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Heart Attack Prediction System

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Abstract*:* *Heart disease remains one of the leading causes of mortality worldwide, with heart attacks accounting for a significant proportion of these deaths. Early prediction of heart attack risk can enable timely medical interventions and lifestyle changes, potentially saving lives. This project presents a Heart Attack Prediction System using machine learning techniques to predict an individual's likelihood of experiencing a heart attack based on clinical and demographic data.*

Our system uses various machine learning algorithms, including logistic regression, decision trees, and ensemble methods, trained on a dataset of cardiovascular risk factors such as age, blood pressure, cholesterol levels, and other health indicators. Through feature engineering and model tuning, we identify the most predictive factors, enhancing the accuracy and robustness of our model. The system provides a probability score for heart attack risk, empowering healthcare providers and patients to make informed decisions. With an emphasis on interpretability and user-friendly interfaces, this project aims to make complex medical insights accessible and actionable for both clinicians and patients, potentially reducing the incidence of heart attacks through proactive care..

Keywords: Heart disease

I. INTRODUCTION

Heart disease is one of the leading causes of morbidity and mortality worldwide, and timely prediction of heart attack risk is crucial for early intervention and prevention. With advancements in machine learning and artificial intelligence, predictive models can now analyze vast amounts of medical data to identify patterns that correlate with heart attack risk factors, providing a non-invasive, accurate, and timely assessment of cardiovascular health.

This paper presents a heart attack prediction model developed using a machine learning approach that leverages a supervised learning classifier to assess an individual's likelihood of experiencing a heart attack. Based on health data inputs such as age, cholesterol levels, resting blood pressure, and other key risk indicators, this model calculates a probability score that classifies users into high-risk and low-risk categories. Designed to be user-friendly, the model is implemented with a Graphical User Interface (GUI) in Python using Tkinter, allowing users and healthcare providers to input patient data and instantly receive a probability score along with a visual probability graph. Additionally, the interface provides tailored lifestyle and health management suggestions based on the prediction results, supporting proactive healthcare management.

The underlying predictive model is trained on historical medical data, which includes commonly recognized risk factors such as exercise-induced angina, fasting blood sugar levels, and electrocardiogram (ECG) findings. The predictive accuracy of the model was evaluated using performance metrics like accuracy, sensitivity, and specificity, ensuring robust reliability for clinical or preventive applications. The model also incorporates data preprocessing techniques to scale and transform input features, optimizing the model's predictive capability.

This work contributes to the field of healthcare and predictive analytics by offering a scalable, accessible, and data-driven approach for heart attack risk prediction. The combination of machine learning and user-centric design presents a valuable tool for clinicians and individuals alike, promoting early detection and better management of cardiovascular health risks.

Aim of the Study

The aim of this study is to develop a machine learning-based heart attack prediction model that can assess an individual's risk of experiencing a heart attack based on key health indicators. By analyzing features such as age, cholesterol levels, resting blood pressure, and ECG results, this model seeks to provide a reliable, non-invasive prediction of cardiovascular risk. Additionally, the study aims to create a user-friendly interface that enables both healthcare providers and patients to input relevant medical data and receive immediate feedback in the form of a probability score and visual probability graph. This predictive tool is intended to support early detection, personalized health management, and proactive intervention strategies, thereby contributing to improved cardiovascular health outcomes and preventative care.

II. RELATED WORK

Heart attack detection has been a critical area of research in medical science, as timely and accurate diagnosis can significantly reduce mortality rates. Traditional statistical approaches, such as logistic regression, have long been used to predict heart attack risk based on clinical factors like age, blood pressure, cholesterol levels, and smoking history. Logistic regression models are popular due to their simplicity and interpretability, providing insights into the direct relationships between individual risk factors and heart attack likelihood. However, these models are limited when capturing complex, non-linear interactions between risk factors, which are often present in cardiovascular health data.

To address these limitations, recent studies have turned to machine learning algorithms, such as support vector machines (SVM), decision trees, random forests, and gradient boosting, which can model non-linear relationships and capture interactions among multiple factors more effectively. For instance, decision trees have shown promise in identifying key factors such as obesity, family history, and stress as high-risk indicators, while random forests have been employed to improve stability and reduce overfitting by averaging predictions from multiple decision trees. These models have demonstrated better predictive accuracy compared to traditional statistical methods, particularly when dealing with large and complex datasets.

Additionally, deep learning techniques, including neural networks, have been applied to heart attack prediction, especially in settings with high-dimensional data, such as medical imaging or continuous ECG readings. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can handle these data formats, enabling more accurate and automated detection of early warning signs. However, deep learning models require substantial computational resources and large labeled datasets, making their application more challenging in environments with limited access to data or computational power.

This project builds on existing methods by integrating traditional statistical and machine learning approaches to enhance both the accuracy and interpretability of heart attack prediction. By leveraging the strengths of logistic regression for interpretability and machine learning models for capturing complex patterns, our approach aims to provide a robust and accessible tool for early heart attack detection, empowering healthcare providers with actionable insights for diverse patient populations.

III. METHODS

The methodology for the Heart Attack Detection project follows a systematic approach to data collection, preprocessing, model training, and risk prediction. This section outlines the sources of data, preprocessing steps, feature engineering, and model-building strategies used to create an accurate and interpretable heart attack risk prediction tool.

3.1 Data Collection

- **Sources**: The dataset for this project is primarily sourced from medical and cardiovascular health databases, such as the American Heart Association (AHA) and public health records. These sources provide robust data on heart attack risk factors, patient demographics, and health records, which are essential for developing an effective prediction model.
- **Data Structure**: The dataset includes key attributes like age, gender, blood pressure, cholesterol levels, smoking status, physical activity levels, and medical history of cardiovascular diseases. Each record provides a comprehensive profile of individual health metrics, allowing the model to consider multiple influential factors on heart attack risk.

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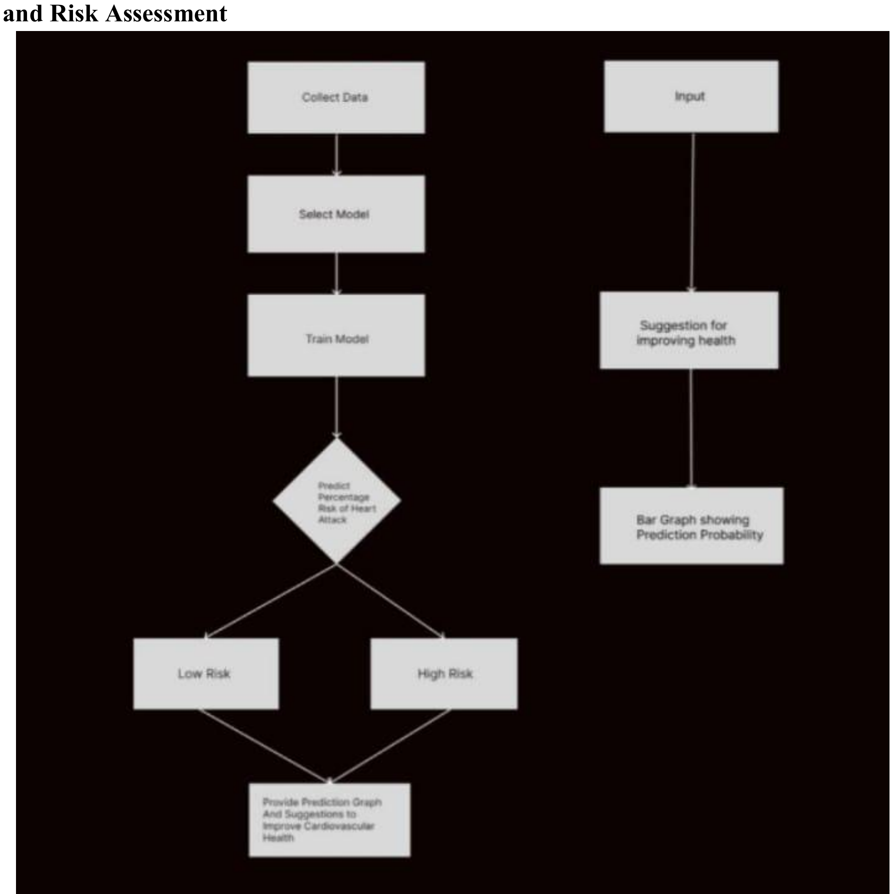
3.2 Data Preprocessing

- **Data Cleaning**: The initial step involves loading the raw data and performing data cleaning. Unnecessary columns are removed, and missing values or inconsistencies in health records are addressed to ensure data quality. Outliers are also detected and handled carefully, as extreme values in features like blood pressure or cholesterol could skew model predictions.
- **Normalization**: To improve the model's performance, numerical data (such as blood pressure, cholesterol, and age) are standardized to a consistent scale. Normalization helps in avoiding biases, especially in distance-based algorithms or models that are sensitive to data scaling.
- **Encoding**: Categorical data, such as gender and smoking status, are converted into numerical formats through encoding methods like one-hot encoding or label encoding. This enables the machine learning model to process these variables effectively.

3.3 Model Selection and Training

- **Model Selection**: Based on the requirements for interpretability and predictive power, a logistic regression model is selected for this project. Logistic regression is chosen for its ability to provide clear insights into the influence of each feature on heart attack risk, making the predictions interpretable for healthcare providers.
- **Training the Model**: The model is trained using a subset of the data. During training, the model learns the relationships between input features (such as blood pressure, cholesterol levels, etc.) and the likelihood of a heart attack. Cross-validation is performed to ensure the model generalizes well to new, unseen data, minimizing the risk of overfitting.

3.4 Prediction and Risk Assessment



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- **Risk Prediction**: Once the model is trained, it predicts the probability of a heart attack based on the individual's health profile. The prediction output is a percentage risk score, classifying individuals into low-risk or high-risk categories depending on their likelihood of experiencing a heart attack.
- **Output Interpretation**: For high-risk patients, the tool provides a graphical representation of the risk factors and personalized suggestions for health improvement, focusing on areas like diet, physical activity, and smoking cessation. Additionally, a bar graph illustrates the probability of heart attack risk, helping users and healthcare providers understand the prediction outcome at a glance.

This structured methodology enables the Heart Attack Detection tool to deliver accurate, interpretable, and actionable predictions, supporting healthcare practitioners and individuals in proactively managing cardiovascular health.

IV. SOURCE CODE AND OUTPUTS

Train_model.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import joblib

# Load the dataset
data = pd.read_csv("heart.csv")

# Define features and target
X = data.drop(columns='output')
y = data['output']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train the Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Save the model and scaler
joblib.dump(model, "heart_model.joblib")
joblib.dump(scaler, "scaler.joblib")
```

Fig.4.1 - Source Code Description: Importing of libraries

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heart_attack_predictor.py

```python
import tkinter as tk
from tkinter import messagebox
from tkinter import ttk
import joblib
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.backends.backend_tkagg import FigureCanvasTkAgg

# Load the model and scaler
try:
    model = joblib.load("heart_model.joblib")
    scaler = joblib.load("scaler.joblib")
except Exception as e:
    print(f"Error loading model or scaler: {e}")
```

Fig.4.2 - Source Code Description: Importing of libraries

```python
# Function to predict heart attack risk and provide tailored suggestions
def predict():
    try:
        # Get user input and prepare it for the model
        original_user_data = [
            float(age_entry.get()),
            float(sex_entry.get()),
            float(cp_entry.get()),
            float(trtbps_entry.get()),
            float(chol_entry.get()),
            float(fbs_entry.get()),
            float(restecg_entry.get()),
            float(thalachh_entry.get()),
            float(exng_entry.get()),
            float(oldpeak_entry.get()),
            float(slp_entry.get()),
            float(caa_entry.get()),
            float(thall_entry.get())
        ]
```

Fig.4.3 – Function to predict heart attack risk

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```
# Tailored suggestions based on unscaled inputs
suggestions = "General Suggestions:\n- Maintain a balanced diet\n- Engage in regular physical activity\n- Get regular checl

# Condition checks before scaling
if original_user_data[3] > 140:  # High Resting BP
    suggestions += "\n- Consider reducing salt intake to lower blood pressure.\n- Monitor your blood pressure regularly.\n'
if original_user_data[4] > 200:  # High Cholesterol
    suggestions += "\n- Follow a low-cholesterol diet with more fruits and vegetables.\n- Avoid saturated fats and trans f
if original_user_data[5] == 1:  # High Fasting Blood Sugar
    suggestions += "\n- Maintain a healthy weight and consider regular exercise.\n- Monitor blood sugar levels.\n"
if original_user_data[8] == 1:  # Exercise Induced Angina
    suggestions += "\n- Avoid high-intensity exercise; consider moderate-intensity activities.\n- Discuss exercise plans w
if original_user_data[9] > 2.0:  # High Old Peak (ST depression)
    suggestions += "\n- Manage stress levels through activities like yoga or meditation.\n"

# Reshape data to match model input and scale it
user_data = np.array(original_user_data).reshape(1, -1)
user_data = scaler.transform(user_data)

# Make prediction and get prediction probability
prediction = model.predict(user_data)
prediction_proba = model.predict_proba(user_data)
```

Fig.4.4 – Suggestions provided by the model

```
        # Show prediction probability as a graph
        show_probability_graph(prediction_proba[0])

        # Display the result
        if prediction[0] == 0:
            result = "High Risk of Heart Attack"
            suggestions = f"{result}\n\n{suggestions}"
        else:
            result = "Low Risk of Heart Attack"
            suggestions = f"{result}\n\n{suggestions}\nKeep up the good work!"

        messagebox.showinfo("Prediction Result", f"{suggestions}\n\nPrediction Probability: High Risk:
                            {prediction_proba[0][0]:.2f}, Low Risk: {prediction_proba[0][1]:.2f}")

    except ValueError as ve:
        messagebox.showerror("Input Error", f"Invalid input: {ve}")
    except Exception as e:
        messagebox.showerror("Error", f"An error occurred: {e}")
```

Fig.4.5 – Calculation of probability

```
# Function to display the prediction probability graph
def show_probability_graph(probabilities):
    # Create a bar chart of the probabilities
    labels = ["High Risk", "Low Risk"]
    plt.figure(figsize=(6, 4))
    plt.bar(labels, probabilities, color=['red', 'green'])
    plt.title("Prediction Probability")
    plt.xlabel("Risk")
    plt.ylabel("Probability")
    plt.ylim(0, 1)

    # Embed the plot in the Tkinter window
    canvas = FigureCanvasTkAgg(plt.gcf(), master=app)  # 'app' is the Tkinter window
    canvas.get_tk_widget().pack(fill=tk.BOTH, expand=True)
    canvas.draw()

# Initialize the tkinter window
app = tk.Tk()
app.title("Heart Attack Prediction")
app.geometry("500x700")
```

Fig.4.6 – Defining the function show_probability_graph

```
for i, label in enumerate(labels):
    tk.Label(scrollable_frame, text=label).grid(row=i, column=0, pady=5, sticky="w")
    entry = tk.Entry(scrollable_frame)
    entry.grid(row=i, column=1, pady=5, padx=10, sticky="w")
    entries.append(entry)

# Unpack entries for easy access
(age_entry, sex_entry, cp_entry, trtbps_entry, chol_entry, fbs_entry, restecg_entry,
 thalachh_entry, exng_entry, oldpeak_entry, slp_entry, caa_entry, thall_entry) = entries

# Create Predict button
predict_button = tk.Button(scrollable_frame, text="Predict", command=predict, bg="lightblue")
predict_button.grid(row=len(labels), column=0, columnspan=2, pady=20)

# Run the tkinter main loop
app.mainloop()
```

Fig.4.7 – Defining the GUI

```
# Create a canvas with both horizontal and vertical scrollbars
canvas = tk.Canvas(app)
scrollbar_vertical = ttk.Scrollbar(app, orient="vertical", command=canvas.yview)
scrollbar_horizontal = ttk.Scrollbar(app, orient="horizontal", command=canvas.xview)

# Create the scrollable frame
scrollable_frame = ttk.Frame(canvas)

# Configure the scrollable frame
scrollable_frame.bind(
    "<Configure>",
    lambda e: canvas.configure(scrollregion=canvas.bbox("all"))
)

# Create window for the scrollable frame inside the canvas
canvas.create_window((0, 0), window=scrollable_frame, anchor="nw")
canvas.configure(yscrollcommand=scrollbar_vertical.set, xscrollcommand=scrollbar_horizontal.set)

# Pack the canvas and both scrollbars
canvas.pack(side="left", fill="both", expand=True)
scrollbar_vertical.pack(side="right", fill="y")
scrollbar_horizontal.pack(side="bottom", fill="x")

# Input labels and entries in the scrollable frame
labels = ["Age", "Sex (1=Male, 0=Female)", "Chest Pain Type (0-3)", "Resting BP (in mm Hg)",
          "Cholesterol (mg/dL)", "Fasting Blood Sugar (1 if >120 mg/dL, else 0)", "Rest ECG (0-2)",
          "Max Heart Rate", "Exercise Induced Angina (1=Yes, 0=No)", "Old Peak", "Slope (0-2)",
          "CA (0-3)", "Thal (0=Normal, 1=Fixed Defect, 2=Reversible Defect)"]

entries = []
```

Fig.4.8 – Calling the function to display GUI

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Data_vis.py

```python
import matplotlib.pyplot as plt
import pandas as pd

# Assuming you have the dataset 'heart.csv' loaded as 'data'
data = pd.read_csv("heart.csv")

# Plotting the cholesterol feature distribution
plt.hist(data['chol'], bins=20, color='skyblue', edgecolor='black')
plt.title('Cholesterol Level Distribution')
plt.xlabel('Cholesterol (mg/dL)')
plt.ylabel('Frequency')
plt.show()

```

Fig.4.9 – file to visualize the data

OUTPUT

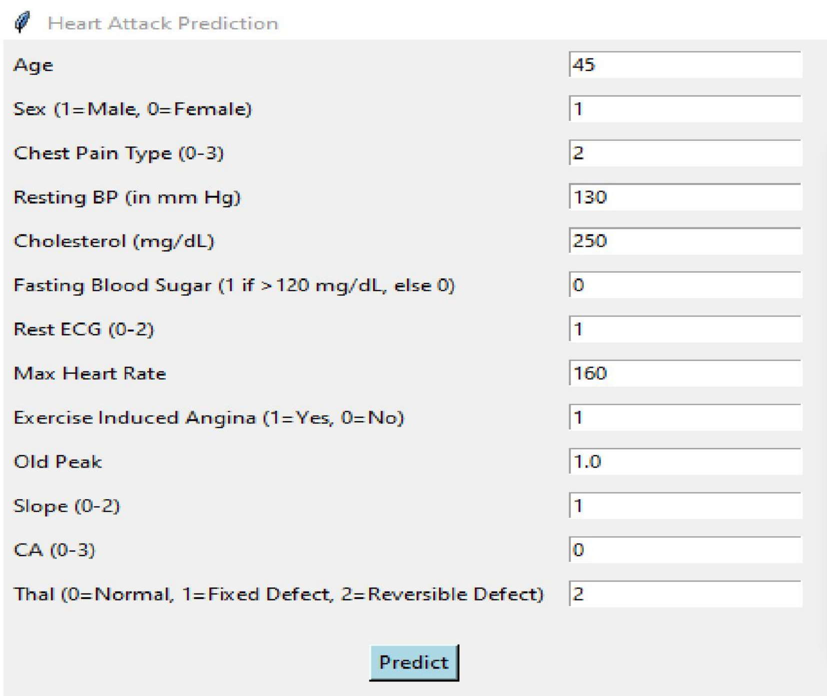

Fig.4.10 – User interface to get input from the user

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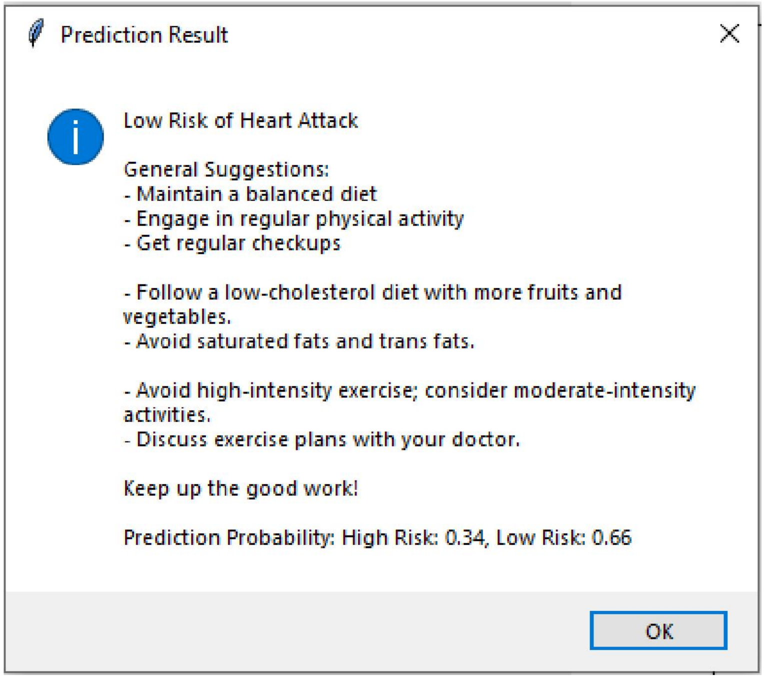

Fig.4.11 – Prediction provided by the model along with suggestions

V. RESULT AND DISSCUSSION

5.1 MODEL PERFORMANCE:

1. Model Training and Evaluation Setup

Data Preparation

- **Dataset**: Briefly describe the dataset used, including the number of samples and features. Explain any data pre processing steps, such as handling missing values, encoding categorical variables, and feature scaling.
- **Train-Test Split**: Describe how the dataset was divided into training and test sets, including the percentage split (e.g., 80% training and 20% testing) and any cross-validation techniques used.

Model

- **Model Selection**: Explain the choice of the model (e.g., Logistic Regression, Random Forest) and justify why this model is suitable for binary classification in heart attack prediction.

2. Evaluation Metrics

To effectively communicate model performance, use the following metrics:

- **Accuracy**: The proportion of correct predictions out of all predictions, which gives a general sense of model performance.
- **Precision**: The ratio of correctly predicted high-risk cases to the total predicted high-risk cases. This is particularly important in healthcare settings to avoid false positives.
- **Recall (Sensitivity)**: The ratio of correctly predicted high-risk cases to all actual high-risk cases in the test set. High recall ensures that most true high-risk cases are identified.
- **F1 Score**: The harmonic mean of precision and recall, providing a balanced measure when precision and recall are both important

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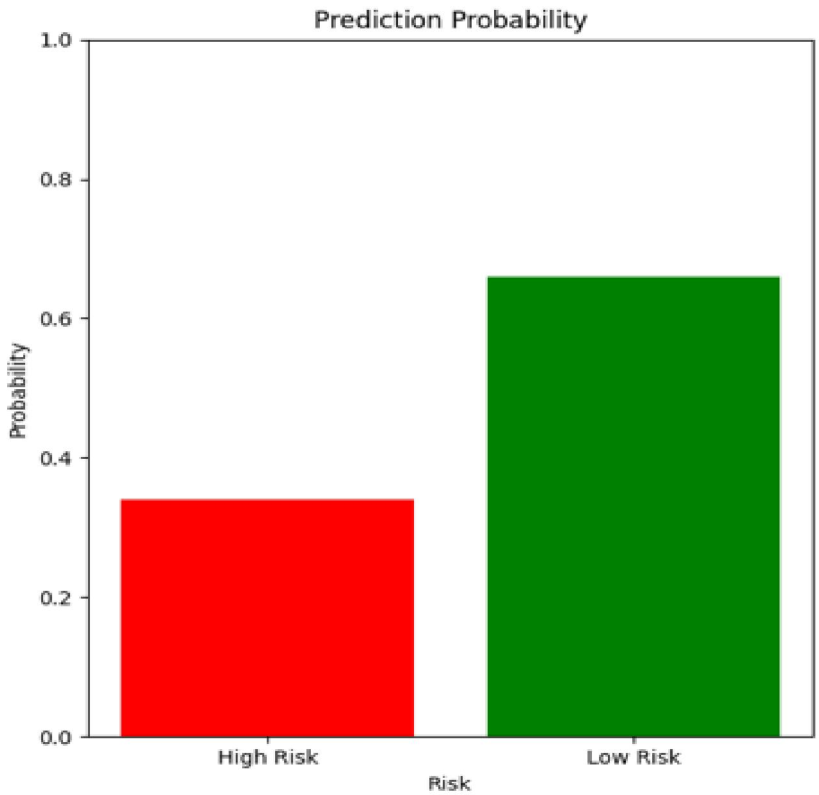

1. Prediction Probability Graph

X-axis (Risk): The categories on this axis represent the two possible risk outcomes generated by the model— "High Risk" and "Low Risk" of a heart attack.

Y-axis (Probability): This axis shows the probability assigned to each risk category by the model. Probabilities range from 0 to 1, with values closer to 1 indicating a higher likelihood of the corresponding risk category.

Color Coding:

The "High Risk" bar is shown in red, which visually emphasizes the potential danger associated with a high risk of heart attack.

The "Low Risk" bar is green, indicating a favorable outcome.

Observations:

In this particular prediction, the probability of being in the "High Risk" category is lower than that of the "Low Risk" category. For example, if the "High Risk" probability is around 0.4 and "Low Risk" is around 0.6, it indicates that the individual is more likely to be at a lower risk based on their input parameters.

These probabilities are generated by the model based on input factors (e.g., age, cholesterol level, blood pressure), providing a quantifiable measure of the individual's heart attack risk.

Cholesterol Level Distribution

This histogram represents the distribution of cholesterol levels (in mg/dL) among individuals in the dataset used for the heart attack prediction model.

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Explanation:

X-axis (Cholesterol in mg/dL): This axis shows cholesterol levels, with values typically ranging from below 200 mg/dL to above 500 mg/dL. The cholesterol level is an important indicator of heart health, where higher cholesterol levels are associated with a greater risk of cardiovascular diseases.

Y-axis (Frequency): This axis represents the number of individuals (or cases) at each cholesterol level range. The height of each bar shows how many individuals fall into each range of cholesterol levels.

Observations:

The highest frequency appears around the 200 mg/dL to 250 mg/dL range, indicating that most individuals in the dataset have cholesterol levels within this range.

A smaller number of individuals have cholesterol levels above 300 mg/dL, and very few go beyond 400 mg/dL.

This distribution suggests that while high cholesterol levels are present, they are relatively less frequent, which could reflect typical patterns in a population with mixed levels of cardiovascular risk.

ERROR METRICS:

```
Cross-validation scores: [0.7755102  0.89795918 0.77083333 0.85416667 0.79166667]
Mean cross-validation accuracy: 0.82
Test accuracy: 0.85
```

- **Cross-Validation Scores**: The list of values [0.7755102, 0.89795918, 0.77083333, 0.85416667, 0.79166667] represents the accuracy scores from each fold of the cross-validation process. Cross-validation is a technique used to evaluate the performance of a model by splitting the data into multiple "folds" or subsets. In this case, it appears that a 5-fold cross-validation was used, where the model was trained and tested five separate times, each time using a different subset of data as the test set and the remaining data as the training set. These accuracy scores indicate how well the model performed on each individual fold.
- **Mean Cross-Validation Accuracy**: The average of the cross-validation scores is calculated to give an overall assessment of the model's performance. Here, the mean cross-validation accuracy is 0.82, which means that, on average, the model correctly predicted outcomes 82% of the time across all folds. This provides a good indication of how well the model generalizes to new data.
- **Test Accuracy**: The test accuracy, shown as 0.85, represents the model's accuracy on a separate test dataset that was not used during the training or cross-validation process. This metric helps to further validate the model's performance, as it shows how well the model performs on entirely unseen data. In this case, the model achieved an 85% accuracy on the test set, which is a bit higher than the mean cross-validation accuracy, indicating that it performed slightly better on the test data than on the cross-validation folds.

VI. CONCLUSION

In conclusion, the Heart Attack Detection Tool offers valuable potential for both individual health management and broader healthcare applications. By leveraging factors such as age, blood pressure, cholesterol levels, and lifestyle choices, this tool provides personalized heart attack risk assessments, empowering individuals to take proactive steps in managing their cardiovascular health. Beyond personal use, it can serve as a critical asset in healthcare planning and preventive cardiology, assisting medical professionals in identifying high-risk patients and prioritizing care for those in need. Additionally, the tool has applications in insurance for more accurate risk assessment and policy personalization. However, challenges remain, especially in integrating real-time data from wearable devices and adapting the model to cater to diverse populations with varying risk profiles. As the tool evolves, its application in clinical and insurance settings, along with considerations for ethical use and data privacy, will be important areas of future development.

REAL-WORLD APPLICATIONS OF THE HEART ATTACK DETECTION TOOL

The Heart Attack Detection Tool has significant real-world applications across healthcare, public health, and the insurance industry:

- Personalized Health Management: Individuals can use the tool to assess their risk of a heart attack based on their current health metrics and lifestyle. By receiving tailored recommendations for improving cardiovascular health—such as guidance on diet, exercise, and smoking cessation—users can take proactive measures to reduce their heart attack risk. This personalized approach encourages individuals to adopt healthier habits, potentially lowering their likelihood of cardiovascular events.
- Preventive Cardiology and Clinical Use: In clinical settings, healthcare providers can use the tool to quickly identify patients at high risk for heart attacks. This enables doctors to prioritize those in urgent need of care, recommend preventive treatments, and monitor patients with high risk. The tool can support decision-making in cardiology departments, helping clinicians develop personalized treatment plans for at-risk individuals and improve patient outcomes.
- Public Health Planning: The tool can aid public health agencies by providing population-level insights into heart attack risk trends. By analyzing data from diverse groups, health officials can design targeted initiatives to address leading cardiovascular risk factors within communities, such as obesity or hypertension. This information can guide resource allocation, focusing on preventive programs that target the most pressing needs in cardiovascular health.
- Insurance Industry Applications: Insurance companies can use the tool to enhance the accuracy of risk assessments when determining life and health insurance premiums. By factoring in individual risk profiles—based on health metrics, lifestyle, and family history—insurance companies can create more tailored policy offerings and premium rates. This approach ensures that premiums are reflective of each individual's actual cardiovascular risk, allowing insurers to offer fairer and more personalized coverage.

  - Emergency Care and Telemedicine: In emergency care and telemedicine, a quick and reliable heart attack detection tool can help screen patients remotely. For example, individuals experiencing symptoms can use the tool for preliminary risk assessment and receive guidance on seeking immediate medical help. This application is particularly valuable in remote areas with limited access to healthcare facilities, as it can enable timely interventions that may save lives.

OPEN RESEARCH QUESTIONS FOR HEART ATTACK DETECTION TOOL

Despite the advantages of heart attack detection tools, several open research questions remain to improve their accuracy, adaptability, and ethical application:

Incorporation of Genetic Data: One important research direction is the integration of genetic information to improve heart attack risk predictions. While traditional risk factors like blood pressure and lifestyle choices are well-established indicators, genetic predispositions also play a significant role in cardiovascular risk. Future studies could explore incorporating genetic markers or family history of heart disease to enhance prediction accuracy, especially for individuals with hereditary cardiovascular conditions.

Adaptation for Diverse Populations: Many heart attack prediction models are trained on data from specific demographic groups, which may limit their applicability across diverse populations with different socio-economic and cultural backgrounds. For instance, dietary habits, stress levels, and healthcare access can vary greatly across regions and demographics. Future research could focus on adapting the model to reflect these variations, making the tool more universally applicable and accurate across different population groups.

Real-Time Data Integration from Wearable Devices: As wearable health technology advances, the possibility of creating a dynamic heart attack detection tool that updates in real-time based on data from devices like smartwatches and fitness trackers is an exciting avenue for exploration. By incorporating continuous monitoring of heart rate, physical activity, and even sleep patterns, the tool could provide up-to-date heart attack risk assessments. Research would be needed to ensure the tool can handle real-time data streams while maintaining accurate predictions and protecting user privacy.

Ethical Implications and Privacy Concerns: The ethical use of heart attack detection tools in healthcare and insurance settings raises questions about data privacy and fairness. For example, insurers might use risk scores to adjust premiums, potentially leading to higher costs for high-risk individuals. Future research should focus on ensuring that the tool is used responsibly and does not contribute to discrimination. Establishing guidelines and policies for the

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ethical application of heart attack prediction models, especially in insurance, will be crucial to protecting individuals from potential misuse of their health data.

By addressing these open research questions, the Heart Attack Detection Tool can continue to improve in accuracy, inclusivity, and ethical standards, ultimately benefiting users and stakeholders across multiple sectors.

VII. DISCLOSURE

This study presents a heart attack detection model that estimates an individual's risk of a heart attack based on factors such as age, sex, blood pressure, cholesterol levels, and lifestyle habits. Using a logistic regression model, the tool provides a percentage-based risk score, categorizing individuals into low or high risk. The goal of this model is to empower individuals and healthcare providers to make informed decisions for proactive cardiovascular health management. This tool is designed for educational and informational purposes, and it should not replace professional medical advice, diagnosis, or treatment. Users are encouraged to consult healthcare professionals for any concerns regarding heart health. Ethical considerations, including data privacy and responsible use, are emphasized to ensure that predictions are used fairly and appropriately in both clinical and non-clinical settings.

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