RESEARCH PAPER

Combining Raw ECG Morphology and Handcrafted Time-Frequency Features for Enhanced Arrhythmia Detection

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ABSTRACT

Accurate classification of electrocardiogram (ECG) signals is essential for early detection and management of cardiac arrhythmias. Conventional methods often rely on either handcrafted features or deep learning on raw signals, which individually fail to fully capture both interpretability and complex temporal dynamics. This research proposes a novel hybrid methodology that integrates raw ECG signal processing with handcrafted time-domain and frequency-domain features to improve classification performance and interpretability. Raw ECG segments are processed through a CNN+GRU+LSTM architecture, where convolutional layers extract local morphological patterns, GRU layers model short-term dependencies, and LSTM layers capture long-range temporal dynamics. In parallel, thirteen handcrafted features including statistical measures (mean, standard deviation, skewness, kurtosis, RMS, zero-crossings, peak-to-peak range, minimum, maximum, median) and frequency-domain characteristics (dominant frequency, spectral entropy, spectral centroid) provide interpretable domainspecific information. These two feature streams are fused via concatenation and passed through dense layers for final classification into four arrhythmia classes. The proposed hybrid model achieved an overall accuracy of 98.75%, outperforming baseline Random Forest (96.63%) and LSTM-only (97.95%) models. Precision, recall, and F1-score were 94.80%, 88.80%, and 91.56%, respectively, demonstrating improved sensitivity, particularly for minority classes. Class-wise ROC-AUC values ranged from 0.99 to 1.0, confirming robust discrimination across all classes. The proposed approach introduces dual-input design, which bridges the gap between interpretable handcrafted features and end-to-end deep learning. By combining morphological, statistical, spectral, and temporal representations, the proposed model not only achieves high predictive performance but also maintains interpretability, offering insights into the ECG signal characteristics driving classification. This hybrid approach provides a comprehensive, clinically relevant framework for arrhythmia detection, addressing limitations of existing methods while improving sensitivity, robustness, and generalization across diverse ECG patterns.

Keywords: *Electrocardiogram (ECG), Arrhythmia Classification, Hybrid Deep Learning, Handcrafted Features, CNN-GRU-LSTM*

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1. INTRODUCTION

Electrocardiography (ECG) remains one of the most widely utilized non-invasive diagnostic tools in clinical practice for assessing the electrical activity of the heart. After the invention of the string galvanometer by Willem Einthoven's in the early 20th century, ECG technology has evolved dramatically from cumbersome laboratory instruments to compact digital systems integrated into portable and wearable devices [1]. The ECG waveform is composed of distinct components, including the P-wave, QRS complex, and T-wave, which reflect atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively. Intervals such as PR, QT, and RR provide additional diagnostic information on conduction pathways and rhythm dynamics [2].

The clinical significance of ECG stems from its ability to capture abnormalities associated with a wide spectrum of cardiac disorders, including arrhythmias, myocardial ischemia, and conduction defects. Early detection of subtle waveform changes can enable timely interventions and prevent severe cardiac events. Cardiovascular diseases (CVDs) remain the leading global cause of mortality, responsible for nearly 18 million deaths annually, underscoring the urgent need for effective diagnostic modalities [3]. ECG is particularly valuable in this context because it is low-cost, widely accessible, and suitable for both advanced healthcare systems and resource-limited environments.

The digitization of ECG signals has also expanded their utility beyond hospital settings. Wearable devices such as smartwatches and portable ECG monitors allow continuous, real-time cardiac monitoring, enabling detection of asymptomatic arrhythmias and providing physicians with longitudinal patient data. These

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developments align with the broader movement toward precision and personalized medicine, where continuous physiological monitoring informs preventive strategies and individualized treatment plans. The integration of ECG with Internet of Things (IoT) platforms, cloud computing, and artificial intelligence has further strengthened its role in telemedicine and remote healthcare delivery [4].

The clinical utility of ECG is closely tied to accurate interpretation and classification of signals. Misinterpretation can lead to delayed diagnoses or inappropriate treatments, which in turn may have life-threatening consequences. Automated ECG classification systems are therefore crucial, as they provide rapid, reliable, and consistent diagnostic support, complementing the expertise of clinicians [5]. Such systems are particularly beneficial in high-volume healthcare settings where manual interpretation of thousands of ECG traces may be impractical.

Furthermore, automated approaches enable large-scale screening programs, particularly in rural or underserved regions where access to trained cardiologists or specialists is limited. By detecting arrhythmias or ischemic changes early, these systems can trigger timely interventions, reducing the risk of sudden cardiac death and lowering the burden on tertiary care centers. Beyond acute care, automated classification contributes to preventive cardiology, perioperative monitoring, and long-term surveillance via devices such as Holter monitors and implantable loop [6]. As healthcare shifts toward digital platforms, accurate ECG classification not only improves patient outcomes but also enhances healthcare efficiency. By reducing misclassification rates, lowering clinical workload, and enabling integration into electronic health records, automated classification systems are becoming a cornerstone of digital cardiology.

Despite notable advances, ECG classification remains a complex challenge due to both physiological and technical factors. Noise and Signal Artifacts: ECG signals are highly susceptible to contamination from various sources. Baseline wander caused by respiration, muscle artifacts from electromyogram activity, electrode motion, and powerline interference are among the most common distortions. These artifacts can obscure clinically relevant features, leading to misclassification if not properly addressed [7]. Although preprocessing methods such as bandpass filtering, wavelet denoising, and adaptive filtering have been applied, achieving robust noise suppression without losing diagnostic information remains difficult. Class Imbalance: Another critical issue arises from the distribution of arrhythmia data. In clinical datasets such as the MIT-BIH Arrhythmia Database, normal beats dominate, while rare but clinically significant arrhythmias account for only a small fraction of the data. This imbalance biases machine learning models toward majority classes, resulting in poor sensitivity for minority arrhythmias [8]. Since the minority classes often correspond to severe conditions such as ventricular fibrillation, overlooking them poses serious clinical risks. Approaches such as oversampling, Synthetic Minority Oversampling Technique (SMOTE), generative models, and cost-sensitive learning have been explored to mitigate this problem [9].

Although deep learning models have demonstrated excellent performance on benchmark ECG datasets, their effectiveness often decreases when deployed in real-world clinical settings due to variations in patient demographics, recording conditions, and ECG acquisition devices. Furthermore, the limited interpretability of deep learning models makes it difficult for clinicians to understand the rationale behind their predictions, reducing trust and hindering clinical adoption. These challenges emphasize the need for robust, generalizable, and explainable ECG classification frameworks capable of delivering reliable performance across diverse healthcare environments. [10]. Together, these challenges highlight the need for advanced, noise-resilient, balanced, and interpretable models capable of operating reliably across diverse healthcare environments. Traditional ECG analysis methods relied heavily on handcrafted feature extraction combined with classifiers such as Support Vector Machines, k-Nearest Neighbors, or Random Forests [11]. While these approaches achieved success in controlled settings, their dependence on expert driven features limited adaptability and scalability across heterogeneous datasets. Deep learning has emerged as a transformative paradigm by learning hierarchical representations directly from raw or minimally preprocessed ECG data. Convolutional Neural Networks (CNNs) are particularly effective at capturing local morphological features such as QRS complexes, P-waves, and ST-segment deviations [12]. Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, excel at modeling sequential dependencies, enabling detection of arrhythmias that unfold across multiple cardiac cycles [13]. More recently, attention mechanisms and transformer based models have enhanced interpretability and improved focus on diagnostically significant signal regions [14]. The strengths of multiple architectures, hybrid models combining CNNs and RNNs have been widely explored. In such frameworks, CNN layers act as feature extractors, while RNN or LSTM layers model temporal relationships. These hybrid CNN-RNN architectures have demonstrated superior performance in benchmark studies, such as the MIT-BIH Arrhythmia Database, compared to individual models [15]. Nevertheless, existing hybrid models face significant limitations. Their high computational cost and risk of overfitting restrict real-time deployment in wearable devices and edge computing platforms [16]. Moreover, many reported studies rely on controlled datasets, raising concerns about their generalizability to noisy, realworld ECG recordings. Addressing these limitations requires designing lightweight, noise-resilient, and clinically validated hybrid models that balance accuracy with computational efficiency.

In summary, while ECG analysis has progressed from traditional feature-based approaches to advanced deep learning methods, challenges such as noise resilience, class imbalance, and real-world generalization remain unsolved. Hybrid deep learning models offer a promising direction by leveraging complementary strengths of CNNs, RNNs, and attention mechanisms. The development of optimized, interpretable, and scalable hybrid architectures can therefore play a pivotal role in advancing automated ECG analysis, supporting telecardiology, and ultimately reducing the global burden of cardiovascular disease.

2. LITERATURE REVIEW

2.1 Evolution of Ecg Classification Approaches

There has been an extraordinary change in electrocardiogram (ECG) classification, which has shifted to adopting the classic statistical methods to pioneering deep learning and hybrid. Initial experiments by Wu et al. (2021) set the potential of the use of convolutional neural networks (CNNs) with a 12-layer architecture trained on the MIT-BIH dataset, which had higher performance compared to traditional methods. Based on such platforms Hazrati- fard et al. (2023) suggested the use of ensemble Siamese networks to perform ECG authentication in telemedicine which considers issues of accuracy and security. The contributions made these ideas the forerunners of more developed application-driven approaches. The ProWSyn over-sampling and PCA dimensionality reduction combined with the fully connected wave network, named FCW-Net, were implemented by Ashfaq et al. (2025) to predict heart disease. Combination of SHAP based interpretability achieved above 92 percent accuracy and AUC of 0.9622, indicating how transparency can be in line with high precision. Equally, Sondkar (2025) focused on a model that can be deployed in the industry, as logistic regression, kNN, XGBoost, and SVMs were applied to hospital-related data to detect myocardial infarction and arrhythmia. Gadag et al. (2025) explored this direction by training using 928 images of ECGs and obtained almost perfect results of classifying between normal, abnormal and infarction, which demonstrates the safety of pairwise models.

2.2 Hybrid and Optimized Deep Learning Models

Lately, there has been an explosion of hybrid designs that incorporate CNNs, recurrent units and optimization methods. Lamba et al. (2025) suggested Bi-LSTM and FCN models, which are optimized by using the Ant Colony Optimization to detect arrhythmia with noise reduction by use of wavelets and feature extraction by use of stationary wavelet-Hilbert transforms where the accuracy is almost 99 percent. Likewise, Ji and Zhu (2024) introduced Grunet, a CNN-GRU, with 99.5% accuracy, and Zakaria et al. (2024) used ensemble learning when doing inter-patient arrhythmia classification across dual-lead ECGs.Other stud- ies went a step further to hybridize. Kim et al. (2025) used CNNs with transformers to extract Stockwell transform features to achieve 97.8% accuracy without R-peak detec- tion. Krishna et al. (2024) made use of genetic algorithm to optimize transformer models that have more than 98 accuracy. Saleh et al. (2025) used LSTM fusion mod- els, and Anu et al. (2025) introduced AQO-CNN-LSTM, utilizing quantuminspired maximization to achieve more accurate results. Bio-inspired optimization also was also found in Aswath et al. (2023), whereas Mahmud et al. (2023) considered transfer learning, and Emara et al. (2023) relied on 2D-CNN with compressive sensing to balance between the effi- ciency and the robustness. All these works manifest the transition of intelligent solutions with multiple layers and the sensitivity of resources.

2.3 Noise, Artifact, and Quality Considerations

Noise and artifacts still continue to be a hindrance in ECG interpretation. The Galeotti et al. (2020) technique of subtracting the median beats to estimate the noise is robust against signal-to-noise ratios. Kumar and Sharma (2020) developed a mixed codebook decomposition-based disturbance detector that performs above 99 percent accuracy on the detection of power-line interference and the presence of total baseline wander anomaly. In the same vein, Moeyersons et al. (2019) presented an intro-duced quality index which connected classifier confidence with expert annotations, which makes it reliable across different datasets. Rodrigues et al. (2017) viewed noise detec- tion as a clustering problem, achieving an accuracy of 91%. On the deep learning level, Islam et al. (2022) used a blend of BiRNNs and dilated CNNs, enhanced with GANs and denoising, which provided almost perfect results in arrhythmia classification. Rotbei et al. (2024) similarly emphasized quality, and using entropy metrics and uncertainty analysis to create beat-level classification obtained 96% accuracy. Collectively, the studies indicate that noise handling has grown beyond being an add-on to preprocessing to being a final process integral in ECG classification pipelines.

2.4 Handling Class Imbalance, Missing Data and Efficient Architectures

The problem of class imbalance is still in the way of ECG classification, which spurs a variety of strate- gies. Najia and Faouzi (2025) based their CNN-BiLSTM on SMOTE with 99 percent success and a physician workload reduction. The accuracy of PCA-based ensemble stacking XGBoost reached 99.58% (Jahangir et al., 2025). Wang et al. (2024) combined SMOTE with SHAP analysis and UMAP dimensionality reducing, which improved understandability and fairness. Tajali et al. (2024) dealt with missing data on the imputation method and Bayesian-optimized XGBoost and SVM, which provided almost perfect results. Increased scope of application, Babaei et al. (2025) directed their focus to detecting sleep apnea using a CNN-GRU model supplemented with multi-domain features and attention mecha- nisms. Panigrahi et al. (2025) coupled the idea of integrating IoT and feature fusion in remote CVD monitoring, a practice where the concept of hybridization helps provide the reality of healthcare delivery. The federated learning approach to atrial fibrillation prediction (Roberto-Alreshidi et al., 2024) emphasizes the use of CNN-LSTM to predict upcoming events at the cost of patient privacy. In addition to accuracy, such factors as efficiency and deployability have become significant. Bontinck et al. (2024) presented a light encoder, ECGencode, which eliminates 90 percent of parameters without degradation, and is as small as eight pixels in size, which is suitable for use in edges. This is familiar to Mahmud et al. (2023) and Emara et al. (2023) who went on search of compressive sensing and transfer learning of small but powerful models. This way, ECG analysis would be able to leave the research laboratories and bedside, as well as portable devices.

3. RESEARCH METHODOLOGY

The present study utilizes the MIT-BIH Arrhythmia Database, a widely recognized benchmark for ECG signal analysis, comprising 48 half-hour, two-channel recordings from 47 subjects sampled at 360 Hz. Expert annotations provide precise beat locations and types, encompassing both normal and abnormal rhythms. To ensure diagnostic consistency, only the Modified Lead II (MLII) signals were considered as input due to their reliability and clinical relevance. Raw ECG signal files in CSV format were programmatically filtered to retain only those containing the MLII lead, and corresponding annotation files were matched using standardized naming conventions. Annotation files were parsed to extract sample indices and beat-type labels, with malformed entries discarded. To improve clinical interpretability, over 20 distinct raw beat types were mapped to five superclasses defined by the American Association for the Advancement of Medical Instrumentation (AAMI): N (Normal), S (Supraventricular), V (Ventricular), F (Fusion), and Q (Unknown/Other). Preprocessing involved fourthorder Butterworth bandpass filtering (0.5-50 Hz) with zero-phase filtering (filtfilt) to remove baseline drift, powerline interference, and high-frequency noise, preserving essential morphological components. Signals were normalized to the range [-1,1] to mitigate inter-subject amplitude variations. ECG segments of 180 samples were extracted around each annotated R-peak, ensuring full waveform coverage via boundary checks. Each segment was assigned an integer label (0-4) according to the AAMI mapping, forming structured input matrices for downstream classification. To enrich feature representation, 13 handcrafted features were computed for each segment, including ten time-domain metrics (mean, standard deviation, skewness, kurtosis, RMS, median, min/max, peak-to-peak, zero-crossings) and three frequency-domain metrics (dominant frequency, spectral entropy, spectral centroid). These features provide interpretable, domain-specific information complementary to the raw waveform.

The proposed hybrid model employs a dual-input architecture: raw ECG segments are processed through convolutional layers to extract morphological patterns, followed by GRU and LSTM layers to capture short- and long-term temporal dependencies. Handcrafted features are processed via dense layers, and the resulting representations are concatenated and passed through fully connected layers with softmax activation for four-class AAMI classification. The model is trained using categorical cross-entropy loss with the Adam optimizer, incorporating early stopping and model checkpointing to prevent overfitting. This hybrid framework effectively integrates deep temporal-spatial signal representations with interpretable handcrafted descriptors, offering a robust, generalizable, and clinically relevant solution for automated arrhythmia detection.

3.1 Dataset Description

The MIT-BIH Arrhythmia Database is a widely recognized benchmark for ECG signal analysis and arrhythmia classification. It comprises 48 half-hour two-channel ECG recordings obtained from 47 subjects, sampled at 360 Hz, with expert annotations identifying the location and type of heartbeats, including normal and abnormal rhythms. This rich diversity makes it ideal for evaluating automated arrhythmia detection models. The dataset is systematically organized into 48 ECG signal files in .csv format containing raw waveforms and 48 corresponding annotation files in .txt format providing time-stamped beat labels. This structured pairing ensures accurate linkage between signals and annotations, thereby supporting reliable preprocessing, model training, and classification of heartbeat categories.

3.2 Data Preprocessing

The MIT-BIH Arrhythmia Database contains recordings from multiple lead configurations; however, not all leads are equally reliable for diagnostic purposes. In this study, the Modified Lead II (MLII) signal was chosen as the primary input, as it is consistently present across most records and widely recognized for its diagnostic accuracy in arrhythmia detection. To extract only compatible data, all .csv and .txt files were programmatically listed from the dataset directory. A filtering mechanism was then applied to verify the presence of the MLII column in each ECG file by scanning only the headers, ensuring efficiency without the need to load the entire signals. Records without MLII were excluded, and only those with verified MLII signals were retained. Corresponding annotation files were matched using consistent naming conventions resulting in a refined dataset of valid ECG records ready for downstream segmentation, labeling, and classification.

Once the valid records were identified, the annotation files underwent a systematic cleaning and structuring process. Each annotation file was parsed line-by-line, with headers excluded, to extract meaningful information. From each valid entry, the sample index and the corresponding beat type label (e.g., N, V, A, L) were retrieved, while malformed or incomplete lines were ignored to maintain robustness. For each ECG record, the extracted information was organized into a pandas DataFrame with two essential columns: Sample and Type. These cleaned annotations were stored in a dictionary indexed by record ID, allowing efficient alignment with the corresponding ECG signals during segmentation and further processing.

Following this, all unique beat types across the dataset were enumerated to capture the diversity of annotations present in the raw MIT-BIH database. More than 20 distinct symbols were identified, highlighting the heterogeneity of the dataset. To reduce this complexity and ensure clinical interpretability, the raw labels were mapped to the five American Association for the Advancement of Medical Instrumentation (AAMI) recommended superclasses: N (Normal), S (Supraventricular), V (Ventricular), F (Fusion), and Q (Unknown/Other). A custom mapping function was implemented to apply this transformation, assigning integer labels (0-4) to each beat. This step introduced a new Class column in every annotation DataFrame, ensuring that all beats were consistently standardized. The outcome was a clinically meaningful, simplified dataset structure that provided a strong foundation for training, validation, and evaluation in the supervised classification pipeline.

Table 1. AAMI Beat Type to Class Mapping

AAMI Class	Description	Beat Types (MIT-BIH labels)
N	Normal	N, L, R, e, j
S	Supraventricular	A, a, J, S
V	Ventricular	V, E
F	Fusion	F
Q	Unknown/Other	!, ”, +, /, Q, [,], f, x, —, ˜

Source: Mapping based on AAMI recommendations for arrhythmia classification

3.3 Signal Preprocessing and Segmentation

The preprocessing pipeline was designed to eliminate noise, standardize amplitude ranges, and extract diagnostically relevant ECG segments suitable for supervised classification. A fourth-order Butterworth bandpass filter (0.5-50 Hz) was applied to each MLII signal using zero-phase filtering (filtfilt), thereby suppressing baseline wander, powerline interference, and high-frequency artifacts while preserving the QRS complex and other clinically relevant components. Following filtration, all signals were normalized to the range [-1, 1] using min-max scaling to mitigate inter-patient variability in amplitude and facilitate stable convergence during model training. This normalization ensured that morphological variations in heartbeat waveforms, rather than amplitude differences, dominated the learning process. For segmentation, each annotated beat was extracted within a fixed temporal window of 180 samples (0.5 seconds at 360 Hz), centered on the annotated R-peak location. Boundary checks were implemented to discard beats where the extraction window extended beyond the available signal length. Segments were subsequently filtered and normalized prior to storage. Each segment was mapped to an integer class label (0-4) based on the AAMI standard, excluding unknown categories. The resulting dataset was compiled into NumPy arrays: X representing standardized ECG segments and y representing corresponding class labels, forming the structured input for downstream deep learning models.

The following mathematical derivation formalizes the preprocessing methodology. It defines the Butterworth bandpass filter design, normalization transformation, and segmentation strategy applied to the ECG signals. These equations ensure reproducibility and clarity, showing how raw signals are filtered, scaled, and structured into fixed-length segments for AAMI-compliant classification.

$$f_N = \frac{F_s}{2} \tag{1}$$

Here, F_s is the sampling frequency (in Hz), and f_N denotes the Nyquist frequency.

$$\omega_{\text{low}} = \frac{f_{\text{low}}}{f_N}, \omega_{\text{high}} = \frac{f_{\text{high}}}{f_N} \tag{2}$$

$$H(z) = \frac{\sum_{k=0}^{M} b_k z^{-k}}{\sum_{k=0}^{N} a_k z^{-k}}, \{b_k\}, \{a_k\} = \text{butter}\left(\text{order}, \left[\omega_{\text{low}}, \omega_{\text{high}}\right]\right) \tag{3}$$

Here, f_{low} and f_{high} are the cutoff frequencies of the bandpass filter, $\omega_{\text{low}}, \omega_{\text{high}}$ are their normalized versions, $H(z)$ is the IIR digital filter transfer function, and $\{b_k\}, \{a_k\}$ are the numerator and denominator coefficients obtained from the Butterworth design.

$$\tilde{x} = \mathcal{F}_{\text{zp}}(x) \equiv \text{reverse}(\mathcal{H}(\text{reverse}(\mathcal{H}(x)))) \text{ with } \mathcal{H}(x) = \text{filter}(\{b_k\}, \{a_k\}, x) \tag{4}$$

Here, $\mathcal{F}_{\text{zp}}$ denotes zero-phase filtering, $\mathcal{H}(x)$ represents forward filtering using coefficients $\{b_k\}, \{a_k\}$, and $\tilde{x}$ is the final zero-phase filtered signal.

$$\hat{x}[n] = \begin{cases} 2\dfrac{x[n]-\min(x)}{\max(x)-\min(x)} - 1, & \max(x) \neq \min(x) \\ x[n], & \max(x) = \min(x) \end{cases} \tag{5}$$

Here, $x[n]$ is the input signal, $\hat{x}[n]$ is the normalized signal, and $\min(x), \max(x)$ denote the minimum and maximum amplitudes of x.

$$s_r = x\left[n_r - \frac{W}{2} : n_r + \frac{W}{2} - 1\right] \in \mathbb{R}^W \tag{6}$$

Here, s_r is the extracted ECG segment of window length W, centered at sample n_r of the original signal x.

$$\text{valid}(s_r): n_r - \frac{W}{2} \geq 0 \ \wedge \ n_r + \frac{W}{2} \leq L \tag{7}$$

Here, valid (s_r) is a Boolean condition ensuring that the segment lies within signal length L.

$$\ell_r = \Phi(\tau_r), \Phi: \{\text{ beat types }\} \to \{0,1,2,3,4\} \tag{8}$$

Here, τ_r is the original annotation (beat type), ℓ_r is the mapped class label, and Φ is the mapping function following the AAMI scheme.

$$\text{include } s_r \text{ iff valid } (s_r) \wedge \Phi(\tau_r) \neq 4 \tag{9}$$

Here, segment s_r is included only if it passes the boundary check and is not mapped to class 4 (unused label).

$$X = \begin{bmatrix} s_1^\top \\ s_2^\top \\ \vdots \\ s_N^\top \end{bmatrix} \in \mathbb{R}^{N\times W}, y = \begin{bmatrix} \ell_1 \\ \ell_2 \\ \vdots \\ \ell_N \end{bmatrix} \in \{0,1,2,3\}^N \tag{10}$$

Here, X is the dataset matrix of N segments, each of length W, and y is the corresponding label vector.

Table 2 Parameters used in ECG signal preprocessing and segmentation

Parameter	Symbol	Value	Description
Sampling Frequency	F_s	360 Hz	Original sampling rate of MIT-BIH ECG signals
Window Size	W	180 samples	Fixed segment length (0.5 seconds)
Half Window	$W/2$	90 samples	Samples on either side of annotated R-peak
Filter Type	–	Butterworth (order 4)	Bandpass filter for noise suppression
Low Cut-off Frequency	*flow*	0.5 Hz	Removes baseline wander
High Cut-off Frequency	*fhigh*	50 Hz	Removes high-frequency noise
Normalization Range	–	[-1, 1]	Min-max scaling of filtered signal
Class Labels	–	0-4	AAMI recommended beat class mapping
Dataset Size (X)	–	(101158, 180)	Total ECG beat segments and segment length
Label Size (y)	–	(101158,)	Corresponding class labels for each segment

All parameters and dataset dimensions are derived from the preprocessing pipeline applied to the MIT-BIH Arrhythmia Database.

3.4 Feature Extraction

Feature extraction plays a crucial role in bridging raw ECG signals and classification models. Instead of feeding only preprocessed waveforms, we computed a set of handcrafted features that capture meaningful statistical and spectral information. Each ECG segment was transformed into a 13-dimensional vector, reflecting both temporal fluctuations and frequency-based characteristics. This approach provides interpretable

Algorithm 1 Preprocess ECG Signals and Extract Segments

Require: List of valid ECG CSV files *valid csvs*, annotation dictionary *all annotations*, AAMI mapping *aami mapping*
Ensure: Arrays X (segments) and y (labels)
1: Define constants: *WINDOW SIZE* ← 180, *HALF WINDOW* ← *WINDOW _SIZE*/2, *FS* ← 360
2: **function** BandpassFilter(*signal,lowcut* = 0.5,*highcut* = 50.0,*fs* = *FS,order* = 4)
3:*nyq* ← 0.5 × *fs*

```
low ← lowcut/nyq, high ← highcut/nyq
Compute filter coefficients (b,a) using Butterworth bandpass
return filtered signal using filtfilt(b,a,signal)
end function
function Normalize(signal)
min ← min(signal), max ← max(signal)
  if max − min = 0 then
  return signal
  else
  return 2 × (signal − min)/(max − min) − 1
  end if
end function
Initialize all segments ← [], all labels ← []
for each record id in valid csvs do
  Remove ".csv" extension from record id
  Load signal dataframe signal df from file record id
  Clean column names of signal df
  if "MLII" ∉ columns of signal df then
  continue
  end if
  signal ← values of "MLII" column
  annot df ← all annotations[record id]
  for each row in annot df do
  beat type ← row[Type], sample ← row[Sample]
  label ← aami mapping(beat type) (default = 4 if not found)
  if label = 4 then
  continue
  end if
if sample − HALF WINDOW < 0 or sample + HALF WINDOW > len(signal) then
      continue
    end if
    segment ← signal[sample − HALF_WINDOW : sample + HALF_WINDOW]
  filtered ← BandpassFilter(segment)
  normalized ← Normalize(filtered)
  Append normalized to all segments
  Append label to all labels
  end for
  Handle exceptions by skipping current record id
end for
end for
X ← array(all segments), y ← array(all labels)
```

features that complement deep learning representations, ensuring hybrid models benefit from both raw signal learning and engineered domain knowledge. Extracted features were organized into NumPy arrays, yielding a feature matrix of shape (101158,13), ready for integration with classification pipelines. Time-domain features were designed to summarize the statistical and morphological properties of ECG waveforms. For each segment, we calculated mean, standard deviation, skewness, kurtosis, median, root mean square (RMS), and peak-to-peak range. Additionally, minimum, maximum, and zero-crossing counts were included to capture signal polarity shifts and amplitude variability. These features highlight both baseline fluctuations and shape dynamics of the ECG signal. For example, RMS and variance indicate signal energy, while skewness and kurtosis reflect waveform asymmetry and peakedness. Together, these descriptors capture arrhythmic variations that may not be directly visible from raw signals, making them valuable for beat classification. Frequency-domain analysis was employed to capture spectral signatures of ECG waveforms. Using the periodogram method, power spectral density (PSD) was estimated for each segment. From this, three key features were derived: dominant frequency, spectral entropy, and spectral centroid. The dominant frequency identifies the most prominent oscillatory component, often linked to rhythm regularity. Spectral entropy quantifies frequency distribution complexity.

Time-Domain Features

Let an ECG segment be $x[n]$, $n = 1,2,...,N$.

Time-domain features summarize the statistical and morphological properties of $x[n]$:

$$\mu=\frac{1}{N}\sum_{n=1}^{N} x[n], \sigma=\sqrt{\frac{1}{N}\sum_{n=1}^{N}(x[n]-\mu)^2}, \text{ RMS }=\sqrt{\frac{1}{N}\sum_{n=1}^{N} x[n]^2}, \text{ PTP }=\max(x[n])-\min(x[n]),$$

along with skewness, kurtcsis, median, zero-crossings, minimum, and maximum values. Frequency-Domain Features

Let $X(f)$ be the periodogram of $x[n]$ computed with sampling frequency F_S.

1. **Dominant Frequency:**

$$f_{\text{dom}}=\arg\max_f|X(f)|(11)$$

2. **Spectral Entropy:**

$$H_a=-\sum_f P(f)\log_2 P(f), P(f)=\frac{|X(f)|^2}{\sum_f |X(f)|^2}(12)$$

3. **Spectral Centroid:**

$$f_c=\frac{\sum_f f\cdot|X(f)|^2}{\sum_f |X(f)|^2}(13)$$

The handerafted feature vector for each ECG segment is then:

$$\mathbf{F}=[\text{ time-domain features, } f_{\text{dom}}, H_{\text{l}}, f_c]$$

3.5 Data Partitioning and Baseline Models

For robust model training and evaluation, the preprocessed ECG dataset and corresponding handcrafted features were partitioned into training (70%), validation (20%), and test (10%) subsets using stratified sampling to maintain balanced class distributions. Initially, a 70-30 split separated the training set from a temporary subset, which was subsequently divided into validation and test sets. Stratification ensured that each subset preserved the proportional representation of the four AAMI classes. Class labels were then one-hot encoded, transforming them into categorical vectors suitable for multi-class classification using categorical cross-entropy loss. The final training set comprised 70,810 ECG segments, each paired with 13 handcrafted features and corresponding one-hot labels. As a baseline, a Random Forest classifier was trained using the handcrafted features, configured with 10 decision trees. Predictions on the test set were evaluated using accuracy, classification reports, and confusion matrices to assess feature discriminability. For temporal feature learning, a deep learning LSTM-only model was implemented. Input ECG segments were reshaped to (180,1) and passed through a single LSTM layer with 64 units, followed by a Dropout layer, a dense ReLUactivated layer, and a softmax output for four-class prediction. The model was trained with Adam optimizer, categorical cross-entropy loss, and early stopping based on validation accuracy. Performance evaluation on the test set demonstrated the model's ability to capture temporal heartbeat dynamics directly from raw ECG signals.

3.6 Proposed Hybrid Deep Learning Model

In this study, a novel hybrid deep learning framework was developed to synergistically exploit both raw ECG waveform morphology and complementary handcrafted feature representations. The proposed model adopts a dual-input architecture to comprehensively capture temporal, spatial, and statistical characteristics of heartbeat signals, enhancing arrhythmia classification performance. The first branch processes raw ECG segments (180 samples) using a cascade of 1D convolutional layers to extract local spatial features, followed by GRU and LSTM layers to model short- and long-term temporal dependencies. Convolutional layers employ kernel size 5 with ReLU activation, while batch normalization and max pooling stabilize training and reduce dimensionality. Dropout (0.3) is incorporated to mitigate overfitting. The GRU layer captures immediate sequential patterns, whereas the LSTM layer encodes broader temporal dependencies, producing a robust spatiotemporal representation of the signal. Simultaneously, the second branch processes 13-dimensional handcrafted features through fully connected dense layers with ReLU activation and dropout, extracting high-level statistical descriptors from time and frequency domains. Outputs from both branches are fused via concatenation, forming an enriched multi-perspective representation. The merged vector passes through additional dense layers, including a 64-unit hidden layer, before a softmax output layer performs four-class AAMI classification. The model is compiled using the Adam optimizer with a learning rate of 0.001 and trained using categorical cross-entropy loss, incorporating early stopping and model checkpointing to optimize validation performance. Unlike conventional single-branch models, this hybrid framework effectively integrates low-level raw waveform features with high-level handcrafted descriptors, enabling enhanced generalization, robustness, and discriminative capability. By combining temporal-spatial dynamics of ECG segments with complementary statistical insights, the model provides a comprehensive and innovative approach for automatic arrhythmia detection. This hybrid architecture **links raw ECG features and handcrafted features** in a single model. The raw branch captures morphological and temporal dynamics via CNN and RNN layers, while the handcrafted branch encodes interpretable statistical and spectral characteristics. Their concatenation allows the model to leverage both deep-learned representations and domain knowledge, improving the ability to discriminate between different beat classes. By fusing these complementary inputs, the model achieves a robust and novel feature representation that outperforms single-input approaches.

Let an ECG segment be represented as a raw signal $\mathbf{x}_r \in R^{180}$ and its corresponding handcrafted feature vector as $\mathbf{x}_h \in R^{13}$. The hybrid model leverages both sources of information for improved classification.

a. Raw Signal Processing (CNN + RNN)

The raw signal x_r is first reshaped for convolutional processing:

$$\mathrm{X}_0 = \mathrm{x}_r[\ldots,1] \in \mathbb{R}^{180\times1}$$

It passes through two convolutional blocks with batch normalization, max pooling, and dropout:

$$\begin{aligned}&\mathbf{X}_1 = \mathrm{ReLU}\left(\mathrm{Conv1D}_{32,5}(\mathbf{X}_0)\right),\quad \mathbf{X}_2 = \mathrm{BatchNorm}(\mathbf{X}_1),\quad \mathbf{X}_3 = \mathrm{MaxPool1D}(\mathbf{X}_2,2),\quad \mathbf{X}_4 = \mathrm{Dropout}(\mathbf{X}_3,0)\\&\mathbf{X}_5 = \mathrm{ReLU}\left(\mathrm{Conv1D}_{64,5}(\mathbf{X}_4)\right),\quad \mathbf{X}_6 = \mathrm{BatchNorm}(\mathbf{X}_5),\quad \mathbf{X}_7 = \mathrm{MaxPool1D}(\mathbf{X}_6,2),\quad \mathbf{X}_8 = \mathrm{Dropout}(\mathbf{X}_7,0)\end{aligned} \tag{15}$$

Sequential temporal dependencies are captured by GRU and LSTM layers:

$$\mathbf{X}_9 = \mathrm{GRU}_{64}(\mathbf{X}_8, \text{return\_sequences=True}), \tag{16}$$

$$\mathbf{X}_{10} = \mathrm{LSTM}_{64}(\mathbf{X}_9) \tag{17}$$

b. Handcrafted Feature Processing

The handcrafted feature vector x_h is processed in parallel using a dense layer with dropout:

$$\mathbf{Y}_1 = \mathrm{ReLU}(\mathbf{W}_h\mathbf{x}_h + \mathbf{b}_h) \tag{18}$$

$$\mathbf{Y}_2 = \mathrm{Dropout}(\mathbf{Y}_1, 0.3) \tag{19}$$

c. Feature Fusion and Classification

Outputs from both branches are concatenated to form a combined representation:

$$\mathbf{Z}_0 = \text{Concatenate}\ ([\mathbf{X}_{10}, \mathbf{Y}_2]) \tag{20}$$

The fused features are further processed by a dense layer with dropout before the final output:

$$\mathrm{Z}_1 = \mathrm{ReLU}\left(\mathrm{W}_f\mathrm{Z}_0 + \mathbf{b}_f\right) \tag{21}$$

$$\mathrm{Z}_2 = \mathrm{Dropout}(\mathrm{Z}_1, 0.3) \tag{22}$$

$$\hat{\mathbf{y}} = \mathrm{softmax}(\mathbf{W}_o\mathrm{Z}_2 + \mathbf{b}_o), \hat{\mathbf{y}} \in \mathbb{R}^4 \tag{23}$$

d. Training Objective

$L = -^{X}y_i \log(y\hat{\ }_i)$ (24)

4. RESULTS

The performance of different models for ECG beat classification was evaluated using both handcrafted features and raw ECG segments. Initially, a Random Forest classifier trained solely on handcrafted time-domain and frequency-domain features achieved an accuracy of 96.63%, with precision, recall, and F1-score of 87.63%, 64.10%, and 70.60% respectively. While this baseline demonstrates that handcrafted features capture meaningful information, it exhibited limited sensitivity for minority classes. Next, a deep learning baseline using an LSTM-only architecture on raw ECG segments achieved higher accuracy (97.95%) and improved precision, recall, and F1-score (91.14%, 81.37%, 85.50%), indicating the effectiveness of sequential modeling for temporal dynamics. However, relying solely on raw signal learning may overlook interpretable statistical and spectral information. The proposed hybrid model integrates raw ECG input via CNN+GRU+LSTM layers with handcrafted features through dense layers. This feature fusion approach achieved 98.75% accuracy, with precision, recall, and F1score of 94.80%, 88.80%, and 91.56%, outperforming both baselines. Detailed class-wise metrics confirmed strong performance even for minority classes, demonstrating that combining deep-learned representations with domain-specific features improves both sensitivity and overall accuracy. These results highlight the novelty and effectiveness of the hybrid approach, providing a robust solution for arrhythmia detection.

The Random Forest classifier was implemented as a baseline for ECG beat classification. This ensemble learning method aggregates predictions from multiple decision trees, enhancing robustness and reducing overfitting. Using

Table 3 Hyperparameters of the proposed hybrid CNN+GRU+LSTM model

Layer / Component	Hyperparameter	Value	Description
Conv1D (1st)	Filters	32	Feature extraction
Conv1D (1st)	Kernel Size	5	Convolution window
Conv1D (1st)	Activation	ReLU	Non-linearity
Conv1D (2nd)	Filters	64	Feature extraction
Conv1D (2nd)	Kernel Size	5	Convolution window
Conv1D (2nd)	Activation	ReLU	Non-linearity
GRU	Units	64	Temporal features
LSTM	Units	64	Long-term memory
Dense (handcrafted)	Units	32	Feature learning
Dense (merged)	Units	64	Post-fusion
Dropout	Rate	0.3	Regularization
Optimizer	Type	Adam	Adaptive learning
Learning Rate	–	0.001	Step size
Loss Function	–	Categorical Crossentropy	Multi-class loss
Batch Size	–	64	Training batch
Epochs	–	100	Max iterations
Early Stopping	Patience	5	Validation stop

Hyperparameters were empirically selected to optimize model performance.

handcrafted time-domain and frequency-domain features only, the model achieved an accuracy of 96.63%, demonstrating its capability to distinguish between different beat types. Precision, recall, and F1-score were 87.63, 64.10, and 70.60 respectively, indicating moderate sensitivity for minority classes. This baseline serves as a benchmark, highlighting the limitations of purely feature-based models. It underscores the need for hybrid approaches combining raw signal learning with engineered features for better performance.

Table 4 Baseline Random Forest Classification Results

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest (Baseline)	96.63	87.63	64.10	70.60

Source: Experimental results using handcrafted features only.

To explore deep temporal patterns in ECG signals, an LSTM-only model was employed. The raw ECG segment was input into stacked LSTM layers to capture sequential dependencies. Using no handcrafted features, the model achieved an accuracy of 97.95%, outperforming the Random Forest baseline. Precision, recall, and F1-score were 91.14, 81.37, and 85.50 respectively, showing improved sensitivity and robustness, particularly for minority classes. This highlights the strength of recurrent neural networks in modeling temporal dynamics. However, the lack of feature-level information leaves some morphological cues underutilized, motivating hybrid approaches that integrate both raw and handcrafted features.

Table 5 Baseline LSTM-Only Model Classification Results

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LSTM (Baseline)	97.95	91.14	81.37	85.50

Source: Experimental results using raw ECG segments only.

The proposed hybrid model combines raw ECG input through CNN+GRU+LSTM layers with handcrafted features processed via dense layers. After feature-level fusion, the model achieved 98.75% accuracy, with precision, recall, and F1-score of 94.80, 88.80, and 91.56 respectively. This improvement over baseline models demonstrates the efficacy of integrating morphological and spectral information with temporal feature learning. A detailed classification report shows high precision and recall across both major and minor classes, confirming that feature fusion enhances minority class recognition while maintaining overall accuracy. This hybrid approach represents a novel strategy in ECG beat classification by combining deep learning with engineered features.

Table 6 Hybrid CNN + GRU + LSTM Model Classification Results

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest (Baseline)	96.63	87.63	64.10	70.60
LSTM (Baseline)	97.95	91.14	81.37	85.50
CNN+GRU+LSTM (Proposed)	98.75	94.80	88.80	91.56

The detailed classification metrics for the proposed hybrid model indicate robust performance across all classes. Class 0 (majority) achieved precision 0.9917 and recall 0.9958, while minority classes 1-3 also showed strong performance (precision 0.92680.9104, recall 0.8201-0.7625). Macro-averaged metrics were 0.9480 (precision), 0.8880 (recall), and 0.9156 (F1-score), highlighting balanced performance. Weighted averages closely matched overall accuracy (0.9875), showing the model's capability to handle class imbalance. These results reinforce the advantage of feature fusion, combining handcrafted and deep-learned representations, to improve both overall accuracy and minority class recognition in ECG beat classification.

The ROC-AUC analysis of the proposed hybrid model demonstrates excellent discriminative ability across all classes. Class 0 achieved an AUC of 0.99, class 1 0.99

Table 7 Classification Report of Proposed Hybrid Model

Class	Precision	Recall	F1-score	Support
0	0.9917	0.9958	0.9938	9035
1	0.9268	0.8201	0.8702	278
2	0.9631	0.9737	0.9684	723
3	0.9104	0.7625	0.8299	80
Accuracy		0.9875		
Macro Avg	0.9480	0.8880	0.9156	10116
Weighted Avg	0.9873	0.9875	0.9873	10116

class 2 1.0, and class 3 0.99, indicating that the model reliably distinguishes between different ECG beat types, including both majority and minority classes.

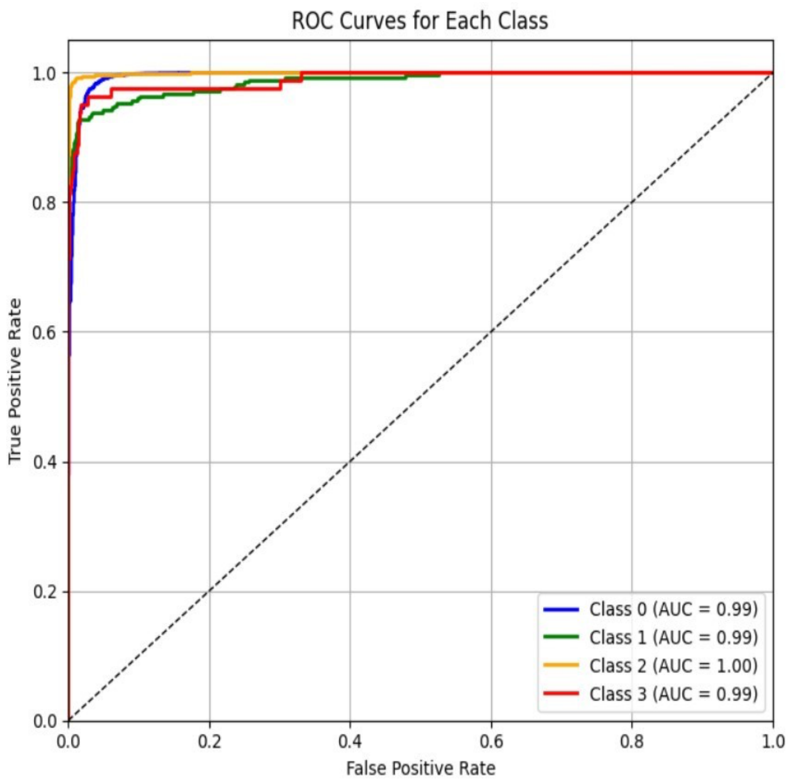

Fig. 1 ROC-AUC Evaluation for Multi Class Classification

The results demonstrate that integrating both raw ECG signals and handcrafted features significantly enhances arrhythmia classification performance. The Random Forest baseline, relying solely on handcrafted features, achieved moderate accuracy and struggled with minority classes, highlighting the limitations of purely feature-engineered approaches. The LSTM-only model improved performance by capturing temporal dependencies in raw signals, yet it lacked the interpretability and domain-specific insights provided by handcrafted features. The proposed hybrid CNN+GRU+LSTM model effectively combines these complementary sources of information. CNN layers extract local morphological patterns, GRU and LSTM layers capture long-range temporal dependencies, and handcrafted features encode statistical and spectral characteristics. Fusion of these representations enables the model to leverage both learned and domain-informed features, resulting in improved overall accuracy (98.75%), higher precision (94.80%), recall (88.80%), and F1-score (91.56%) compared to both baselines. Class-wise analysis shows robust performance even for minority classes, demonstrating the hybrid model's ability to address data imbalance. The novelty of this approach lies in its dual-input architecture, where handcrafted and deep-learned features are simultaneously utilized, bridging the gap between interpretable feature engineering and end-to-end deep learning. This strategy provides a comprehensive framework for ECG beat classification, offering both high performance and insights into signal characteristics, making it a promising tool for clinical arrhythmia detection.

4. CONCLUSION

In this study, a novel hybrid approach for ECG beat classification was proposed, integrating raw ECG signals processed through a CNN+GRU+LSTM deep learning architecture with handcrafted time-domain and frequency-domain features. The dual-input model effectively captures complementary information, including local morphological patterns, temporal dependencies, and interpretable statistical and spectral characteristics. Experimental results demonstrated the superiority of the hybrid approach, achieving an overall accuracy of 98.75%, precision of 94.80%, recall of 88.80%, and F1-score of 91.56%, surpassing both the Random Forest baseline and LSTM-only deep learning model. Class-wise ROC-AUC analysis further confirmed robust discrimination across all arrhythmia categories, including minority classes, highlighting the model's ability to address class imbalance and maintain generalization. The proposed methodolog's novelty lies in bridging handcrafted feature engineering with end-to-end deep learning, providing not only high predictive performance but also interpretability for clinical applications. The framework can be extended to include multi-lead ECG recordings to capture spatial correlations across leads, potentially improving classification accuracy and clinical relevance. Advanced attention mechanisms or transformer-based architectures could be incorporated to enhance temporal modeling and feature selection, particularly for rare arrhythmia classes. Additionally, integrating real-time deployment pipelines for wearable devices or remote monitoring systems can enable early detection of cardiac abnormalities in real-world settings. Finally, explainable AI techniques can be applied to provide deeper insights into model decisions, increasing clinician trust and facilitating adoption in healthcare environments. Overall, the hybrid feature-fusion strategy presents a scalable, interpretable, and high-performance solution for automated arrhythmia detection, laying the foundation for future advancements in intelligent cardiac monitoring systems.

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