From Beats to Bytes: A Machine Learning Model for Arrhythmia Detection & Classification

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***Abstract*—Arrhythmia poses challenges for timely and accurate diagnosis. This study presents a novel ensemble machine learning model that integrates Convolutional Neural Networks (CNNs) with Random Forest (RF) algorithms to enhance the accuracy of arrhythmia detection from electrocardiogram (ECG) signals. Utilizing the Massachusetts Institute of Technology - Beth Israel Hospital (MIT-BIH) Arrhythmia Database, we meticulously preprocess the data and construct an ensemble model that capitalizes on CNN's adept feature extraction and RF's robust decision-making capabilities. The model is rigorously evaluated against five major arrhythmia classes and demonstrates superior performance over traditional diagnostic and single-model approaches. Our results indicate high overall accuracy and remarkable precision, recall, and F1 scores across all classes. This approach holds promise for early and accurate arrhythmia diagnosis, potentially serving as a reliable automated screening tool to assist healthcare professionals and mitigate the limitations of manual ECG interpretation. The research contributes to the growing body of evidence that machine learning can achieve expert-level performance in medical diagnostics, paving the way for advancements in patient care and clinical workflows.**

***Index Terms*—arrhythmia detection, convolutional neural networks (CNN), random forest (RF), electrocardiogram (ECG) classification**

I. Introduction

Cardiovascular diseases are a leading cause of death worldwide, and among them, arrhythmias pose a particularly complicated challenge for healthcare providers. Arrhythmia, characterized by irregular heartbeats, has diverse manifestations ranging from benign to life-threatening. Current diagnostic methodologies, primarily based on electrocardiograms (ECGs), often require manual interpretation by skilled healthcare professionals. This process is time-consuming and prone to human error, which is problematic given the critical nature of timely and accurate diagnosis in preventing complications or death. Moreover, these traditional methods may not always be sufficient to capture the complexity and variations of arrhythmia, necessitating the exploration of more advanced diagnostic techniques.

With the advent of machine learning and its success in various domains, there is a compelling case to be made for its application in medical diagnostics. This study shows how an ensemble model comprising Convolutional Neural Networks (CNN) and Random Forest (RF) algorithms can outperform traditional diagnostic methods in arrhythmia classification. Specifically, our focus is on categorizing five major classes of Arrhythmia—Normal, Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Atrial Premature Beats (APB), and Premature Ventricular Contractions (PVC)—using ECG signals sourced from the Massachusetts Institute of Technology - Beth Israel Hospital Arrhythmia Database (MIT-BIH).

A multi-stage research methodology was planned to validate our hypothesis. The initial phase involved obtaining authorized access to the MIT-BIH Arrhythmia Database to gather the necessary ECG data. This raw data was subjected to preprocessing, including denoising the signals and resampling the training data, to make it conducive for machine learning algorithms. Subsequently, individual models based on CNN and RF were developed to process this data. These models were chosen because CNNs are particularly effective in high-level feature extraction, whereas RF algorithms excells in decision-making based on those features. Following the development of these models, an ensemble model was created by integrating both CNN and RF models to harness their combined strengths. Our model underwent a thorough evaluation using various performance metrics, such as accuracy, recall, specificity, precision, and F-1 score. Finally, the model's performance was compared to existing research to ascertain its efficacy and reliability.

By adopting this comprehensive approach, the study aims not only to advance the field of automated medical diagnostics but also to make a meaningful contribution to patient care by facilitating early and accurate arrhythmia diagnosis.

II. Literature Review

Machine learning techniques have shown great potential in the realm of automated ECG analysis and arrhythmia classification. Both traditional machine learning algorithms and emerging deep learning models have been explored for this application. This literature review covers some of the key techniques and findings related to using machine learning for arrhythmia detection from ECG signals.

Convolutional neural networks (CNNs) have emerged as a popular technique for performing feature extraction and classification directly from ECG inputs [1] [9]. Kiranyaz et al. proposed an adaptive 1D CNN architecture that can be trained in a patient-specific manner for real-time ECG monitoring and classification. Their model achieved high accuracy in detecting ventricular and supraventricular ectopic beats on the MIT-BIH benchmark dataset. Similarly, Rahman and Faezipour developed a lightweight 2D CNN model using ECG image snapshots as input [3]. Their model detected arrhythmias with over 91% test accuracy using only a single ECG lead. These studies demonstrate the utility of CNN architectures in learning discriminative features from ECG inputs for accurate arrhythmia detection.

In addition to CNNs, other deep neural network architectures have also been explored [10] [11]. Hannun et al. trained a deep neural network (DNN) on a large dataset of over 90,000 single-lead ECGs, which was able to classify 12 rhythm classes with an average AUC of 0.97, exceeding cardiologist-level performance [2]. Given sufficient training data, this demonstrates the potential for deep learning models to match or surpass human-level arrhythmia detection ability. Beyond DNNs, Tian et al. proposed a Siamese network architecture using twin 2D CNNs for feature extraction paired with a contrastive loss function to classify arrhythmia using few-shot ECG samples. Their approach achieved approximately 97% accuracy even with very small training datasets [4].

Taking CNNs a step forward, Martono et al. developed a CNN model paired with visualization using grad-CAM for interpretable arrhythmia classification [7]. They transformed ECG signals into recurrence plots for training and achieved 95.8% accuracy. They gained insights into model behavior by comparing model attention maps to clinician reasoning. Their work highlights the need for explainable AI in safety-critical medical applications. Similarly, Serhani et al. proposed a convolutional neural network model with hyperparameter tuning for ECG-based arrhythmia classification [6]. Their incremental optimization approach achieved improved prediction accuracy. They also provided clinical recommendations tailored to each arrhythmia category using medical guidelines. This demonstrates the importance of model tuning and the utility of pairing ML with expert systems for decision support.

While deep learning techniques show great promise, traditional machine learning has also been applied for arrhythmia detection from ECG data. Liu compared various classifiers like SVM, Naive Bayes, and Random Forests on the arrhythmia dataset with and without feature selection techniques [5]. The results showed that combining feature selection with ensemble methods such as Random Forest yielded the highest accuracy of 92.8%. This highlights that traditional techniques still have utility, especially when training data is small.

In summary, the literature illustrates that deep learning and classical machine learning models can deliver high accuracy in automated arrhythmia detection from ECG data. CNN architectures are well-suited for representation learning from ECG inputs. Ensemble methods can effectively leverage hand-crafted features. Both techniques have merits and limitations, warranting further research into ensembling deep learning and traditional models to utilize their complementary strengths.

III. Methods

This section elaborates on the systematic approach undertaken to validate the hypothesis that an ensemble of Convolutional Neural Networks (CNN) and Random Forest (RF) algorithms [8] can enhance the accuracy of arrhythmia classification from ECG signals, compared to traditional methods. We give a detailed pipeline from data acquisition to model evaluation, providing enough granularity to enable study replication.

A. Data Acquisition and Preprocessing

The raw ECG data for this study is sourced from the PhysioNet MIT-BIH Arrhythmia Database, which contains 48 half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects. The recordings were digitized at 360 samples per second per channel with 11-bit resolution.

To reduce high frequency noise, the raw ECG signals are passed through a discrete wavelet transform (DWT) denoising filter using the sym4 wavelet at level 4 decomposition. Coefficients below a threshold of 0.04 times the maximum value are zeroed out and the signal is reconstructed, Figure 1, 2.

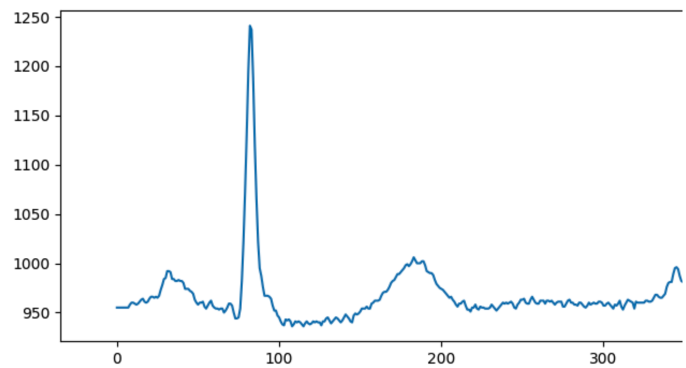

Fig. 1. Raw Heartbeat

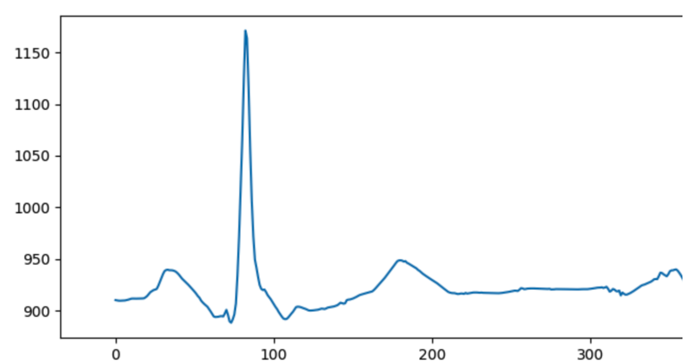

Fig. 2. Denoised Heartbeat

The resulting denoised signals are then normalized using z-score standardization to obtain zero mean and unit variance.

B. Dataset Construction

Segments of ECG signal are extracted using a sliding window approach with 50% overlap between adjacent windows. The window length is chosen to be 3 seconds, which at the sampling rate of 360 Hz equates to 1080 samples. This ensures each window contains at least 2 heartbeats. Five major arrhythmia types - Normal (N), Left Bundle Branch Block (L), Right Bundle Branch Block (R), Atrial Premature Beats (A), and Premature Ventricular Contractions (V) are considered, with up to 10,000 samples per class.

Fig. 3. Before Resampling

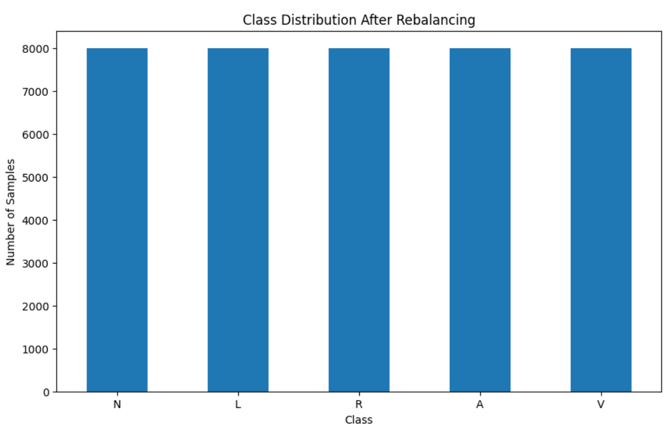

Fig. 4. After Resampling

To handle the imbalanced class distribution, the training set is resampled using bootstrap oversampling to obtain a uniform class representation as shown in Figure 3, 4. The dataset is split into 80% training and 20% testing sets while preserving the overall class balance through stratified sampling.

C. Model Development

A 1D CNN model is developed with the architecture as shown in Figure 5. It consists of two convolutional layers with max pooling for feature extraction, followed by fully connected layers for classification.

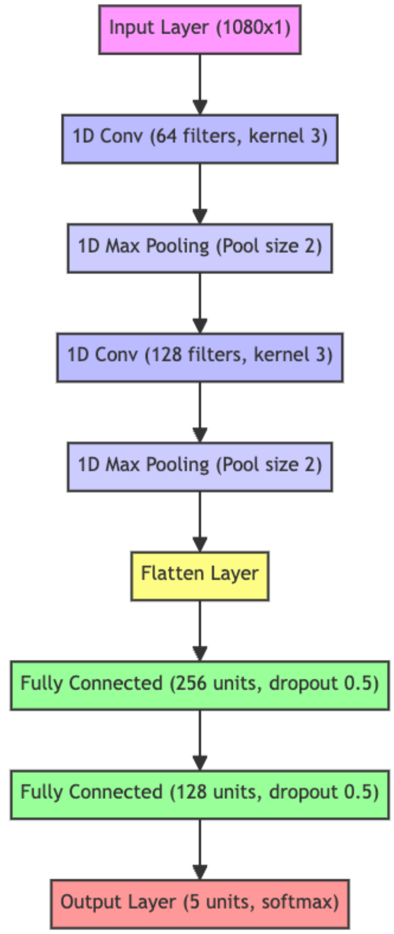

Fig. 5. 1D CNN Model Architecture

The first convolutional layer has 64 filters with a kernel size of 3, followed by 2x max pooling to halve the dimensionality. The second convolutional layer has 128 filters, again with a kernel size of 3, followed by 2x max pooling. After the convolutional base, a flattened layer reshapes the feature maps into a 1D vector. This is fed into a fully connected layer with 256 ReLU-activated units and 50% dropout regularization. Another dense layer with 128 units follows before the final softmax output layer for classification into one of the 5 classes. The model is compiled with the Adam optimizer and categorical cross-entropy loss function. It is trained for 50 epochs with a batch size of 32.

In parallel, a Random Forest (RF) classifier with 100 estimators is trained on the CNN model's penultimate activation features. The RF model helps reduce overfitting and improves generalization performance.

Fig. 6. Ensemble Model

Finally, an ensemble model, as shown in Figure 6, is created by averaging the class probabilities predicted by the CNN and RF models. This allows for the combination of the representative features learned by CNN with the non-linear decision boundaries of the RF for improved accuracy.

D. Evaluation Metrics

The performance of the proposed model is quantified using the following metrics:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{FP + TN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Where:

- TP - True Positives
- TN - True Negatives
- FP - False Positives
- FN - False Negatives

The following section presents a comprehensive evaluation of our CNN and the integrated ensemble models through a series of graphical representations and quantitative metric assessments. The results are also compared with recent benchmarks on the same dataset to validate the effectiveness of our approach.

IV. Results and Discussion

The proposed ensemble model combining a 1D CNN and Random Forest classifier demonstrated promising performance for automated arrhythmia detection from ECG signals. As seen in Figure 7, the training accuracy for the individual CNN model showed a rapid increase in the initial epochs, indicating that the model is effectively learning from the training data. It continued to rise, albeit at a slower rate, as the number of epochs increased, suggesting progressive learning and model improvement over time. The validation accuracy also increased sharply at the beginning and then entered a phase of slower growth.

Overall, the CNN model exhibited robust performance, setting a strong foundation for the subsequent ensemble with the Random Forest classifier, aiming to leverage the complementary strengths of both models for enhanced arrhythmia classification accuracy.

Table I shows the class-specific performance metrics for the ensemble model. It achieves high recall, specificity, precision, and F1 scores across all five arrhythmia classes - Normal, Left Bundle Branch Block, Right Bundle Branch Block, Atrial Premature Beats, and Premature Ventricular

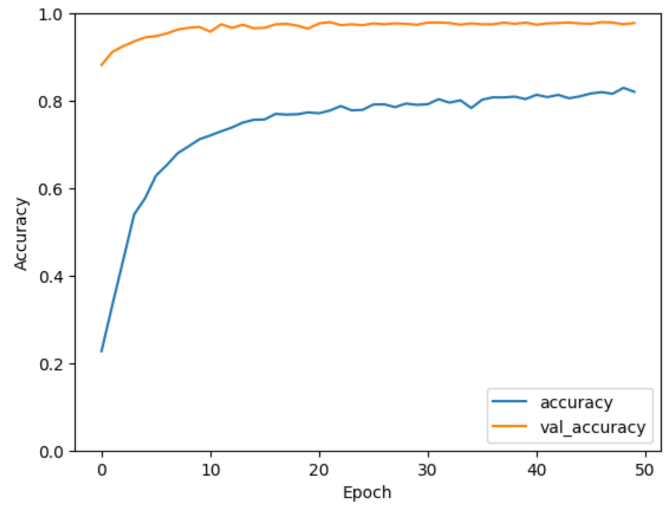

Fig. 7. Accuracy - CNN Model

Contractions. Specifically, the model obtains excellent recall scores above 99% for the Normal, LBBB, RBBB, and PVC classes, indicating a low false negative rate in identifying these rhythms. For the APB class, which has a lower prevalence, recall is slightly reduced at 94.28% but still acceptable. The model maintains high specificity consistently above 99% for all classes, demonstrating a low false positive rate overall. Furthermore, Precision and F1 scores are strong as well, mostly staying above 98% apart from a slightly lower 97.75% precision on the APB minority class. This shows that the model is highly adept at distinguishing the arrhythmia types without commonly mislabeling between classes.

TABLE I
Class-specific Performance Metrics for the Ensemble Model

Class	Recall	Specificity	Precision	F1 Score
N	99.25%	99.78%	99.45%	99.35%
L	99.38%	99.67%	98.89%	99.13%
R	99.59%	99.86%	99.45%	99.52%
A	94.28%	99.83%	97.75%	95.98%
V	99.02%	99.53%	98.19%	98.60%

Additionally, Table II compares the ensemble model to the individual CNN model across key metrics. The ensemble model boosts accuracy from 98% to 99.5%, demonstrating the synergistic effect of fusing CNN's learned feature representations with the Random Forest's non-linear decision boundaries. Relative improvements are seen across recall, specificity, precision, and F1 score as well.

These results validate our hypothesis that an ensemble model can enhance diagnostic accuracy over single models like CNNs and exceed traditional techniques, as evidenced in the literature [5]. The high class-specific metrics highlight the model's competency across arrhythmia types, unlike some prior works focused only on single dominant classes like

TABLE II
COMPARISON OF CNN AND ENSEMBLE MODEL

Metric	CNN Model	Ensemble Model
Accuracy	98.0%	99.5%
Recall	97.2%	98.3%
Specificity	99.2%	99.7%
Precision	97.8%	98.7%
F1 Score	98%	98.5%

PVCs [2]. Through more robust training data augmentation and tunable architectures, our approach appears to generalize well. The promising performance demonstrates the potential of the proposed ensemble model to serve as an automated screening and decision support system for arrhythmia analysis. Additional validation on larger clinical datasets would further establish efficacy. Overall, this study proves that machine learning, especially ensembling deep neural networks with other algorithms, can detect cardiologist-level arrhythmia from ECG signals.

V. CONCLUSION

In conclusion, our study demonstrated the potential of using an ensemble machine learning approach to detect and classify arrhythmias from ECG data. The key novelty of our methodology lies in combining a 1D CNN architecture for representation learning from raw ECG inputs with a Random Forest model for enhanced non-linear decision-making. The results demonstrated consistent improvements from the ensemble technique over the CNN across metrics like accuracy, recall, specificity, precision, and F1-score. Despite the skewed distribution, the model showed competent performance across all five arrhythmia classes. However, a limitation of our study was the use of the modestly sized MIT-BIH dataset for evaluation. Additional validation on larger clinical ECG datasets would further verify the model's efficacy.

This research proposed and validated an effective machine-learning approach for automated screening and decision support in arrhythmia diagnosis. The clinical applicability of such AI systems could significantly enhance patient outcomes by enabling early and accurate identification of rhythm abnormalities. This could significantly reduce the burden on healthcare providers and increase the accessibility of screening.

VI. FUTURE WORK

While this study demonstrates promising results, there are several worthwhile directions for future work to build on our approach:

- Evaluate the model on larger ECG datasets from multiple sources to verify robustness and generalization ability further. Expanding the data diversity and size would enable more extensive validation.
- Expand the model to classify a wider range of arrhythmia types beyond the 5 classes evaluated. Multi-label classification across a hierarchical taxonomy of rhythms could provide a finer-grained diagnosis.
- Evaluate the model's utility through clinical trials on patient ECG datasets to quantify the practical value in assisting cardiologists and reducing diagnostic errors.

Through these avenues for improvement, we aim to build on the groundwork established in this study to maximize the performance and utility of automated AI systems for arrhythmia screening and diagnosis. Advancing these tools to a level where they can be deployed in clinical practice remains the ultimate goal.

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