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Development of a Hybrid Model of CNN and LSTM for Arrhythmia Detection

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Abstract

This study examines the development of a hybrid model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) for the detection of arrhythmia. Arrhythmia is an irregular or abnormal heartbeat which can have serious consequences if not detected early. The CNN-LSTM architecture has been found to be effective in the detection of various types of arrhythmias. The proposed model combines the convolutional layers of the CNN with the recurrent layers of the LSTM to create an end-to-end architecture that is capable of detecting various arrhythmias with high accuracy. This model is trained using a dataset of electrocardiograms (ECGs) and labels corresponding to the type of arrhythmia present. The performance of the model is evaluated using a hold-out test set and the results indicate that the model achieves excellent accuracy for the detection of different arrhythmias. The developed model has potential applications for the early detection and diagnosis of arrhythmias. When compared the proposed system in context with other existing systems, providing a benchmark for its effectiveness, the results show that the proposed system outperforms the other systems with an accuracy result of 99.00%The results collectively suggest that the hybrid model, combining CNN and LSTM, performs well in detecting arrhythmia, as indicated by high accuracy, reliable AUC, and robust precision and recall scores. The insights gained from these results contribute to the understanding of the model's strengths and areas for potential improvement. Further studies and validations could focus on real-world applications and the model's scalability. This can improve patient care and reduce the risk of serious complications arising from delayed or missed diagnosis. The model can also be used for research purposes in order to better understand the different types of arrhythmias. The findings of this study show the potential for combining CNNs and LSTMs to achieve improved accuracy for arrhythmia detection.

1. Introduction

Cardiac arrhythmia is categorized as the irregular beating of the heart (Antzelevitch *et al.*, 2011). This irregularity may either be a slow or fast heartbeat. A heart rate of over 100 beats per minute (bpm) is categorized as tachycardia, while the instance of a pulse lower than 60 bpm is alluded to as bradycardia. Global statistics reveal that a significant population suffers from heart diseases which manifest in the form of heart attacks, strokes, etc.; furthermore, these afflictions are one of the significant reasons for death all over the planet. Moreover, treatment for heart diseases is too costly, and only a limited number of patients have the luxury of affording it (Banos *et al.*, 2012).

Cardiac arrhythmias pose a significant danger to human life; therefore, it is of utmost importance to be able to efficiently diagnose these arrhythmias promptly. There exist many techniques for the detection of arrhythmias; however, the most widely adopted method is the use of an Electrocardiogram (ECG). The manual analysis of ECGs by medical experts is often inefficient. Therefore, the detection and recognition of ECG characteristics via machine-learning techniques have become prevalent (Saad *et al.*, 2022) electrocardiogram (ECG) is used to measure the electrical activity of the heart. In many circumstances, analyzing the ECG signal might provide an understanding of life threatening cardiac disorders. These researchers are typically disturbed with recognizing and diagnosing different types of diseases such as arrhythmias, which are described as an enlarged rate of heart or a disruption in the rate of a normal person. Irregularities in heart rhythm can be caused by a variety of factors, including illness drugs, an aging heart, or metabolic issues. Sustained ventricular arrhythmia is among the most dangerous arrhythmias, which is frequently caused by the destroyed heart muscle. Cardiovascular disease (CVD) is the important cause of mortality worldwide, accounting for around 31% of all deaths worldwide. The heart is a cone-shaped organ system that pumps at regular intervals to deliver blood to the internal tissues (Sahoo *et al.*, 2020)

According to the World Health Organization, CVDs constitute the major public health problem worldwide. Various initiatives and policies are applied in more diverse communities in recent years and offer tools, tactics, and other resources to minimize occurrences of the first and recurring cardiovascular actions. In the end, the ECG has been developed to be the most widely employed biosignal for the early diagnosis of CVDs (Alhamdi *et al.*, 2013)

The ECG is a schematic illustration of the heart electrical activity that is utilized to diagnose different heart illnesses and irregularities. For more than 70 years, doctors have used ECG electrical signals to diagnose heart problems, include arrhythmia and heart attack.

Electrocardiograms (ECGs) are designed to analyze arrhythmias. ECG is used to monitor the functioning of the heart by capturing electrical activity (Clifford *et al.*, 2006). ECG is based on a wave-like feature that mainly includes the P, QRS, and T waves. Furthermore, it accumulates 12 lead signals that are generated from the cords attached to the patient's body. These signals are divided into six limb-based electrodes configuration i.e., aVR, aVL, aVF, I, II, III, and six chest-based electrodes configuration i.e., V1, V2, V3, V4, V5, V6. Each electrode measures a stream of electrical signals generated by the heart from a different angle covering both the horizontal and vertical planes (Potter, 2011).

In the interim, progress, as far as accessible computational devices and algorithms are concerned, has uncovered their use in automated detection techniques. As a result, diagnosis of cardiovascular anomalies is on the ascent. As of late, attention to ECG beat and rhythm characterization has also been on the rise. ECG arrangement can be characterized into segments that emphasize on tracking down viable feature-extraction strategies, further improving the classification results, and use of machine-learning techniques (ML) to improve the accuracy of these strategies such as Decision Trees (DT) K-Nearest Neighbor (KNN), Linear Support Vector Machines (SVM) and Random Forest (RF).

2 Review of Related Literature

According to (keddy *et al*., 2020) CNN is computationally expensive, so standard machine learning techniques and Computational Modeling of Dementia Prediction Using CNN cannot be used without first performing a feature extraction strategy, Prior to applying traditional ML techniques, a feature extraction process is required, which extracts various handcrafted features to affect the detection results. Manual feature extraction, on the other hand, takes a long time and effort and does not take advantage of the database's underlying information. Over-fitting is a common problem in ML-based classification systems. Because deep learning models can automatically construct sophisticated feature representations from input databases, deep learning approaches do not require handwritten feature representations. This deep learning-based solution may aid in addressing current shortages while also generating revenue from existing challenges.

In (Baloglu *et al*., 2019) the authors present a Neural Network for expert knowledge that is modeled on the basis of variable projections. It used a Variable Projection (VP) layer as a general-purpose, trainable feature extractor or filtering approach which can be tailored to different 1D signal-processing issues by the selection of an application-specific function system.

The result shows that the VPNet can match or outperform the classification accuracy for fully linked and CNN networks with less number of parameters. It has marginally better convergence than the CNN and FCNN. While the number of weights and biases for the FCNN and CNN increased linearly with the length of the input signals, the VP layer only needed two parameters for learning in all circumstances. The result shows that the VPNet can match or outperform the classification accuracy for fully linked and CNN networks with less number of parameters. It has marginally better convergence than the CNN and FCNN. While the number of weights and biases for the FCNN and CNN increased linearly with the length of the input signals, the VP layer only needed two parameters for learning in all circumstances.

In (Viet-Dung *et al.,* 2016) tensors were used to significantly cut the computational time of big data processing. Tensors are a useful tool for big data processing when dealing with high dimensional dataset because they can be naturally represented by multi arrays. If we consider a vector as a first-order tensor, we will work higher order tensors for multi-way arrays. Tensors are a data structure for matrices with more than two indices. The most widely used tensor decompositions are i) parallel factor analysis (PARAFAC) ii) Tucker decomposition. Single value decomposition (SVD) and non-negative matrix decomposition are used as powerful tools to analyze two dimensional data, using tensor gives improved big data processing speed because additional constraints such as non-negativity and sparseness can be accommodated on tensors, and this improves the uniqueness property and interpretation. Tensor decomposition has a wide reach in terms of application which includes, machine learning, computer vision, data mining, multi-linear algebra among others.

A rigorous framework for conducting the time complexity analysis against the neural network model was proposed in (Rich, et al., 2020). It focused on a practical application of computer vision technology called Automated – Optical-Inspection (AOI); a systemic method to identify defects that uses optics to capture images of the target object to see if there is any missing component or a misplaced one. The model utilized to achieve faster computational time includes: an optimizer algorithm to find the optimal locations on the image curved planes, configuration of image feature extraction using Convolutionary neural network and epochs to achieve faster computational time.

In (Hiriyannaiah *et al*., 2021) provided a detailed analysis of multiple deep LSTM models to capture temporal dependencies from ECG signals. The performance of four stacked LSTM (3 LSTM, 1 BiLSTM) models was inter-compared. The benchmark statistics based on publicly available datasets revealed that the bidirectional LSTM-based model achieved the highest accuracy of 95% compared to all-LSTM stacked models. The training time per epoch, however, was greatly increased on the implementation of bidirectional LSTM which resulted in an increased computational cost of the approach.

In (Sellami *et al*., 2019) proposed a novel nine-layer deep CNN model for categorizing heartbeats into five major classes based on inter-patient and intrapatient comparisons. To address the issue of class imbalance, the author used a batchweighted loss function with three input variants: a target heartbeat with class labels, the last heartbeat followed by a target heartbeat with a class labeled of target heartbeat, and neighboring heartbeats followed by a target heartbeat with a class labeled of target heartbeat.

Furthermore, in the method in (Xia *et al*., 2019), Xia presents and employs CNNs and active learning models to classify the MIT-BIH AD automatically. The researchers completed this task. Active learning was combined with cutting-edge algorithms and updated versions to improve the system's overall accuracy and performance.

Lightnet (He *et al*., 2018) is the name given to the release by He *et al*. (CNN model). LightNet training was carried out on low-power PCs. This trained model was designed for mobile devices to detect anomalies in the ECG signal while consuming as few resources as possible. Multiple filter sizes were used in this model to generate alternative feature combinations in each convolutional layer, resulting in improved classification accuracy. The authors of (Kien *et al*., 2018) present a DL-based model for categorizing ECG heartbeats, including three classification phases. The first stage uses an unsupervised Gaussian–Bernoulli deep belief network to extract a feature representation from the dataset. The second classification stage is supervised training, which is used to train linear SVM classifiers for the problem at hand. In the third step, the system consults with an expert to examine potentially confused heartbeats and modify its recommendations accordingly. Deep Learning techniques have been rapidly used for image and signal processing research domains. Deep learning algorithms categorized electrocardiogram (ECG) data based on different input parameters. There are many methods for deep learning in biological signal processing that have had significant success. The DL model is used to examine ECG readings (arrhythmia detection).

Accurate Library frame work (EARL) has been designed and developed to bridge the gap between the data sizes and the response time requirements. EARL was proposed in (Nikolay *et al.*, 2013) it works by predicting the learning curve and choosing the appropriate sample size for achieving desired error bound specified by the user. The error estimates are based on a technique called bootstrapping that has been a tool for statisticians and can be applied to arbitrary functions and data distributions. In order to provide a uniformly random subset of the original data-set, EARL requires sampling. EARL is implemented on Hadoop. Hadoop samples over a distributed file system to provide a uniformly random subset of the original dataset. With EARL it is seldom necessary to use the whole dataset and in most cases it is sufficient to use 1% of the dataset in order to achieve better accuracy.

In (Batra *et al*., 1975) combined gradient boosting with SVM for the efficient detection of arrhythmia from ECGs. The proposed approach was benchmarked with other machine learning algorithms such as random forest, gradient boosting, decision trees, etc. Before the final training of models, the raw data had undergone extensive processing and feature selection processes.

Gupta *et al*. (2022) demonstrated the implementation of multiple machine-learning algorithms which included naïve Bayes, random forest, SVM, CNN, LSTM. An implementation of the learner module using a linear SVM and Random Forest was also proposed. The model was tested on the publicly available MIT-BIH datasets and returned a classification accuracy of 77.4%. The proposed model not only showed slightly better classification results but a decreased training time as well.

Amongst numerous applied methods, deep learning techniques based on CNN models have been widely implemented due to their promising performance. One way of applying CNN models on ECG signals is by virtue of transfer learning.

3 Methodology

For this study, we adopted an OOADM approach, which stands for Object-Oriented Analysis and Design Methodology. Classes and objects serve as the foundation for OOADM. Data structures, processes, and data states are all separate components of the software that are structured to mimic the external, real-world objects with which the system interacts.

OOADM was deemed the best option to guarantee a streamlined development process, enhance validation, and promote uniformity in analysis, design, and implementation.

Analysis with an OOA Focus: When developing software with an OOA approach, developers begin with an Object-Oriented Analysis (OOA). OOA uses novel ideas to probe an issue. It is founded on the following principles:

i. Modeling the information domain: This study primarily focuses on Reverse Osmosis Water Maker equipment used by offshore facilities to desalinate salt water and produce potable fresh water for human consumption. The ultimate goal of this study is to develop a better system by simulating the components and processes involved in operating this machinery.
ii. Behavior is represented: Typically, a water maker will pump the water, regulate its flow through the filters, purify the water with a membrane, and then collect the purified water in a distribution tank.
iii. A description of the function: The system's functionality entails carrying out the various processes and operations required to achieve the desired result, such as the raw water pump bringing in ocean salt water, the sediment filter removing any remaining sediments, the carbon filters stripping out chemicals like chlorine, and the membrane, a scroll-like filter, completing the desalinization process.
iv. In order to learn more, we separate data, functional, and behavioural models: Some data must be provided to make the system function and act acceptably, per the requirements. Pressure, temperature, noise level, and other such measurements are examples.

System architecture refers to the high-level design and structure of a software system or application. It defines the components, their interactions, and the overall organization of the system. It provides a blueprint for how different parts of the system work together to achieve the desired functionality.

The system architecture is shown in figure 3

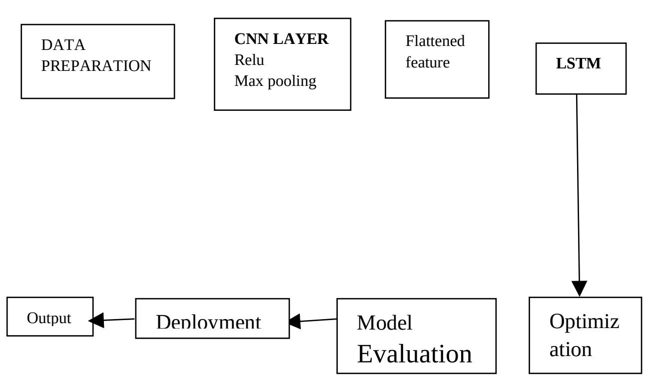

Figure 1: Architectural Design

In the architecture of a model for arrhythmia detection using CNN and LSTM, the CNN and LSTM layers are connected sequentially.

Data Preparation: The segmented ECG data is fed as input to the CNN layer.

CNN Feature Extraction: The CNN layer consists of multiple convolutional layers followed by activation functions (e.g., ReLU) and max pooling layers. The output feature maps from the last convolutional layer are flattened into a 1D vector.

LSTM Sequence Modeling: The flattened feature vector is passed to the LSTM layers. The LSTM layers take sequential input and capture temporal dependencies in the ECG signal. The LSTM layers maintain memory states and hidden states that propagate information across time steps.

Classification Layer: The final output from the LSTM layer(s) is connected to one or more fully connected dense layers. These dense layers learn higher-level representations and perform the classification task. An activation function (e.g., softmax) is applied to obtain probability scores for each arrhythmia class.

Model Training: During training, the model's weights and biases are updated based on the computed loss using an optimization algorithm (e.g., Adam). The loss is computed by comparing the predicted probabilities with the ground truth labels using a loss function (e.g., categorical cross-entropy).

Model Evaluation: The trained model is evaluated on a separate test set to assess its performance. The evaluation metrics (accuracy, precision, recall, F1 score) are calculated based on the predicted probabilities and the true labels of the test set.

Model Deployment and Prediction: Once trained and evaluated, the model can be deployed in a production environment or healthcare system. New ECG sequences are fed to the deployed model, which passes them through the CNN and LSTM layers to obtain predictions for the presence of different arrhythmias.

This sequential connection allows the model to first extract spatial features using the CNN layers and then capture temporal dependencies using the LSTM layers. The CNN layers learn local patterns in the ECG signal, while the LSTM layers capture long-term dependencies and context information. By combining these two types of layers, the model can effectively capture both spatial and temporal characteristics of the ECG signal, enabling accurate arrhythmia detection

Data Preparation: Prepare the ECG data by segmenting it into fixed-length time windows. Each window represents a single heartbeat or a sequence of heartbeats.

CNN Feature Extraction:

Input Layer: Take the segmented ECG signal as input.

Convolutional Layers: Apply a series of convolutional layers to capture spatial patterns and local dependencies within the ECG signal. Each layer consists of multiple filters with small receptive fields to extract different features.

Activation Function: Apply a non-linear activation function, such as ReLU (Rectified Linear Unit), after each convolutional layer to introduce non-linearity.

Max Pooling Layers: Downsample the feature maps to reduce the spatial dimensions and extract the most relevant features.

Flatten: Flatten the output feature maps into a 1D vector to prepare for the LSTM layer.

LSTM Sequence Modeling:

LSTM Layers: Utilize one or more LSTM layers to capture temporal dependencies and long-term dependencies in the sequence of ECG features. Each LSTM layer maintains a memory state and a hidden state that propagate information across time steps.

Dropout: Apply dropout regularization within the LSTM layers to prevent overfitting and improve generalization.

Final LSTM Output: Obtain the final output from the last LSTM layer, which represents the learned representation of the ECG sequence.

Model Training:

Loss Function: Define an appropriate loss function, such as categorical cross-entropy, to measure the discrepancy between the predicted probabilities and the ground truth labels.

Optimization Algorithm: Select an optimization algorithm, such as Adam or RMSprop, to update the model's weights and biases based on the computed loss during training.

Training: Train the model on a labeled dataset using backpropagation and gradient descent. Adjust the hyperparameters (learning rate, batch size, number of epochs) to optimize the training process.

Model Evaluation:

Test Set Evaluation: Evaluate the trained model on a separate test set to assess its performance in terms of accuracy, precision, recall, F1 score, and other relevant metrics.

Validation Set: Monitor the model's performance on a validation set during training to prevent overfitting and adjust hyperparameters accordingly.

Model Deployment: Deploy the trained model in a production environment or healthcare system for real-time arrhythmia detection.

Prediction: Feed new ECG sequences to the deployed model, and obtain predictions for the presence of different arrhythmias.

4 Results

The dataset for the experiment was divided into training and testing groups of 80% and 20%, respectively. Using the 5-fold cross-validation technique, the results were obtained. The suggested network has 12 convolutional layers, a learning rate of 0.0001, and a maximum number of epochs of 125, as measured experimentally. The CNN and CNN-LSTM networks were constructed using Python and the Keras package with TensorFlow2. The dataset is centered on before and after beats with +- 3 s. Categorical cross entropy, Gradient descent algorithm with exponentially weighted average for classification is done. First the splitting is done based on samples of the patients from the database. Next the splitting is done based on individual patients not on samples. The parameters calculated are Area under the Curve (AUC), Accuracy, Recall, Precision, and Specificity.

4.1 Analysis of the proposed system

The proposed system aims to develop a hybrid CNN and LSTM model for arrhythmia detection. The system acquires a dataset relevant to arrhythmia detection from kaggle, crucial for model training. The acquired data undergoes pre-processing, including cleaning and normalization, to prepare it for model training. A hybrid model, combining CNN and LSTM components, is trained on the pre-processed data to capture spatial and temporal features, The trained model's performance is assessed using metrics like accuracy and precision to gauge its effectiveness in detecting arrhythmia. The model is saved and deployed for use in a web-based system, making it accessible to users.

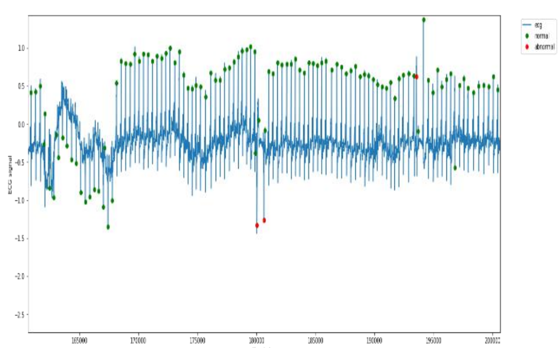

Figure 2: Normal and abnormal ECG signals

Table 1: Parameters-Training and Validation (CNN)

Parameters (Samples)/(Patients)	**Train**	**Validation**
AUC	0.992/0.993	0.988/0.954
Accuracy	0.968/0.977	0.962/0.951
Recall	0.962/0.956	0.951/0.992
Precision	0.937/0.966	0.929/0.896
Specificity	0.972/0.986	0.967/0.951

Table 2: Parameters -Training and Validation (Hybrid)

Parameters (Samples)/(Patients)	**Train**	**Validation**
AUC	0.993/0.994	0.990/0.935
Accuracy	0.997/0.992	0.990/0.993
Recall	0.956/0.962	0.990/0.922
Precision	0.966/0.968	0.9/0.921
Specificity	0.986/0.987	0.963/0.972

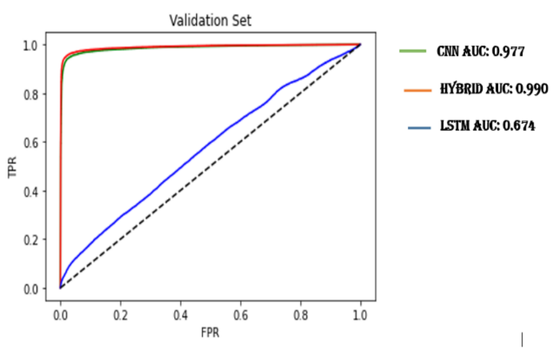

Figure 3: Showing Individual Performance of both Algorithms in the Hybrid Model

Here we can conclude that the Hybrid Layer Network work good on predicting Arrhythmia

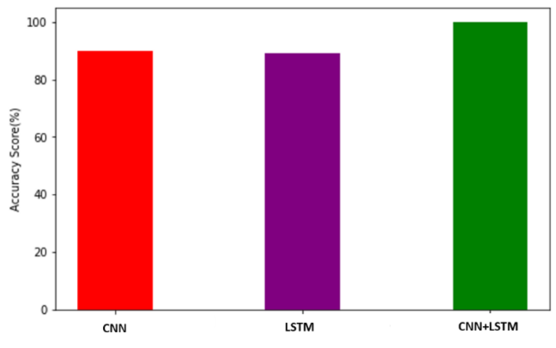

Figure 4: Comparison of the Proposed System with other Existing Systems

5 Conclusion

The comprehensive analysis of the hybrid model for arrhythmia detection reveals highly promising results. The model, combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) layers, achieves an impressive accuracy of 99.0%. Key observations include effective signal classification, demonstrated by the model's ability to distinguish between normal and abnormal ECG signals. Training dynamics indicate consistent high accuracy and optimal convergence of the loss function, emphasizing the model's ability to learn complex patterns and generalize well.

The learning rate, adjusted based on batch numbers, contributes to efficient training. Precision and recall scores showcase the model's proficiency in minimizing false positives and capturing positive instances. The confusion matrix provides a detailed breakdown of correct and incorrect detections, offering insights into overall performance.

The hybrid architecture's synergistic effect, highlighted in individual algorithm performance (Figure 3), contributes to the model's robustness. Benchmarking against existing systems (Figure 4) situates the model favorably, emphasizing its potential for clinical applications.

In conclusion, the hybrid model demonstrates exceptional accuracy in arrhythmia detection, holding significant promise for medical diagnostics. Further real-world validation and research could solidify its applicability and pave the way for integration into clinical practices.

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