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MULTI-SOURCE ECG SIGNAL-BASED CARDIAC-ABNORMALITY PATTERN CLASSIFICATION WITH FAST-SLOW LEARNING DNNS

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Abstract

The classification of cardiac-abnormality patterns with ECG data plays a crucial role in the diagnosis as well as treatment and prognosis of diseases related to the human heart. With the advent of deep learning techniques, particularly convolutional, recurrent, and generative neural networks , there has been a significant advancement in the accuracy and efficiency of cardiac-abnormality pattern classification with electrocardiogram (ECG) data. However, with the availability of multitudes of freely available multi-source ECG data today, more attempts are required to develop new models that can handle and perform well on these datasets simultaneously. In this study, an attempt is made to develop a novel deep learning classification model with multi-source ECG dataset for cardiac abnormality pattern classification.The model uses the power of Transformer networks in their ability to produce low inductive bias towards learning representations and the power of Recurrence networks to memorize a compressed representation of a sequence is that it is beneficial for generalization. The transformers are the fast-stream component due to their sensitivity to sensory input and the RNs are slow-stream component due to their long-term memory sustenance. The multi-source ECG dataset is composed of 4 different and popular 12-lead ECG datasets available publicly for research purposes. The proposed model performed satisfactorily overall on a 27-class classification scenario.

Keywords: Multi-source ECG data, Cardiac response abnormality pattern, Fast-slow learning, deep learning

1. Introduction

Cardiac-abnormality pattern classification using ECG data is essential for early detection and diagnosis of various cardiac abnormalities. According to the World Health Organization, the classification of cardiac-abnormality pattern plays a crucial role in the diagnosis and treatment of cardiovascular diseases. The examination of variation in ECG waves can be used to detect several cardiovascular abnormalities. An electrocardiogram (ECG) is a visual depiction of the electrical signals produced by the heart [1]. It is employed to detect and diagnose a range of cardiac conditions and irregularities., A wide variety of heart conditions can be identified by studying the changes in these waves. The extraction of waveforms from the ECG cycle has been the subject of several techniques [1]. Filtering the data, making unique, engaging blocks for each peak, and establishing a constant threshold point are all parts of these techniques. The classification of cardiac abnormality patterns using ECG data is another important goal for determining the heart's health. Traditional methods were limited in their ability to capture complex patterns present in multi-source ECG signals as they relied on handcrafted features and rule-based strategies [2]. Deep learning techniques have emerged as powerful tools for automated feature extraction and classification, enabling more accurate and robust analysis. With the establishment of recurrent neural networks (RNNs), generative adversarial networks (GANs), and convolutional neuralnetworks (CNNs), there has been a significant advancement in the accuracy and efficiency of cardiac-abnormality pattern classification using ECG data [3, 4]. Especially, the surge in studies involving use of novel strategies such as transformer and attention mechanisms is notable.

Several reviews and studies have been reported utilizing RNNs and Transformers in ECG signal analysis. However, here the review is exhaustive and limited to the issue at hand. The paper in [3] provides critically and exhaustively reviews studies that used deep learning methodologies, especially recurrent and convolutional nets (RNNs and CNNs) for the purpose of detecting arrhythmia in Electrocardiogram (ECG) signals. Amongst other models, the paper also reviews the exploration and utilization of more than 15 RNN structures, usually long short-term memory (LSTM) and gated recurrent unit (GRU) based, and with or without CNNs, for the purpose of sequence modelling and classification tasks. The review offers valuable insights into the capabilities of these RNN-based methods via performance metrics such as overall accuracy, inter-patient accuracies, and intra-patient accuracies, and identifies intriguing avenues for future research in this field. However, model-wise limitations are not included in the review. The challenges with RNNs and in general with other DNN models as well are generically out forward as generalizability, visualization-ability, interpretability, and reliability. The issue of inductive bias with use of RNNs in ECG signal analysis is not discussed in the review and remains open for discussion.

In attempt to diving deeper into more novel studies (in context to DL in ECG signal analysis), study reported in [5] introduces an innovative deep learning framework for classifying ECG arrhythmias. Their framework combines a 2-D CNN with an attention mechanism module and a LSTM in bidirectional fashion, to build a hybrid model. The attention strategy employed within the 2D-CNN segment enables the overall model to selectively concentrate on individual portions of the input ECG signals separately, while the bidirectional LSTM component successfully captures temporal relationships. Their suggested model demonstrates a high level of performance in accurately classifying arrhythmias on widely recognized datasets. However, the utility of such a hybrid model in classification of multiple labels present within a single recording is not yet explored. Also, such a model is yet to be evaluated on multi-source ECG signal- based datasets. The study in [6] introduces a new deep neural network called ECGDETR, which is based on a transformer model. ECGDETR is designed to identify arrhythmia in continuous ECG segments from a single lead. Their suggested technique achieves comparable performance in heartbeat placement and classification when compared to prior efforts where classification is done by leveraging factors such as inter-heartbeat interdependence. Furthermore, their model utilizes a more concise inference approach since it does not need explicit segmentation of heartbeats. The model has been tested on three distinct arrhythmia detection tasks to demonstrate its capacity to perform well across varied scenarios. It is notable here that transformer-DNN based models do not require pre-processing of ECG signals to segment heartbeats separately. In another study, a robust and effective unsupervised transformer anomaly detection model in time series data is presented in [7]. The proposed model was employed to identify abnormalities in human cardiac time series data, including premature ventricular contractions (PVC), supraventricular premature (SP), and other electrocardiogram (ECG) anomalies. The model design consists of a transformer encoder network, a series of linear dense layers, and a decoder network. The strategy for detecting anomalies in ECG time series is based on a two-stage sequence prediction method. Their findings from two popular datasets i.e. the MIT-BIH and the ECG5000 Arrhythmia datasets, indicated towards the effectiveness of transformer encoder replacing over the existing methods (conventional encoders) for the purpose of ECG signal analysis and classification. The transformer encoder was evaluated against many cutting-edge deep learning models in further studies. They were successful in establishing that their model surpassed the other models in terms of various performance metrics. In summary, combining conventional DNN architectures such as CNNs/RNNs with more novel strategies such as transformer and attention mechanisms is noteworthy and more such studies must be encouraged.

Parallel to the development of DL models for ECG signal analysis, recently, multitudes of ECG data are made available for algorithm development and analysis. The datasets are available with varied lead-counts and signal lengths. Also, each recorded ECG is multi-label. These variations in ECG data characteristics makes it difficult for deep learning models to provide high performance over each of these datasets and classes. In light of these issues, handling multi- source ECG data is a challenge and developing more sophisticated deep learning models that can perform well on such datasets is always beneficial. Especially models that can extract both, short- as well as long-term variability-based cardiac abnormalities present in ECG signals.

Therefore, in this study, a fast-slow stream architecture based DNN model is proposed. This model, composed of Transformers and RNNs , is utilized to perform cardiac-abnormality pattern classification given multi-source ECG data. The reason for a hybrid architecture is as follows. It is computationally very expensive to supply the entire raw ECG signal directly to a simple RNN and if we compress the signal, then during the learning of these temporally compressed ECG signal representations, the same RNN poses severe inductive bias. There is an upside to learing from a compressed representation of a sequence as it is beneficial for generalization. Attaining generalization is one of the most desirable attribute of RNNs and in fact for every machine learning

model. In contrast, there are few DNN architectures that incur low inductive bias towards learning temporally compressed representations. One such architecture is a transformer network. Howevert these Transformers also have the fimiliar downside of incurring heavy computation costs on the process. Therefore, the idea of utilizing a hybrid (Transformers-RNN) architecture is intuitive and straightforward. The fast stream component of the architecture i.e. Transformers, are sensitive to sensory input and can capture localized or short-term details. In contrast, the slow-stream component of the architecture i.e. recurrent units, can memorize representation in long-term. Such strategies have been used earlier however it will help develop efficient model in multi-source ECG data based cardiac-abnormality pattern classification. Therefore, in this study, the proposed hybrid architecture is utilized in multisource ECG data.
The rest of the paper is divided into sections. Section 2 and its sub-sections incorporates the materials and methods utilized in the study. Section 3 provides results obtained and its discussion. Section 4 concludes the study.

2. Materials and Methods

2.1 Dataset: Description and Preparation: The 12-Lead multi-source ECG Database, Statistics, and Preprocessing

Overall, the 12-Lead multi-source ECG Database considered here for study is composed of 4 different databases. Individual database summaries are provided in Table 1. A total of 27 cardiac abnormalities are captured in the multi- source ECG data. Single or multiple cardiac abnormalities could be present in a single recording. These cardiac abnormalities along with abbreviations are listed in Table 2 and corresponding sample proportions in the consolidated database is shown in Figure 1. From Figure 1, it is clear that 'Sinus Rhythm' or 'SNR' has the largest number of samples whereas the 'Premature Ventricular Contractions' or 'PVC' has the lowest number of samples.

Table 1 Multi-source 12-lead ECG database summary

Database Attribute	CPS	Georgia	INCART	PTB and PTB-XL
Subjects	9458	15742	32	290, 18885
Records (length in seconds)	13256 (6-60)	20678 (10)	74 (NA)	516, 21837 (NA)
Sampling rate (Hz)	500	500	257	1000 (PTB), 500 (PTB-XL)
Mean Age	61.1	60.5	56	56.3, 59.8
Male, n (%)	5013 (53.1)	8500(54)	17(54)	211 (73), 10197 (54)
Lead, n	12	12	12	12
Classes	23	24	10	9, 71

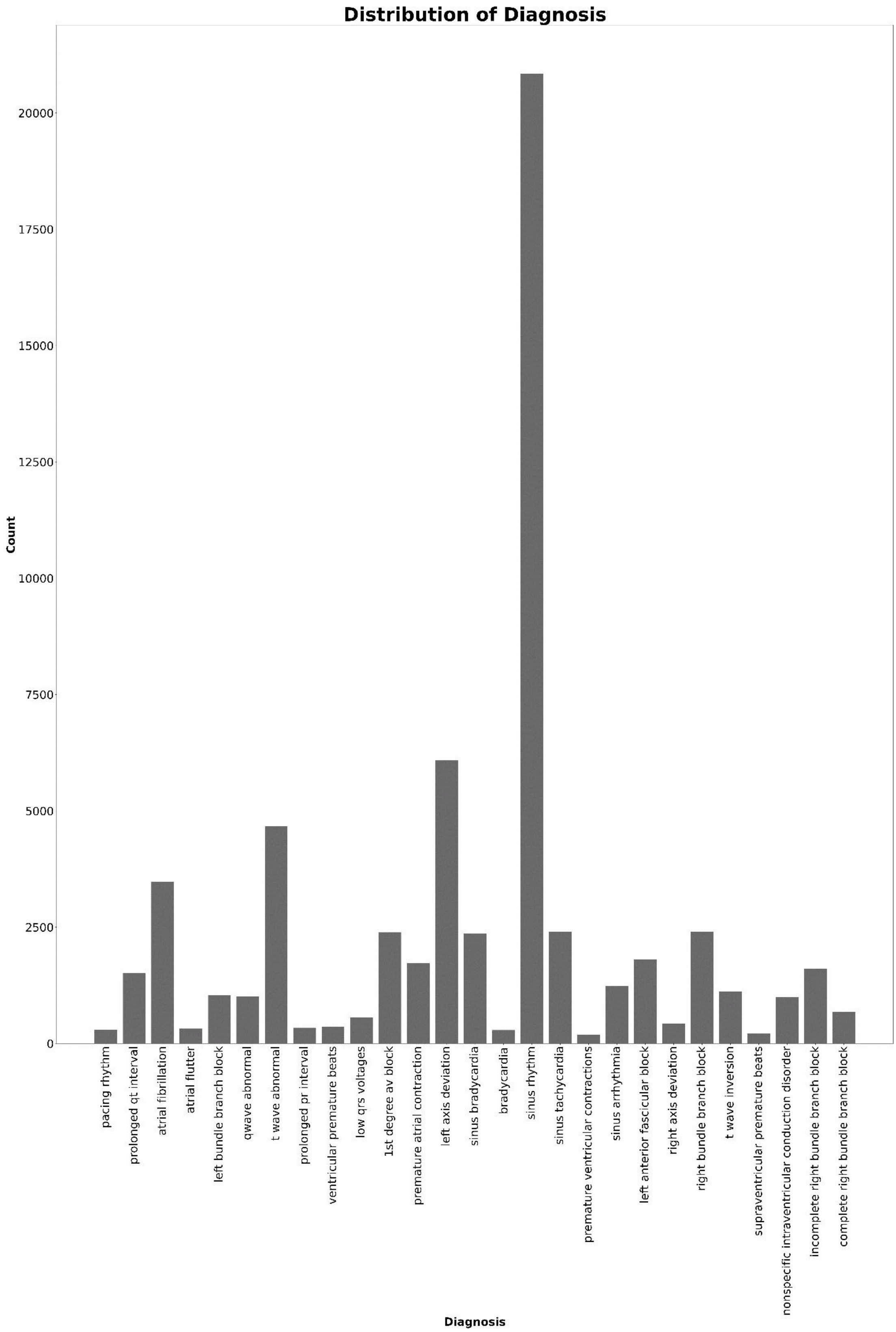


Figure 1 Bar chart showing the class-wise distribution of data samples.

Table 2 Summary of ECG data diagnosis sample proportions in individual database .

Diagnosis Abbreviation(Total samples)	**Sample proportions**					
PVC (188)	188	0	0	0	0	0
LPR (340)	0	0	0	340	0	0
SVPB (215)	53	4	0	157	1	0
Brady (289)	271	11	0	0	6	1
PR (301)	30	0	0	296	0	2
CRBBB (701)	113	0	0	542	28	18
RAD (465)	10	0	0	343	83	38
NSIVCB (1093)	4	1	0	789	203	96
AFL (423)	54	0	1	73	186	109
LAnFB (1916)	0	0	0	1626	180	110
LBBB (1197)	274	0	0	536	231	156
VPB (543)	8	0	0	0	357	178
LQRSV (748)	0	0	0	182	374	192
IRBBB (1871)	86	0	0	1118	407	206
SA (1476)	11	2	0	772	455	236
QAb (1252)	1	0	0	548	464	239
TInv (1550)	5	1	0	294	812	438
PAC (2188)	689	3	0	398	639	459
LAD (6564)	0	0	0	5146	940	478
IAVB (2946)	828	0	0	797	769	552
AF (4026)	1274	2	14	1514	571	552
STach (3050)	303	11	1	826	1261	648
RBBB (3051)	1858	2	0	0	542	649
LQT (2253)	4	0	0	118	1391	740
SB (3219)	45	0	0	637	1677	860
NSR (21944)	922	0	78	18092	1752	1100
TAb (5792)	22	0	0	2345	2306	1119
Dataset	CPSC (10330)	INCART (74)	PTB (490)	PTB-XL (21837)	Georgia (10344)	Validation (6630)

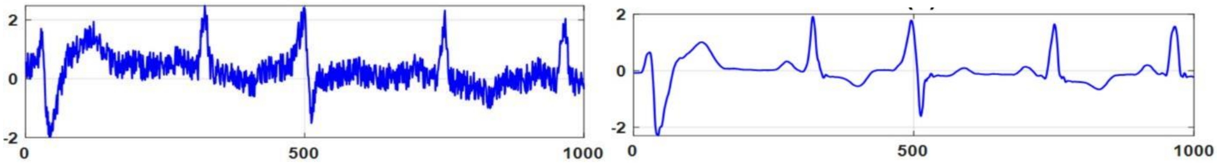
2.2 Data Preparation

The inherent noise in the recordings and the imbalance in cardiac-abnormality sample proportion are the issues thatneed attention and are addressed in this section.

Signal Denoising and Filtering

Observed ECG signals are subject to corruption by many types of noise, including baseline wander (BW), power-line interference (PLI), motion artefacts, and physiological artefacts. Of these, BW and PLI are the most significant factors that degrade the signal quality and render the visual and automated diagnostic inaccurate. Also, the frequency response of the ECG signals varies with time. Hence, it is necessary to eliminate artefacts and noise from these electrocardiogram (ECG) data in order to guarantee proper and reliable ECG signal analysis. During the preprocessing of electrocardiogram (ECG) data, several transformations are utilized in order to eliminate artefacts and noise. [8].

In this study, a denoised version is obtained after removal of noise incurred due to electrode contact noise, power line interference, muscle contraction, motion artefacts, baseline wandering, and random noise[9]. A sequential noise- reduction approach is followed to reduce noise from the raw ECG signals. Figure 2(a) shows a random sample ECG signal that is affected by these noises and artefacts. Frequency components above 50 Hz are removed using a Butterworth low pass filter. A LOESS smoother is then employed to supress the effects caused by the wandering baseline phenomena. Finally, non-local mean algorithm is used to handle other noises. Figure 2(b) shows the resulting ECG signal after the above-mentioned preprocessing steps are applied.



(a) (b)

Figure 2 (a) Raw signal, and (b) Filtered and denoised signal.

<u>*Imbalanced data*</u>

Another major issue with multi-source database is the imbalance in sample proportions which can adversely affect the performance of any machine learning oriented algorithm [10]. Here, this issue is handled via employing an empirical sample-weight allocation strategy. To compensate for the imbalanced data, we calculate a weight for each of the 27 diagnosis. The weight-value for each diagnosis is listed in Table 3. The weight decides how much any machine learning algorithm will learn from the different data labels (diagnosis). This filtered and balanced data is used for algorithm development is this study.

Table 3 ECG diagnosis label weight values.

Class	**Weight value**	**Class**	**Weight value**
0	72.08	14	74.83
1	14.24	15	1.03
2	6.20	16	8.97
3	68.63	17	114.63
4	20.70	18	17.38
5	21.27	19	11.93
6	4.61	20	50.47
7	63.38	21	8.97
8	59.04	22	19.38
9	38.76	23	100.23
10	9.00	24	21.62
11	12.46	25	13.38
12	3.54	26	31.55
13	9.14		

2.3 Fast-Slow Stream DNN for ECG Signal classification

Transformers are known for their ability to capture global dependencies in data, making them suitable for tasks where long-range dependencies are important such as the case in hand in this study. ECG signals reflect long-range dependencies. Transformers excel in tasks such as ECG signal analysis, where interpreting context over long sequences is critical for performance. Recurrent neural networks (RNNs), particularly LSTMs and GRUs, are suitable for capturing temporal dependencies in ECG data. Furthermore, during the learning of temporally compressed representations, a simple RNN poses a severe inductive bias. The upside of a compressed representation of a sequence is that it is beneficial for generalization. This is because the compressed representations have fewer irrelevant details and hence can be relatively easily re-used and re-purposed. In contrast, low inductive bias towards learning temporally compressed representations is shown by Transformers [11, 12]. Transformer has achieved SOTA results in physiological signal analysis with its pairwise attention mechanism with downside of having heavy computation costs. In fact, the computation attention mechanism in sections of signals is quadratic in nature. The Fast-Slow Stream Architecture DNNs proposed by [13] provides a model that utilizes these above tow strategies in a balancing manner such that optimal results are obtained.

The present study inspires from the fact that one can leverage both architectures for enhanced learning dynamics in ECG signal analysis and come up with a hybrid architecture. Incorporating transformers into the initial layers of a DNN model enables the model to rapidly grasp high-level features and relationships within the input ECG signal features. Incorporating RNNs deeper into a DNN architecture allows the model to refine its understanding of temporal dynamics in the data.

Inspired from this fast stream and slow stream computation, in this study, a novel model is developed and used for ECG analysis. The fast stream component i.e. the 'Transformers' has two properties; high capacity to react quickly to the ECG input variations and, a short-term memory whereas the slow stream i.e. the 'RNN' component, updates at a slower rate due to its long-term memory capacity and therefore able to summarize the most relevant information from a lengthy ECG observation sequence. Figure 3 shows the architecture of the fast-slow stream learning based deep neural network model. In the context of realization, first, we break the input electrocardiogram signal up into chunks of a definite size. This step provides the notion of creating small memory segments from the lengthier signal. While the slow stream consolidates and aggregates information across multiple ECG chunks, the fast stream component or the transformers operates within each ECG signal chunk. The slow stream updates itself per chunk on average. For example, a random ECG signal is broken down into 10 chunks that are termed as '*t_i*' where i varies from 1 to 10. Each chunk is fed into a separate transformer cell that contains a self-attention and a cross-attention module. Each transformer cell feeds into an RNN cell supplying it a transformative representation of the corresponding ECG chunk. The different RNN cells from each chunk are interconnected to each other as a timeline. This timeline is a course-grained or compressed representation of the original ECG observation. However, it appropriately reflects the variations in the ECG response of a patient over a longer period of time. The LSTM-RNN layer of the model shown in Figure 3 exploits this temporally compressed yet relevant information and helps in cardiac abnormality pattern classification. In short, the slow stream contains coarse-grained information that is present in the ECG signal, whereas the fast stream contains fine-grained local information of the input electrocardiogram. This information asymmetry improves generalization and adaptation performance of the model [14]. The fast and slow streams interact with each other though bottleneck of attention [13]. This hybrid architecture prevents the model from capturing extraneous ECG signal that lacks relevance for subsequent tasks.

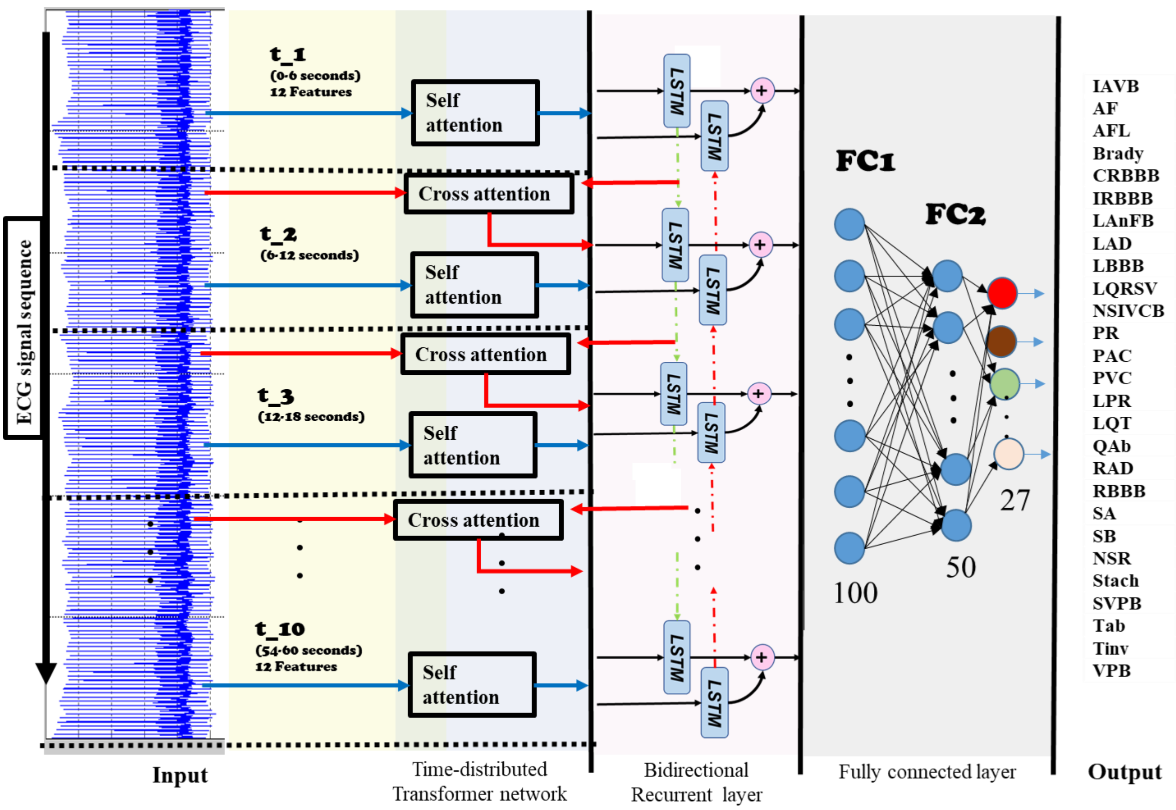


Figure 3 Figure showing the hybrid architecture of proposed Fast-Slow learning model.

3 Experiment Setup, Results, and Discussion

3.1 Setup

A cardiac abnormality pattern classification model is built based on the Fast-Slow Stream DNN discussed in section 2.3 for utilization with multi-source ECG data. The overall model architecture is shown in Figure 3. The model is composed of a data-transformation layer, a transformer layer, a recurrent layer, and a classification layer. The data-transformation layer breaks the entire input ECG signal into equal sized segments to be used as input to the transformer layer. The transformer layer is composed of several self-attention--cross-attention modules that are sensitive to subtle variations in truncated ECG signal. Each module has 1 cross-attention and 2 self-attention blocks with ReLU activations. The block interactively forms a compressed representation of the ECG timeline. Then the recurrent layer accepts input from each of these 10 modules and extracts information from the temporally compressed signal. ReLU activations and sigmoid activations are used in the recurrent layer. The extracted data is flattened via dense layer (with 100 nodes and ReLU activation) and then the dimensionality is reduced to 50 nodes (with ReLU activation). This 50- diemnsional feature is fed into a 27-node classification layer with sigmoid activation at each node for multi-label classification. The sigmoid activation in the classification layer allows multiple classes to be *true* simultaneously. This helps the current study. The model architecture summary and hyperparameter settings are listed in Table 4. Amongst all the DNN model hyperparameters, this model settles on specific values of few hyperparameters based on empirical testing or hyperparameter tuning and others based on literature references. For example, the chunk size is finalized via grid-search hyperparameter tuning strategy applied on 3 different values. This model is trained on the ECG dataset discussed in section 2.1. The model is trained on 80% of the samples from the entire dataset and 10% of the it is used for model validation. It is notable here that the training and validation splits are composed from different classes based on their proportions in the entire dataset. Lastly , a 10% of the entire dataset is used for model testing. Model performances are reported on this set.

Table 4 The proposed model architecture and hyperparameter settings.

ECG signal classification model with Fast-Slow stream DNN	
Number of layers	4
Attention mechanism	Multiple head attention
Feedforward network dropout size	0.2
Attention network dropout size	0.1
Chunk size	500
‘r’ (One Cross Attention per *r* Self Attention)	2
Number of classes	27
Epochs	30
Learning rate	1e-4
Weight decay rate	1e-4
Number of heads	1
Cross-validation folds	3
Activation functions	Gaussian error linear unit for FFN
loss	Categorical Cross-Entropy
Optimizer	Adam
Performance metric	Accuracy

3.2 Model performance: Results, and Discussion

The proposed model performed satisfactorily on the ECG data. A confusion matrix normalized over the number of total recordings is reported. Since multiple labels can be assigned to one recording, the proposed model is capable of producing multiple outputs for. To obtain the scoring metric, contribution from each recording are normalized. This is achieved by dividing by the number of output classes with positive value. For each recording $k = 1$ to n, let y_k be the set of positive classifier outputs and x_k be the set of positive labels. The new confusion matrix is calculated as

$$a_{ij} = \sum_{k=1}^{n} a_{ijk},$$

Where,

$$a_{ijk} = \begin{cases} \frac{1}{|x_k \cup y_k|}, & \text{if } c_i \in x_k \text{ and } c_j \in y_k, \\ 0, & \text{otherwise.} \end{cases}$$

Here, for any recording k , the number of distinct classes with a positive label and/or classier output isrepresented by the quantity $|x_k \cup y_k|$.

Figure 4 presents the performance score matrix for the proposed model. From figure 4, it is evident that the

proposed model performs satisfactorily given 27-class classification problem with multi-source ECG data. The proposed model is able to classify the 'Brady' with highest score of 0.59 and is able to classify ;SICV' with lowest score of 0.12. It is also evident from the matrix is that the 'SNR' class is mixing with all other classes. This is may be due to the large proportion of SNR samples (say 54% in case of CPS) in the whole dataset and even after weight allocation, the number of samples are still able to bias the model's performance.

This issue could be a scope for further investigation. It seems as if the model is giving a lot of false negatives as well

i.e. a cardiac abnormality pattern is present in the signal but the model is identifying the signal as normal. For example, the 'SA' cardiac abnormality pattern is identified as SNR with a significantly high score of 0.37 whereas the score for it being correctly identified is only 0.20. In summary, the model is able to perform satisfactory classification over 27 classes however there is scope for improvements.

To compare the performance of the proposed model, a one-dimensional fully connected network or FCN, one- dimensional Resnet-1D (Residual network) that has been used for RCG signal classification in [3, 15] are considered here. Also, and a LSTM-RNN model is also considered however its results ate only listed in table since detailed comparison with two referenced models is sufficient. Figure 5(a), and 5(b) present the performance score matrices for the FCN and the Resnet-1D model respectively. Table 5 tabulates the performance of the models. It is evident that average score over the digonal elements is best for the Resnet-1D model at 0.32. However, the proposed model also provides a score of 0.31 that is significantly comparable to Resnet-1D. Moreover, the lowest score for Resnet-1D is 0.0 for 'RAD' which means the Resnet-1D wasn't able to classify a single recording of 'RAD' class correctly. Same goes for the FCN model as it is unable to classify a single recording of 'RAD' correctly. In contrast, the proposed model provides a score of 0.12 for 'RAD'.

These inferences indicate to the bias nature of Resnet-1D and FCN model towards classes with high sample proportions. The proposed model is better in terms of generalization and hence superior for multi-source ECG data of variable class sample proportions. However, the proposed model also reflects a higher 'true-negative' score over each class. This is interpretable from the high scores of SNR i.e. sinus normal rhythm in each of the diseases. This could be due to the presence of numerous SNR segments along with abnormality patterns in each ECG observation. This leads to leaking of SNR and different abnormality patterns into each other during transformations through the DNN model layers. This process confuses the proposed model as it considers and exploits long-term time dependency. Therefore, the model suffers from this issue. A deeper dive into the weights of long- and short-term memory components is needful in futurestudies.

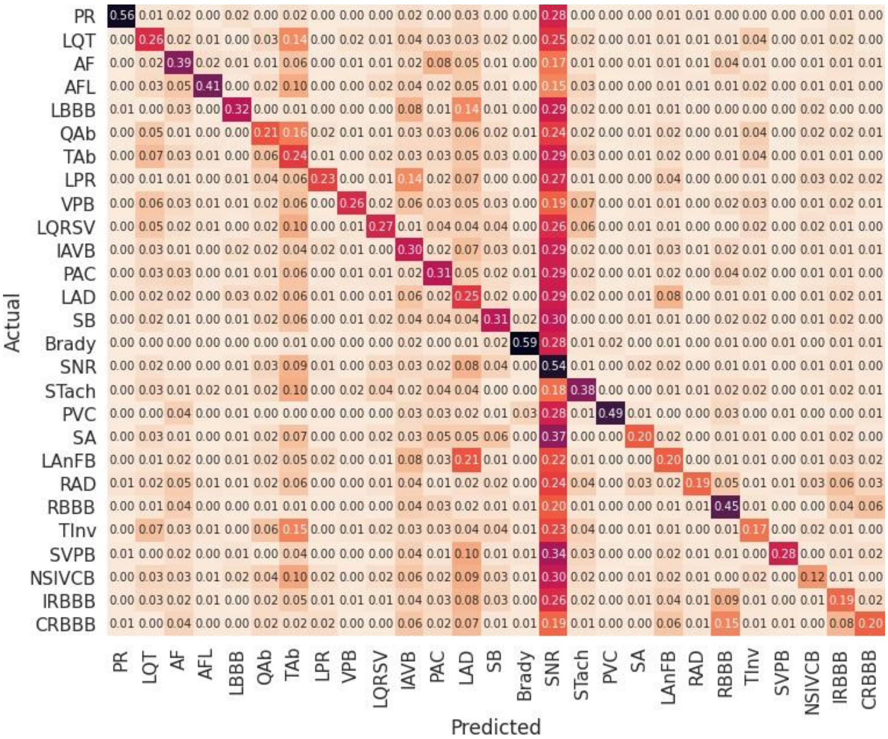


Figure 4 Proposed model performance score matrix.

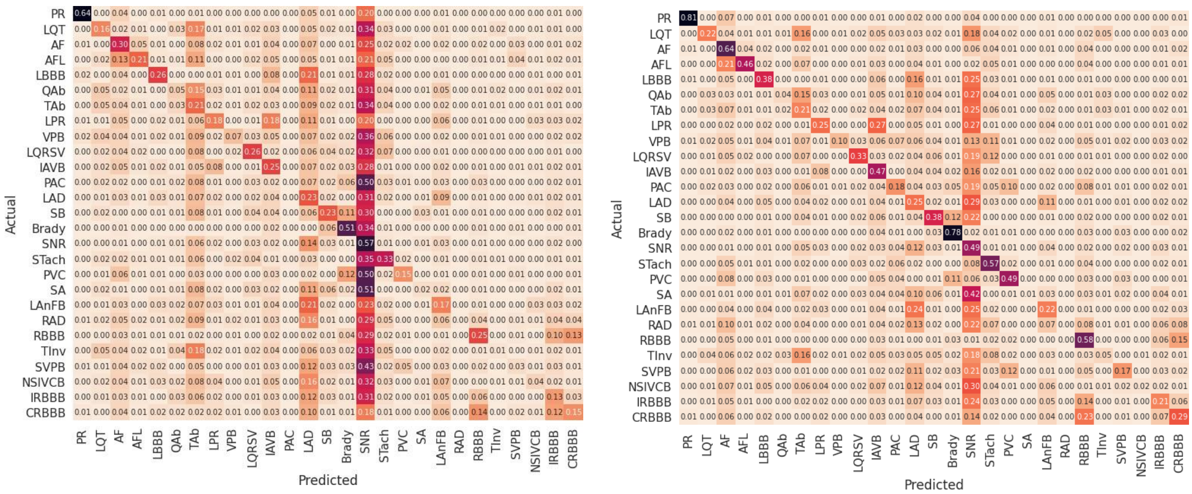


Figure 5 Performance score matrix for (a) fully connected dense model, and (b) Resnet-1D model.

Table 5 Summary of model performances over the multi-source ECG data

Model	**Scores (over only the diagonal elements)**		
	Best score	**Worst score**	**Average score**
Proposed	0.56	0.12	0.31
Fully connected	0.64	0.0	0.30
Resnet-1D	0.81	0.0	0.32
LSTM-RNN	0.70	0.05	0.28

4 Conclusion

In this study, a cardiac-abnormality pattern classification approach is developed successfully for use in multi- source ECG data. The 27-class multi-source ECG dataset is prepared using 4 popular datasets i.e. the CPS dataset, theINCART dataset, the PTB and PTB-XL, and the Georgia dataset that are available publicly. Each dataset has multi- label 12-lead dataset. The inherent issues of class sample imbalance and noisy samples is addressed as well. Overall, 27 cardiac abnormality conditions are identified as target class labels or patterns. The use of a fast-slow stream DNN architecture is considered to build a 27 cardiac-abnormality patterns classifier. The fast-stream component of the architecture helped capturing subtle details of the ECG signal on a localized level i.e. at *chunk* level.

Whereas, the slow-stream component was able to memorize long-term compressed representations in the multi-source ECG signals. The model performed satisfactorily overall with highest classification score of 0.59 and lowest score of 0.12. In future, the impact of inter-leakage of SNR class ECG patterns to abnormality patterns needs investigation. Further to this, a deeper dive into the weights of long- and short-term memory components is also needful in future studies to counter this impact. Also, readers may attempt to change the class weight strategy used here in handling class-sample imbalance with imputer strategy to investigate the effect.

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