Heart Attack Risk Detection Using Eye Retinal Images

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Publication Date: 2025/01/24

Abstract

With the rising incidence of heart attacks, early detection systems have become essential in providing timely intervention to reduce fatalities and complications. This project presents a non-invasive heart attack risk prediction system designed to analyze retinal images for identifying vascular patterns indicative of heart attack risks. By leveraging advanced artificial intelligence techniques, including Recurrent Neural Networks (RNNs) and Expectation-Maximization (EM) algorithms, the system detects subtle abnormalities in retinal blood vessels that correlate with cardiovascular health. Upon detection, the system provides real-time risk assessments through a web-based platform, enabling individuals and healthcare providers to take proactive measures. This innovative solution offers a reliable, efficient, and scalable approach to heart attack risk prediction, ensuring improved accessibility and enhanced preventive care.

***Keywords**: Retinal Imaging, Cardiovascular Diseases, Heart Attack Prediction, Artificial Intelligence, Non-Invasive Diagnostics, Recurrent Neural Networks, Expectation-Maximization.*

I. INTRODUCTION

Heart attacks remain one of the leading causes of mortality worldwide, posing a severe threat to global health. According to the World Health Organization (WHO), approximately 85% of over 15 million deaths out of 17.9 million cardiovascular disease-related deaths—are caused by heart attacks and strokes, every year. This alarming statistic underscores the critical need for early detection systems that can identify risks and prevent fatalities. However, conventional diagnostic methods, including coronary angiography, stress tests, and biomarker analysis, are invasive, costly, and often inaccessible, especially in underserved or rural areas with limited healthcare infrastructure.

This project presents an innovative approach to heart attack risk prediction through non-invasive diagnostics, leveraging retinal imaging as a tool to identify early warning signs. The retina, a highly vascularized tissue, mirrors the systemic vascular condition, making it a powerful indicator of cardiovascular health. Subtle changes in retinal blood vessels, such as variations in vessel diameter and tortuosity, have been correlated with early indicators of heart attack risks. By focusing on these vascular patterns, retinal imaging offers a cost-effective and safer alternative to traditional diagnostic methods, particularly in preventive healthcare settings.

This study introduces an advanced AI-powered system that analyzes retinal images using state-of-the-art algorithms such as Recurrent Neural Networks (RNNs) and Expectation-Maximization (EM). The system identifies and interprets vascular abnormalities indicative of potential heart attack risks. Integrated into a user-friendly web platform, this solution enables real-time risk assessment and supports timely interventions, ensuring a scalable and efficient approach to heart attack prevention.

This approach highlights the transformative potential of technology in improving healthcare outcomes and addresses the urgent need for scalable, reliable, and non-invasive diagnostic tools in the fight against heart attacks.

II. LITERATURE SURVEY

By carefully reviewing earlier work, it helps identify gaps and shortcomings in current approaches and gives insights into unresolved problems. A thorough literature survey also compares different techniques and solutions, showing their strengths and weaknesses. This not only sets the background for the current project but also opens the door for new improvements and innovations. In short, a literature survey connects past research with future ideas, highlighting the importance of learning and improving continuously in any area of study.

- *Heart Disease Prediction Using Eye Retinal Images (Shaikh, S. et al., 2023):*

This study employed transfer learning with the Inception v3 model and convolutional neural networks (CNNs) to analyze over 6000 retinal images, achieving impressive accuracy rates of 97% during training and 96% during testing. The research demonstrated the effectiveness of automated feature extraction for detecting cardiovascular risks and highlighted the value of transfer learning in addressing challenges associated with smaller datasets. By utilizing a robust yet efficient model, the study paved the way for non-invasive diagnostic methods that require minimal manual intervention. However, limited diversity in the dataset affected the model's generalizability, and its reliance on specialized imaging equipment, along with the opaque "black-box" nature of CNNs, hindered clinical adoption. The methodology involved preprocessing retinal images, applying transfer learning with Inception v3 for feature extraction, and validating the model's performance. This non-invasive diagnostic approach offers early detection capabilities, high accuracy, and automated feature extraction, which collectively enhance its potential for improving cardiovascular risk prediction. Future research could explore integrating explainable AI methods to improve the interpretability of the results for clinical acceptance.

- *Cardiovascular Disease Prediction from Retinal Images Using Machine Learning (Rose, B. et al., 2023):*

This study explored the use of Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance retinal vessel segmentation, comparing the performance of Support Vector Machines (SVM) and CNNs. SVM achieved superior accuracy of 97.46%, emphasizing its efficiency over CNN in this context. The study demonstrated the significant role of preprocessing techniques like CLAHE in boosting the clarity of critical retinal features, improving overall model performance. The research underscored the importance of preprocessing techniques like CLAHE in improving segmentation and identifying retinal features such as vessel diameter and tortuosity, which are linked to cardiovascular health. Challenges included computationally intensive feature extraction, limiting scalability, and the use of small, non-representative datasets, which increased the risk of overfitting. The methodology involved CLAHE for image contrast enhancement, feature extraction based on vessel attributes, and classification using SVM and CNN for comparison. The study demonstrated the non-invasive diagnostic potential of retinal imaging, with high accuracy and enhanced segmentation capabilities using CLAHE. It also emphasized the need for developing lighter algorithms to improve scalability and deployment in real-world settings.

- *Identifying Retinal Abnormalities for Cardiovascular Risk Assessment (Prakash, A. P. et al., 2024):*

This research introduced the Arteriolar to Venular Ratio (AVR) as a biomarker for cardiovascular risk assessment and utilized the UNET architecture for precise retinal vessel segmentation. The classification model based on VGG-16 achieved an accuracy of 97%, showcasing its reliability. With its ability to detect subtle vascular irregularities, the study demonstrated the relevance of AVR as an indicator for predicting systemic cardiovascular conditions. The study highlighted the utility of AVR as an indicator of vascular health and demonstrated UNET's effectiveness in accurate vessel segmentation. Challenges included the reliance on datasets like MESSIDOR and DRIVE, which limited generalizability, and the "black-box" nature of VGG-16, which created interpretability issues critical for clinical adoption. The methodology involved preprocessing images from datasets, segmenting retinal vessels using UNET, and computing AVR for risk assessment. This non-invasive diagnostic approach offers high accuracy, automated segmentation, and early detection of cardiovascular risks, further strengthening its potential for clinical use. Expanding dataset diversity and enhancing model explainability are critical steps for future research in this domain.

- *Heart Attack Risk Prediction Using Retinal Images (Pailla Teena Reddy et al., 2023):*

This study focused on extracting features from retinal images to detect patterns indicative of heart attack risks, employing supervised learning methods for prediction. It emphasized the potential of retinal imaging as a non-invasive and scalable diagnostic tool for early detection and population-level screening. By bridging the gap between data accessibility and early-stage diagnosis, this study highlighted the advantages of automated techniques in resource-limited environments. However, challenges included the limited availability of advanced imaging systems in resource-constrained regions and the need for extensive validation across diverse datasets to ensure clinical reliability. The methodology involved preprocessing retinal images to enhance relevant features, using algorithms for feature extraction, and training supervised learning models for risk prediction. The system provides early detection capabilities, automated analysis, and accessibility, making it a safer and more efficient alternative to traditional diagnostic methods. Future work could focus on integrating cloud-based solutions to make this approach widely accessible in low-resource settings.

- *Prediction of Cardiovascular Risk Factors from Retinal Fundus Images via Deep Learning (Poplin, R. et al., 2018):*

This study utilized convolutional neural networks (CNNs) trained on datasets from UK Biobank and EyePACS to predict cardiovascular risk factors such as age, gender, and smoking status from retinal fundus images. The research achieved high accuracy in predicting key cardiovascular indicators, demonstrating its potential for risk stratification and offering performance comparable to existing clinical risk calculators. By establishing correlations between retinal features and systemic risk factors, the study provided a novel avenue for non-invasive cardiovascular diagnostics. Challenges included limited dataset diversity, which restricted broader applicability, and the absence of biochemical markers like lipid panels, which reduced the comprehensiveness of predictions. The methodology involved applying deep learning techniques to retinal fundus images, training CNN models on large datasets, and evaluating the models using metrics like MAE and AUC. This non-invasive approach supports population-level screenings, providing efficient and accurate predictions of cardiovascular risk factors. Scaling up this approach and incorporating additional health indicators could further enhance its clinical relevance and reliability.

III. OBJECTIVES

- Achieve a highly accurate model that enables early detection of heart attack risks, facilitating timely medical intervention.
- Build a user-friendly website where users can upload retinal images and receive real-time risk assessments.
- Use a dataset representing a diverse population with varying retinal patterns to ensure generalization and prevent bias.
- Develop a non-invasive heart attack risk detection system using retinal imaging as a safer and more accessible alternative to traditional diagnostic methods.
- Upload processed data and risk assessment results to a cloud-based platform for real-time monitoring and remote access by caregivers or healthcare professionals.

IV. PROPOSED SYSTEM

The proposed system is a non-invasive, AI-based solution designed to predict heart attack risks by analyzing retinal images. Traditional methods for heart attack risk assessment often involve expensive and invasive procedures. This system takes a simpler and safer approach by using the similarities between retinal and cardiovascular blood vessels to identify potential risks. Advanced deep learning algorithms help detect patterns in the retinal images linked to heart health.

Key features of the Proposed System Include:

- *Non-Invasive Approach:*

It uses retinal images to detect heart attack risks early without the need for invasive procedures.

- *Smart AI Models:*

Combines Recurrent Neural Networks (RNN) with Expectation-Maximization (EM) for analyzing patterns. This is different from other systems that mostly use CNNs or SVMs. The RNN helps pick up sequences and trends in the data, making the predictions more accurate.

- *Better Preprocessing:*

The system uses techniques like cropping, resizing, and normalization to ensure the data is clean and consistent. It also balances the dataset to avoid biased results, something many existing studies don’t focus on enough.

- *Easy-to-Use Web Platform:*

Users can upload retinal images on a simple web interface and get real-time analysis, making it practical and accessible for both healthcare professionals and individuals.

- *Affordable and Scalable:*

It is designed to be cost-effective and adaptable, with careful consideration for different populations and varying health conditions.

V. IMPLEMENTATION

The implementation of the proposed system involved several important steps, starting from preparing the data to training and deploying the model. Each step was carefully designed to ensure the system performs accurately and is easy to use. The fig 3 shows the architecture of the proposed system.

- *Data Collection:*

Retinal images were sourced from the RFMiD dataset, which provides a variety of images required for training and testing the system.

- *Preprocessing:*

To improve the quality and consistency of the input data, the following techniques were used:

- Image Augmentation: Enhanced the dataset by adding variations through rotation, flipping, and other transformations.
- Square Padding: Ensured that all images had the same dimensions by adding padding where needed.
- Retinal Cropping: Focused only on the relevant parts of the retina, removing unnecessary details from the image.
- Resizing: Standardized image sizes to make them compatible with the AI model.
- Normalization: Scaled the pixel values to a uniform range, improving the model's ability to process the images effectively.

- *Feature Analysis and Clustering:*

- Clustering: Used Density-based clustering algorithm to group similar patterns or features in the retinal images based on density of blood vessels, to make the data more organized for the next stage, as shown in fig 1.

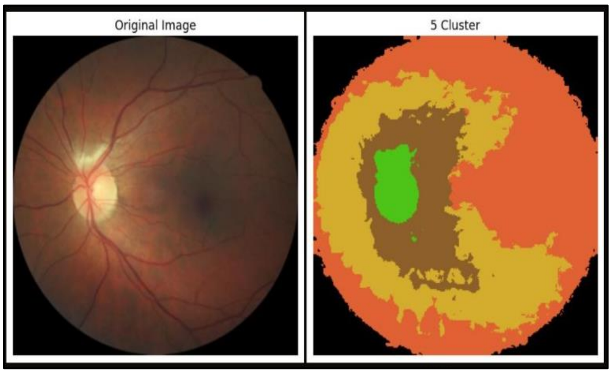

FIG 1: IMAGE CLUSTERING

- *Model Training:*

- The system used Recurrent Neural Networks (RNN), particularly LSTM and GRU, to detect patterns in the data.
- These features were then classified using an Expectation-Maximization (EM) model, combining the strengths of both approaches.
- The training process was optimized using:
  - ✓ Categorical Cross-Entropy as the loss function to measure prediction accuracy.
  - ✓ Adam Optimizer to adjust model weights and improve performance.
  - ✓ Batch Size, Epochs, and Validation were tuned for better results.

- *Evaluation:*

  The model was tested using metrics such as:

- Accuracy: It measures the overall correctness of the model by calculating the proportion of correctly classified instances out of the total instances. It gives a general measure of model performance but can be misleading in imbalanced datasets.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Number of Samples}}$$

- Precision: It measures the proportion of correctly predicted positive observations to the total predicted positives

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- Recall (Sensitivity): It measures the proportion or actual positives correctly identified by the model. It focuses on how well the model captures positive cases out of all actual positive cases. The term **sensitivity** also refers to the true- positive rate.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- Specificity (False negative rate): The proportion of actual negatives that are correctly identified by the model, it tells us how well the model avoids false positives. It tells us how well the model avoids false positives. For instance, in medical testing, a high specificity means fewer healthy patients are wrongly diagnosed as having the disease.

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}$$

- F1 Score: It is a measure of a model's accuracy that considers both precision and recall. It is a balanced metric that takes both false positives and false negatives into account, especially important when the classes are imbalanced (For example, in medical diagnostics where positive cases might be rare). A high F1-score indicates that both false positives and false negatives are minimized.

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The results confirmed the system's ability to make reliable predictions.

- *Deployment:*

  The final system was deployed on a web-based platform, allowing users to upload retinal images and receive real-time analysis. The platform ensures accessibility and ease of use, making it practical for everyday healthcare applications.

VI. RESULT AND ANALYSIS

The heart attack risk detection system demonstrated exceptional performance, achieving an accuracy of 98.6% with the available data set, which highlights its capability to classify heart attack risks with high reliability.

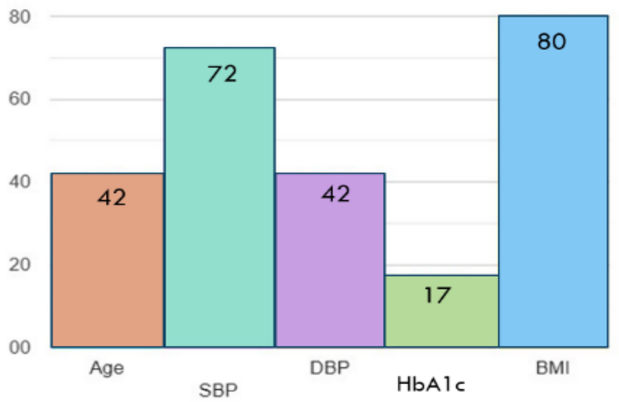

Fig 2: Features Affecting Heart Attack Risk

A significant insight from the analysis is the contribution of various features to heart attack risks, as shown in fig 2. Among 100 individuals, 80 with higher BMI (body mass index) were identified as having a high risk of heart attack, making BMI the most influential factor. Systolic blood pressure (SBP) followed closely, with 72 individuals showing a correlation to increased risk, while features such as age and diastolic blood pressure (DBP) contributed equally, affecting 42 individuals each. HbA1c levels were less impactful, influencing 17 individuals. These findings demonstrate how different health indicators influence cardiovascular risks, with BMI and SBP being the most significant predictors.

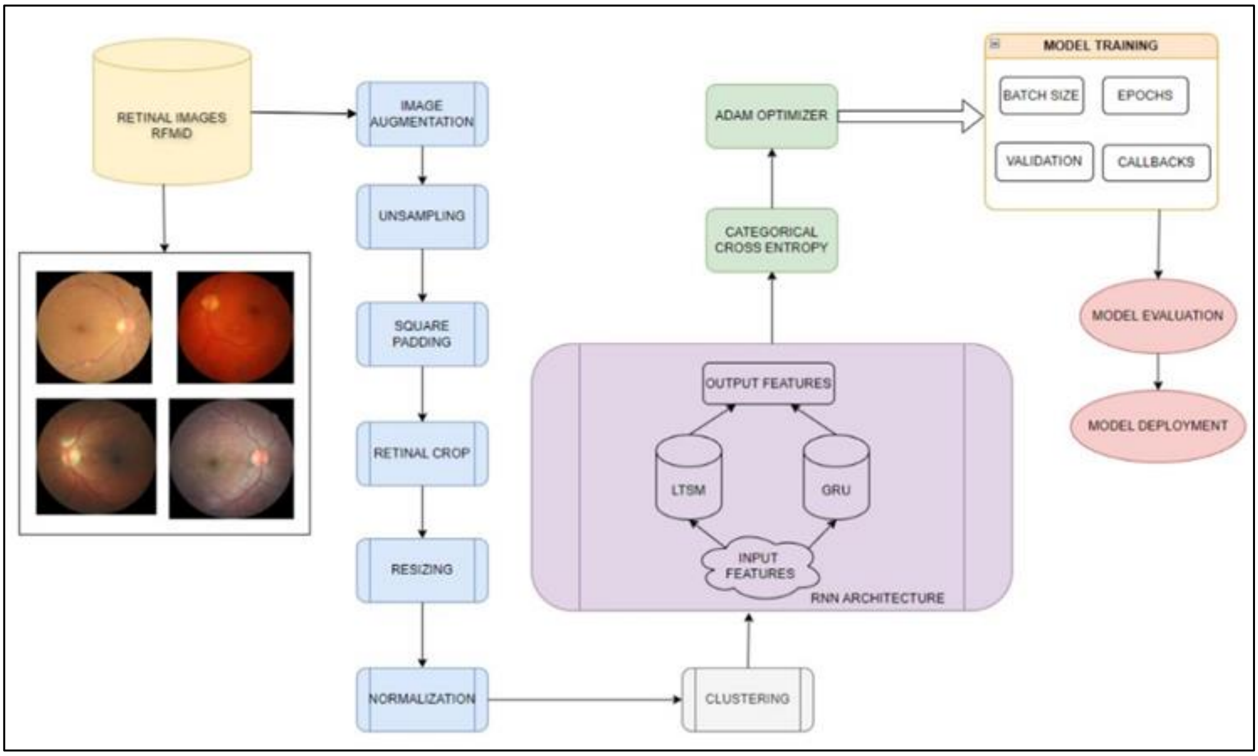

Fig 3: System Architecture

VII. CONCLUSION AND FUTURE SCOPE

The project showcases how artificial intelligence can revolutionize healthcare by using retinal images to predict heart attack risks. By incorporating advanced deep learning techniques like RNNs and clustering, the system is able to detect even subtle vascular changes associated with heart health issues. Its non-invasive, easy-to-use, and affordable design makes it particularly beneficial for increasing access to preventive healthcare, especially in areas with limited medical resources. By providing reliable risk predictions and actionable health advice, the system overcomes many of the challenges posed by traditional diagnostic methods, promoting early detection and timely treatment. As the system evolves, refining it to work effectively with diverse datasets and undergoing thorough clinical validation will be key to its widespread acceptance. This innovation has the potential to make a real difference in reducing deaths caused by heart disease and marks a step forward in using AI to create smarter healthcare solutions worldwide.

Future enhancements for the project focus on expanding the dataset by including more retinal images from diverse demographics, which will help improve the model's ability to generalize across different populations. Collaborating with healthcare institutions for clinical validation will ensure the system meets regulatory standards and can be seamlessly integrated into real-world medical workflows. Additionally, the system could be extended to assess risks for other cardiovascular conditions, further broadening its scope and impact. Optimizing the platform for mobile devices would make this technology more accessible, especially in underserved and resource-limited areas, enhancing its potential to improve public health on a broader scale.

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