Deep Learning-Based Classification of Premature Ventricular Contractions and Supraventricular Tachycardia Using ECG Signals

R. S. Lakshmi Balaji, Napat Joijinda and Thaweesak Yingthawornsuk

***Abstract*— This study provides comparative evaluation of deep learning models for the classification of PVC and SVT from ECG signals. We evaluate ResNet, DenseNet, VGGNet, InceptionNet, and WaveNet performance on various measures like accuracy, precision, recall, F1 score, AUC, MCC and log loss. The findings are that ResNet performs the best for both PVC and SVT classification tasks with 94% for PVC and 98% for SVT. Whereas all the models perform best for PVC detection, DenseNet experiences a steep drop in performance for SVT classification, indicating that it requires optimization. The results show the effectiveness of deep learning models, ResNet and WaveNet, in the correct diagnosis of arrhythmias from ECG signals.**

***Keywords*— Deep learning, ECG classification, Premature Ventricular Contractions, Supraventricular Tachycardia.**

I. Introduction

Arrhythmias including Premature Ventricular Contractions (PVC) and Supraventricular Tachycardia (SVT), are prevalent cardiac conditions that may cause severe health issues such as heart failure, cerebrovascular accident, or sudden cardiac death. Cardiovascular diseases including arrhythmias, are responsible for almost 17.9 million deaths every year across the globe, as per the World Health Organization (WHO), which calls for the importance of early diagnosis to enhance clinical outcomes [1]. PVCs are abnormal heartbeats that occur in the ventricles, and though usually harmless in healthy individuals, frequent PVCs can predispose to more dangerous arrhythmias such as ventricular tachycardia (VT).

In contrast, SVT refers to the rapid heartbeats that occur due to disturbances within the atria or AV node, usually causing discomfort but perhaps less immediately dangerous. Although they differ, both arrhythmias need prompt diagnosis and treatment in order to prevent long-term problems. The evolution of deep learning models has initiated tremendous advancement in arrhythmia detection, especially from the analysis of Electrocardiogram (ECG) signals. Conventional arrhythmia detection methods predominantly relied on feature extraction methods in the Time Domain, Frequency Domain and Heart Rate Variability (HRV) measures. Although these approaches provide valuable information, they tend to fail in effectively representing the non-linearities and complexity present in ECG signals [2]. Time Domain features such as RR intervals are widely used to investigate arrhythmic disorders such as VT and AV Block. However, they are poor in identifying subtle changes in ECG signals [3]. Frequency Domain analysis through power spectral analysis has been utilized to quantify autonomic nervous system activity and its effects on arrhythmias. It is too reductionist to manage the dynamics of real-time arrhythmia detection in the majority of cases. HRV analysis, measuring variability between beats, is a useful instrument in identifying dangerous arrhythmias like VT and BBB, but on its own, it is not sufficiently discriminative for complex arrhythmic events [4]. In the last couple of years, Convolutional Neural Networks (CNNs) have become the method of choice for ECG-based arrhythmia detection with a solid framework for hierarchical feature extraction from raw ECG signals without any need for manual preprocessing. ResNet, DenseNet, VGGNet, and InceptionNet are some of the CNN models that have been effective in classifying various arrhythmias, such as PVC and SVT [5][6]. Specifically, WaveNet, originally designed for speech synthesis, has been successfully transferred to ECG signal classification, allowing for strong temporal modeling capacity that enhances performance, particularly in noisy conditions [7].

This paper investigates the PVC and SVT classification using a variety of deep learning architectures like ResNet, DenseNet, VGGNet, InceptionNet, and WaveNet. Utilizing both traditional feature extraction and recent deep learning techniques, we aim to enhance the classification accuracy of these arrhythmias for a more precise and clinically viable system in real-time detection.

II. Methodology

In this work, we integrate deep learning techniques with conventional signal processing techniques for identifying PVC and SVT arrhythmias. The process includes the selection of an appropriate ECG dataset, filtering of the signals, extraction of required features and model development via CNNs and WaveNet, as illustrated in Figure 1.

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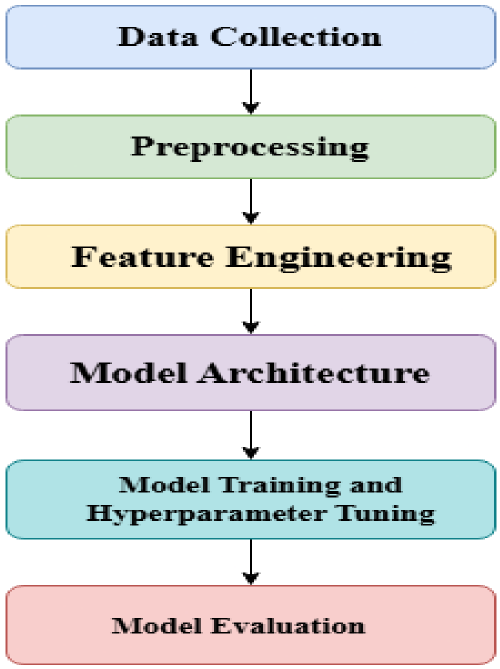

Fig.1. Flow map of the Research

A. Data Collection

We Utilized the MIT-BIH Arrhythmia Database, a standard arrhythmia detection benchmark. The database consists of 48 half-hour ECG recordings with a sampling frequency of 360 Hz from 47 subjects. From among the variety of arrhythmias present in the database, we considered Supraventricular Tachycardia (SVT) and Premature Ventricular Contractions (PVC). The dataset is high-resolution in nature, enabling precise training and testing of the classification models. The complete dataset can be utilized to test arrhythmia detection algorithms effectively.

B. Pre-processing

The ECG signals from the MIT-BIH Arrhythmia Database were filtered through several preprocessing techniques to achieve clean and reliable data for feature extraction and model training. 0.5-50 Hz bandpass filter was applied to eliminate noise and baseline wander, focusing on the frequency range of interest for the electrical activity of the heart. All segments of the ECG were normalized to zero mean and unit variance so that the models could not learn features based on signal amplitude variation. The filtered and R-peak-detected signals were divided into 8-second segments with enough information about the heart rhythm but with uniformity across the dataset. The Pan-Tompkins algorithm was used for accurate R-peak detection and making use of differentiation, squaring and moving window integration to highlight the QRS complex and increase peak detection accuracy. These pre-processing steps enabled the dataset to be effectively prepared for time-domain, frequency-domain and HRV feature extraction in arrhythmia detection.

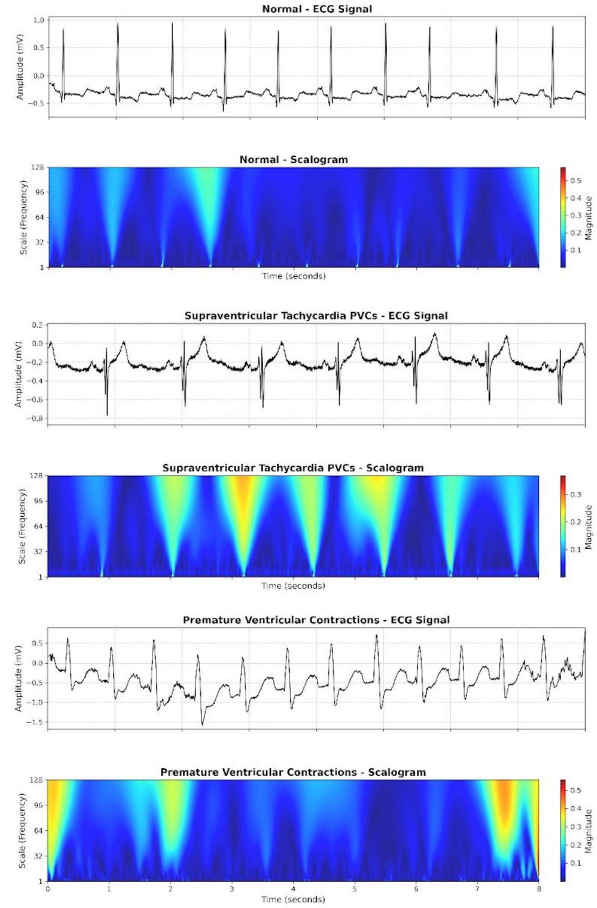

Fig. 2. Scalogram of the ECG Signals

C. Feature Engineering

Feature extraction was performed to analyze ECG signals effectively, focusing on three key areas: Time-Domain, Frequency-Domain, and Heart Rate Variability (HRV) features. These features help distinguish between different types of arrhythmias such as Premature Ventricular Contractions (PVC) and Supraventricular Tachycardia (SVT).

Time-Domain Features describe the ECG signal’s basic characteristics, including average signal value, variability, peak amplitude, and overall energy. These features help in identifying abnormal heart rhythms by capturing changes in signal patterns.

Frequency-Domain Features analyze how the ECG signal's energy is distributed across different frequencies. Power Spectral Density (PSD) helps detect abnormal rhythms and is computed using the Welch method:

$$P_{xx}(f) = \frac{1}{K}\sum_{k=1}^{K}\frac{|X_k(f)|^2}{N} \tag{1}$$

where $P_{xx}(f)$ represents the power spectral density at frequency f_1, $X_k(f)$ is the Fourier transform of the *k*-th segment, and *N* is the number of points in each segment.

Spectral Entropy, which quantifies irregularities in frequency distribution, is given by:

$$H = -\sum_{i=1}^{N} P_i \log_2 P_i\,, \quad P_i = \frac{S_i}{\sum_{j=1}^{N} S_j} \tag{2}$$

where S_i represents power at the *i*-th frequency bin

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A scalogram, obtained using the Continuous Wavelet Transform (CWT) which provides a detailed time-frequency representation as illustrated in Figure 2.

$$S(a,b) = |W_x(a,b)|^2, \quad W_x(a,b) = \int x(t)\psi^*_{a,b}(t)dt \tag{3}$$

where S(a,b) represents energy distribution over time and frequency, and ψa,b(t) is the wavelet function.

HRV Features focus on the time between heartbeats, measured using RR intervals. Metrics like mean RR interval, standard deviation, and RMSSD provide insights into heart rate variability, which is crucial for diagnosing arrhythmias. These extracted features were used as inputs for deep learning models to classify ECG signals accurately.

D. Model Training and Hyperparameter Tuning

The extracted features were used to train deep learning models including Convolutional Neural Networks (CNNs) and WaveNet for classifying Premature Ventricular Contractions (PVC) and Supraventricular Tachycardia (SVT). The training process involved splitting the dataset into training (70%), validation (15%), and test (15%) sets to ensure robust evaluation. To optimize model performance, various hyperparameters were fine-tuned including learning rate, batch size, number of layers and dropout rates. The Adam optimizer was selected for efficient gradient updates and the Binary cross-entropy loss function was used to handle Binary-class classification. Early stopping and K-fold cross-validation were applied to prevent overfitting and enhance generalization. Regularization techniques such as dropout and L2 weight decay were incorporated to improve model robustness. The final models were evaluated using accuracy, precision, recall and F1-score to ensure reliable detection of arrhythmias.

E. Model evaluation

The performance of the trained models was assessed using multiple evaluation metrics to ensure reliable classification of Premature Ventricular Contractions (PVC) and Supraventricular Tachycardia (SVT). The key metrics included:

- **Accuracy:** Measures the overall correctness of predictions.
- **Precision:** Indicates the proportion of correctly identified positive cases.
- **Recall:** Represents the model's ability to detect actual positives.
- **F1 Score:** The harmonic means of precision and recall and It balancing the false positives and false negatives.
- **Area Under the Curve (AUC):** Evaluates the model's ability to distinguish between classes.
- **Matthews Correlation Coefficient (MCC):** A balanced measure even for imbalanced datasets.
- **Cohen's Kappa:** Measures agreement between predicted and actual classifications.
- **Log Loss:** Quantifies prediction uncertainty; lower values indicate better confidence.
- **Balanced Accuracy:** Adjusted accuracy to handle class imbalance.
- **F2 Score:** A variation of F1 Score, giving more weight to recall for better sensitivity.

These metrics provided a comprehensive evaluation of model effectiveness, ensuring robustness in arrhythmia detection.

III. Result and Discussion

The performance evaluation of deep learning models for the classification of Premature Ventricular Contractions (PVC) and Supraventricular Tachycardia (SVT) was conducted using multiple statistical metrics. The results as detailed in Tables 1 and 2. It demonstrates the effectiveness of various architectures in detecting these arrhythmias. The evaluation metrics include accuracy, precision, recall, F1-score, AUC (Area Under the Curve), MCC (Matthews Correlation Coefficient), Cohen's Kappa, Log Loss, Balanced Accuracy and F2-score to provide a comprehensive analysis of model performance.

A. PVC Classification Performance

Table 1 presents the classification results for PVC detection. Among the tested models, ResNet achieved the highest performance, with an accuracy of 0.94, precision of 0.94, recall of 0.94, and an F1-score of 0.94. These results indicate that ResNet consistently classifies PVC occurrences with minimal false positives and false negatives. Furthermore, the AUC of 0.99 suggests that the model exhibits a strong ability to distinguish between normal and PVC beats, ensuring high reliability in real-world applications.

DenseNet and VGGNet followed closely behind ResNet, both achieving an accuracy of 0.93 with similar precision and recall values. This slight drop in performance suggests that while these models are still highly effective, it have ability to generalize to unseen data may be slightly lower than ResNet's. InceptionNet and WaveNet exhibited marginally lower accuracy (0.93) with slightly reduced MCC and Cohen's Kappa values which indicating that reliability. It's not robust as ResNet.

Another key observation is the Log Loss values where ResNet recorded the lowest at 0.114 and reinforcing its ability to make confident predictions with minimal uncertainty. The Balanced Accuracy metric also confirms that all models maintain an equitable classification of positive and negative classes. It ensuring that neither class is disproportionately represented in predictions. Overall, the high performance of all models in PVC detection demonstrates the effectiveness of deep learning in identifying arrhythmic patterns in ECG signals. However, the minor differences in accuracy, MCC and Cohen's Kappa suggest that certain architectures may be better suited for specific classification challenges.

TABLE I. PREMATURE VENTRICULAR CONTRACTIONS (PVC) PERFORMANCE

Model	Accuracy	Precision	Recall	F1 Score	AUC	MCC	Cohen Kappa	Log Loss	Balanced Accuracy	F2 Score
ResNet	0.94	0.94	0.94	0.94	0.99	0.883	0.878	0.114	0.939	0.971
DenseNet	0.93	0.94	0.93	0.93	0.99	0.868	0.863	0.129	0.932	0.963
VGGNet	0.93	0.94	0.93	0.93	0.99	0.867	0.863	0.129	0.932	0.961
InceptionNet	0.93	0.93	0.93	0.93	0.98	0.861	0.855	0.146	0.928	0.964
WaveNet	0.93	0.93	0.93	0.93	0.98	0.858	0.853	0.148	0.927	0.959

B. *SVT Classification Performance*

TABLE II: SUPRAVENTRICULAR TACHYCARDIA (SVT) PERFORMANCE

Model	Accuracy	Precision	Recall	F1 Score	AUC	MCC	Cohen Kappa	Log Loss	Balanced Accuracy	F2 Score
ResNet	0.98	0.98	0.98	0.98	1.00	0.963	0.962	0.059	0.981	0.992
DenseNet	0.99	0.99	0.99	0.99	0.38	-0.091	-0.043	0.697	0.478	0.780
VGGNet	0.98	0.98	0.98	0.98	0.99	0.968	0.967	0.038	0.984	0.975
InceptionNet	0.99	0.99	0.99	0.99	0.99	0.974	0.974	0.034	0.987	0.989
WaveNet	0.99	0.99	0.99	0.99	0.99	0.984	0.984	0.026	0.992	0.992

Table II provides a detailed breakdown of the models' performance in classifying SVT occurrences. Compared to PVC detection, the models performed exceptionally well in identifying SVT, with most achieving accuracy values close to or exceeding 0.98.

ResNet demonstrated remarkable results by achieving an accuracy of 0.98, precision and recall of 0.98, and an F1-score of 0.98. The AUC score of 1.00 further confirms its outstanding ability to separate SVT from normal beats. Similarly, VGGNet and InceptionNet achieved near-identical performances with accuracy of 0.98 and 0.99, respectively and It is robust precision-recall scores by making them highly reliable for clinical use.

Interestingly, WaveNet outperformed all other models achieving an accuracy of 0.99 with high MCC value of 0.984 and the lowest Log Loss of 0.026 indicating that it makes highly confident predictions with minimal uncertainty. This suggests that WaveNet architecture is particularly well-suited for analyzing SVT-related ECG patterns making it a strong candidate for real-time monitoring applications. However, DenseNet exhibited an anomaly in performance. While its accuracy and precision remained high, its AUC dropped significantly to 0.38, with a negative MCC value (-0.091). This unexpected result suggests that DenseNet struggled to effectively distinguish between SVT and normal beats, potentially due to class imbalance or suboptimal feature extraction. This requires further investigation, the architecture may benefit from additional fine-tuning or balanced data augmentation strategies.

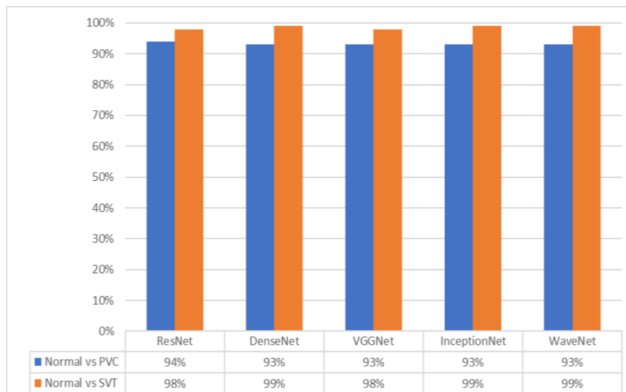

Fig. 3. Accuracy comparison of Normal Vs PVC and Normal vs SVT

ResNet consistently outperformed other models in both PVC and SVT detection by achieving high accuracy, precision and recall across the board. This highlights its suitability for ECG-based arrhythmia classification tasks. WaveNet exhibited superior performance in SVT classification, with an AUC of 0.99 and demonstrating its potential as a leading model for complex arrhythmia detection. DenseNet's performance inconsistency in SVT detection raises concerns about its robustness. Further investigation is necessary to determine whether this drop in AUC and MCC resulted from data imbalance, misclassification or architectural limitations. Figure 3 illustrates the overall accuracy comparison between Normal vs. PVC and Normal vs. SVT, showing that models perform slightly better in SVT detection than PVC detection.

The results obtained in this study have significant implications for automated ECG analysis and arrhythmia detection. The ability of deep learning models, particularly ResNet and WaveNet to classify PVC and SVT with high accuracy highlights their potential in real-time cardiac monitoring applications. These models can be integrated into wearable ECG devices and telemedicine platforms enabling early detection and intervention for patients at risk of developing severe cardiac conditions. DenseNet's AUC drop in SVT classification suggests that some models may struggle with specific arrhythmia types which requiring further data preprocessing or model adjustments. The slight performance variation among models in PVC detection indicates that architectural choices impact classification robustness, necessitating hybrid approaches or ensemble techniques for improved reliability. Real-world ECG signals often contain noise and artifacts which requiring enhanced preprocessing techniques to further improve classification performance. Future research should focus on enhancing model generalization through additional datasets, transfer learning techniques and explainability methods to understand how these models make decisions. Additionally, incorporating real-time deployment and clinical validation will be crucial in transitioning these deep learning models from research settings to practical healthcare applications. This study demonstrated the feasibility of deep learning-based PVC and SVT classification using ECG signals. Among the models evaluated, ResNet and WaveNet consistently achieved the highest accuracy and reliability, making them ideal candidates for clinical use. While all models performed well, DenseNet exhibited instability in SVT classification, highlighting the need for further model refinement. The results reinforce that deep learning can serve as a valuable tool in automated arrhythmia detection, enabling efficient and accurate diagnosis in clinical environments. Future work should address model optimization, explainability and real-world deployment challenges to maximize the impact of deep learning in cardiac healthcare applications.

IV. Conclusion

This study evaluated the performance of deep learning models for detecting Premature Ventricular Contractions (PVC) and Supraventricular Tachycardia (SVT) using ECG signals. Among the models, ResNet achieved the highest accuracy for both PVC 94% and SVT 98%, demonstrating superior performance across multiple metrics. WaveNet and InceptionNet also performed well, particularly for SVT, with WaveNet achieving an accuracy of 99%. DenseNet showed an anomaly in SVT classification with a lower AUC, though its accuracy remained high 99%. Overall, ResNet and WaveNet exhibited the most reliable performance, suggesting their potential for real-time cardiac monitoring applications. Further optimization of DenseNet is needed to improve its stability.

V. Future Directions

Future work should focus on improving model generalization through larger, diverse datasets and addressing class imbalance. Expanding the models for multi-class classification of various arrhythmias will increase their clinical applicability. Optimizing DenseNet's performance and exploring transfer learning and explainability methods will enhance model stability and adaptability. Finally, real-time deployment and clinical validation are crucial for enabling early detection and intervention for a wide range of cardiac arrhythmias.

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