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A Hybrid AI Model for Early Detection of Heart Disease Using Clinical and ECG Data

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Abstract

One of the main causes of morbidity and death is still cardiovascular diseases (CVDs) thereby stressing the need for developing effective early diagnostic tools. This paper proposes a hybrid approach using AI that combines deep ECG feature learning with clinical data to enhance early heart disease diagnosis. The ECG signals were preprocessed, divided into 2-second epochs, and then represented as 128-dimensional embedding using a 1D CNN-based feature extractor. At the same time, a set of 13 clinical risk factors was normalized and used to construct a lightweight clinical prediction branch. Both were then fused using a multimodal neural network that learns both ECG and clinical features. The findings of the experiment have demonstrated the effectiveness of the proposed hybrid framework, which has achieved 97.56% accuracy, 0.996 AUC, 99.0% sensitivity, and 96.0% specificity, significantly outperforming the individual models. Furthermore, the SHAP values-based explain ability method has assisted in revealing the most important clinical variables and ECG embedding features, thereby making the prediction results interpretable and meaningful from the clinical perspective. In summary, the proposed approach has shown how multimodal AI systems might help with early heart disease diagnosis and offers a promising solution for future real-time applications.

1. Introduction

An estimated 18.6 million deaths worldwide are attributed as the primary source of morbidity and mortality, to cardiovascular diseases (CVDs) [1]. The increasing prevalence of CVDs globally highlights the need for new approaches to enhance early diagnosis, risk prediction, and tailored management strategies [2]. More than 70% of deaths worldwide are caused by heart disorders, especially cardiovascular diseases (CVDs), which are the leading cause of illness and death globally. The Global Burden of Disease report from 2017 states that approximately 43% of all deaths are attributable to CVD. [3]. A study found that being overweight affects high blood pressure, high cholesterol, and—above all—the effect of stress hormones on heart disorders, contributing to the death of 2.8 billion people from heart problems [4].

In 2008, heart disease claimed 17.3 million lives. By 2030, it is predicted that more than 23.6 million individuals

will die from heart disease [5]. When part of the heart muscle is lost, it is referred to as a heart attack or myocardial infarction. The loss of cardiac muscle will cause the heart organ's blood flow to be interrupted or stopped. Blood pumping into the circulatory system is the primary function of the heart in both people and animals. If one of the heart's ventricles fails, the heart will be attacked, and if resuscitation is not performed right once, the patient will die [6]. As a result, these sudden assaults may cause a patient to pass away before seeking medical help [7].

Heart disease risk is "reversible," according to epidemiological study, meaning that risk factors can be decreased to lower the chance of heart disease developing or postponing it [8]. Early management relies on prediction and monitoring because heart disease often has no symptoms [9]. Considering the health and medical background of a patient, AI and machine learning can forecast heart attacks, reducing the chance of death. There are numerous applications for machine learning. Additionally, it works well for detecting heart disease [10]. Several research, have tried to predict cardiac attacks using machine learning [11]. Even though they constitute the cornerstone of cardiovascular treatment, traditional diagnostic techniques can sometimes fail to capture the complexity and diversity of modern practice. With the promise to produce more precise and understandable outcomes on patient health, artificial intelligence has recently surfaced as a game-changing development in the field of cardiovascular medicine [12].

In decision support systems, machine learning (ML) can effectively provide trustworthy predictions [13]. Wearable Internet of Things (IoT) technology is used to collect medical records from the patient's body and utilize machine learning to assess the risk of CVDs [14]. Algorithms for machine learning learn from historical data and make predictions based on current data. Algorithms are able to process large amounts of data and extract valuable information [15]. In a comparison of feature selection techniques for heart attack prediction, the top classifiers were Naive Bayes, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) [7]. In this work, we describe a unique hybrid artificial intelligence (AI) method that integrates clinical data and deep ECG feature representations in order to detect heart problems early.

The proposed framework takes advantage of a multimodal architecture where deep learning-based representations of ECG signals are integrated with key patient-specific clinical features to improve the predictive accuracy. By incorporating both physiological patterns extracted from ECG waveforms and key risk factors derived from clinical data, the proposed framework offers a more comprehensive insight into cardiac health than conventional diagnostic methods. Moreover, the proposed hybrid framework is intended to improve the accuracy, sensitivity, and resilience of the diagnostic process by capitalizing on the complementary strengths of signal-based and attribute-based analysis. By doing so, the proposed framework seeks to provide accurate, interpretable, and meaningful predictions to enable early interventions and personalized cardiovascular care.

2. Materials and techniques

2.1 Description of the Data

In this study, a hybrid framework is developed that has the ability to combine the ECG signals with the clinical attributes to detect heart disease at an early stage. This research uses two different datasets to develop the hybrid AI model. The first dataset is used to obtain high-resolution electrocardiogram (ECG) signals. The second dataset contains clinical and demographic risk factors that are associated with cardiovascular disease.

A. ECG Dataset (ECG Signals)

The ECG part of this work is based on a well-known and widely used benchmark database for cardiac signal processing. This database holds 48 half-hour samples of two-channel ambulatory ECG recordings from 47 different patients. The recordings are a mix of inpatients and outpatients to address a broad spectrum of clinical variability. The data was chosen randomly from a larger pool of 24-hour Holter recordings, and some examples were chosen to include less common but clinically important arrhythmias that might not be seen as often in random selections. All ECG signals were digitized at a sampling rate of 360 samples per second per channel with 11-bit resolution over a 10mV dynamic range. Each record was annotated independently by several cardiologists, and inconsistencies were resolved to generate accurate beat-by-beat labels. The dataset provides around 110,000 annotated heartbeats, which is sufficiently comprehensive for learning deep learning models for arrhythmia analysis and ECG-based cardiac classification [17]. In this paper, the entire ECG dataset was used to learn deep temporal features using a convolutional neural network-based feature extractor. The learned features represent the

physiological input branch of the proposed hybrid diagnostic system.

B. Heart Disease Dataset (Clinical Data)

The clinical component of the model is based on a merged Heart Disease Dataset, which was derived from the Cleveland, Hungary, Switzerland, and Long Beach V databases (1988). Although the full dataset contains 76 medical features, the most popular set of existing literature, including this study, uses the established set of 14 proven clinical features. These features are widely recognized as key indicators of cardiovascular risk and are frequently employed in clinical settings for assessing the likelihood of heart disease [18].

2.2 Data Preprocessing

In an effort to ensure the quality, consistency, and usability of both ECG and clinical data, before the model was developed, a number of preprocessing processes were completed. Preparing the modalities for multimodal fusion in the hybrid framework, managing data format variability, and guaranteeing noise reduction all required preprocessing processes.

It is crucial to state here that ECG and clinical data from the experiments are associated with different individuals and not the same patients. As such, it would be impossible to conduct a patient-level fusion. In light of this challenge, a feature level integration technique was implemented, which involves merging embeddings obtained from ECG data with those extracted from clinical data. In the experiments, a statistical matching methodology involving random index matching was considered for aligning ECG samples with clinical data. It allows us to conduct multimodal learning without having to make any assumption about true associations between the patients. Preprocessing steps were performed independently to avoid information leakage.

A. ECG Signal Preprocessing

The ECG signals were processed using a comprehensive preprocessing task to ensure the quality of the signals and the removal of noise. The preprocessing task involved the following steps: The first step of the preprocessing task involved the use of a band-pass filter having a 5–40 Hz frequency range. The main aim of this step was the removal of noise that was related to muscle activity and high-frequency noise while ensuring that the essential parts of the waveform were maintained, especially the QRS complex. After the preprocessing task, the R-peaks of the ECG signals were identified using an appropriate peak detection algorithm, as shown in figure 1.

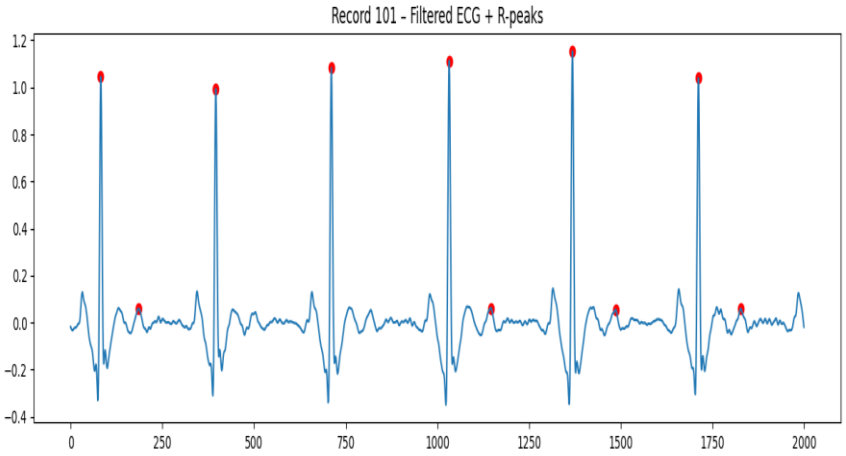

Figure (1): ECG Signal Filtered with Identified R-Peaks (Record 100)

For the purpose of supervised learning, the ECG signals were divided into fixed-size windows of 2 seconds (720 samples). Further, each window was classified as either normal or abnormal based on the beat labels provided by the dataset's expert. To train and test the model, the entire dataset was divided using a stratified sample technique. This ensures that the training and testing datasets have an equal number of normal and abnormal

Table (1): Sample of Clinical Heart Disease Dataset

heartbeats. Around 80% of the dataset was used for training the model.

B. Clinical Data Preprocessing

The clinical dataset contains 1,025 samples and 14 features, which include demographic information, laboratory results, symptoms, and diagnostic features. The target feature is whether heart disease is present (1) or not (0). The initial analysis of the dataset revealed that all features are completely full with no missing or corrupted values, making it perfect for a supervised learning task. To ease the training process of the model on the dataset, the clinical features were distinguished from the target features. The numerical features were normalized using z-score normalization. This is a critical step in the process for enhancing the robustness of the model and ensuring that the features with higher numerical values are not given more weightage throughout the training procedure. An 80/20 split was used to separate the dataset into training and testing sets. To ensure that the same number of samples with and without illness were included in both sets, a stratified sampling technique was used. This made sure that 205 samples were used for testing and 820 samples were used for training.

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

2.3 Convolutional Neural Network-Based ECG Feature Extraction

For the purpose of extracting relevant and distinctive features from the ECG signal segments, a customized one-dimensional Convolutional Neural Network (CNN) architecture was developed and trained on the preprocessed ECG dataset. The CNN architecture features three convolutional modules, each module having a max-pooling layer, a Conv1D layer, and a batch normalization layer come next. These layers allow the CNN to learn hierarchical temporal and morphological features of the ECG signal, such as the QRS complex morphology and beat rate, as well as arrhythmia-related patterns. Following the convolutional layers, a Global Average Pooling layer was introduced to reduce the learned feature maps into a compact representation. This is followed by a fully connected dense layer with 128 neurons, which is specifically defined as the ECG embedding layer. This layer is the central feature extractor, learning deep physiological patterns of cardiac function. The CNN was trained as a supervised classifier to distinguish between normal and abnormal ECG segments. After the training process was finished, the network was converted to a feature extractor by extracting the embedding layer. Another feature extraction model was built to extract only the 128-dimensional embedding vector for each ECG segment. This produced a discriminative and compact feature representation that could be easily combined with clinical information in the

proposed hybrid framework. The CNN model had excellent learning ability, achieving 96.8% training accuracy and 96.4% validation accuracy by the end of the epoch. with steadily decreasing loss values, which indicated excellent feature learning and generalization to unseen ECG segments.

2.4 Hybrid Model Architecture

The proposed hybrid framework combines the two different information sources: deep ECG signal embeddings and clinical features, to achieve a more comprehensive and accurate risk assessment of heart disease. Unlike the traditional single-modality diagnostic system, the hybrid framework combines the advantages of both physiological waveform analysis and clinical analysis. The multi-channel approach of the hybrid model allows it to capture the subtle electrical patterns of the ECG signal, as well as the demographic, symptomatic, and laboratory-based indicators of cardiovascular disease progression, as shown in figure2.

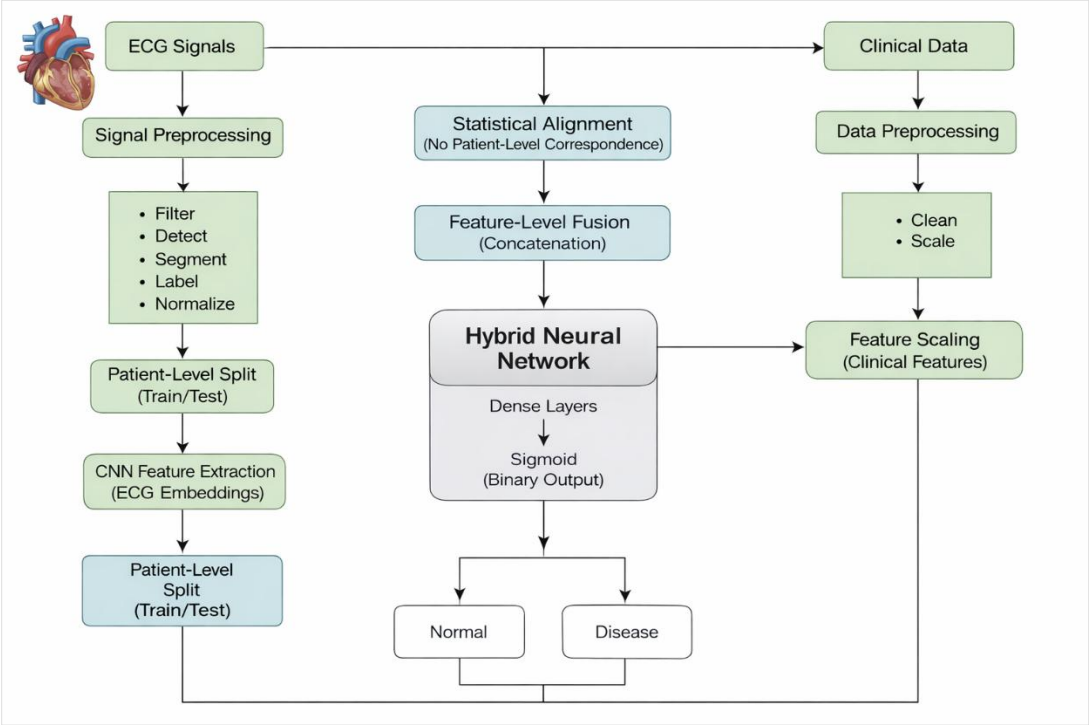

Figure (2): Workflow of The Proposed Method

For this integration to be achieved, the model uses a dual-branch neural network architecture, which has one branch for learning high-level features from ECG embeddings obtained from the CNN and another branch for processing numerical clinical variables. The two branches are then combined to create a single feature representation, which enables the model to learn cross-modal associations.

$$F = [E_{ECG} \| E_{\text{clinical}}] \qquad (1)$$

Where $E_{ECG} \in$ R^ {128} represents the ECG embedding vector, and $E_{\text{clinical}} \in$ R^ {13} represents the clinical feature vector. The operator (||) denotes feature concatenation.

After the completion of all the preprocessing steps for both ECG and clinical data, the two sources were aligned and combined to create a hybrid diagnostic system. The first 1,025 ECG embedding vectors, each of which represented 128 deep features extracted from the CNN encoder. The next step involved stratified sampling to

divide each of the two data sets into training (80 percent) and testing (20 percent) groups. The reason behind this was that an alignment process based on indexing could be employed in each subgroup since there was no matching at patient level between the two data sets. This ensured that each patient sample was accompanied by its clinical data as well as its ECG-derived deep feature.

Later, the entire data was split into 820 training samples and 205 testing samples with a balanced ratio of normal and diseased samples. Additionally, all clinical variables were normalized with the Standard Scalar to have the same numerical scale during modeling. The hybrid model was designed as a two-input neural network. The ECG network processed the 128-dimensional embedding features with a sequence of dense layers (256, 128, and 64 units), each of which is followed by a dropout rate of 0.3 and Batch Normalization in order to enhance generalization and avoid over-fitting. At the same time, the clinical network took 13 structured clinical variables and transformed them with a lightweight multilayer perceptron consisting of Dense layers (64 and 32 units) with Batch Normalization and a dropout rate of 0.2. The two branches' outputs were then combined using a concatenation layer, creating a new 96-dimensional representation.

This combined vector was then further transformed using two more dense layers with 128 and 64 units to allow the model to learn the cross-modal associations between the ECG patterns and the clinical risk factors. Finally, a sigmoid output neuron was employed to predict the probability of heart disease for each patient sample.

$$\hat{y} = \sigma(WF + b) \qquad (2)$$

Where W and b represent the learnable weights and bias parameters, and σ(.) denotes the sigmoid activation function.

The Adam optimizer was used to train the combined model from beginning to end, loss function for binary cross-entropy, and evaluation criteria of accuracy and AUC.

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \qquad (3)$$

With a batch size of 32, the model was trained across 100 epochs to enable to learn the combined representations from both the clinical and ECG datasets as shown in table 2.

Table (2): Training Hyper Parameters

Hyper parameter	Value
Optimizer	Adam
Learning Rate	0.0005
Loss Function	Binary Crossentropy
Metrics	Accuracy, AUC
Epochs	100
Batch Size	32
Validation Split	20% (stratified)
Regularization	Dropout (0.2–0.3), BatchNorm

3. Results

The entire process was developed in a Python setting within Google Colab. The required libraries for ECG processing, most importantly WFDB, were installed using common pip commands (for example, pip install wfdb) to facilitate the loading, filtering, annotating, and segmentation of the ECG signals used in this study. After the successful installation, the ECG and clinical datasets were preprocessed and combined into the hybrid classification system. The ECG signals were filtered, segmented, normalized, and converted to 128-dimensional deep feature embeddings, which were further aligned with 13 structured clinical attributes derived from the heart disease dataset. The suggested hybrid neural network was trained using the feature space, allowing for a comprehensive assessment of the model's functionality based on a number of diagnostic standards.

The results clearly demonstrate the hybrid model's efficacy, as the model performed very well in terms of accuracy, sensitivity, specificity, and AUC, outperforming the ECG-only and clinical-only models. The following subsections will elaborate on the outcome, providing an understanding of the performance of the model through ROC curves, precision-recall plots, confusion matrices, and calibration plots. The outcome clearly indicates the suggested hybrid model's efficacy in terms of its performance. After 100 epochs of training, the model was able to achieve a really remarkable 97.73% training accuracy and 97.56% validation accuracy. The validation AUC value of 0.9962 indicates that the model has almost perfect discriminatory power between healthy and diseased samples. Moreover, the clinical efficacy of the model was found to be highly reliable, as it attained a Sensitivity of 0.9904, which indicates Since practically all of the individuals with heart disease could be accurately identified by the model, and a Specificity of 0.96, which indicates a high level of accuracy in identifying healthy patients. The well-balanced performance on both Sensitivity and Specificity metrics confirms that the hybrid integration of ECG embeddings and clinical features has a significant effect on improving the accuracy of the predictions by reducing both false negatives and false positives. To further assess the hybrid model's discriminatory capacity, Figure 3 shows the use of a Receiver Operating Characteristic (ROC) curve.

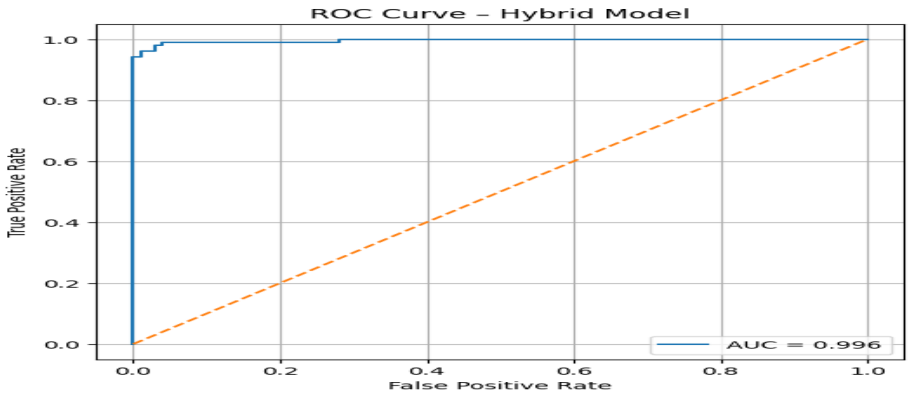

Figure (3): ROC Curve

The hybrid framework has good precision–recall performance, particularly under imbalanced classification settings, as shown in Figure 4.

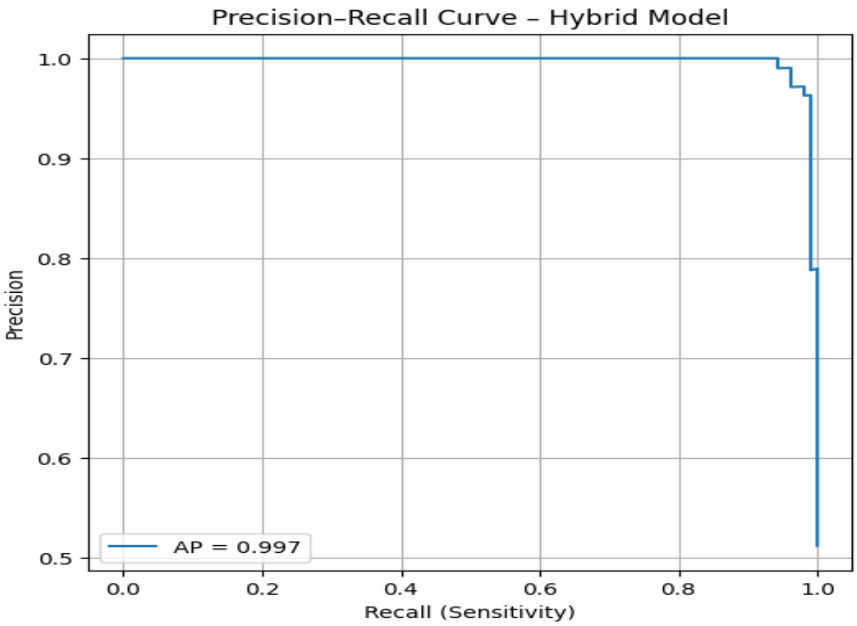

Figure (4): Precision–Recall Curve

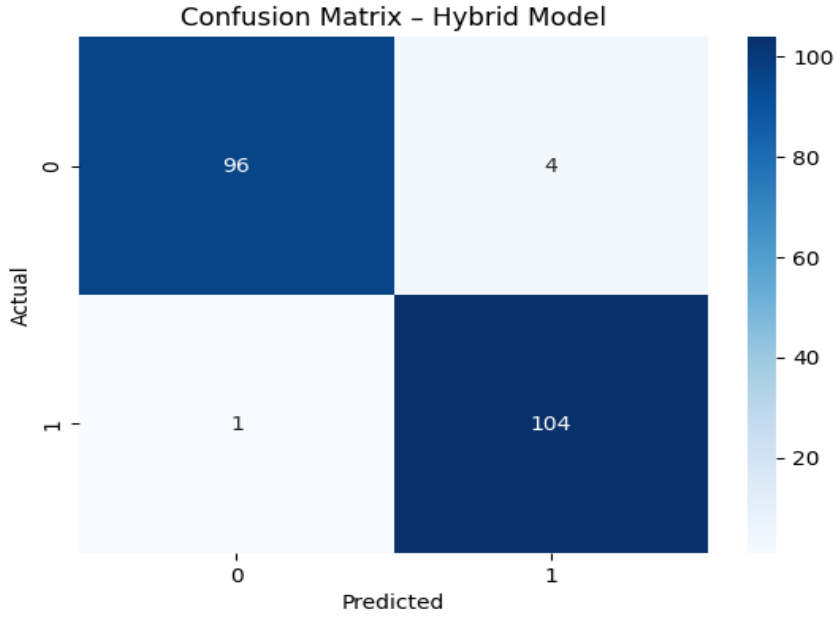

Figure (5): Matrix of Confusion

The confusion matrix is used to analyze the model's classification accuracy which is able to distinguish between those who are in good health and those who are not, as Figure 5.

Table (3): Classification Report of the Hybrid Model

Class	Precision	Recall	F1-Score	Support
Normal (0)	0.99	0.96	0.97	100
Disease (1)	0.96	0.99	0.98	105
Accuracy	—	—	0.98	205
Macro Avg	0.98	0.98	0.98	205
Weighted Avg	0.98	0.98	0.98	205

The strength of the proposed hybrid framework is demonstrated by the thorough classification report in Table 3, which includes the F1-score, recall, and precision for both classes. Furthermore, to evaluate the calibration of the predicted probabilities provided by the model, a calibration curve is also plotted. As evident in Figure 6, the hybrid model has an outstanding probability calibration, as its calibration curve is almost identical to the diagonal line representing the perfect calibration. This reveals that the hybrid model not only has high accuracy in classification but also provides accurate risk probabilities, which means that the predicted probabilities provided by the hybrid model are accurate estimates of the true risk of heart disease.

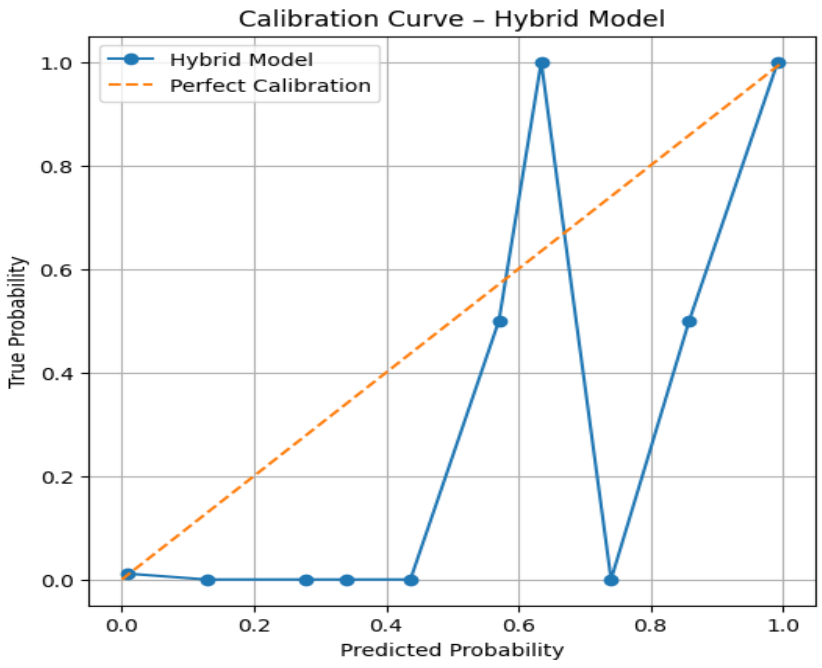

Figure (6): Calibration Curve

4. Model Explain-ability

Following the computation of SHAP values for both inputs of the hybrid model, individual summary plots were created to demonstrate the impact of each feature on the model's ultimate forecast. Figure 7(a) illustrates the SHAP

summary plot for the 13 structured clinical attributes (features), including but not limited to age, blood pressure, cholesterol, and ST depression, to demonstrate their global effect on heart disease classification. The features with the highest contributions include thalach, oldpeak, cp, and chol. Similarly, Figure 7(b) shows the SHAP summary plot for the 128-dimensional ECG embedding features extracted by the CNN. Each "ECG_feat_i" corresponds to a deep-learned pattern from the ECG signal. The SHAP distribution emphasizes the most important ECG-derived features, indicating the role of morphological and temporal ECG features (represented by deep embeddings) in distinguishing between normal and diseased heart conditions. Figures 7(a) and (b) illustrate how the hybrid model integrates the clinical variables with the deep ECG features, giving a clear insight into what is driving the decision-making process, which is a crucial step in gaining the trust of the clinical community.

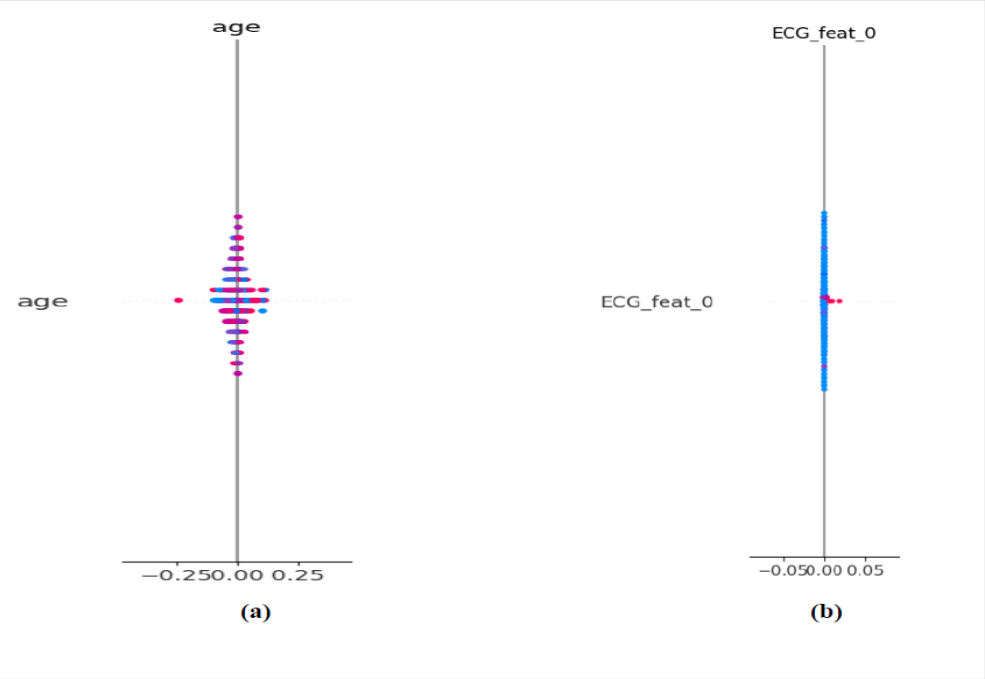

Figure (7): Feature Importance Analysis (a) Clinical Features (b) ECG Embedding Features

5. Conclusion

In this study, we have presented a novel hybrid framework to predict heart disease at an early stage utilizing deep ECG signal embedding and structured clinical features. Specifically, our suggested method uses CNN to extract deep temporal features from ECG data and MLP to process clinical factors. The results of experiments show the benefits of the hybrid framework, which outperforms the models working on one modality with accuracy equal to 97.56%, AUC equal to 0.996, sensitivity of 99.0% and specificity of 96.0%. It is possible to suggest that our approach can effectively use combined information about physiology and clinical parameters to predict heart disease. At the same time, we applied the technique of explainable AI based on SHAP analysis that helped to evaluate the contributions of both clinical factors and embeddings from ECG data. Specifically, we found out that important clinical features are ca, thal, and oldpeak. Nevertheless, it should be mentioned that the ECG data and the clinical data employed in the current research have no patient matching and independent external validation has not been carried out. For these reasons, further work will include model evaluation on real-world patient-matched datasets and investigating the use of other biosignals. In conclusion, the presented research has demonstrated the possible benefits of using the hybrid framework for supporting CVD analysis.

6. Future Work

On the basis of the strong performance of the proposed hybrid ECG-clinical framework, there are some promising directions that can be explored to further improve and extend the clinical application of the framework. Firstly, the future work can focus on the use of multi-lead ECG signals, echocardiography parameters, or wearable sensor signals to develop a more comprehensive and physiologically detailed diagnostic framework. Secondly, the collection and integration of real-world data from Iraqi hospitals will contribute to increasing the framework's accuracy for a given population. Furthermore, the exploration of employing more intricate deep learning models such as Transformers, CNN-LSTM hybrids, or attention-based fusion models, may have the potential to further improve the model's capacity to depict intricate relationships. The model's incorporation into an actual clinical decision support system or a mobile health application may also have the potential to further apply the research to real-world applications for early screening and remote patient monitoring. Finally, improving the explain ability capabilities of the model using advanced XAI methods would improve clinician trust.

References

[1] Alhabib KF, Batais MA, Almigbal TH, Alshamiri MQ, Altaradi H, Rangarajan S, Yusuf S: Demographic, behavioral, and cardiovascular disease risk factors in the Saudi population: results from the Prospective Urban Rural Epidemiology study (PURE-Saudi). BMC Public Health. 2020, 20:1213.

[2] Schneeberger D, Stoeger K, Holzinger A: The European legal framework for medical AI. Machine Learning and Knowledge Extraction. Holzinger A, Kieseberg P, Tjoa A, Weippl E (ed): Springer, 2020. 209-26.

[3] Bhatt, C.M.; Patel, P.; Ghetia, T.; Mazzeo, P.L. Effective heart disease prediction using machine learning techniques. *Algorithms* **2023**, *16*, 88.

[4] Momin, M.A.; Bhagwat, N.S.; Dhiwar, A.V.; Chavhate, S.B.; Devekar, N.S. Smart body monitoring system using IoT and machine learning. *engrXiv* **2021**.

[5] Yahyaie, M.; Tarokh, M.J.; Mahmoodyar, M.A. Use of internet of things to provide a new model for remote heart attack prediction. *Telemed. J. e-Health* **2019**, *25*, 499–510.

[6] Abba, S.; Garba, A.M. An IoT-based smart framework for a human heartbeat rate monitoring and control system. *Proceedings* **2020**, *42*, 36.

[7] Gupta, S.K.; Shrivastava, A.; Upadhyay, S.P.; Chaurasia, P.K. A machine learning approach for heart attack prediction. *Int. J. Eng. Adv. Technol.* **2021**, *10*, 124–134.

[8] Taylor, O.E.; Ezekiel, P.S.; Deedam-Okuchaba, F.B. A model to detect heart disease using machine learning algorithm. *Int. J. Comput. Sci. Eng.* **2019**, *7*, 1–5.

[9] Khan, M.A. An IoT framework for heart disease prediction based on MDCNN classifier. *IEEE Access* **2020**, *8*, 34717–34727.

[10] Lakshmanarao, A.; Swathi, Y.; Sundareswar, P.S. Machine learning techniques for heart disease prediction. *Forest* **2019**, *95*, 97.

[11] Ghosh, P.; Azam, S.; Jonkman, M.; Karim, A.; Shamrat, F.J.; Ignatious, E.; Shultana, S.; Beeravolu, A.R.; De Boer, F. Efficient prediction of cardiovascular disease using machine learning algorithms with relief and LASSO feature selection techniques. *IEEE Access* **2021**, *9*, 19304–19326.

[12] Benjamin EJ, Virani SS, Callaway CW, et al.: Heart disease and stroke statistics-2018 update: a report from the American Heart Association. Circulation. 2018, 137:e67-e492.

[13] Rao, G.M.; Ramesh, D.; Sharma, V.; Sinha, A.; Hassan, M.M.; Gandomi, A.H. AttGRU-HMSI: Enhancing heart disease diagnosis using hybrid deep learning approach. *Sci. Rep.* **2024**, *14*, 7833.

[14] Islam, M.N.; Raiyan, K.R.; Mitra, S.; Mannan, M.R.; Tasnim, T.; Putul, A.O.; Mandol, A.B. Predictis: An IoT and machine learn-ing-based system to predict risk level of cardio-vascular diseases. *BMC Health Serv. Res.* **2023**, *23*, 171.

[15] Sharma, V.; Yadav, S.; Gupta, M. Heart disease prediction using machine learning techniques. In Proceedings of the 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida, India, 18–19 December 2020; pp. 177–181.

[16] Available: https://physionet.org/content/mitdb/1.0.0

[17] Available: https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset