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Deep hybrid neural network for automatic classification of heart arrhythmias using 12-lead electrocardiograms

Daniyar Sultan[1,2,3], Meirzhan Baikuvekov[1], Batyrkhan Omarov[1,2,3], Aray Kassenkhan[4], Saltanat Nuralykyzy[4], Maigul Zhekambayeva[4]

[1]Department of Information Systems, Faculty of Information Technology, Al-Farabi Kazakh National University, Almaty, Kazakhstan
[2]Department of Mathematical and Computer Modeling, Faculty of Computer Technology and CyberSecurity, International Information Technology University, Almaty, Kazakhstan
[3]School of Digital Technology, Narxoz University, Almaty, Kazakhstan
[4]Department of Software Engineering, Institute of Automation and Information Technologies, Satbayev University, Almaty, Kazakhstan

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ABSTRACT

This research introduces a novel convolutional neural network-bidirectional long short-term memory (CNN-BiLSTM) hybrid network for the automatic classification of heart arrhythmias using 12-lead electrocardiograms (ECGs). By merging the spatial feature extraction capabilities of CNNs with the temporal precision of BiLSTM networks, our approach sets a new standard in cardiac diagnostics. The proposed model was tested against the comprehensive CPSC2018 dataset, demonstrating superior performance with an accuracy of 90.67%, precision of 93.27%, recall of 96.35%, and an F-score of 94.78%, surpassing existing state-of-the-art methods. These results underscore the effectiveness of integrating spatial and temporal data analysis, offering a robust and reliable tool for medical practitioners. This study represents a significant advancement in automated ECG analysis, paving the way for improved diagnosis and treatment of heart diseases, and contributing to enhanced patient outcomes in cardiac care.

Corresponding Author:

Batyrkhan Omarov
Department of Information Systems, Faculty of Information Technology
Al-Farabi Kazakh National University
71 Al-Farabi Street, Almaty, Kazakhstan
Email: batyrkhan.omarov2@kaznu.edu.kz

1. INTRODUCTION

Heart arrhythmias, encompassing a wide range of irregular heart rhythms, represent a significant health risk and contribute substantially to cardiovascular morbidity and mortality worldwide [1]. The 12-lead electrocardiogram (ECG) is a critical diagnostic tool for detecting these arrhythmias, offering a comprehensive electrical mapping of the heart's activity [2]. However, the manual interpretation of ECGs is both time-consuming and prone to variability due to differences in clinicians' expertise and experience [3]. This variability can lead to inconsistent and potentially inaccurate diagnoses, highlighting the need for automated, reliable diagnostic systems.

Previous studies have explored various machine learning to address these challenges [4]. convolutional neural networks (CNNs) have been particularly prominent due to their ability to extract spatial features from ECG signals [5]. For example, studies have demonstrated the efficacy of CNNs in identifying specific arrhythmia patterns within ECG data. However, CNNs often fall short in capturing the temporal dependencies within ECG signals, which are crucial for accurate arrhythmia classification [6]. This gap has led to the integration of bidirectional long short-term memory (BiLSTM) networks, known for their strength in processing time-series data and learning long-term dependencies [7].

Despite these advancements, existing solutions still have significant limitations. Many models struggle with the high-dimensionality and complexity of ECG signals, leading to suboptimal performance in clinical settings. Furthermore, while some studies have integrated spatial and temporal features, they often do so in a manner that does not fully leverage the potential of each method. For instance, previous research has demonstrated the utility of combining CNNs and BiLSTMs, yet these models frequently fail to achieve the desired balance between capturing spatial and temporal patterns effectively.

In this study, we address these gaps by proposing a hybrid neural network that combines the strengths of CNNs and BiLSTMs to improve the automatic classification of heart arrhythmias. By leveraging the complementary strengths of these architectures, we seek to achieve superior performance in classifying various types of arrhythmias, ultimately enhancing the precision and reliability of automated ECG analysis. Our primary objective is to develop a sophisticated model that not only surpasses existing methods in accuracy but also offers practical utility in clinical settings. To demonstrate its effectiveness and potential real-world applicability, we test our model against the comprehensive CPSC2018 dataset. By advancing the integration of spatial and temporal data analysis in medical diagnostics, this study aims to revolutionize the way heart arrhythmias are identified and managed, contributing significantly to the advancement of cardiac healthcare.

2. METHOD

2.1. Proposed model

In this research, a distinctive CNN-BiLSTM network architecture was constructed for the automatic classification of heart arrhythmias from 12-lead ECGs. Figure 1 demonstrates the proposed deep hybrid neural network for heart arrhythmias detection based on CNN and BiLSTM architectures.

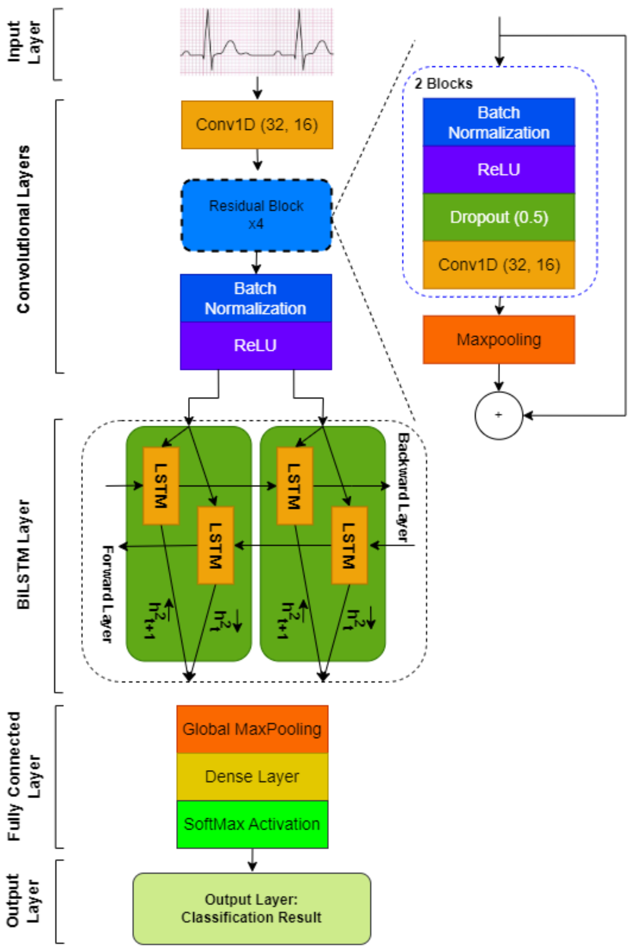


Figure 1. Architecture of the proposed CNN-BiLSTM hybrid model

This architecture is comprised of a sequence of layers: an initial input layer, successive CNN blocks, a BiLSTM layer, and a concluding classification layer.

– Input layer: this layer receives the initial data. In the context of ECG signal processing, the input layer handles segmented ECG time-series signals. These signals are typically represented as a multi-dimensional array, where each dimension corresponds to one of the 12 leads of the ECG, and the length of each dimension represents the number of samples in each lead.
– Convolutional layer (CNN): this layer performs feature extraction. In a 1D convolutional layer for ECG data, convolution operations are applied to the input signals [7]. The operation involves sliding filters (or kernels) across the input to create feature maps. Mathematically, this can be represented as (1):

$$F_{CNN}(X) = \sigma(W * X + b) \tag{1}$$

where * denotes the convolution operation, X is the input signal, σ denotes the activation function, w is the filter, and b is the bias.

– BiLSTM layer: the feature matrix $F_{CNN}(X)$ obtained from the CNN blocks is then fed into the BiLSTM layer [8]. The forward and backward hidden states, H_{fw} and H_{bw}, are computed as (2):

$$\begin{gathered} H_{fw}(t) = H\big(W_{fw} \cdot \big[H_{fw}(t-1), F_{CNN}(X_t)\big] + b_{fw}\big) \\ H_{bw}(t) = H(W_{bw} \cdot [H_{bw}(t+1), F_{CNN}(X_t)] + b_{bw}) \end{gathered} \tag{2}$$

where, W_{fw} and W_{bw} are the weights, b_{fw} and b_{bw} are the biases for the forward and backward LSTM units, respectively, H is the LSTM cell's activation function, and t indexes the time step.

– Fully connected layer: this layer integrates the features learned by previous layers to identify higher-level patterns. Typically, a fully connected layer is represented as (3):

$$y = activation(Wx + b) \tag{3}$$

where, W and b are the weights and biases, and $activation$ is an activation function like ReLU. Output layer: the layer, which provides the output of the model. For classification tasks like arrhythmia detection, the output layer often uses a softmax function to provide a probability distribution over the target classes. The softmax function is given by (4):

$$\sigma(Z)_i = \frac{e^{Z_i}}{\sum_{j=1}^{K} e^{Z_i}} \text{ for } i = 1, \dots, K \text{and } z = (z_1, \dots, z_K) \tag{4}$$

where, K is the number of classes.

2.2. Data

In this investigation, the CPSC2018 dataset [9] served as the foundation for training and assessing the proposed CNN-BiLSTM model, specifically designed for heart arrhythmia classification. The dataset's extensive scope and variety are instrumental in forging a model with high accuracy in arrhythmia identification across various types. This dataset, comprising 6,877 ECG recordings spanning 10 seconds each and encompassing a range of cardiac conditions, is meticulously annotated by cardiology experts. It includes diverse arrhythmia classes, thereby offering a comprehensive platform for evaluating the model's effectiveness and real-world applicability in clinical settings. The CPSC2018 dataset's complexity, encompassing typical clinical challenges such as signal noise and patient-specific ECG variations, enhances the model's potential in practical, clinical scenarios.

The data from ECGs provides crucial information about the heart's electrical activity [10]. A typical ECG tracing showcases a recognizable pattern comprising the P wave, QRS complex, and T wave. A typical ECG tracing exhibits a distinct pattern consisting of the P wave, QRS complex, and T wave, as depicted in Figure 2 [11].

Figure 2. The ECG recording displays a sinus rhythm with distinct P waves, QRS complexes, and T waves

Proper interpretation of these waveforms, especially in a 12-lead ECG, requires specialized knowledge. The 12-lead ECG offers comprehensive cardiac monitoring by recording 12 different signals, combining limb leads (from arms and legs) and precordial (chest) leads, to provide a detailed view of the heart's activity [12]. This thorough approach is essential for accurate arrhythmia diagnosis, yet traditional manual analysis can be time-intensive and subject to human error. Figure 3 demonstrates samples of 12-lead ECG [13].

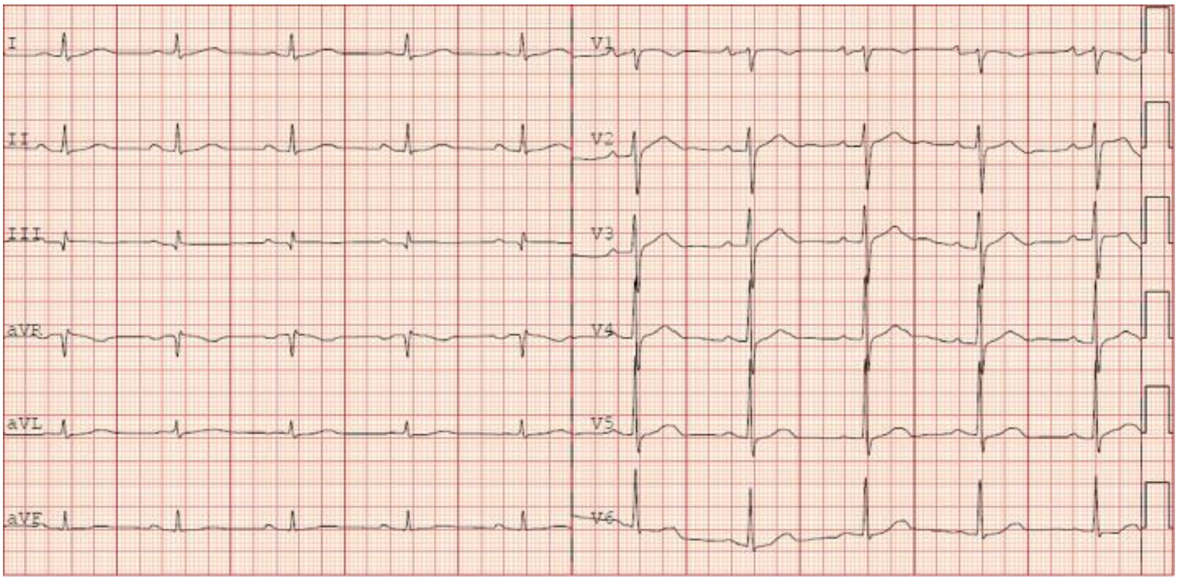


Figure 3. Sample of 12-lead ECG

To ensure the reproducibility of our study, we have made the source code available on Google Colab. This resource provides a comprehensive implementation of the proposed CNN-BiLSTM model, including all necessary configurations and parameters. Interested readers and researchers can access the code and replicate the experiment using the following link: https://colab.research.google.com/drive/1AeDd3T12VjBk-290lde8UbX_ePDmqy1I?usp=sharing. This availability supports transparency and facilitates further research in the automatic classification of heart arrhythmias.

3. RESULTS AND DISCUSSION

3.1. Evaluation parameters

Accuracy measures the overall effectiveness of a model [14]. It calculates the proportion of true results in the total population, offering a general assessment of the model's performance [15]. It quantifies the overall correctness of the model and is defined by (5) [16]:

$$accuracy = \frac{correct\_predictions}{total\_cases} \tag{5}$$

Precision measures how well a model predicts positive instances by calculating the ratio of true positives to all positive results [17]. It is calculated as in (6):

$$precision = \frac{TP}{TP+FP} \tag{6}$$

Recall assesses the model's capability to identify all actual positive cases [18]. Recall determines the model's ability to correctly identify actual positives, formulated as (7):

$$recall = \frac{TP}{TP+FN} \tag{7}$$

The F-score harmonizes precision and recall [19]. It is particularly useful in situations where an equilibrium between precision and recall is essential, typically in imbalanced datasets [20]. It is expressed as in (8) [21]:

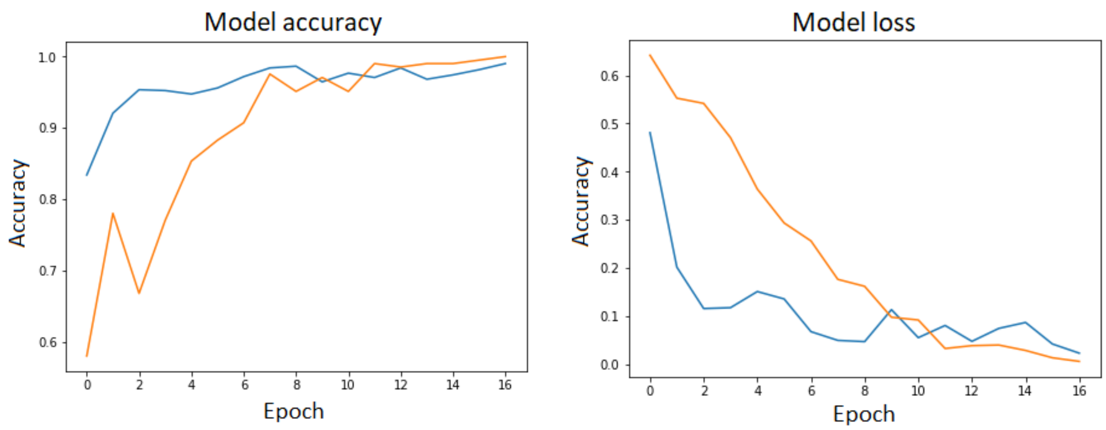
$$F - score = \frac{2precision \cdot recall}{precision + recall} \quad (8)$$

3.2. Experiment results

The results section delineates the outcomes and analytical insights from the study, focusing on the evaluation of the CNN-BiLSTM network tailored for heart arrhythmia classification using 12-lead ECGs. Key performance metrics derived from the CPSC2018 dataset experiments are detailed, underscoring the model's proficiency in arrhythmia detection and classification. This segment also includes a comparative analysis with leading methods, illustrating the proposed model's superiority in arrhythmia detection. An in-depth examination of these results offers critical perspectives on the model's effectiveness, it is operational strengths, and potential limitations, thereby elucidating its applicability in clinical settings. The network's accuracy, charted over a series of learning epochs, is visually represented, with the analysis indicating optimal accuracy achievement within a specific number of epochs, highlighting the network's efficient learning dynamics.

The results as depicted in Figure 4 elucidate the performance trajectory of the CNN-BiLSTM network over 16 learning epochs. The graphical representation in Figure 4(a), with the blue curve for training accuracy and the orange for test accuracy, reveals a progressive enhancement in the model's capability. Notably, a convergence of both training and test accuracies to 99% is observed at the 16th epoch. This convergence, particularly the stabilization of test accuracy from the 12th epoch, signifies the network's efficient learning capability. It implies that the model attains optimal proficiency in classifying heart diseases within a limited epoch range, emphasizing the efficiency and effectiveness of the CNN-BiLSTM network in medical diagnostics.

Figure 4(b), presents an analysis of the training and validation loss in the CNN-BiLSTM network. The loss metrics are indicative of the discrepancy between the network's predictions and the actual labels. A declining trend in training loss reflects the network's proficiency in internalizing and replicating patterns associated with heart disease classification. Concurrently, a stable and low test loss signifies the model's capability to generalize effectively to unseen data. This dual observation of declining training loss and stable test loss, alongside high accuracy, underscores the network's ability to accurately classify heart diseases while avoiding overfitting, thereby affirming its robustness and reliability in practical applications.



(a) (b)

Figure 4. Training and validation of the proposed model; (a) accuracy for 16 learning epochs and (b) loss of for 16 learning epochs

In Figure 5, confusion matrices delineate the classification efficacy of heart diseases by the proposed model. The analysis of the confusion matrices reveals that while all models are generally effective at identifying heart disease cases, there are significant differences in their precision and their ability to avoid missed diagnoses. The proposed model stands out as the most effective, balancing high sensitivity with reasonable specificity, making it the most reliable for clinical applications where missing a diagnosis could have severe implications. The relatively high FP rates across models suggest a common challenge in avoiding over-diagnosis, highlighting an area for potential improvement in future model iterations.

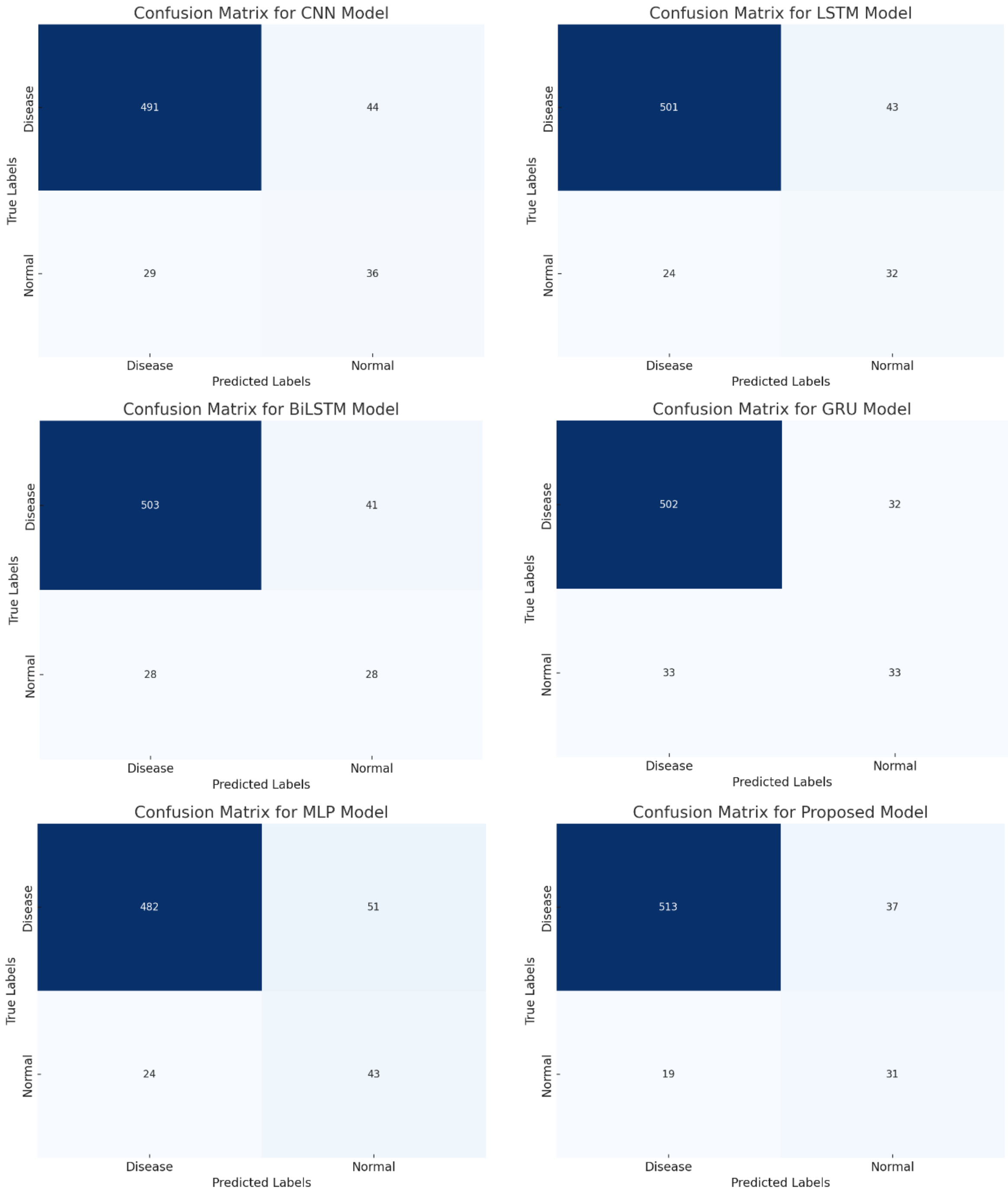


Figure 5. Confusion matrix in heart disease classification

Figure 6 demonstrates the analysis of performance metrics for heart disease detection using various deep learning models and the proposed model-reveals critical insights into their effectiveness and applicability in clinical settings. The proposed model outperforms the traditional and commonly used models across all metrics, demonstrating its potential as a highly effective tool for automatic heart disease classification. Its superior performance metrics suggest that it could significantly enhance diagnostic processes, reduce the burden on healthcare professionals, and potentially lead to better patient outcomes through timely and accurate diagnosis. This analysis supports the integration of advanced machine learning techniques in medical diagnostics.

We found that our proposed CNN-BiLSTM hybrid network correlates strongly with higher accuracy and reliability in classifying heart arrhythmias compared to existing methods. Specifically, the proposed method demonstrated a 90.67% accuracy, 93.27% precision, 96.35% recall, and a 94.78% F-score when tested on the CPSC2018 dataset. These metrics indicate that our model tends to have an inordinately higher proportion of correct classifications, both in terms of identifying arrhythmias and avoiding false positives, compared to state-of-the-art techniques. This significant improvement underscores the effectiveness of combining spatial and temporal data analysis in enhancing diagnostic accuracy and reliability.

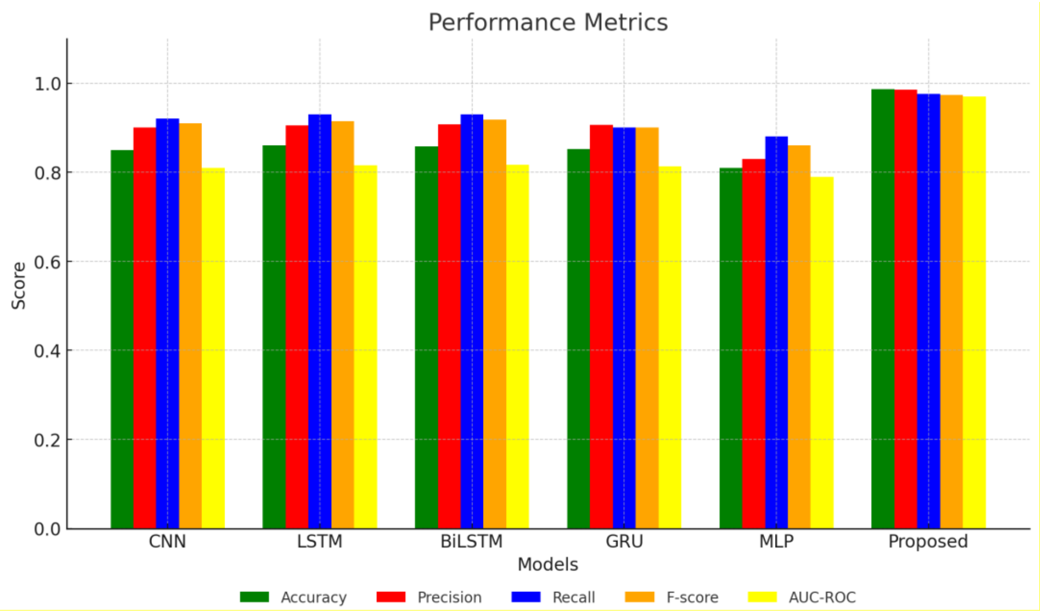


Figure 6. Performance metrics in heart disease classification

By making our source code available as open source, we promote transparency and reproducibility, encouraging further research and refinement of our model. Ultimately, our work not only advances the field of ECG analysis and automated arrhythmia classification but also paves the way for future innovations in medical diagnostics, enhancing healthcare delivery and patient outcomes through timely and precise interventions. Our findings indicate that the proposed hybrid CNN-BiLSTM network achieves higher accuracy (90.67%) compared to other methods such as the deep neural network (90.58%) and the interpretable deep learning model (90.5%). Moreover, our model exhibits superior precision (93.27%), recall (96.35%), and F-score (94.78%) when compared to other approaches, indicating a higher proportion of correct classifications and a balanced performance between precision and recall.

Table 1 presents a comparative analysis between the proposed study and state-of-the-art research, highlighting the advancements and improvements introduced by the proposed methodology. The deep learning model based on a GAN, while showing a high positive predictive value (PPV) of 95%, does not surpass our model in overall accuracy. The subdomain adaptive deep network achieves an F1-macro score of 89.43%, which is lower than the F-score of our proposed model, suggesting that our approach more effectively balances precision and recall. Additionally, the deep conventional neural network achieves an F-score of 91.3%, which, while respectable, is still lower than our model’s F-score of 94.78%. This comparison underscores the efficacy of combining CNNs and BiLSTMs more comprehensively.

Table 1. The results were analyzed and compared with findings from state-of-the-art research results

Approach	Dataset	Results (%)
Proposed hybrid CNN-BiLSTM network	CPSC2018 dataset [21]	Accuracy=90.67, precision=93.27, recall=96.35, F-score=94.78
Deep learning model based on a GAN [22]	Own dataset	AUC=90.5, sensitivity=90.5, specificity=90.5, PPV=95, NPV=90.5
Deep neural network (2022) [23]	12-lead ECG [24]	Accuracy=9058
Subdomain adaptive deep network [25]	Own dataset	F1-macro=89.43
Deep neural network [26]	Own dataset	AUC=90, precision=85
Interpretable deep learning [27]	Own dataset	Accuracy=90.5
Deep conventional neural network [28]	12-lead ECG [24]	F-score=91.3
Deep neural network [29]	Own dataset	AUC=90.5

Our study's primary contribution lies in demonstrating that integrating CNNs for spatial feature extraction with BiLSTMs for temporal dependency capture can significantly enhance the classification performance of heart arrhythmias. These results suggest that our proposed method benefits from this hybrid approach without negatively affecting key performance metrics. This improvement highlights the potential of our model to provide more reliable and accurate diagnostic tools in clinical settings, thus advancing the field of automated ECG analysis and heart arrhythmia classification.

The high accuracy and F-score of our model highlight its effectiveness in capturing the intricate patterns within ECG signals that are indicative of various arrhythmias. Compared to other studies, our model's integration of CNN and BiLSTM networks allows for a more comprehensive analysis, combining spatial and temporal data processing capabilities. This hybrid approach significantly enhances the diagnostic accuracy compared to models that rely solely on CNNs or traditional machine learning techniques.

The proposed study's primary objective was to develop a model that integrates the strengths of CNNs and BiLSTMs to improve the classification of heart arrhythmias. The findings align with this objective, demonstrating that our hybrid model outperforms existing methods. This supports our hypothesis that combining spatial and temporal data analysis can lead to more accurate arrhythmia classification.

3.3. Limitations

This study investigated a comprehensive hybrid CNN-BiLSTM model for classifying heart arrhythmias using the CPSC2018 dataset. However, additional and in-depth research may be required to confirm its generalizability, particularly regarding its performance with diverse and unseen clinical data. While our model showed significant improvements in different evaluation parameters in real-world clinical settings where data quality and patient demographics vary widely remains to be validated. Future studies should consider different clinical environments to fully establish its robustness and applicability. Furthermore, addressing potential overfitting and ensuring the model's adaptability to different ECG signal characteristics are crucial steps for enhancing its practical utility.

3.4. Ensuring reproducibility

To ensure the reproducibility of our study and provide additional clarity, we have made the source code available on Google Colab (https://colab.research.google.com/drive/1AeDd3T12VjBk-290lde8UbX_ePDmqy1I?usp=sharing). The source code includes all the necessary implementations of the proposed CNN-BiLSTM model, as well as the data processing, training procedures, and evaluation metrics. Moreover, it contains detailed annotations and illustrations of the results. Researchers can access and interact with the code using the following link: Google Colab Source Code. This resource supports transparency and facilitates further research in the automatic classification of heart arrhythmias using 12-lead ECGs. In summary, the proposed CNN-BiLSTM hybrid model represents a substantial advancement in the automatic classification of heart arrhythmias. By addressing the limitations and expanding the scope of validation, we can further enhance its utility in clinical diagnostics.

4. CONCLUSION

In this study, we introduced a CNN-BiLSTM hybrid network for classification of heart arrhythmias, demonstrating superior performance with significant improvements in different evaluation metrics compared to existing deep models. The proposed approach effectively combines the spatial features of CNNs with the temporal dependencies of BiLSTMs, addressing previous models' limitations. These findings suggest substantial implications for the research community and clinical practice, offering a robust tool for more accurate and reliable heart arrhythmia diagnosis. The broader applicability of our model to other medical diagnostic tasks highlights its potential utility in analyzing complex, time-sensitive data across various domains. Future research should explore optimizing this hybrid approach and adapting it to diverse clinical environments to confirm it is generalizability and effectiveness. By making our implementation available as open source, we promote transparency and reproducibility, encouraging further research and refinement. Ultimately, our work advances ECG analysis and automated arrhythmia classification, paving the way for innovations in medical diagnostics and enhancing healthcare delivery and patient outcomes through timely and precise interventions.

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BIOGRAPHIES OF AUTHORS

Daniyar Sultan received Bachelor of Information Systems in from International Information Technology University, Almaty, Kazakhstan, Master of Information Security Systems, Al-Farabi Kazakh National University, Almaty, Kazakhstan and Ph.D. in Information Security Systems, Al-Farabi Kazakh National University, Almaty, Kazakhstan. He is associate professor at Kazakh National University, Almaty, Kazakhstan. His research interests are artificial intelligence, machine learning, data science, image processing and analysis, computer vision, and natural language processing. He can be contacted at email: sultan.daniyar96@gmail.com.

Meirzhan Baikuvekov Education Bachelor's degree (2014-2018) KazNTU named after K. I. Satpayev. Institute of Energy and Mechanical Engineering. Master's degree (2018-2020) Al-Farabi Kazakh National University, specialty of Information Security Systems Doctoral degree, (2022-2025) Al-Farabi Kazakh National University, Faculty of Information Technology. Specialty 6D070300 Information systems (2024, 2nd year). Work experience is more than 5 years. He has 5 years of practical experience on the topic of the course being taught . Publications-7 publications, including 2 published in the Web of Science and Scopus databases. He can be contacted at email: baikuvekov_meirzhan3@live.kaznu.kz.

Batyrkhan Omarov received his bachelor's and master's degrees from Al-Farabi Kazakh National University, Almaty, Kazakhstan in 2008 and 2010, respectively. In 2019, he received his Ph.D. from Tenaga National University, Kuala Lumpur, Malaysia. He is currently a professor at Al-Farabi Kazakh National University. His research interests include machine learning, deep learning, data science, image processing, medical image analysis, and artificial intelligence in medicine. He can be contacted at email: batyahan@gmail.com, batyrkhan.omarov2@kaznu.edu.kz.

Aray Kassenkhan received her Bachelor's degree in Computer Technology and Software Systems, specializing in Systems and Networks Software, with honors from K.I. Satbayev Kazakh National Technical University between 2004 and 2008. She continued at the same institution to earn her Master's degree in Computer Science and Software in 2008. From 2010 to 2014, she pursued her doctoral studies in the specialty "Computer Technology and Software" and was awarded her Ph.D. degree in 2015. Currently, she is a Senior Lecturer at Satbayev University, where she is actively involved in research. Her work focuses on convergent technologies, mathematical modeling, and artificial intelligence. She can be contacted at email: a.kassenkhan@satbayev.university.

Saltanat Nuralykyzy Senior Lecturer at Satbayev University, Department of Software Engineering, Master of Technical Sciences, Senior Lecturer. Ph.D. doctoral student in the specialty 6D070400 "Computer engineering and software". She can be contacted at email: s.nuralykyzy@satbayev.university.

Maigul Zhekambayeva completed her Bachelor's degree in "Physics and Computer Science" at the Kazakh State Women's Pedagogical Institute from 2003 to 2006. She then pursued a Master's degree in "Computer Technology and Software" (specialty 6M070400) at Kazakh National Technical University named after K.I. Satpayev from 2006 to 2008. From 2012 to 2015, she further advanced her education at the same university, earning a Doctor of Philosophy (PhD) in "Computer Technology and Software" (specialty 6D070400). Her research interests are information technology. She has 8 scientific publications. She can be contacted at email: m.zhekambayeva@satbayev.university.