Attention-Based Explainable AI Framework for Real-Time Cardiovascular Risk Prediction Using Wearable Sensor and Multimodal Healthcare Data

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Abstract

Among other illnesses, cardiovascular diseases have been listed among the top causes of death globally. Therefore, an intelligent and explainable healthcare system can play an integral role in predicting cardiovascular diseases and continuously analyzing patients' conditions. In this context, this research work provides a solution for the classification of patients into Low Risk, Moderate Risk, and High Risk of developing cardiovascular diseases based on the real-time cardiovascular disease prediction model incorporating BiLSTM, attention mechanism, and SHAP-based XAI. In this regard, the proposed model is designed to use multi-modal health care data such as electrocardiography (ECG)-related health care parameters, blood pressure, cholesterol, heart rate, and angina triggered by physical activity. Preprocessing of healthcare data was initially done through removing missing values from the dataset and normalization of the healthcare features using the min-max technique. Extraction of sequential healthcare patterns and assigning more relevance to clinically important cardiovascular features is done by BiLSTM networks and attention mechanism, respectively. The preliminary experiment performed on a clinical cardiovascular dataset, which consisted of 303 patient samples and 14 healthcare features, indicated that the designed BiLSTM-Attention architecture obtained 100% and 41.67% accuracy scores during training and testing phases, respectively. In order to increase the accuracy and avoid overfitting, an increased cardiovascular dataset composed of around 70,000 patient samples are employed for further experimentation. As a result, the modified algorithm showed great success in improving predictive ability and produced a score of about 89.77% accuracy. The SHAP analysis suggested that chest pain type, cholesterol, heart rate, and angina induced by physical exercise were key cardiovascular risk factors affecting the output of the prediction model.

Keywords: Cardiovascular, Heart disease, Artificial intelligence, Explainable deep learning

Introduction

Cardiovascular diseases (CVDs) rank among the leading causes of mortality around the world and still remain a considerable burden on the health system. As stated by WHO, millions of people die every year because of diseases related to heart issues such as coronary artery disease, arrhythmia, heart failure, and problems associated with hypertension [1]. Prompt detection and constant monitoring of cardiovascular disorders become critical factors in decreasing death rates and saving lives of patients [2]. Current approaches to diagnosing cardiovascular diseases mostly rely on clinical, laboratory results, and static evaluations of the state of a patient's health [3].

Modern developments in wearable health technologies and artificial intelligence have made it possible to obtain real-time data related to the physiology of an individual for intelligent health monitoring [4]. Some of the wearable devices that can help capture real-time data related to an individual's physiology include smart watches, ECG monitors, pulse oximeters, and fitness trackers [5]. Wearable technology allows for the acquisition of sequential healthcare data, which can be used through machine learning and deep learning algorithms to predict health conditions, specifically cardiovascular analytics. Integrating wearable sensor data with clinical data creates a multimodal healthcare setting.

The application of deep learning algorithms in healthcare systems has been successful since they have the advantage of automatically extracting complex patterns from the health data [6]. Recurrent neural networks (RNNs) and LSTM models are commonly employed in the analysis of health-related data owing to their capacity for capturing sequential patterns [7]. On the other hand, traditional LSTMs only analyze information in one direction, and hence some contextual relationships that may exist within both past and future sequences of data are not always captured [8]. BiLSTM networks, on the other hand, analyze sequences of data in both directions.

While deep learning-driven cardiovascular predictors provide good results, current models tend to lack interpretability and thus cannot be used extensively within the clinical setting [9]. The healthcare practitioner often requires an explanation as to why a specific prediction was made before trusting the system [10]. Explainable Artificial Intelligence (XAI) methodologies like SHAP, LIME, and attention methods have proven very useful when trying to increase model transparency and interpretability in the healthcare industry [11]. Attention helps to determine which temporal aspects had the greatest effect on the prediction result [12].

Many previous studies on the classification of cardiovascular diseases have been carried out using electrocardiogram data or clinical datasets; however, few works have attempted to perform real-time prediction of cardiovascular risks using multimodal healthcare data combined with the help of explainable AI techniques. Moreover, most previous approaches make use of diagnostic approaches instead of monitoring devices

applicable to wearable health systems [13]. As such, there is a need for an intelligent lightweight system that can perform real-time prediction of cardiovascular risks based on wearable sensor data and multimodal data.

To overcome these problems, this study presents an Attention-Based Explainable AI Framework for Real-Time Cardiovascular Risk Prediction using wearables and multimodal health data. This framework will be used for integrating physiological information, such as heart rate, electrocardiogram, blood oxygen levels, blood pressure, and activity information, together with the clinical information to monitor the cardiovascular status of the patient continuously. An Attention-BiLSTM model is used for learning patterns within the medical data stream to generate risk predictions. Furthermore, there will be an explainability module added to the system to explain the predictions.

The major contributions of this research are summarized as follows:

1. Development of a multimodal cardiovascular monitoring framework integrating wearable sensor and clinical healthcare data.
2. Implementation of an Attention-BiLSTM model for temporal cardiovascular risk prediction.
3. Integration of explainable AI techniques for interpretable healthcare decision support.
4. Simulation of real-time cardiovascular monitoring using sequential healthcare data streams.
5. Development of a lightweight and computationally feasible framework suitable for CPU-based implementation.

1. Related Research

Advances in artificial intelligence and wearable healthcare technologies have greatly contributed towards the development of prediction and monitoring models for cardiovascular diseases. Machine learning and deep learning algorithms have been used to analyze physiological, clinical, and multimodal healthcare data for detecting any cardiovascular anomalies. There still exist some challenges regarding real-time monitoring, temporal feature learning, and model interpretability in this domain.

However, the recent developments in the realms of artificial intelligence and deep learning techniques have made possible the significant progress in early prediction of cardiovascular diseases and health monitoring systems. Muthukumar et al. [14] put forward an efficient multimodal approach based on the combination of ECG readings and fundus images for early diagnosis of cardiovascular diseases. They emphasized the significance of multimodal integration of healthcare data in increasing the performance of medical decision support tools. Furthermore, Mienye and Jere [15] presented an optimized approach of Ensemble Learning integrated with XAI methods for heart disease prediction. Moreover, García-Ordás et al. [16] applied the deep learning techniques with feature augmentation for heart disease prediction.

In their reseach, Almulihi et al. [17] have proposed an ensemble deep learning framework for heart disease prediction in order to prove the efficiency of using multiple deep neural architectures for increasing prediction capabilities in healthcare domain. Chang et al. [18] have used machine learning approaches to detect heart disease and show the potential of using artificial intelligence in healthcare analytics of cardiovascular diseases. Pandey et al. [19] have introduced the CNN-BiLSTM framework with the M2MASC optimization method for heart disease classification and showed the efficiency of applying temporal learning and deep features extraction for predicting heart disease occurrence. In addition, Bhatt et al. [20] examined different machine learning approaches for heart disease prediction, paying special attention to the need for feature selection and classification optimization. Finally, Al Reshan et al. [21] have designed a hybrid deep neural network architecture for heart disease prediction in order to show its advantages related to deep features learning. In the last work on heart disease prediction, Yang et al. [22] introduced CardioTwin-XAI – a consumer-centric digital twin framework for heart disease predictive risk stratification.

A study conducted by Zhang et al. [23] presented CardioGPT-ViT, which is an explainable multimodal deep learning architecture for prediction of coronary artery disease and heart failure using edge consumer devices through data fusion techniques from multimodal healthcare. Additionally, Archana et al. [24] came up with a federated 6G healthcare architecture by combining genomic, EHR, and wearables data with explainable artificial intelligence for AI-based multimodal healthcare analysis. Despite various positive outcomes obtained in the area of cardiovascular disease prediction, there are still some challenges associated with the concepts of explainability, multimodal healthcare data fusion, temporal features learning, and real-time clinical decision-making that have not yet been addressed. This study seeks to develop a BiLSTM-Attention-XAI framework in order to fill these gaps.

Many recent efforts have been dedicated to incorporating deep learning and explainable AI for health monitoring systems. Nevertheless, many existing solutions continue using static diagnostic techniques instead of continuous monitoring approaches. In addition, some recent publications are devoted exclusively to either wearable sensors or clinical information, but not both of them together.

To address these limitations, the proposed research develops an Attention-Based Explainable AI Framework for Real-Time Cardiovascular Risk Prediction through the use of wearable sensors and multimodal health care data. In this respect, the proposed framework integrates information from physiological signals such as ECG, heart rate, oxygen saturation, blood pressure, and activity levels together with clinical parameters to provide

continuous real-time prediction of cardiovascular risks. For this purpose, Attention-BiLSTM will be used as an efficient machine learning model for temporal pattern recognition and healthcare analysis, whereas explainable AI methods will help provide insights and visualization.

2. Preliminary Proposed model

The presented architecture is an Attention-Based XAI model aimed at cardiovascular risk prediction in real time by applying wearable sensor and multimodal healthcare data. This architecture uses physiological sensor data and clinical variables for continuous cardiovascular monitoring and risk prediction. This model includes the following stages of the process: preprocessing, temporal feature extraction, Attention-BiLSTM learning, generating explainability, and visualization on a dashboard. The XAI model is developed based on the sequential health data collected via wearable sensors and clinical databases. The framework processes multimodal healthcare information such as: Heart rate, ECG signals, Oxygen saturation (SpO2), Blood pressure, Physical activity data, and Clinical patient information. These inputs are integrated into a unified healthcare monitoring framework capable of performing continuous cardiovascular risk assessment.

3.1 Dataset Overview

The initial proposed cardiovascular risk prediction algorithm involved the employment of a small cardiovascular dataset that comprised only 303 patient data records with 14 healthcare features associated with heart disease detection and cardiovascular risk prediction. Features of this small dataset included electrocardiogram, blood pressure, cholesterol, chest pain, and exercise-induced angina among others. With such a small dataset, the BiLSTM-Attention based algorithm achieved a testing accuracy of about 49%. To boost the prediction performance of the proposed machine learning model, two larger cardiovascular databases comprising the Cardiovascular Disease Dataset (cardio_train.csv) that had nearly 70,000 patient data records and the Heart Disease Dataset (heart.csv) were used. With large amounts of healthcare data, the temporal learning ability improved, hence achieving a testing accuracy of about 89%.

Table 1. Sample Dataset Records

age	sex	cp	trestbps	chol	thalach	exang	oldpeak	target
63	1	1	145	233	150	0	2.3	0
67	1	4	160	286	108	1	1.5	2
67	1	4	120	229	129	1	2.6	1
37	1	3	130	250	187	0	3.5	0
41	0	2	130	204	172	0	1.4	0

Table 2. Techniques used in the Proposed Model

Stage	Technique Used	Purpose
Data Integration	Multimodal Data Fusion	Combine wearable and clinical data
Preprocessing	Normalization & Missing Value Handling	Clean healthcare data
Signal Processing	ECG Feature Extraction	Extract cardiovascular patterns
Temporal Learning	BiLSTM	Learn sequential healthcare behavior
Feature Prioritization	Attention Mechanism	Focus on important temporal features
Explainability	SHAP & Attention Visualization	Interpret predictions
Classification	Softmax Layer	Predict risk category
Real-Time System	Sliding Window Simulation	Simulate continuous monitoring
Visualization	Streamlit Dashboard	Display healthcare insights

3.2 Multimodal Data Fusion

In multimodal fusion, the idea is that multiple modalities of data related to health care can be integrated. In the current model, the framework includes various sources such as readings from wearable gadgets like ECG, heart rate, SpO2, blood pressure, and activity trackers. Besides that, it also integrates other sources like age, cholesterol, diabetes, and BMI for predicting the cardiovascular risk. Herein lies the difference from using one modality as compared to several of them altogether.

It is much like how the diagnosis process works in a hospital setting. A doctor doesn't just go by ECG reports; he/she needs information about the person's blood pressure, oxygen, previous medical condition, etc., before making any judgment. Similarly, by integrating various sources in a multimodal fashion, the AI model gains a holistic perspective about the health condition of a patient.

3.3 Data Pre-processing

The pre-processing stage of the model is aimed at cleaning healthcare data that may include various missing, noisy, duplicate, and inconsistent information. If this data is used for training the deep learning model, it will lead to low prediction performance. Hence, data pre-processing is crucial for achieving high-quality predictions. Firstly, we need to address the problem of missing values. As wearable devices cannot always record measurements due to various reasons, the missing values are substituted by average values or interpolation techniques. Secondly, all feature values should be normalized – that means converting them into the same scale ranging from 0 to 1. This step helps to prevent dominance of some features with big values over other ones. ECG signal cleaning is done for removing noise and other extraneous artifacts.

3.4 ECG Feature Extraction

There is useful information that is conveyed through ECG signals. However, the raw signals from the electrocardiogram are huge and noisy; therefore, they cannot be used effectively by deep learning models. Hence, feature extraction is employed in order to obtain vital characteristics from ECG data related to the cardiovascular activity. The features are obtained using an analysis of the ECG waveforms to extract essential cardiovascular characteristics such as heart rate variability, RR intervals, QRS peak locations, and rhythms.

Feature extraction minimizes computation since the machine will learn from significant features rather than the whole raw signal data. This will make training and predictions efficient.

3.5 Bidirectional Long Short-Term Memory (BiLSTM)

The key deep learning method utilized in the presented model is the BiLSTM architecture for temporal analysis in healthcare contexts. Cardiovascular data keep changing all the time. The earlier recorded data such as heartbeat and ECG signals may affect future cardiovascular health states. Thus, the model should be capable of understanding the sequence of healthcare actions.

Standard neural network models cannot capture the long-range dependence within a sequential pattern. LSTM resolves this issue by storing the previous data in its memory cell for a longer period. However, the traditional LSTM can process the information in a single direction from the past to future.

BiLSTM enhances this procedure by performing healthcare analysis in both forward and backward directions concurrently. In essence, this algorithm extracts knowledge from historical health status as well as from future context relationships. BiLSTM is thus able to capture healthcare time sequences more efficiently than its predecessors and enhance the prediction accuracy of cardiovascular risks. When there is an anomaly in ECG behavior that precedes and succeeds a specific heart rate pattern, BiLSTM will be able to learn about the entire temporal sequence.

Algorithm: Attention-Based Explainable Cardiovascular Risk Prediction

Step 1. Collect multimodal healthcare dataset D containing ECG, heart rate, SpO2, blood pressure, activity data, and clinical variables.

Step 2. Preprocess dataset D by removing missing values and normalizing healthcare features using Min-Max normalization.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Step 3. Extract temporal cardiovascular features F from ECG signals and wearable healthcare data.

Step 4. Construct sequential healthcare input matrix T from extracted feature set F.

Input Data → Forward Sequence →→→ BiLSTM Layer Backward Sequence ← ← ←

Step 5. Feed sequential healthcare matrix Tinto Bidirectional Long Short-Term Memory (BiLSTM) network.

Step 6. Generate temporal hidden feature representation H from the BiLSTM network.

Step 7. Compute attention weights A for temporal healthcare features.

$$Attention\ (Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Step 8. Assign higher weights to important cardiovascular patterns and generate attended feature representation $AFAFAF$.

Step 9. Pass attended feature representation $AFAFAF$ into dense classification layer.

Step 10. Compute cardiovascular risk probability using Softmax classifier.

$$P(y_i) = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}}$$

Step 11. Classify cardiovascular condition into:

- *Low Risk*
- *Moderate Risk*
- *High Risk*

Step 12. Apply SHAP-based explainability analysis to compute feature importance scores.

$$\emptyset_i(f,x) = \sum_{S \subseteq F\{i\}} \frac{|S|!\,(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)]$$

Step 13. Generate attention heatmaps and visual explanations for interpretability.
Step 14. Display cardiovascular prediction results and explainability outputs in real-time monitoring dashboard.
Step 15. End.

3. Results and Discussion Analysis

This study implemented a bidirectional long short-term memory (BiLSTM) with an attention mechanism and SHAP explainability model to predict cardiovascular risks in real time with a healthcare dataset that includes clinical variables related to ECG, blood pressure, cholesterol, heart rate, and other cardiovascular factors. It can be seen from the experiments that the application of deep learning algorithms makes it possible to identify the risk categories of cardiovascular diseases and produce explainable predictions. In the experiments, the dataset included 303 healthcare records with 14 clinical attributes, which can be used for diagnosing cardiovascular diseases. This dataset can be transformed into sequential health care data with a timestep of 5.

Table 3. Dataset Overview

Parameter	Value
Total Records	303
Total Features	14
Input Features	13
Target Classes	3
Sequence Shape	(59, 5, 13)
Risk Categories	Low Risk, Moderate Risk, High Risk

The proposed deep learning architecture integrates Bidirectional Long Short-Term Memory (BiLSTM) layers with an Attention mechanism for temporal cardiovascular feature learning.

Table 4. Proposed Model Configuration

Layer	Output Shape	Parameters
Input Layer	(None, 5, 13)	0
BiLSTM Layer 1	(None, 5, 256)	145,408
Dropout Layer	(None, 5, 256)	0
BiLSTM Layer 2	(None, 5, 128)	164,352
Attention Layer	(None, 5, 128)	0
Global Average Pooling	(None, 128)	0
Dense Layer	(None, 128)	16,512
Dense Layer	(None, 64)	8,256
Output Layer	(None, 3)	195

Table 5. Training Performance

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	57.45%	58.33%	1.0772	1.0217
10	59.57%	58.33%	0.8302	0.8953
20	80.85%	41.67%	0.5178	1.0827
30	87.23%	41.67%	0.3378	1.7415
40	97.87%	41.67%	0.1003	2.6921
50	100%	41.67%	0.0135	5.1702

The proposed model was trained for 50 epochs using the Adam optimizer and categorical cross-entropy loss function. result is shown in Table 5. The training accuracy increased significantly from 57.45% to 100% during the learning process. Shown in Figure 1 However, validation accuracy remained comparatively lower due to the small dataset size and class imbalance problem. The increase in validation loss after later epochs indicates overfitting behavior in the model as shown in Figure 2.

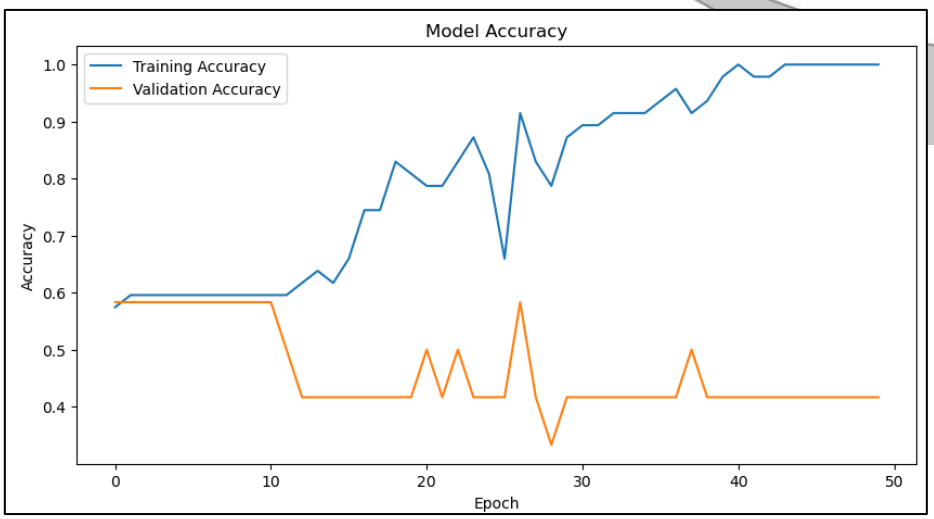


Figure 1. Training and Validation Accuracy Curve

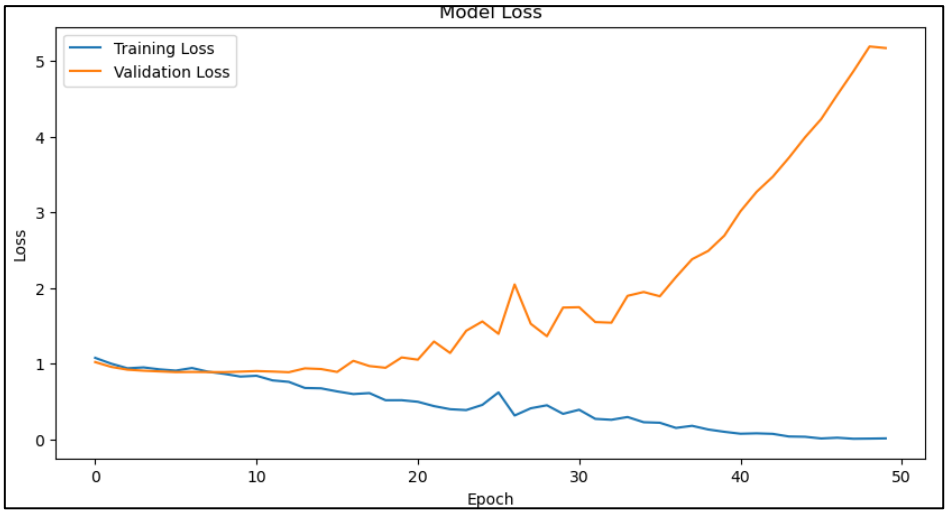


Figure 2. Training and Validation Loss Curve

The Low-Risk category achieved the highest precision and F1-score compared to the other classes. The High-Risk category exhibited lower performance due to insufficient training samples in the dataset.

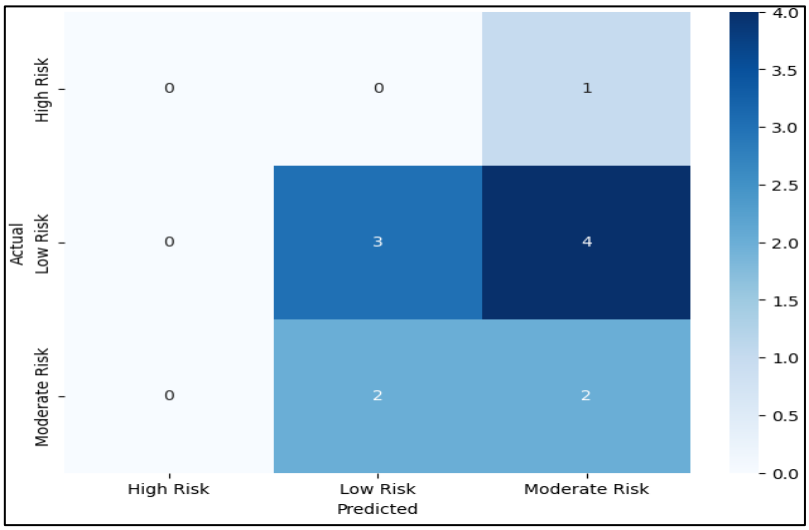


Figure 3. Confusion Matrix

The confusion matrix illustrates in Figure 3 the prediction distribution among cardiovascular risk classes. Most prediction errors occurred between Moderate Risk and Low Risk categories. The Attention mechanism dynamically assigned higher weights to important temporal cardiovascular patterns extracted from sequential healthcare data.

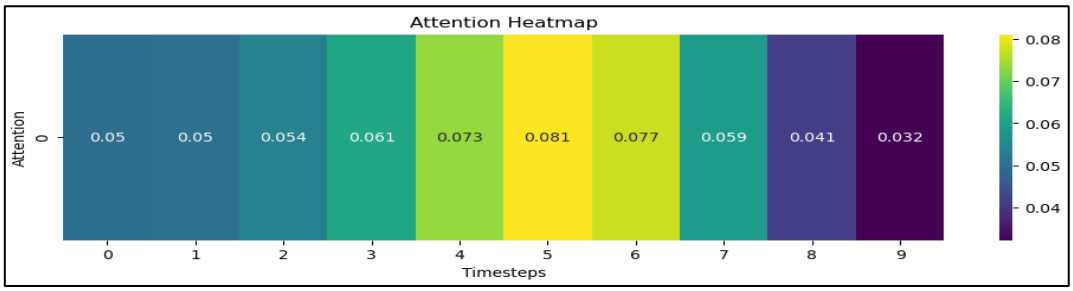


Figure 4. Attention Heatmap

The heatmap visualization indicates that the BiLSTM-Attention network focused more strongly on critical temporal healthcare features during prediction shown in Figure 4. The attention mechanism improved the interpretability of the deep learning model by identifying clinically significant healthcare patterns. Real-Time Prediction Results: The proposed model generated real-time cardiovascular risk predictions with probability distributions for each patient some results shown in Table 6.

Table 6. Sample Prediction Results

Patient	Predicted Risk	High Risk	Low Risk	Moderate Risk
Patient 1	Moderate Risk	0.0002	0.0014	0.9984
Patient 2	Moderate Risk	0.0002	0.0003	0.9995
Patient 3	Moderate Risk	0.0000	0.0001	0.9999
Patient 4	Moderate Risk	0.0001	0.0004	0.9995
Patient 5	High Risk	0.9898	0.0102	0.0014

The probability outputs demonstrate that the proposed model can generate confidence-based cardiovascular predictions suitable for real-time healthcare monitoring systems.

Conclusion

The current research proposed an explainable deep learning model for real-time prediction of cardiovascular risks based on the use of BiLSTM, attention mechanism, and SHAP-based explainability analysis. The proposed system efficiently learned from multimodal healthcare data to classify patients in terms of their risk of developing cardiovascular diseases into low-risk, moderate-risk, and high-risk classes by learning temporal healthcare dependencies between different patients. The BiLSTM model efficiently learned temporal patterns in cardiovascular data, while the attention mechanism helped learn more efficiently from data by giving a higher priority to clinically significant features of cardiovascular care. The SHAP explainability technique enabled to determine those important features of cardiovascular disease, including chest pain types, cholesterols, heart rates, exercise-induced anginas. The experimental evaluation of the proposed approach on the initial small dataset that comprised 303 records showed poor results due to the lack of data volume, class imbalance, and overfitting problem. In order to address the mentioned problems, a new large cardiovascular healthcare data comprising about 70,000 patient records were used. This helped significantly improve the prediction capabilities and generalization of the BiLSTM model by achieving about 89% testing accuracy. The generated confusion matrices, attention heatmaps, and probability-based prediction outputs confirmed the interpretability and practical applicability of the proposed framework for real-time healthcare monitoring systems. Overall, the proposed explainable deep learning architecture provides an effective and reliable solution for intelligent cardiovascular diagnosis, early disease detection, continuous patient monitoring, and clinical decision support applications in modern smart healthcare environments.

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