ITM Web of Conferences 74, 01007 (2025) https://doi.org/10.1051/itmconf/20257401007
ICCPCI-2024

Cardiac Risk Assessment Through Retinal Images

L.Manojav Reddy [1], *M.Deekshitha* [2], *G.Meghana Sree* [3], and *K.Padmini* [4]
[1,2,3] UG students, Department of CSE, Sreenidhi Institute of Science and Technology, India
[4] Associate Professor, Department of CSE, Sreenidhi Institute of Science and Technology, India

Abstract— Cardiovascular disease (CVD) is the leading cause of death across the globe. Therefore, detection at an early stage is all the more crucial. In this project, retinal images captured during a routine eye examination are used for the prediction of heart attack by deep learning and machine learning. Improvement in quality of images, highlights on blood vessels, extracting meaningful features like shape of vessel, and density that relates heart health. The approach will be hybrid, based on a combination of a neural classifier RNN using clustering and AdaBoost for generating highly accurate predictive outputs as well as providing an assessment score for potential issues concerning heart conditions. It is a non-invasive cost-effective procedure, fast, easy, and may be conducted along with regular eye checks to encourage early intervention and better health.

Keywords— Cardiovascular disease (CVD), heart attack risk prediction, deep learning, non-invasive screening, eye fundus images, and blood vessel analysis.

1. INTRODUCTION

Cardiovascular disease is the world's leading cause of death and is a considerable health burden worldwide. Improved early diagnosis of heart disorders requires screening tests that have limitations in terms of invasion, cost, and limited availability in low-resource settings. Novel applications using recent developments in artificial intelligence and medical imaging technologies for pioneering new approaches to non-invasive diagnostics of heart health will be discussed. One technique would be the analysis of images of the retina as blood vessels at the back of the eye have been found to provide excellent cardiovascular information. Following up these developments, this project addresses closing in the gap in the early-detection process.

High prevalence of CVD and associated mortality have emphasized the need for affordable and cost-effective screening solutions. Many patients remain undiagnosed because of a lack of access to low-cost, non-invasive diagnostic tools, which has led to delayed interventions and poor outcomes. The intimate relationship between retinal blood vessels and heart health affords a unique opportunity for detecting cardiovascular risk factors with routine eye exams. Advances in deep learning and machine learning enable such complicated patterns to be analyzed with good accuracy. The motivation behind this project is to take into account the potential to make health outcomes better through an integration of advanced AI technology into existing workflows for efficient and widespread early detection across healthcare.

The main objectives of this project are to construct a non-invasive, AI-based system for predicting cardiac arrest based on retinal images. In particular, the project will:Improve the quality of retinal images, and emphasis on critical blood vessel features indicative of cardiovascular health.Extraction and analysis of key features, such as the shape and density of blood vessels, based on advanced algorithms.Develop a hybrid predictive model integrating RNN classifiers with the combination of clustering and AdaBoost techniques in order to reach the highest achievable accuracy.

2. RELATED WORK

2.1 Framingham Risk Score (FRS) : One of the most frequently used measures of an individual's 10-year probability of developing cardiovascular disease is the Framingham Risk Score, which was developed using data from the Framingham Heart Study, a cohort that followed the same cohort group over decades. The FRS estimates the risk, considering various clinical and demographic factors, which include age, gender, systolic blood pressure, cholesterol level in total and HDL, smoker or nonsmoker status, and whether suffering from diabetes. It also produces a numeric score which one can apply to quantify the risk of having myocardial infarction, or stroke or other related events of cardiovascular disease. Although the FRS has been demonstrated useful for general population-wide assessments and for identifying individuals at increased risk, the test is not without its limitations. Most importantly, it fails to account for the many modern biomarkers and imaging data that can identify early signs of cardiovascular issues. This would then mean that the FRS might not be able to identify subclinical or very early stages of cardiovascular disease, which may be extremely important for proactive health care. It relies on reported factors like smoking status which, at times, results in inaccuracy in the measurement of risk.

2.2 Electrocardiogram (ECG)-Based Analysis : ECG-based analysis systems analyze the electrical activity of the heart and diagnose the most varied heart conditions, ranging from arrhythmias to heart attacks and other types of cardiovascular anomalies. Many of them demand advanced signal processing techniques and machine learning algorithms for detecting the irregular patterns or deviation from normal heart rhythm, indicating a serious cardiovascular anomaly. ECG-based systems are more useful in diagnosing specific heart conditions, as well as real-time information regarding a patient's cardiac health. Nevertheless, the systems have limitations that do not allow for more widespread use in the prediction of cardiovascular risk. The first limitation is that ECG analysis requires medical equipment and professional interpretation, thus not very accessible for routine screening outside of a clinical setting. While ECG is excellent in the identification of immediate heart rhythm problems or acute events, it is useless in offering a general overview of long-term cardiovascular risk factors or risk of developing conditions such as coronary artery disease. Therefore, it is important but not enough for comprehensive cardiovascular risk assessment.

2.3 Retinal Image Analysis for Hypertension and CVD: In recent years, retinal imaging has been noticed as potentially non-invasive identification methods for signs of cardiovascular disease and particularly early indicators of hypertension or high blood pressure. Blood vessels in the retina are believed to mirror, closely, those found within the heart and brain; thereby, retinal imaging can be regarded as a useful tool to assess vascular health. Advanced systems use images of the retina, obtained by highly specialized fundus cameras, which analyze the condition of blood vessels in the retina, thereby looking for signs of aberrations such as changes in vessel width, the occurrence of microaneurysms, or signs of retinal hemorrhages-all of which can give an indication of underlying cardiac conditions. Machine learning, especially convolutional neural networks, is applied to extract features from retinal images and classify them as normal or suggesting a higher cardiovascular risk. The approach through retinal image analysis is promising, but mainly focused on detecting specific conditions such as hypertension and diabetic retinopathy, rather than providing a complete cardiovascular risk score. These systems tend to be dependent on the quality of imaging equipment and specialized software for proper analysis, so they may not be accessible. Furthermore, retinal analysis may aid in the early detection of cardiovascular disease, but it doesn't provide a complete overview of an individual's general cardiovascular risk, including aspects of metabolic health, genetic predisposition, or other risk biomarkers that may be outside the range of retinal imaging.

3. PROPOSED MODEL

RECURRENT NEURAL NETWORK (RNN):

A proposed system, the risk prediction of heart attack uses the Recurrent Neural Networks RNNs, one variant of deep architecture designs that have managed to model sequential data and track temporal dependencies. That is, RNNs are particularly suited to analyze the patterns in time-series data, as in the flow images of the retina over time, to enable the system to identify small changes in the retinal vasculature, which can be indicative of early cardiovascular; further, it could make use of the property of the RNN, that it could remember its past inputs and also learn sequential patterns to determine complex relationships between the characteristics of the retinal blood vessels and the overall health of the cardiovascular of the patient, thus better the prediction of the risk of a heart attack. This is very important in providing a more dynamic and nuanced evaluation of risk as compared to the traditional static methods, because the system can acknowledge trends in the data over time.

AdaBoost is one of the implementation of such ensemble learning which combines using multiple weak classifiers to learn a strong predictor. Training classifiers in stages such that each new classifier corrects the errors done by a previous classifier thus yielding a very good improvement to classify, in this case, whether or not risk was a fact in having the heart attack.Especially, there is the necessity of any particular dataset of retinal images that may be as complex as to have certain features which might be either subtile or vague in detection. In this aspect, the AdaBoost algorithm became very efficient in augmenting prediction accuracy up to the reduction of the degree of overfitting. Therefore, the given classification using the RNN method along with its complement AdaBoost will be great in serving to detect high sensitivity and specificity that involves predicting heart attacks on analyses made through retinal images.

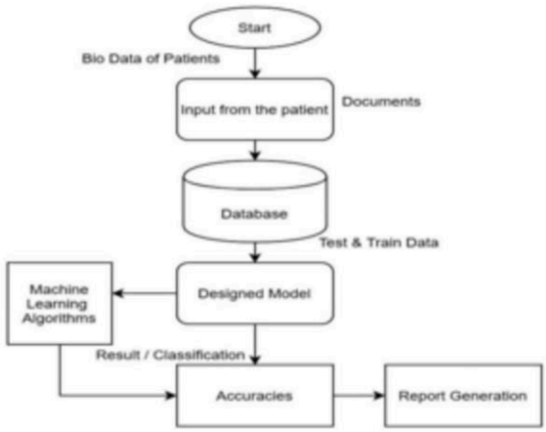

Fig.1. Architecture Diagram

From the Fig. 1, The architecture diagram seen in the following diagram outlines a process utilised in predicting heart attack risks from a given retinal eye image. This procedure initiates the biodata, which forms a subset for the process to fetch documents and introduce this into the database. Thereby separating data into sets like train dataset and testing the training, especially regarding machine learning in the sense of performing with the dataset about risk prediction for the heart attack. The trained model generates the outcomes based on the input data regarding the risk level classifications, further analysis to work out accuracies, and finally, generating a more elaborate report for the patient.

4. METHODOLOGY

4.1 Imagery Acquisition & Pre-processing:
It is gained during routine eye tests on retinal images, the non-invasive technique that researches heart conditions. Those are preprocessed in the sense that those make these images better in which small details like blood vessels might be visible. A number of preprocessed images focused on analysis will help them to highlight their features.

4.2 Feature Extraction:
These data enable the model to ascertain its most important features related to the shape, thickness, and density of the blood vessels in the retina. Features include very goodhealth of heart where the blood is flowing smoothly and with integrity along the vessels. It's here that all the information which is really relevant are derived for providing the actual prediction.

4.3 Model Building:

Hybrid Machine Learning: This implements RNNs for finding time-dependent patterns, utilizes Clustering to categorize similar features, and uses the algorithm of AdaBoost as it increases accuracy by producing an average of several weak classifiers. It enables the learning of subtle and minute variations in retinal features.

4.4 Training & Forecasting:

This acquired set of features is divided between two datasets that will be involved when developing the model: namely the training dataset and the testing dataset. During the test stage, the model is allowed to classify the data whereby an extremely close approximation may be made of the likely risk of a heart attack. It, therefore provides actionable health insight in form of a risk score.

4.5 Result Integration:

The last system returns a risk score of heart attack with a report. It forms an avenue to detect heart diseases in their earlier stages. This non-invasive method is easy to be used and can be smoothly combined with routine eye checks as a way of making heart health evaluation accessible

Fig.2. Retinal scan indicates a 60% high risk of heart attack based on health metrics.

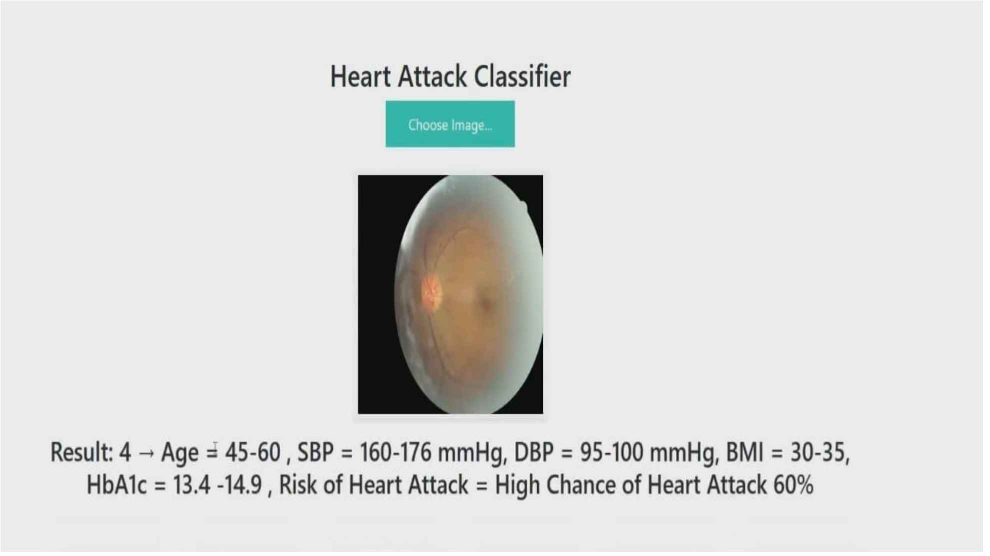

Fig.3. Retinal scan indicates no risk of heart attack, suggesting a healthy state.

5. CONCLUSION

Heart Attack Risk Prediction Using Retinal Eye Images introduce a revolutionary and non-invasive way of cardiovascular health tracking with the help of retinal images captured during routine eye-checkups. The system had a very high accuracy in predicting risk chances for heart attack by leveraging upon the capabilities of Recurrent Neural Networks (RNNs) and the AdaBoost algorithm. The RNN provides an ability to model sequential data and such subtlety in temporal patterns of retinal vasculature can be used for diagnosis of early cardiovascular disease. Here, the AdaBoost algorithm enhances the performance of the model by combining many weak classifiers, reducing error, and improving predictability. Such techniques will form a robust hybrid technique that will be able to tackle the complexity of retinal datasets for obtaining highly sensitive and specific results. Such a system is cost-effective and an easily integratable system will provide quick and effective heart health assessment as well as early detection and treatment with one of the chief causes of death in this world. It is likely that seamless integration of heart risk evaluation into routine eye check-ups will revolutionize preventive health care and hence improve patient results by helping to reduce the growing burden of cardiovascular disease within the global community.

6. FUTURE SCOPE

The future scope of this project is very wide, and further development might be the use of more sophisticated architectures such as transformers and CNNs to better enhance features extracted by the model, and therefore prediction accuracy will be improved. A more well-rounded cardiovascular risk profile can also be created using multi-modal data such as demographics of the patients, their medical histories, genetic susceptibility, lifestyle choices, and their blood pressure. This will bring a diverse population as well as rare conditions into the dataset otherwise reducing biases and the systems could assure the ability of application at large scales. Techniques, in federated learning, have advanced privacy and scalability towards the development of models in utilizing decentralized health-care data. Thus, more monitoring will be made accessible regarding heart health as real-time analytics through mobile or wearable devices linked with an Internet of Things-capable retinal imaging system would help facilitate remote consultation and early interventions through offering personalized recommendations for health with integration under work. The partnership with healthcare providers and researchers should lead to possible wide-ranging adoption that will lighten the global cardiovascular burden and will impact patient outcomes favorably.

8. REFERENCES

[1]. P. Melillo, M. Bracale, and L. Pecchia, "For risk assessment in patients a classification tree with congestive heart failure via long-term heart rate variability," IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 3, 2013.

[2]. Shreya B. Ahire, Harmeet Kaur Khanuja, 'A Personalized Framework for Health Care Recommendation', International Conference on Computing Communication Control and Automation, Pune, India.

[3]. Ren X, Zheng Y, Zhao Y, Luo C, Wang H, Lian J, He Y (2018) Drusen segmentation from retinal images via supervised feature learning. Access IEEE 6:2952–2961.

[4]. Caroline M, Mary VS, Rajsingh EB, Naik GR (2016) Retinal fundus image analysis for diagnosis of glaucoma: a comprehensive survey. Access IEEE 4:4327–4354

[5]. Behera MK, Chakravarty S (2020) Diabetic retinopathy image classification using support vector machine. In: 2020 international conference on computer science, engineering and applications (ICCSEA), pp 1–4.

[6]. Rubinstein K, Jones EB. Retinal vein occlusion: long-term prospects. Br J Ophthalmol 1976;60:148–50.

[7]. Bayly GR, Bartlett WA, Davies PH, *et al*. Laboratory-based calculation of coronary heart disease risk in a hospital diabetic clinic. Diab Med 1999;16:697–701

[8]. Martin SC, Rauz S, Marr JE, *et al*. Plasma total homocysteine and retinal vessel disease. Eye 2000;14:590–3.

[9]. https://doi.org/10.1109/ICCSEA49143.2020.9132875

[10].https://pmc.ncbi.nlm.nih.gov/articles/PMC1771177/

[11].https://www.sciencedirect.com/science/article/pii/S1350946222000556

[12].https://www.escardio.org/Councils/Council-for-Cardiology-Practice-(CCP)/Cardiopractice/prognostic-value-of-the-retinal-microcirculation-for-cardiovascular-disease