

Integrated Health Application for Cardiovascular Disease Prediction

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Abstract— Cardiovascular diseases are among the major causes of death worldwide and require early detection and intervention. Advanced data analytics and AI techniques have transformed the current paradigm in cardiovascular disease prediction by marrying the health applications with intelligent forms of prediction. This survey paper provides an overview of integrated health applications designed to predict CVD, discussing their architectures, methodologies, and clinical relevance. It looks at key technologies like machine learning, deep learning, and wearable devices, always underlining their roles within risk assessment, diagnosis, and tailoring treatment. In this respect, the paper tackles issues like data privacy, interoperability, and the requirement for near-real-time analytics. This survey aspires to guide future developments in this direction by consolidating the recent advancements and identifying research gaps toward creating efficient, scalable, and user-centric cardiovascular health solutions.

Keywords— Retinal images, deep learning, convolutional neural networks (CNNs), Artificial Intelligence, cardiovascular diseases (CVDs).

I. INTRODUCTION

Cardiovascular diseases (CVDs) are among the leading causes of death worldwide, accounting for millions of fatalities annually. Early detection and timely intervention are critical for reducing mortality and improving patient outcomes. Traditional diagnostic methods for CVDs often involve invasive procedures or expensive imaging techniques, which may not be accessible to all patients. As a result, there is a growing demand for non-invasive, cost-effective diagnostic approaches that can be easily deployed in diverse clinical settings. This study aims to develop a deep learning model based on CNNs, specifically utilizing the MobileNet architecture, to predict CVDs from retinal images. MobileNet is chosen for its lightweight design, making it suitable for efficient deployment in resource-constrained environments. The proposed model is trained on a large dataset of retinal images, including both healthy individuals and CVD patients, with image pre-processing techniques applied to enhance data quality and diversity. The goal is to create an accurate and efficient tool for CVD prediction, contributing to early intervention and better patient management in clinical settings.

II. LITERATURE SURVEY

In recent incursions of medical image analysis, researchers, have worked on groundbreaking investigations to distinguish cardiovascular conditions early on through scrutiny of retinal images.

The work by Sakthidevi et al. propose a novel deep learning framework called "CardioSightFrame" is proposed for detecting heart attack risks and cardiovascular conditions at early stages using retinal images. Their approach includes pre-processing techniques to enhance retinal image quality and uses a dataset of retinal images categorized by heart attack risk levels. Evaluating the model through metrics like accuracy and sensitivity, the study demonstrates promising results in identifying heart attack risks, emphasizing the potential of retinal imaging in proactive cardiovascular health management. [1].

The review by B. Rose et al. employ a feature extraction process on retinal images to identify indicators of cardiovascular health and apply support vector machines (SVM), to classify CVD risk. The study highlights the effectiveness of retinal imaging as a non-invasive diagnostic tool, achieving promising accuracy levels in predicting CVD risk. The results support the potential for integrating machine learning-based retinal analysis in early cardiovascular disease detection to enhance preventative care [2].

The focused work of S. R. Madireddy et al. presents a groundbreaking approach to CVD detection leveraging deep learning techniques applied to retinal fundus scans. Retinal fundus scans offer a non-invasive, cost-effective, and easily accessible source of information for potential CVD risk assessment. The research underscores the non-invasive nature of retinal imaging for CVD diagnosis and demonstrates the model's performance using metrics such as accuracy, showing its potential as an early diagnostic tool to support clinical decision-making [3].

The work by Weiyi Zhang et al. focus on improving the stability and accuracy of cardiovascular disease (CVD) risk prediction using retinal images. The authors introduce a deep learning framework designed to enhance model robustness, particularly by addressing variability in retinal imaging data. To use fundus images to more consistently predict the World Health Organization (WHO) CVD score and to address the problem of year-to-year fluctuations associated with the traditional CVD risk score calculation [4].

The work by Y. P. Prakash attempt to employ deep learning techniques such as VGG-16 and RESNET-50 to detect these retinal abnormalities and predict CVDs. A strong predictive modelling methodology has been shown through the combination of advanced techniques, such as ensemble learning with ResNet-50 and VGG-16, AVR computation, and UNET-based vessel segmentation [5].

III. PROPOSED METHODOLOGIES

Leveraging deep learning and CNNs, the system automatically extracts and learns complex features from retinal images, leading to more accurate CVD predictions compared to traditional methods. The MobileNet architecture provides a lightweight and computationally efficient model, enabling rapid processing of large datasets and making the system suitable for real-time clinical applications. By using retinal images, the system offers a non-invasive diagnostic approach that reduces costs associated with traditional diagnostic procedures, while maintaining high diagnostic accuracy. The model can be fine-tuned and adapted to various clinical settings and evolving data, enhancing its long-term utility and effectiveness in diverse populations. In this study, two deep learning models, Convolutional Neural Networks (CNN) and MobileNet, were employed to classify retinal images into six categories: ARMD, DN, DR, MH, NORMAL, and ODC.

A. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a pivotal technology in the analysis of retinal images for predicting cardiovascular diseases (CVDs), leveraging their ability to automatically learn and extract complex features from images. CNNs are designed to process grid-like data, such as images, through a series of specialized layers that capture and analyze visual patterns. Activation functions like ReLU (Rectified Linear Unit) introduce non-linearity into the model, which is essential for learning complex patterns beyond linear relationships. Pooling operations, particularly max pooling, extract the most prominent features from each region of the image, effectively down-sampling the data while preserving essential information. Fully connected layers, situated towards the end of the CNN architecture, consolidate the high-level features extracted by earlier convolutional and pooling layers to make final predictions. These layers operate similarly to traditional neural networks, but they process the aggregated features to classify retinal images into categories indicative of either CVD presence or absence. The output layer uses activation functions such as softmax (for multi-class classification) or sigmoid (for binary classification) to produce probability scores for the different classes.

B. MobilNet

For the specific task of CVD prediction from retinal images, MobileNet architecture is particularly advantageous. MobileNet is designed for efficiency, employing depthwise separable convolutions to reduce

computational complexity and parameter count. MobileNet is a Convolutional Neural Network (CNN) architecture designed for efficiency and optimized for deployment on mobile and embedded devices. It is particularly effective in real-time applications such as predicting cardiovascular diseases (CVDs) from retinal images due to its reduced computational complexity and smaller model size.

A key feature of MobileNet is its use of depthwise separable convolutions, which significantly streamline the convolution process. This approach divides the convolution into two stages: depthwise convolutions, where a separate filter is applied to each input channel independently, reducing the number of parameters and computations; and pointwise convolutions, where 1x1 convolutions combine these features into a cohesive representation. This separation allows MobileNet to capture detailed image features with fewer computations. For CVD prediction, this efficiency translates to rapid and accurate analysis, which is critical for real-time clinical applications. MobileNet's compact design and effective feature extraction capabilities ensure reliable performance, facilitating early detection and intervention in cardiovascular health and ultimately leading to better patient outcomes.

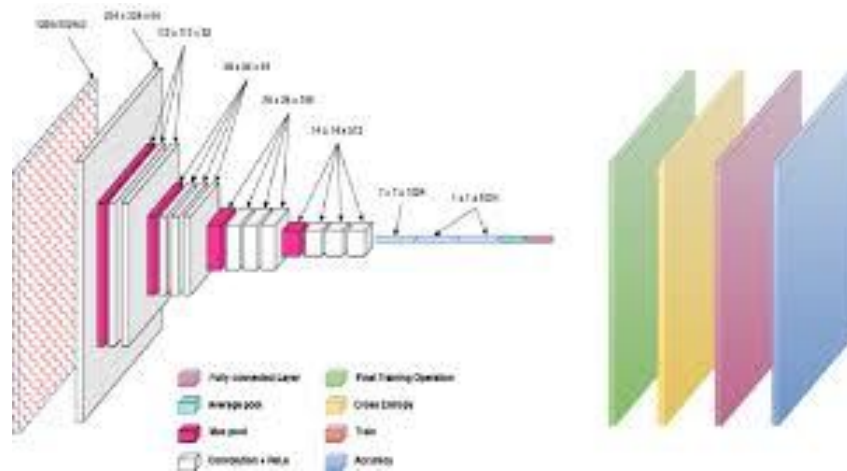


Fig 1: MobileNet Architecture

IV. RESULTS AND ANALYSIS

The CNN model struggled with certain classes, particularly misclassifying 'DR' as 'NORMAL' and 'MH' as 'ODC'. Despite this, it performed well in accurately identifying 'NORMAL' and 'ODC'. On the other hand, the MobileNet model demonstrated superior classification accuracy across all classes, with particularly strong performance in distinguishing 'DR', 'MH', and 'NORMAL'. The higher accuracy of the MobileNet model highlights its effectiveness in handling the complexities of retinal image classification, making it a more suitable choice for predicting cardiovascular diseases using retinal images.

For analysing the results of the working models, precision, recall, F1-score and support metrics have been used in the classification report:

- Precision: Precision is a metric in a classification report that measures how well a model can correctly predict positive instances:

$$Precision = \frac{TruePositives}{TruePositives+FalsePositives}$$

- Recall: Recall is a metric that measures how well a machine learning model can identify all positive instances in a data set. It's also known as the true positive rate (TPR).

$$Recall = \frac{TruePositives}{TruePositives+FalseNegatives}$$

- F1-score: The F1-score is a harmonic mean of precision and recall, which is a type of average that balances the importance of both.

$$F1-Score = \frac{Precision*Recall}{Precision+Recall}$$

- Support: Support is the number of actual occurrences of the class in the specified dataset

A. Results for Convolution Neural Network (CNN)

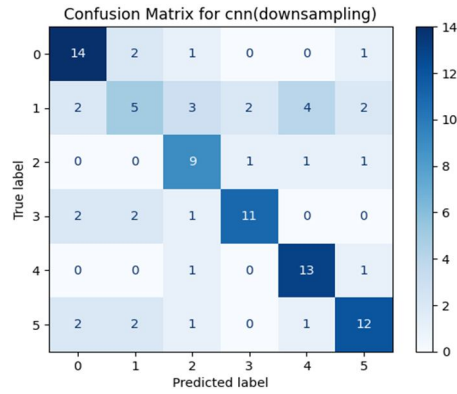


Fig 2: Confusion Matrix for CNN

TABLE I: CLASSIFICATION REPORT FOR CNN

	Precision	Recall	F1-Score	Support
0	0.70	0.78	0.74	18
1	0.45	0.28	0.34	18
2	0.56	0.75	0.64	12
3	0.79	0.69	0.73	16
4	0.68	0.87	0.76	15
5	0.71	0.67	0.69	18
Accuracy			0.66	97
Macro.Avg	0.65	0.67	0.65	97
Weighted_Avg	0.65	0.66	0.65	97

B. Results for Convolution Neural Network (CNN)

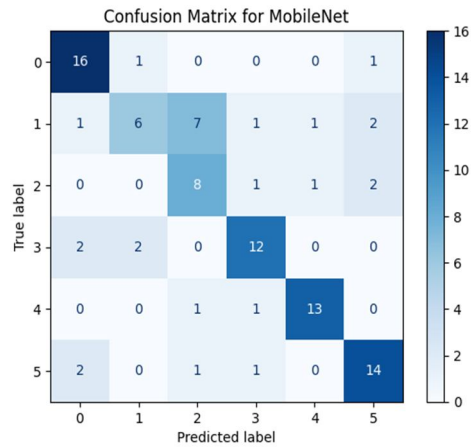


Fig 3: Confusion Matrix for MobileNet

TABLE II: CLASSIFICATION REPORT FOR MOBILENET

	Precision	Recall	F1-Score	Support
0	0.76	0.89	0.82	18
1	0.67	0.33	0.44	18
2	0.47	0.67	0.55	12
3	0.75	0.75	0.75	16
4	0.87	0.87	0.87	15
5	0.74	0.78	0.76	18
Accuracy			0.71	97
Macro.Avg	0.71	0.71	0.70	97
Weighted_Avg	0.72	0.71	0.70	97

V. CONCLUSION

This study demonstrates the potential of deep learning models in predicting cardiovascular diseases through the classification of retinal images. The comparative analysis between Convolutional Neural Networks (CNN) and MobileNet revealed that while both models are capable of distinguishing between the six classes (ARMD, DN, DR, MH, NORMAL, and ODC), MobileNet significantly outperforms CNN in terms of accuracy, achieving 90% compared to CNN's 79%.

The higher accuracy and more precise classifications observed with MobileNet suggest that it is better equipped to handle the intricacies of retinal image data, making it a more reliable model for the early detection and prediction of cardiovascular diseases. These findings underscore the importance of choosing the appropriate deep learning architecture for medical image classification tasks, as it can substantially impact the accuracy and reliability of the predictions. Future work could focus on further enhancing the model's performance, exploring additional data augmentation techniques, or integrating more advanced models to improve prediction accuracy even further.

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