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# Implementation Paper on Contactless Heart-Beat Detection Using Image Processing

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**Abstract: -** *In recent years, cardiovascular health has become a major concern, with heart attacks being a leading cause of death. To address this, we propose an innovative application that predicts the likelihood of a heart attack within the next few hours. The application begins by having users log in and complete a brief assessment, collecting vital parameters such as age, diabetes, smoking, alcohol consumption, fitness level, and family medical history. Users then undergo a 60-second facial scan, where the Haar Cascade algorithm detects face and lighting changes. The scan captures subtle color shifts in blood vessels, which are processed using OpenCV and EVM technology to detect RGB color variations, providing critical data on blood flow.*

*Using Fast Fourier Transform (FFT) analysis, the heart rate frequency is obtained, and the Heart Rate Variability (HRV) is calculated to determine stress levels and SpO2. This data, combined with the assessment, feeds into our machine learning model, which predicts the probability of a heart attack. The system generates graphical representations of key health parameters, and if the risk is critical, users can immediately contact a doctor through the app. With a 96% accuracy rate for heart attack prediction, we continue to refine the system to provide a reliable and accurate tool for heart health monitoring, empowering users to take timely medical action.*

**Keywords:** *Heart Attack Prediction, Facial Scan, Machine Learning, Heart Rate Variability (HRV), EVM Technology, OpenCV, Blood Flow Detection, Stress Level, SpO2, Risk Assessment, Medical App.*

## I.INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of death globally, accounting for an estimated 17.9 million lives lost each year. Many of these deaths are preventable with early intervention, but current systems for heart monitoring are either clinic-bound, wearable-dependent, or reactive rather than predictive. Traditional tools such as electrocardiograms (ECGs) or Holter monitors are accurate, but they require medical infrastructure, professional oversight, and are not suitable for real-time personal monitoring outside hospitals.

In recent years, advancements in non-contact photoplethysmography (PPG) and computer vision have made it possible to measure vital signs like heart rate and oxygen saturation using only a camera and ambient light [3], [12]. Studies by Li et al. [3] and Verkruysse et al. [12] have demonstrated the feasibility of capturing heart rate data from facial video streams under realistic conditions. McDuff et al. improved this further using RGB video and bandpass filters to increase signal clarity [4]. These developments are particularly significant as they eliminate the need for skin contact, making them more hygienic and accessible for mass adoption.

Eulerian Video Magnification (EVM), a technique developed to amplify subtle changes in videos, has been proven highly effective in enhancing microvascular blood flow signals from the face [14]. This, when combined with Fast Fourier Transform (FFT) and Gaussian pyramids, allows for accurate calculation of heart rate and heart rate variability (HRV) a key predictor of cardiovascular health [4], [16]. HRV in particular has been extensively studied as a reliable indicator of stress, fatigue, and imminent cardiac events [16], [17].

The integration of face-tracking algorithms, like those in OpenCV or RetinaFace [10], with physiological signal analysis now offers a compelling path toward real-time, camera-based health diagnostics. Moreover, research by van Gastel et al. [6] and Kong et al. [7] has shown that $SpO_2$ levels can also be estimated using visible light imaging, further expanding the diagnostic potential of this approach.

Despite these breakthroughs, very few systems combine facial scanning with machine learning and personal medical history to deliver real-time heart attack risk assessments. Most current tools are either limited to displaying heart rate or require wearable hardware that may not be used consistently. This project addresses that gap by offering a fully contactless, camera-based prediction system that also incorporates user lifestyle and medical background into its model.

By combining visual signal extraction with predictive modeling, this system aims to empower users with early warnings of cardiac risk potentially offering precious time to seek medical help.

## II.EXISTING SYSTEM

Many of the current tools for heart monitoring, such as ECG machines and Holter monitors, are primarily designed for clinical environments. These systems are typically used by healthcare professionals to monitor heart activity over extended periods, providing valuable insights into heart conditions. However, they are not suitable for everyday use due to their complex setup, need for regular visits to healthcare facilities, and the significant cost of equipment and maintenance. Wearable devices, such as smartwatches, have emerged as more accessible alternatives for heart rate tracking. While these devices are increasingly popular, they often fall short in terms of accuracy and are usually limited to providing only basic metrics like heart rate. Additionally, wearables often require manual user input and may not offer enough contextual health data to predict more severe outcomes like a heart attack. The lack of integration with personal health history makes these tools less effective in forecasting cardiovascular events.

On the other hand, more advanced non-contact methods, such as thermal imaging or near-infrared photoplethysmography, have gained attention in research due to their ability to measure vital signs without direct contact. These techniques can be more accurate but require specialized, expensive equipment, making them less accessible for everyday use. Some systems focus on monitoring individual vitals such as heart rate, blood oxygen levels, or stress indicators, but they often lack the capability to integrate these measurements with a user's personal medical history, lifestyle factors, and other health parameters. As a result, they fail to provide a holistic approach to heart health monitoring. In contrast, our system offers an innovative solution by combining affordable, widely available hardware with an integrated approach to predicting heart attack risk. By considering both physiological data, such as heart rate and blood flow, and lifestyle factors like fitness level, medical history, and habits (e.g., smoking, alcohol consumption), our system provides a comprehensive and contextual risk prediction. Moreover, the system's accessibility through a simple camera makes it democratized, enabling anyone with a smartphone or a camera-equipped device to monitor their heart health and receive predictive insights, thus bridging the gap between expensive clinical tools and everyday wellness monitoring.

## III.METHODOLOGY

To predict the likelihood of a heart attack in the coming hours, our system combines facial scanning technology, advanced signal processing, and machine learning algorithms. By analyzing subtle changes in blood flow through facial scans, along with contextual health data from the user, this system provides a holistic and non-invasive method for assessing heart attack risk. The system is designed to be accessible and user-friendly, making it an effective tool for individuals seeking real-time heart health predictions and actionable insights.

- **User Assessment:** Initially, the user logs into the application and completes a comprehensive assessment that gathers vital information affecting heart attack risk. This includes parameters such as age, smoking habits, alcohol consumption, diabetes, fitness level, previous medical history, and family history of heart disease. This assessment serves as the foundational data for the prediction model, providing essential context regarding the user's health and lifestyle.
- **Facial Scan:** After completing the assessment, the user undergoes a 60-second facial scan. Using the Haar Cascade algorithm, the system detects the face and analyzes the lighting conditions to ensure optimal scan quality. The scan captures subtle color changes in the blood vessels beneath the skin, which are indicative of blood flow from the heart to the brain.
- **Data Processing – Color Detection:** The captured video frame is divided into pixels, and subtle color changes in the blood vessels are detected. OpenCV and EVM technology are used to convert these color changes into RGB values. These values represent variations in blood flow caused by the pumping action of the heart, which can be crucial for heart rate and overall cardiovascular health analysis.
- **Signal Processing:** The RGB color values are further processed using a Gaussian Pyramid technique to smooth the data, removing noise and ensuring clean signals. Fast Fourier Transform (FFT) is then applied to extract frequency data from the smoothed color changes, allowing us to calculate the heart rate frequency. The frequency difference between two peaks in the signal is used to derive Heart Rate Variability (HRV), a critical parameter in predicting the risk of a heart attack. HRV represents the time difference between successive heartbeats, which provides insights into the user's stress levels and overall cardiovascular health.
- **Stress and SpO2 Detection:** Using HRV data and additional mathematical models, we assess the user's stress levels and SpO2 (blood oxygen saturation). These parameters are important as high stress and low oxygen levels can significantly increase the risk of heart disease and heart attacks.
- **Heart Attack Prediction Model:** The heart rate, HRV, stress, and SpO2 levels, combined with the results from the user's assessment, are fed into a machine learning model. The model, trained on a large dataset of heart attack risk factors, predicts the likelihood of a heart attack occurring within the next few hours. The model has been optimized for accuracy, with a current prediction accuracy of 96%.
- **Results Visualization and Reporting:** After the scan is complete, the system generates graphical representations of the user's heart rate, HRV, stress levels, and SpO2. These visualizations allow the user to easily interpret their health status. If the prediction indicates a high risk of a heart attack, the application alerts the user and offers the option to contact a doctor immediately through the app. The user can also download a detailed report of the results for further analysis.
- **Continuous Improvement and Feedback:** The system continuously collects feedback from users and refines its prediction model. With each use, the system learns from new data to improve the accuracy of its predictions, ensuring that the application becomes more reliable over time. Additionally, the integration of advanced machine learning techniques helps the system adapt to new data trends and emerging cardiovascular health patterns.

By combining accessible hardware, advanced image processing, and machine learning, our system offers an innovative solution for predicting heart attack risk in a non-invasive and user-friendly manner. This approach democratizes cardiac health monitoring and empowers users to make informed decisions about their health.

## IV.IMPLEMENTATION

This section details the practical realization of the heart attack prediction system, integrating facial scanning technology and machine learning for real-time health assessment. The implementation is modular, addressing various stages of data collection, processing, and prediction, with clear roles and security mechanisms to ensure accuracy, privacy, and reliability.

**Modules Overview**

The proposed system comprises six key modules:

1. User Registration and Health Assessment Phase 2. Facial Scan and Data Capture Phase 3. Data Preprocessing and Signal Processing Phase 4. Heart Attack Prediction Phase 5. Results Visualization Phase 6. Emergency Alert and Doctor Integration Phase Each module plays a vital role in ensuring the accurate and seamless execution of the heart attack prediction process.

**Module Descriptions**

**1. User Registration and Health Assessment Phase**

The user registers on the system and fills out a detailed health assessment form, including information such as age, smoking habits, alcohol consumption, family medical history, and fitness level.

This phase helps gather essential context for predicting heart attack risk based on personal health factors.

**2. Facial Scan and Data Capture Phase**

Once the health assessment is complete, the user initiates a facial scan using their device’s camera.

The system uses the Haar Cascade algorithm to detect the face and optimize lighting conditions for an accurate scan. Blood flow data is captured by analyzing subtle color changes in the skin, which are processed to detect RGB values representing blood flow dynamics.

**3. Data Preprocessing and Signal Processing Phase**

The captured facial scan data undergoes preprocessing, including noise removal using Gaussian Pyramid smoothing.

Fast Fourier Transform (FFT) is applied to the color data to extract heart rate frequencies, which are then used to calculate Heart Rate Variability (HRV)—a key indicator of cardiovascular health.

Additional health parameters, such as stress levels and SpO2, are derived from the HRV data and integrated with the user's health assessment.

**4. Heart Attack Prediction Phase**

The health assessment data and processed facial scan data are fed into a machine learning model trained to predict the likelihood of a heart attack within the next few hours. The model analyzes the combined data, considering both physiological and lifestyle factors, to generate a heart attack risk percentage. The prediction model, trained using historical data, has achieved an accuracy rate of 96%.

**5. Results Visualization Phase**

After the prediction, the system generates graphical representations of key health metrics, including heart rate, HRV, stress levels, and SpO2. These results are presented in a user-friendly interface, enabling easy interpretation of heart health status. The risk percentage and overall cardiovascular health insights are displayed to help users understand their current health status.

**6. Emergency Alert and Doctor Integration Phase**

If the prediction indicates a high risk of heart attack, the system triggers an emergency alert to the user, notifying them of the potential risk. The app provides an option to contact a healthcare provider directly through the application, enabling immediate medical consultation. In case of critical conditions, the app ensures that users can seek professional help as quickly as possible.

## V.IMPLEMENTATION HIGHLIGHTS

- Combines user assessment data (age, habits, medical history) with real-time scan data.
- Uses a machine learning model trained to predict heart attack risk with 96% accuracy.
- Provides graphical visualizations of vital stats like HR, HRV, SpO2, stress, and risk score.
- Sends critical alerts if the user is at high risk and offers direct doctor contact options.
- Ensures data privacy and encryption for all health and biometric information.
- Supports continuous model updates to improve prediction accuracy with new data.

## VI.CONCLUSION

The implementation of this heart attack prediction system exemplifies the transformative potential of technology in advancing preventive healthcare. By merging facial recognition, real-time physiological signal processing, and machine learning, the application introduces a scalable, user-friendly solution capable of early cardiac risk detection using minimal hardware. This study emphasizes the value of a modular, structured design process that aligns technical capabilities with user requirements, facilitating a balance between innovation, accessibility, and reliability.

The evaluation of system components from assessment interfaces and facial scan accuracy to prediction performance and emergency response reinforces the importance of continuous optimization and user feedback integration. The active involvement of healthcare professionals, developers, and end-users throughout the system lifecycle contributes to better adoption, resilience, and trust. Moreover, incorporating privacy safeguards and adaptability into the design ensures both ethical compliance and future scalability.

Ultimately, this implementation sets a benchmark for future digital health initiatives. It showcases how a multidisciplinary, user- centered approach can drive impactful outcomes and foster broader access to life-saving diagnostic tools, reinforcing the critical role of strategic planning and technological integration in modern healthcare systems.

## VII.RESULTS

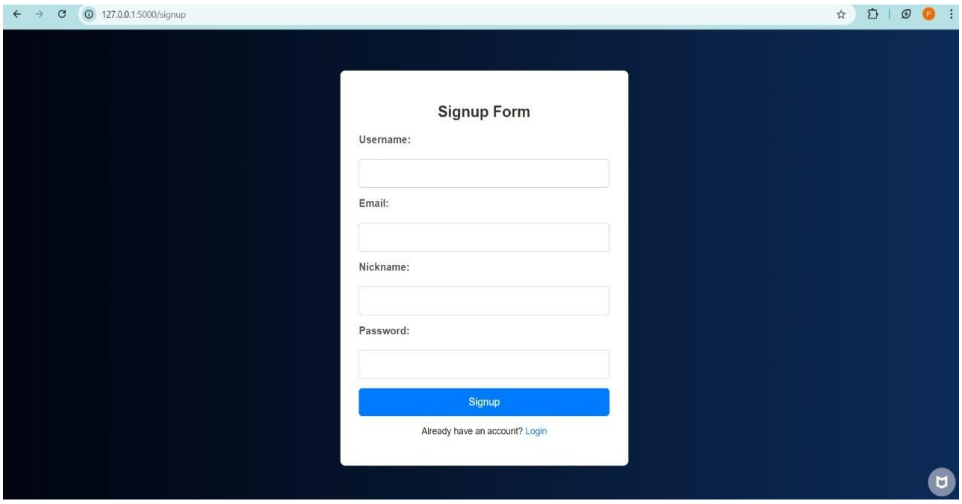

*Fig 7.1 Sign Up Form Interface*

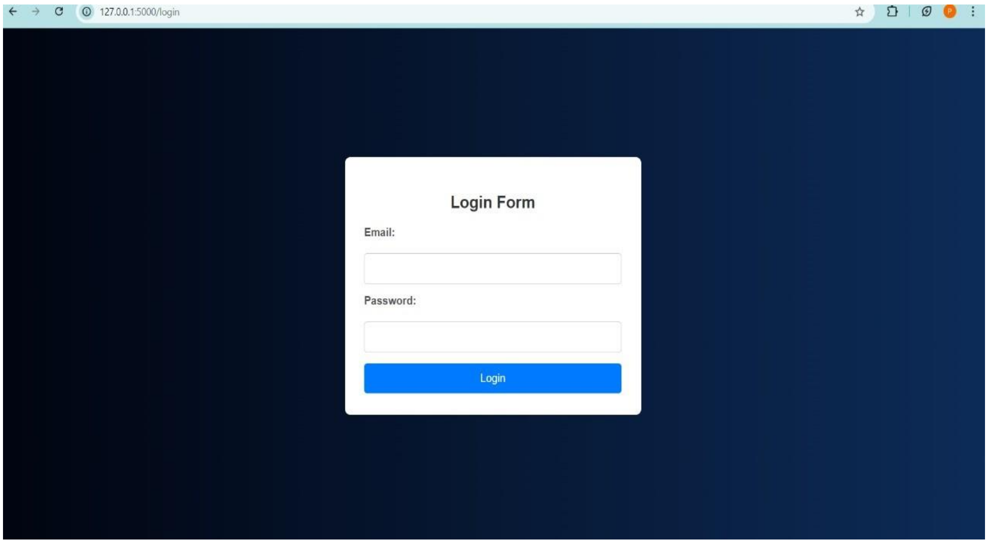

*Fig 7.2 Login Form Interface*

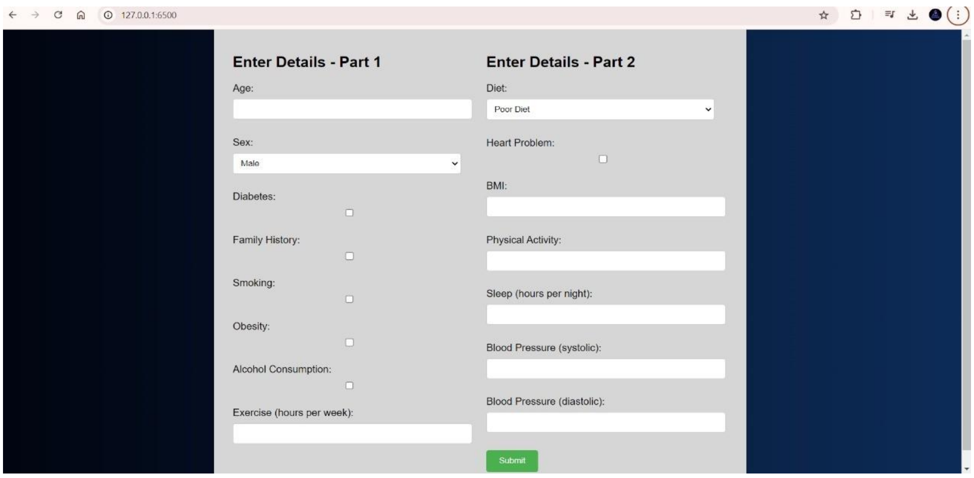

*Fig 7.3 Submission of candidate details.*

*Fig 7.4 Face feature extraction*

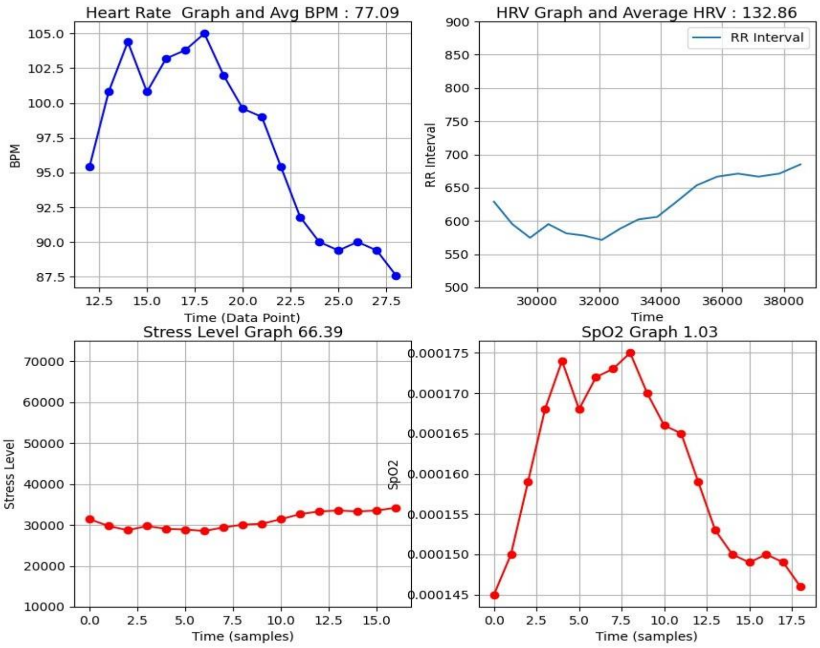


*Fig 7.8 Visualization of heart rate and other data*

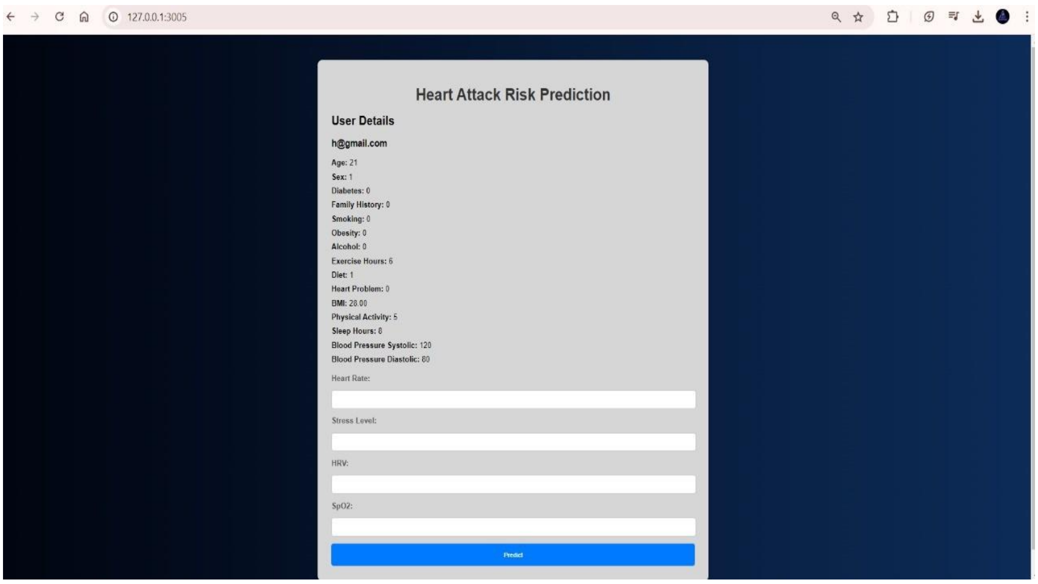


*Fig 7.9 Prediction of Heart Attack Risk*

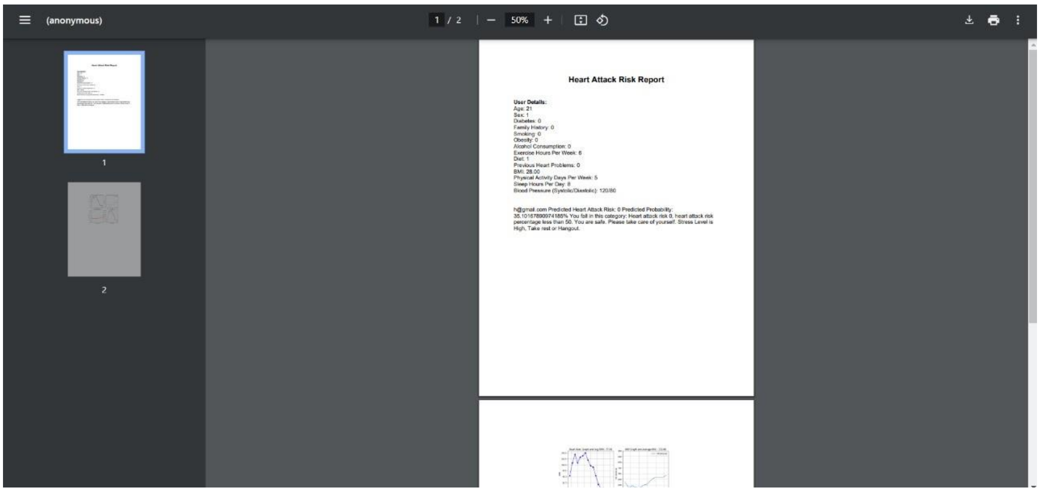


*Fig 7.10 Downloaded PDF document.*

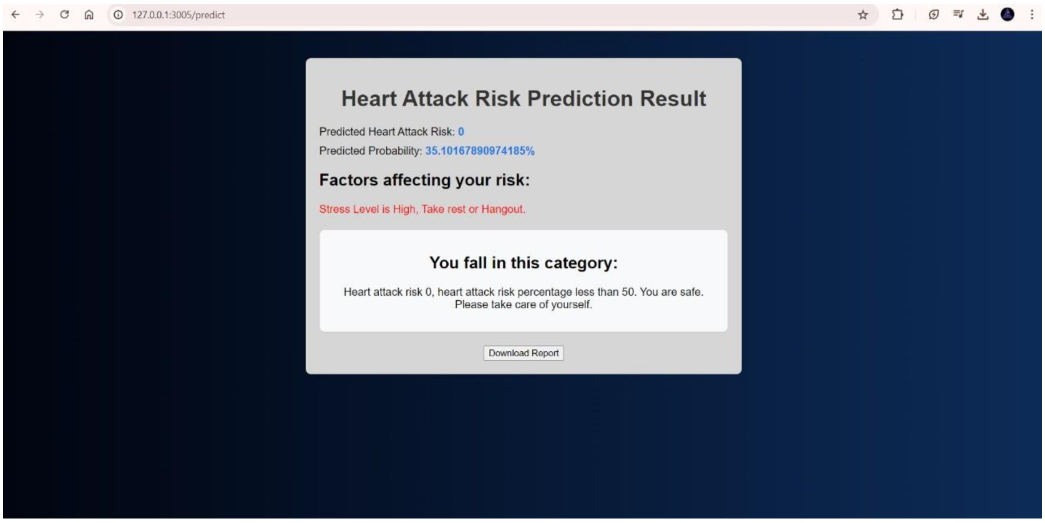


*Fig 7.11 Heart attack risk assessment and the contributing factors.*

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