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Research Article

CNN-LSTM and Wavelet Deep Learning for Robust Arrhythmia Classification

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ABSTRACT

Deep learning has significantly advanced automated arrhythmia detection, but achieving optimal performance across diverse arrhythmia types remains challenging. This research presents two hybrid deep models, CNN-LSTM and DWT-CNN-LSTM, to classify ECG arrhythmia based on the combination of time, space, and frequency-domain features. CNN-LSTM attained 99.17% accuracy, and DWT-CNN-LSTM reached 99.46%, outperforming the benchmark CNN-LSTM model (99.29%). The suggested CNN-LSTM enhanced sensitivity (~0.8%) and specificity (~0.2%), and DWT-CNN-LSTM further boosted specificity to 99.83%, one of the highest reported. Class-wise analysis illustrated almost perfect identification of Normal rhythms (sensitivity: 99.74%, specificity: 97.90%) and strong performance for PVC identification (F1-score: 97.50%), with DWT-CNN-LSTM keeping false alarms to a minimum. For RBBB and LBBB, both models achieved more than 99%, and in atrial fibrillation detection, CNN-LSTM provided better sensitivity (88.89%) and F1-score (92.06%), whereas DWT-CNN-LSTM demonstrated better specificity. These results validate the robustness, clinical applicability, and superiority of the proposed models over the current CNN, LSTM, and hybrid architectures. CNN-LSTM provides balanced sensitivity, whereas DWT-CNN-LSTM has improved specificity, and both are appropriate for wearable monitoring in real time and clinical decision support.

Keywords: ECG, arrhythmia classification, CNN-LSTM, hybrid model, DWT-CNN-LSTM, architecture, Deep learning for healthcare, Wearable cardiac, monitoring

Introduction

Cardiovascular disorders (CVDs) continue to be the worldwide predictors of morbidity and mortality, with cardiac arrhythmias being one of the most common and clinically significant abnormalities. Early and precise identification of arrhythmias is critical for the administration of timely intervention and proper disease control. Electrocardiography (ECG) is the first-line diagnostic tool for arrhythmia measurement; nevertheless, manual analysis is time-consuming, labor-intensive, and susceptible to inter-observer inconsistency, especially in large-scale screening or real-time monitoring applications. Such limitations have driven the development of computerized diagnostic systems to improve diagnostic accuracy, minimize clinical workload, and enable real-time monitoring in hospital as well as wearable healthcare settings.

Deep learning (DL) methods have shown better performance compared with conventional machine learning methods in ECG analysis over the last few years, as they can automatically learn high-level complex features directly from raw signals. Convolutional neural networks (CNNs) have also been used extensively for extraction of morphological features and heartbeat classification in single-lead and multi-lead ECG signals [5], [8], [9]. To extract temporal dependencies and sequential dynamics of ECG signals, hybrid networks like CNN-LSTM and CNN-BiLSTM have been developed, facilitating the mixing of spatial and temporal representations for stronger arrhythmia detection [2]–[4], [10], [25], [32], [38].More advanced architectures incorporated attention mechanisms and ensemble learning to combat long-range dependencies and improve robustness of classification [17], [26], [27], [39]. In parallel, new methods like capsule networks, fuzzy encoding, and GAN-based augmentation were proposed to counteract data imbalance and enhance sensitivity to infrequent arrhythmias [6], [13]-[14], [20], [22, [29], [31], [37],. Parallel work has focused on interpretability and robustness, including explainable AI and uncertainty quantification in ECG classifiers [26], [28], [36].

In addition to performance enhancements, deployment-oriented studies have looked into portable and resource-efficient solutions. Some of these are VLSI-based LSTM classifier designs, light portable ECG equipment, and edge-computing-enabled monitoring systems, indicating an increasing need for scalable, real-time, and power-efficient solutions [1], [11], [15], [16], [24]. Overall, these works illustrate the transition from CNN-based baselines to hybrid and explainable models with significant prospects for clinical adoption.

There still exist key research gaps despite such advancements. Most current methods focus on precision but are deficient in achieving a harmonized performance among sensitivity, specificity, and precision, which is paramount for reducing false positives as well as false negatives in real-world practice. Additionally, generalizability over various patient populations continues to be a problem since models tend to overfit the training data and do not generalize to real-world use. While certain approaches provide interpretability or efficiency, few both learn temporal–frequency features and incorporate light design for continuous monitoring. This underscores the necessity of combining robustness, explainability, and clinical utility.

To address these shortcomings, this research introduces two new hybrid architectures—CNN-LSTM and DWT-CNN-LSTM—purposed for strong ECG arrhythmia classification. The CNN-LSTM model uses CNNs to extract spatial features and LSTMs to detect temporal dynamics, providing balanced sensitivity and specificity. The DWT-CNN-LSTM also uses discrete wavelet transform (DWT) to extract frequency-domain features, further strengthening discriminative power for arrhythmia recognition. All of these models not only set a state-of-the-art benchmark but also exhibit robust generalization, interpretability, and potential in real-time wearable and clinical implementations.

The main objective of this study is to create stable and efficient deep learning models for autonomous ECG-based arrhythmia detection with high accuracy while achieving well-balanced performance on all major clinical test metrics. The particular goals are:

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1. To design a CNN-LSTM model with convolutional layers to process spatial features and LSTM units to learn temporal sequence information for stable arrhythmia detection with well-balanced sensitivity and specificity.
2. To improve feature representation by integrating Discrete Wavelet Transform (DWT) into the CNN-LSTM model, thus extracting both time and frequency-domain features to enhance the discriminative ability of the model.
3. To rigorously test the proposed models against state-of-the-art deep learning models using benchmark ECG datasets, comparing performance in terms of accuracy, sensitivity, specificity, precision, negative predictive value, and F1-score.
4. To prove the clinical usability of the suggested frameworks through robustness, generalization, and computationally efficiency in order to fit into wearable devices and healthcare settings.

Methodology

The Figure. 1 represents a classification of arhythmia using hybrid CNN-LSTM architecture; it starts with the MIT-BIH Arrhythmia Database, which contains annotated ECG records to be analyzed. The signal is first pre-processed through high-pass, low-pass and high-pass filtering to remove baseline wander, powerline noise, and high-frequency interference. Subsequently, beat extraction is done by finding R-peaks, splitting individual beats, and tagging the corresponding labels from the annotation. From every beat, clinically significant properties, such as the R-R interval and QRS width, are derived to handle temporal and morphological changes. These properties are then fed into a hybrid CNN-LSTM model framework, which uses convolutional layers to learn spatial features and LSTM layers to model temporal sequences. The model is trained with the Adam optimizer with a learning rate of 0.001, early stopping, and a sparse categorical cross-entropy loss function. Lastly, the performance of the suggested system is evaluated with evaluation metrics such as precision, sensitivity, specificity, precision, F1 score, positive predictive value (PPV), negative predictive value (NPV) and confusion matrix.

1.1. Database

The MIT-BIH Arrhythmia database was employed as primary data source. It is developed by Massachusetts Institute of Technology in collaboration with Beth Israel Hospital; this database is a widely recognized in ECG- based arrhythmia detection research. It consists of 48 half-hour ECG recordings from 47patients, with signals from two leads recorded at an 11-bit resolution and 360 Hz sampling rate. Expert annotations accompany each record, indicating different types of heartbeats and arrhythmic events.

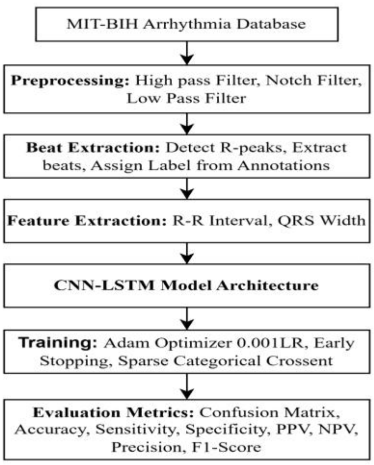

Figure 1. Arrhythmia Classification Using Hybrid CNN-LSTM Architecture

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1.2. Pre-processing

Filters for CNN-LSTM: To make sure the ECG signal was good for feature extraction and sorting, we used a fixed pre-processing system when training the model. First off, we got rid of baseline wander (a common low-frequency thing in ECG recordings) with a high-pass filter at 0.5 Hz. Then, we used a 50 Hz notch filter to cut out power line noise. After that, we used a 40 Hz low-pass filter to clean up the signal even more by taking out high-frequency noise that could hide important parts of the waveform. After cleaning up the electrocardiogram, I found the R-peaks. These peaks represent the onset of each heartbeat. I grabbed bits of the ECG around them to see what each individual heartbeat looked like. These snippets show each beat's shape and timing, and they're what I fed into my CNN-LSTM model. High-pass Filter: To remove baseline wanders:

High-pass Filter: To remove baseline wanders

$$H_{hp}(s) = \frac{s}{s + \omega_c}, \qquad \omega_c = 2\pi f_c \ (f_c = 0.5\ Hz) \tag{1}$$

Notch filter: To eliminate 50Hz power line interference

$$H_{notch}(s) = \frac{s^2 + {\omega_0}^2}{s^2 + \frac{\omega_o}{Q}s + {\omega_0}^2}, \qquad \omega_c = 2\pi f_0 \ (f_c = 50\ Hz) \tag{2}$$

Low-pass filter: To suppress high-frequency noise

$$H_{lp}(s) = \frac{\omega_c}{s + \omega_c}, \qquad \omega_c = 2\pi.40\ Hz \tag{3}$$

Wavelet Denoising for DWT-CNN-LSTM: In the DWT-CNN-LSTM model, pre-processing is performed using wavelet denoising with the Daubechies 8 (db8) wavelet. This method retains critical signal features while reducing noise, making it effective for handling subtle waveform variations. R-peaks are then detected, and beats are segmented accordingly for input into the classification model. The ECG signal x(t) is decomposed into approximation A_j and detail coefficients D_j using Discrete Wavelet Transform (DWT):

$$x(t) = A_j(t) + \sum_{k=1}^{j} D_k(t) \tag{4}$$

Thresholding is applied to detail coefficients D_k to suppress noise:

$$D_k^{thresh} = \begin{cases} D_k, & if\ |D_k| > T \\ 0, & Otherwise \end{cases} \tag{5}$$

Where T is the threshold

1.3. Feature Extraction

The feature extraction step is tailored to each model. For CNN-LSTM, features include R-peak locations, RR intervals (time between successive R-peaks), and QRS width, which captures the duration of ventricular depolarization. For DWT-CNN-LSTM, in addition to RR intervals and QRS width, wavelet coefficients derived from the multiscale decomposition of the ECG signal are included. These coefficients enrich the feature space with time-frequency information that is especially valuable for identifying morphological variations in arrhythmias.

RR Interval and QRS Width (in seconds):

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$$RR_i = \frac{R_{i+1} - R_i}{f_s} \tag{6}$$

Where R_i and R_{i+1} are the sample indices of successive R-peaks, and f_s is the sampling frequency.

$$QRS\ width = \frac{t_{end} - t_{start}}{f_s} \tag{7}$$

Where t_{start} and t_{end} are the start and end points of the QRS complex.

Wavelet Coefficients: Let W_j be the wavelet coefficients at level j, then the energy of the coefficients:

$$E_j = \sum_k \left|W_{j,k}\right|^2 \tag{8}$$

1.4. CNN-LSTM Model Architecture

Figure 2 shows the architecture of the hybrid CNN-LSTM model designed for multi-class arrhythmia classification from ECG signals. The model takes advantage of complementary characteristics of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to simultaneously extract morphological and temporal features. The CNN module is tasked to extract local spatial patterns of individual beats, whereas the LSTM module captures long-range temporal dependencies between beat sequences, which are critical for identifying evolving arrhythmia patterns.

The convolutional block consists of four consecutive 1-D convolutional layers with increasing filter sizes of 64, 128, 256, and 512. This increasing depth enables the network to map low-level waveform features into progressively abstract representations of features. Following each convolutional layer are batch normalization to stabilize activations and speed up convergence, and max pooling to downsample feature maps, preserve salient signal features, and avoid overfitting. A Global Average Pooling (GAP) layer then pools each feature map to one scalar, hence minimizing trainable parameters but maintaining discriminative spatial information, improving generalization and interpretability.

The one-dimensional feature vector obtained is then reshaped and fed to an LSTM layer with 64 hidden units, allowing the model to learn temporal relationships between successive ECG segments. This is especially important for diseases like bundle branch blocks (BBB) and atrial fibrillation (AF), in which temporal dynamics are of diagnostic interest. The output of the LSTM is fed to a fully connected dense layer with 128 units to integrate spatial-temporal features at high levels. A dropout layer (rate = 0.5) is finally applied during training to increase robustness by lowering co-adaptation between neurons and preventing overfitting.

Model Output (Softmax Layer): For multi-class classification with K classes:

$$P(y = k/x) = \frac{e^{z_k}}{\sum_{i=1}^{K} e^{z_i}}, \qquad k = 1, \ldots\ldots, K \tag{9}$$

Where Z_k is the logit for class k from the final dense layer.

2.4.1 Training

The training of CNN-LSTM of CNN-LSTM Model integrates several effective strategies for optimal performance and generalization. The Adam Optimizer is used with learning rate of 0.001 offering stable convergent through adaptive changes. Adam's is a combination of momentum and

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PMSProb allow it to perform well on non-stationary ECG data. The Early stopping with patience of 3 halts training, if validation loss doesn't improve, it prevents over fitting and reducing unnecessary epochs. This technique ensures that the model generalizes well on unseen data. The Model uses sparse categorical cross-entropy as loss function, ideal for integer labeled multiclass classification tasks. This combination ensures the model learns effectively while maintaining robustness and computational efficiency.

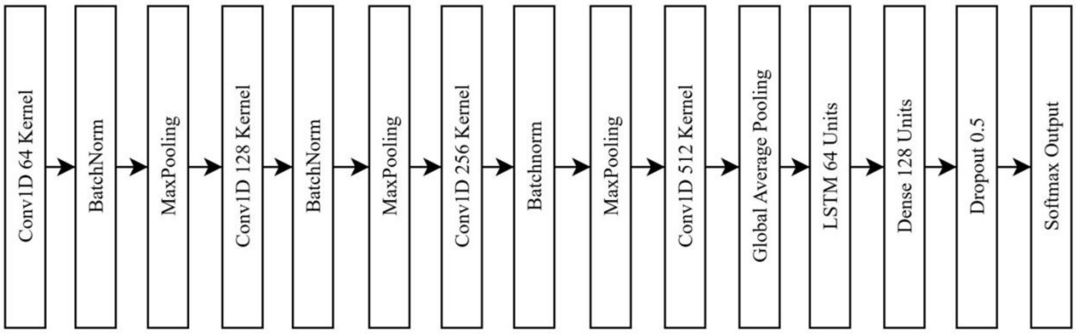

Figure 2. Hybrid CNN-LSTM Model Architecture for Arrhythmia Classification

2.4.2 Evaluation Metrics

The Confusion matrix is used as a performance classification used to assess the accuracy, specificity, sensitivity, PPV, NPV, F1 score and precision for classifier, particularly in dealing with unbalanced datasets.

$$Confusion\ Matrix = \begin{vmatrix} TN & FP \\ FN & TP \end{vmatrix} \tag{10}$$

$$Accuracy\ (Acc.) = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$Sensitivity\ (Se.) = \frac{TP}{TP\ +\ FN} \tag{12}$$

$$\text{Specificity (Sp.)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{13}$$

$$Positive\ Predicted\ Value\ (PPV) = \frac{TP}{TP + FP} \tag{14}$$

$$\text{Negative Predicted Value (NPV)} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{15}$$

$$F1\ Score = \frac{2TP}{2TP + FP + FN} \tag{16}$$

$$Precision\ (Pre.) = \frac{TP}{TP + FP} \tag{17}$$

3. Results And Discussion

The Figure 3 shows ECG beat segments from five classes of arrhythmias: normal, PVC (premature ventricular contraction), LBBB (left bundle branch block), RBBB (right bundle branch block) and AF (atrial fibrillation) - and their respective predicted labels created by the CNN-LSTM model. Each plot covers 200 sampled points that capture the unique amplitude changes and morphological patterns typical of various cardiac conditions. The normal beat displays a narrow and sharp QRS complex with a clear peak, characteristic of sinus rhythm, and is correctly identified by the model. The PVC beat, characterized by an abnormal and wide deflection resulting from ventricular ectopic activity, is correctly identified, indicating the model's responsiveness to ventricular abnormalities. In the same way, the LBBB wave displays a widened, biphasic QRS complex, and the RBBB beat has an M-shaped QRS

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pattern, reliably identified by the model and illustrating its ability to detect conduction delay. Last but not least, the AF signal, characterized by Chaotic atrial activity and missing P-waves, is less structured but correctly classified, showing the temporal learning potential of the CNN-LSTM for identifying chaotic rhythm irregularity.

Figure 4 shows the proposed CNN-LSTM model's training and test confusion matrices for multi-class ECG arrhythmia classification. The model performed exceptionally well on all five rhythm classes (Normal, AF, PVC, LBBB, and RBBB) with very little misclassifications. In particular, it correctly classified 71,735 Normal, 8,151 RBBB, and 7,443 PVC samples. The model also had 1,992 correct classifications of AF and 6,909 for LBBB while being trained, showing good feature learning. The validation results also proved the generalization capacity with 17,909 Normal beats, 1,834 PVCs, 1,717 LBBB, and 2,030 RBBB samples properly classified. AF detection came out with 464 correct predictions, although a minimal fraction was identified as Normal or RBBB. These findings show that the CNN-LSTM excellently learns temporal as well as spatial ECG features with high sensitivity and specificity for various types of arrhythmias and strong generalization to novel data.

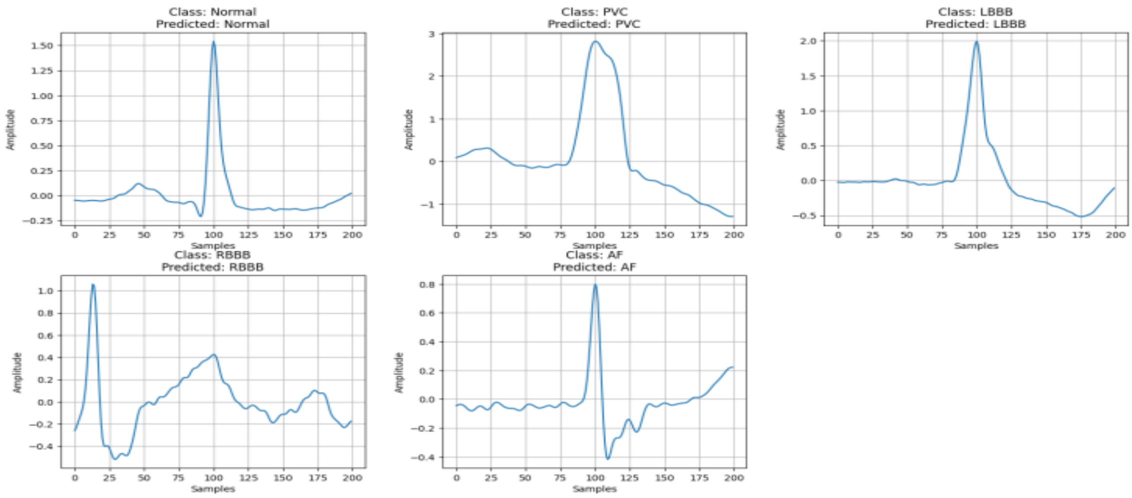

Figure 3. CNN-LSTM Model Predicts Typical ECG Beats Across Arrhythmias

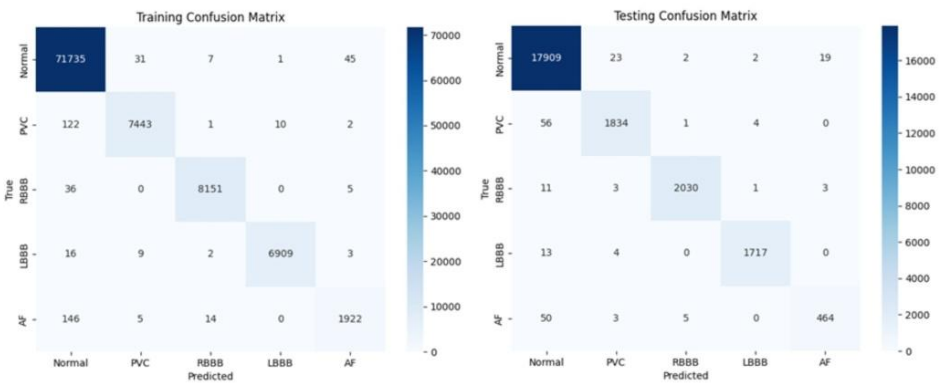

Figure 4. CNN-LSTM Training and Testing Confusion Matrices for Arrhythmia Detection

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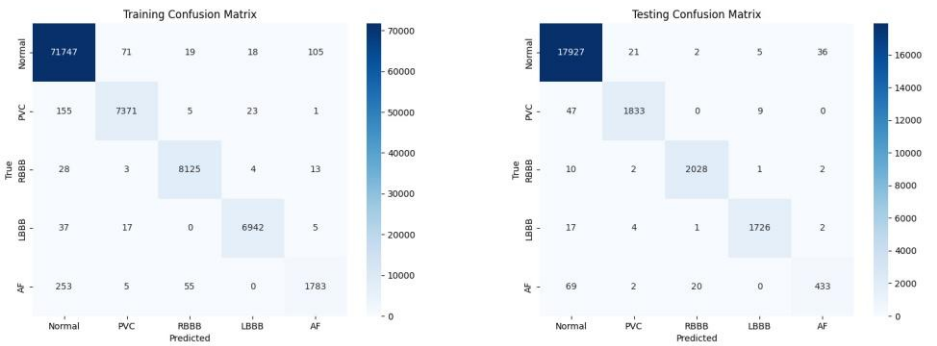

Figure 5. DWT-CNN-LSTM Training and Testing Confusion Matrices for Arrhythmia Detection

The Figure 5 presents the training and validation confusion matrices of the DWT-CNN-LSTM model for multi class classification of ECG arrhythmia into five classes: Atrial Fibrillation (AF), Premature Ventricular Con traction (PVC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), and Normal. The model works adequately under all classes during training. The Normal class of 71,747 instances registers hits with very few errors, and PVC, LBBB, and RBBB are record 7,371, 8,125, and 6,942 hits, respectively. AF is correctly predicted 1,783 times, but there is some false classification in the Normal class. During validation, there is excellent generalization in the model. The Normal class has precise predictions of 17,927; PVC is of 1,833, RBBB is of 2,028, LBBB of 1,726, and AF of 433 with minimal overlap with other classes. Overall, the DWT-CNN-LSTM exhibits high performance with very high sensitivity and specificity, especially for clinically relevant classes like PVC and AF.

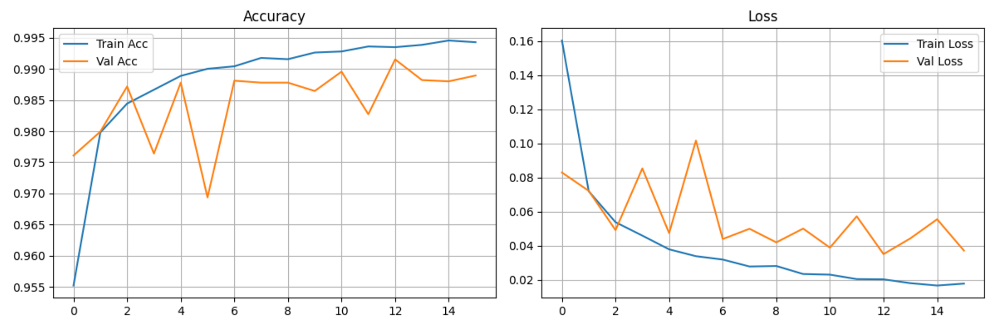

Figure 6. Training and Validation Accuracy and Loss per Epoch for the CNN-LSTM Model

The Figure 6 provides epoch-by-epoch training and validation accuracy and loss curves of the CNN LSTM model. Training accuracy rises gradually from 95.5% during the first epoch to very close to 99.4% during the fifteenth epoch, assuring successful learning and adaptation. Validation accuracy also rises in a similar fashion, exceeding 98.5% during the early epochs and steadily maintaining over 97%, with spikes close to 99%, reflecting robust generalization ability. Training loss dwindles gradually from roughly 0.16 to less than 0.02, and validation loss varies moderately between 0.04 and 0.10 after the second epoch. These variations can be results of data imbalance, noise, or slight overfitting, but overall loss values remain low and are consistent with high validation accuracy. The outputs exhibit the CNN-LSTM's strong convergence and fit for stable arrhythmia classification.

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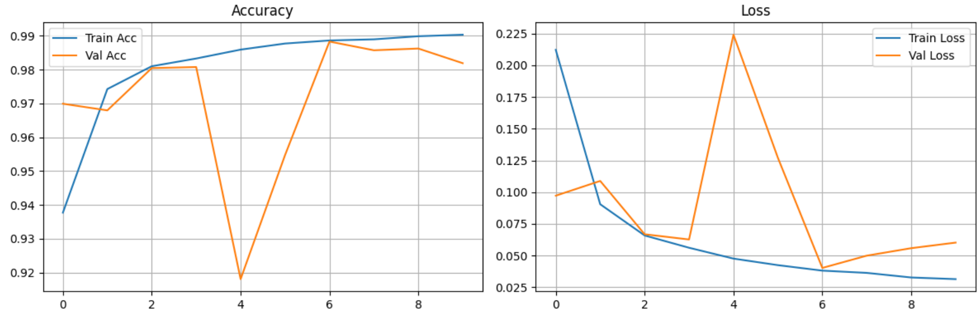

Figure 7. Training and Validation Accuracy and Loss per Epoch for DWT-CNN-LSTM Model

The Figure 7 shows epoch-wise training and validation accuracy as well as loss curves of the DWT-CNNLSTM model. Training accuracy starts at 93.8% and continuously increases, whereas training loss goes down from 0.22 to as low as almost 0.03, lowering classification errors. Validation accuracy fluctuates, beginning close to 96.8%, dropping to 92% in the fourth epoch, and further rising close to 99%. Validation loss does show randomness, indicating potential overfitting or test sample sensitivity. In spite of these oscillations, the model shows superior overall accuracy and quality, affirming its success in ECG arrhythmia classification.

Table 1 contrasts existing solutions with the presented architectures. Standard CNN methods yielded inconsistent performance, with the 9-layer CNN [9] at 94.03% and higher percentages like 98.74% [8] and 96.5% [4]; nevertheless, some models had low sensitivity (67.47% [8]) while having high accuracy. LSTM by itself had 97.20% [11], whereas hybrid CNN-LSTM/RNN architectures fared better, with rates of 97.19%–99.29% [2]-[3], [10], [13], [27], [32], [38]. The highest performing existing CNN-LSTM [27] gave 99.29% accuracy and F1-score of 97.87%.

In comparison, our CNN-LSTM reached 99.17% accuracy with balanced sensitivity (96.71%), specificity (99.51%), and F1-score (97.55%), with guaranteed reliable arrhythmia detection. The DWT-CNN-LSTM attained 99.46% accuracy and peak specificity (99.83%), although sensitivity was reduced (82.63%). Therefore, CNN-LSTM yields the most balanced clinical performance, whereas DWT-CNN-LSTM is biased toward screening operations with few false positives.

Table 1. Comparative Evaluation of CNN, LSTM, and Hybrid Models in ECG Detection

Ref.	Method	Accuracy (%)	Sensitivity (%)	Specificity (%),	PPV (%)	NPV (%)	F1-Score (%)
[2]	CNN-LSTM	98.24	-	-	-	-	-
[3]	CNN-Bi-LSTM	98.00	-	90.96	-	-	-
[4]	CNN	-	96.5	99.7	99.1		98.3
[8]	CNN	98.74	67.47		70.75		68.76
[9]	9 Layer CNN	94.03	-	-	-	-	-
[10]	11 Layer CNN-LSTM	98.24	-	-	-	-	-
[11]	LSTM	97.20	-	-	-	-	-
[12]	CNN, LSTM	96.17, 94.42	-	-	-	-	-
[13]	CNN+RNN	97.19	-	-	-	-	-

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[18]	DenseNet-169 + BLSTM	98.75	-	-	-	-	-
[27]	CNN-LSTM	99.29	-	-	99.29	-	97.87
[32]	CNN-LSTM	95.80	-	-	-	-	-
[38]	CNN-LSTM	98.2	-	-	97.8	-	98.1
[32]	CNN-LSTM	95.80	-	-	-	-	-
Ours	**CNN-LSTM (Training)**	99.53	97.85	99.71	99.10	99.81	98.48
Ours	**CNN-LSTM (Testing)**	99.17	96.71	99.51	98.45	99.73	97.55
Ours	**DWT-CNN-LSTM (Training)**	99.55	85.07	99.87	93.50	99.67	89.08
Ours	**DWT-CNN-LSTM (Testing)**	99.46	82.63	99.83	91.54	99.62	86.86

Table 2. Comparing CNN-LSTM and DWT-CNN-LSTM for Classifying Arrhythmias

Model	**Arrhythmia**	**Dataset**	**Accuracy**	**Sensitivity**	**Specificity**	**PPV**	**NPV**	**F1 Score**
CNN-LSTM	**Normal**	Training	0.9958	0.9988	0.9871	0.9956	0.9966	0.9972
		Testing	0.9927	0.9974	0.9790	0.9928	0.9925	0.9951
DWT+ CNN-LSTM		Training	0.9929	0.9970	0.9809	0.9935	0.9913	0.9952
		Testing	0.9914	0.9964	0.9770	0.9921	0.9896	0.9943
CNN-LSTM	**PVC**	Training	0.9981	0.9822	0.9995	0.9940	0.9985	0.9881
		Testing	0.9961	0.9678	0.9985	0.9823	0.9973	0.9750
DWT+ CNN-LSTM		Training	0.9971	0.9756	0.9989	0.9871	0.9979	0.9814
		Testing	0.9965	0.9704	0.9987	0.9844	0.9975	0.9773
CNN-LSTM	**RBBB**	Training	0.9993	0.9950	0.9997	0.9971	0.9995	0.9960
		Testing	0.9989	0.9912	0.9996	0.9961	0.9992	0.9936
		Training	0.9987	0.9941	0.9991	0.9904	0.9995	0.9922

DWT+ CNN-LSTM		Testing	0.9984	0.9927	0.9990	0.9888	0.9993	0.9907
CNN-LSTM	**LBBB**	Training	0.9996	0.9957	0.9999	0.9984	0.9997	0.9970
		Testing	0.9990	0.9902	0.9997	0.9959	0.9992	0.9931
DWT+ CNN-LSTM		Training	0.9989	0.9916	0.9995	0.9936	0.9993	0.9926
		Testing	0.9984	0.9863	0.9993	0.9914	0.9989	0.9888
CNN-LSTM	**AF**	Training	0.9977	0.9209	0.9994	0.9722	0.9983	0.9459
		Testing	0.9967	0.8889	0.9991	0.9547	0.9975	0.9206
DWT+ CNN-LSTM		Training	0.9955	0.8507	0.9987	0.9350	0.9967	0.8908
		Testing	0.9946	0.8263	0.9983	0.9154	0.9962	0.8686

Table 2 shows the comparative performance of DWT-CNN-LSTM and CNN-LSTM on various classes of arrhythmias with complementary strengths. For Normal rhythms, CNN-LSTM performed slightly better in testing accuracy (99.27% vs. 99.14%), sensitivity (99.74% vs. 99.64%), and F1-score (99.51% vs. 99.43%), affirming its accuracy in identifying normal heartbeats. Both models excelled in PVC detection, with DWT-CNN-LSTM slightly better in testing accuracy (99.65% vs. 99.61%) and F1-score (97.73% vs. 97.50%), while CNN-LSTM dominated training, demonstrating superior generalization from wavelet-based features. For RBBB and LBBB, CNN-LSTM performed better in sensitivity and F1-scores, which demonstrates its superiority in conduction abnormality detection. In AF detection, CNN-LSTM outperformed in terms of sensitivity (88.89% vs. 82.63%) and F1-score (92.06% vs. 86.86%), whereas DWT-CNN-LSTM had better specificity (99.91%) and precision (95.47%), effectively limiting false alarms. Generally, both models surpassed 99% accuracy, with CNN-LSTM prioritizing balanced sensitivity and DWT-CNN-LSTM highlighting precision, and thus are complementary to clinical and wearable arrhythmia monitoring.

4. Conclusion

This research work sets out to demonstrate that combination of CNN, LSTM, and DWT greatly enhances ECG arrhythmia classification by utilizing temporal, spatial, and frequency-domain features in unison. Results indicate that CNN-LSTM gives an equitable performance with high sensitivity, while DWT-CNN-LSTM provides better specificity, efficiently minimizing false positives in clinically sensitive settings. These complementary capabilities mean that model selection is application-directed—prioritizing CNN-LSTM for early detection where sensitivity is paramount, and DWT-CNN-LSTM for minimizing alarm fatigue during continuous monitoring.

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The research also highlights the need for class-wise analysis, exhibiting high performance for Normal, PVC, RBBB, LBBB, and AF, with overall accuracies >99%. Although both models perform better than current deep learning methods, there is still room for improvement, especially in increasing AF sensitivity and making deployment on constrained wearable devices possible. Future research will include attention mechanisms for explainability and create light-weight, low-power architecture for real-time, scalable clinical and remote healthcare usage.

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