Multi-Task Deep Learning for Electrocardiogram Classification

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**Abstract.** In today's high-tech age, cardiovascular diseases and mental health disorders remain major global health challenges but an AI system that is capable of detecting both emotion and cardiac conditions are quite scarce. Hence, this research focused on developing a CNN-BiLSTM model that combined two types of deep learning methods such as Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) layers. This model leveraged two different types of datasets including MIT-BIH for cardiac conditions detection and DREAMER for emotion detection based on the electrocardiogram (ECG) signal of the patients. The experimental results obtained indicate that the proposed model outperforms other models like standalone CNN and BiLSTM as it achieved approximately 97% of accuracy on the cardiac conditions detection and 91-94% of accuracy on the emotion recognition. These results indicate that the effectiveness of the hybrid CNN-BiLSTM model applied in both cases and its potential to employ in healthcare application for monitoring of both cardiac and emotional states.

# Introduction

Nowadays, cardiovascular diseases have gradually become a more focus field in healthcare because according to World Health Organization (WHO), cardiovascular diseases are considered as the main killer in the world with over 18 million deaths annually [1], [2], [3]. Based on their research, there was about 85% of all the deaths of heart diseases because of the heart attacks which are also known as myocardial infarction [1]. Besides that, there is credible evidence that some emotional states such as stress and anxiety will affect people’s cardiovascular health [4]. This is because the emotions can influence the autonomic nervous system which controls the rhythm of heart beats [4]. For instance, arachnophobia, which is a type of anxiety disorder where the patients will experience bad emotional reactions such as fear, panic or nervousness when faced with the phobic object like spiders which can cause their breathing rate and cardiovascular activity increases [5]. These changes can increase the possibility of getting severe cardiovascular disease like heart attacks. Hence, the early diagnosis of mental illnesses and cardiovascular diseases is important preventive steps against severe disorders and improved delivery of health care services.

Electrocardiogram signals or ECG are considered as one of the most conventional physiological signals that can be used in both emotional detection and heart diseases detection based on current research as it records the electrical impulses of the heart to detect irregularities [3]. However, existing diagnostic AI systems often treat these conditions separately using different tools and models as most of the deep learning or machine learning methods employed are single task oriented that focus solely on either emotion recognition or cardiac condition detection.

To address this limitation, this project aims to develop a multi-task deep learning model that can perform two tasks at the same time. The model is based on a hybrid CNN-BiLSTM architecture that is capable to perform cardiac condition detection and emotion recognition by using two different datasets. The first dataset used was MIT-BIH that specifically for cardiac conditions detection while the second one was DREAMER that specifically for emotional recognition. The project involves datasets preprocessing, model design, performance evaluation, and analysis of the model's strengths and limitations. The goal is to create an effective, comprehensive, and cost-efficient AI system for ECG-based emotion and cardiac condition monitoring in the healthcare field.

# Literature review

Emotions are typically classified into three categories such as arousal, valence, and dominance [6], [7], [8], [9]. In order to detect emotions from ECG data, DL models like CNN and Long Short-Term Memory networks (LSTM), as well as ML models like Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Model-Agnostic Meta-Learning (MAML), are commonly used. CNNs are the most widely used model in emotion detection because of their strong abilities in feature learning. For example, 1D CNN achieved 83.29% of accuracy in detecting anxiety in arachnophobia subjects by using ECG data [5]. A 7-layer CNN outperformed SVM and Neural Network (NN) on the DREAMER dataset by achieving about 95.16%, 85.56%, and 77.54% accuracy in valence, arousal, and dominance, respectively [6].

Besides that, other CNN variants include VGG16, which also outperformed others like CNN and AlexNet for classifying four emotion classes, such as amusing, boring, relaxing, and scaring [10] while MobileNet, which achieved the best performance on the AMIGOS dataset in both speed and accuracy [7]. Other CNN adaptations like MultiResUNet3p also outperformed traditional ML classifiers with 96.12% and 94.25% accuracy in binary and multiclass emotion classification, respectively [11]. Advanced CNN models like the CBAM-enhanced CNN improved feature extraction and achieved high accuracy across WESAD, DREAMER, and ASCERTAIN datasets [12]. Similarly, a timescale 2D transformed CNN ensemble obtained a 98.41% accuracy on ASCERTAIN, which outperforms the basic CNN and ResNet18 [13].

Though CNNs do well at learning spatial features, they are limited in representing the temporal pattern of ECG data. This issue is addressed by using LSTMs which are meant to find connections in the data over time. For instance, the application of LSTM on multimodal signals like EEG, ECG, and EMG achieved an F-score of 95% [9] even though they often require multiple sensors and higher deployment complexity. Another example is the application of bidirectional LSTM able to perform better than SVM and FNN on the MAHNOB-HCI dataset by achieving 78.28% accuracy for valence and 83.61% for arousal [8]. Furthermore, a hybrid CNN–LSTM model often outperforms standalone models. For instance, a hybrid model with Bayesian inference outperformed standalone CNN and LSTM as it achieved about 90% and 86%, respectively, on both AMIGOS and DREAMER datasets [14]. Another hybrid model combining CNN, LSTM, ensemble learning, and MAML achieved 98.2% accuracy on the AMIGOS dataset, so it is significantly better than models without MAML [15], even though it required high computational resources and was tested on limited datasets.

In detection of heart disease, modern approaches that primarily use ECG include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and their variants, as well as hybrid and ensemble methods. CNNs are widely adopted because of their ability to learn features directly from raw ECG data without heavy preprocessing, which shows a strong performance in both heart disease and emotion detection [16]. For instance, the CNN-based SEER model achieved an AUC of 0.83, which proves to outperform conventional models like Random Forest, which only obtained an AUC of 0.68 [17]. Another notable model, which is a modified VGG-16 trained on the China Physiological Signal Challenge 2018 dataset, achieved about 96.2% subset accuracy and outperformed ensemble classifiers and other CNN variants due to its use of Grad-CAM for interpretability [18]. CNNs also presented their superiority over human experts, as seen in the ECG12Net model, which achieved an AUC of 0.947 for pneumothorax detection, utilizing an 82-layer convolutional architecture and attention mechanisms to uncover subtle ECG patterns [19],[20].

Moreover, RNNs also achieved strong performance in sequential ECG data for heart condition predictions. A two-stage LSTM model trained on the MIT-BIH dataset achieved 89.3% in terms of classification efficiency, which outperforms 1D-CNN in certain aspects due to its ability to model temporal dependencies [3]. Finally, the hybrid methods that integrate CNN and LSTM have shown excellent results. For example, a 2D-CNN-LSTM model transformed 1D ECG into 2D scalograms and achieved about 98.7% accuracy for arrhythmia detection.

Current models usually concentrate on either recognizing emotions or diagnosing the cardiac conditions separately, but the CNN–BiLSTM model fills this gap by using CNN’s abilities in spatial detection and BiLSTM’s time-aware learning in one design which helps improve the performance more accurately in multi-task learning based on the ECG data from different datasets.

# Methodology

In the study, the ECG signal records obtained from both MIT-BIH and DREAMER datasets underwent different kinds of data preprocessing methods separately to ensure that the heart-related features, such as P waves, QRS complexes, and T waves, can be extracted. After that, two hybrid CNN-BiLSTM models were developed with similar architecture but different hyperparameter settings that were determined using the Optuna hyperparameter optimization method to train on the preprocessed MIT-BIH and DREAMER datasets.

## Data Preprocessing

The DREAMER and MIT-BIH datasets selected because DREAMER includes noise as well as real‐world ECGs and labels that describe how aroused and valence each person was while MIT-BIH includes ECGs with precise annotations and beat‐by‐beat labels that ideal for working on arrhythmia classification. Both datasets have undergone different types of data preprocessing methods because the characteristics of both datasets are different. The ECG signals from the MIT-BIH dataset are less noisy compared to the DREAMER dataset since it was captured under medical settings that are primarily used for the detection of arrhythmia. In contrast, the DREAMER dataset was captured in an environment induced by emotions, which may affect the consistency of the dataset.

### DREAMER Dataset

The DREAMER dataset consists of EEG, ECG, and respiration signals from 23 participants, where 13 males and 10 females between the ages of 22 to 33 were recorded while watching 18 video clips [12], [14]. Each participant then rated their emotional response using arousal, valence, and dominance scores on a scale of 1 to 5 [14]. The data is stored in a .mat file containing nested cell arrays for baseline and stimulus signal recordings from two ECG channels.

The .mat file of DREAMER dataset was loaded in the MATLAB platform, and the dataset structure, which includes participant count and sampling rate, was examined. Each ECG signal underwent the initial preprocessing step, which was detrending to remove slowly changing trends that were potentially due to the baseline wandering of sensor drift. Then, the outlier correction is performed using a moving median with linear interpolation applied to replace the outliers with the new values computed by linear interpolation. Next, the bandpass filtering with the range between 0.5 to 30 Hz was applied on the signals to isolate relevant cardiac frequencies. Additional noise reduction methods, such as median filtering and moving average smoothing, were conducted. After that, the signals were then standardized by subtracting the mean of the signal and dividing by its standard deviation, and then the missing values were handled by using linear interpolation. To ensure uniform input length, a sliding window of 1000 samples with 50% overlap was utilized in order to extract ECG segments, and with zero-padding applied to those shorter signals. Each window was then stored with the corresponding participant ID, stimulus index, and emotional scores. Then, the arousal and valence scores were converted to binary classes where the scores below three as class 1 and scores of 3 or above as class 2. Then, one-hot encoding is applied to the binary labels to convert categorical class values into a numerical format. Finally, the ECG segments with their corresponding participant and emotion labels in arousal and valence were compiled into a structured table and saved as a file named DREAMER.csv. The DREAMER.csv file was then loaded into Google Colab to apply oversampling to balance the class distributions and then split into 70% training and 30% testing sets.

### MIT-BIH Dataset

The MIT-BIH dataset consists of two-channel ECG recordings from 47 patients, where 25 of them with abnormal rhythms and another 22 of them with normal cardiac activity which sampled at 360 Hz over approximately 30 minutes [3]. Each patient’s data includes a .dat file with raw signals, a .hea file with metadata, and an .atr file containing annotations for beat types and R-peak locations [3].

The MIT-BIH dataset in a zip file format was extracted to ensure that all necessary files, such as .dat, .atr, and .hea were loading properly. The raw ECG signals and corresponding annotations for each record were read and visualized for the first 1000 samples by using the wfdb library. The preprocessing steps began with applying a bandpass Butterworth filter to preserve the frequencies between the range of 0.5 Hz and 40. Next, the baseline wander caused by patients’ breathing and electrode movement was removed using detrending from the NeuroKit2 library, followed by additional denoising via the ecg\_clean() function to eliminate high-frequency noise and small artifacts. The cleaned signals were then normalized to a range of [-1, 1] using MinMaxScaler so that the proposed model can converge faster. Then, the ECG signals were segmented around R-peaks by capturing 200 ms before and 400 ms after each peak, and those noisy or invalid beats, such as “~” and “|”, were removed. These segmented beats were padded to ensure uniform input lengths required for batch processing. The corresponding beat labels were then mapped to the categories and encoded numerically for model interpretation. There are a total of 14 classes of the beat labels such as Normal Beat, Left Bundle Branch Blok Beat, Right Bundle Branch Block Beat, Premature Ventricular Contradiction, Atrial Premature Beat, Fusion of Ventricular and Normal Beat, Ventricular Escape Beat, Nodal (Junctional) Escape Beat, Aberrated Atrial Premature Beat, Nodal (Junctional) Premature Beat, Supraventricular Premature Beat, Fusion of Paced and Normal Beat and Unclassifiable Beat. Due to the dataset is quite imbalanced so both Random Oversampling and the Synthetic Minority Oversampling Technique (SMOTE) were employed to balance the classes. Finally, the dataset was split into 70% training and 30% testing sets, and then a random subsampling method was conducted to reduce the size of the dataset and further improve the efficiency of training.

## Model Development

The proposed model combined two DL methods such as CNN and BiLSTM. The CNN layers in the hybrid model focused on extracting spatial features like P-waves, QRS complexes, and T-waves from ECG signals and then passed them to BiLSTM layers to capture temporal dependencies in both forward and backward directions of the signals. Even though the models used in both emotional recognition and cardiac conditions used the same DL methods but the model for emotional recognition was multi-output where it split into two branches at the end, one for arousal classification and the other for valence classification while the model for cardiac conditions detection was single output that ended with a softmax layer.

### Emotional Recognition

The model used in emotional recognition begins with three layers of 1D convolutional, followed by a batch normalization layer, a max pooling layer, and a dropout layer to extract key features of ECG signals. These features then flow to the two BiLSTM layers to learn the temporal dependencies in both forward and backward directions. Then, a shared dense layer merges the sequential data and passes it to the separate branches for arousal and valence, where each of them has its own dropout layer and softmax layer. The key hyperparameters of the model, like the number of convolutional filters, dropout rates, number of LSTM units, and learning rate, were automatically tuned by Optuna with early stopping and pruning. At the end, the Optuna found out that a model with 32, 96, and 256 CNN filters in the three convolutional layers, dropout rates of 0.2, 0.3, and 0.5, two BiLSTM layers where each with 96 units, an RMSprop optimizer at a learning rate of 0.0006, categorical cross-entropy loss, and task-specific loss weights of 0.83 for arousal and 1.48 for valence perform the best in both arousal and valence classifications. Figure 1 shows the structure of the model used in emotional recognition.

A diagram of a computer

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**Figure 1.** Block diagram of the hybrid CNN-BiLSTM model in emotional recognition

### Cardiac Conditions Detection

The model used in cardiac conditions detection begins with three layers of 1D convolutional each, followed by a max pooling layer to decrease the dimensions of spatial, and a dropout layer to prevent overfitting. After the CNN layers, the model included two BiLSTM layers with one dropout layer between them. The final part of the model consists of a softmax output layer that performs multi-class classification. L2 regularization was applied to the dense layer to further improve generalization. In order to fine-tune the architecture, the Optuna framework used to optimize the number of filters in each convolutional layer that range from 16 to 256, dropout rates between 0.2 and 0.5 after CNN and LSTM layers, the number of LSTM units with a range from 32 to 128, and the choice of optimizer between Adam and RMSprop. Finally, the best combination found included 32 filters in the first CNN layer, 128 in the second, and 256 in the third, with 32 LSTM units and RMSprop as the optimizer, as this combination helps to achieve the highest validation accuracy during the testing process. Figure 2 presents the overall architecture of the model.

A diagram of a flowchart

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**Figure 2.** Block diagram of the hybrid CNN-BiLSTM model in cardiac conditions detection

# Results

The hyperparameter settings identified from the Optuna framework were then used to train the final hybrid CNN–BiLSTM model for both cardiac condition and emotion classification tasks. Hence, this section presents the performance of the model in some of the performance metrics such as accuracy, precision, recall, and F1-score on DREAMER and MIT-BIH datasets. The accuracy gives the overall correctness of the predictions made by the model.

The proposed model achieved an accuracy of about 94.22% and 90.46% for arousal and valence classification, respectively, in emotional classification. Besides that, in the cardiac condition detection, the model achieved an accuracy of 97.46% in classifying 14 distinct heartbeat classes. The precision depicts the proportion of the predicted positive samples that are classified correctly. In emotional recognition, the model achieved about 94.25% and 90.51% in arousal and valence, respectively, while in cardiac condition detection, the model achieved about 97.46% of precision. The recall or sensitivity refers to the actual positive samples that are correctly classified. In emotional recognition, the model obtained 94.22% and 90.46% in arousal and valence, while for cardiac conditions detection, the model obtained about 97.46%. F1-score refers to the harmonic mean of precision and recall, as it balances both into a single metric. The model used in emotional recognition can reach about 94.22% and 90.46% for arousal and valence, while the model used in cardiac conditions detection reaches 97.45%.

For arousal, the model correctly identified 11362 low-arousal and 11038 high-arousal samples with only 525 false positives and 850 false negatives. For valence, the model accurately predicted 10957 negative-valence and 10550 positive-valence samples with 931 false positives and 1337 false negatives. These results indicate the model can predict most of the emotions correctly in both arousal and valence. Besides that, the confusion matrix of the proposed hybrid model shows that most of the heartbeat classes were correctly classified. Some of the classes, like Aberrated Atrial Premature Beat, Supraventricular Premature Beat, Unclassifiable Beat, and Ventricular Escape Beat, achieved perfect classification with zero misclassified samples. However, some classes, such as Atrial Premature Beat and Normal Beat, do not perform well in classification, where the correctly classified samples are below 1700 out of 1833 samples. The results show that even though the proposed model can differentiate most beat types but some of the beat categories were not able to differentiate so well.

The model for emotional recognition shows strong and balanced performance in distinguishing low- and high-arousal states and the precision, recall, F1-score and Support for each class as shown in Table 1. For valence, the model able to perform consistently across negative and positive class with closely matched F1-score that indicates the minimal bias towards either class and the precision, recall, F1-score and Support for each class as shown in Table 2. Besides that, the model for cardiac conditions detection maintains high precision and recall for all 14 cardiac classes so it can distinguish both common and clinically subtle heart rhythm abnormalities reliably as presented in Table 3.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TABLE 1.** Performance metrics of each class for Arousal Classification in emotional recognition | | | | |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| Class Low | 0.9034 | 0.9558 | 0.9429 | 11887 |
| Class High | 0.9546 | 0.9285 | 0.9414 | 11888 |
| Macro Avg | 0.9425 | 0.9422 | 0.9422 | 23775 |
| Weighted Avg | 0.9425 | 0.9422 | 0.9422 | 23775 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TABLE 2.** Performance metrics of each class for Valence Classification in emotional recognition | | | | |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| Class Negative | 0.8912 | 0.9217 | 0.9062 | 11888 |
| Class Positive | 0.9189 | 0.8875 | 0.9029 | 11887 |
| Macro Avg | 0.9051 | 0.9046 | 0.9046 | 23775 |
| Weighted Avg | 0.9051 | 0.9046 | 0.9046 | 23775 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TABLE 3.** Performance metrics of each class in Cardiac Conditions Detection | | | | |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| Aberrated Atrial Premature Beat Class | 0.9844 | 1.0000 | 0.9922 | 1833 |
| Atrial Premature Beat Class | 0.9422 | 0.9253 | 0.9337 | 1833 |
| Fusion of Paced and Normal Beat Class | 0.9950 | 0.9858 | 0.9904 | 1833 |
| Fusion of Ventricular and Normal Beat Class | 0.9641 | 0.9825 | 0.9733 | 1833 |
| Left Bundle Branch Block Beat Class | 0.9939 | 0.9787 | 0.9863 | 1833 |
| Nodal (Junctional) Escape Beat Class | 0.9429 | 0.9913 | 0.9665 | 1833 |
| Nodal (Junctional) Premature Beat Class | 0.9685 | 0.9907 | 0.9795 | 1833 |
| Normal Beat Class | 0.9437 | 0.8958 | 0.9191 | 1833 |
| Premature Ventricular Contraction Class | 0.9537 | 0.9449 | 0.9493 | 1833 |
| Right Bundle Branch Block Beat Class | 0.9967 | 0.9836 | 0.9901 | 1833 |
| Supraventricular Premature Beat Class | 0.9995 | 1.0000 | 0.9997 | 1833 |
| Unclassifiable Beat Class | 0.9924 | 1.0000 | 0.9962 | 1833 |
| Unknown Class | 0.9693 | 0.9656 | 0.9675 | 1833 |
| Ventricular Escape Beat Class | 0.9978 | 1.0000 | 0.9989 | 1833 |
| Macro Avg | 0.9746 | 0.9746 | 0.9745 | 25662 |
| Weighted Avg | 0.9746 | 0.9746 | 0.9745 | 25662 |

The proposed model outperforms other models like CNN and CNN+CBAM approaches on the DREAMER dataset by achieving 94.22% for arousal and 90.46% for valence. Besides that, another model also outperforms the standalone model, like LSTM with an accuracy of 97.46% on MIT-BIH compared to its accuracy of 89.3% when it comes to classifying multiple classes of beat types, as shown in Table 4.

|  |  |  |  |
| --- | --- | --- | --- |
| **TABLE 4.** Accuracy comparison of the methods applied on DREAMER and MIT-BIH datasets | | | |
| **Paper** | **Application** | **Method** | **Accuracy (%)** |
| [4] | Emotion | CNN | 77.1(arousal), 74.9 (valence) |
| [12] | Emotion | CNN+CBAM | 83.6 (arousal), 84.2 (valence) |
| Proposed | Emotion | CNN-BiLSTM | 94.22 (arousal), 90.46 (valence) |
| [3] | Heart Condition | LSTM | 89.3 |
| Proposed | Heart Condition | CNN-BiLSTM | 97.46 |

# CONCLUSION

This paper proposed two hybrid CNN-BiLSTM models to perform both emotional recognition and cardiac condition detection. The multi-output model used in emotional recognition helps to classify the binary classes of arousal and valence, and it achieved an accuracy of 94.22% and 90.46%, respectively. The single-output model used in cardiac condition detection classified 14 distinct classes of beat types and achieved an accuracy of 97.46%. Clinically, 97% accurate in detecting arrhythmias could allow monitoring systems to have fewer false alarms and being 94% accurate in detecting arousal and 90% in detecting valence shows that it can detect emotion states in controlled settings reliably. Both models were not only capable of outperforming other existing methods but also indicated that they were able to effectively learn both spatial and temporal features for comprehensive ECG-based analysis. However, there are only two relatively small and controlled datasets used. Future work can gather larger and multi-center ECG data so that rare arrhythmias and subtler emotional signals will be captured. Besides that, future work can also include confidence intervals to enhance the performance evaluation of the model. Also, using techniques such as federated learning would ensure that the training of the model could be done across several hospital databases without having to share patients’ private records. Making parts of the ECG more understandable to clinicians by using SHAP or attention maps can build their trust in the system. Finally, the model can be more precise for each patient by adjusting it to their own heart rate patterns which helps it work well in all groups. By closing these gaps in statistics, interpretation and analysis, it will help the future works to develop ECG monitoring systems that are reliable, open and put patients first.

# Acknowledgments

The authors would like to thank everyone for their direct or indirect support and encouragement.

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