Classification of electrocardiogram (ECG) data using deep learning methods

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***Abstract*— Classification is one of the most widely used techniques in healthcare, especially concerning diagnosing cardiac disorders. Arrhythmia is a disorder of the heartbeat rate or rhythm, which may occur sporadically in daily life. Electrocardiogram (ECG) is an important diagnostic tool for analysing cardiac tissues and structures. It includes information about the heart structure and the function of its electrical conduction system. Since manual analysis of heartbeat rate is time-consuming and prone to errors, automatic recognition of arrhythmias using ECG signals has become an increasingly popular research focus in recent years. Current ECG analysis systems in literature generally have implemented well known machine learning algorithms. Due to the advent of powerful parallel computing hardware and the big data technologies, deep learning has also become a widely preferred technique in healthcare applications. In our study, we use ECG data in MIT–BIH Arrhythmia Database to develop a Convolutional Neural Networks (CNN) which is a deep feed-forward neural network type. The parameter tuned/optimized version of the proposed algorithm on top of the reduced feature dimension is more efficient than state of the art in terms of accuracy. Finally, we also compare the results of the proposed algorithm with Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and we provide the corresponding results in related sections.**

Keywords— Electrocardiogram, cardiac disorders, cardiac arrhythmia, machine learning, deep learning, Recurrent Neural Networks, Long Short-Term Memory, Gated Recurrent Unit, Convolutional Neural Networks.

I. INTRODUCTION

The electrocardiogram (ECG) trace represents cardiac features that are unique to an individual [1]. Consequently, analyzing ECG signals is essential for the pre-detection of cardiac disorders. The classification of arrhythmias can be challenging for humans because it may be necessary to analyze high volume data during long periods. An alternative is to use ECG data as a diagnostic tool to classify heartbeats (e.g., normal, abnormal) using intelligent computational methods with the recent advances in data science.

In the past, automatic ECG analysis systems in literature generally implement well-known signal processing methods (e.g., discrete wavelet transforms, dynamic mode decomposition, and principal component analysis) on unstructured biological signals [2]. Recent studies show that utilizing machine learning to classify patterns increase the accuracy of arrhythmia detection and interpretation of findings. Deep learning is a subtype of machine learning that describes complex data models using more superficial hierarchized structures defined from a specific feature set. With the advent of powerful parallel computing hardware and the availability of large datasets, deep learning has also become a state-of-the-art technique in automatic recognition of abnormal heartbeats.

In this paper, we utilize four deep learning methods (Conventional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU)) for ECG beat classification. We conduct the experiments on the well-known MIT–BIH arrhythmia database [3] and compare our results with the scientific literature reviewed. The results show that our proposed model is more efficient than state of the art in terms of accuracy.

The remainder of this article is structured as follows. Section 2 briefly introduces types of cardiac arrhythmia. In Section 3, related works in the literature are overviewed and discussed. After that, Section 4 gives information about the experimental dataset and introduces deep learning methods used in the current study. In Section 5, the results of the performed methods are overviewed. The last section concludes the paper and gives possible future research directions.

II. CLASSIFICATION OF CARDIAC ARRYTHMIA

ECG emphasizes various heartbeat segments including prominent electrocardiographic patterns such as P waves, T waves, and QRS complex waves as seen in Figure 1 [4]. The P wave is a small deflection wave that represents atrial depolarization. The three waves in the QRS complex represent ventral depolarizations. T wave represents ventricular repolarization. The patterns provoked by arrhythmias alternate the form of these waves. Moreover, lead V, and its correlate leads (V1, V2) help to classify ventricular arrhythmias since electrodes improving the registry of action potentials on ventricular muscle [4].

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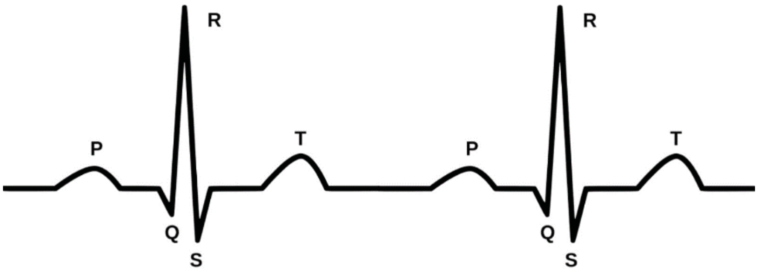

Figure 1Illustration of ECG signal including P wave, QRS complex, and T wave..

A cardiac arrhythmia can be classified as supraventricular tachycardia, ventricular tachycardia, atrial flutter, ventricular flutter, and ventricular fibrillation (see Figure 2). Ventricular arrhythmias occur in the lower chambers of the heart, called the ventricles. Supraventricular arrhythmias occur in the area above the ventricles, usually in the heart's upper chambers, called the atria.

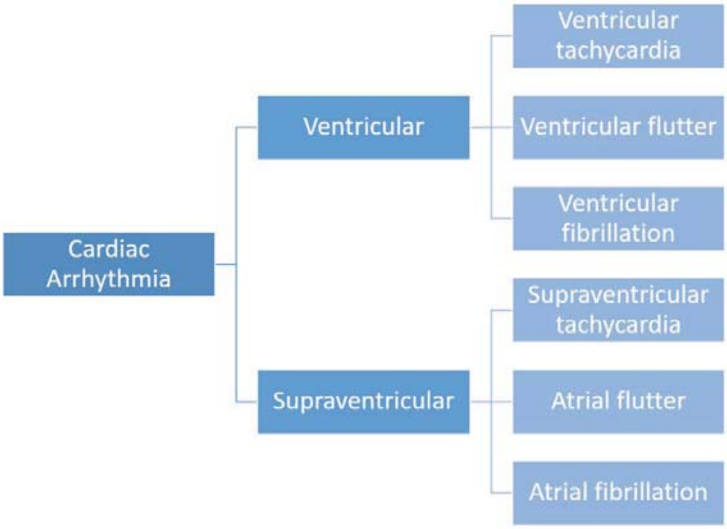

Figure 2 Classification of the arrhythmia.

III. Related Works

With the experiments to strengthen the neural networks in the past decades, deep learning has become an extremely active area of researches. For example, it is a widely used approach in healthcare applications to address critical tasks like diagnosis of cardiac disorders in recent times. For instance, Sannino and Pietro propose a deep learning approach for arrhythmia classification using ECG data in the MIT–BIH Arrhythmia Database [6]. They also perform baseline machine learning classifiers such as C4.5, Random Forest (RF), Support Vector Machine (SVM), AdaBoost, Bagging, Naive Bayes (NB), and Multilayer Perceptron (MLP) classifiers to compare their results with the success of the proposed model. They indicate that the proposed deep learning model outperforms the reported state-of-the-art results. In another study, Mathew et al. present the application of the Restricted Boltzmann Machine (RBM) and deep belief networks (DBN) for the detection of ventricular and supraventricular ectopic beats [6]. The effectiveness of the proposed algorithm is illustrated on the MIT–BIH Arrhythmia Database. Evaluation results demonstrate that parameter tuned RBM and DBN algorithms can achieve high average recognition accuracy for ventricular ectopic beats (93.63%) and supraventricular ectopic beats (95.57%). In another study, Yıldırım et al. employ deep learning approach for cardiac arrhythmia detection based on long-duration electrocardiography (ECG) signal analysis [7]. They develop 1D-CNN model on 1000 ECG signal fragments from forty-five persons. The proposed model achieves 91.33% accuracy over 17 cardiac arrhythmia disorders. Acharya et al. develop 11-layer deep CNN on the Physikalisch-Technische Bundesanstalt diagnostic ECG database to automatically detect myocardial infarction [8]. Evaluation results show that the model achieves an average accuracy, sensitivity, and specificity of 93.53%, 93.71%, and 92.83%, respectively. It is concluded that the proposed model performs well even though there are noises. Alfaras et al. present Echo State Networks based ECG arrhythmia classifier [9]. The heartbeat classifier is evaluated on the widely used ECG databases from the literature, the MIT - BIH Arrhythmia. The proposed system achieves a sensitivity of 92.7% and a positive predictive value of 86.1% for the ventricular heartbeats, using the single lead II, and a sensitivity of 95.7% and positive predictive value of 75.1% when using the lead V1'. Jiang et al. conduct a novel multi-module neural network system for ECG heartbeats classification [10]. Researchers highlight the imbalance problem of heartbeats and present alternatives to solve it. Denoising autoencoder (DAE) and CNN are used as feature extractors of ECG heartbeats. The designed system achieves 97.3% and 98.8% accuracies for the supraventricular, ventricular classes in using MIT-

Arrhythmia Database. Lu et al. perform CNN and RF to classify the MIT-BIH Arrhythmia data [11]. They focus on the data balance problem and employ the Random Over Sampler algorithm to solve this issue. Evaluation results show that the accuracy of the proposed model is above 99%. They also utilize inter-patient and intra-patient experiments separately to evaluate the performance of classifiers. Gao et al. conduct an LSTM network structure to classify the imbalanced ECG signals [12]. Experimental results demonstrate that the LSTM network with focal loss (FL) achieves a reliable solution to imbalanced datasets in ECG beat classification and is not sensitive to ECG signals' quality.

TABLE I. COMPARISON OF THE REVIEWED STUDIES

Study	Dataset	Used Method	Proposed Method	Predicted class
Sannino and Pietro (2018)	MIT–BIH Arrhythmia database	AdaBoost, Bagging, MLP, RF, SVM, CNN	CNN (93.53%)	Cardiac arrhythmia
Mathew et al. (2018)	MIT–BIH Arrhythmia database	RBM, DBN	DBN (ventricular beats (93.63%), supraventricular beats (95.57%))	Ventricular and supraventricular beats
Yıldırım et al. (2018)	MIT–BIH Arrhythmia database	1D-CNN	1D-CNN (91.33%)	Cardiac arrhythmia
Acharya et al. (2017)	Physikalisch-Technische Bundesanstalt diagnostic dataset	CNN (93.53%)	CNN (93.53%)	Myocardial infarction
Alfaras et al. (2019)	MIT–BIH Arrhythmia database	Echo State Networks	single lead II (92.7%), lead V1 (95.7 %)	Ventricular ectopic beats
Jing et al. (2019)	MIT-BIH Arrhythmia database	DAE, CNN, multi-module neural network	multi-module neural network system (96.6%)	Ventricular and supraventricular topic beats
Lu et al. (2018)	MIT-BIH Arrhythmia database	RF, CNN	CNN	Cardiac arrhythmia
Gao et al. (2019)	MIT-BIH Arrhythmia database	LSTM	LSTM	Cardiac arrhythmia

IV. MATERIALS AND METHODS

An automatic system to identify the type of heartbeat from ECG signals can be divided into four steps (see Fig. 3). First, pre-processing is utilized to remove noises from the raw ECG records. Then heartbeat segmentation is performed to extract different segment waveforms (P-QRS-T) in ECG data. After segmentation, the feature extraction process is applied to determine fundamental features (amplitudes and intervals) to be used in the learning model to achieve high diagnostic accuracy. The last step is modelling a classifier, which enables the diagnosis of cardiac disorders.

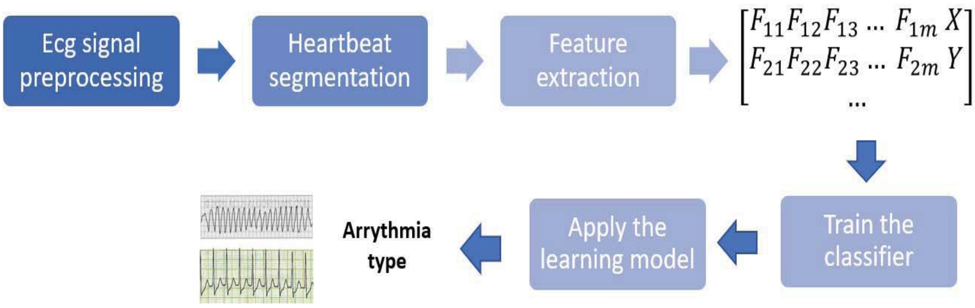

Figure 3 Workflow of the arrythmia classification task.

A. *Dataset*

In this study, we use MIT-BIH Arrhythmia public dataset for the evaluation of Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and the proposed CNN model. The database includes continuous beats of 48 half-hour records of 47 patients. The database has the annotation labels for 16 different heartbeat types and 15 different types of rhythms [13]. The leading five classes are normal beats (N), atrial premature beats, left bundle branch block (LBBB), right bundle branch block (RBBB), and premature ventricular contraction (PVC).

B. *Pre-processing and Segmentation*

In the pre-processing section, the preliminary task is segmentation of the ECG records into heartbeat waveforms. Since the R peak is the most distinguished property, it is used as a feature of a given heartbeat waveform. After the peaks are detected, such samples before and after a given R peak are catenated to create a vector representing the heartbeat waveform. Then, each heartbeat waveform is standardized using Z-score. Finally, some heartbeat waveforms are aggregated to form a given input sequence.

C. The Proposed Approach

CNN is a deep learning method that includes a sequence of convolutional layers and ends with some fully connected layer [14]. Each layer is fed with the previous layer's values and converts them to information then passes to the next layer for more processing and generalization (see Figure 3). The CNN model builds new features from the training set by reducing the network parameters.

To implement the diagnosis of cardiac disorders, first, the ECG recordings are divided into training and testing sets. Each training or testing sequence is of size N × D, where N is the number of heartbeats in a given sequence, and D is the dimension of each heartbeat waveform [4]. Then, the optimal parameters of the proposed CNN algorithm are determined using Grid Search algorithm to achieve high classification accuracy. In the last step, the hidden layer which outputs summary vector, is optimized during the training process. Finally, it is inputted to the softmax function which distributes probabilities over the classes. After the weights are fixed in the training phase, instances in the testing set are inputted to the trained model. A classification of each input is completed by selecting the class having the highest assigned probability. A block diagram illustrating how the CNN deep learning model is used to classify heartbeats is demonstrated in Figure 4.

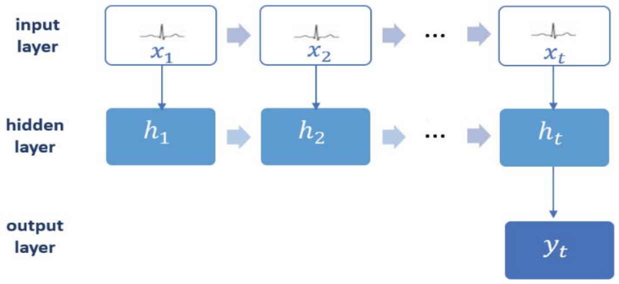

Figure 4. Illustration of a traditional CNN applied to an input sequence of t heartbeats.

D. Other Applied Methods

The most widely used type of RNN architecture is LSTMs. LSTM networks consist of an input layer, a recurrent hidden layer, an output layer an external memory unit [15]. Multiplicative input gate units are used to manage the adverse results that irrelevant inputs can create. The input layer holds the input flow to the memory unit, and the output layer controls the output stream of the memory unit to other LSTM blocks.

A gated recurrent unit (GRU) enables each recurrent unit to adaptively capture dependencies of different time scales. Like the LSTM unit, GRU has gates that organize data flow inside the unit without having a separate memory cell.

V. EXPERIMENTAL STUDIES

A. Implementation Details

In this study, the methods applied for cardiac arrhythmia detection based on long-duration electrocardiography (ECG) signal analysis. (CNN, RNN, LSTM, and GRU) are implemented using Python with Scikit-learn and Keras libraries.

For each performed algorithm, parameters are tuned to achieve high accuracy classification results. The applied parameters for CNN, RNN, LSTM and GRU algorithm are listed as follows:

RNN: Activation parameter is chosen as softmax, loss is selected as mean squared error (mse), and the epoch number is assigned as 20. To evaluate the performance of RNN, we use Accuracy (Acc.) to observe overall classification results and mean squared error (MSE) to figure out the divergences between predicted arrythmia tags and the ground truth one's accuracy.

LSTM: Activation parameter is chosen as softmax, loss is selected as categorical cross entropy, epoch is specified as 10, and learning rate is set as 0.01. To evaluate the performance of LSTM, we use Accuracy (Acc.) to observe overall classification results and mean squared error (MSE).

GRU: Activation parameter is chosen as softmax, loss is selected as categorical cross entropy, epoch is specified as and learning rate is set as 0.001. To evaluate the performance of GRU, we use Accuracy (Acc.) to observe overall classification results and mean squared error (MSE).

CNN: Activation parameter is chosen as softmax, loss is selected as categorical cross entropy, epoch is specified as 10. To evaluate the performance of GRU, we use Accuracy (Acc.) to observe overall classification results and mean squared error (MSE).

B. Experimental Results

In the experimental studies, the ECG data in MIT–BIH Arrhythmia Database is used to perform experiments. In order to observe the effect of the DL approaches, every model is trained with and without the parameter optimization process. Table 2 compares the accuracy and MSE results obtained when the parameter optimization process is applied and not applied. The results indicate that the proposed approach, which is fine tuned, provides an improvement in prediction accuracy for almost all algorithms. For example, when using the LSTM technique, the prediction model built by the proposed approach has a lower error value (0.6577) compared to the model constructed without the feature generation process (0.7229). The MSE value of ANN remains the same after optimization process. It is observed from Table 3 that among the algorithms performed in this study, CNN (proposed model) has superiority in terms of accuracy and MSE measures. After CNN, the most successful algorithms are GRU, RNN, and LSTM, respectively.

TABLE II. PERFORMANCE RESULTS OF EXPERIMENTED METHODS

	Accuracy		MSE	
	Without optimization	**With optimization**	**Without optimization**	**With optimization**
RNN	0.8775	0.9702	0.1084	0.1088
LSTM	0.7897	0.8276	0.7229	0.6577
GRU	0.9652	0.97716	0.07852	0.0894
CNN	0.9147	0.9846	0.0418	0.0622

The parameter-tuned/optimized version of the proposed algorithm on top of reduced feature dimension has produced an accuracy value of 97.02% higher than the performances conducted in [6, 7, 8, 9, 10, 11, 12, and 13].

VI. CONCLUSION AND FUTURE WORKS

Classification of arrhythmias from ECG data is challenging due to the high variability of the signals between different patients. It is seen that deep learning techniques provide increasingly accurate predictions in the arrhythmia identification tasks in recent times. In this paper, we examine the success of different deep learning methods to detect cardiac arrhythmias. For this reason, we investigate and compare four deep learning algorithms (RNN, LSTM, CNN, and GRU). The experimental results demonstrate the efficiency of our proposed approach (CNN) in heartbeat classification on MIT–BIH Arrhythmia Database. The results show that CNN is the best algorithm having 0.97 accuracy and 0.10 MSE values. The worst performing algorithm is the LSTM algorithm with a 0.6577 MSE value.

For the next study, we aim to prepare a well-formed, including more real-life samples than current datasets in the literature. Moreover, we plan to increase the number of features in the dataset by adding new features, such as patient gender, age, other chronic illnesses, etc. In this way, it may be possible to produce better prediction results.

REFERENCES

[1] A. Gacek and W. Pedrycz, ECG Signal Processing Classification and Interpretation *A Comprehensive Framework of Computational Intelligence*, London, U.K., Springer, 2012.

[2] E.J.S. Luz, W.R. Schwartz, G. Cámara-Chávez and D. Menotti, “ECG-based heartbeat classification for arrhythmia detection: A survey”, *Comput. Methods Programs Biomed*., vol. 127, pp. 144-164, 2016.

[3] G. Sannino and G. De Pietro, “A deep learning approach for ECG-based heartbeat classification for arrhythmia detection”, *Future. Gener. Comput. Syst*., 2018.

[4] G. B. Moody and R. G. Mark, “The impact of the MIT-BIH Arrhythmia Database,” in *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45-50, May-June 2001

[5] S. Singh, S. K. Pandey, U. Pawar and R. R. Janghel, “Classification of ecg arrhythmia using recurrent neural networks”, *Procedia computer scienc*e, vol. 132, pp. 1290-1297, 2018.

[6] S. M. Mathews, K. Chandra and K. E. Barner, “A novel application of deep learning for single-lead ECG classification”, *Comput. Biol. Med*., vol. 99, pp. 53-62, Aug. 2018.

[7] Ö. Yıldırım, P. Plawiak, R.-S. Tan and U. R. Acharya, “Arrhythmia detection using deep convolutional neural network with long duration ECG signals”, *Comput. Biol. Med.*, vol. 102, pp. 411-420, Nov. 2018.

[8] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan and M. Adam, “Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network”, *Inf. Sci*., vol. 405, pp. 81-90, 2017.

[9] M Alfaras, MC Soriano and S Ortín, “A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection”, *Frontiers in Physics*, vol. 7, pp. 103, 2019.

[10] J. Jiang, H. Zhang, D. Pi and C. Dai, “A novel multi-module neural network system for imbalanced heartbeats classification”, *Expert Syst*. Appl. X, vol. 1, Apr. 2019.

[11] W. Lu, H. Hou and J. Chu, “Feature fusion for imbalanced ECG data analysis”, *Biomed. Signal Process*. Control, vol. 41, pp. 152-160, Mar. 2018.

[12] J., Gao, H., Zhang, P., Lu, Z, Wang. “An effective LSTM recurrent network to detect arrhythmia on imbalanced ECG dataset”, *Journal of healthcare engineering*, 2019.

[13] H.Z. Li and P. Boulanger. “A survey of heart anomaly detection using ambulatory Electrocardiogram (ECG).” *Sensors*, 20(5), 2020.

[14] R. Salloum and C. -. J. Kuo, "ECG-based biometrics using recurrent neural networks," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, New Orleans, LA, 2017, pp. 2062-2066.

[15] S.H.I., Xingjian, Z., Chen, H., Wang, D.Y., Yang, W.K., Wong, W.C, Woo. “Convolutional LSTM network: A machine learning approach for precipitation nowcasting”, in *Advances in neural information processing systems*, pp. 802-810, 2015.

[16] J., Chung, C., Gulcehre, K., Cho, Y. Bengio. “Gated feedback recurrent neural networks”, in *International conference on machine learning*, 2015, pp. 2067-2075.