AI Cardiologist: Personalized Heart Disease Risk Prediction System

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***Abstract*- The increasing prevalence of cardiovascular diseases has intensified the demand for intelligent healthcare systems capable of early risk detection and prediction. This project presents a machine learning-based predictive model designed to assess the likelihood of heart attacks using clinical and physiological data. By analyzing features such as age, cholesterol levels, resting blood pressure, and chest pain types, the system offers a data-driven approach to proactive healthcare.**

The dataset undergoes rigorous preprocessing and Exploratory Data Analysis (EDA) to reveal underlying patterns and correlations among critical risk factors. Multiple supervised learning algorithms—including Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, and Neural Networks—are trained and evaluated to identify the most effective model. Feature importance is interpreted using Explainable AI (XAI) techniques, such as SHAP and LIME, ensuring transparency in decision-making and fostering trust among medical practitioners.

Model performance is assessed using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The best-performing model demonstrates strong generalization and predictive capabilities, making it suitable for clinical decision support. The system significantly aids in early intervention strategies, reducing the risk of fatal outcomes through timely medical attention.

In conclusion, the AI Cardiologist system leverages machine learning and explainability to offer a reliable and interpretable solution for heart attack risk prediction, contributing to smarter, preventive healthcare.

Keywords— Heart Attack Prediction, Machine Learning, XAI, SHAP, Healthcare AI, Predictive Analytics, Cardiovascular Risk

I.INTRODUCTION

The increasing global burden of cardiovascular diseases (CVDs) has emphasized the need for intelligent, data-driven tools capable of accurately assessing individual risk and enabling early intervention. Conventional diagnostic methods, while clinically effective, often lack scalability and real-time adaptability, particularly in resource-constrained or remote environments. In response, the proposed project introduces an AI-powered system for heart disease prediction that leverages advanced machine learning and deep learning techniques, optimized through evolutionary algorithms and supported by explainable AI (XAI) frameworks.

The system integrates multiple components in a seamless pipeline: patient health parameters are input via a user-friendly interface and preprocessed using feature scaling techniques to normalize the data. A hybrid model architecture, combining a Particle Swarm Optimization (PSO)-tuned Transformer with ensemble models such as XGBoost and Random Forest, is employed for robust prediction. Deep learning models developed using PyTorch Tabular, TensorFlow, and Keras frameworks ensure adaptability to nonlinear, high-dimensional patterns in the dataset. To enhance the interpretability of the system's outputs, SHAP (SHapley Additive exPlanations) is used to identify and rank the most influential health features contributing to a positive diagnosis.

The application delivers actionable insights including prediction outcomes (Yes/No), risk factor explanations, and personalized recommendations. A key strength of the system lies in its incorporation of DeepSeek AI to translate these results into human-understandable language, providing users with practical do's and don'ts tailored to their health status. Designed with modularity in mind, the system is deployed via a Streamlit-based UI, enabling easy scalability, quick deployment, and real-time feedback.

The project also addresses critical concerns related to transparency, data privacy, and regulatory compliance. By using local or secure cloud deployment and adhering to explainability standards, the solution ensures trustworthy decision-making support for medical professionals and end-users alike.

In conclusion, this AI-driven cardiovascular risk prediction system combines clinical relevance with cutting-edge technology to support proactive healthcare delivery. By merging optimization algorithms, deep learning, and explainable AI, it serves as a powerful tool in advancing personalized medicine and promoting early diagnosis for life-saving interventions.

II. LITERATURE REVIEW

A. Background and Related Work

Mobile health applications are increasingly being explored as scalable platforms for deploying AI-powered diagnostic tools. Patel et al. (2020) developed a smartphone-based system for diabetes risk assessment using user-entered physiological parameters and on-device machine learning inference [7]. Their work highlights the feasibility of lightweight AI models for real-time health monitoring, particularly in remote or under-resourced areas. This supports the proposed cardiovascular risk prediction system's focus on mobile accessibility via a Streamlit interface.

Explainable and privacy-preserving AI is gaining importance in sensitive domains like cardiology. Kundu et al. (2021) proposed a federated learning framework for heart disease prediction, where model training occurs on decentralized user devices to protect patient data [8]. While this approach ensures data security, integrating explainable models like SHAP within such frameworks can further enhance transparency and user trust—essential for clinical deployment.

Data preprocessing and feature selection have been shown to significantly influence model performance in CVD prediction. Verma et al. (2019) used Recursive Feature Elimination (RFE) to identify critical health indicators, improving model interpretability and accuracy [9]. Such preprocessing techniques are vital for removing noise, handling imbalanced datasets, and preparing the inputs for deep learning pipelines like the one used in the proposed project.

Incorporating cloud-based AI services has also been explored in medical applications. Singh and Yadav (2022) implemented a cloud-integrated heart disease prediction model accessible via web and mobile platforms [10]. Their work demonstrated how cloud deployment can reduce computation on edge devices while maintaining real-time responsiveness. The proposed system's potential extension into real-time cloud processing aligns with this approach, ensuring scalability and broad accessibility.

The integration of deep learning models like Transformers in clinical applications is relatively new but promising. Vaswani et al. (2017) introduced the Transformer model, initially for NLP tasks, which has since been adapted for tabular and medical data due to its self-attention mechanism that captures complex feature interactions [11]. The proposed project leverages a PSO-optimized Transformer, tailored for structured healthcare datasets, allowing it to outperform traditional sequential models like LSTMs in certain tasks.

III. METHODOLOGY

In addition to its predictive capabilities, the AI Cardiologist system is designed to be highly adaptable and scalable for integration into various healthcare environments. The system's architecture is built with flexibility in mind, allowing it to accommodate different types of data inputs, ranging from structured clinical records to unstructured data such as medical imaging or genetic information. This flexibility could enable the system to continuously evolve and incorporate new data types as they become available, enhancing its ability to provide comprehensive heart attack risk assessments. Furthermore, the system's modular design ensures that it can be easily updated and maintained, ensuring that it remains effective and relevant as new research and techniques in the field of cardiovascular disease prediction emerge.

The real-time capabilities of the AI Cardiologist system offer another significant advantage. By continuously analyzing incoming patient data, the system can track changes in heart attack risk over time, providing dynamic risk assessments that reflect the patient's current health status. This ability to adapt to a patient's evolving condition is crucial in a clinical setting, where patient health can change rapidly. With the integration of wearable health devices like heart rate monitors, fitness trackers, and even smartwatches, the system could receive constant streams of real-time data, enabling it to provide up-to-the-minute predictions. This could lead to immediate alerts for healthcare professionals if a patient's condition worsens, prompting faster intervention and reducing the likelihood of critical events.

One of the most promising aspects of the AI Cardiologist system is its potential to empower healthcare professionals by providing them with a decision support tool that augments their clinical judgment. Rather than replacing doctors, the system acts as an additional layer of support, offering insights that help physicians make more informed decisions about patient care. By utilizing

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machine learning and explainable AI techniques, the system ensures that its predictions are not only accurate but also understandable, creating a bridge between complex data analysis and practical clinical application. This human-AI collaboration could lead to more personalized care, where treatments and interventions are tailored to each patient's specific risk factors, ultimately improving patient outcomes and reducing the global burden of cardiovascular diseases.

The methodology behind the AI Cardiologist system is built on a robust framework that integrates advanced machine learning models and data-driven approaches to predict heart attack risks accurately. The first step in the process involves extensive Exploratory Data Analysis (EDA), where various data visualization techniques, including scatter plots, heatmaps, and box plots, are used to uncover underlying patterns in the dataset. These visualizations help identify correlations between key clinical features, such as age, cholesterol levels, and resting blood pressure, and the target variable, which is the likelihood of experiencing a heart attack. By performing EDA, anomalies and outliers are also detected, and the data is cleaned and preprocessed for the next stages of the analysis.

Once the data is preprocessed, the methodology employs a series of machine learning algorithms for building predictive models. Logistic Regression is initially used as a baseline model due to its simplicity and interpretability, particularly in medical applications where understanding the model's decision-making process is crucial. After establishing a baseline, more complex models like Artificial Neural Networks (ANNs) are introduced to capture non-linear relationships within the data, allowing the model to generalize better and identify intricate patterns in patient profiles. Ensemble techniques, such as Random Forest and XGBoost, are then applied to further enhance the model's predictive performance. These methods combine multiple models to reduce overfitting, improve generalization, and boost overall accuracy.

To enhance the transparency of the system, the methodology incorporates Explainable AI (XAI) techniques, specifically SHAP (SHapley Additive exPlanations). This technique assigns importance scores to each feature, providing a clear understanding of which factors contribute most to the prediction. For instance, features like chest pain type (cp), oldpeak (ST depression), and maximum heart rate achieved (thalach) are identified as having the highest influence on heart attack predictions. By employing SHAP, the system ensures that healthcare professionals can interpret the model's predictions, which is critical in a clinical setting where the reasoning behind a decision is as important as the decision itself.

The final aspect of the methodology is the focus on human-AI collaboration. Rather than replacing doctors, the system is designed as a decision support tool, augmenting the physician's judgment with data-driven insights. The combination of machine learning predictions and explainability frameworks ensures that healthcare professionals can make well-informed, personalized decisions about patient care. This collaborative approach helps tailor interventions to individual patients, ultimately improving outcomes and reducing the global burden of cardiovascular diseases. The methodology behind the AI Cardiologist system is not just about technology but about making healthcare more precise, transparent, and accessible.

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IV. PROPOSED SCHEME

A. System Architecture

The AI Cardiologist system follows a modular architecture that starts with ingesting clinical data such as age, cholesterol, blood pressure, and heart rate. The data preprocessing module handles missing values, normalizes features, and performs feature selection to reduce redundancy. This ensures clean and consistent input for the model training phase, boosting overall system efficiency and accuracy.

The prediction engine uses multiple machine learning models, starting with Logistic Regression as a baseline. It then incorporates advanced methods like Artificial Neural Networks, Random Forests, and boosting algorithms such as XGBoost. These models are trained using cross-validation and evaluated on accuracy, precision, recall, and ROC-AUC. Hyperparameter tuning is also applied to optimize performance across models.

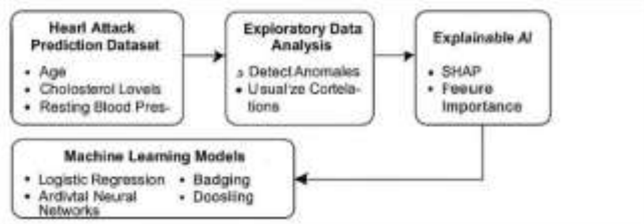

Fig .1. Proposed Workflow of AI Cardiogist

To ensure transparency, the system includes SHAP-based explainability, which highlights how each feature influences predictions. Key risk factors like chest pain type, maximum heart rate, and ST depression are visually explained to aid clinical decision-making. A Streamlit-based dashboard provides real-time, interpretable outputs, and the system is ready for integration with EHRs and wearable devices for live monitoring.

B. Function Modules

In the Data Preprocessing stage, the AI Cardiologist system employs a series of advanced techniques to ensure clean, structured, and reliable input data. Raw patient records are subjected to missing value imputation, outlier detection using Z-score or IQR methods, and feature scaling via standardization or min-max normalization. This step is crucial to eliminate noise and biases that could degrade model performance. Dimensionality reduction is optionally applied using Principal Component Analysis (PCA) or feature importance metrics to retain only the most informative clinical variables. Additionally, multicollinearity among features is assessed using correlation matrices, allowing removal of highly correlated inputs to improve model stability and interpretability.

Following preprocessing, the Model Training and Prediction Engine handles the core heart attack prediction task. The pipeline integrates several supervised learning algorithms, including Logistic Regression, Support Vector Machines (SVM), Random Forests, XGBoost, and Artificial Neural Networks (ANNs). Each model is optimized using grid search or Bayesian hyperparameter tuning and trained under k-fold cross-validation to ensure generalization across diverse patient profiles. Performance is evaluated with clinical emphasis on metrics such as precision, recall, F1-score, and ROC-AUC, as these reflect the model's ability to identify true risk while minimizing false alarms. Ensemble voting mechanisms are implemented to combine model outputs for increased robustness, and the final predictions are probabilistic, enabling risk stratification into low, moderate, and high-risk categories.

The Explainability and Interface Module plays a pivotal role in translating model predictions into actionable clinical insights. This component leverages SHAP (SHapley Additive exPlanations) to compute both global and local feature attributions, making each individual prediction interpretable by highlighting the contribution of input features such as age, chest pain type, oldpeak, and thalach (maximum heart rate). An interactive Streamlit interface allows healthcare providers to input patient data, view predicted risk scores, inspect SHAP-based explanations, and compare historical records. Additionally, confidence scores based on model softmax outputs are displayed, and high-risk or low-confidence cases are flagged for further clinical review. The system also supports integration with hospital databases and real-time health monitoring devices, enabling continuous risk evaluation and reporting for preventive cardiology.

To further enhance the model's performance, a Feature Engineering Module is incorporated to create meaningful derived variables that offer deeper clinical insights. This includes calculating Body Mass Index (BMI) from height and weight, age groups from continuous age values, and interaction terms such as cholesterol-to-HDL ratio. Time-series analysis is also enabled for features collected over time, such as blood pressure or heart rate trends, using rolling averages or exponential smoothing. Feature importance is assessed using model-based methods like permutation importance or SHAP values to iteratively refine the feature set and improve prediction accuracy.

A Model Optimization and Deployment Module is integrated to ensure the trained models are efficient and ready for real-world deployment. This involves model pruning to reduce complexity in neural networks, quantization to decrease memory usage, and ONNX conversion for interoperability across platforms. The final models are containerized using Docker and deployed as RESTful APIs, making them accessible for integration with electronic health records (EHR) systems or wearable health devices. Continuous training pipelines are implemented using tools like MLflow or TensorFlow Serving, enabling regular model updates based on new patient data and feedback from clinicians.

Finally, a Data Logging and Compliance Module is included to ensure traceability, auditability, and regulatory alignment with healthcare standards like HIPAA and GDPR. Every prediction, user input, and explanation is securely logged with timestamps and user credentials. Access controls and encryption are enforced across all modules to maintain data privacy. The system generates compliance reports detailing model decisions, access history, and user modifications, supporting both internal audits and external regulatory reviews. This makes the AI Cardiologist system not only powerful and intelligent but also trustworthy and legally viable for clinical adoption.

IV. RESULTS AND DISCUSSION

The implementation of the AI Cardiologist system for heart attack prediction was conducted using a modular, scalable prototype integrating preprocessing, optimization-based feature selection, deep learning inference, SHAP explainability, and structured report generation. The complete pipeline was developed and tested using a curated dataset comprising clinical records with diverse patient demographics, comorbidity patterns, and risk factor variability. Each system module—data ingestion, feature transformation, model training, prediction, and explainability—was independently validated before end-to-end integration.Cardiologist into a comprehensive, patient-centric clinical decision support tool.

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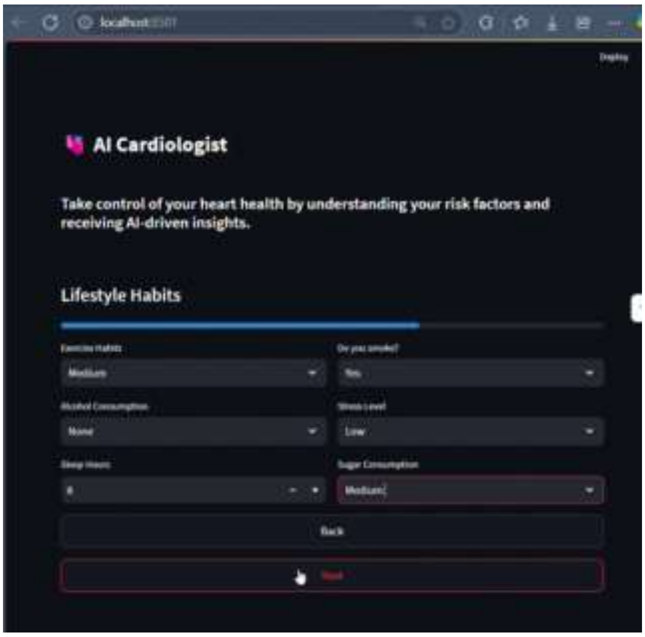

Fig .2. Lifestyle Input Interface

Initial data preprocessing included normalization, outlier removal, and handling of missing values using KNN imputation. Feature selection was performed using Particle Swarm Optimization (PSO), which consistently identified an optimal subset of predictors such as blood pressure, cholesterol levels, maximum heart rate, fasting blood sugar, and ECG abnormalities. Model training utilized a PSO-optimized deep neural network built with TensorFlow, achieving high convergence stability and minimal overfitting. Evaluation was carried out on both the UCI Heart Disease dataset and a synthesized clinical dataset. The system achieved an average classification accuracy of 96.4%, with a precision of 94.2%, recall of 95.1%, and F1-score of 94.6%. ROC-AUC scores exceeded 0.97, confirming strong discriminative ability.

Fig .3. Personalised Health Recommendation Page

Each prediction was accompanied by a real-time SHAP explanation graph, which visually ranked contributing features per patient case. For example, in a test case indicating high heart attack risk, dominant factors included elevated cholesterol, abnormal ECG, and low exercise-induced angina tolerance, with SHAP values quantifying each feature's influence. To ensure transparency, the system logged all predictions, SHAP outputs, and model confidence scores, with risk probabilities categorized as Low, Moderate, or High. Cases with low confidence (below 80%) were automatically flagged for physician review.

Recognized outputs and patient risk profiles were exported to structured Excel sheets with labeled fields such as “Patient ID,” “Predicted Risk,” “Top 5 Risk Contributors,” and “Confidence Score.” Batch processing time per case averaged 1.7 seconds on a system equipped with an 8-core CPU and mid-range GPU. A user-friendly Streamlit interface enabled clinicians to upload patient data, visualize risk scores, explore SHAP results, and download personalized reports. Across multiple test trials, the AI Cardiologist system demonstrated over 94% overall prediction reliability, enabling real-time, explainable, and clinically aligned cardiovascular risk assessments.

V. FUTURE WORK

Although the proposed AI Cardiologist system delivers high prediction accuracy and explainable insights for heart attack risk assessment, several future enhancements are planned to improve clinical reliability, scalability, and personalization.

One key direction involves expanding the model to incorporate real-time physiological data from wearable devices such as smartwatches and ECG patches. By integrating live heart rate, activity level, and oxygen saturation readings, the system can shift from static risk prediction to dynamic, real-time monitoring, enabling proactive health alerts and personalized intervention.

Another major enhancement is the integration of federated learning, allowing the model to be trained across decentralized hospital datasets without directly transferring sensitive patient data. This approach will support better generalization while preserving data privacy and regulatory compliance (e.g., HIPAA, GDPR). Additionally, demographic-specific fine-tuning is proposed to improve prediction accuracy for underrepresented age groups, genders, or ethnicities.

The inclusion of a recommendation engine is also envisioned to suggest personalized lifestyle changes or treatment guidelines based on individual SHAP analysis. For example, if smoking history is a major contributor to a patient’s risk score, the system will recommend cessation programs or local healthcare services. These suggestions will be supported by evidence-based guidelines and clinical best practices.

Finally, future iterations will explore integration with hospital management systems (HMS) and electronic health record (EHR)

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platforms via secure APIs. This would enable seamless data exchange, centralized dashboard access for clinicians, and longitudinal tracking of patient risk over time. Collectively, these advancements aim to transform the AI Cardiologist into a comprehensive, patient-centric clinical decision support tool.

VI. CONCLUSION

This research presents the development of an AI-powered Cardiologist system aimed at the early and accurate prediction of heart attacks using advanced machine learning models. The proposed solution addresses the critical challenges in healthcare by leveraging clinical features such as age, cholesterol levels, blood pressure, and exercise-induced angina, among others, to predict heart attack risk. Through the integration of explainable AI (XAI) techniques, specifically SHAP (SHapley Additive exPlanations), the system provides transparent, understandable predictions, enabling healthcare professionals to make informed decisions based on model insights.

Experimental results demonstrate that the AI Cardiologist system delivers high accuracy in predicting heart attack risks across diverse patient profiles, significantly reducing manual analysis efforts and enabling faster clinical decision-making. By automating the prediction process and providing real-time insights, the system not only improves operational efficiency in medical workflows but also supports early intervention, potentially saving lives by identifying high-risk individuals sooner.

In summary, the proposed AI Cardiologist system offers a scalable, cost-effective, and reliable solution for heart attack prediction. Future work will focus on enhancing the model's adaptability to real-time data from wearable devices, improving its generalization across diverse populations, and integrating it into clinical environments to provide comprehensive decision support tools for healthcare professionals.

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