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Intelligent Arrhythmia Classification Using Deep Learning on Multichannel ICU Physiological Signals

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Abstract: Arrhythmias is an abnormality that is found in heart rhythm which poses risks to cardiovascular health this abnormality is very critical for ill patients those are in intensive care units (ICUs). Electrocardiogram signals can be used to serve as valuable alternatives or complements to ECG data for arrhythmia detection which ensures a continuous monitoring of ECG signals when they are unavailable. In this study, different deep learning-based approach to classify arrhythmias using a combination of electrocardiogram (ECG), arterial blood pressure (ABP), central venous pressure(CVP) signals, including long short-term memory (LSTM) networks and convolutional neural networks (CNN), with various residual CNNs like ResNet architectures for arrhythmia classification. Among all these models evaluated ResNet50 has achieved the highest training accuracy of 98.77% and validation accuracy of 98.88% from all five of the arrhythmia classes when utilizing all three signal types (ECG, ABP, and CVP). ResNet50 has also demonstrated strong performance results when being trained solely on ABP and CVP signals which have achieved accuracies of 98.79% and 96.67%. Furthermore, when it was applied to the MIT-BIH arrhythmia database on the ResNet50 model, it had an accuracy of 98.88%. These results have highlighted both the scalability and robustness of the different deep learning models it also has shown the potential of ABP and CVP signals that they are reliable inputs for arrhythmia detection.

Keywords: Artificial Intelligence; Deep Learning; Arrhythmia Detection; ECG; ResNet; ABP; CVP; CNN-LSTM

1. Introduction

Cardiovascular diseases (CVDs) have always remained the leading cause of mortality worldwide, accounting for approximately 30% of deaths annually as shown by the World Health Organization (WHO). Primary detection and diagnosis are also essential for doing timely medication to improve patient outcomes for these critical conditions [1]. Arrhythmias are the irregularities in the heart's rhythm which are particularly significant they are among the various indicators of CVDs. Arrhythmias are also then classified into two groups those are non-life-threatening types and life-threatening types. The ECG is among the most commonly used diagnostic tool which is known as a non-invasive tool for detecting arrhythmias. It is used to capture electrical activity in the hearts by using electrodes that are placed on the skin which provide waveform patterns that are characteristic of specific arrhythmias. These waveform morphologies are used to offer essential diagnostic cues for clinicians in identifying, treating, and monitoring cardiac rhythm disorders.

In the development of computer-aided diagnosis (CAD) systems, ECG signals have been playing a very important role by using machine learning and signal processing algorithms like Support Vector

Machines (SVMs) and deep learning architectures like Convolutional Neural Networks (CNNs). So, for the last four decades, the basic role of ECG monitoring in hospitals has evolved into complex arrhythmia classification from a simple heart rate tracking system. Even with the use of all these technological advancements, there are still issues with the interpretation of ECG data in intensive care units (ICUs) which still heavily rely on human oversight. This is particularly important in ICUs where patients are there with complex medical conditions can receive medications that can be a cause for inducing or exacerbating arrhythmias [2]. ICU patient mobility often the issue that the ECG leads are disconnected which compromises the performance of CAD systems and hinders reliable results of arrhythmia detection [3]. To deal with these limitations other physiologic signals are routinely monitored in ICUs like arterial blood pressure (ABP) and central venous pressure (CVP) theses can be leveraged as alternative source or complementary sources of information.

Arterial line blood pressure (ABP) signals are typically obtained by using a catheter inserted into the radial artery with which the feature components such as the systolic upstroke, dicrotic notch, and diastolic downslope are present. CVP signals are recorded through a central venous catheter placed in the superior vena cava that comprises phases including a wave, c wave, v wave, and x descent. Even though there is no direct link between these signals to any cardiac electrical activity directly, their morphology reflects the patient's hemodynamic and cardiac functional status [4]. For example, in ABP signals AF has been shown to produce irregular pulse waves [5] and it can eliminate or distort a wave in CVP recordings [6]. So, incorporating ABP and CVP data into arrhythmia detection systems can be used as a resilient alternative in cases where ECG data is compromised or unavailable.

In this paper, the proposed method of a deep learning approach for classifying types of arrhythmias those are using single-lead ECG data alongside ABP and CVP waveforms. Furthermore, we have also demonstrated the feasibility and effectiveness of using signals of ABP and CVP independently to detect arrhythmias with high accuracy. By integrating ECG and hemodynamic data now our models contribute to the advancement of robust CAD systems that are tailored for ICU environments in which rapid changes in patient condition are continuous and need reliable monitoring.

2. Contribution Clarification

The key contributions of this research are as follows:

1) We propose a novel AI-based framework that integrates deep learning models including ResNet50, ResNet34, ResNet152, and CNN-LSTM for the classification of arrhythmias using multimodal physiological signals (ECG, ABP, and CVP).
2) We demonstrate the ABP and CVP signals, often overlocked in conventional studies, can independently achieve high classification performance, making them viable alternatives when ECG data is compromised.
3) Our experiments using the MIT-BIH Arrhythmia Database show that the ResNet50 model provides superior accuracy and robustness across multiple signal types, highlighting its scalability and adaptability for ICU environments.
4) This study contributes to the development of intelligent, continuous monitoring system capable of reliable arrhythmia detection in real-world clinical settings, especially in scenarios with missing data, signal noise, or lead disconnection.

3. Related Work

Recent progressions in the field of deep learning and machine learning have been very helpful for the accuracy of arrhythmia detection with the help of ECG signals. The traditional machine learning approaches typically needed a manual feature extraction and selection before its classification. Characteristics of the QRS complex, RR intervals, heart rate variability, and frequency-domain metrics features are also included in them. These generate features like Wavelet-based methods like Continuous Wavelet Transform (CWT) [7] and Discrete Wavelet Transform (DWT) [8] are also used. Seeing the effeteness of these methods there was a demand for expert knowledge, and these aspects have promoted a shift toward deep learning-based techniques that automate feature extraction.

Convolutional Neural Networks (CNNs) [9–11], Recurrent Neural Networks (RNNs) [12], Long Short-Term Memory (LSTM) networks with autoencoders [13], and hybrid CNN-LSTM architectures [14–16] are the deep learning models those have been showing great progress in arrhythmia classification. CNNs have shown promising results in handling multidimensional signal data and have also been widely applied in ECG-based diagnostics. Early implementations in these involve transforming ECG signals into 2D images, spectrograms, or representations of time-frequency [17,18]. Today more recent models can directly process raw 1D ECG signals by reducing preprocessing steps and maintaining high classification performance.

For example, the 1D CNN model of the 9-layer that is presented in [9] has been classified from the MIT-BIH arrhythmia database with the use of five types of heartbeats with an accuracy of 94.47%. A hybrid CNN-LSTM approach that is in [15] has achieved 98.10% accuracy on the same dataset. In [11], a 4-layer CNN is combined with max pooling and dense layers which along with SMOTE for class balancing has reached 98.30% accuracy. Houssein et al. [19] also used a combination of SMOTE and random under-sampling by extracting six types of features before doing classification with a 1D CNN also achieving strong results.

In [20], there is a 34-layer deep CNN which was developed using ambulatory monitoring devices from single-lead ECG. Its performance for diagnosing has surpassed average cardiologists with the ability to detect subtle waveform patterns. Although these deep CNNs are dealing with the vanishing gradient problem in which the effectiveness of learning diminishes in deeper layers. This issue has also been addressed through Residual Neural Networks (ResNets) [21] that use skip connections to preserve key features and stabilize gradient propagation.

In ECG-based classification of arrhythmia, ResNet architectures have always been proven highly effective. Zhang et al. [22] introduced a way of converting ECG signals into 2D time-frequency images in a 101-layer ResNet (ResNet101) by using the Wigner-Ville Distribution and Hilbert Transform that have achieved 99.75% accuracy. Another study by Rahman et al. [23] used applied transfer learning as a pre-trained ResNet50 model and reached 91% accuracy with ECG image inputs. More recent work eliminates the uses of 2D transformations by applying 1D ResNet models directly into ECG waveforms [24,25]. Khan et al. [24] also developed the uses of three max-pooling layers and six convolutional in a 1D ResNet that attains 98.63% accuracy, 99.06% specificity, and 92.41% sensitivity by using SMOTE for class balancing.

Despite these advanced improvements, most research is also focused exclusively on ECG signals by overlooking multimodal physiological signals. ABP and photo platysma gram (PPG) signals are the first ones used for arrhythmia classification by Kalidas et al. [26] from the PhysioNet/Computing in Cardiology 2015 Challenge which aimed to reduce false alarms in ICU settings. They used spectral and time-domain features from ECG, ABP, and PPG to achieve 94% sensitivity and 86% specificity by using an SVM classifier.

Arvanaghi et al. [27] used a way to extract features like power, frequency, and entropy from ECG and ABP by using Least Squares SVM (LS-SVM) for achieving 95.75% accuracy, 96.77% sensitivity, and 96.32% specificity. In a follow-up study [28], the ABP was used alone with a CNN in the form of scalograms for reaching an F1-score of 90.16%, accuracy of 89.03%, and sensitivity of 81.46%. It has also shown the benefit of combining ABP with ECG which was further highlighted in [28] in which the two-class arrhythmia model improved from 89% (ECG only) to 96.6% (ECG + ABP).

Even though existing methods have been achieving high performance using ECG signals alone this limited work has explored integrating other signals for physiological which are ABP, CVP, and PPG. These signals can also routinely be available in the ICUs and can provide redundancy or complementary information about those cases where ECG leads are disconnected due to patient movement or unconsciousness. Using such multimodal data holds promise in critical care settings for enhancing the robustness of arrhythmia detection.

Table 1. Summary of Notable Studies on Arrhythmia Classification

Authors	Methodology	Data Set	Key Techniques	Accuracy
Kiranyaz, Ince, T., & Gabbouj, M. [9]	9-layer 1D CNN	1-lead ECG (MIT-BIH)	Synthetic data augmentation	94.47%
Yildirim, O. [15]	Hybrid CNN-LSTM	1-lead ECG (MIT-BIH)	CNN + LSTM	98.10%

Acharya, Fujita, H., Lih, Hagiwara, Y., Tan, & Adam [11]	4-layer CNN + SMOTE	1-lead ECG (MIT-BIH)	Max pooling, FC layers	98.30%
Hussein et al. [19]	Feature extraction + 1D CNN + SMOTE	1-lead ECG	Feature-based CNN	High accuracy
Hannun, Rajpurkar, Haghpanahi, M., et al. [20]	Deep 34-layer CNN	Ambulatory ECG	Deep CNN	Exceeded cardiologist accuracy
Zhang et al. [22]	101-layer ResNet + 2D transforms	1-lead ECG (MIT-BIH)	Hilbert & Wigner-Ville transforms	99.75%
Rahman et al. [23]	ResNet50 + transfer-learning	ECG images	Transfer learning	91%
Khan et al. [24]	1D ResNet + SMOTE	1-lead ECG	6 conv + 3 max pool layers	98.63%
Kalidas et al. [26]	SVM with features from ECG, ABP, PPG	Multimodal ICU signals	Spectral and time-domain features	Sensitivity 94%, Specificity 86%
Arvanaghi et al. [27]	LS-SVM with frequency, power, and entropy features	ECG + ABP	Feature-based SVM	95.75%
Arvanaghi et al. [28]	CNN on ABP scalograms	ABP signals	CNN classifier	89% (ABP only)
Arvanaghi et al. [28]	Combined ECG + ABP features	ECG + ABP	CNN classifier	96.6%

4. Methodology

The first overview of the methodology is shown in Figure 1. Pre-processing is doing the noise filtering and normalization process after that the signal segmentations are done which is first done for individual heartbeats. Classifications are made on the set of signals (ECG+ABP+CVP) at first with the help of different deep learning architectures like as CNN-LSTM, ResNet152, ResNet32, and ResNet50. The model provides the maximum accurate results which then are used to measure the potential of every signal. MIT-BIH arrhythmia database is being used.

4.1. Dataset

To evaluate the importance of our model against existing research we have also utilized lead II ECG recordings from the MIT-BIH Arrhythmia Database. This is a publicly available dataset that was developed by the Massachusetts Institute of Technology which contains long-term ECG recordings sampled at 360 Hz that are used specifically for arrhythmia analysis. The dataset labels each heartbeat into one of six categories which are F, M, N, Q, S, and V.

4.2. Pre-processing

Signals that are recorded by patients in the ICU most often contain noise caused because of medical equipment, patient movement, or poor electrode contact. For example, the CVP signal is affected by breathing which is rising during inhalation and falling during exhalation whereas ECG signals often include motion-related and electrode noise. To clean the signals the method of Discrete Wavelet Transform

(DWT) is used. Different types of wavelets were used for each signal: biorthogonal for ECG, Daubechies for ABP, and CVP. After removing noise, we normalized all signals to the range [-1, 1] and detected R-peaks in the ECG using the Pan-Tompkins algorithm.

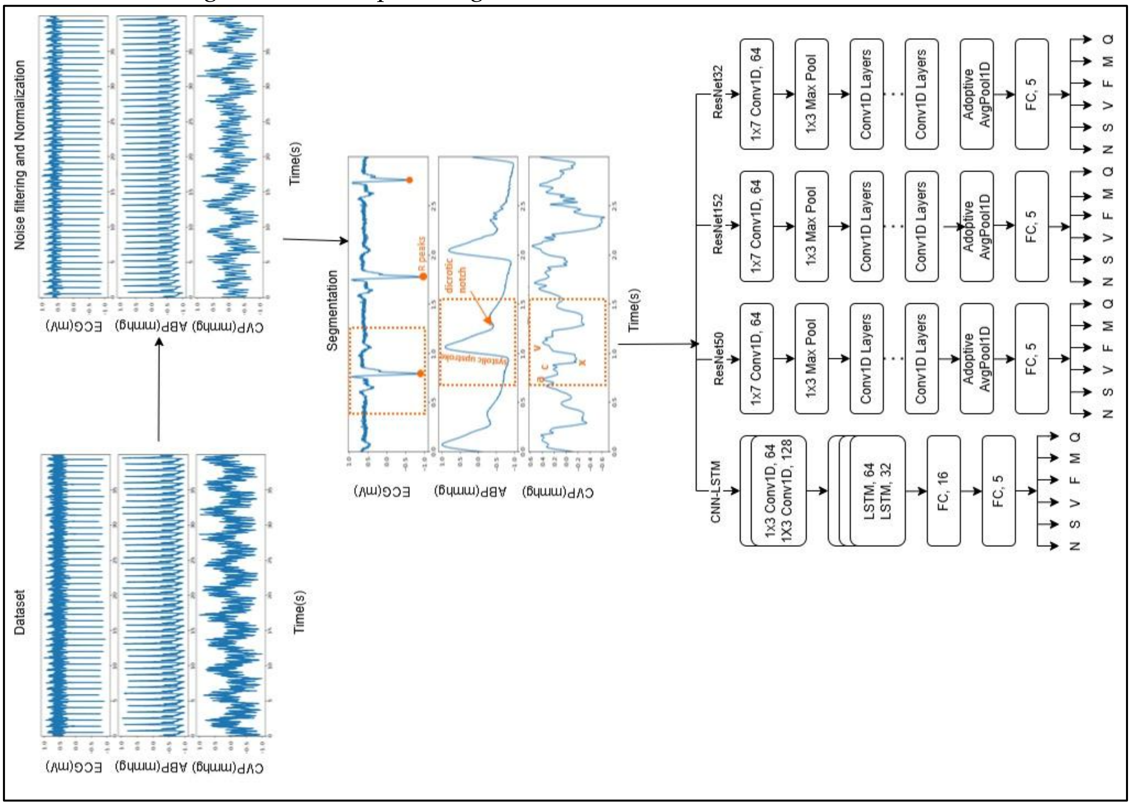

Figure 1. Overall System Overview

We have also used different methods to segment the heartbeats for ECG and blood pressure signals. Since we know there is a small delay between the electrical signal of the heart (seen in the ECG) and the blood pressure response (seen in ABP and CVP) so we have adjusted the segmentation windows. For ECG, we took an 800 ms window around each R peak. For ABP and CVP, we have used a window starting 200 ms before and ending 600 ms after each R peak. In this way, all three signals are aligned correctly for each heartbeat.

4.3. Classification

We have used two types of models for arrhythmia classification: a hybrid CNN-LSTM model and a ResNet model architecture. CNN and LSTM networks are both well-known models that are used for performing well in arrhythmia detection. By combining them in a model it can learn both short-term patterns (using CNN) and long-term dependencies (using LSTM) for data. CNN-LSTM model has two 1D convolutional layers which are each followed by group normalization, a ReLU activation function, max pooling, and dropout layers. After the convolutional layers at the end, there are two LSTM layers which are followed by two fully connected layers.

We also tested ResNet models based on the popular ResNet152, ResNet50, and ResNet34 architectures. However, instead of using the original 2D layers in the model we used 1D layers that can work directly with one or multiple signal channels. This helps us avoid the need to convert and merge the signals before input is done. As it has been mentioned earlier ResNet models are valid and increasingly popular approaches in deep learning to improve performance can often perform better than standard CNNs because they can only pass information through deep layers more effectively. That's why we chose to explore their performance for classifying arrhythmias using signals from multiple sources.

4.4. Evaluation Table

Multi-class classification models' performance is evaluated using a set of standard metrics like **accuracy (Acc)**, **sensitivity (Sen)**, **precision (Pre)**, and **F1-score**. In which each metric offers unique insights into the model's prediction capabilities.

Accuracy reflects on the overall effectiveness of the model to measure the proportion of correctness of predictions in both true positives (TP) and true negatives (TN) from that of the total number of predictions. It is the mathematical representation:

$$\mathbf{Acc = (TP + TN) / (TP + TN + FP + FN)} \quad (1)$$

Sensitivity is the true positive rate that is used for evaluating the model's ability to correctly identify the model's actual positive instances. It is calculated as:

$$\mathbf{Sen = TP / (TP + FN)} \quad (2)$$

Precision is used to quantify true positive predictions proportion from those of all instances in a predicted as positive. This is used to indicate how reliable the model is when it is predicting a positive case:

$$\mathbf{Pre = TP / (TP + FP)} \quad (3)$$

F1-score is known as a harmonized mean of precision and sensitivity, providing a balanced measure that is used to account for both false positives and false negatives:

$$\mathbf{F1 = 2 \times (Pre \times Sen) / (Pre + Sen)} \quad (4)$$

These metrics are used collectively for providing a comprehensive evaluation of the classification model's performance and for imbalanced datasets where relying solely on accuracy can be misleading.

5. Results and Discussion

ECG-based arrhythmia classification we have evaluated and compared the performance of three prominent deep learning models those are ResNet50, ResNet34, and ResNet152 alongside a hybrid architecture that is CNN-LSTM. Each of these models was assessed based on a core classification table like accuracy, sensitivity, precision, and F1-score to determine its effectiveness in detecting cardiac irregularities.

Table 2. Models Performance with signals: ECG, ABP and CVP

Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-Score (%)
CNN-LSTM	98.12	98.15	98.10	98.12
ResNet50	**98.88**	**98.86**	**98.89**	**98.57**
ResNet152	98.55	98.56	98.55	98.54
ResNet34	98.38	98.41	98.38	98.41

5.1. ResNet-50 Performance

The ResNet-50 model is showing strong performance in the six target classes of F, M, N, Q, S, and V. Based on these key evaluation metrics of accuracy, sensitivity, F1-score, and support. We can say that the best-performing class is Class 'N' with an accuracy of 0.97, sensitivity of 0.99, and F1-score of 0.98, supported by 15,140 instances. Class 'M' has been also performing very well by achieving values of 0.97 from all three metrics over 1,680 examples. The class 'V' is showing signs of a well-balanced performance that has accuracy, sensitivity, and F1-score of 0.93, 0.95, and 0.94, respectively. But in class 'Q' shows a sensitivity of 0.76 and an F1-score of 0.8 has inconsistencies even after having an accuracy of 0.94. Classes that have lower support are giving some modest metrics like class 'S' has an F1-score of 0.88 and class 'F' is struggling with its sensitivity of only 0.73 and F1-score of 0.81 with a little better precision of 0.91. These results are also shown in Table 3.

Table 3. Class-wise Training Table for classification

Class	Precision	Sensitivity	F1-score
N	0.97201	0.995403	0.98356
M	0.973872	0.973872	0.97387
Q	0.944615	0.756158	0.83994
V	0.931034	0.950704	0.94076
S	0.901786	0.855932	0.87826
F	0.90909	0.73170	0.81081

Validation performance is seen in the process of training in which class 'N' is again at the top with an accuracy of 0.9894, sensitivity of 0.9960, and an F1-score of 0.9927. Class 'M' follows similarly with high values showing the model's capability to correctly detect these instances. Classes 'Q', 'V', and 'S' have some respectable validation scores even though class 'F' is showing some performance issues for a sensitivity of only 0.4291 and an F1-score of 0.5707, even with high precision. These results show some difficulties in recalling the true positives in class 'F'. The training matrix of class 'N' is yields 14,980 true positives and only minor misclassifications. These results can also be seen in Table 4.

Table 4. Class-wise Evaluation table for classification

Class	Precision	Sensitivity	F1-score
N	0.989442	0.996031	0.99272
M	0.966061	0.971265	0.968665
Q	0.949556	0.953806	0.951776
V	0.964779	0.937709	0.950442
S	0.842442	0.937443	0.887407
F	0.851573	0.429124	0.570781

As shown in Table 5 training and validation losses are decreasing over time and converge those have final values of 0.0314 and 0.0305. Accuracy metrics are high 0.9877 for training and 0.9888 for validation with proximity of precision and sensitivity with the values of 99%. The model is achieving some near-perfect AUC scores of 0.9998 for training and 0.9997 for validation by showing some excellent class discrimination ability.

Table 5. Performance Evaluation

Metric	Train	Validation
Train loss	0.0314	0.0305
Train accuracy	0.9877	0.9888
Train precision	0.9879	0.9888
Train sensitivity	0.9877	0.9887
Train AUC	0.9998	0.9997

6. Conclusion

In this study there has been use of diverse deep learning models like CNN-LSTM and many types of ResNet architectures were developed to classify five types of arrhythmias with the help of ECG, ABP, and CVP signals which were collected by use of MIT-BIH Arrhythmia Database. To use these signals more effectively and correctly they are aligned for ECG heartbeat with the help of waves in the ABP and CVP signals we have used the process of segmentation that is used to account for the delay in ECG heartbeat or hemodynamic waveform responses. ResNet50 has demonstrated strong capabilities in feature extraction and heartbeat classification across all other channels additionally without requiring any prior feature extraction techniques. Furthermore, the results also highlight the individual ability of hemodynamic signals (ABP and CVP) to detect any changes associated with arrhythmias. This finding underscores the potential of using ABP and CVP signals for an accurate classification of arrhythmia in ICU settings where these are routinely monitored. Comparing our results with existing studies (see Table 2), we conclude that our approach has achieved significant performance improvements both on our dataset and on the widely used MIT-BIH arrhythmia database.

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