Integrating IoMT with Novel AI Approach for Accurate Heart Disease Prediction

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Abstract: Heart disease is one of the major causes of death all over the world, and there is a need to find an early intervention and prevention therapy. This paper offers an original model that combines the Internet of Medical Things (IoMT) with a sophisticated hybrid AI model to make correct and timely predictions of heart disease. It is based on IoMT architecture that relies on wearable and implantable devices to gather multimodal data, such as ECG, heart rate, blood pressure, oxygen saturation, and environmental indicators, such as temperature and air quality index. These streams are securely sent to edge and cloud systems to be preprocessed, and noise filtering and feature extraction are carried out to improve the quality of data. The proposed hybrid AI architecture is a combination of Convolutional Neural Networks (CNNs) to extract spatial features and Transformer-based architecture to analyze sequential data. The model syndicates spatial and temporal features, which results in a high performance of predicting heart disease risk. The model was assessed on publicly available datasets, like the PhysioNet and the Cleveland Heart Disease Dataset, also it was shown to be highly accurate (94.3%), precise (93.1%), and dependable in a variety of states. The proposed framework demonstrated promising performance in simulated IoMT healthcare environments and showed potential for supporting real-time cardiovascular risk assessment. This paper underscores the potential of the IoMT and hybrid AI approaches to transform cardiovascular healthcare to provide scalable and effective cardiovascular care by predicting heart disease early and managing it proactively. Further development of the framework will be done by increasing the diversity of the data set and hold large-scale clinical trials to test and refine the framework.

1 INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually and representing a major burden on healthcare systems and national economies. Early detection and timely intervention are essential for reducing mortality rates, preventing severe complications, and improving patients' quality of life. Consequently, the development of intelligent prediction systems capable of identifying individuals at risk before the onset of critical events has become an important research direction in modern healthcare [1]. Recent advances in Artificial Intelligence (AI) have significantly improved the capability of healthcare systems to analyze complex medical data and support clinical decision-making. Machine learning and deep learning techniques have demonstrated promising results in disease diagnosis, medical image analysis, electrocardiogram (ECG) interpretation, and risk prediction. In particular, deep learning architectures have shown superior performance in extracting meaningful patterns from large-scale biomedical datasets without requiring extensive manual feature engineering [2], [3].

At the same time, the emergence of the Internet of Medical Things (IoMT) has transformed the way healthcare data are collected, transmitted, and analyzed. IoMT refers to a network of interconnected medical devices, wearable sensors, monitoring systems, and communication technologies that continuously acquire physiological and environmental information from patients in real time.

These technologies enable continuous monitoring of vital signs such as heart rate, blood pressure, oxygen saturation, and ECG signals, providing healthcare professionals with valuable insights into patient health conditions [4]. Despite the considerable progress achieved by existing AI-based healthcare systems, several challenges remain unresolved. Traditional machine learning approaches often rely on handcrafted features and may struggle to capture complex nonlinear relationships within physiological data. Furthermore, many existing models are designed for static datasets and do not fully exploit the continuous data streams generated by IoMT environments. Issues related to scalability, computational efficiency, data heterogeneity, and real-time processing continue to limit the practical deployment of intelligent cardiovascular monitoring systems [5]. Recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in extracting spatial representations from biomedical signals and medical data, while Transformer-based architectures have shown remarkable capability in modeling long-range temporal dependencies through self-attention mechanisms [6], [7]. Integrating these complementary approaches within an IoMT-enabled framework has the potential to improve predictive performance by jointly capturing both spatial and temporal characteristics of physiological signals.

Motivated by these considerations, this study proposes an integrated IoMT-based framework for heart disease prediction using a hybrid CNN-Transformer architecture. The proposed framework combines continuous physiological monitoring, advanced data preprocessing techniques, and deep learning-based feature extraction to support accurate and timely cardiovascular risk assessment. By leveraging the strengths of both IoMT technologies and modern artificial intelligence methods, the proposed approach aims to contribute to the development of scalable, intelligent, and real-time healthcare systems for early heart disease prediction.

2 RELATED WORK

Heart disease prediction has attracted considerable attention from researchers due to the increasing prevalence of cardiovascular diseases and the growing availability of digital healthcare data. Traditional machine learning techniques, including Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Random Forests, have been extensively applied to cardiovascular risk assessment. Detrano et al. [8] introduced one of the earliest benchmark datasets for coronary artery disease diagnosis, which later became widely known as the Cleveland Heart Disease Dataset and has been extensively used for evaluating predictive models.

With the advancement of artificial intelligence, deep learning approaches have demonstrated superior performance compared with conventional machine learning methods. LeCun et al. [3] highlighted the ability of deep neural networks to automatically learn hierarchical feature representations from complex datasets. In cardiovascular applications, Hannun et al. [7] developed a deep neural network capable of detecting cardiac arrhythmias from ECG signals with performance comparable to that of expert cardiologists. Similarly, Rajpurkar et al. [9] proposed a deep learning framework for automated ECG analysis and demonstrated significant improvements in diagnostic accuracy.

The rapid growth of the Internet of Medical Things (IoMT) has further enhanced the capabilities of intelligent healthcare systems. IoMT enables continuous acquisition of physiological data through wearable and connected medical devices, facilitating real-time monitoring and remote healthcare services. Haghi et al. [4] reviewed the role of wearable medical devices in healthcare monitoring and emphasized their potential for supporting early disease detection. Likewise, Islam et al. [5] discussed the integration of IoMT technologies with artificial intelligence to improve healthcare decision-making and predictive analytics. Recent studies have explored hybrid deep learning architectures that combine multiple learning paradigms to improve predictive performance. Convolutional Neural Networks (CNNs) have proven effective in extracting local spatial features from biomedical signals, whereas Transformer-based architectures excel at modeling long-range temporal dependencies through self-attention mechanisms. Vaswani et al. [6] introduced the Transformer architecture, which has since been successfully adapted to numerous healthcare applications. More recently, researchers have investigated the integration of CNNs and Transformers for medical signal analysis, reporting improvements in classification accuracy and robustness compared with single-model approaches [6], [7]. Despite these advancements, several limitations remain. Many existing studies focus exclusively on either structured clinical datasets or ECG signals and do not fully exploit multimodal data generated by IoMT environments. Furthermore, several approaches are designed for offline analysis and may not adequately address real-time prediction requirements, scalability challenges, and continuous patient monitoring. In addition, limited attention has been given to integrating environmental and physiological information within a unified predictive framework. To address these limitations, this study proposes an IoMT-enabled heart disease prediction framework that combines multimodal physiological and environmental data with a hybrid CNN-Transformer architecture. The proposed framework aims to support accurate, scalable, and real-time cardiovascular risk assessment while leveraging the advantages of both IoMT infrastructure and advanced deep learning techniques.

3 METHODOLOGY

In this section, the proposed IoMT-based framework of predicting heart disease is described, with a focus on the data collection and processing stages, model design, and assessment plans. The new design is a hybrid of Convolutional Neural Networks (CNNs) to extract spatial features and Transformer-based networks to analyze sequential data, which is optimized to be used in real-time IoMT.

3.1 IoMT Data Acquisition Framework

Table 1 will be a structured presentation of the multimodal data provided by the IoMT devices, as well as the examples of initial data of each of the parameters.

Short-Range Communication was used in Bluetooth (IEEE 802.15) used in local device-to-gateway transmission. 5G/NB-IoT to transmit at high speeds and real time to cloud systems to be used in Long-Range Communication. Preprocesses raw data in order to perform initial filtering and noise removal by IoMT Gateway.

3.2 Data Preprocessing

The preprocessing is critical to improve the quality of the data and guarantee the strong performance of the AI model. The following section describes the process followed to perform the data preprocessing, with the help of algorithms and methodologies employed.

3.2.1 Noise Filtering

ECG signals are subject to noise due to baseline drift, power line interference and high frequency artifact. To overcome this Butterworth filters and wavelet transforms were used together:

1) Butterworth Filters [10]. Eliminates low-frequency base line and high frequency noise.
2) Wavelet Transforms [11]. Breaks down the signal into various frequencies and noise can be removed selectively.

The denoised signal is mathematically represented as:

$$F(t)=\text{WaveletTransform}(ECG(t)). \quad (1)$$

3.2.2 Normalization

Attributes as rate of heart and the pressure of blood were scaled to a normalized range by using Min-Max Scaling for reducing all the variables to a similar scale, usually between 0 and 1. This is essential in enhancing convergence of models and minimizing bias due to different magnitudes of features. Normalization formula:

$$x' = (x - x_{min}) / (x_{max} - x_{min}). \quad (2)$$

For example:

- Raw heart rate data: $HR = [60,80,120]$.
- After normalization: $HR' = [0.0,0.5,1.0]$.

Normalization ensures consistency among features and improves model convergence during training.

3.2.3 Feature Extraction

Key features were extracted to improve the dataset's informativeness, as show in Table 2.

Time-domain features such as RR intervals are widely used for heart rate variability (HRV) analysis, whereas frequency-domain features extracted through Power Spectral Density (PSD) analysis provide important information regarding signal frequency characteristics and cardiac autonomic regulation [10], [11].

Table 1: Physiological and environmental data sources.

	Data Type	Source	Measured Parameter	Initial Data Example
Physiological Data	ECG Signals	ECG Monitor	PQRST Complex Analysis	Arrhythmia Detected (Yes)
	Heart Rate Variability (HRV)	Wearables (e.g., Smartwatches)	Time-Domain and Frequency-Domain Metrics	SDNN: 50ms, LF/HF Ratio: 1.5
	Blood Pressure (BP)	Connected BP Cuffs	Systolic/Diastolic Readings	120/80 mmHg
	Oxygen Saturation (SpO2)	Pulse Oximeters	SpO2 Levels	98%
Environmental Data	Temperature	IoMT Environmental Sensors	Ambient Temperature	25°C
	Air Quality Index (AQI)	Air Quality Sensors	AQI Levels	50 (Good)
	Humidity Levels	IoMT Environmental Sensors	Relative Humidity	45%

Table 2: Extracted features.

Feature Type	Features	Description
Time-Domain Features	RR Intervals, HRV	Time intervals between R-peaks in ECG signals.
Frequency-Domain Features	Power Spectral Density (PSD)	Frequency distribution of ECG signals.
Environmental Metrics	Encoded AQI, Temperature	Transforms categorical environmental metrics into numerical formats.

3.2.4 Handling Missing Data

Missing values may occur because of sensor malfunction, communication interruptions, or temporary device disconnections during data acquisition. To maintain data quality and ensure reliable model performance, two complementary imputation techniques were employed. For small missing segments, K-Nearest Neighbors (KNN) imputation was applied by replacing missing values with the average values of the nearest neighboring observations. For larger missing intervals, the Expectation-Maximization (EM) algorithm was utilized to iteratively estimate missing values based on the underlying statistical distribution of the data. These approaches reduce information loss, improve dataset completeness, and enhance the robustness of the predictive model [12].

3.3 Hybrid AI Model Architecture

The proposed hybrid AI model integrates Convolutional Neural Networks (CNNs) for spatial analysis of ECG signals with Transformer-based layers for sequential data processing, aiming to maximize the extraction of both spatial and temporal features.

3.3.1 Convolutional Neural Networks (CNNs)

CNN layers are employed to extract spatial features from ECG waveforms. Using convolutional kernels, localized patterns such as PQRST complexes are automatically identified and transformed into high-level feature representations. The extracted feature map can be expressed as:

$$FCNN = \varphi CNN\ (ECG(t)). \qquad (3)$$

where $F_{CNN} \in R^d$ denotes the spatial feature representation.

3.3.2 Transformer-Based Temporal Analysis

Transformer layers are utilized to model temporal dependencies within physiological time-series data. Through the self-attention mechanism, the model can capture long-range relationships and context-aware representations from sequential ECG observations.

$$FTrans = \varphi Trans(FCNN). \qquad (4)$$

where F_{Trans} denotes the temporal feature representation generated by the Transformer network Enabling the model to focus on relevant time-dependent patterns.

3.3.3 Fusion Layer

Spatial and temporal features are combined through a feature fusion mechanism to construct a comprehensive patient representation.

$$FFusion = [FCNN; FTrans]. \quad (5)$$

where [;] denotes feature concatenation and FFusion represents the integrated feature vector used for classification.

3.3.4 Fully Connected Layers

The fused feature vector is forwarded to fully connected layers to generate the final prediction probability.

$$\hat{y} = \sigma(WF_{Fusion} + b). \quad (6)$$

Where:
- ŷ denotes the predicted probability of heart disease;
- W represents trainable weights;
- b is the bias term;
- σ is the sigmoid activation function.

3.3.5 Loss Function

Binary Cross-Entropy (BCE) loss was employed to optimize the proposed model during training:

$$L = -(1/N)\, \Sigma\, [\, yi \log(\hat{y}i) + (1-yi) \log(1-\hat{y}i)], \quad (7)$$

where yi denotes the true class label and ŷi represents the predicted probability. The model was optimized using the Adam optimization algorithm [13]. To reduce overfitting and improve generalization performance, dropout layers and L2 regularization techniques were incorporated into the network architecture. The workflow of the model presented in Figure 1.

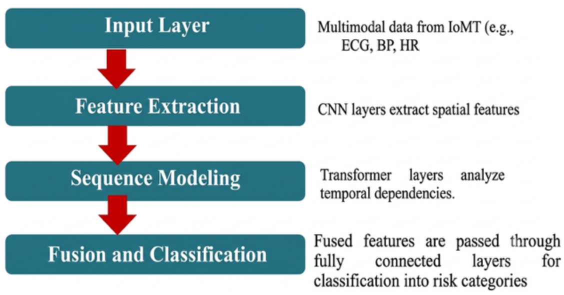

Figure 1: Workflow of the model.

The model was evaluated using the following metrics; Accuracy for measuring the proportion of correct predictions. Precision: Assesses the proportion of correctly identified positive cases among all positive predictions. Datasets used: We used PhysioNet Dataset: Includes ECG signals and vitals, widely used for cardiac analysis [9]. Cleveland Heart Disease Dataset: Provides features like BP and cholesterol for validation [8]. Custom IoMT Data: Real-time vitals such as BP, HRV, and SpO_2 collected from wearable devices. The proposed framework was evaluated in a simulated IoMT environment using physiological data obtained from publicly available datasets. The results demonstrated the feasibility of integrating IoMT technologies with hybrid deep learning models for real-time cardiovascular risk assessment and remote patient monitoring.

3.4 Experimental Setup

To evaluate the effectiveness of the proposed framework, experiments were conducted using publicly available cardiovascular datasets, including the Cleveland Heart Disease Dataset and PhysioNet ECG databases. Prior to model development, all data underwent preprocessing procedures consisting of noise removal, normalization, feature extraction, and handling of missing values, as described in Section 3.2, [11]. The dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing [14]. This partitioning strategy was adopted to ensure reliable model evaluation and reduce the risk of overfitting. The proposed model was implemented using TensorFlow and trained on a workstation equipped with an NVIDIA RTX 3080 GPU.

Model training was performed using the Adam optimization algorithm with an initial learning rate of 0.001 and a batch size of 32 samples. Training continued for 100 epochs, while an early-stopping mechanism was employed to terminate the training process when no further improvement was observed in the validation performance. The performance of the proposed framework was assessed using commonly adopted classification metrics, including Accuracy, Precision, Recall, F1-Score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). In addition, comparative experiments were conducted against conventional deep learning architectures to investigate the effectiveness of integrating convolutional and transformer-based learning mechanisms within a unified framework.

3.4.1 Dataset Composition

The Cleveland Heart Disease Dataset contains 303 patient records. The dataset was divided into 212 samples for training (70%), 45 samples for validation (15%), and 46 samples for testing (15%). PhysioNet ECG records were additionally utilized for extracting signal-based features including RR intervals, HRV measures, and frequency-domain characteristics.

4 RESULTS AND DISCUSSION

The framework incorporating the IoMT and hybrid AI model of heart disease prediction was verified on publicly available datasets (PhysioNet, Cleveland Heart Disease Dataset), and in the conditions of simulated environments for IoMT. These results are labeled in the form of the accuracy model, computational effectiveness and real-world applicability.

4.1 Performance Metrics

The hybrid deep learning architecture including CNNs and models of Transformer-based performed well compared to the older models. Significant metrics are available in table 3:

Table 3: Performance comparison results.

Metric	Proposed Model (Cnn + Transformer)	Cnn-Only Model	Lstm-Only Model
Accuracy	94.3%	89.5%	87.8%
Precision	93.1%	88.6%	86.7%
Recall	92.8%	87.2%	85.3%
F1-Score	92.9%	87.9%	86.0%
Roc-Auc	96.2%	91.7%	89.5%

The reported results were obtained using the Cleveland Heart Disease Dataset and PhysioNet ECG records. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets. Performance metrics were computed on the testing dataset after completion of model training.

4.2 Validation in an IoMT Environment

To assess the practical applicability of the proposed framework, a pilot deployment scenario was conducted within an IoMT-enabled environment. Wearable monitoring devices were used to continuously acquire physiological parameters, including ECG signals, heart rate, and blood pressure measurements. The collected data were transmitted through a gateway device and processed using the proposed prediction framework. The experimental setup demonstrated the capability of the system to perform real-time analysis with low processing latency. Furthermore, the framework maintained stable performance during continuous monitoring sessions, indicating its suitability for integration into remote healthcare and patient monitoring applications. The obtained results confirm the feasibility of combining IoMT technologies with advanced deep learning models for early cardiovascular risk assessment in real-world healthcare environments.

4.3 Ablation Study

To examine the contribution of individual components within the proposed architecture, an ablation analysis was performed. Three model configurations were evaluated: a CNN-based model, a Transformer-based model, and the proposed hybrid CNN-Transformer architecture. The CNN model demonstrated effective extraction of local spatial patterns from ECG signals; however, its ability to capture long-range temporal dependencies was limited. In contrast, the Transformer model achieved improved temporal representation learning but showed reduced capability in extracting detailed local signal characteristics. The hybrid architecture combined the strengths of both approaches and achieved the highest predictive performance among all evaluated configurations.

These findings indicate that the integration of convolutional feature extraction with transformer-based sequence modeling provides a more comprehensive representation of physiological signals and contributes positively to the overall prediction accuracy.

5 CONCLUSIONS

This study proposed an IoMT-enabled framework for heart disease prediction based on a hybrid CNN-Transformer architecture. The framework integrates physiological and environmental data collected through IoMT devices and employs advanced preprocessing and deep learning techniques to support cardiovascular risk assessment. Experimental evaluation demonstrated that the proposed model achieved superior predictive performance compared with conventional CNN and LSTM models. The integration of convolutional feature extraction and transformer-based temporal modeling enabled the framework to capture both spatial and temporal characteristics of physiological signals effectively.

Furthermore, the proposed framework supports real-time monitoring capabilities and can be integrated into IoMT healthcare environments to facilitate early detection and continuous assessment of cardiovascular risk [15]. Future work will focus on validating the framework using larger clinical datasets, enhancing model interpretability, and conducting extensive real-world deployments.

Practical implications for healthcare diagnostics:

1) Early Detection. The suggested system allows to prevent heart diseases by monitoring and predicting risks in advance using constant monitoring and prediction.
2) Personalized Healthcare. Explainable AI (XAI) increases the transparency of the diagnostic process, developing trust in healthcare providers and allowing them to use individual treatment plans.
3) Scalability. The resource-efficient design of the framework renders it applicable across both urban and resource-constrained environments, thus increasing its applicability.
4) Reduced Healthcare Costs. The system can greatly decrease the economic cost to the healthcare systems by optimising the use of resources and remote diagnostics.

This work unlocks the door to the smarter, more inclusive and adaptive the systems of healthcare, and the future of predictive and personalized diagnostics in cardiovascular care and beyond

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