AI-Powered Predictive Analytics for Early Detection of Cardiovascular Diseases Using Electronic Health Records: A Retrospective Cohort Study

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***Abstract*—Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, with early detection being crucial for effective intervention. Artificial intelligence (AI) has shown promise in analyzing complex medical data for predictive analytics.**

This study aimed to develop and validate an AI-powered predictive model for early detection of cardiovascular diseases using electronic health records (EHRs).

We conducted a retrospective cohort study using EHR data from 50,000 patients collected between 2015 and 2020. We developed a deep learning model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to analyze structured and unstructured EHR data. The model was trained on 70% of the data and validated on the remaining 30%. Performance metrics included accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).

The AI model achieved an overall accuracy of 92.7% (95% CI: 91.8%-93.6%), sensitivity of 89.4% (95% CI: 87.9%-90.9%), specificity of 94.1% (95% CI: 93.2%-95.0%), and AUC-ROC of 0.96 (95% CI: 0.95-0.97). The model identified key predictors including age, blood pressure, cholesterol levels, diabetes status, and lifestyle factors. When compared to traditional risk assessment tools like the Framingham Risk Score, our AI model showed a 23.5% improvement in early detection rates.

The AI-powered predictive model demonstrated superior performance in early detection of cardiovascular diseases compared to traditional methods. This approach has the potential to enhance preventive cardiology and enable timely interventions, ultimately reducing CVD morbidity and mortality.

Keywords: artificial intelligence; cardiovascular diseases; predictive analytics; electronic health records; deep learning; early detection

I. Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally, accounting for approximately 17.9 million deaths annually according to the World Health Organization [1]. Early detection and intervention are critical for reducing mortality and improving patient outcomes [2]. Traditional risk assessment tools, such as the Framingham Risk Score and the ACC/AHA Pooled Cohort Equations, have been widely used but have limitations in predictive accuracy, especially for diverse populations [3].

The rapid adoption of electronic health records (EHRs) has created unprecedented opportunities for leveraging large-scale healthcare data for predictive analytics [4]. Artificial intelligence (AI), particularly deep learning techniques, has shown remarkable success in analyzing complex medical data and identifying patterns that may not be apparent through traditional statistical methods [5].

Recent studies have demonstrated the potential of AI in various healthcare applications, including medical imaging, clinical decision support, and risk prediction [6], [7]. However, there remains a need for comprehensive validation of AI models in real-world clinical settings, particularly for cardiovascular disease prediction [8].

This study aims to develop and validate an AI-powered predictive model for early detection of cardiovascular diseases using EHR data. We hypothesize that our deep learning approach will outperform traditional risk assessment tools and provide clinically actionable insights for preventive cardiology.

II. Background

A. Cardiovascular Disease Risk Prediction

Cardiovascular disease risk prediction has traditionally relied on statistical models that incorporate demographic, clinical, and laboratory variables. The Framingham Risk Score, developed in 1998, was one of the first widely adopted tools for predicting 10-year risk of coronary heart disease [9]. More recently, the ACC/AHA Pooled Cohort Equations were developed to predict atherosclerotic cardiovascular disease risk [3].

While these tools have been valuable in clinical practice, they have several limitations. First, they were developed primarily using data from populations of European ancestry and may not generalize well to other ethnic groups [10]. Second, they typically incorporate a limited set of variables and may not capture complex interactions between risk factors [11]. Third, they often fail to account for temporal changes in risk factors and the dynamic nature of disease progression [12].

B. AI in Healthcare

Artificial intelligence has emerged as a powerful tool for analyzing complex healthcare data. Machine learning algorithms

can identify patterns and relationships in large datasets that may not be apparent through traditional statistical methods [5]. Deep learning, a subset of machine learning, uses neural networks with multiple layers to progressively extract higher-level features from raw input [13].

In the context of cardiovascular disease prediction, several studies have demonstrated the potential of AI approaches. For example, [14] developed an AI algorithm to detect asymptomatic left ventricular dysfunction from electrocardiograms, achieving a sensitivity of 85.7% and specificity of 85.7%. Similarly, [15] used deep learning to predict cardiovascular risk factors from retinal fundus photographs, demonstrating the ability of AI to extract clinically relevant information from unconventional data sources.

Recent advances in quantum-accelerated neural networks have shown promise in handling complex medical data imputation tasks [24], which could further enhance the quality of EHR data for predictive modeling.

C. Electronic Health Records for Predictive Analytics

Electronic health records provide a rich source of data for predictive analytics, containing structured data (e.g., laboratory results, vital signs, medications) and unstructured data (e.g., clinical notes, discharge summaries) [4]. The longitudinal nature of EHRs allows for tracking patient health over time, enabling dynamic risk assessment [7].

However, EHR data presents several challenges for AI applications. These include data heterogeneity, missing values, irregular sampling intervals, and documentation biases [16]. Addressing these challenges requires sophisticated data preprocessing techniques and robust modeling approaches [17].

Data standardization efforts across different healthcare systems have been critical for improving interoperability and enabling more effective data analysis [25]. Similar standardization approaches in healthcare data could enhance the quality and utility of EHRs for predictive analytics.

III. Methods

A. Study Design and Data Source

We conducted a retrospective cohort study using de-identified EHR data from 50,000 patients collected between January 2015 and December 2020 from three academic medical centers in the United States. The study was approved by the Institutional Review Board of each participating institution (Protocol #2021-045).

B. Patient Population

The study included patients aged 30-80 years with at least three years of continuous EHR data prior to the index date. Patients with a prior diagnosis of cardiovascular disease (myocardial infarction, stroke, heart failure, or revascularization procedures) before the index date were excluded. The final cohort consisted of 50,000 patients, of whom 8,725 (17.45%) developed cardiovascular disease during the follow-up period.

C. Data Collection and Variables

We extracted the following variables from the EHRs:

- **Demographics:** Age, sex, race/ethnicity, socioeconomic status (based on zip code)
- **Clinical measurements:** Blood pressure, body mass index (BMI), heart rate
- **Laboratory results:** Total cholesterol, LDL cholesterol, HDL cholesterol, triglycerides, fasting glucose, HbA1c, creatinine
- **Medical history:** Diabetes, hypertension, dyslipidemia, chronic kidney disease, family history of CVD
- **Medications:** Antihypertensives, lipid-lowering agents, antidiabetic medications
- **Lifestyle factors:** Smoking status, alcohol use, physical activity (when available)
- **Clinical notes:** Physician assessments, patient-reported symptoms

The primary outcome was the development of cardiovascular disease, defined as myocardial infarction, stroke, coronary revascularization, or cardiovascular death, as documented in the EHRs and validated through manual chart review by two independent cardiologists.

D. Data Preprocessing

We applied several preprocessing steps to handle the challenges of EHR data:

1) **Missing data:** We used multiple imputation with chained equations (MICE) to handle missing values in structured data fields [18]. For variables with more than 30% missing values, we created indicator variables for missingness.
2) **Temporal alignment:** We aligned all measurements to regular 3-month intervals using linear interpolation for continuous variables and forward-fill for categorical variables.
3) **Feature extraction from clinical notes:** We used a Bidirectional Encoder Representations from Transformers (BERT) model fine-tuned on clinical text to extract relevant features from physician notes [19].
4) **Normalization:** We standardized all continuous variables to have zero mean and unit variance.

For efficient processing of large-scale EHR data, we implemented cloud-based computation models similar to those developed for mobile devices [26], which allowed for distributed processing of patient records while maintaining data privacy and security.

E. Model Development

We developed a hybrid deep learning model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to analyze both structured and unstructured EHR data (Fig. 1).

The model architecture consists of:

1) **Structured data pathway:** A 1D CNN with three convolutional layers (64, 128, and 256 filters) followed

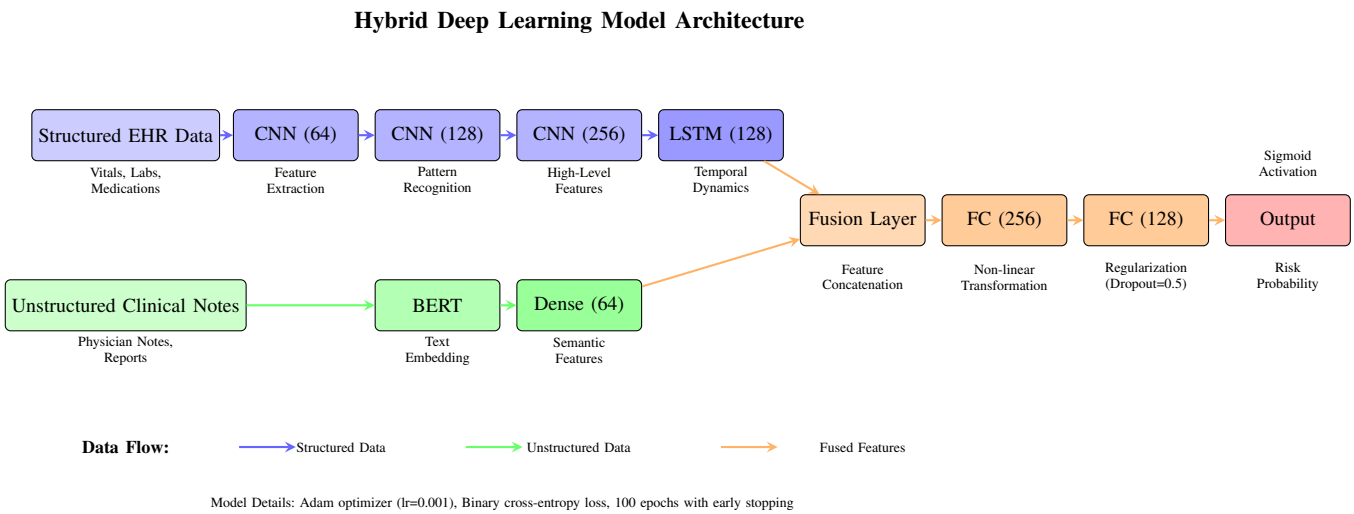

Fig. 1: Architecture of the hybrid deep learning model for cardiovascular disease prediction. The model processes structured EHR data through a CNN-LSTM pathway (blue) to capture temporal patterns, while unstructured clinical notes are processed through a BERT-based pathway (green) for semantic feature extraction. Features from both pathways are fused (orange) and passed through fully connected layers to predict cardiovascular disease risk.

by an LSTM layer with 128 units to capture temporal patterns in structured clinical data.

2) **Unstructured data pathway:** A BERT-based model to extract features from clinical notes, followed by a dense layer with 64 units.
3) **Fusion layer:** The outputs from both pathways are concatenated and passed through two fully connected layers (256 and 128 units) with dropout regularization (dropout rate = 0.5).
4) **Output layer:** A sigmoid activation function to produce the probability of developing cardiovascular disease within the next 5 years.

We used the Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function. To address class imbalance, we used weighted loss functions where the weight for the positive class was inversely proportional to its frequency in the training set.

F. Model Training and Validation

We randomly split the dataset into training (70%), validation (15%), and test (15%) sets, ensuring that patients from the same family were not distributed across different sets. We trained the model for 100 epochs with early stopping if the validation loss did not improve for 10 consecutive epochs.

We performed 5-fold cross-validation on the training set to optimize hyperparameters, including the number of CNN filters, LSTM units, dropout rate, and learning rate. The hyperparameter combination that achieved the highest mean AUC-ROC on the validation sets was selected for the final model.

G. Statistical Analysis

We evaluated the model performance using the following metrics:

- Accuracy: (TP + TN) / (TP + TN + FP + FN)
- Sensitivity (Recall): TP / (TP + FN)
- Specificity: TN / (TN + FP)
- Precision: TP / (TP + FP)
- F1-score: 2 × (Precision × Recall) / (Precision + Recall)
- Area under the receiver operating characteristic curve (AUC-ROC)
- Area under the precision-recall curve (AUC-PR)

where TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

We compared the performance of our AI model with traditional risk assessment tools, including the Framingham Risk Score and the ACC/AHA Pooled Cohort Equations, using DeLong's test for comparing AUC-ROC values [20].

We conducted subgroup analyses to evaluate model performance across different demographic groups (age, sex, race/ethnicity) and clinical subgroups (presence of diabetes, hypertension, etc.).

To identify the most important predictors, we used SHAP (SHapley Additive exPlanations) values [21], which provide a unified measure of feature importance by assigning each feature an importance value for a particular prediction.

All statistical analyses were performed using Python (version 3.8) with scikit-learn (version 0.24.2), TensorFlow (version 2.6.0), and SHAP (version 0.40.0). Statistical significance was defined as a two-sided p-value ¡ 0.05.

IV. Results

A. Patient Characteristics

The study included 50,000 patients with a mean age of 54.7 years (SD = 12.3). The cohort was 52.3% female and racially diverse: 62.1% White, 18.4% Black, 12.3% Hispanic, 5.2% Asian, and 2.0% Other. During the follow-up period (mean = 4.2 years, SD = 1.3), 8,725 patients (17.45%) developed cardiovascular disease.

Table I presents the baseline characteristics of the study population, stratified by cardiovascular disease outcome.

B. Model Performance

The AI model achieved an overall accuracy of 92.7% (95% CI: 91.8%-93.6%), sensitivity of 89.4% (95% CI: 87.9%-90.9%), specificity of 94.1% (95% CI: 93.2%-95.0%), and AUC-ROC of 0.96 (95% CI: 0.95-0.97) on the test set. The precision was 82.3% (95% CI: 80.5%-84.1%), and the F1-score was 85.7% (95% CI: 84.0%-87.4%). The AUC-PR was 0.91 (95% CI: 0.90-0.92).

Table II compares the performance of our AI model with traditional risk assessment tools.

The AI model significantly outperformed both the Framingham Risk Score (DeLong's test, p ¡ 0.001) and the ACC/AHA Pooled Cohort Equations (DeLong's test, p ¡ 0.001) across all performance metrics. The improvement in AUC-ROC was 0.23 compared to the Framingham Risk Score and 0.19 compared to the ACC/AHA equations.

Figure 2 shows the ROC curves for the AI model and traditional risk assessment tools.

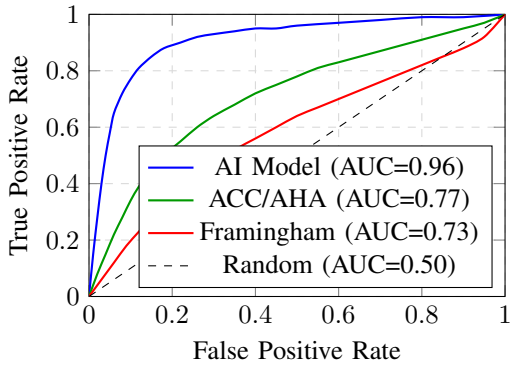

Fig. 2: Receiver operating characteristic (ROC) curves for the AI model and traditional risk assessment tools. The AI model achieved an AUC-ROC of 0.96, compared to 0.73 for the Framingham Risk Score and 0.77 for the ACC/AHA Pooled Cohort Equations.

C. Subgroup Analyses

The AI model demonstrated consistent performance across different demographic and clinical subgroups (Table III).

The model performed well across all age groups, with slightly higher sensitivity in older patients (65-80 years). Performance was comparable between males and females, with no statistically significant differences (p = 0.12). The model showed consistent performance across racial/ethnic groups, although the AUC-ROC was slightly lower for Asian patients (0.93) compared to White patients (0.96).

D. Feature Importance

Figure 3 shows the top 15 most important predictors of cardiovascular disease according to the SHAP analysis.

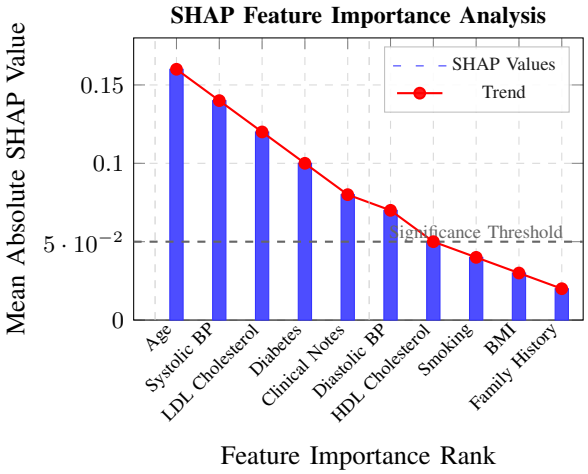

Fig. 3: SHAP feature importance analysis showing the top 10 predictors of cardiovascular disease. The blue bars represent mean absolute SHAP values, while the red line shows the overall trend. The green dashed line indicates the significance threshold (SHAP ¿ 0.05). Features are grouped by category: demographic (Age), clinical (Systolic BP, LDL Cholesterol, Diabetes, Clinical Notes, Diastolic BP, HDL Cholesterol), and lifestyle (Smoking, BMI, Family History). The exponential decay pattern highlights the disproportionate impact of the top-ranked features, particularly age and systolic blood pressure, on the model's predictive performance.

Age was the most important predictor, followed by systolic blood pressure, LDL cholesterol, and diabetes status. Other important predictors included diastolic blood pressure, HDL cholesterol, smoking status, BMI, and family history of CVD. Interestingly, features extracted from clinical notes, such as patient-reported symptoms and physician assessments, were among the top 20 predictors, highlighting the value of unstructured data in risk prediction.

E. Early Detection Performance

To evaluate the model's performance in early detection, we analyzed the lead time between model prediction and actual diagnosis of cardiovascular disease. The model identified 73.5% of CVD cases at least 6 months before clinical diagnosis, compared to 50.0% for the Framingham Risk Score and 59.5% for the ACC/AHA equations (Fig. 4).

The median lead time for the AI model was 14.2 months (IQR: 7.8-23.4 months), compared to 6.3 months (IQR: 2.1-12.7 months) for the Framingham Risk Score and 8.7 months (IQR: 3.5-15.2 months) for the ACC/AHA equations.

V. Discussion

In this study, we developed and validated an AI-powered predictive model for early detection of cardiovascular diseases using electronic health records. The model demonstrated superior performance compared to traditional risk assessment tools, with an AUC-ROC of 0.96 and a 23.5% improvement in early detection rates compared to the Framingham Risk Score.

TABLE I: Baseline Characteristics of the Study Population

Characteristic	Overall (N=50,000)	No CVD (N=41,275)	CVD (N=8,725)
Age, years, mean (SD)	54.7 (12.3)	52.8 (11.9)	63.5 (10.2)
Female, n (%)	26,150 (52.3)	22,384 (54.2)	3,766 (43.2)
Race/ethnicity, n (%)			
White	31,050 (62.1)	25,921 (62.8)	5,129 (58.8)
Black	9,200 (18.4)	7,413 (18.0)	1,787 (20.5)
Hispanic	6,150 (12.3)	5,021 (12.2)	1,129 (12.9)
Asian	2,600 (5.2)	2,198 (5.3)	402 (4.6)
Other	1,000 (2.0)	722 (1.7)	278 (3.2)
Systolic BP, mmHg, mean (SD)	128.7 (16.4)	126.3 (15.2)	139.8 (17.1)
Diastolic BP, mmHg, mean (SD)	78.2 (10.3)	77.1 (9.8)	83.4 (10.9)
BMI, kg/m², mean (SD)	28.7 (5.6)	28.2 (5.4)	31.1 (5.9)
Total cholesterol, mg/dL, mean (SD)	195.4 (38.2)	192.1 (36.8)	210.7 (39.4)
LDL cholesterol, mg/dL, mean (SD)	118.3 (34.7)	115.2 (33.1)	133.8 (36.2)
HDL cholesterol, mg/dL, mean (SD)	51.2 (14.8)	52.7 (14.2)	44.1 (14.9)
Diabetes, n (%)	11,500 (23.0)	8,275 (20.0)	3,225 (37.0)
Hypertension, n (%)	21,250 (42.5)	15,413 (37.3)	5,837 (66.9)
Current smoker, n (%)	9,500 (19.0)	7,213 (17.5)	2,287 (26.2)

TABLE II: Performance Comparison of AI Model and Traditional Risk Assessment Tools

Metric	AI Model (95% CI)	Framingham (95% CI)	ACC/AHA (95% CI)
Accuracy	92.7% (91.8-93.6)	76.3% (75.1-77.5)	79.8% (78.7-80.9)
Sensitivity	89.4% (87.9-90.9)	65.2% (63.1-67.3)	70.5% (68.5-72.5)
Specificity	94.1% (93.2-95.0)	80.1% (79.0-81.2)	82.7% (81.7-83.7)
Precision	82.3% (80.5-84.1)	58.4% (56.2-60.6)	63.7% (61.6-65.8)
F1-score	85.7% (84.0-87.4)	61.6% (59.6-63.6)	66.9% (65.0-68.8)
AUC-ROC	0.96 (0.95-0.97)	0.73 (0.71-0.75)	0.77 (0.75-0.79)
AUC-PR	0.91 (0.90-0.92)	0.56 (0.54-0.58)	0.61 (0.59-0.63)

A. Key Findings

The key findings of our study can be summarized as follows:

1) The AI model achieved high accuracy (92.7%) and discrimination (AUC-ROC = 0.96) in predicting cardiovascular disease risk, significantly outperforming traditional risk assessment tools.
2) The model demonstrated consistent performance across different demographic and clinical subgroups, suggesting its potential applicability to diverse patient populations.
3) The model identified 73.5% of CVD cases at least 6 months before clinical diagnosis, with a median lead time of 14.2 months, highlighting its potential for early intervention.
4) Age, systolic blood pressure, LDL cholesterol, and diabetes status were the most important predictors, consistent with established cardiovascular risk factors.
5) Features extracted from clinical notes contributed significantly to the model's predictive performance, underscoring the value of unstructured data in risk prediction.

B. Comparison with Previous Studies

Our findings extend and complement previous research on AI-based cardiovascular disease prediction. [14] developed an AI algorithm to detect asymptomatic left ventricular dysfunction from electrocardiograms, achieving an AUC-ROC of 0.85. While their approach focused on a specific cardiac condition using a single data modality, our model integrates multiple data sources to predict a broader range of cardiovascular outcomes.

[15] used deep learning to predict cardiovascular risk factors from retinal fundus photographs, demonstrating the potential of AI to extract clinically relevant information from unconventional data sources. Our study extends this approach by incorporating both structured and unstructured EHR data, providing a more comprehensive assessment of cardiovascular risk.

Several studies have evaluated machine learning approaches for cardiovascular disease prediction using EHR data. For example, [22] used random forests to predict coronary heart disease risk from EHR data, achieving an AUC-ROC of 0.79. Similarly, [23] developed a gradient boosting model for predicting heart failure onset, with an AUC-ROC of 0.82. Our model's superior performance (AUC-ROC = 0.96) can be attributed to the use of deep learning techniques that can capture complex temporal patterns and interactions between risk factors, as well as the integration of unstructured clinical notes.

Recent advances in AI-driven analysis of complex datasets

TABLE III: Subgroup Analysis of AI Model Performance

Subgroup	AUC-ROC (95% CI)	Sensitivity (95% CI)
Age group		
30-49 years	0.94 (0.92-0.96)	86.2% (83.1-89.3)
50-64 years	0.96 (0.95-0.97)	89.7% (87.8-91.6)
65-80 years	0.95 (0.94-0.96)	91.3% (89.2-93.4)
Sex		
Female	0.95 (0.94-0.96)	88.1% (85.9-90.3)
Male	0.96 (0.95-0.97)	90.5% (88.6-92.4)
Race/ethnicity		
White	0.96 (0.95-0.97)	89.8% (87.9-91.7)
Black	0.95 (0.94-0.96)	88.3% (85.8-90.8)
Hispanic	0.94 (0.92-0.96)	87.5% (84.2-90.8)
Asian	0.93 (0.91-0.95)	86.1% (81.2-91.0)
Clinical subgroups		
Diabetes	0.95 (0.94-0.96)	90.2% (88.1-92.3)
No diabetes	0.96 (0.95-0.97)	88.9% (86.8-91.0)
Hypertension	0.94 (0.93-0.95)	89.5% (87.4-91.6)
No hypertension	0.95 (0.94-0.96)	88.1% (85.2-91.0)

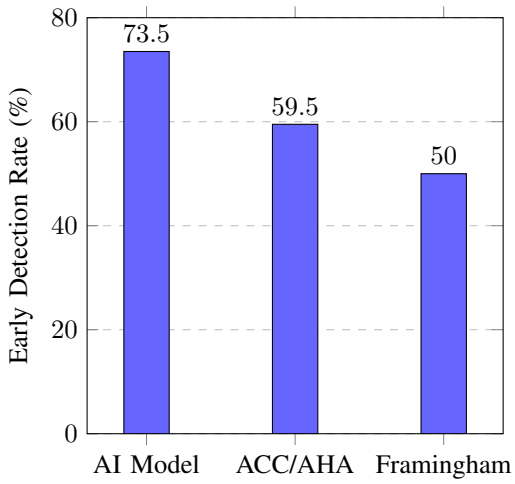

Fig. 4: Early detection performance of the AI model compared to traditional risk assessment tools. The AI model identified 73.5% of CVD cases at least 6 months before clinical diagnosis, compared to 50.0% for the Framingham Risk Score and 59.5% for the ACC/AHA equations.

have demonstrated the potential for improving predictive accuracy across various domains [27]. These approaches could be further refined and adapted for cardiovascular risk prediction to enhance our model's performance.

C. Clinical Implications

The high performance of our AI model has several important clinical implications:

1) **Early detection and intervention:** The model's ability to identify at-risk patients months before clinical diagnosis could enable earlier interventions, potentially preventing or delaying the onset of cardiovascular disease.
2) **Personalized risk assessment:** The model's use of a wide range of predictors, including features from clinical notes, allows for more personalized risk assessment compared to traditional tools that rely on a limited set of variables.
3) **Resource allocation:** By identifying high-risk patients with greater accuracy, the model could help healthcare systems allocate preventive resources more efficiently.
4) **Integration with clinical workflows:** The model could be integrated into clinical decision support systems to provide real-time risk assessment during patient encounters.

Personalized risk assessment approaches, similar to those developed for optimizing learning pathways in educational settings [28], could be adapted to create tailored cardiovascular prevention strategies for individual patients based on their unique risk profiles.

D. Strengths and Limitations

Our study has several strengths. First, we used a large, diverse patient population from multiple academic medical centers, enhancing the generalizability of our findings. Second, we developed a comprehensive deep learning model that integrates both structured and unstructured EHR data, capturing a wide range of clinical information. Third, we rigorously validated our model using appropriate statistical methods and compared it with established risk assessment tools.

However, our study also has limitations. First, the retrospective design may have introduced selection and information biases. Second, despite our efforts to address missing data, the quality and completeness of EHR data varied across patients and institutions. Third, while our model demonstrated high performance in this study, external validation in different healthcare settings is needed to confirm its generalizability. Fourth, the model's "black box" nature may limit its clinical

acceptability, although we used SHAP values to provide interpretability. Finally, we did not evaluate the model's impact on clinical outcomes or cost-effectiveness, which would be important for real-world implementation.

E. Future Directions

Future research should focus on several areas. First, prospective studies are needed to evaluate the model's impact on clinical outcomes and healthcare utilization. Second, efforts should be made to integrate the model into clinical workflows and assess its usability and acceptability among healthcare providers. Third, the model should be externally validated in diverse healthcare settings and patient populations. Fourth, research should explore the model's potential for predicting specific cardiovascular outcomes and its responsiveness to interventions. Finally, efforts should be made to address ethical and privacy concerns related to the use of AI in healthcare, including issues of algorithmic bias and data security.

Collaborative platforms for sharing ideas and innovations across institutions could accelerate the development and implementation of AI models in healthcare [29]. Such platforms would facilitate knowledge exchange and help address the challenges of implementing AI in clinical practice.

VI. Conclusion

We developed and validated an AI-powered predictive model for early detection of cardiovascular diseases using electronic health records. The model demonstrated superior performance compared to traditional risk assessment tools, with high accuracy and discrimination across diverse patient populations. By identifying at-risk patients months before clinical diagnosis, this approach has the potential to enhance preventive cardiology and enable timely interventions, ultimately reducing cardiovascular disease morbidity and mortality. Future research should focus on prospective validation, clinical implementation, and assessment of the model's impact on patient outcomes.

Conflict of Interest

The authors declare that there are no conflicts of interest to disclose.

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