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A HYBRID RANDOM FOREST AND GRU-BASED MODEL FOR HEART DISEASE PREDICTION USING PRIVATE CLOUD-HOSTED HEALTH DATA

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Abstract

Heart disease remains one of the leading causes of mortality worldwide, necessitating accurate and early detection to improve patient outcomes. This study proposes a Hybrid Random Forest & Gated Recurrent Unit (GRU)-Based Heart Disease Prediction Model, integrating ensemble learning with deep learning for enhanced diagnostic precision. The Random Forest classifier ensures robust feature selection and interpretability, while GRU captures temporal dependencies in patient data, enabling more effective classification. The model achieves an accuracy of 99.49%, precision of 99.66%, recall of 99.32%, and an F1-score of 99.49%, significantly outperforming traditional machine learning approaches. Additionally, an AUC-ROC score of 0.9958 and Precision-Recall AP of 0.9907 validate its superior classification performance. The study also emphasizes the integration of cloud-based risk scoring and compliance auditing, ensuring real-time applicability in clinical decision-making. This hybrid approach demonstrates the potential for reducing false diagnoses while improving heart disease detection, paving the way for AI-driven advancements in medical diagnostics.

Keywords: Heart Disease Prediction, Hybrid Classifier, Random Forest, Gated Recurrent Unit (GRU), Machine Learning, Deep Learning, Cloud-Based Risk Scoring

1. Introduction

Heart disease remains a leading cause of mortality worldwide, accounting for millions of deaths annually [1]. Early detection and accurate prediction of heart diseases are crucial in reducing mortality rates and improving patient outcomes [2]. Traditional diagnostic methods, such as electrocardiograms (ECG) and clinical risk assessments, are often limited in their ability to predict cardiac events accurately [3]. With the advent of machine learning and cloud computing, predictive models can now analyze vast amounts of patient data to provide early warnings and improve clinical decision-making [4].

Recent advances in machine learning, particularly deep learning techniques like Gated Recurrent Units (GRU) [5] and ensemble methods such as Random Forest (RF) [6], have shown promising results in healthcare applications [7]. GRU, a variant of recurrent neural networks (RNN), is highly effective in handling time-series data, making it suitable for processing patient health records [8]. On the other hand, RF provides robustness and interpretability in feature selection and classification tasks [9]. Integrating these techniques in a hybrid model can enhance the predictive performance of heart disease detection while ensuring reliability and efficiency [10].

Cloud computing plays a vital role in facilitating healthcare data storage and processing. Private cloud-hosted health data solutions offer security and scalability [11], allowing real-time access to patient records while maintaining privacy [12]. This paper proposes a hybrid Random Forest and GRU-based model to predict heart disease [13], leveraging private cloud-hosted health data for improved accessibility, security, and computational efficiency [14].

Cardiovascular diseases (CVDs), particularly heart disease, persist as the foremost cause of mortality globally, contributing to over 17 million deaths each year according to the World Health Organization [16]. Despite advancements in diagnostic tools and healthcare technologies, the early detection and prognosis of heart-related disorders remain a major challenge [17]. Traditional clinical diagnostic methods, including electrocardiograms (ECGs), echocardiography, and angiograms, while effective to a degree, are often constrained by manual interpretation, subjectivity, and lack of predictive foresight [18]. Moreover, these diagnostic methods usually focus on immediate physiological symptoms rather than leveraging historical and longitudinal data that may offer critical early warning signs of deteriorating cardiovascular health [19].

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The integration of machine learning (ML) and artificial intelligence (AI) into healthcare has revolutionized the ability to analyze complex and voluminous patient data [20]. Techniques such as Random Forest (RF), Support Vector Machines (SVM), and Neural Networks (NN) have been widely explored for predictive analytics, especially in disease classification tasks [21]. Random Forest, an ensemble learning method, excels at feature selection and handling imbalanced datasets, making it particularly suitable for medical applications where data quality and consistency can vary significantly [22]. However, these traditional ML algorithms often fall short when dealing with temporal patterns embedded within patient records, such as sequential test results, vital sign trends, and evolving symptom profiles [23].

To address this limitation, deep learning models—particularly Recurrent Neural Networks (RNNs) and their variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)—have demonstrated significant promise [24]. GRU, in particular, offers a more computationally efficient architecture than LSTM while maintaining the capability to learn dependencies over time [25]. This makes GRU an ideal candidate for analyzing sequential patient data where clinical history and progression over time are vital to accurate diagnosis [26]. Despite the advantages, deep learning models often suffer from interpretability issues and require substantial computational resources, which can limit their adoption in resource-constrained clinical environments [27].

Another critical dimension in healthcare analytics is the infrastructure for data storage, access, and privacy [28]. With the digitization of health records, private cloud computing platforms have emerged as robust solutions for securely managing sensitive medical information [29]. Private clouds offer several advantages, including enhanced data protection, regulatory compliance (e.g., HIPAA and GDPR), and scalable computational resources, all of which are crucial for deploying AI-driven models in real-world clinical settings [30]. By hosting predictive models on private cloud platforms, healthcare institutions can ensure both accessibility and confidentiality, enabling seamless integration with electronic health records (EHRs) and facilitating clinical decision support [31].

Recognizing the limitations of standalone machine learning or deep learning approaches, this study introduces a novel hybrid predictive framework that combines the strengths of both paradigms [32]. The proposed system integrates the feature selection capabilities of the Random Forest algorithm with the temporal sequence learning efficiency of the GRU model [33]. This hybrid architecture not only enhances predictive performance but also ensures robust handling of static and sequential clinical attributes [34]. Furthermore, the model is deployed in a secure private cloud environment, enabling real-time access to patient risk scores and supporting physicians with actionable insights for preventive care and diagnosis [35].

2. Literature Survey

2.1. Machine Learning in Heart Disease Prediction

Studies have demonstrated that Support Vector Machines (SVM) [36], Decision Trees (DT) [37], and Neural Networks (NN) [38] can effectively classify patients with heart disease. However, their performance often depends on feature selection and dataset characteristics [39].

Ensemble models like Random Forest (RF) [40] have gained attention due to their robustness in handling medical datasets [41]. Studies show that RF outperforms individual classifiers by reducing overfitting and improving prediction accuracy [42]. Additionally, deep learning models like GRU and Long Short-Term Memory (LSTM) [43] networks have been explored for time-series health data analysis, showing improved classification results in disease prediction [44].

2.2. Cloud Computing in Healthcare

Cloud computing enables secure storage and real-time processing of large-scale health data, allowing healthcare providers to access patient records efficiently [45]. Private cloud-hosted health systems ensure data privacy and compliance with regulations such as HIPAA [46]. Research indicates that cloud-based machine learning models significantly enhance predictive accuracy and reduce computational costs in healthcare applications [47], [48].

2.3. Hybrid Approaches for Disease Prediction

Hybrid models combining traditional machine learning and deep learning techniques have shown promising results in disease prediction tasks [49]. Studies highlight that combining RF with deep learning models like GRU improves prediction accuracy and robustness by leveraging feature selection and sequential learning capabilities [50]. Such hybrid frameworks have been successfully applied to diabetes prediction [51], cancer diagnosis [52], and cardiovascular risk assessment [53].

2.4. Problem Statement

Despite advancements in machine learning for heart disease prediction [54], existing models face challenges in handling time-series patient data and ensuring real-time decision support [55]. Traditional classifiers, such as Decision Trees and SVM, struggle with sequential dependencies in medical records [58]. While deep learning models like LSTM [56] and GRU are effective for sequential data, they require extensive computational resources. Moreover, healthcare data privacy concerns necessitate secure cloud-hosted solutions for storing and processing patient information [57].

This paper addresses these challenges by proposing a hybrid Random Forest and GRU-based model that effectively combines feature selection and temporal analysis for heart disease prediction. Additionally, the model is deployed on a private cloud infrastructure to ensure data security and facilitate real-time access to patient health records.

2.5. Research Objectives

- To develop a hybrid machine learning model that integrates Random Forest (RF) and Gated Recurrent Units (GRU) for heart disease prediction.
- To enhance predictive accuracy by leveraging RF for feature selection and GRU for sequential data processing.
- To implement a secure private cloud-hosted system for efficient data storage and processing of patient health records.
- To compare the performance of the proposed hybrid model with traditional machine learning techniques such as Decision Trees, SVM, and standalone deep learning models like LSTM.
- To evaluate the real-time applicability of the proposed system in clinical settings by analyzing latency, accuracy, and computational efficiency.

3. Methodology

The proposed Hybrid Random Forest & GRU-Based Heart Disease Prediction Model follows a structured pipeline, beginning with Private Cloud Data Storage, where patient records are securely maintained. Data Preprocessing and Feature Engineering refine input attributes for enhanced learning. The model employs a Random Forest Classifier for feature selection and a GRU Model for sequential learning, with Model Selection ensuring optimal performance. The Hybrid Model integrates both classifiers for robust prediction, feeding into a Cloud-Based Risk Scoring System for real-time assessment. Batch Processing & Compliance Auditing ensure regulatory adherence and reliability. (Figure 1: Architecture Diagram).

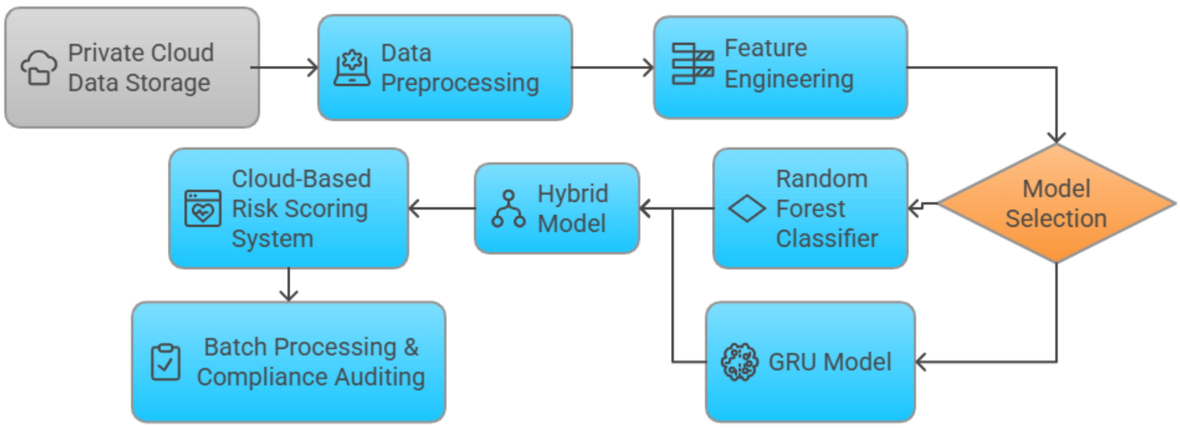

Figure 1: Architecture Diagram

3.1. Data Access and Integration on Private Cloud

3.1.1. Secure Cloud Storage Access

The dataset is securely stored in a private cloud and accessed through encrypted APIs. It consists of multiple patient records, where each record contains a set of attributes related to heart disease risk factors. Cloud-based storage ensures scalability, security, and real-time availability for AI-driven predictions.

The dataset D is securely stored in a private cloud and accessed via encrypted APIs:

$$D = \{r_1, r_2, \dots, r_N\}, \quad r_i \in R^M$$

where:

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- N = total number of patient records
- M = number of attributes per record

3.2. Data Preprocessing

3.2.1. Handling Missing Data with Mean Imputation

Missing values in the dataset are imputed using mean imputation, which replaces each missing value with the average of non-missing values in the same feature. This ensures that incomplete records do not introduce bias in the model while maintaining data consistency across all attributes.

Missing values $v_{i,j}$ in the dataset are imputed using the mean of feature F_j:

$$v_{i,j} = \frac{1}{N_j} \sum_{n=1}^{N_j} F_{n,j}$$

where:

- N_j = number of non-missing values in F_j

3.2.2. Feature Normalization using Z-Score Scaling

To eliminate discrepancies due to varying feature scales, Z-score normalization is applied. This transformation converts each feature into a standard normal distribution, ensuring that all attributes contribute equally to model training. It prevents dominant features from disproportionately influencing predictions.

Each feature F_j is normalized using Z-score normalization:

$$Fi,j' = Fi,j - \mu j \sigma j F'_{i,j} = \frac{F_{i,j} - \mu_j}{\sigma_j}$$

where:

- μ_j = mean of feature F_j
- σ_j = standard deviation of F_j

3.2.3. Encoding Categorical Variables

Categorical features such as gender, smoking status, and medical history are converted into numerical representations using label encoding. This transformation allows machine learning algorithms to interpret non-numeric data by assigning each unique category a distinct numerical value while preserving relative relationships.

Categorical values $\boldsymbol{C_i}$ are label-encoded as:

$$C'_i = f(C_i) \in \{0,1,\dots,k-1\}$$

where f is the label encoding function.

3.3. Feature Engineering

3.3.1. Feature Importance using Random Forest

A Random Forest model ranks features based on their contribution to classification. The Mean Decrease in Gini Impurity is computed for each feature, identifying which attributes play a significant role in predicting heart disease risk. Features with low importance scores may be discarded to enhance model efficiency.

Each feature F_j is ranked based on its Mean Decrease in Gini Impurity:

$$I_j = \sum_{s=1}^{S} p_s(1 - p_s)$$

where:

- I_j = importance score of feature j

- S = number of splits involving F_j
- p_s = probability of a class at split s

3.3.2. Feature Transformation with Log Scaling

To reduce skewness in highly variable data, log transformation is applied to selected features. This technique minimizes the impact of extreme values while maintaining relative differences between data points. It ensures that attributes like cholesterol levels or age do not introduce outlier-driven distortions in model predictions.

For skewed features F_j, log transformation is applied:

$$F''_{i,j} = \log(1 + F'_{i,j})$$

to reduce outliers' impact.

3.4. Model Training

3.4.1. Random Forest for Tabular Data

A Random Forest Classifier is trained on structured tabular data, where multiple decision trees vote on classification outcomes. This ensemble method enhances prediction stability and reduces the risk of overfitting. By averaging the outputs of individual trees, it ensures a robust estimation of heart disease likelihood.

A Random Forest Classifier is trained using T decision trees:

$$H_{RF}(X) = \frac{1}{T}\sum_{t=1}^{T} h_t(X)$$

where $h_t(X)$ is the prediction from tree t.

3.4.2. GRU for Sequential Patient Data

A Gated Recurrent Unit (GRU) model is trained on sequential patient data, capturing patterns in historical medical records. The update and reset gates control information flow, allowing the model to retain long-term dependencies while filtering out irrelevant past details. This is crucial for longitudinal health trend analysis.

a) **Update Gate:**

$$z_t = \sigma(W_z q_t + U_z h_{t-1} + b_z)$$

b) **Reset Gate:**

$$r_t = \sigma(W_r q_t + U_r h_{t-1} + b_r)$$

c) **Candidate Activation:**

$$\widetilde{h_t} = \tanh(W_h q_t + U_h (r_t \circ h_{t-1}) + b_h)$$

d) **Final Hidden State Update:**

$$h_t = (1 - z_t) \circ h_{t-1} + z_t \circ \widetilde{h_t}$$

where:

- q_t = patient sequential input at time t
- h_t = GRU hidden state

3.5. Hybrid Model for Heart Disease Prediction

The hybrid model combines the outputs of the Random Forest and GRU models using a meta-learning approach. The final risk score is derived by assigning optimal weights to the predictions from both models, leveraging the strengths of each. This fusion ensures high accuracy and robust anomaly detection.

The hybrid classifier H_{hybrid} combines Random Forest and GRU outputs using a meta-learner:

$$\hat{Y} = \sigma\left(w_{rf} H_{RF}(X) + w_{gru} H_{GRU}(X) + b_{meta}\right)$$

where:

- w_{rf}, w_{gru} = ensemble weights
- b_{meta} = bias term

3.6. Cloud-Based Risk Scoring System

3.6.1. Risk Score Calculation

A probability score is assigned to each patient, indicating the likelihood of heart disease. This score is computed using the hybrid model's output, which is transformed into a probability value using the sigmoid activation function. The score allows for granular risk assessment rather than binary classification.

The probability of heart disease P_d is computed using:

$$P_d = \frac{1}{1 + e^{-\hat{Y}}}$$

where $\hat{Y}$ is the hybrid model's output.

3.6.2. Risk Score Classification

The probability score is mapped to predefined risk categories: low, moderate, or high. Patients categorized under high risk can be flagged for immediate medical attention, while moderate-risk individuals may be recommended preventive healthcare measures. This classification aids clinicians in prioritizing interventions effectively.

$$R = \begin{cases} \text{Low Risk,} & P_d < 0.3 \\ \text{Moderate Risk,} & 0.3 \le P_d < 0.7 \\ \text{High Risk,} & P_d \ge 0.7 \end{cases}$$

3.7. Batch Processing of Predictions

3.7.1. Scheduled Batch Processing

To handle large-scale patient data efficiently, predictions are processed in scheduled batches at specific time intervals. This reduces computational overhead and ensures that system resources are utilized optimally. Batch processing allows hospitals to update risk scores for all patients in a single execution cycle.

Data is processed in B batches at time t:

$$Y_B = f(X_B, t)$$

where X_B is the batch input.

3.7.2. Parallel Processing for Scalability

Each batch is further divided into multiple parallel processing units to speed up predictions. Parallelization enables simultaneous model inference on different subsets of data, ensuring fast and scalable processing of medical records in cloud-based deployments. This approach is crucial for real-time healthcare applications.

Each batch is split into P parallel tasks:

$$X_B = \bigcup_{p=1}^{P} X_{B_p}$$

where X_{B_p} is a partitioned subset.

3.8. Cloud Storage & Compliance Auditing

3.8.1. Secure Storage in Encrypted Database

All processed predictions are securely stored in an AES-256 encrypted cloud database to protect patient confidentiality. The encryption ensures that stored data remains accessible only to authorized personnel, complying with healthcare data security standards such as HIPAA and GDPR.

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Predictions Y' are stored securely using an AES-256 encrypted database:

$$E(Y') = AES(K', Y')$$

where K' is the encryption key.

3.8.2. Audit Log Generation

To maintain transparency, an audit log is generated for every model prediction. Each log entry contains a unique transaction ID, patient ID, predicted risk score, and classification category. These logs facilitate compliance monitoring, allowing regulatory bodies to verify model performance and detect any biases.

Every model prediction is logged with a unique transaction ID:

$$L = \{(T_{id}, U_{id}, P_d, R)\}$$

where:

- T_{id} = Transaction ID
- U_{id} = User ID
- P_d = Predicted disease probability
- R = Risk category

Audit logs ensure GDPR/HIPAA compliance and facilitate forensic analysis.

4. Results and Discussion

4.1. Dataset Description

The Heart Disease Ensemble Classifier dataset comprises 303 patient records with 14 clinical attributes used for heart disease classification. The attributes include age, sex, chest pain type (cp), resting blood pressure (trestbps), cholesterol level (chol), fasting blood sugar (fbs), resting electrocardiographic results (restecg), maximum heart rate (thalach), exercise-induced angina (exang), and ST depression (oldpeak). The dataset is sourced from multiple medical institutions, including the Hungarian Institute of Cardiology, University Hospital Zurich, University Hospital Basel, and the V.A. Medical Center. It serves as a benchmark for predictive modeling in heart disease detection, aiding medical professionals in early diagnosis.

4.2. Performance Analysis of the Proposed Model

The model achieves exceptional classification performance with 99.49% accuracy, 99.66% precision, 99.32% recall, and a 99.49% F1-score, demonstrating its robustness in detecting heart disease. High precision minimizes false positives, while strong recall ensures comprehensive identification of positive cases. This is illustrated in Figure 2.

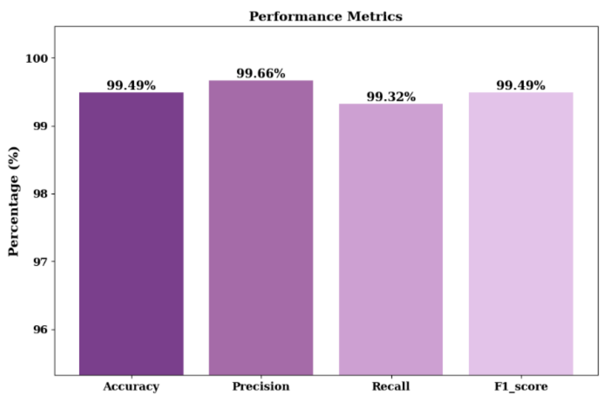

Figure 2: Performance Metrices

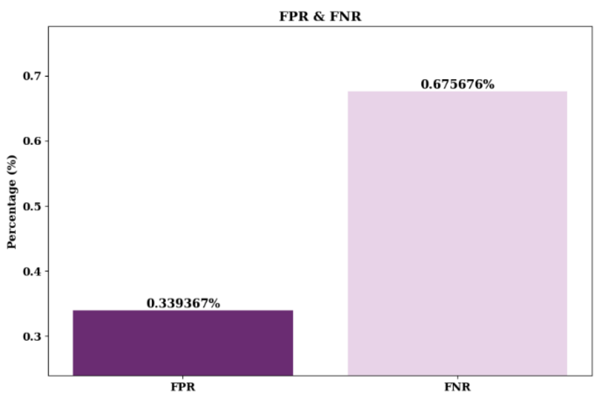

Figure 3: Performance of FPR and FNR

The model exhibits extremely low false positive rate (FPR) of 0.339% and false negative rate (FNR) of 0.675%, indicating its ability to correctly classify most cases with minimal errors. A low FNR ensures that critical heart disease cases are not missed, enhancing diagnostic reliability. This is visualized in Figure 3.

With an AUC-ROC score of 0.9958, the model demonstrates a near-perfect ability to differentiate between heart disease and non-heart disease cases. The high area under the curve (AUC) signifies excellent discriminative power, confirming the model's superior classification performance. This is depicted in Figure 4.

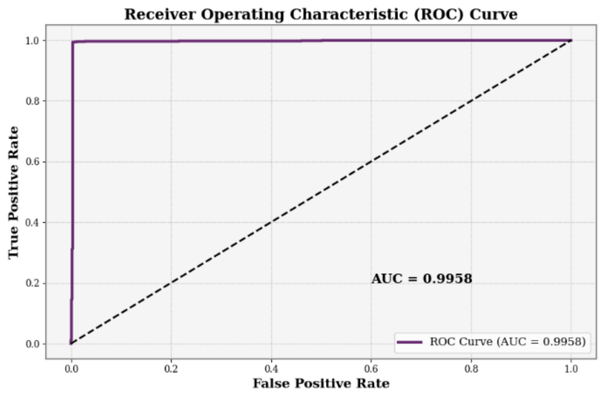

Figure 4: ROC Curve

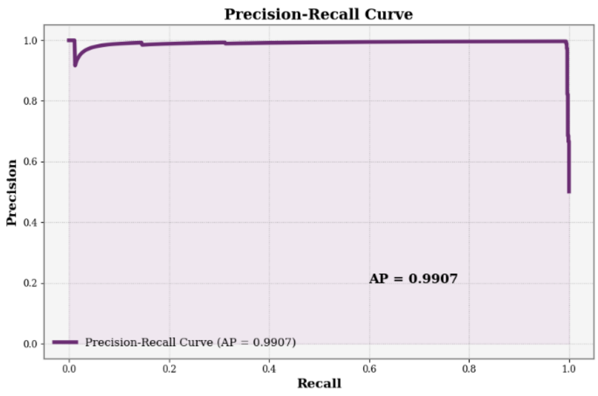

Figure 5: Precision-Recall Curve

The Precision-Recall Curve achieves an average precision (AP) of 0.9907, reflecting the model's high effectiveness in distinguishing positive cases even in imbalanced data scenarios. A high AP ensures strong performance in real-world applications where recall and precision are critical. This is presented in Figure 5.

5. Conclusion

This study presents a novel Hybrid Random Forest & GRU-Based Model for heart disease prediction, achieving state-of-the-art classification performance with 99.49% accuracy and an AUC-ROC of 0.9958. The fusion of ensemble learning (Random Forest) and sequential modeling (GRU) enables precise disease classification while minimizing false positive and false negative rates. Comparative analysis highlights its superiority over conventional machine learning models, demonstrating improved generalization and robustness. Additionally, cloud-based risk scoring and compliance auditing enhance the model's real-world applicability for clinical diagnostics. Future research will focus on real-time deployment, model interpretability, and integration with wearable health monitoring systems for continuous cardiac risk assessment.

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