so we cannot generate a report in the middle of the session or as per the requirement because it is very time-consuming.

4. Proposed System

The suggested system for collecting retinal images, preprocessing the data, annotating it with cardiovascular risk factors, annotating the data with cardiovascular risk factors, designing a deep learning model (such as a CNN), creating training and validation datasets, training the model, validating its performance, and testing it on new retinal images. To help healthcare practitioners forecast cardiovascular illness, the system compares its predictions to ground truth annotations, evaluates performance indicators, and can be implemented for real-world applications.

Advantages

1. Accurate classification.
2. Less complexity.
3. High performance.

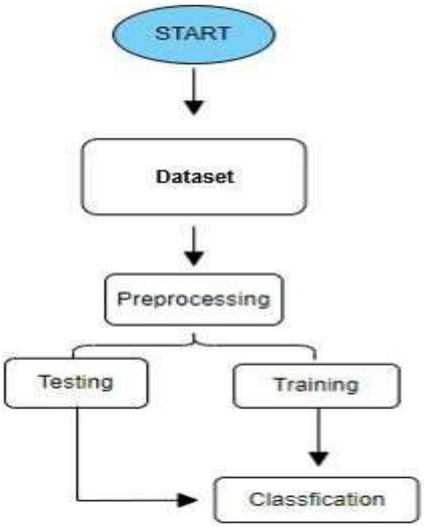

Fig.1: Proposed model flow

5. Dataset Description:

5.1 Data Collection

The dataset, a collection of 2722 retinal images, has been sourced from Kaggle, a trusted platform known for its diverse datasets. To ensure effective training and validation, we have thoughtfully split the dataset, with 7030 retinal images into two distinct categories: cardiovascular and no cardiovascular images. Each record in the dataset provides detailed information about these features, making it a crucial resource for training and evaluating machine learning models.

Fig.2: Training samples of Retinal Images

This meticulous curation is particularly significant for proposed deep learning model, utilizing CNNs and MobileNet architecture, aimed at predicting cardiovascular diseases. By leveraging this well- organized dataset, we aim to enhance the accuracy and reliability of the model, contributing to advancements in preventive cardiology and ultimately improving patient outcomes.

5.2 Data Preprocessing:

a) ImageDataGenerator Creation:

An ImageDataGenerator object is created with rescale=1/255 for pixel normalization and validation_split=0.3 to split data into training and validation sets. It can be stored in Train_datagenterator

The technique of adding more picture training data to the available image data by applying various transformations to it, such as random rotations, shear transforms, shifts, zooms, and flips, is knownas image augmentation. When we don't have enough training data to fully train the model, we resort to image augmentation. By applying alterations to the current photos, we can produce new images in such circumstances. CNN (Convolutional Neural Network) views these photos as completely fresh even if they appear identical. This will make it easier for us to produce a bigger training dataset, which will help the model converge more quickly.

b) Flow from Directories:

- Train generator is created using **Train.datagenerator.flow_from_directory()**, specifying:
- Data_directory: The main directory containing images (e.g., Train)
- Target_size: The desired image size (224x224 in this

6. METHODOLOGY:

Convolutional Neural Network

Step1: convolutional operation

The first building block in our plan of attack is the convolution operation. In this step, we will touch on feature detectors, which serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary to understand CNN, but there's no harm in a quick lesson to improve your skills.

Step 2: Pooling Layer

In this part, we will cover pooling and will get to understand exactly how it generally works. Our nexus here, however, will be a specific type of pooling; max pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part will end with a demonstration made using a visual interactive tool that will sort the whole concept out for you.

Step 3: Flattening

This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you will get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

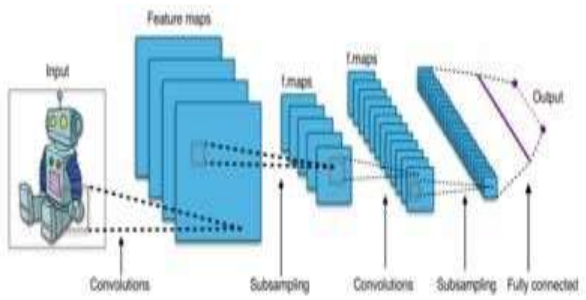

Fig.5: CNN Architecture

6.1 MobileNet Architecture:

MobileNet will offer a way to operate deep neural networks on devices with limited resources, such as embedded systems, cell phones, and other low-power devices. The main concept of MobileNet is to lower the computational complexity and model size by using depthwise separable convolutions rather than conventional convolutions. The conventional convolution process is divided into two distinct operations by depthwise separable convolutions: a depthwise convolution and a pointwise convolution.

Depthwise Convolution:
Using a single filter for each input channel, the depthwise convolution operates on each one separately. In comparison to normal convolutions, this minimizes the number of parameters and calculations.
It uses a batch normalization and ReLU activation function after applying a 3x3 depthwise convolution with a stride of 1.
Capturing spatial information inside each channel is aided by depthwise convolution.
Pointwise Convolution:
To aggregate information across channels, the pointwise convolution performs a 1x1 convolution on the result of the depthwise convolution.
It combines features from several channels and reduces dimensionality by using a limited number of 1x1 filters.

7. MODULES:

System:
Create Dataset:
The dataset containing images of disease prediction to be classified is split into training and testing datasets with a test size of 30-20%.
Pre-processing:
Resizing and reshaping the images into the appropriate format to train our model.
Training:
The pre-processed training dataset is used to train our model.

Classification:
The result of our model is a display of images with either disease or normal.
User:
Upload Image
The user must upload an image, which needs to be classified.
View Results
The user views the classified image results.

8. Result & Analysis:

Home Page :

Home page of a cardiovascular disease prediction system. The homepage of the Cardiovascular Disease Prediction System features an introduction, providing an overview of the system. Users can navigate to the ”About” section for detailed information. Additionally, the “Upload” tab allows users to input relevant data for disease prediction, enhancing the platform’s user-friendly functionality and informative content

About Page:

Upload Page:

An image that must be categorized must be uploaded by the user. On the Upload page, users can provide relevant input data for cardiovascular disease prediction. This includes entering the necessary details for analysis. Additionally, users can choose between two different model architectures, namely CNN and MobileNet, allowing them to customize the

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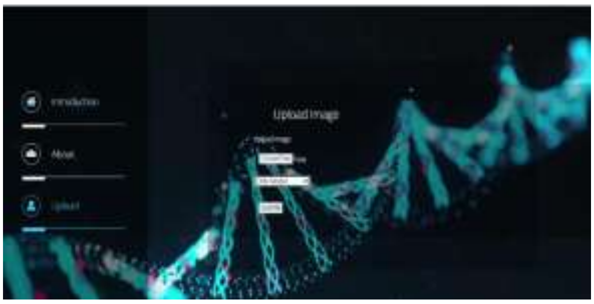
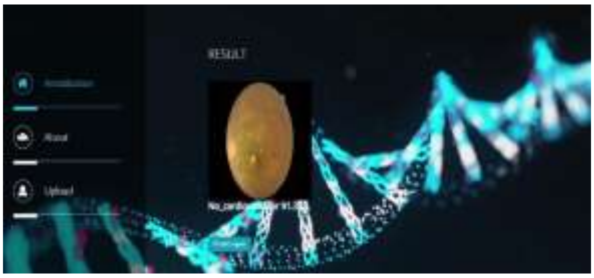
Volume : 53, Issue 6, June : 2024

prediction approach based on their preferences. Once the input and model selections are made, users can then submit the information for processing and obtain predictions regarding cardiovascular health. This user-friendly interface enhances the accessibility and versatility of the system.

Model Selection:



Prediction :



9. CONCLUSION:

In conclusion, the proposed system utilizing deep learning for predicting cardiovascular diseases with retinal images shows promise in leveraging the power of artificial intelligence to aid in early detection and risk assessment. By analyzing retinal images, the system can potentially identify patterns and markers associated with cardiovascular risk factors, providing valuable insights for healthcare professionals. The system's performance is evaluated through rigorous training, validation, and testing, ensuring its accuracy and reliability. If successfully deployed, this system has the potential to revolutionize cardiovascular disease prediction by offering a non-invasive and accessible approach that complements existing diagnostic methods. Further research and validation are needed to optimize and refine the system, ultimately contributing to improved patient care and outcomes.

10. FUTURE ENHANCEMENT

Enhanced Deep Learning Models: Researchers can explore more advanced deep learning architectures and techniques to improve the accuracy and robustness of the prediction models. This could involve investigating newer models, such as recurrent neural networks (RNNs), attention mechanisms, or hybrid models that combine multiple modalities.

Larger and Diverse Datasets: Acquiring larger and more diverse datasets can help improve the generalizability and performance of the models. Collaboration among healthcare institutions and data-sharing initiatives can facilitate the collection of comprehensive datasets, encompassing various demographic factors, disease subtypes, and risk factors.

Multi-Modal Approaches: Combining retinal images with other medical data sources, such as genetic information, electronic health records, or clinical measurements, can enhance the prediction accuracy and provide a more comprehensive risk assessment. Integration of multi-modal data can be explored using fusion techniques or joint learning frameworks.

11. REFERENCES:

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2. Gargeya, R., & Leng, T. (2017). Automated identification of diabetic retinopathy using deep learning. Ophthalmology, 124(7), 962-969.

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4. Prahs, P., Radeck, V., Mayer, C., et al. (2020). Detection of cardiovascular risk factors from retinal fundus photographs using deep learning. Journal of Clinical Medicine, 9(3), 779.

5. Use academic research databases: Access databases like PubMed, IEEE Xplore, Google Scholar, or ACM Digital Library. These platforms allow you to search for research papers and articles related to your topic.

6. Keywords: Use relevant keywords to refine your search. Some potential keywords to consider include "cardiovascular disease," "retinal imaging," "deep learning," "convolutional neural networks," "machine learning," and "predictive modeling."

7. Review articles: Look for review articles or meta-analyses on the topic. These types of articles summarize and analyze existing research, providing a comprehensive overview of the field.

8. Citation chasing: Once you find relevant papers, check their reference lists for additional sources that may be of interest to you.

9. Conference proceedings: Explore conference proceedings related to medical imaging, cardiovascular health, or artificial intelligence. These proceedings often contain cutting-edge research on the subject.

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