Time-Frequency Feature Integration with Deep Neural Networks for Robust Bundle Branch Block Classification

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ABSTRACT

Bundle Branch Block (BBB) is a conduction disorder where electrical impulses are delayed or blocked in the heart's Right or Left BBBs (RBBB or LBBB), causing abnormal ventricular depolarization, seen as a widened QRS complex on an Electrocardiogram (ECG). It can be without symptoms or associated with conditions such as cardiovascular disease or high blood pressure. This research aims to design an inter-patient heartbeat classification approach capable of reliably differentiating between LBBB, RBBB, and Normal heart rhythms. This study presents a comparative analysis of various ECG classification models, focusing on the integration of advanced pre-processing techniques with Deep Learning (DL) architectures using the MIT-BIH Arrhythmia database. The proposed work introduces three Convolution Neural Networks and Long Short Term Memory (CNN-LSTM)-based models: Standard CNN-LSTM, Discrete Wavelet Transform (DWT) enhanced CNN-LSTM, and Hilbert Transform-Wigner Ville Distribution (HT-WVD) enhanced CNN-LSTM. Among these, the latter delivers the best classification accuracy of 99.6%, along with a superior sensitivity of 98.83%, specificity of 99.43%, and an F1- Score of 98.98%. The DWT with CNN-LSTM and the Standard CNN-LSTM models also demonstrate high performance, confirming the effectiveness of the hybrid time-frequency domain pre-processing for capturing intricate ECG patterns, especially as RBBB and LBBB. The results show that combining signal processing with DL techniques can lead to accurate and trustworthy ECG interpretation.

Keywords-bundle branch block; deep learning; discrete wavelet transform; Hilbert transform-Wigner Ville distribution

I. INTRODUCTION

The heart's natural rhythm is disrupted and ventricular co-ordination is compromised when electrical impulses travelling via the heart bundle branches are delayed or blocked, a condition known as the BBB. The latter is especially important for people with underlying heart-related issues because it frequently signals a deterioration in the electrical conduction system of the heart [1]. ECGs are still a vital diagnostic tool for arrhythmia, but manual interpretation of data by cardiologists can be time-consuming and delay critical interventions [2, 3].

In the general population, both RBBB and LBBB can occur although their existence may indicate an elevated risk for cardiovascular disease [4, 5] The LBBB is closely linked to myocardial infarction, which can result in a life-threatening situation when it occurs in the setting of acute chest discomfort [6-8]. Also, it is frequently associated with a variety of cardiac conditions [9, 10]. The main characteristics of LBBB are the taller R-wave, Q-S, or R-S patterns in Leads V1 and V2, a longer QRS of 120 ms length, and mid QRS notches or slurs in at least two leads (I, V1, V2, V5, V6 or aVL) [11-13]. As the heart's function gradually degenerates, the LBBB changes from its initial state [1, 4-16]. The right ventricular activation is delayed in the RBBB due to obstruction of the electrical conduction through the right bundle branch [17-19]. Instead, it proceeds according to the normal pathway in which an impulse first activates the left ventricles by passing via the LBBB before moving to the right ventricle via the myocardium [20, 21].

ECG signal can be used in numerous ways to diagnose BBB automatically. Higher order Statistics (HoS) and wavelet packet decomposition were utilized in [22] to identify a BBB. The dual event-related moving average and a fractional Fourier transform were proposed in [23] to categorize different cardiac arrhythmias. A wavelet-based bidirectional LSTM was proposed for BBB detection in [24]. In [25, 26], it has been demonstrated that 1-D CNNs successfully identify cardiac arrhythmias by extracting features from the ECG signal. ECG classification has been used in [27] to analyze a variety of signal aspects, including wavelet transformations, frequency domain features, and time domain characteristics. In that direction, DL models have been utilized to classify ECG signals [28-30]. Automating the classification of the ECG beats is essential for computer-aided diagnostic systems, especially for the quick identification of arrhythmias in critical care settings.

Authors in [1] implemented an automated system for the detection of BBB based on Vectorcardiagram (VCG) signals, analyzed using Fourier Bessel Series Expansion-based Empirical Wavelet Transform. They used machine learning classifiers on the PTB dataset and obtained 99.57% accuracy, 99.68% sensitivity, and 99.18% specificity. Authors in [2] designed a 9-layer CNN to classify ECG beats (Normal, Premature Ventricular Contraction (PVC), RBBB), which resulted in 98.92% accuracy, 98.37% sensitivity, and 99.19% specificity. Furthermore, authors in [9] employed QRS segmentation and Maximal Overlap Discrete Wavelet Transform-based kurtosis features with an Adaptive Neuro-Fuzzy Inference System (ANFIS) for the detection of LBBB, achieving 99.88% accuracy, 99.81% sensitivity, and 100% specificity. Moreover, a self-attention CNN with Squeeze and Excitation (SE) residual blocks for detecting LBBB from 12-lead ECGs was proposed in [11]. The model had 98.91% accuracy, 99.28% specificity, an F1-score of 77.5%, and an AUC of 0.91. In [14], it was found that LBBB patients have more significant Continuous Wavelet Transform (CWT) coefficients for lower frequencies, facilitating diagnosis with the visual inspection of ECG and CWT plots. Authors in [15] used explainable AI for LBBB identification with biologically inspired features. Feature importance analysis facilitated model reduction without loss of performance, enhancing clinical confidence. Authors in [16] employed morphological and statistical characteristics of ECGs with classifiers (K-Nearest Neighbors (KNN), Linear Discriminate Analysis (LDA), Support Vector Machine (SVM)), and obtained 98.2% accuracy when using KNN. A three-classifier method was presented in [17], which integrated minimum distance, weighted LDA, and linear SVM. The two-lead ECG configurations performed better than the single-lead ones, recording 91.4% sensitivity for LBBB and 92.8% for RBBB, although the Positive Predictive Value (PPV) for LBBB was low (37.3%). Authors in [18] used statistical and temporal ECG features, deploying feature selection methods and classifiers (KNN, ANN, SVM). Backward elimination with KNN scored 99.82% accuracy. A comparison between DL, rule-based, and feature-based models for LBBB detection was demonstrated in [31]. The DL model using Residual Network (ResNet) and Shapley Additive exPlanations (SHAP) interpretability scored 93.1% accuracy. Furthermore, authors in [32] proposed a Multiple Instance Learning (MIL) framework for the classification of RBBB, LBBB, and other beats. Its accuracy on MIT-BIH was 78.58%, with LBBB and RBBB sensitivity of 84.78%, and 99.92%, respectively. Authors in [33] employed AlexNet and a dual-branch fusion network for the classification of ECG on PTB data with a test accuracy of 99%, surpassing hybrid models. Authors in [34] proposed an algorithm to detect strict LBBB with 12-lead Holter ECGs. The proposed SVM-based method had 81% accuracy and 88% sensitivity, however, specificity was somewhat inferior (75%). Authors in [35] introduced a residual block-based CNN to classify ECGs into five arrhythmia classes based on MIT-BIH, and obtained 98.2% accuracy.

Most methods for detecting LBBB and RBBB rely on either time-domain or frequency-domain features alone, limiting diagnostic precision. A few studies have explored the synergy between high-end time-frequency analysis (e.g., HT-WVD, DWT) and hybrid DL architectures (CNN-LSTM) for BBB classification. The present work bridges this gap by proposing a new fusion method based on both temporal and spectral ECG characteristics, significantly improving the classification accuracy and clinical utility.

II. METHODOLOGY

Figure 1 shows the DL pipeline design for ECG-based BBB detection using the MIT-BIH Arrhythmia database [36]. The process begins with the acquisition of ECG signals from the database. The initial step involves noise removal, targeting common interferences, to ensure signal clarity. Subsequently, the data undergo pre-processing using two parallel approaches: DWT, which enables an effective time-frequency analysis of non-stationary ECG signals by decomposing them into multiple resolution levels, and HT-WVD, which provides a high-resolution time frequency representation and captures the instantaneous characteristics of a signal.

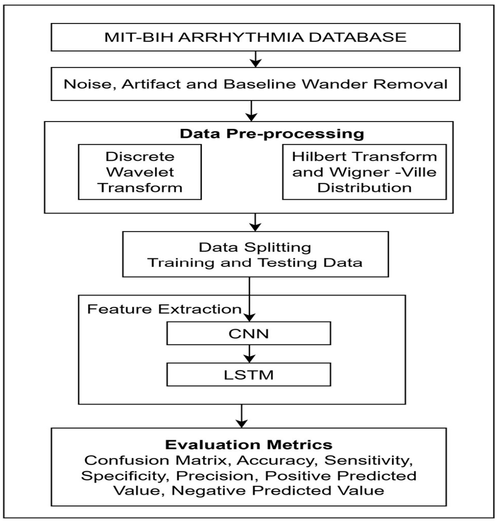

Fig. 1. Proposed methodology for ECG-based BBB identification.

Once the preprocessing step is complete, the dataset is split into training and testing sets in an 80:20 ratio to facilitate model learning and performance validation. The core of the feature extraction process integrates a hybrid DL model, comprising a CNN followed by an LSTM network. The CNN extracts spatial features, such as waveform morphology, while the LSTM captures the temporal dependencies inherent in ECG signals to enhance the model's capability to detect complex arrhythmias [37, 38]. Finally, the model's performance is assessed using a comprehensive set of evaluation metrics.

A. Database Collection

The MIT-BIH Arrhythmia database comprises 48 half-hour two-channel ECG recordings obtained from 47 subjects. Of these recordings, 23 are randomly selected from a large set of 4000 24-h ECG recordings collected from a mixed clinical population at Boston's Beth Israel hospital. Each ECG recording was digitized at a sampling rate of 360 Hz/channel, with an 11-bit resolution across a 10 mV dynamic range. For annotation reliability, two or more expert cardiologists independently annotated each record, and any discrepancies were resolved through consensus to produce the final reference annotations.

B. Data Pre-Processing

A wavelet-based denoising technique, which reduces the noise in the wavelet domain before signal reconstruction, a low-pass filter for high frequency components, and notch filters for power line noise were used to handle disturbances [1, 7]. To maintain a waveform and improve the precision of tasks, like heartbeat recognition, feature extraction, classification, or noise, baseline wander removal and artifact removal are fundamental in analyzing ECG signals [9, 14]. High-pass filter, wavelet decomposition, or the subtraction of estimated trends via polynomial fitting or moving averages, are employed to correct the baseline wander removal, a low-frequency drift usually below 0.5 Hz caused by things like respiration or electrode movement [7, 24]. The ECG signals are susceptible to a variety of noise sources beyond baseline drift, such as muscle activity (EMG), high-frequency electrode noise, and power line interference [1, 3].

C. Feature Extraction

1) Daubechies Wavelet

The signal analysis is performed using the Daubechies 6 (db6) wavelet, which is widely used for ECG processing due to its ability to capture sharp transitions, like QRS complexes, while preserving important waveform characteristics [7, 24]. A 1D ECG signal $x[n]$ is broken into approximation and detail coefficients on several scales using the DWT. To accomplish this, the signals are sent through two filters: a high-pass filter $g[k]$ to collect detailed coefficients $D_j[n]$, and a low-pass filter $h[2k]$ to capture approximation coefficients $A_j[n]$. Mathematically, this is expressed as:

$$A_j[n] = \sum_k x[k] * h[2n-k] \tag{1}$$

$$D_j[n] = \sum_k x[k] * g[2n-k] \tag{2}$$

The db6 wavelet specific filters are made to separate frequency components across various scales while maintaining the signal characteristics of the ECG signal [1, 9]. Soft thresholding is frequently used to minimize noise, especially in the detailed coefficients that commonly capture high-frequency noise. Each coefficient $D_j[n]$ is altered by the denoising procedure, which shrinks it towards zero and sets it to zero if it falls below a specified threshold λ:

$$D_j[n] = \begin{cases} D_j[n](|D_j[n]|-\lambda), & \text{if } |D_j[n]| > \lambda \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The ECG signal is reconstructed from the processed coefficients using the inverse DWT after denoising. The convolution of approximation and denoised detail coefficients with matching synthesis filters are required for this reconstruction.

$$x[n] = \sum_k A_j[k] * h'^{[2k-n]} + \sum_k \widetilde{D_j}[k] * g'[2k-n] \tag{4}$$

where $h'[k]$ and $g'[k]$ are reconstruction filters.

The approximation coefficients acquired at each level are recursively transmitted to the subsequent step of decomposition in multilevel wavelet decomposition [3, 7, 14]. As a result, the signal becomes increasingly coarsely represented, allowing for a thorough analysis of its frequency content at various scales [1, 24].

2) Hilbert Transform

The ECG data can be analyzed using the Hilbert approach, which is useful for collecting time varying features, including instantaneous amplitude, phase, and frequency [1, 7, 12]. When applied to an ECG signal, it generates an analytic signal, which is a complex representation, where the imaginary component is generated from the Hilbert transform [2, 11] and the real part corresponds to the original signal. For a real-valued ECG signal $x(t)$, the Hilbert transform $\tilde{x}(t)$ is defined as:

$$\tilde{x}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{x(t)}{t-\tau} d\tau \tag{5}$$

3) Analytic Signal

The analytic signal $z(t)$ is formed by combining the original signal and its Hilbert transform:

$$z(t) = x(t) + j\,\tilde{x}(t) \tag{6}$$

4) Instantaneous Amplitude

The envelope or instantaneous amplitude is the magnitude of the analytic signal [4, 8, 23]:

$$A(t) = |z(t)| = \sqrt{x(t)^2 + \tilde{x}(t)^2} \tag{7}$$

5) Instantaneous Phase

The instantaneous phase is the angle of the analytic signal:

$$\emptyset(t) = arg\big(z(t)\big) = arctan\left(\frac{\tilde{x}(t)}{x(t)}\right) \tag{8}$$

6) Instantaneous Frequency

The instantaneous frequency refers to the time-based rate of change of the signal's phase [6, 16, 25]:

$$f(t) = \frac{1}{2\pi}\frac{d\emptyset(t)}{dt} \tag{9}$$

7) Wigner-Ville Distribution

The WVD is a high-resolution time-frequency analysis method used to analyze the ECG signals. WVD provides a joint representation of a signal's energy across both time and frequency, making it ideal for capturing dynamic changes in ECG signals [9, 17, 24]. The WVD of a signal $x(t)$ is defined as:

$$W_x(t,f) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right)\tilde{x}\left(t+\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \tag{10}$$

D. The CNN-LSTM Model

The hybrid CNN-LSTM model starts with a series of Conv 1D layers with increasing filter sizes of 64, 128, 256, and 512, each followed by batch normalization and Max pooling to extract and down sample temporal features. After the final convolutional block, a Global Average Pooling layer reduces the dimensionality of the output, which is then reshaped to match the expected input format of an LSTM layer. The LSTM layer with 64 units captures temporal dependencies across the extracted feature sequences. This is followed by a dense layer with 128 units and Rectified Linear Unit (ReLU) activation, a dropout layer to prevent over fitting, and a final dense layer with a sigmoid activation function that outputs a probability for binary classification. The model is compiled with the Adam optimizer [32].

E. Classification

The confusion matrix provides the basis for calculating metrics such as accuracy, sensitivity, specificity, precision, negative predictive value, and F1 score. It comprises the total True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The evaluation metrics are defined by:

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

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

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

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

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

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

III. RESULTS AND DISCUSSION

Figure 2 depicts an ECG signal after applying DWT filtering. The R-peaks are highlighted, indicating improved feature visibility and accurate detection. This demonstrates the effectiveness of DWT in preserving important morphological characteristics while eliminating unwanted artifacts from the ECG signals. Figure 3 demonstrates that the DL model achieves a high and stable accuracy of approximately 99.6% for both training and validation over 16 epochs. While training, the loss steadily decreases, the validation loss exhibits occasional spikes, likely due to mini batch variability or minor over fitting. Despite the fluctuations, the model generalizes well. However, performance stability could be further improved using early stopping or smoothing techniques.

In the classification of Normal, RBBB, and LBBB signals, all CNN-LSTM architectures performed well, as shown in Figure 4, with accuracy, sensitivity, specificity, and F1-score values continuously over 0.98. With an accuracy rate of 99.68%, sensitivity of 98.83%, specificity of 99.43%, and F1-score of 98.98%, the HT-WVD + CNN-LSTM model demonstrated the most dependable performance among the tested models. Compared to the baseline CNN-LSTM, which showed somewhat poorer results, especially in sensitivity and Negative Predictive Value (NPV) for RBBB, the DWT + CNN-LSTM model exhibited lower but still competitive results.

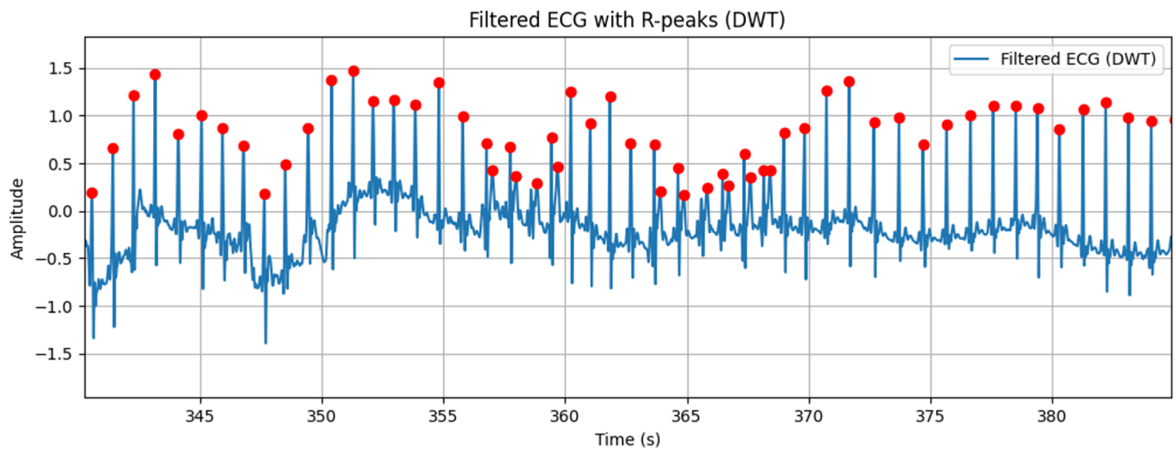

Fig. 2. ECG signal after DWT filtering with highlighted R-peaks.

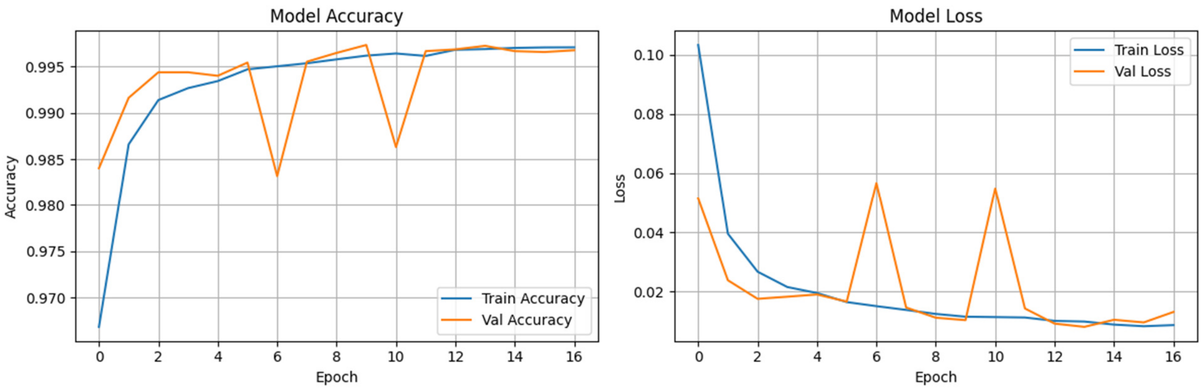

Fig. 3. Learning curves showing the convergence of the CNN-LSTM model.

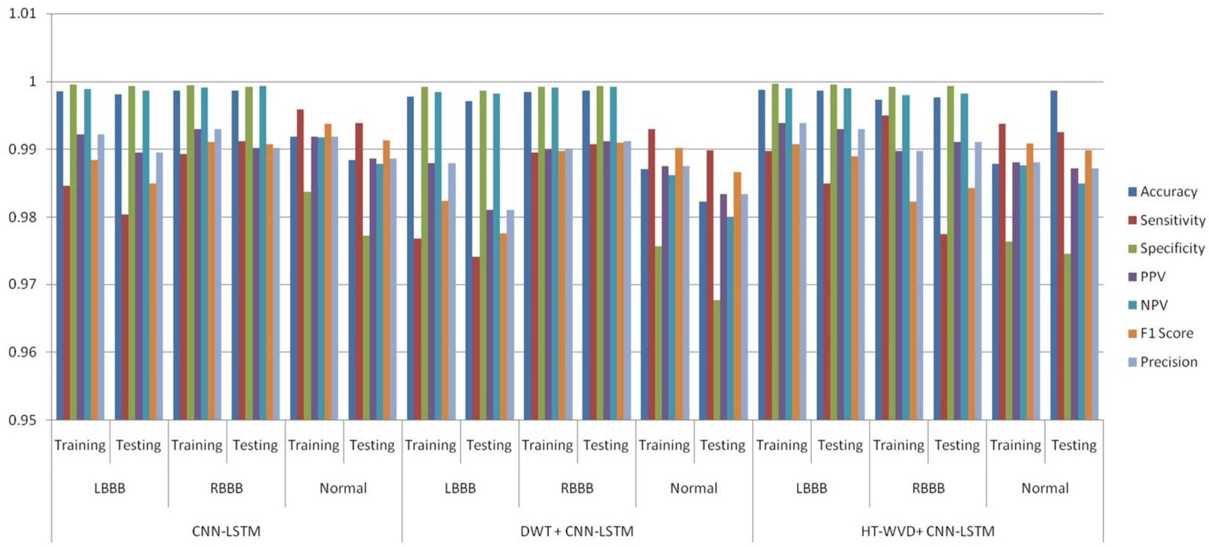

Fig. 4. Performance metrics of CNN-LSTM architectures for BBB and Normal ECG identification under various pre-processing conditions.

Table I compares various ECG classification models across databases like MIT-BIH, PTB, and MADIT-CRT, focusing on their evaluation metrics. Models like KNN, CNN, SVM, ANFIS, and ResNet were evaluated using various datasets. The current study, which utilizes the MIT-BIH arrhythmia database and incorporates CNN-LSTM, DWT+CNN-LSTM, and HT-WVD+CNN-LSTM models, shows better performance results. The DWT+CNN-LSTM model obtained an accuracy of 99.35%, a sensitivity of 98.57%, and a specificity of 98.99%. The HT-WVD+CNN-LSTM model outperformed the others, with an F1 score of 98.98%, sensitivity of 98.83%, specificity of 99.43%, and accuracy of 99.68%. The standard CNN-LSTM model performed well, with an accuracy of 99.53%.

TABLE I. PERFORMANCE COMPARISON OF ML AND DL MODELS ON ECG DATABASE FOR BBB CLASSIFICATION

Ref	Database	Model	Evaluation metrics
[1]	PTB	KNN	Acc-99.57, Se-99.68, Sp-99.18
[2]	MIT-BIH	CNN	Acc-98.92, Se-98.37, Sp-99.19
[4]	MIT-BIH	Linear SVM	RBBB:Se-92.8, LBBB:Se-91.4
[5]	MIT-BIH	KNN	Acc-99.82
[6]	MIT-BIH	ANFIS	Acc-99.88, Se-99.81, Sp-100
[9]	MIT-BIH	KNN, SVM	SVM Acc-94.7, KNN Acc-98.2
[11]	Physionet 2020	SACNN	Acc-98.91, Sp-99.28, F1-77.5
[14]	MIT-BIH	Depth-wise CNN	Acc-96.3, Pr-96.7, F1 – 96.1
[15]	MADIT-CRT	ResNet 18	Acc-93.1
[16]	CPSC2018	CNN+BiLSTM	RBBB :Se-99.92
[17]	PTB	AlexNet	Acc-99.00
[18]	MADIT-CRT	SVM	Acc-81, Se-88, Sp-75
[20]	MIT-BIH	CNN	Acc-98.2
[22]	12-Lead ECG	CNN	Acc-97
Present work	MIT-BIH	DWT+CNN+LSTM	Acc-99.35, Se-98.57, Sp-98.99, PPV-98.69, NPV-99.35, F1-98.63
		HT-WVD-CNN-LSTM	Acc-99.68, Se-98.83, Sp-99.43, PPV-98.98, NPV-99.07, F1-98.98
		CNN-LSTM	Acc-99.53, Se-98.72, Sp-99.31, PPV-98.72, NPV-99.23, F1-98.83

IV. CONCLUSION

Research into the classification of Bundle Branch Block (BBB) commonly uses features of either the time or the frequency domain and has been susceptible to interference and low generalizability. In an attempt to overcome this deficiency, a hybrid Deep Learning (DL) architecture is proposed that entails the use of both the Discrete Wavelet Transform (DWT) and the Hilbert Transform–Wigner Ville Distribution (HT-WVD) and CNN-LSTM networks. This architecture enables the simultaneous use and exploitation of both spectral and temporal features, as well as superior extraction of dynamic features from Electrocardiogram (ECG) data. When validated with the MIT-BIH Arrhythmia database, the HT-WVD + CNN-LSTM system achieved very high performance with an accuracy of 99.68%, a sensitivity of 98.83%, a specificity of 99.43%, and an F1-score of 98.98%. These results, therefore, demonstrate the excellent capability of the HT-WVD + CNN-LSTM system in distinguishing RBBB and LBBB from normal beats, and thus a high potential for to be used as an automated clinical decision support system. Despite the promising findings, it is important that the to validate the models in larger populations and more challenging real-world datasets. Future work directions should apply explainable AI, implement the approach to other arrhythmias, and optimize lightweight versions for real-time point-of-care ECG diagnosis.

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