

Hybrid Deep Learning based approach for ECG Heartbeat Arrhythmia Classification

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Research Article

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Abstract

Background: Myocardial infarction, or heart attack, is caused by a blockage of a coronary artery, which prevents blood and oxygen from accessing the heart properly. Arrhythmias are a form of CVD that refers to irregular variations in the normal heart rhythm, such as the heart beating too quickly or too slowly. Arrhythmias include **Atrial Fibrillation(AF),Premature Ventricular Contraction(PVC), Ventricular Fibrillation(VF), and Tachycardia** are just a few examples of arrhythmias. It aggravates if not detected and treated on time i.e., on-time /proper diagnosis of arrhythmias may minimize the risk of death. It is very labor-intensive to externally evaluate ECG signals, due to their small amplitude. Furthermore, the analysis of ECG signals is arbitrary and can differ between experts. As a consequence, a computer-aided diagnostic device that is more objective and reliable is needed.

Methods: In the recent era, Machine Learning based approaches to detect arrhythmias has been established proficiently. In this view, we proposed a hybrid Deep Learning-based model to detect three types of arrhythmias on MIT-BIH arrhythmia databases. In particular, this paper makes two-fold contributions. First, we translated 1D ECG signals into 2D Scalogram images. When one-dimensional ECG signals are turned into two-dimensional ECG images, noise filtering and feature extraction are no longer necessary. This is notable since certain ECG beats are ignored by noise filtering and feature extraction. Then, based on experimental evidence, we suggest combining two models, 2D-CNN-LSTM, to detect three forms of arrhythmias: Cardiac Arrhythmias (ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR).

Results: The experimental findings indicate that the model attained 99\% accuracy for "normal sinus rhythm," 100\% accuracy for "cardiac arrhythmias," and 99\% accuracy for "congestive heart failures," with an overall classification accuracy of 98.6\%. The sensitivity and specificity were 98.33\% and 98.35\%, respectively. The proposed model, in particular, will aid doctors in correctly detecting arrhythmia during routine ECG screening.

Conclusion: As compared to the other State-of-the-art methods our proposed model outperformed and will greatly minimise the amount of intervention required by doctors.

Full Text

This preprint is available for [download as a PDF](#).

Figures

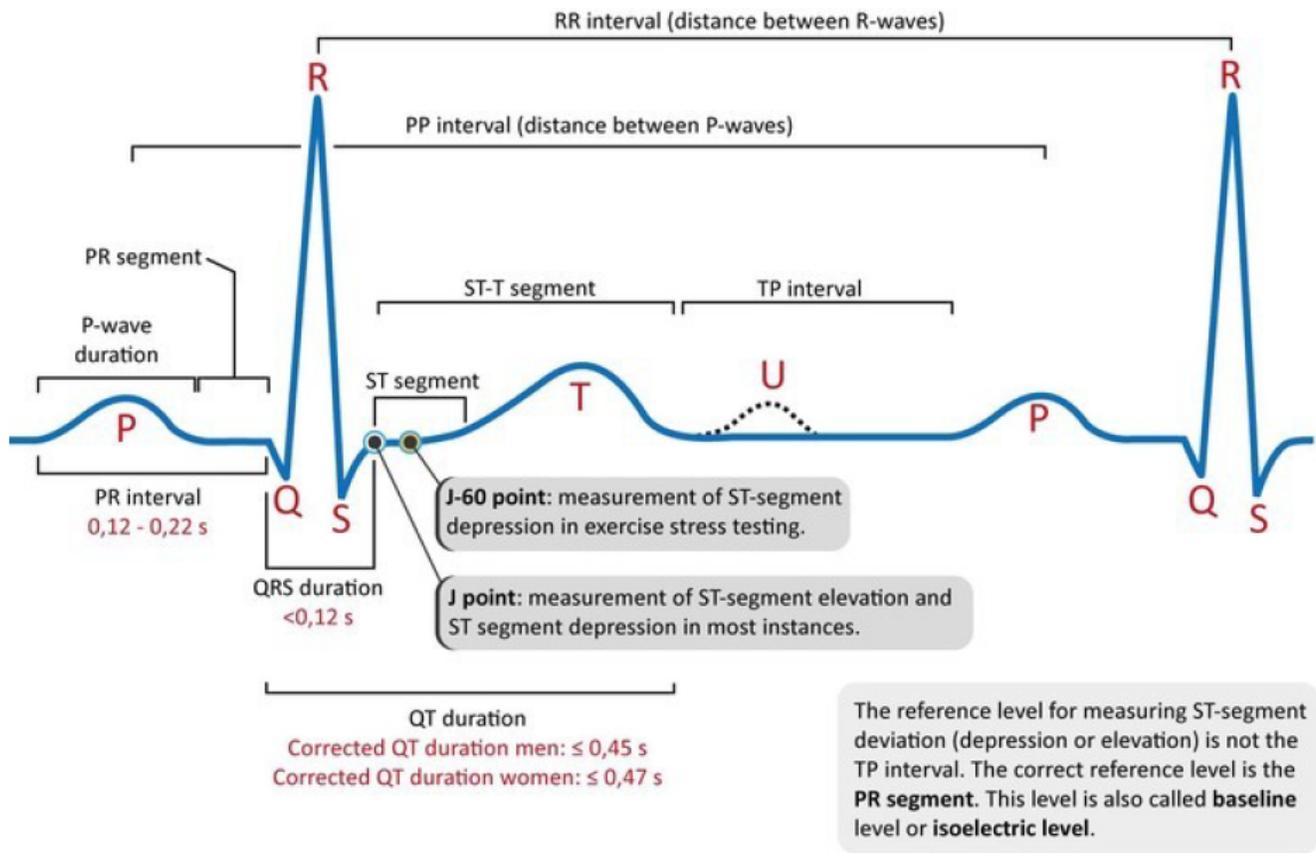


Figure 1

Representation of different ECG waveforms [42]

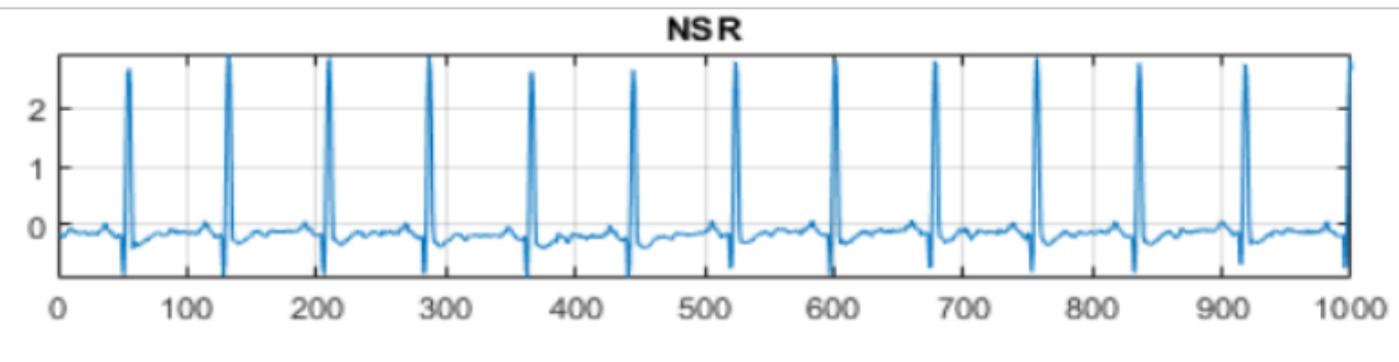
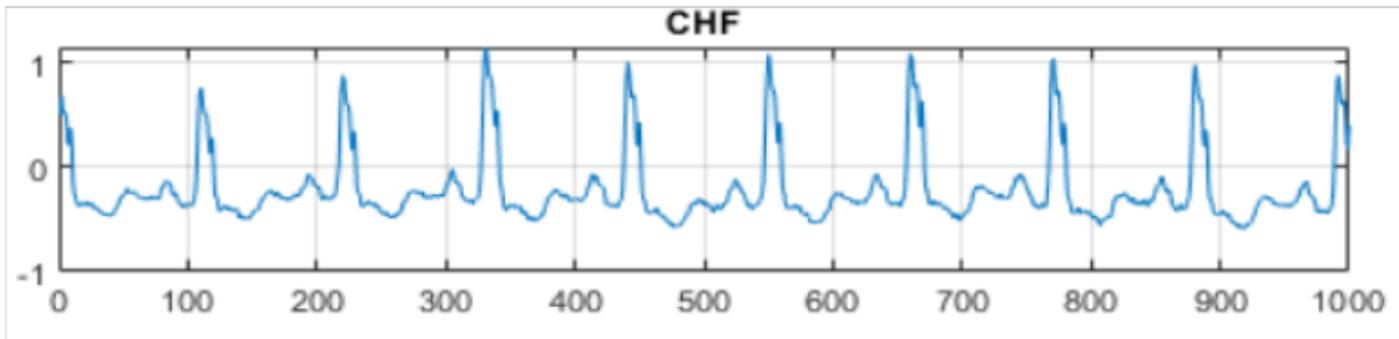
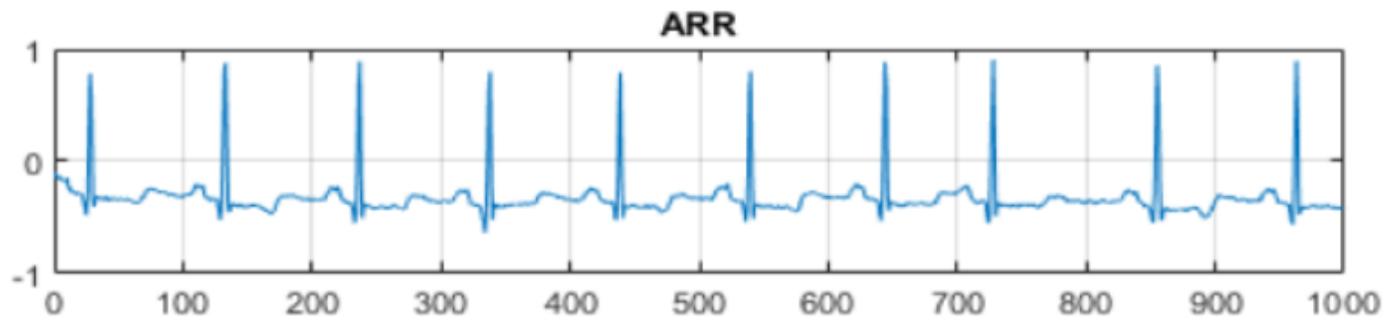


Figure 2

Distribution of ECG waveforms from three classes of arrhythmias

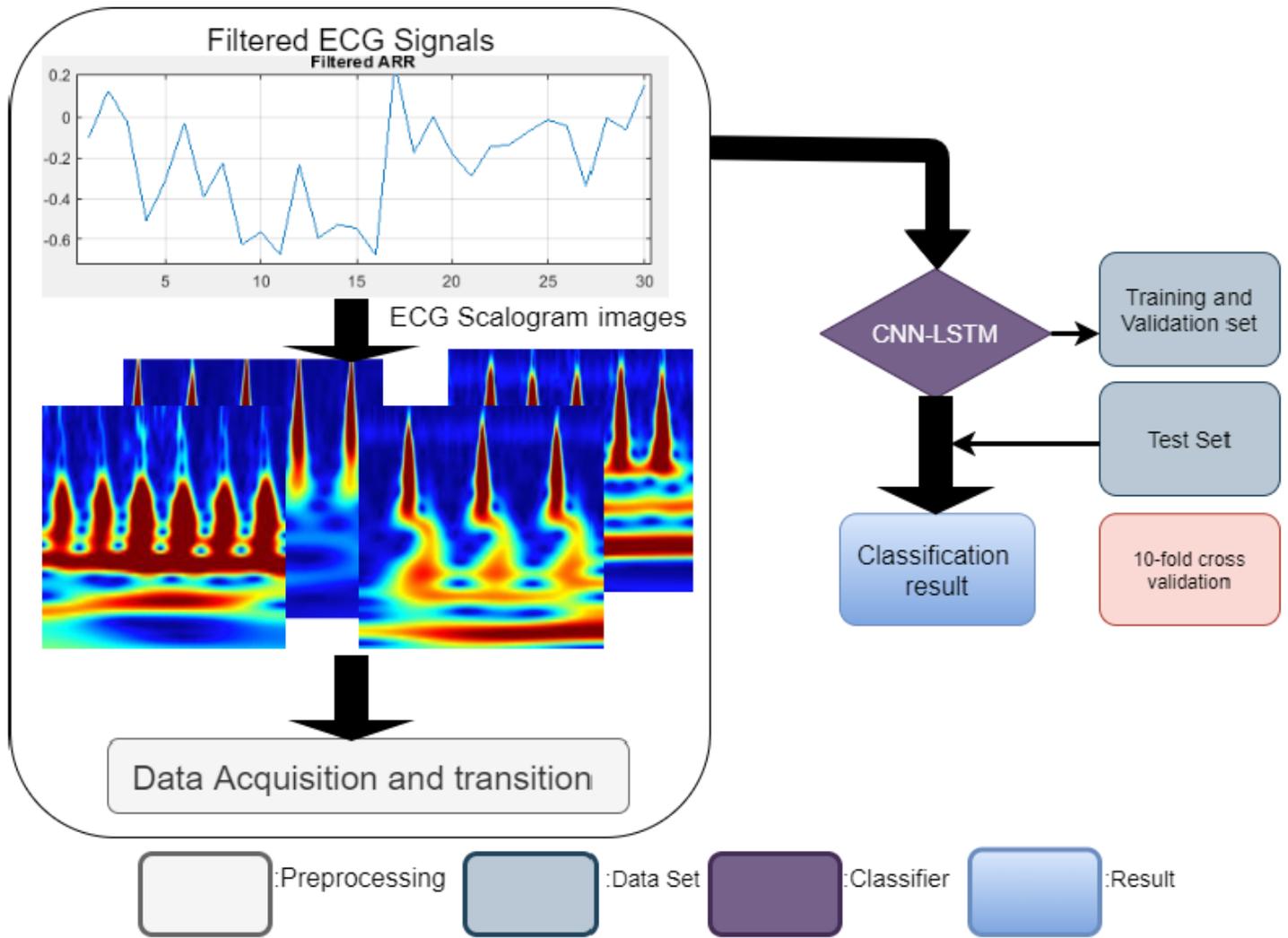


Figure 3

Complete procedure followed in classification of Arrhythmia's

$\text{Re}[\omega(t)]$

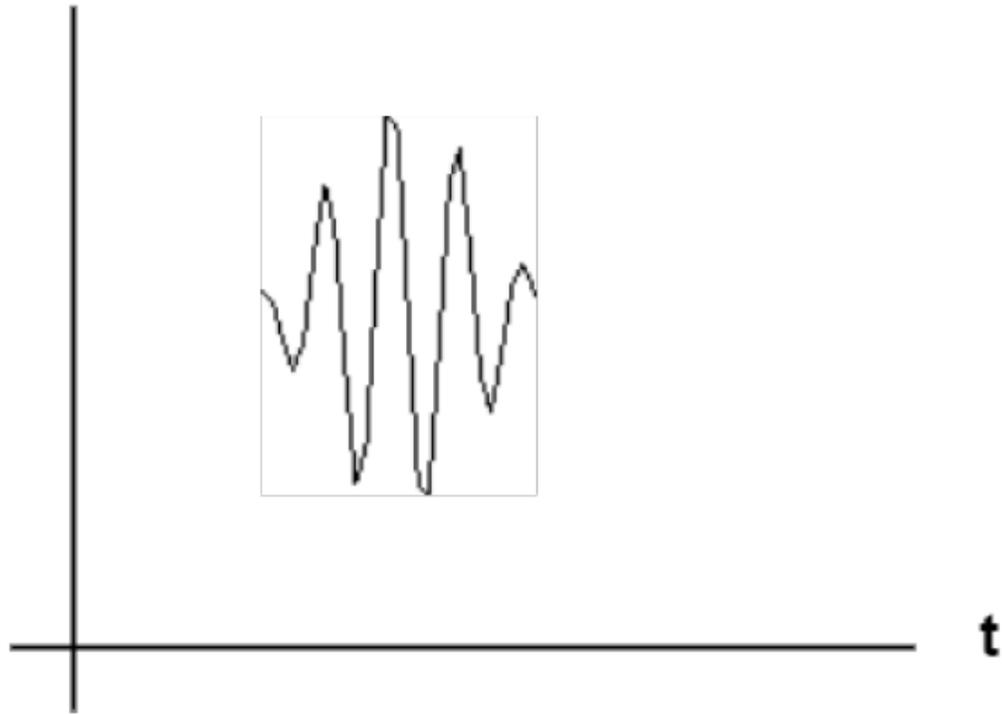


Figure 4

Magnitude representation of Morlet Wavelet

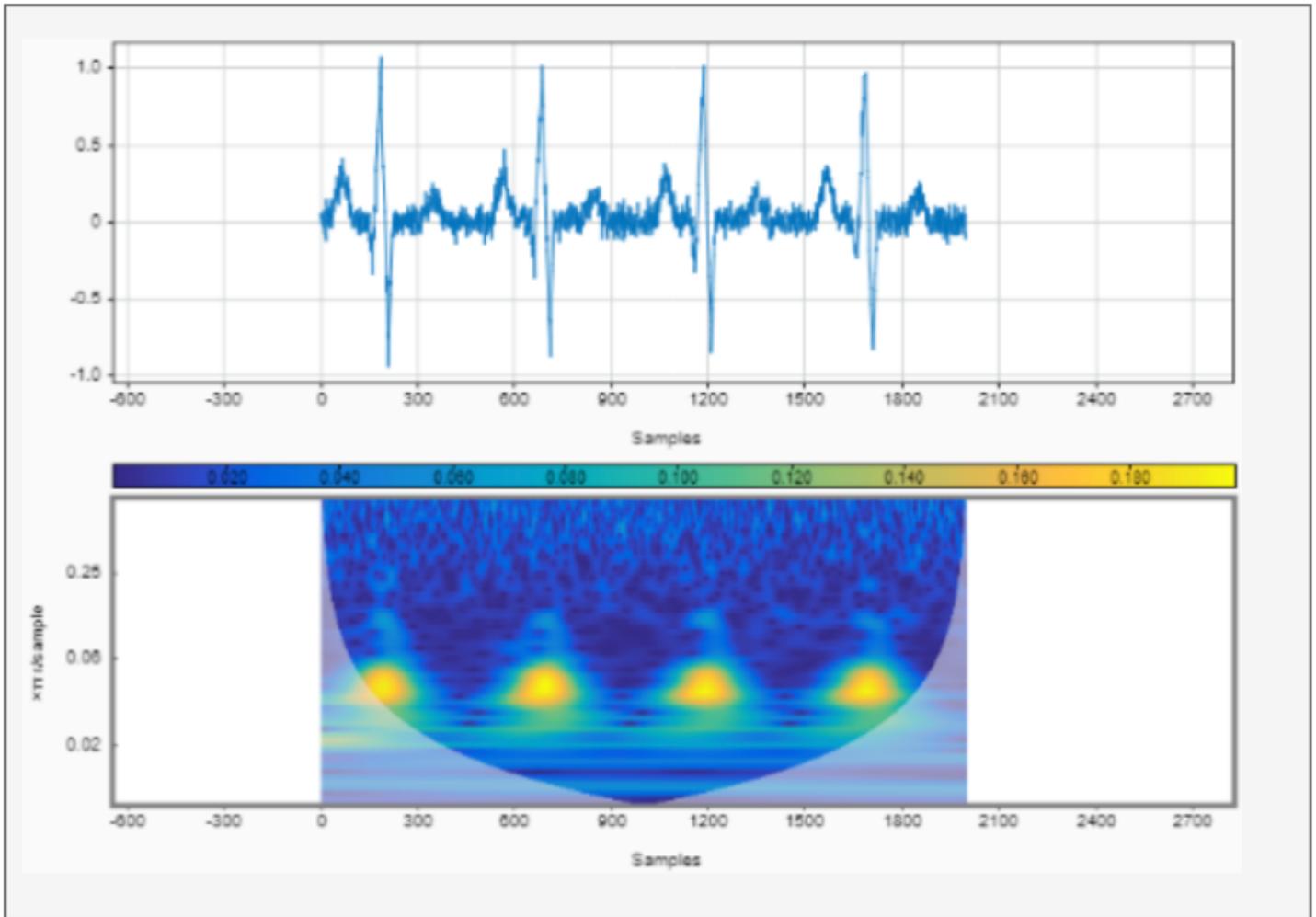
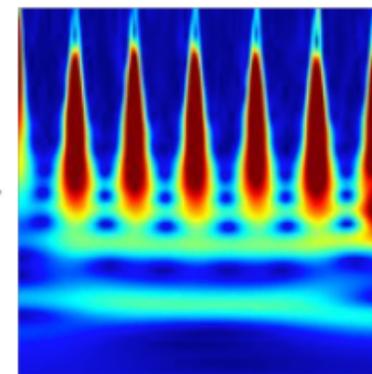
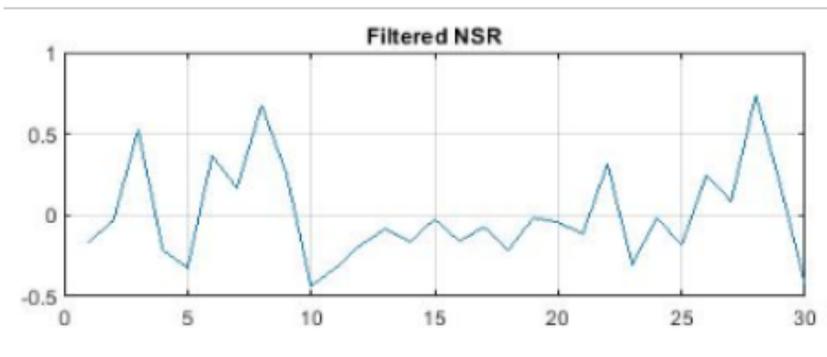
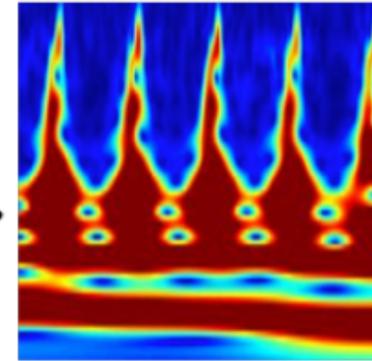
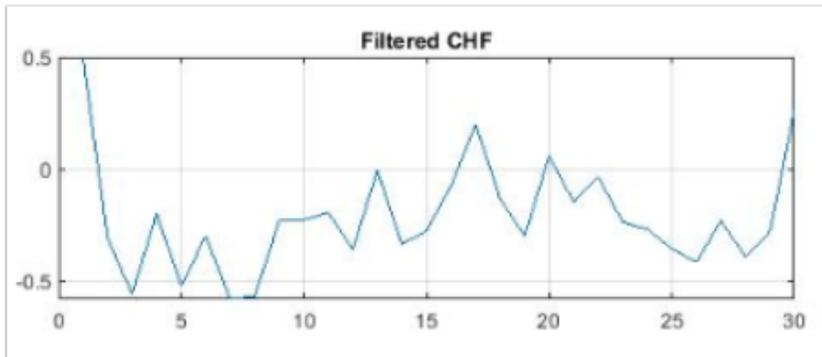
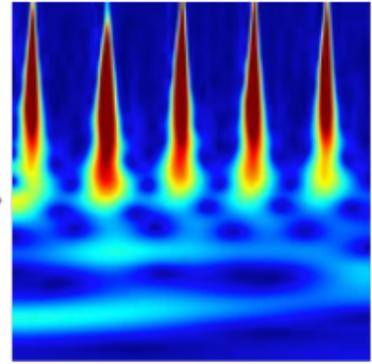
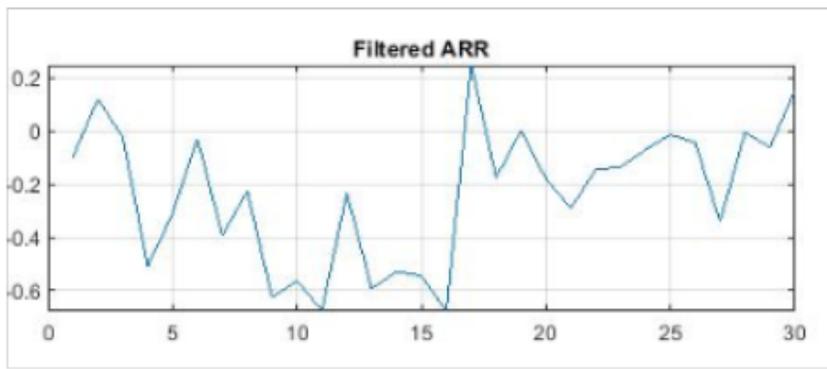


Figure 5

Different coefficient representation of Scalogram.



ECG Signals

Scalogram Images

Figure 6

Conversions of 1D ECG signals into Scalogram images using CWT

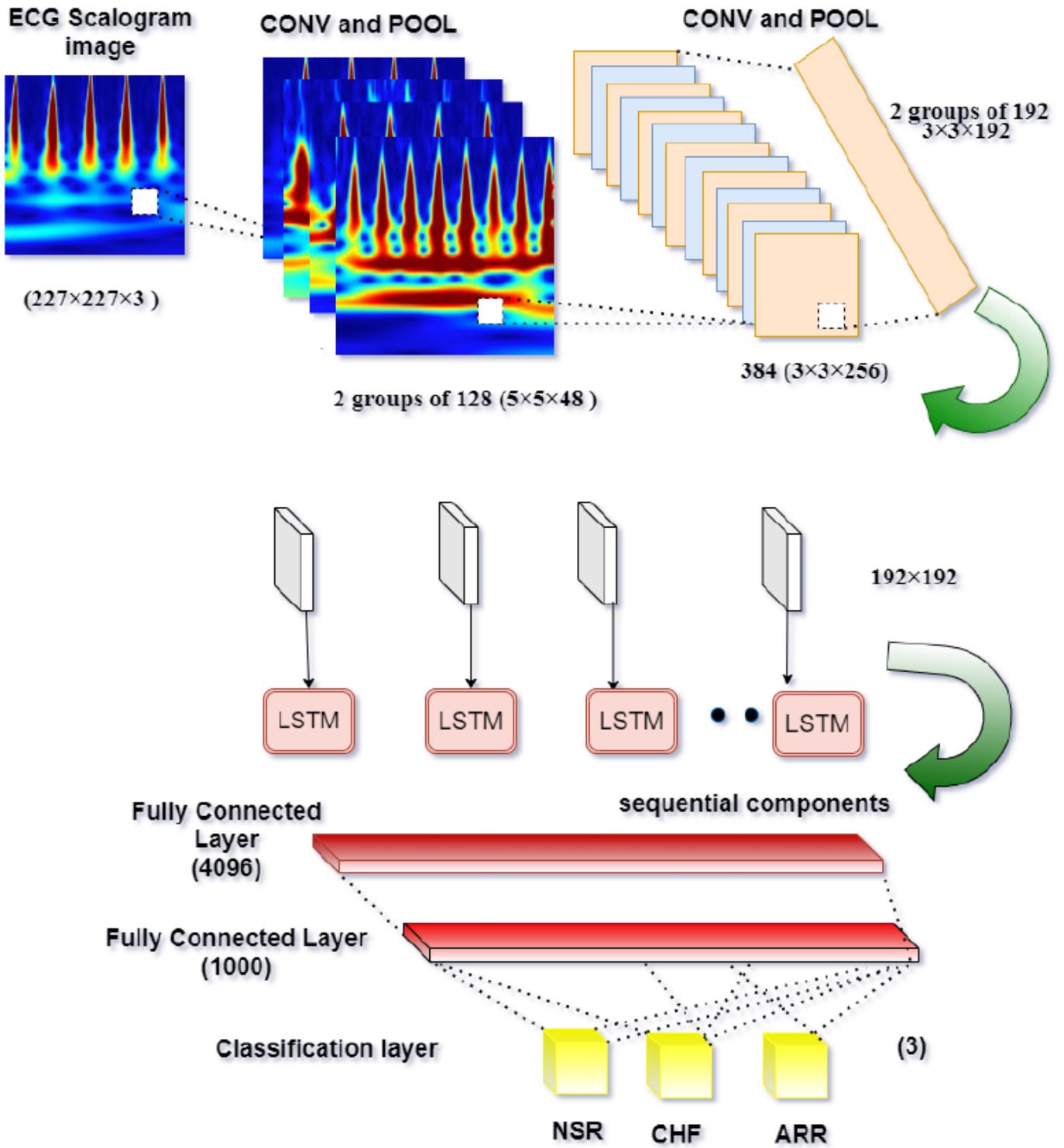


Figure 7

Architectural details of the proposed model.

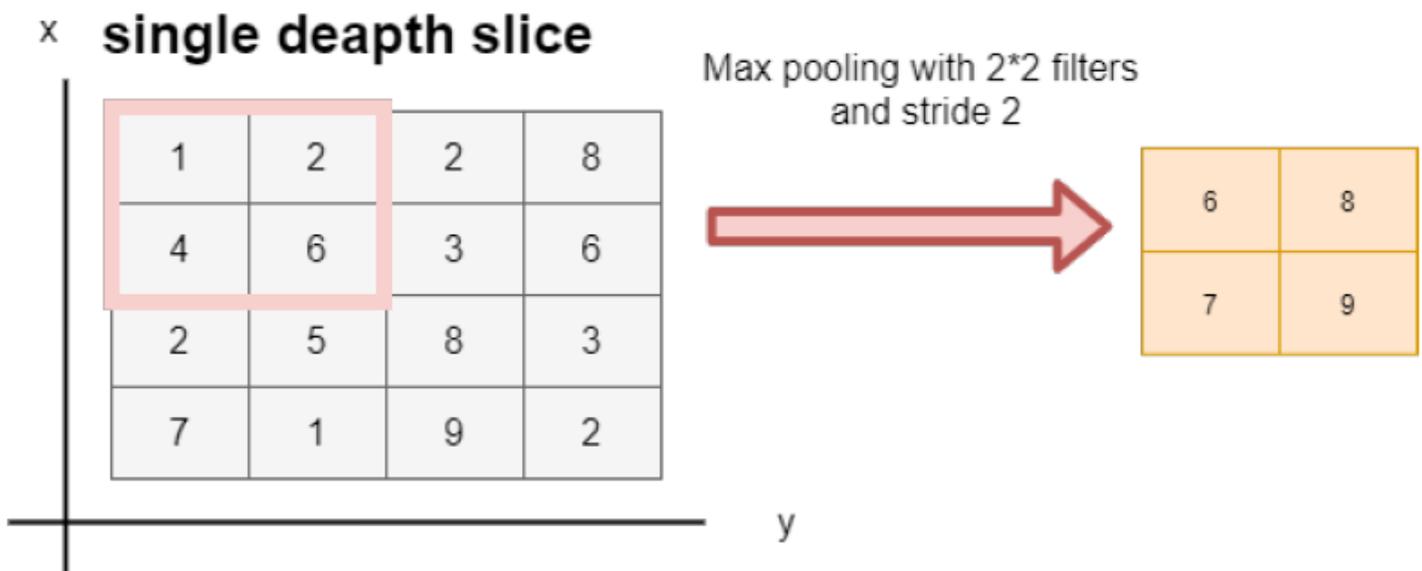


Figure 8

Describes Process of Max Pooling Layer.

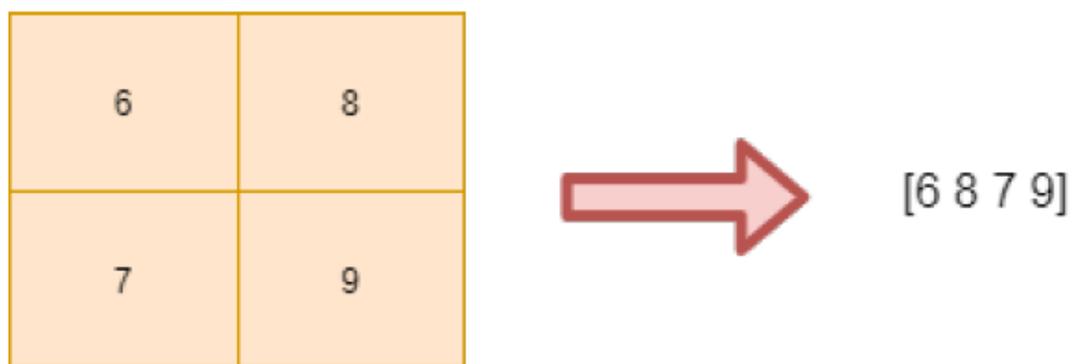


Figure 9

Conversions of 2D matrix to 1D vector.

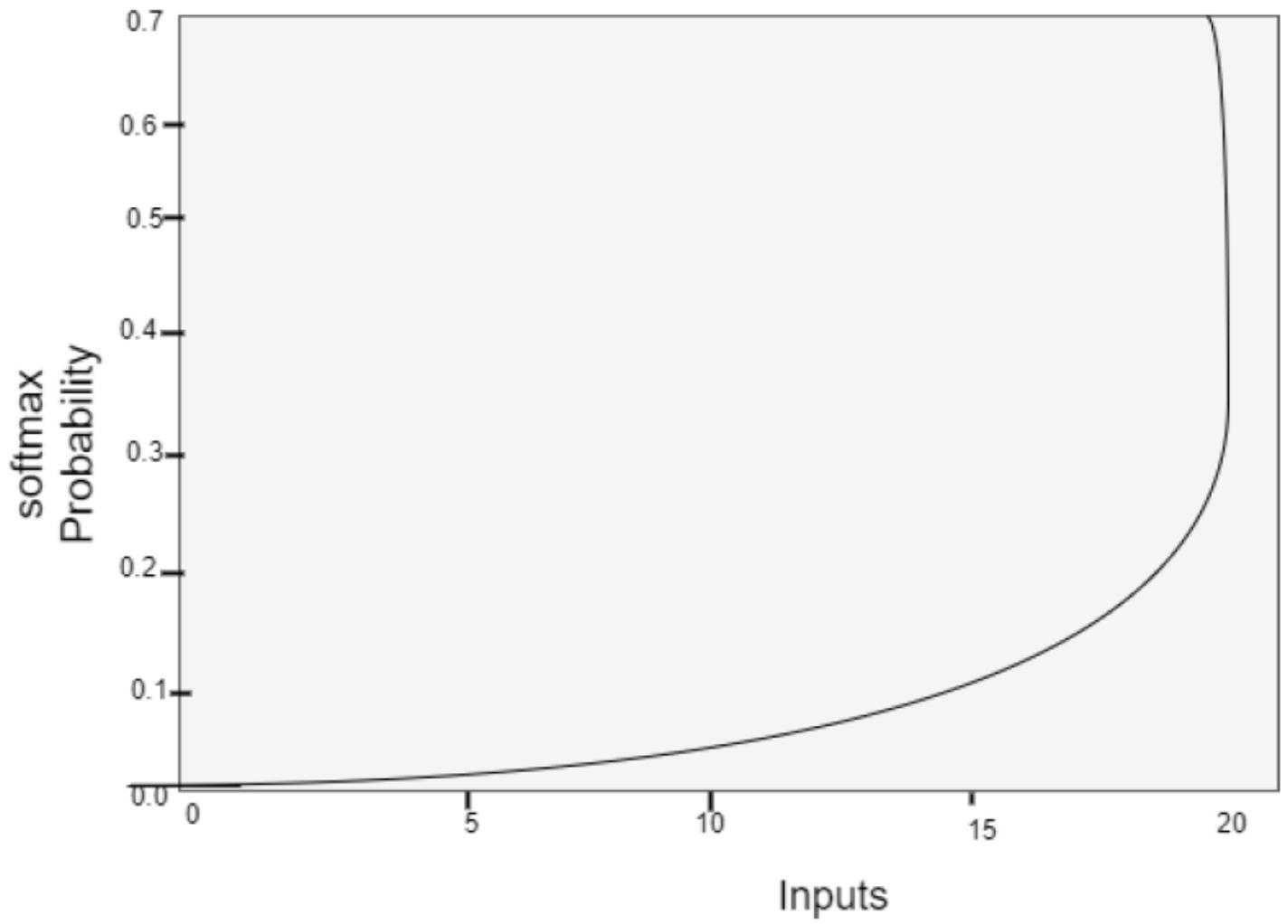


Figure 10

Softmax function for multi-class classification.

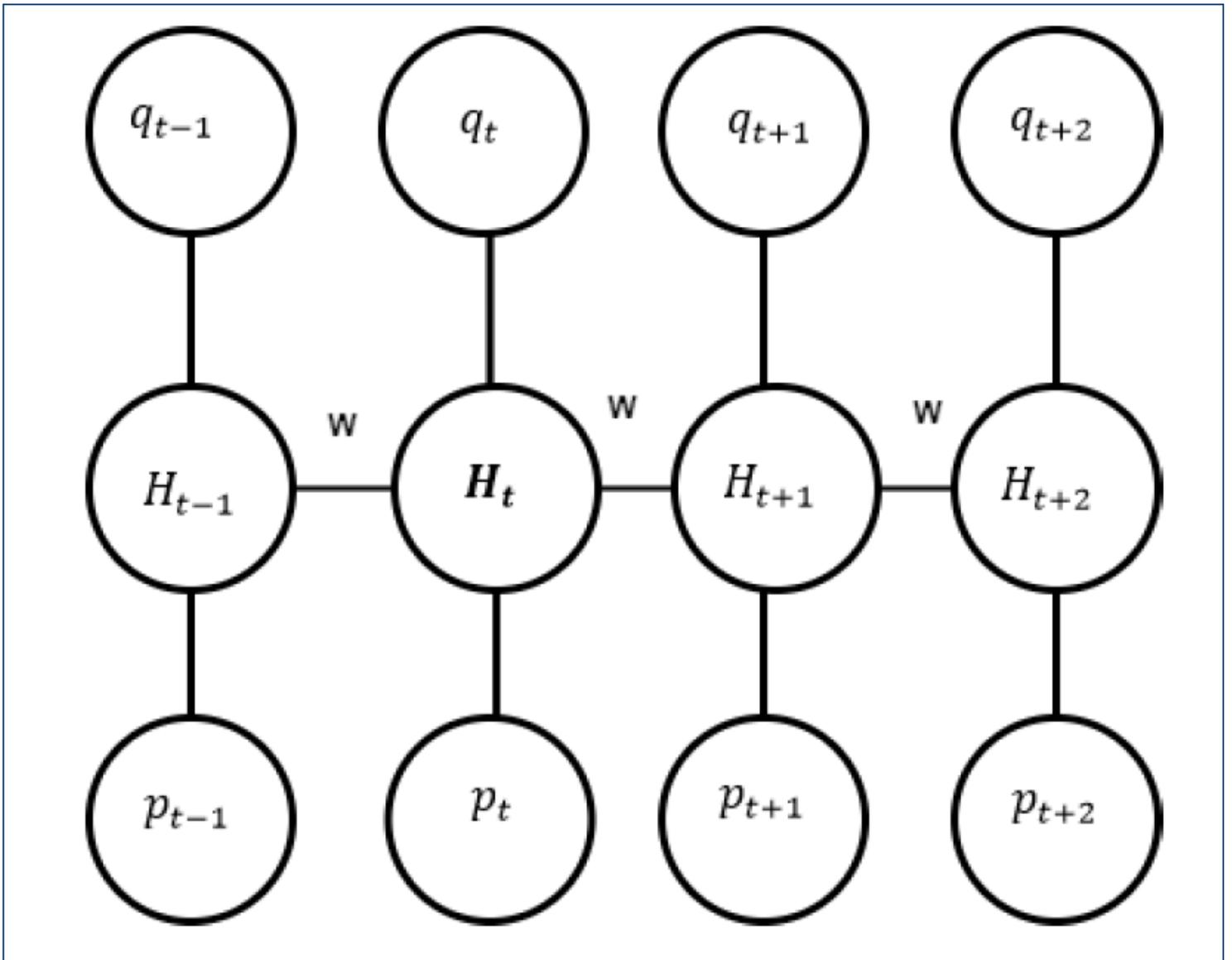


Figure 11

working of Recurrent Neural Network.

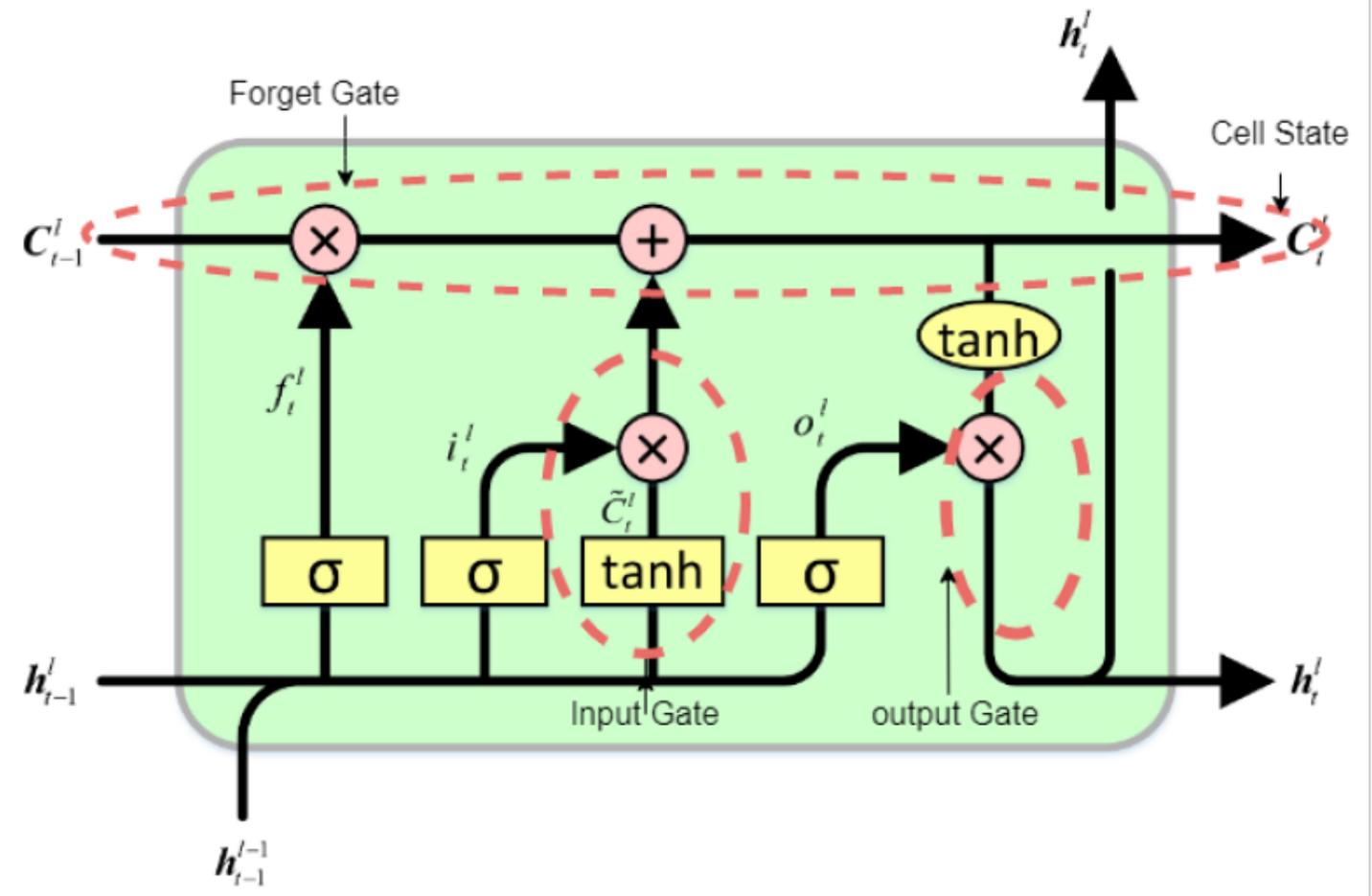


Figure 12

Long Short Term Memory Cell

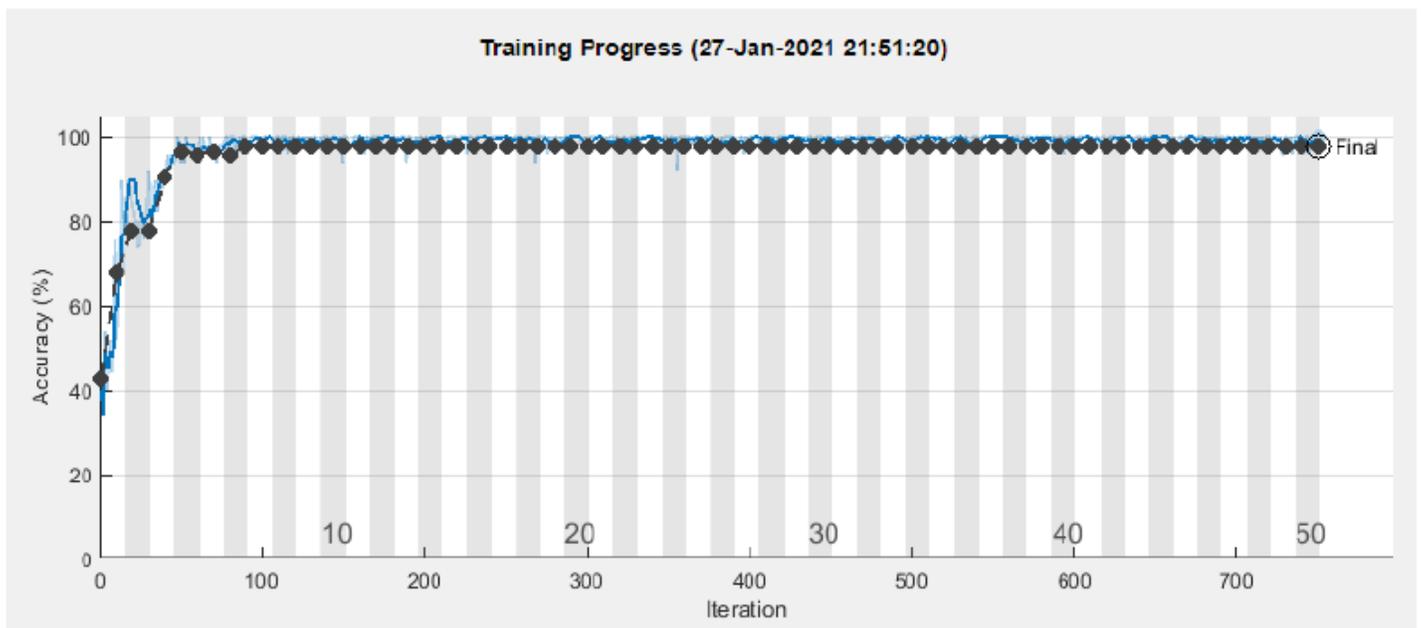


Figure 13

Progress of the training and validation accuracy with dropout regularization

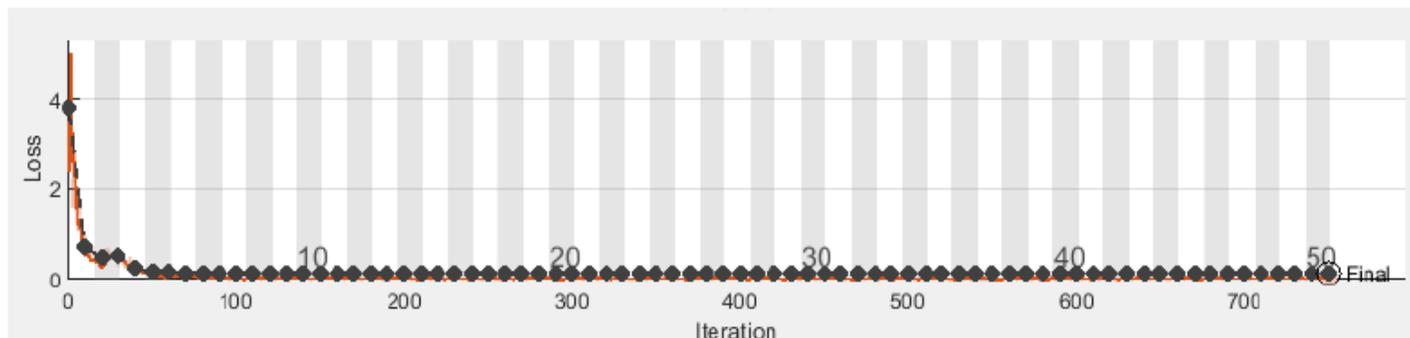


Figure 14

Progress of the training and validation loss

Confusion Matrix

	ARR	CHF	NSR	
ARR	48 32.0%	0 0.0%	0 0.0%	100% 0.0%
CHF	1 0.7%	50 33.3%	0 0.0%	98.0% 2.0%
NSR	1 0.7%	0 0.0%	50 33.3%	98.0% 2.0%
	96.0% 4.0%	100% 0.0%	100% 0.0%	98.7% 1.3%
	ARR	CHF	NSR	
	Target Class			

Figure 15

Confusion Matrix represents accuracy of 2D-CNN-LSTM