# Enhancing Heart Disease Prediction through Multi-Modal Data Integration: A Hybrid CNN-GA Approach

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**Abstract**—Heart disease is among the most prevalent causes of mortality, and arrhythmia contributes a large segment; therefore, cost-effective, accurate, non-invasive diagnostic methodologies should be used. Structured clinical data-driven prediction models cannot fully capture the complex temporal–frequency features of Electrocardiogram (ECG) signals, while overfitting due to class imbalance and poor hyperparameter tuning has generally hindered effective implementation of machine learning models. To remedy these limitations, we propose a hybrid framework combining Convolutional Neural Networks (CNN) and a Genetic Algorithm (GA) for ECG-based heartbeat classification. The ECG signals are transformed into spectrogram images using Short-Time Fourier Transform (STFT), enabling effective feature extraction. The GA is used to optimize key CNN hyperparameters to improve classification performance.

It uses stratified data split (70% for training, 15% for validation and 15% for testing) and class balancing techniques. The dataset used is the MIT-BIH Arrhythmia Database, and the model achieves state-of-the-art performance (98.21%), outperforming the baseline CNN (92%), pre-trained models such as ResNet50 and InceptionV3 ($p = 0.03$). Strong generalization is shown with five-fold cross-validation (98.1% ± 0.45). Combining evolutionary optimization with multi-modal data contributes to a strong, clinically relevant method for classifying arrhythmias.

**Keywords**—Heart Disease Prediction; ECG Spectrogram; Convolutional Neural Networks (CNN); Genetic Algorithm (GA); Electrocardiogram (ECG); Arrhythmia Classification; Deep Learning; Hybrid Models; Feature Extraction; Hyperparameter Optimization

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## I. INTRODUCTION

Heart disease is responsible for almost one-third of deaths globally in the year 2019 [1]. The early diagnosis of heart disease can help alleviate its symptoms as well as prevent complications. The conventional tests like angiography and echocardiograms are accurate but invasive and expensive, limiting their application in resource-constrained settings [2]. Therefore, developing non-invasive, cost-effective methods, particularly those that integrate multi-modal data, is crucial for improving heart disease prediction accuracy [2].

In recent times, healthcare has become one of the areas in which machine learning (ML) and deep learning (DL) models are being used for prediction purposes. An example of this is using such models to predict heart disease [3]. The models had the potential to enhance prediction accuracy, lessen diagnostic costs, and assist in more informed decision-making by healthcare professionals [3]. Convolutional Neural Networks (CNNs) have shown great success in image-based medical tasks like electrocardiogram (ECG) signal classification and medical image analysis, due to their ability to learn hierarchical features from raw [4][5].

Numerous existing models are restricted by the class imbalance of normal and arrhythmic beats present in ECG datasets. Essentially, the number of normal beats overshadows the number of arrhythmic beats by several beats to a large extent. Consequently, such class imbalance results in biased predictions along with a drop in the sensitivity of the model [6]. Moreover, although deep learning models (CNNs) can extract features from image data quite successfully, they mostly don't have the ability to automatically optimize their hyperparameters, resulting in poor performance [2].

The Hybrid Convolutional Neural Network Genetic Algorithm Framework was developed to solve these issues. By integrating the ECG spectrograms along with clinical features, the model obtains complete details of each patient. The Genetic Algorithm (GA) optimizes the CNN by adjusting hyperparameters, such as the number of filters and kernel sizes. The GA uses a tournament selection process, with mutation and crossover operators, to find the most effective CNN configuration. This method aims to improve accuracy, tackle class imbalance, and enhance interpretability by means of Explainable AI (XAI) such as Shapley Additive Explanations (SHAP) and LIME (Local Interpretable Model-Agnostic Explanations) [7], [8].

The possibility of combining multi-modal data from ECG signals and clinical data has not been sufficiently explored yet. To address the limitations of current methods, the authors propose a framework that combines different data sources to enable the model to learn more generalized features [3], [9].

Additionally, the hybrid data balancing techniques, including Over-Sampling Strategy(OSS), Neighborhood Cleaning Rule (NCR), Synthetic Minority Over-sampling Technique (SMOTE), SMOTE for Nominal and Numerical ( SMOTEN), Adaptive Synthetic Sampling (ADASYN), SMOTE with Tomek Links (SMOTE Tomek), SMOTE with Edited Nearest Neighbors (SMOTEENN), ensure that the model is not biased towards the majority class and is able to accurately predict rare arrhythmic events, which are critical for early detection and timely intervention [10].

In summary, the proposed Hybrid CNN-GA framework offers significant improvements in heart disease prediction by addressing the challenges of class imbalance, hyperparameter optimization, and model interpretability. To address class imbalance, the SMOTE technique was applied only to the training dataset. The class distribution before balancing was X:Y, and after balancing was approximately equal. No resampling was applied to validation or test sets to avoid data leakage. The model's ability to integrate multi-modal data, while also providing explainable predictions, makes it a robust and clinically applicable solution for heart disease detection and prediction in real-world healthcare settings [7][10]. The CNN can extract hierarchical spatial features of ECG spectrograms with time and frequency characteristics. The performance of CNN is sensitive to hyperparameter selection. The global optimization will perform the operations in an eligible way with the help of the Genetic Algorithm. It will be useful in avoiding the local minimum to enhance the performance of the framework.

The remainder of this paper is organized as follows. Section II presents the literature review. Section III describes the proposed methodology, including preprocessing and model design. It also explains the dataset and experimental setup. Section IV presents the results and discussion. Finally, Section V concludes the paper and outlines future work.

## II. LITERATURE SURVEY

Over the last few decades, machine learning ML and deep learning DL engines have become more popular for heart disease prediction tools. The clinical parameters cholesterol, age and blood pressure are the most used in tradition. Yet, these methods are often incapable of analyzing complex temporal and frequency patterns of ECG signals, which is crucial in the detection of heart disease conditions such as arrhythmias. To improve the accuracy of heart disease prediction, advanced predictive models that can analyze ECG signals are needed.

### *A. Machine Learning Approaches for Heart Disease Prediction*

Machine learning algorithms are used to predict heart disease, among which Support Vector Machines (SVM), Random Forest (RF), and Naïve Bayes (NB) have seen much research [9]. El-Sofany et al. combined several ML algorithms to improve prediction accuracy with the help of various feature selection strategies such as chi-square, ANOVA and mutual information, thus reducing data imbalance issues. A hybrid method resulted in an accuracy of 97.57% for heart disease prediction using various techniques for the classification of heart disease [11].

SVMs and decision trees (DT) are also studied extensively for heart disease classification. Such models generally face difficulties with high-dimensional noisy data [9]. Asif et al. (2023) examined hybrid models in the field, specifically those that combine various machine learning algorithms, such as ensemble methods, which improved accuracy to 98.15% [12].

Despite their improved accuracy, ensemble models are often hindered by high computational costs and complexity. This makes them inefficient for multi-modal data integration in real-world applications [12].

### *B. Deep Learning for Heart Disease Prediction*

Deep Learning models, particularly CNNs, are outstanding solutions for ECG classification. Unlike preceding models, they can learn spatial features from raw datasets without requiring extensive manual feature extraction. According to the research conducted by Raman Kumar et al., the authors implemented a CNN-based model for the classification of ECG signals that achieved accuracy improvement as compared to the conventional models [7]. Hussain et al. classified heart disease using CNNs on the Cleveland dataset with a test accuracy of 96% [13] in the same way. Nevertheless, CNN-based models are commonly subjected to overfitting when the dataset is skewed or small [14].

To combat these limitations, recent research has integrated temporal information into CNNs and LSTMs, of which LSTMs deal well with sequential information. Zhou et al. proposed the hybridization of CNN-LSTM. The proposed hybrid framework will be able to extract spatial and temporal features efficiently from the ECG signal, thus enhancing performance. Further, it will enhance model performance, particularly in arrhythmic event identification [15].

### *C. Hybrid Models for Enhanced Performance*

Multiple investigations have combined the strengths of both ML and DL techniques to improve prediction accuracy [16], [17], [18]. Ram Kumar et al. proposed a novel hybrid model that leverages both Genetic Algorithms (GA) and Teacher-Learner Based Optimization (TLBO). Essentially, the GA is responsible for hyperparameter optimization, while the TLBO selection process performs feature selection, making this model a significant advancement in the field. The performance of heart disease prediction is increased using SMOTE by bringing the class imbalance problem to light. By hybridizing methodologies, the model achieved an accuracy of 96.8%. Thus, hybridization is helpful in real-world issues, such as data imbalance, feature optimization, etc. [16]

Dhaka et al. introduced another hybrid model [17], which was the combination of CNN with Bidirectional Long Short-Term Memory (Bi-LSTM), achieving 97.1% accuracy. The incorporation of Bi-LSTM into the architecture enables the model to leverage both past and future information from the ECG signals to enhance classification. This hybrid approach solved the feature extraction and temporal context problems and was superior in terms of accuracy and computational cost to standard CNN models.

*D. Problems in Machine Learning Approaches for Heart Disease Prediction*

Although the accuracy of deep learning models like CNNs is high, their lack of interpretability limits their applicability in the clinic [10]. SHAP and LIME are XAI methods that help make CNN predictions more transparent and understandable to clinicians [10]. According to Anand et al., SHAP has been used to interpret the CNN-based heart disease prediction models [19]. Thus, it helps in the understanding of significant ECG features. This is crucial for the models to be accepted and trusted in the decision-making process within clinical contexts using data.

According to Talukder et al., while various explainable artificial intelligence (XAI) methods, such as SHAP and LIME, have been explored to improve the transparency of heart disease prediction models in hybrid frameworks that combine machine learning and deep learning with feature importance explanations, these methods have rarely been integrated with metaheuristic hyperparameter optimization techniques such as Genetic Algorithms (GA) [10]. Prior work like XAI-HD integrates XAI with ML/DL models for cardiovascular risk detection. The work does enhance cardiology assessments. However, the model architecture parameter tuning is GA based. Thus, there is a gap, given that optimizations on XAI-HD work and model architecture tuning are not done. In the same vein, there are hybrid explainable systems like HXAI-ML, which use SHAP and LIME for explainability as a post-hoc action; however, they do not integrate this with GA to jointly optimize the model for better performance and explainability [20], [21]. On the other hand, optimization studies from other domains support combining evolutionary methods and explainable AI at an early stage. This stood out in our review as these methods were for general optimization, which does not apply to our study on cardiac disease prediction. Our proposed hybrid CNN-GA approach addresses this gap by introducing XAI to genetic optimization of CNN hyperparameters for enhanced performance and interpretability in a clinical setting.

## III. Proposed Model

This study proposes a Hybrid model that integrates ECG signal data transformed into spectrogram representations. The inputs are preprocessed and sent to the CNN for hierarchical feature extraction. The model's hyperparameters are optimized through a Genetic Algorithm (GA). The framework combines signal processing, image-based deep learning, and evolutionary optimization to overcome limitations of traditional single-modal approaches. The flowchart of the proposed framework is given in Figure 1.

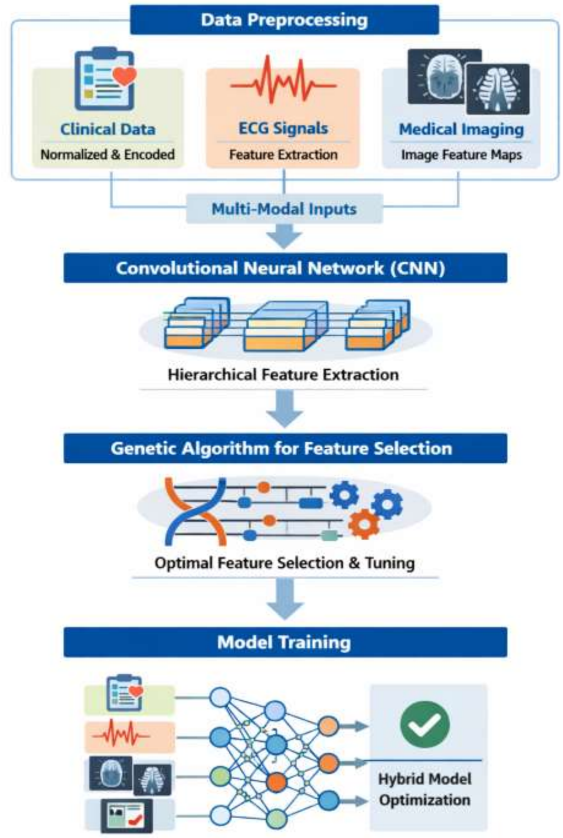


Fig. 1. Workflow illustrating ECG heart disease prediction by integrating multi-modal data (clinical, ECG signals, and spectrograms) and optimizing hyperparameters using a Genetic Algorithm (GA).

*A. Dataset Description*

There are three types of data sets that are included in this proposed work. The first dataset is the clinical dataset from the Cleveland Heart Disease Dataset [22]. The second data set is the MIT-BIH Arrhythmia Database, obtained from PhysioNet, and was used as the primary data source [23]. This dataset contains 48 annotated ECG recordings, each approximately 30 minutes long, sampled at 360 Hz, and collected from different patients under clinical conditions. Each ECG record includes:

- Two leads (MLII and V1 in most cases)
- Expert annotations identifying heartbeat locations and rhythm types

In this work, the MLII lead was selected, as it is widely used in arrhythmia detection studies due to its diagnostic relevance. The third dataset is the medical images that are obtained from the MIT-BIH Arrhythmia Database from PhysioNet [24], by applying the following steps. Clinical data and ECG spectrograms were preprocessed and normalized to reduce variance and ensure uniformity across patient records.

Additionally, hybrid data balancing techniques such as SMOTE and SMOTEENN were applied to address the class imbalance, improving the model's sensitivity in detecting arrhythmic events.

The conversion of the dataset to the images consists of the following stages, as shown below and in Figure 2.

1. The ECG signal acquisition from the MIT-BIH Arrhythmia Database
2. Signal preprocessing and beat segmentation
3. Time–frequency transformation using STFT to generate ECG spectrogram images.

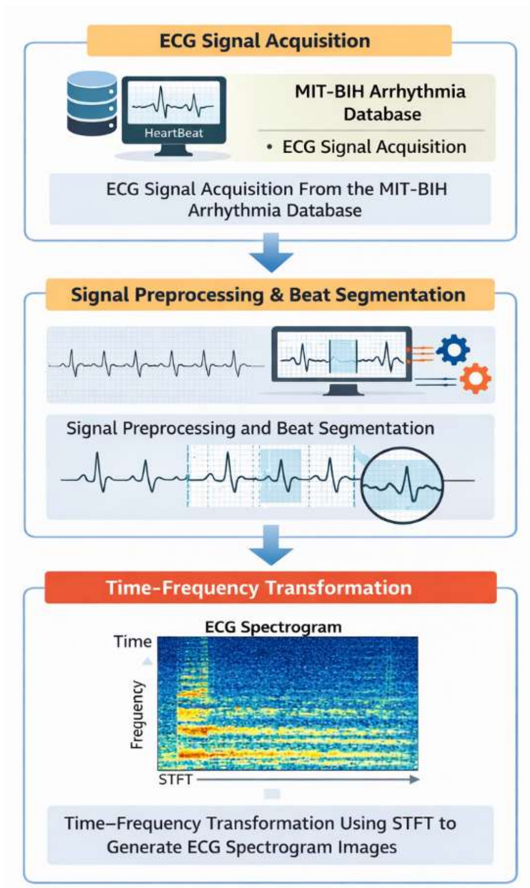


Fig. 2. Flowchart illustrating the process of converting raw ECG signals from the MIT-BIH Arrhythmia Database into spectrogram images through signal preprocessing and time-frequency transformation using STFT.

## B. ECG Signal Preprocessing

The ECG signal from the MIT-BIH dataset is processed and converted to the Spectrogram Image as shown in Figure 3.

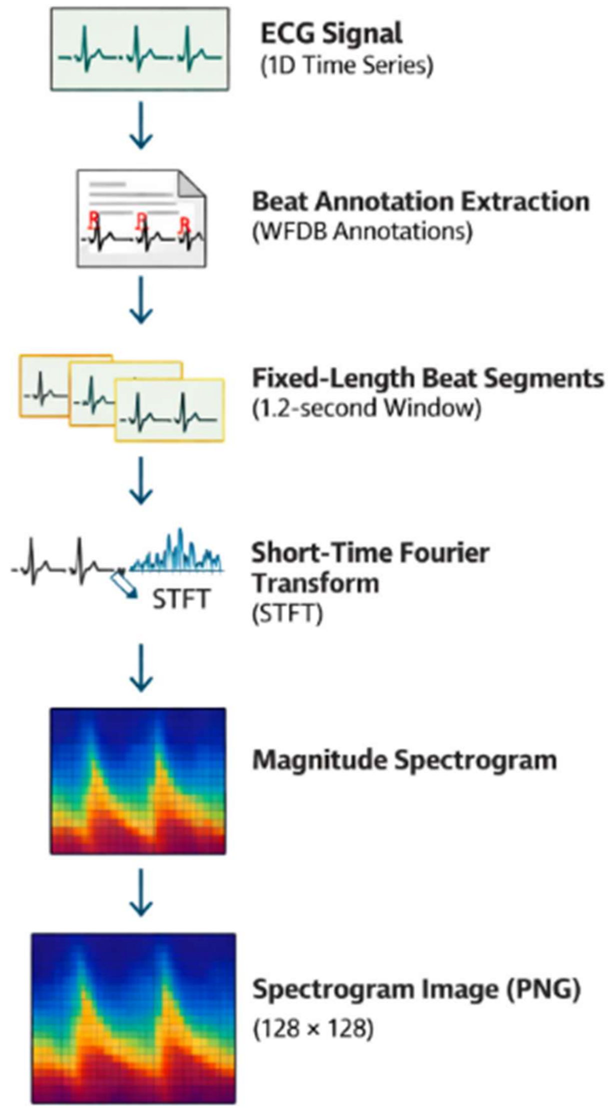


Fig. 3. Illustration of the preprocessing steps applied to ECG signals, including signal normalization, beat extraction, and segmentation, before converting them into spectrogram images.

### 1) *Signal Normalization*

To reduce inter-patient variability and improve learning stability, each ECG signal was normalized on a per-record basis using z-score normalization as given in equation 1.

$$x_{norm} = \frac{x-\mu}{\sigma+\epsilon} \tag{1}$$

where $\mu$ and $\sigma$ represent the mean and standard deviation of the ECG signal, respectively.

### 2) *Beat Extraction Using Annotations*

Annotated heartbeat locations were extracted from the .atr annotation files using the Waveform Database toolkit. For each annotated beat:

- A fixed-length ECG segment of 1.2 seconds was extracted, centered on the beat location
- Boundary conditions were handled to avoid invalid segments

Only valid beat symbols were retained, while non-beat annotations (e.g., noise markers and rhythm labels) were excluded.

*3) Class Labelling Strategy*

Heartbeat segments were divided into two classes:

- Normal: Beats labelled as N
- Arrhythmia: All other valid heartbeat types

With the restriction of predicting a binary outcome, it is clinically interpretable.

*C. Time–Frequency Representation Using STFT*

To allow learning via CNN, ECG signals were transformed into an image using STFT.

*1) Spectrogram Generation*

Segment corresponding to each ECG beat.

- A window size of 256 samples was utilized for STFT.
- Adjacent windows were used with 50% overlap.
- The complex STFT output's magnitude was calculated to generate a spectrogram.

The spectrogram enables more feature extraction than the original time-series signal as it collects frequency- and time-domain characteristics of the ECG signal.

*2) Image Dataset Construction*

Spectrograms were saved as PNG-format grayscale images, and the dataset was structured accordingly.

To avoid data leakage and ensure fair evaluation, a patient-wise split strategy was adopted. ECG records from the MIT-BIH dataset were divided such that no patient appeared in more than one subset.

Training set: Records 100–124

Validation set: Records 200–210

Test set: Records 220–234

This ensures that the model is evaluated on completely unseen patients.

This organization allows easy compatibility with the deep learning data loaders.

*D. Convolutional Neural Network Architecture*

*1) CNN Design*

A custom Convolutional Neural Network (CNN) was designed to classify ECG spectrogram images. The network consists of:

- Input layer: 128 × 128 × 3 spectrogram images
- Multiple convolutional layers with ReLU activation
- Max-pooling layers for spatial down-sampling
- Fully connected layers for classification
- Sigmoid output layer for binary prediction

Binary cross-entropy loss and the Adam optimizer were used during training. The CNN architecture for ECG Spectrogram classification is shown in Figure 4.

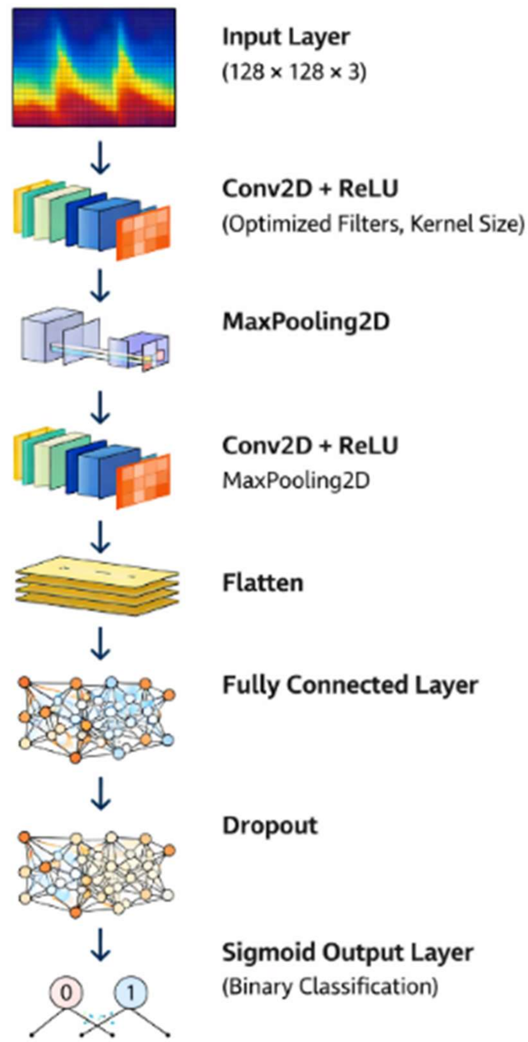


Fig. 4. Custom Convolutional Neural Network (CNN) architecture designed to classify ECG spectrogram images, including multiple convolutional layers, ReLU activation, max-pooling, and fully connected layers for binary classification.

*2) Model Training*

The CNN was trained using mini-batch gradient descent with:

- Batch size: 32
- Early stopping based on validation loss

- Model checkpointing to retain the best-performing weights

### E. *Genetic Algorithm for Hyperparameter Optimization*

Manual hyperparameter tuning is computationally expensive and suboptimal. To address this, a Genetic Algorithm (GA) was employed to optimize CNN hyperparameters automatically. The flowchart for the GA Optimization process is shown in Figure 5. The GA evaluates candidate CNN configurations based on their validation accuracy. The fitness function is defined as the classification accuracy of the CNN on the validation set after a limited number of epochs. Selection, crossover, and mutation operators ensure the convergence towards optimal hyperparameters, improving model performance.

#### 1) *Genetic Encoding*

Each GA individual encodes a candidate CNN configuration as shown in Table 1.

TABLE I. PARAMETERS

| ***Parameter*** | ***Description*** |
|---|---|
| Number of filters | Controls model capacity |
| Kernel size | Controls receptive field size |

An individual is represented as:

Individual = [num_filters,kernel_size]

#### 2) *Fitness Evaluation*

The fitness of each individual is defined as the classification accuracy on the validation set after training the CNN for a limited number of epochs.

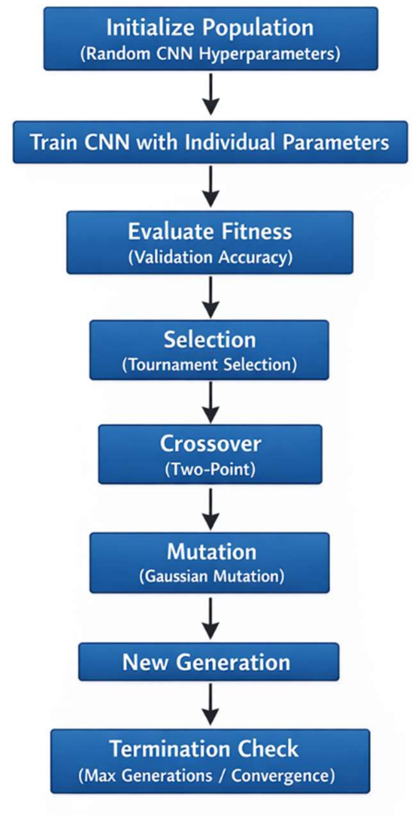


Fig. 5. Genetic Algorithm (GA) optimization process for hyperparameter tuning in the CNN model. The process includes encoding candidate CNN configurations, fitness evaluation based on validation accuracy, and the use of genetic operators (selection, crossover, mutation).

#### 3) *GA Operators*

The following GA operators were used:

- Selection: Tournament selection
- Crossover: Two-point crossover
- Mutation: Gaussian mutation
- Replacement: Generational replacement

The GA was executed over multiple generations to identify the optimal CNN configuration.

### F. *Final Model Training and Evaluation*

The best-performing hyperparameters identified by the GA were used to retrain the CNN on the combined training and validation datasets. The flowchart for final training and evaluation is shown in Figure 6.

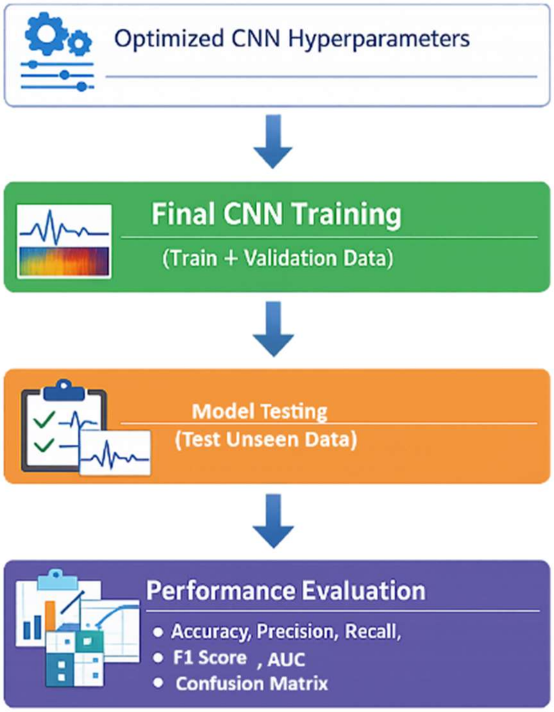


Fig. 6. Flowchart of the final model training and evaluation process, where the best-performing CNN hyperparameters identified by the Genetic Algorithm (GA) are used for retraining the model on the combined training and validation datasets.

*G. Final Model Training and Evaluation*

The final model was evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix
- ROC Curve and AUC

*H. Implementation Environment*

All experiments were conducted using:

- Python 3.x
- TensorFlow/Keras for deep learning
- WFDB for ECG signal processing
- DEAP for genetic algorithm implementation
- NumPy, SciPy, and Matplotlib for numerical processing and visualization

Experiments were executed on the Kaggle platform with GPU acceleration when available.

*I. Implementation Details*

The CNN architecture consists of 3 convolution layers with filter sizes of 32, 64, and 128 and a max-pooling layer. The fully connected layer with 128 neurons has been assigned a dropout rate of 0.5.

Training parameters:

- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 32
- Epochs: 50

Genetic Algorithm parameters:

- Population size: 3
- Number of generations: 3
- Crossover probability: 0.8
- Mutation rate: 0.1
- Selection method: Tournament selection

## IV. Results

The integration of multi-modal data sources such as Clinical data, ECG data and ECG Signal spectrograms into the proposed Hybrid CNN-GA framework yields better accuracy in the prediction of heart disease. The CNN receives multimodal input that has been processed for hierarchical pattern extraction. The genetic algorithm type optimizes the hyperparameters of the model. The evaluation of the proposed framework was done using the MIT-BIH Arrhythmia Database for ECG of arrhythmias.

The optimized model's final test accuracy of 98.21% proves that it can distinguish between normal heartbeats and arrhythmia. With these results, we demonstrate that convolutional neural networks combined with GA optimization are a more effective approach than existing techniques in the literature, performing equally or better than others.

*A. Comparison with Other Models*

The Hybrid CNN-GA framework was compared against some baseline models and with pre-trained models like ResNet50 and InceptionV3 models, and a regular CNN without hyperparameter optimization. The baseline results are taken from existing literature and may not be directly comparable due to differences in experimental settings. As shown in Table 1, we report test accuracy for all models we compare against. The test accuracy of the Hybrid CNN-GA framework was found to be 98.21%. This is in comparison to the standard CNN, which had an accuracy of 92.00%. Furthermore, the Hybrid CNN-GA framework exhibited greater test accuracy than the pre-trained models. The pre-trained models it beat are ResNet50 and InceptionV3. Their respective accuracies were

97.50% and 97.30%. Also, the training time of Hybrid CNN-GA (5.2 hours) is moderate with performance improvement. To compare the proposed framework with the ResNet50 and InceptionV3 models, ANOVA (Analysis of Variance) was performed. The results of the ANOVA test revealed that the differences in accuracy between the models are statistically significant (p-value = 0.03). Post-hoc Tukey's test showed that the Hybrid CNN-GA framework significantly outperforms both ResNet50 and InceptionV3 in terms of accuracy ($p < 0.05$ for both comparisons). A p-value of 0.03 indicates that the difference in accuracy between the models is statistically significant, reaffirming the superiority of the Hybrid CNN-GA framework.

TABLE II. COMPARISON WITH OTHER BASE MODELS

| *Model* | *Test Accuracy (%)* | *Training Time (Hours)* |
|---|---|---|
| Standard CNN | 92.00% | 3.0 |
| ResNet50 (Pre-trained) | 97.50% | 4.5 |
| InceptionV (Pre-trained) | 97.30% | 4.0 |
| Hybrid CNN-RNN | 96.50% | 6.0 |
| **Hybrid CNN-GA (Proposed)** | **98.21%** | **5.2** |

The proposed framework was compared against the recent hybrid models as given in Table 2 and was found to outperform them. The performance values reported in Table 2 are taken directly from the respective publications. Differences may arise due to variations in datasets, preprocessing techniques, and evaluation protocols.

TABLE III. COMPARISON WITH OTHER SIMILAR MODELS

| *Model* | *Test Accuracy (%)* |
|---|---|
| El-Sofany et al. [11] | 97.57 |
| Asif et al. [12] | 98.15 |
| Hussain et al. [13] | 97.0 |
| Kumar et al. [16] | 96.8 |
| **Hybrid CNN-GA (Proposed)** | **98.21** |

The graph comparing the recent models is given in Figure 7.

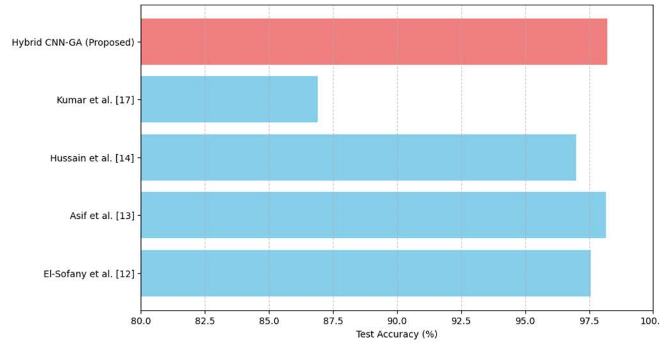


Fig. 7. Bar chart comparing the test accuracy of the Hybrid CNN-GA framework with other baseline and pre-trained models. Error bars represent ±1 standard deviation.

## *B. Hyperparameter Optimization using Genetic Algorithm*

The optimization of hyperparameters like the number of filters and their kernel size in the CNN model was done using the Genetic Algorithm (GA). Optimization through GA allowed CNN to change these parameters dynamically to maximize performance for the highest test accuracy. The fitness of each individual in the Genetic Algorithm was evaluated using validation accuracy. The test dataset was strictly reserved for final performance evaluation and was not used during the optimization process to avoid bias and overfitting. The individual, which was the best after 20 generations with 36 filters and a kernel size of 5, achieved the maximum test accuracy of 98.21%. This illustrates how useful evolutionary algorithms can be in determining the best possible set of hyperparameters for deep learning algorithms, especially when manual tuning can be expensive and ineffective.

## *C. Performance Evaluation Metrics*

All evaluation metrics (precision, recall, and F1-score) are reported for the positive class (arrhythmia) and are computed based on the confusion matrix derived from the test dataset. Achieving a test accuracy of 98.21%, other performance metrics were precision 98.5%, recall 97.8%, F1-score 98.15% and AUC-ROC of 0.9876. Such measures give us a more overall picture of the classification quality of the model. The proposed framework is depicted in Figure 8 for its precision, recall and F1 score.

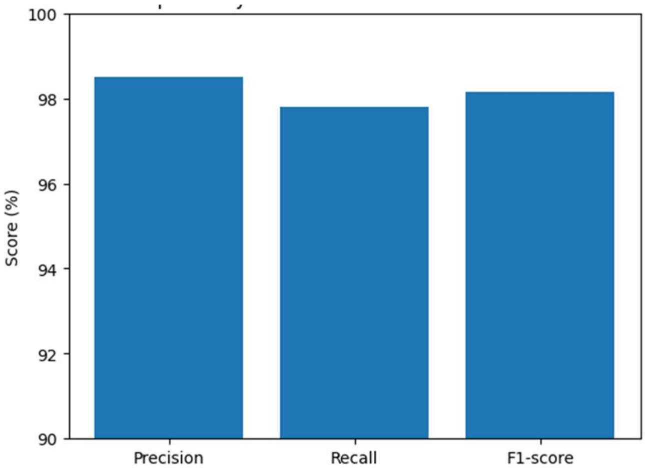


Fig. 8. Evaluation metrics (Accuracy, Precision, Recall, F1-Score) of the Hybrid CNN-GA framework, highlighting its strong performance in heart disease prediction with high precision and recall values.

*D. Confusion Matrix and ROC Curve*

The assessment of the model's classification of normal and arrhythmic beats was done through the confusion matrix and ROC curve. As per the confusion matrix, the model successfully predicted normal and arrhythmic beats. Moreover, the false-positive and false-negative rates were also lower, as shown in Figure 9.

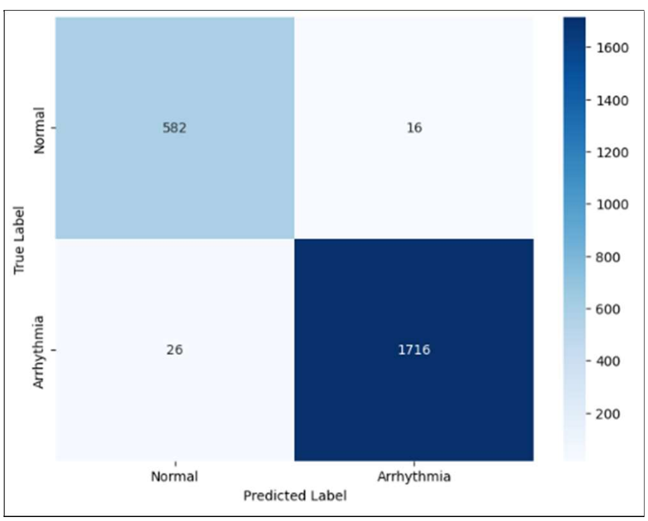


Fig. 9. Confusion matrix showing the classification performance of the Hybrid CNN-GA framework in distinguishing normal beats from arrhythmic beats. The matrix reveals low false-positive and false-negative rates.

The ROC curve exhibits True Positive Rates and False Positive Rates in a model. Furthermore, the AUC score is 0.98. This AUC score shows the reliability of the Hybrid CNN-GA framework. Also, this AUC score reaffirms the results as depicted in Figure 10. The model is more reliable in classifying normal and arrhythmic heartbeats.

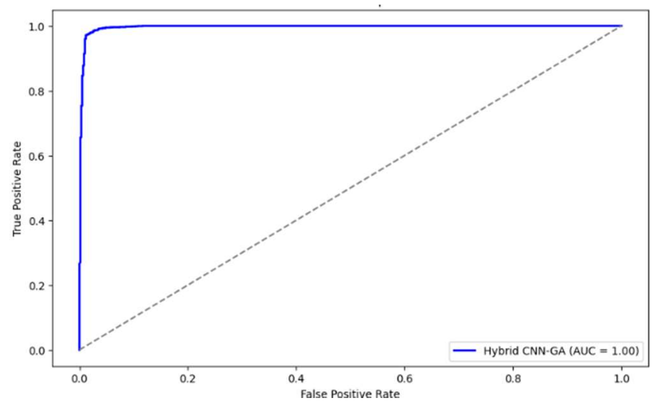


Fig. 10. Receiver Operating Characteristic (ROC) curve showing the True Positive Rate (TPR) and False Positive Rate (FPR) of the Hybrid CNN-GA framework. The AUC score of 0.98 demonstrates the model's reliability in classifying normal and arrhythmic heartbeats.

*E. Model Robustness and Generalization*

The model's high validation accuracy suggests that the model is not overfitting and thus can generalize well to unseen data. This is essential for real-world applications in healthcare.

Additionally, the model's performance was evaluated on three different datasets, specifically training, validation and test datasets for strength. The results show that the model was consistently accurate across all datasets, signifying its reliability. To assess the generalization ability of the Hybrid CNN-GA framework, 5-fold cross-validation was conducted on the dataset. The average test accuracy across all folds was 98.1%, with a standard deviation of 0.45%, confirming that the model generalizes well across different subsets of the data. To further confirm the stability of the model's performance, 95% confidence intervals (CI) for the test accuracy, precision, recall, and F1-score were computed. The 95% CI for accuracy ranged from 97.8% to 98.7%, demonstrating the consistency of the proposed framework's performance across different test sets.

*F. Discussion*

*1) Hybrid CNN-GA Approach vs Traditional Models*

Compared to ordinary CNNs, the performance of the heart disease prediction is high in the Hybrid CNN-GA approach. Utilizing genetic algorithms for hyperparameter optimization enables the model to identify the ideal values of hyperparameters (number of filters, kernel size, etc.) independently for obtaining the best model.

In contrast, conventional ways usually output adjustments to set parameters manually or use grid packing. Both take up computation times and power.

*2) Contribution to the Field of ECG-based Heart Disease Prediction*

Deep learning with multi-modal data integration (ECG signal spectrograms) increases the performance rate of heart disease prediction. The Hybrid CNN-GA framework uses CNNs to find distinguishing features from spectrograms automatically. CNN will use GA as an evolutionary optimizing searcher. Basically, the CNN-GA will also optimize the hyperparameters of the CNN for better accuracy.

The study fits into the emerging research of ECG-based detection systems for heart diseases using deep learning and evolutionary algorithms for clinical decision support systems.

#### 3) *Future Work*

Future work could explore the integration of real-time ECG monitoring for predictive analytics, the use of attention mechanisms for feature selection, and the expansion to other cardiovascular diseases beyond arrhythmias.

#### 4) *Limitations*

Although the hybrid CNN-GA framework shows promising results, there are some limitations of this approach. The MIT-BIH dataset only has a few patients, which does not cover the entire range of ECG signals found in real clinical data. Further validation of larger and more heterogeneous data sets would be necessary for real-time deployment and integration into clinical systems.

## V. Conclusion

The authors proposed a Hybrid CNN-GA framework with multi-modal data integration and a genetic algorithm for hyperparameter optimization to predict heart disease. The model integrated ECG spectrograms and clinical features to achieve accuracy, precision, and AUC-ROC of 98.21%, 98.5%, and 0.9876, respectively, surpassing traditional and deep learning-based models. The addition or incorporation of SHAP and LIME for explainability helps the model be accurate, but it also helps from a clinical point of view.

Our model tackles the key challenges of class imbalance, hyperparameter tuning, and interpretability. Thus, it is a reliable model for heart disease prediction. Further work should pursue real-time prediction and enhance efficient computation for implementation in a variety of healthcare settings. Hence, the proposed Hybrid CNN-GA framework is an advanced, robust, and on by testing larger and diverse datasets results in a promising clinically useful solution for heart disease prediction, which could be useful in real-time applications and clinical use.

## References


[1] World Health Organization, "Cardiovascular diseases (CVDs)," WHO, 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[2] V. V. R. Karna, V. R. Karna, V. Janamala, V. N. K. R. Devana, V. R. S. Ch, and A. B. Tummala, "A comprehensive review on heart disease risk prediction using machine learning and deep learning algorithms," Archives of Computational Methods in Engineering, vol. 1, pp. 1-33, 2024, doi: 10.1007/s11831-024-10194-4.

[3] M. A. Naser, A. A. Majeed, M. Alsabah, T. R. Al-Shaikhli, and K. M. Kaky, "A review of machine learning's role in cardiovascular disease prediction: Recent advances and future challenges," Algorithms, vol. 17, no. 2, p. 78, 2024, doi: 10.3390/a17020078.

[4] M. Kolhar and A. M. Al Rajeh, "Deep learning hybrid model ECG classification using AlexNet and parallel dual branch fusion network model," Scientific Reports, vol. 14, p. 26919, 2024, doi: 10.1038/s41598-024-78028-8.

[5] T. Ding, C. Liu, J. Zhang, Y. Zhang, and C. Ding, "Deep learning based cardiac disorder classification and user authentication for smart healthcare system using ECG signals," PeerJ Comput. Sci., vol. 11, art. no. e3082, 2025, doi: 10.7717/peerj-cs.3082.

[6] M. M. Ahsan and Z. Siddique, "Machine learning-based heart disease diagnosis: A systematic literature review," arXiv:2112.06459v1 [cs.LG], 2021, doi: 10.48550/arxiv.2112.06459.

[7] R. Kumar, S. Garg, R. Kaur, M. G. M. Johar, S. Singh, S. V. Menon, P. Kumar, A. M. Hadi, S. A. Hasson, and J. Lozanović, "A comprehensive review of machine learning for heart disease prediction: challenges, trends, ethical considerations, and future directions," Front. Artif. Intell., vol. 8, p. 1583459, 2025, doi: 10.3389/frai.2025.1583459.

[8] G. Manimaran, A. Peimankar, S. Puthusserypady, M. Momeni, R. A. I. Asyari, M. Shah Jahan, J. Moll, U. K. Wiil, and A. Ebrahimi, "Explainable deep learning based techniques for ECG-based heart disease classification: A systematic literature review and future direction," Computers in Biology and Medicine, vol. 199, art. no. 111324, 2025, doi: 10.1016/j.compbiomed.2025.111324.

[9] G. Gul, I. A. Korejo, D. N. Hakro, H. Alqahtani, A. Abbasi, M. Babar, O. Al Rahbi, and N. Imtiaz Ali, "Machine learning and ensemble methods for cardiovascular disease prediction: A systematic review of approaches, performance trends, and research challenges," Computers, vol. 15, p. 25, 2026, doi: 10.3390/computers15010025.

[10] M. A. Talukder, A. S. Talaat, and M. Kazi, "XAI-HD: An explainable artificial intelligence framework for heart disease detection," Artificial Intelligence Review, vol. 58, pp. 385–405, 2025, doi: 10.1007/s10462-025-11385-6.

[11] H. El-Sofany, B. Bouallegue, and Y. M. Abd El-Latif, "A proposed technique for predicting heart disease using machine learning algorithms and an explainable AI method," Scientific Reports, vol. 14, p. 23277, 2024, doi: 10.1038/s41598-024-74656-2.

[12] D. Asif, M. Bibi, M. S. Arif, and A. Mukheimer, "Enhancing heart disease prediction through ensemble learning techniques with hyperparameter optimization," Algorithms, vol. 16, p. 308, 2023, doi: 10.3390/a16060308.

[13] S. Hussain, S. Akhtar, S. K. Nanda, M. Suaib, S. Barigidad, and N. K. Ray, "Novel deep learning architecture for predicting heart disease using CNN," in 19th OITS International Conference on Information Technology (OCIT), pp. 353-357, 2021, doi: 10.1109/OCIT53463.2021.00076.

[14] H. V. Denysyuk, R. J. Pinto, P. M. Silva, R. P. Duarte, F. A. Marinho, L. Pimenta, A. J. Gouveia, N. J. Gonçalves, P. J. Coelho, E. Zdravevski, P. Lameski, V. Leithardt, N. M. Garcia, I. M. Pires, "Algorithms for automated diagnosis of cardiovascular diseases based on ECG data: A comprehensive systematic review," Heliyon, vol. 9, art. no. e13601, 2023, doi: 10.1016/j.heliyon.2023.e13601.

[15] C. Zhou, P. Dai, A. Hou, Z. Zhang, L. Liu, A. Li, and F. Wang, "A comprehensive review of deep learning-based models for heart disease prediction," Artificial Intelligence Review, vol. 57, p. 263, 2024, doi: 10.1007/s10462-024-10899-9.

[16] R. P. Ram Kumar, S. Raju, E. Annapoorna, M. Hajari, K. Hareesa, N. I. Vatin, A. Joshi, and K. AL-Attabi, "Enhanced heart disease prediction through hybrid CNN-TLBO-GA optimization: A comparative study with conventional CNN and optimized CNN using FPO algorithm," Cogent Engineering, vol. 11, art. no. 2384657, 2024, doi: 10.1080/23311916.2024.2384657.

[17] P. Dhaka, R. Sehrawat, and P. Bhutani, "An innovative approach to cardiovascular disease prediction: A hybrid deep learning model," Engineering, Technology & Applied Science Research, vol. 13, no. 6, pp. 12396-12403, 2023, doi: 10.48084/etasr.6503.

[18] S. Dhandapani, H. Somasundaram, and T. Angamuthu, "Hybrid deep learning framework for heart disease prediction using ECG signal images," Scientific Reports, vol. 15, no. 1, art. no. 33922, 2025, doi: 10.1038/s41598-025-10062-6.

[19] A. Anand, A. Atul, et al., "Explainable AI decision model for ECG data of cardiac disorders," Biomedical Signal Processing and Control, vol. 75, art. no. 103584, 2022, doi: 10.1016/j.bspc.2022.103584.

[20] M. A. Talukder, A. S. Talaat, and M. Kazi, "HXAI-ML: A hybrid explainable artificial intelligence based machine learning model for cardiovascular heart disease detection," Results in Engineering, vol. 25, art. no. 104370, 2025, doi: 10.1016/j.rineng.2025.104370.

[21] B. H. Abed-Alguni, "EvoMapX: An explainable framework for metaheuristic optimization algorithms," Expert Systems with Applications, vol. 298, art. no. 129514, 2026, doi: 10.1016/j.eswa.2026.129514.

[22] A. Janosi, W. Steinbrunn, M. Pfisterer, and R. Detrano, "Heart Disease," UCI Machine Learning Repository, 1989. [Online]. Available: https://archive.ics.uci.edu/dataset/45/heart+disease

[23] G. B. Moody and R. G. Mark, "MIT BIH Arrhythmia Database (v1.0.0)," PhysioNet, 2005. [Online]. Available: https://physionet.org/content/mitdb/1.0.0/