Journal of Physics: Conference Series

PAPER • OPEN ACCESS

Detection and Classification of Arrhythmias by Deploying Deep Learning Models

To cite this article: T Padma *et al* 2022 *J. Phys.: Conf. Ser.* **2325** 012053

Detection and Classification of Arrhythmias by Deploying Deep Learning Models

T Padma[1], A Uday Kiran[2], C Jahnavi[3], S Rahul[4], Nehaa Raja[5], M Kamal Kumar[6]

[1] Professor, ECE, Gokaraju Rangaraju Institute of Engineering and Technology, Bachupally, Hyderabad, India.
[2,3,4,5,6] UG Students, ECE, Gokaraju Rangaraju Institute of Engineering and Technology, Bachupally, Hyderabad, India.

E-mail: profpadmat@gmail.com, adluriuday08@gmail.com, jahnavichsreenivas@gmail.com, siripuramrahul9@gmail.com, nehaaraja0804@gmail.com and mandrukamalkumar@gmail.com

Abstract. Arrhythmias can be detected using an ECG signal, which is an important tool in the healthcare industry. ECG overall variation trends, original variation features, and their relative positions are used to classify arrhythmias according to sphere knowledge and large-scale data analysis. They haven't been fully explored by being styles. CNN and hybrid CNN-LSTM models are used to address this problem. A LSTM and CNN are used to separate the ECG's overall variation trends and its unique features. In this project the implemented models are CNN and Hybrid LSTM models to check which model is better in identifying the arrythmias based on the ACC, SEN, and SPE scores. The Accuracy of the CNN model is 74.4 percent, respectively, while the Hybrid-CNN LSTM scores are 83.5 on the MIT-BIH arrhythmias dataset.

Keywords*:* Arrythmias, Convolutional Neural Network, Variation trends, Long Short-Term Memory, Electrocardiogram

1. Introduction

More than a third of all human deaths in 2016 were due to Cardio Vascular Disease (CVD) **[1]** and 86% of those deaths were due to a heart attack. The medical history and physical examination of each patient are the mainstays of the traditional approach to the diagnosis of CVD. The taxonomy of medical diseases is used to categorize patients in this study using quantitative medical parameters. As a result of the enormous amount of heterogeneous data that must be analysed and interpreted, the traditional rule-based diagnostic paradigm is often ineffective. The problem will be exacerbated if there aren't enough medical professionals and facilities, especially in developing countries. Thus, a monitoring and diagnosis system must be developed that is both accurate and affordable. using computer systems to assist in diagnosis Healthcare providers are increasingly requiring Computer-Aided Diagnosis (CAD) and appropriate medical assessments, which can be linked to this requirement CADS.

CADS are designed to monitor and evaluate an organ's performance by analyzing physiological signals. In order to educate people about their illnesses, CADs are convenient and easy to use. The ElectroCardioGram (ECG) is a non-stationary physiological signal that shows the heart's electrical activity. Other indications can be checked, such as the regularity of the pulse and the amount of psychological stress. A wide range of applications, including classification and prediction, have made use of deep neural networks (DNNs). For example, DNNs have had a significant impact on the accuracy of many medical tasks in recent years. Arrhythmias in ECG signals are now detected by modern CADS systems using DNN, which lowers the cost of continuous heart monitoring while also improving prediction accuracy. Automatic arrhythmia classification based on ECGs, on the other hand, typically faces a number of significant difficulties.

1.1. Arrhythmia Classification Challenges
CADS arrhythmia classification challenges can be summarized as:

- Even if arrhythmia symptoms are present, they may not be detected while the ECG signal is being recorded [2].
- A range of characteristics, such as age, gender, physical condition, and lifestyle, impact the amplitude and duration of people's ECGs. Finding a broad framework and corresponding standards that can be utilized by the general public is difficult.
- Physical activity, such as running, walking, and sleeping, can affect the ECG signal's morphology.
- ECG signal analysis requires a significant amount of data to be considered. As a result, it is more likely that an arrhythmia will be misdiagnosed.
- The recorded ECG signal may show morphological variations and discrepancies as a result of noise, artefacts, and interference.
- The model accuracy can be improved by eliminating noise by using high pass filter and notch filter.

2. Related work
Depending on the type of CA, each lead's ECG signal has unique characteristics [3]. The P wave or QRS shape (PAC/PVC) of early atrial and early ventricular contractions may be aberrant [4]. Both STE and STD must be greater than 0.1 mV in order to be considered abnormal [5].

To be able to correctly identify these complex ECG characteristics associated with CA, extensive training is necessary. Internal medicine doctors and cardiologists have been found to make diagnostic errors on occasion [6]. Physicians' workload is exacerbated by the rapid growth of ECG examinations. Computer algorithms that generate accurate and automated diagnoses could be beneficial to doctors. In spite of the wide range of ECG signal characteristics, recent years have seen significant progress in the area of ECG signal processing [7].

Using the first technique, ECG signals may be split into heartbeat, or cycles. For a small number of subjects, machine learning requires a huge amount of data to train predictive classification models using this beat-based approach. ECG signal delineation can be difficult because ECG morphological features are frequently extracted with high levels of imprecision [**7**]. This could be due to the fact that the same person creates both the training and test beats, resulting in a prediction accuracy of 99.9%. When test beats from patients who were not part of the training set were added in the cross-validation, the accuracy for six CA categories fell to 81.5 percent from 99.7%. [8].

Despite the fact that only ECG data from 48 and 452 subjects are publicly available, previous CA prediction studies have relied on these two databases regardless. A lack of subjects in neural network databases can lead to over-fitting issues in neural network algorithms [9]. For example, over-representation of certain CA types in the data can lead to over-fitting of models. UCIAD and MIT-BIH AD may be impacted as a result of these problems. Using UCIAD, it was possible to achieve a high level of CA classification accuracy (92%), but this accuracy dropped to 60% when training and testing were split 80/20. Muhammad and his co-workers (2018a) While UCIAD features (average width, amplitude, and so on) are only extracted for 12-leads in UCIAD's Only two leads of ECG data are included in the MIT-BIH AD ECG data (MIT-BIH AD ECG data only includes two leads) [10].

No downside to the second approach, which solves the beat-based problem completely. To put this technique into action, you'll need a lot of ECG data and a sophisticated artificial neural network with deep learning capabilities. Due to recent developments in both elements, the second strategy has grown more desirable. The 2017 Physio Net/Computing in Cardiology Challenge is now open for entries. [**11**] shared data from 8,528 people who had a variety of cardiac rhythms (AF, normal, other rhythms, and noise) to show how open-source research may benefit science. [12].

This article was written by [13]. Based on the complementing properties of ME and NCL, this research provides an ECG arrhythmia classification approach (NCL) [14]. ME includes a control parameter for NCL in its error function, allowing the training process to manage bias-variance-covariance trade-offs. [15] In addition to maintaining and alleviating the disadvantages of its basis approaches, the proposed classification method offers significantly better performance than the original methods.

3. System analysis

3.1. Existing system

In the Recent advances in deep learning, particularly LSTM networks and convolutional neural networks (CNNs), have demonstrated important information lines and befitting capabilities Disease detection and picture categorization, for example, are only a few of the uses. CNN is excellent at extracting the original features while LSTM is excellent at mining long-term time-series dependencies. Arrhythmias can be classified using LSTM or CNN, and researchers have had success. Despite this, there are a few things that could be done better.

3.2. Proposed system

This System Proposes CNN model which is an effective model for classification of irregular heartbeats and hybrid CNN-LSTM model which uses dropout layers to improve the model accuracy this paper involves a comparitive study between CNN and Hybrid CNN LSTM model.

4. Dataset

The MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database are used to classify heartbeats. The heartbeat signals in this dataset are separated into two groups. To test deep learning models, researchers employed a dataset with a sampling frequency of 125 hertz and a total of 109446 ECG signals. The Dataset contains the various signals and separated into five sub classes these classes are a group of signals which contains various categories like Normal and Abnormal conditions of detected signals from ECG.

5. Implementation

The following are the steps involved in putting the model into action.

- Data Collection
- Data Pre-processing
- Modelling

5.1. Data Collection

The information comes from the MIT-BIH database. The database is further divided into the two datasets called Training and Testing Datasets. In the figure.1 the heart beat for each target label of five sub-classes of arrythmias are plotted which are detected based on the number of occurrences in the database.

5.2. Pre-processing

The data is Pre-processed to eliminate unwanted noises by oversampling on training dataset to balance the dataset. In the figure.1 the heart beat for each target label of five sub-classes of arrythmias are plotted which are detected.

5.3. Modelling

Deep Learning models in Figure 1 is the future extraction and classification is done on the input and output which is generated by the using models such as CNN and Hybrid CNN LSTM.

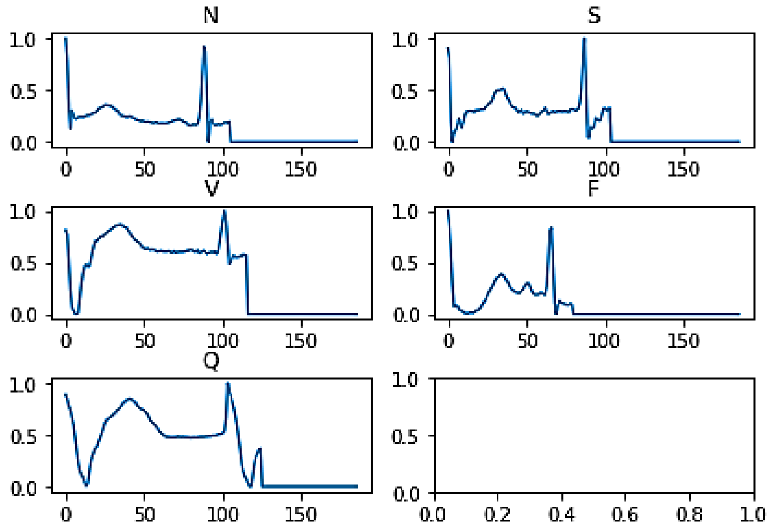

Figure 1. Sub-classes of Arrythmias

6. Block diagram

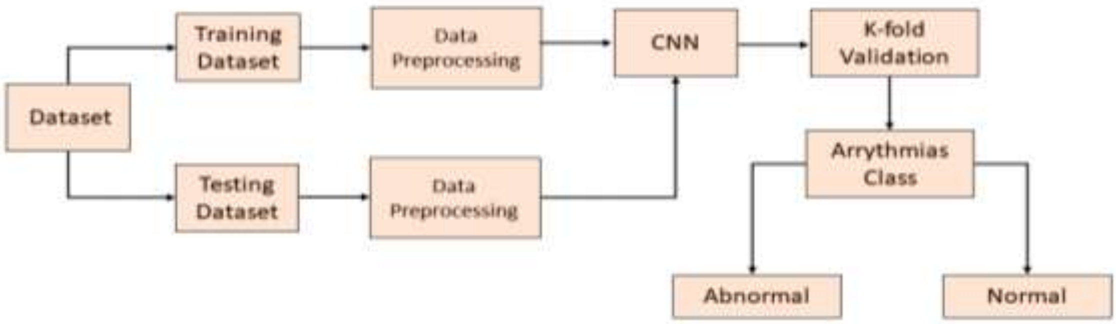

Figure 2. Block diagram of CNN

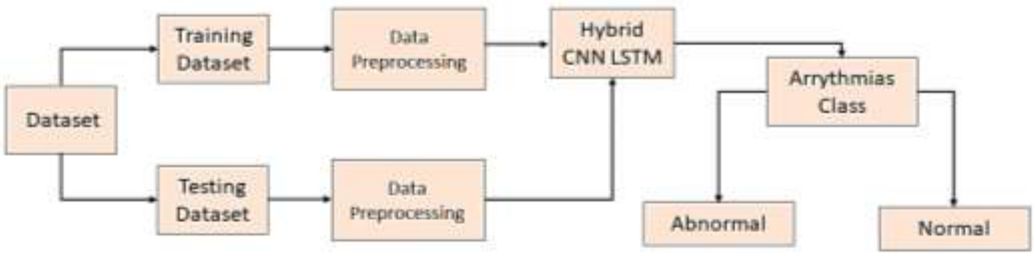

Figure 3. Block diagram of Hybrid CNN- LSTM

The Figure 2 and Figure 3 contains the functionality of each blocks used for classifying Arrythmias.

7. Deep learning models

7.1. Convolutional Neural Network

- CNNs are neurons that, like ordinary neural networks, have learnable weights and biases. Each neuron receives a large number of inputs, calculates a weighted sum of them, sends them via an activation function, and then outputs.
- As shown in Figure 4, CNN has three types of layers: convolution, pooling, and fully connected layers.
- Fully linked input layer (flatten): Takes the previous layer's output and "flattens" it into a single vector that may be used as an input for the following level.
- Unrolling (flattening): Converting a matrix to a vector.

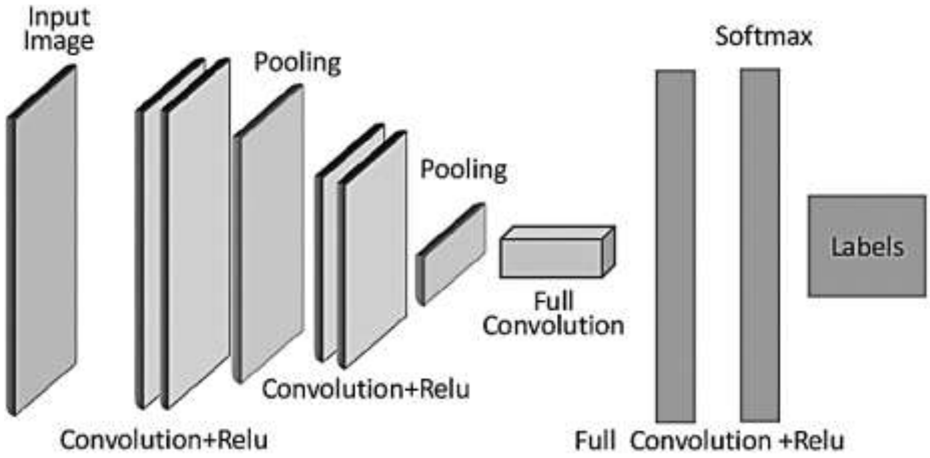

Figure 4. Basic CNN Architecture

7.2. Hybrid CNN LSTM

- CNN has only conv1D and max1D blocks. The result of the max1D block is transmitted to the input layer of the following system in hybrid system.

  yi (CNN xi) (1)

- xi is the CNN network's initial input vector, containing a class label for each type of data. The CNN network's output is yi. It's the feature vector created by CNN's max-pooling process. This information is integrated into the next deep learning architecture that is employed. In this study, CNN-LSTM, hybrid networks are used, and their performance is compared.

8. RESULTS AND DISCUSSION

The functional conditions or overall description papers comprise information on the product's viewpoint and features, the operating system and operational environment, graphics, design limits, and user evidence of the product's usefulness. Examining the project's circumstances and restrictions, which indicate how to address each, provides an overview of the project's strengths and shortcomings. This project was built on a PC, and the minimal hardware requirements for Enthought Python, Canopy, and VS Code users are different. As a result, processes that require a large number of calculations or tasks to be completed rapidly require more RAM and a quicker processor.
The proposed model’s performance was trained with minimum of 50 epoch values and the following results are acquired which are shown in Table 1.

Table 1. Comparison of CNN And Hybrid CNN- LSTM

Parameters	CNN	Hybrid LSTM	CNN
Accuracy	74.4	83.5	

```
cnn_predictcv=np.argmax(cnnpredictionscv,axis=1)
cnn_actual_valuecv=np.argmax(Y_test,axis=1)
showResults(cnn_actual_valuecv, cnn_predictcv)

Accuracy  : 0.7441074365064864
Precision : 0.901016675905698
f1Score : 0.7937238346648685
[[13029  1856  1597  1153   483]
 [  107   405    28    14     2]
 [   76    41  1223    95    13]
 [    8     5     8   141     0]
 [   43     4    59    10  1492]]
```

Figure 5. Accuracy of CNN

```
predictcv=np.argmax(predictions,axis=1)
actual_valuecv=np.argmax(Y_test,axis=1)
showResults(actual_valuecv, predictcv)

Accuracy  : 0.8354193312625616
Precision : 0.9241890591689367
f1Score : 0.866545503401796
[[14914  1172   506  1004   522]
 [   83   449    10    10     4]
 [   76    39  1246    73    14]
 [    9     1     6   146     0]
 [   46    13    13     2  1534]]
```

Figure 6. Accuracy of Hybrid CNN- LSTM

9. Conclusion

To classify arrhythmias, this paper proposes two different models: a hybrid LSTM-CNN-CNN and a CNN. In this model structure appears to be the most effective based on the results of the tests. In terms of ACC which is shown in Figure 5 the CNN model achieves 74.4 percent accuracy. From the Figure 6 there is 83.5 percent accuracy in ACC for the hybrid CNN LSTM. An attention-based model should be developed to supplement the current model.

10. References

[1] Benjamin, Emelia J., et al. "Heart disease and stroke statistics—2019 update: a report from the American Heart Association." *Circulation* 139.10 (2019): e56-e528.

[2] Ceylan, R., & Özbay, Y. (2007). Comparison of FCM, PCA and WT techniques for classification ECG arrhythmias using artificial neural network. *Expert Systems with Applications*, *33*(2), 286-295.

[3] O'NEAL, WESLEY T., et al. "Atrial fibrillation and cardiovascular outcomes in the elderly." *Pacing and Clinical Electrophysiology* 39.9 (2016): 907-913.

[4] Senzaki, Hideaki, et al. "Ventricular afterload and ventricular work in Fontan circulation: comparison with normal two-ventricle circulation and single-ventricle circulation with Blalock-Taussig shunts." *circulation* 105.24 (2002): 2885-2892.

[5] Martin, Luis Cuadrado, et al. "Association between hypervolemia and ventricular hypertrophy in hemodialysis patients." *American journal of hypertension* 17.12 (2004): 1163-1169.

[6] Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature medicine*, *25*(1), 65-69.

[7] Gorter, Thomas M., et al. "Right heart dysfunction and failure in heart failure with preserved ejection fraction: mechanisms and management. Position statement on behalf of the Heart Failure Association of the European Society of Cardiology." *European journal of heart failure* 20.1 (2018): 16-37.

[8] Xue, Yong, et al. "Application of deep learning in automated analysis of molecular images in cancer: a survey." *Contrast media & molecular imaging* 2017 (2017).

[9] Zaroug, Abdelrahman, et al. "Lower limb kinematics trajectory prediction using long short-term memory neural networks." *Frontiers in Bioengineering and Biotechnology* 8 (2020): 362.

[10] Mustaqeem, Anam, Syed Muhammad Anwar, and Muahammad Majid. "Multiclass classification of cardiac arrhythmia using improved feature selection and SVM invariants." *Computational and mathematical methods in medicine* 2018 (2018).

[11] Yazdani, Sasan, et al. "Heart rhythm classification using short-term ECG atrial and ventricular activity analysis." *2017 Computing in Cardiology (CinC)*. IEEE, 2017.

[12] Clifford, Gari D., et al. "AF classification from a short single lead ECG recording: The PhysioNet/computing in cardiology challenge 2017." *2017 Computing in Cardiology (CinC)*. IEEE, 2017.

[13] Javadi, M., Arani, S. A. A. A., Sajedin, A., & Ebrahimpour, R. (2013). Classification of ECG arrhythmia by a modular neural network based on mixture of experts and negatively correlated learning. *Biomedical Signal Processing and Control*, *8*(3), 289-296.

[14] Vivekanandam, B. "*Speedy Image Crowd Counting by Light Weight Convolutional Neural Network.*" Journal of Innovative Image Processing 3, no. 3 (2021): 208-222.

[15] Vijayakumar, T. "*Neural network analysis for tumor investigation and cancerprediction*." Journal of Electronics 1, no. 02 (2019): 89-98.