Deep Learning Approaches for Early Detection of Cardiovascular Diseases Through Retinal Imaging

K. KAVITHA [1], Dr. A. SURESH BABU [2]

1Department of CSE, JNTUA College of Engineering, Ananthapuramu, Andhra Pradesh,

2Department of CSE, JNTUA College of Engineering, Ananthapuramu, Andhra Pradesh,

Abstract- Worldwide, cardiovascular diseases (CVDs) continue to be the primary cause of mortality. The World Health Organization estimates that 17.9 million deaths worldwide in 2019 were related to CVDs, accounting for 32% of all fatalities. Effective clinical therapy requires early detection of CVDs, and deep learning algorithms can help with this by assisting in the diagnosis process. Thus, from retinal images, a deep learning model for the prediction of CVDs is created using CNNs (i.e., Convolutional Neural Networks) and MobileNet architecture. CNNs automatically extract pertinent information from retinal images, while the model's lightweight MobileNet design allows for efficient deployment. Pre-processing techniques are used to increase the quality and diversity of the data used in the model's training and evaluation on a large dataset that includes both healthy persons and CVD patients. Based on MobileNet, CNN's architecture includes extra layers designed specifically for CVD prediction. The model successfully classifies retinal images as suggestive of the presence or absence of CVD after extensive training and fine-tuning. Error and other standard measures are used in performance evaluation, showing encouraging outcomes for the economical and early identification of CVDs. Clinical value and influence on patient care must be evaluated in conjunction with integration into clinical settings and additional validation.

Keywords: Cardiovascular Diseases (CVDs), deep learning algorithms, CNNs (i.e., Convolutional Neural Networks), MobileNet, and retinal images.

I. INTRODUCTION

Worldwide, CVDs (i.e., cardiovascular diseases) continue to be the primary cause of death, which drives up the expenses of the healthcare sector in numerous nations [1] [2]. The World Health Organization (WHO) [3] reports that cardiovascular diseases (CVDs) have caused 32% of all deaths worldwide, with low- and middle-income nations accounting for two-thirds of these cases. Additionally, of all NCD (i.e., non-communicable diseases)-related premature deaths in adults under the age of 70, 38% are attributable to CVD [4].

Over the past 20 years, AI (i.e., Artificial Intelligence) systems have become more and more important in medical research imaging. Between 2007 and 2008, there were around 100–150 articles on AI related to diagnostic imaging alone; by 2017–2018, that number had risen to 1000–1100 [5]. Thanks to recent advancements in computer systems, deep learning (DL), a subfield of artificial intelligence, is now a viable tool for analyzing complicated data sources, namely medical images. Impressive results have been obtained with deep learning in a variety of applications, including the prediction of COVID-19 [6], segmentation of brain lesions [7], classification of skin lesions [8], and classification of mammography masses [9]. Concerning medical image processing, [10] provides a thorough overview of the primary architectures, methods, and uses of deep learning. Since retinal photographic analysis is noninvasive and inexpensive, it has become more and more common among medical imaging techniques [11]. Using a monocular camera, the fundus which is the back portion of the eye is projected onto a two-dimensional plane to create RFI (i.e., Retinal Fundus Images).

An RFI may be used to identify many biomarkers and structures within the eye. These biomarkers are crucial in the identification of retinal disorders and abnormalities, including DR (i.e., Diabetic Retinopathy), degeneration of macular edema, and glaucoma. The scientific community has shown a considerable deal of interest in deep learning applications in oculomics in recent years. Researchers in the field are becoming more and more interested in studies on the discovery and prediction of ocular biomarkers of systemic disorders [12]. Renal impairment [13], traumatic brain injury [14], cardiovascular disease [15], musculoskeletal diseases [16], anemia detection [17], Alzheimer's disease [18], and other complex disorders are better understood thanks to deep learning techniques that use retinal morphology analysis to provide insights about eye-body associations.

The research paper [19] states that in 2015, ischemic heart disease and stroke alone caused 15.2 million fatalities or 85.1% of all deaths caused by cardiovascular events. When risk factors are addressed, most cardiovascular illnesses may be avoided. These include metabolic issues like glucose and cholesterol levels as well as individual ones like BMI (i.e., body mass index), blood pressure, gender, age, and smoking status [20].

A. *Problem Statement*

The primary cause of death globally is cardiovascular illnesses. For successful management and better patient outcomes, early diagnosis is essential. It can be expensive, time-consuming, and intrusive to use traditional diagnostic procedures. Assessment of CVD risk may be done non-invasively using retinal scans, which show the vascular health state of the body. Early detection and preventative treatment tactics might be revolutionized by using deep learning algorithms to scan retinal images and potentially deliver quick, accurate, and affordable forecasts of CVD risk. Using cutting-edge AI methods, this strategy aims to manage CVD proactively.

II. LITERATURE SURVEY

[21] attempted to diagnose CVD with a unique technique involving details from data corresponding to dual-energy X-ray absorptiometry and retina pictures. They evaluated a grown-up Qatari sample of five hundred individuals from a Qatar-based database, comprising the same percentages in the CVD and dominance categories. They conducted case-dominance research using a unique multifaceted approach (blending information gathered from databases) to put forward a deep learning-oriented strategy for distinguishing the CVD category from the dominance category.

[22] verified Reti-CVD, a biological indicator, for identifying risk groups of greater than or equal to ten per cent in ten-year risk factors for CVD and increase assessment of risk in persons using QRISK3 (risk evaluation tool) of seven and a half per cent up to ten per cent via the Biobank based out of the United Kingdom. The ratings of the considered biological indicator were generated and divided into 3 risk categories using the optimal thresholds of Biobank based out of the United Kingdom for risk assessment. The potential of the considered biological indicator was assessed by using Cox proportional-risks frameworks in forecasting CVD occurrences in people of all ages.

The goal of [23] was to see if deep learning on pictures of the retina from a diabetic retinopathy examination initiative improved the forecasting of cardiovascular events. The frameworks built based on deep learning were taught to forecast prospective risk factors for CVD and hazards simultaneously, and a deep learning-based rating was generated. Poisson regression frameworks incorporating and excluding a deep learning-based rating were applied to investigate populations comprising 2,072 CVD incidents (type 1 diabetes) and 38,730 CVD incidents (type 2 diabetes).

[24] proposed a new Inception version 3 model incorporating the VGG16 model to anticipate the levels of coronary artery disease using non-invasive and easily accessible fundus pictures. This method utilized sophisticated image investigation approaches such as reduction of noise and improvement of contrast. The fundus pictures were used for separating the vessels that carry blood and identifying the important characteristics of the optical disc of the eye. Within this setting, the Inception version 3 framework was first utilized for capturing complicated ordered correlations inside the photos.

[25] performed a backwards-looking analysis comprising ultra-widefield colour fundus photography pictures from individuals diagnosed with 3 retina vascular disorders and individuals who were healthy. The photos were deployed to train a multilayered deep Convolutional Neural Network (CNN) to distinguish between vascular illnesses and individuals who were healthy using ultra-widefield colour fundus photography. Over two hundred ultra-widefield colour fundus photography pictures were incorporated, with 55 photos representing healthy individuals and 169 photos representing retinal vascular disorders.

Having considered the fact that diabetes was an important driver for CVD, [26] sought to investigate using frameworks based on deep learning on Retinal Fundus Imaging as a means to forecast cardiovascular susceptibility in the considered patient population. They utilized the Coronary Artery Calcium (CAC) rating as an indicator and trained a CNN to forecast if it exceeds an acceptable level established by specialists. The earliest studies on a smaller sample of medically validated individuals reveal encouraging results.

[27] created an Artificial Intelligence-based framework to detect cardiovascular disease based on multiple modalities by combining fundus photos obtained from Samsung Medical Center (SMC) and medical risk factors for construction and intrinsic verification, and fundus photos obtained from a Biobank based out of the United Kingdom for extrinsic verification.

[28] determined if Optical Coherence Tomography Angiography and machine learning can forecast the existence or lack of coronary artery disease along with its related risk variables in individuals. In this study, individuals participating had undergone 3×3 millimeters, 6×6 millimeters, and 8×8 millimeters Optical Coherence Tomography Angiography imaging by employing the Carl Zeiss CIRRUS HD-OCT structure 5000. Information related to the population and concurrent conditions was obtained for every individual participating in their study.

[29] intended to see if retina pictures could be utilized to estimate the likelihood of coronary artery disease in persons suffering from cardiometabolic conditions. Based out of Shenzhen Traditional Chinese Medicine Hospital, this work undertook sample-control research by enrolling one hundred and twenty-eight controlled patients having cardiometabolic diseases and one hundred and eighty-eight patients suffering from coronary artery disease. Within 2-week duration of being admitted, retina pictures were acquired. The automated retinal scan investigation technique was used to determine the properties of the retina. Machine learning algorithms were used to create risk prediction models for patients suffering from coronary artery disease. For the sensitivity assessment, those with coronary artery disease were separated into two groups: non-diabetes and diabetes.

[30] looked at the use of optical coherence tomography as an extra diagnostic tool for forecasting prospective coronary artery disease. They used a deep learning strategy (self-supervised-typed) utilizing Variational Autoencoders (VAE) for learning reduced-dimensional depictions of raised-dimensional three-dimensional optical coherence tomography pictures while also capturing distinguishing properties of various retina tiers inside the image of optical coherence tomography. To identify patients who were susceptible to coronary artery disease (stroke or myocardial infarction) and who were not susceptible to coronary artery disease (stroke or myocardial infarction), a classification technique - random forest was trained to utilize the learnt salient characteristics, as well as individual's medical and demographic information. Their prediction framework, taught on multimodal information, was evaluated for the capacity to accurately determine patients who were anticipated to have coronary artery disease (stroke or myocardial infarction) during the 5 years following the capture of images.

[31] conducted potential research to evaluate the effectiveness of automated retina processing of images in detecting coronary artery disease in individuals suffering from AIDS. They included individuals suffering from AIDS having at least one cardiovascular-related concern. Everyone who participated underwent computed tomography coronary angiography and digitized pictures of the fundus. In their investigative study, the main result was obtained for coronary atherosclerosis, while the auxiliary result was obtained for obstruction-related coronary artery disease.

[32] looked into the relationship between the stiffness measure of arterial regions, retina age disparity, and acute coronary artery disease. To estimate the age of the retina, a framework based on deep learning was built using over nineteen thousand fundus pictures of over eleven thousand individuals having no illness histories at baseline. For the remainder of participating individuals of over thirty-five thousand, a retinal age disparity (difference between the sequential age and forecasted age of the retina) was calculated by them.

[33] proposed a unique framework based on deep learning known as "CardioSightFrame" for predicting threats related to cardiac attack and cardiovascular disorders in the beginning phases utilizing pictures of the retina. This method used both the Vision Transformers (ViTs) and Graph Convolutional Networks (GCNs) to regulate local architectural data and broader contextual insight based on scans of the retina regions.

[34] assessed the capacity of Reti-CVD, a cardiovascular illness retina biological marker (deep learning-based), to recognize patients at moderate and elevated risk categories for cardiovascular illness. By using the altered Framingham Risk Score (FRS), QRISK3 (a cardiovascular risk rating), and the Pooled Cohort Equation (PCE), moderate and elevated risk populations were identified by this work.

By concentrating on images of the retinal fundus, [35] came up with a method named Osprey Gannet optimization (OGO) by relying upon transfer learning. The input picture detailing the fundus was first permitted into the pre-processing phase by using a bilateral-typed filter. With training powered by OGO and the developed Osprey Gannet-active counter framework, the identification of OD was done. Their method was formed by combining Gannet Optimization (GO) with Osprey Optimization (OO) approaches.

III. PROPOSED CVD PREDICTION MODEL

Two architectures, namely, MobileNet and CNN are being utilized for developing our novel model concerned with the retinal imaging-based detection of CVD. The automatic extraction of important traits from retina pictures has been facilitated by CNNs, whereas effective implementation has been facilitated by MobileNet owing to its lightweight design. Training entails adjusting the parameters of the model to classify pictures of the retina for obtaining appropriate insights for indicating CVD.

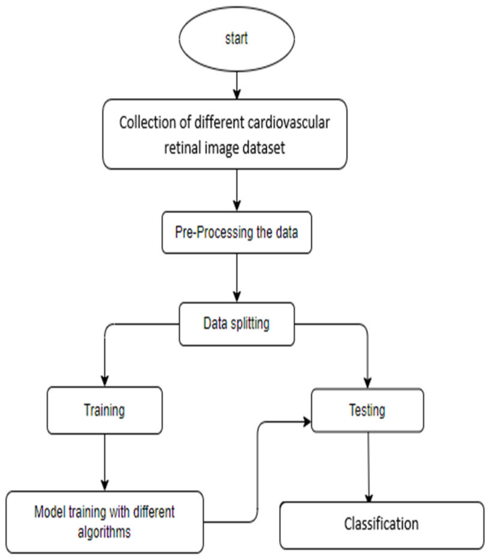

Figure 1 Block Diagram of the Proposed Method

In the above figure 1, there are 6 operational stages, namely, generation of unique dataset comprising retinal images; pre-processing of data; data splitting; training stage; testing stage; and classification. These 6 operational stages will be briefed below.

B. Operational Stages

In this section, we will brief 6 operational stages of our model incorporating two architectures, namely, MobileNet and CNN.

1. Generation of unique dataset comprising retinal images

In this stage, we are generating our own unique dataset by collecting wide range of retinal images that could correspond to the stature of CVD risks in human beings. Using this uniquely created dataset, our two architectures, namely, MobileNET and CNN are being trained followed by testing.

1. Pre-processing of data

Pre-processing is a critical step in getting the picture data ready for examination. Noise decrement, the normalization process, picture enrichment, and scaling may all be used to increase the capacity of models to gain knowledge using input.

2. Data Splitting

Once the pre-processing of the dataset has been split into two subsets: one set has been deployed for training purposes and the other set for performance assessment purposes. Data frequently splits into two portions: between seventy and eighty per cent for training and twenty per cent to thirty per cent for testing.

3. Training Stage

During this stage, the model develops skills to recognize trends and features in retina pictures, indicating CVD. The same has been accomplished by submitting the training portion of the photos to 2 deep learning architectures.

4. Testing Stage

The testing stage entails assessing the way the trained model performed on the testing group of pictures. This contributes to determining the model's correctness and usefulness in recognizing CVD from fresh, unnoticed pictures.

5. Classification

Following testing, the model is utilized to determine if fresh retina pictures indicate whether there is any trace of CVD. The classification findings can subsequently be utilized to help clinicians with diagnosis and treatment at an early stage.

C. Methods for CVD

In this section, we will brief 2 of our architectures (MobileNet and CNN) used in our model concerned with the retinal imaging-based detection of CVD.

1. MobileNET

MobileNETs are built on a simplified design that employs depth-based isolatable convolutions to generate deep neural networks that are lightweight [36]. MobileNET can provide better image recognition prospects when coupled with other deep learning structure like CNN using modest quantum of training data across the restricted resources containing ARM-oriented central processing units [37].

MobileNet is used as the deep learning model's core structure for making the retina pictures-based CVD prediction. Its lightweight architecture enables excellent picture processing, allowing for quick interpretation on platforms having restricted central processing unit resources. The model may be used in healthcare environments for prompt identification and risk evaluation of CVD disorders utilising the efficacy of MobileNet architecture.

2. CNN

CNNs present cutting-edge designs and are commonly employed for picture classification remedies [38]. CNNs are built up of neurons which can learn biases as well as weights. All neurons take inputs, execute a dot product, and alternatively apply by using non-linear dynamics. The entire network continues to convey only distinguishable scoring functional units from pixels of an unprocessed picture on the one side to category ratings on the other side [39].

The CNN structure functions as the deep learning model's foundation, enabling for the automated retrieval of key characteristics from CVD-related retina pictures. CNN adapts to categorize pictures of the retina as indicative of whether there's CVD or not after extensive training and adjustments, allowing for prompt diagnosis and evaluation of risk factors.

IV. RESULT AND ANALYSIS

In this section, we will present the common performance measures like accuracy, precision, and recall for both MobileNET and CNN architectures in our novel model concerned with the retinal imaging-based detection of CVD. First, we present the results for MobileNET followed by the results for CNN.

A. MobileNET

Firstly, we present the performance measures like accuracy, precision, and recall for the MobileNET architecture.

In the below figure 2, a comparison graph showing training accuracy Vs training loss and validation accuracy Vs validation loss for MobileNET architecture has been plotted, which reveals that there is less deviation when comparing training and validation instances.

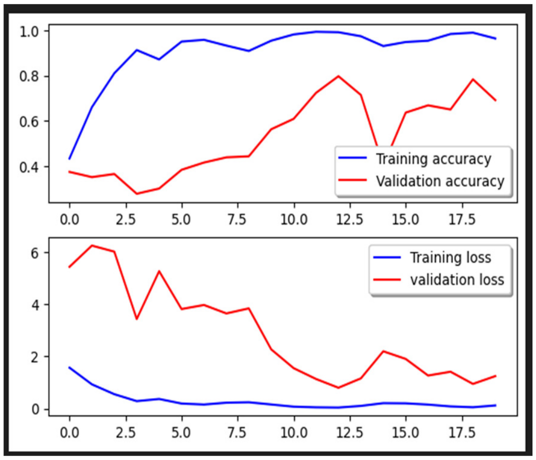

Figure 2 Comparison of Accuracy Vs Loss for MobileNET architecture

In the below figure 3, a comparison graph showing training precision Vs training loss and validation precision Vs validation loss for MobileNET architecture has been plotted, which reveals that there is less deviation when comparing training and validation instances.

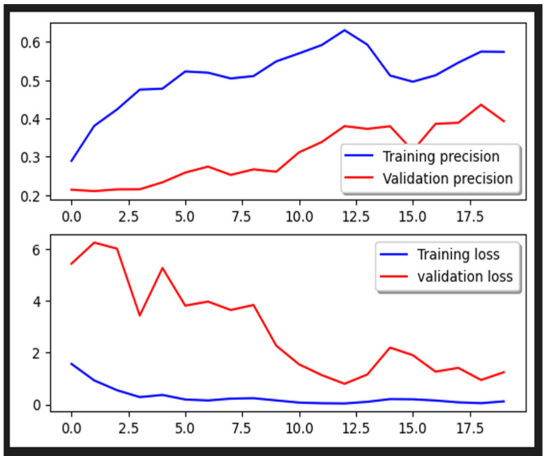

Figure 3 Comparison of Precision Vs Loss for MobileNET architecture

In the below figure 4, a comparison graph showing training recall Vs training loss and validation recall Vs validation loss for MobileNET architecture has been plotted, which reveals that there is less deviation when comparing training and validation instances.

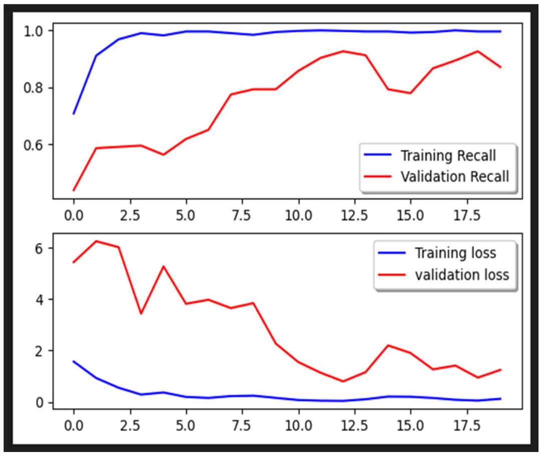

Figure 4 Comparison of Recall Vs Loss for MobileNET architecture

B. CNN

Nextly, we present the performance measures like accuracy, precision, and recall for the CNN architecture.

In the below figure 5, a comparison graph showing training accuracy Vs training loss and validation accuracy Vs validation loss for CNN architecture has been plotted, which reveals that there is less deviation when comparing training and validation instances.

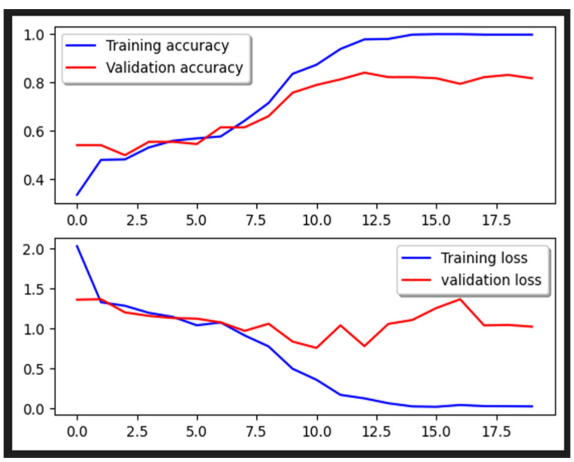

Figure 5 Comparison of Accuracy Vs Loss for CNN architecture

In the below figure 6, a comparison graph showing training precision Vs training loss and validation precision Vs validation loss for CNN architecture has been plotted, which reveals that there is less deviation when comparing training and validation instances.

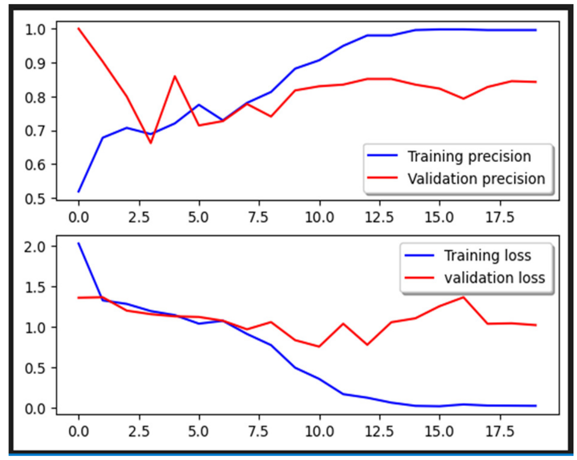

Figure 6 Comparison of Precision Vs Loss for CNN architecture

In the below figure 7, a comparison graph showing training recall Vs training loss and validation recall Vs validation loss for CNN architecture has been plotted, which reveals that there is less deviation when comparing training and validation instances.

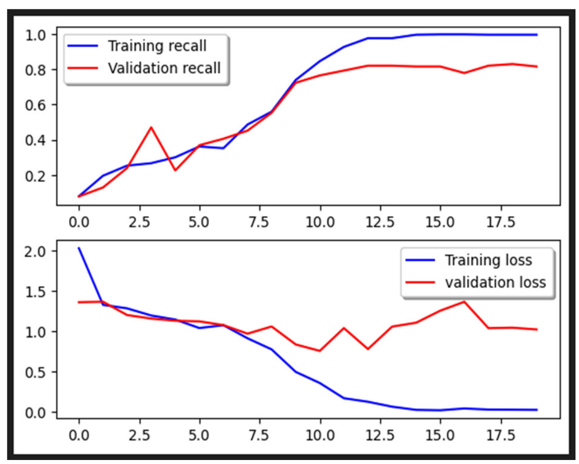

Figure 7 Comparison of Recall Vs Loss for CNN architecture

Algorithm	Accuracy	Precession	Recall
ANN	65	58	73
SVM	60	50	52
CNN	**60**	**62**	**67**
Mobile Net	**68**	**70**	**72**

D. Inference/ Discussion

Outcomes as expected were obtained for our deep learning-based model incorporating two architectures like MobileNET and CNN, demonstrating outstanding CVD prediction from retinal images. Our model attempting the CVD prediction exhibited accurate classification potential that can distinguish both the existence and non-existence of

CVD risks in people based on the retinal image indications. Extensive comparative study undertaken by us also confirmed that our model was efficient in making the prompt detection and affordable diagnosis of CVD risks in people and showed its considerable influence over the clinical settings.

V. CONCLUSION

The suggested method that uses retinal pictures and deep learning to predict cardiovascular disorders shows potential in applying artificial intelligence to support early identification and risk assessment. The technology may be able to detect patterns and indicators linked to cardiovascular risk factors by examining retinal images, giving medical practitioners important new information. Thorough training, validation, and testing are used to assess the effectiveness of the system and guarantee its accuracy and dependability. Incorporating a non-invasive and easily accessible technique to enhance current diagnostic procedures, this technology has the potential to completely transform the prediction of cardiovascular disease if it is implemented properly. To improve patient outcomes and treatment, further investigation and validation are required to optimize and fine-tune the system.

Still, additional verification along with implementation in healthcare environments are required to determine the model's practical applicability and role in improving the treatment of patients. Tackling issues about generalization and sustainability is critical for securing broad acceptance and optimizing the model's favourable influence on how healthcare is provided.

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