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# Noise Mitigation in ECG Signal Using Unidirectional and Bidirectional Long Short-Term Memory (LSTM) Neural Network

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**Abstract**

Effective and proper analysis of Electrocardiogram (ECG) signal is important for accurate diagnoses of patient ECG. However, ECG signal is frequently corrupted with different artifacts such as 50Hz powerline noise, baseline wander noise, and motion artifact, etc. Consequently, these interferences that affect the ECG signal may leads to inaccurate diagnoses of patient ECG. Several researches have been done to reduce these interferences using recurrent neural network and unidirectional long short term memory (LSTM) neural network. However, recurrent neural network suffers from vanishing gradient problem and fails to learn the long term dependencies of the sequence data. Although, the unidirectional LSTM neural network was able to solve the vanishing gradient problem but then it fails to learn future data which is needed to improve the network performance. Hence, this work presents a novel approach to de-noise ECG signals, utilizing unidirectional and bidirectional long-short term memory (UBLSTM) neural network. This technique allows the networks to learn both past and future data. The network is trained using ECG data collected from physionet challenge 2017. The validation results showed clearly that the proposed model has successfully filtered the ECG signal corrupted with powerline noise and baseline wander noise with an improved signal to noise ratio (SNR) of 22.8dB, 22.1dB and 20.2dB for all the three records ECG signals considered in this work.

**Keywords:** Baseline wander noise, LSTM, Powerline noise, SNR, UBLSTM.

## 1. Introduction

Heart diseases are ranked high among the major causes of death in both men and women. Early diagnosis and prompt medical treatment of heart diseases can prevent sudden death of the patients who have any form of cardiac disorder (Rosiek and Leksowski 2016). One of the basic diagnostic workup for patients with cardiac disorders is electrocardiogram (ECG or EKG) signals. This ECG signal represents an extremely important measure for doctors as it provides vital information about a patient's cardiac condition and general health. ECGs are often performed when a patient complains of palpitations, lightheadedness, or syncope (passing out). ECG is a diagnostic tool that measures and records the electrical activity of the heart from electrodes placed on the skin in specific locations (Bommadevara, Rao and Kumar 2011). Figure 1 depicts the standard ECG signal.

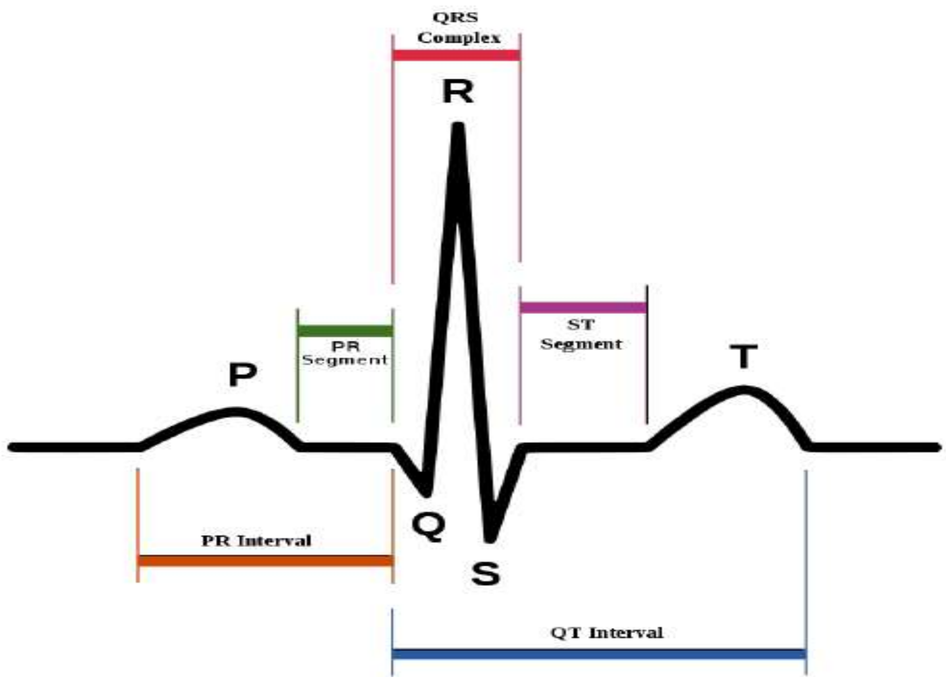



**Figure 1: Standard ECG signal (Anthony, 2007)**

The changes in the *P* wave, QRS complex, and *T* wave parameters indicate an illness of the heart that may occur by any reason. Cardiologist readily interprets the ECG waveforms and classifies them into normal and abnormal patterns (Narwaria, Verma and Singhal 2011). The frequency bandwidth for therapy of the ECG signal is from 0.05Hz to 100Hz, and the highest peak is about 1mV (Duong, Nguyen and Dang 2015). When diagnosing patient with cardiac disorder the ECG signal is usually disrupted with different types of artifacts such as power line interference, electrode contact noise, motion artifacts, muscle contraction, base line drift, and instrumentation noise generated by electronic devices, electrosurgical noise (Narwaria, Verma and Singhal 2011). From various artifacts that contaminate ECG recording, the most common is the power line interference and baseline wander noise. The power line noise is predominant within a frequency of 50Hz. The interference may be due to stray effect of the alternating current fields due to loops in the patient's cables. Other causes are loose contacts on the patient's cable as well as dirty electrodes. When the machine or the patient is not properly grounded, power line interference may even completely obscure the ECG waveform. Care should be taken to suppress these transients (Kadam and Bhaskar 2012).

Baseline wander is another artifact that corrupts the recorded ECG signal and can hinder the correct diagnosis of patient ECG. Baseline wander noise is a low-frequency noise of around 0.5 to 0.6 Hz (Aswathy and Soniya 2016). This type of noise arises as a result of body movement and respiration during ECG recording. Therefore, how to eliminate or reduce the effect of 50Hz interference and baseline wander noise has been one of the most important problems in biomedical signal measurement. During the last twenty years, literature has proposed several solutions to remove the power line interference and baseline wander from ECG signals. In recent years, one can observe an appearance of novel approaches to signal filtering, utilizing machine learning methods although, much work have not been done in this area. However, numerous researchers have addressed different methods of eliminating these interferences in ECG signal. Below are reviews of some of their efforts. Imteyaz, Ansari and Dey (2015) did a comparative study on power line noise removal in ECG signal. The authors designed a digital notch FIR filter using different window types. Based on analysis done by the authors, it was concluded that rectangular window has the least performance because of Gibb's phenomena while the Kaiser window based on FIR filter has the highest performance since it has the lowest mean square error (MSE) and the highest signal to noise ratio (SNR). Mbachu and Nwabueze (2013) designed and implemented FIR digital filter for reducing 50Hz interference in ECG signal, with Hanning window function**.** From their findings it was concluded that the performance of the adaptive notch filter designed with Hanning window in removing power line interference from ECG signal was better than the FIR notch filter designed with Hanning window. However, the work proposed by these two authors (Imteyaz, Ansari and

Dey 2015; Mbachu and Nwabueze 2013) suffers from delay in computation time and also lacks intelligence. Fatemeh, Nafiseh and Fariba (2013) presented a paper on Electrocardiogram (ECG) signal modeling and noise reduction using Hopfield neural network. The authors measured the performance of the model using mean square error. They observed that the mean-square value of the error signal decreases as the number of iterations increases. Finally, it was deduced that the method works excellently well in removing high frequency noise from the ECG signal and also displays a low SNR. However this model suffers from vanishing gradient problem. Corneliu *et al*. (2019) presented two deep learning (DL) models, together with a standard wavelet-based technique for de-noising ECG signals. The first DL model was a Convolutional Neural Network (CNN) consisting of six layers. The second DL model was a two Long Short-Term Memory (LSTM) model with 140 hidden nodes per layer. Karol (2018) in their work proposed a novel approach to de-noise electrocardiographic signals (ECG), utilizing deep recurrent neural network (DRNN) built of Long-Short Term Memory (LSTM) units. It was observed that the model filtered the noisy ECG signal with a reduced mean square error of 0.012. However, this model learns only the forward (past) information about the sequence but fails to learn the backward (future) information.

In the quest to provide reliable and intelligent system which mitigates noise in ECG signal, an extension of recurrent neural network that consist of unidirectional and bidirectional long short term memory (UBLSTM) model was proposed. A UBLSTM is a type of deep learning techniques that can learn both forward and backward information about the sequence of data. The proposed model was trained with data sourced from physionet challenge 2017 database and later applied in filtering ECG signal corrupted with baseline wander and 50Hz powerline noise.

## 2.0 Material and methods

### 2.1 Data collection

3,760 clean ECG data record consisting of 1600 sample points was sourced from PhysioNet/Computing in Cardiology (CinC) Challenge 2017 database. PhysioNet/(CinC) Challenge 2017 database is an open source training database that contains 8,528 single lead ECG recordings. This ECG records represent a serendipitous sample of patient-initiated recordings of one minute or less at sampling rate of 300Hz. The dataset have all been labeled for rhythm by hand into one of four categories: Normal rhythm, atrial fibrillation, other rhythm or too noisy to classify (Goldberger *et al.*2000).

### 2.2 Data preprocessing/Augmentation

The 3,760 dataset consisting of 1,600 ECG sample points that was sourced from physionet challenge 2017 database, was augmented by splitting each record into 4 resulting to 15,040 dataset with 400 data points of clean ECG signals. Then, we modeled a noisy ECG signal of 50Hz power line noise with amplitude of 0.1mV and 0.5Hz baseline noise with amplitude of 0.3mV as shown in Eq. (1) and Eq. (2).

$$Noise_{PLI}(t) = Asin2\pi ft \tag{1}$$
$$Noise_{BLI}(t) = Acos2\pi ft \tag{2}$$

Where A is the amplitude and f is the frequency.
The 15,040 clean ECG dataset was further divided into three equal segments. First, the generated powerline noise was added to the first segment, then baseline wander noise was added to the second segment and the mixture of the two afore mentioned noise was added to the last segment as shown in Eq.(3), Eq.(4) and Eq.(5).

$$ECG\ signal\ corrupted\ with\ powerline\ noise = Clean\ ECG\ signal + \ Noise_{PLI}(t) \tag{3}$$
$$ECG\ signal\ with\ baseline\ wander\ noise = Clean\ ECG\ signal + \ Noise_{BLI}(t) \tag{4}$$
$$ECG\ signal\ corrupted\ with\ powerline\ and\ baseline\ noise = Clean\ ECG\ signal + \ Noise_{PLI}(t) + \ Noise_{BLI}(t) \tag{5}$$

Finally, the entire data set was mixed together to ensure even learning of the parameters during training.

### 2.3 The model architecture

The architecture of the proposed model comprises of a unidirectional LSTM layer, bidirectional LSTM layer and a dense layer. Existing study (LeCun 2015) have shown that deep LSTM architectures with several hidden layers can build up progressively higher level of representations of sequence data, and therefore, performs better than a single layer LSTM. The model architecture is depicted in Figure 2.

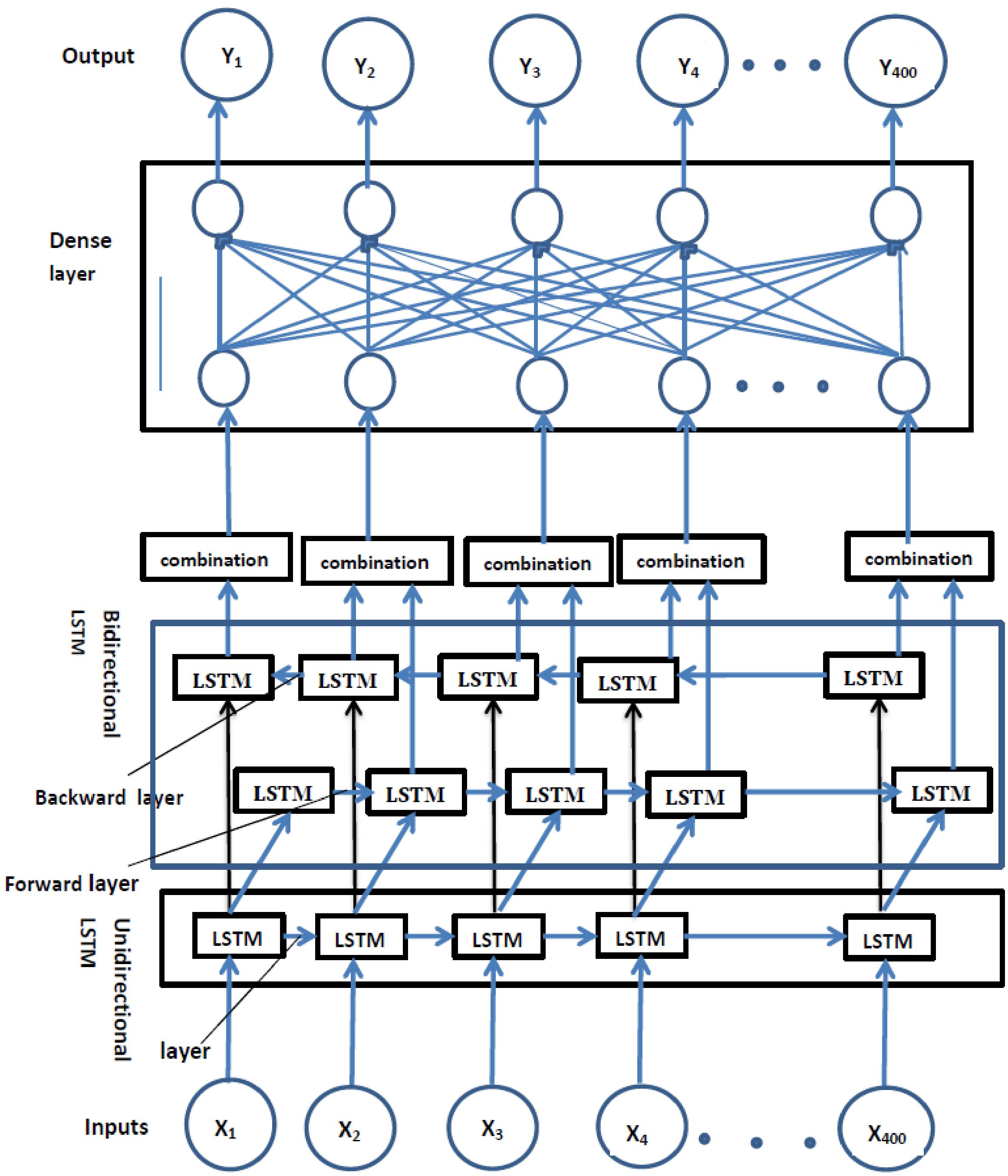



**Figure 2: The architecture of the proposed model**

The structure of a single LSTM cell as shown in the model architecture with the states equation is presented in Figure 3.

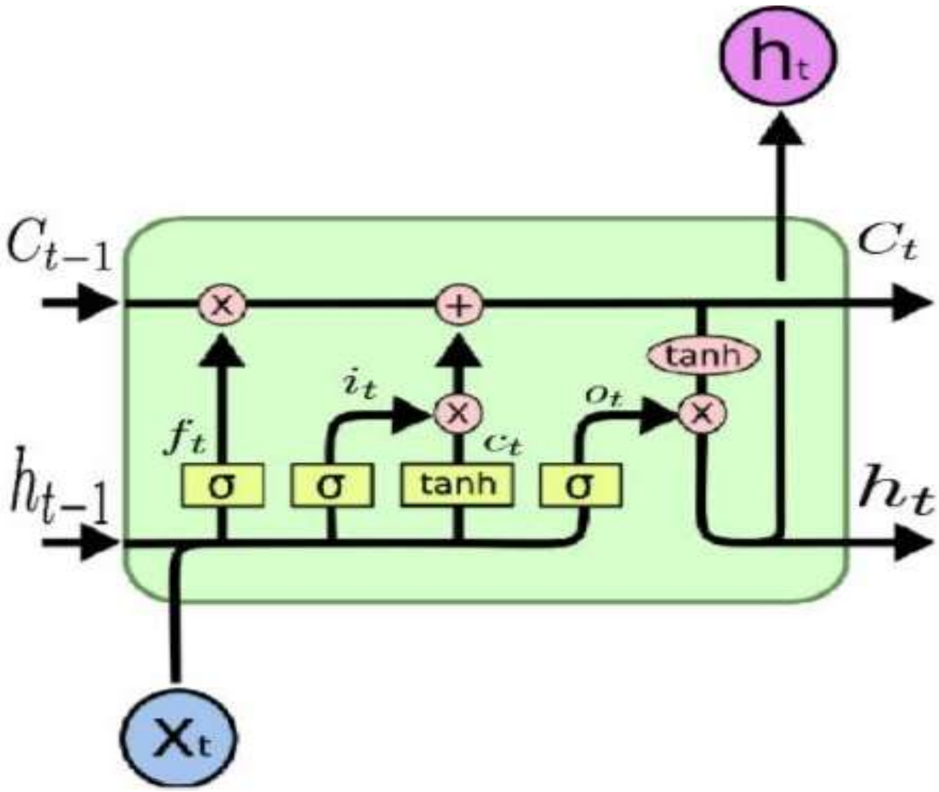



**Figure 3: LSTM cell structure**

A single LSTM cell comprises of the cell state, hidden state, the forget gate, input gate and the output gate.

**The cell state**
The cell state is the long term memory which stores the long term dependency in the ECG data.

**The hidden state**
The hidden state is the short term memory which stores the short term dependency in the ECG data.

**The forget gate**
This gate tells the cell state what to forget from the ECG data given to it as input. It comprises of the sigmoid dense layer. The forget gate matrix equation at time t is expressed mathematically as:

$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f) \tag{6}$$

$W_f$ is the weight matrix for the forget gate , $h_{t-1}$ is the hidden state from the previous time step, $X_t$ is the data input at the current time step.
The sigmoid function $\sigma$ shrinks the resulted values between 0 and 1. The values that are closer to 1 are values that will be keep in the cell state while values that are closer to 0 are values that will be forget in the cell state
The LSTM cell forgets or keeps these values by performing element wise multiplication with the cell state at previous time step $\boldsymbol{C_{t-1}}$ and forget gate matrix at time t $\boldsymbol{f_t}$ as shown in Eq. (7).

$$\boldsymbol{C_t^f = C_{t-1} * f_t} \tag{7}$$

$\boldsymbol{C_t^f}$ is the cell state from the previous time step that helps to decide what to forget at this time step.

**The input gate** The Input gate decides which new information from the ECG data to add to the cell state. It comprises of sigmoid dense layer and tanh dense layer.

Input gate matrix $\boldsymbol{i_t}$ at time t is express as:

$$\boldsymbol{i_t = \sigma(w_i\ [h_{t-1},\, x_t\ ] + b_i\ )} \tag{8}$$

Where $W_i$ is weight matrix for the input gate and $b_i$ is the input bias. The sigmoid function shrinks the resulted value between 0 and 1. The new cell state $\boldsymbol{C'_t}$ after the tanh layer is presented in Eq. (9).

$$\boldsymbol{C'_t = tanh(w_c\ [h_{t-1},\, x_t\ ] + b_c\ )} \tag{9}$$

The new information to be added to the cell state is obtain by doing element wisemultiplication between the $\boldsymbol{i_t}$ and $\boldsymbol{C'_t}$ as shown in Eq. (10).

$$\boldsymbol{C^i_t = C'_t * i_t} \tag{10}$$

Finally, information from $\boldsymbol{C^f_t}$ *and* $\boldsymbol{C^i_t}$ ***is*** then use to update the cell state. Thus, cell state at current time step $C_t$ is obtain by doing element wise addition between $\boldsymbol{C^f_t}$ and $\boldsymbol{C^i_t}$ .

$$\boldsymbol{C_t = C^f_t + C^i_t} \tag{11}$$

Where $\boldsymbol{C^f_t}$ contains information on ECG data that is important to foget and $\boldsymbol{C^i_t}$ contains information on ECG data that is important to add to the cell state.

**Output gate**

The last component of the LSTM is the output gate and it consists of sigmoid layer. The output gate decides what the next hidden state should be. The output gate at time t is express in Eq. (12).

$$\boldsymbol{O_t = \sigma(w_o\ [h_{t-1},\, x_t\ ] + b_o\ )} \quad ` \tag{12}$$

Where $\mathbf{W_0}$ and $b_0$ is the output weight matrix and bias.

The current hidden state is then obtain by element wise multiplication between the output at time t with the cell state pass through tanh function as shown in Eq. (13). The tanh squeezes the value at $\boldsymbol{C_t}$ between -1 and 1

.

$$\boldsymbol{h_t = O_t * tanh(C_t\ )} \tag{13}$$

$h_t$ serves as the hidden state for the current time step which will be fed to the next LSTM cell and also output that will be fed to the dense layer which is bidirectional LSTM in this context.

## 2.4 Training

The dataset used for training the proposed model was split into 90% training dataset and 10% testing data set. The parameters used for the training includes: batch size of 32, adam optimizer, sequence length of 400. Back propagation algorithm through time was adopted in training the model and mean absolute error was used to calculate the loss.

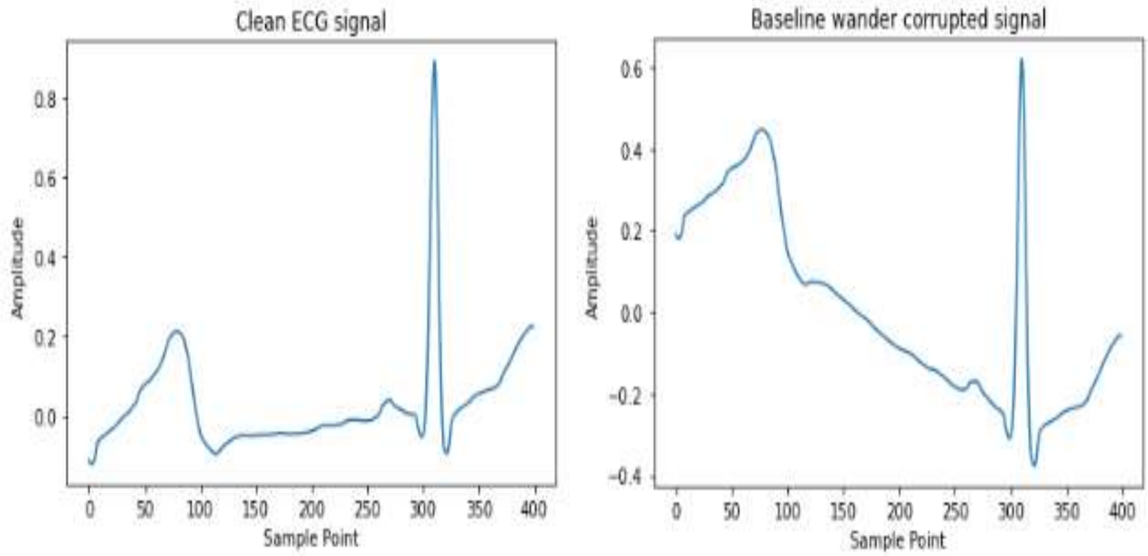
## 2.5 Filtering process

After training the UBLSTM recurrent neural network model, the proposed model is then validated with the test data. First, noisy ECG signal is fed into the trained model. The model then checks whether the ECG signal is corrupted with powerline noise or baseline noise or both. It then filters only 50Hz if the ECG signal is corrupted with powerline noise or 0.5Hz if it is corrupted with baseline noise or both 0.5Hz and 50Hz if it is corrupted with both baseline and powerline noise

# 3.0 Results and Discussions

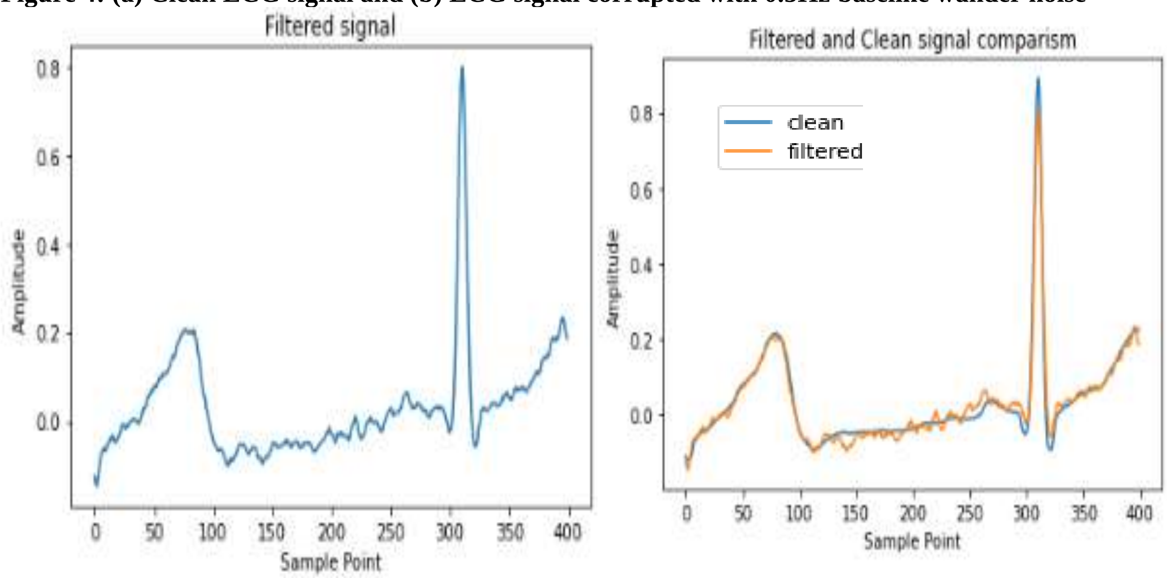
## 3.1 Simulation Results obtained from Filtering Noisy ECG signal with the proposed UBLSTM model

To validate the trained model, three noisy ECG records (record1, record 2 and record 3) from the test dataset were filtered using the proposed model. Figures 4, 6 and 8 depicts the clean and corrupted ECG signals with baseline noise, powerline noise and both noise respectively. The filtered ECG signals with the proposed UBLSTM model and the comparison of the clean and filtered ECG signals are presented in Figures 5, 7 and 9.Table 1 depicts the signal to noise before and after filtering of ECG signal.



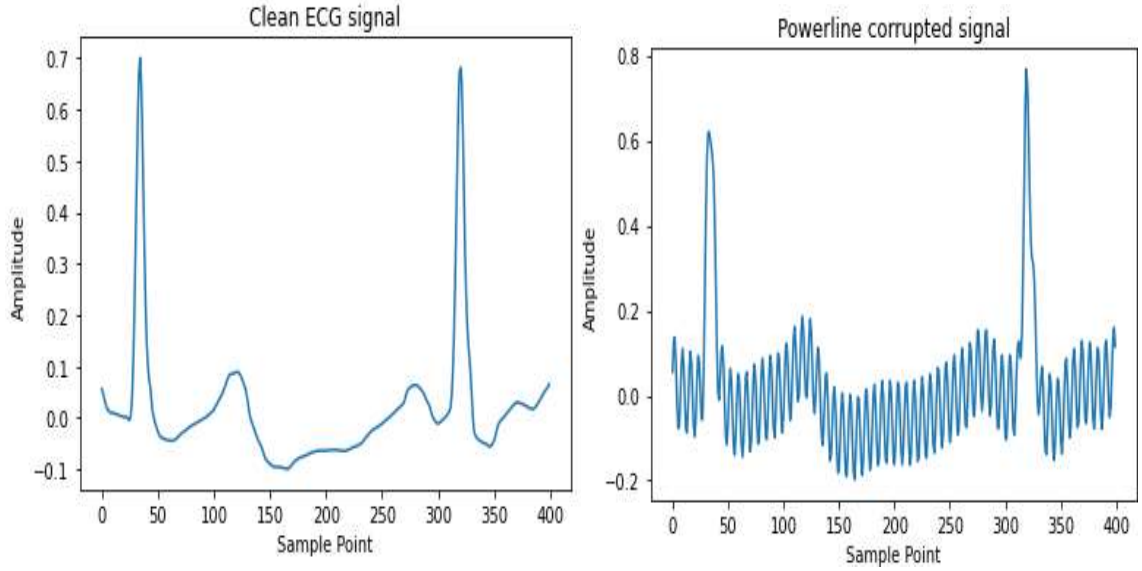

**(a) (b)**

**Figure 4: (a) Clean ECG signal and (b) ECG signal corrupted with 0.5Hz baseline wander noise**



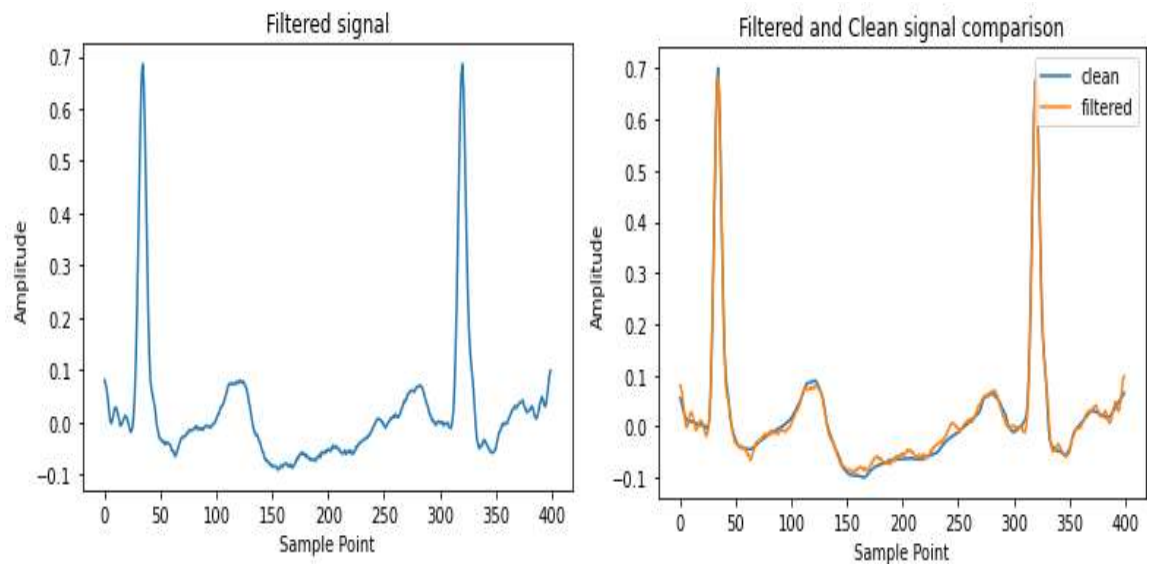

**(a) (b)**

**Figure 5: (a) ECG signal record1 filtered from baseline wander noise (b) Comparison of Clean ECG signal and ECG signal filtered from baseline wander noise**



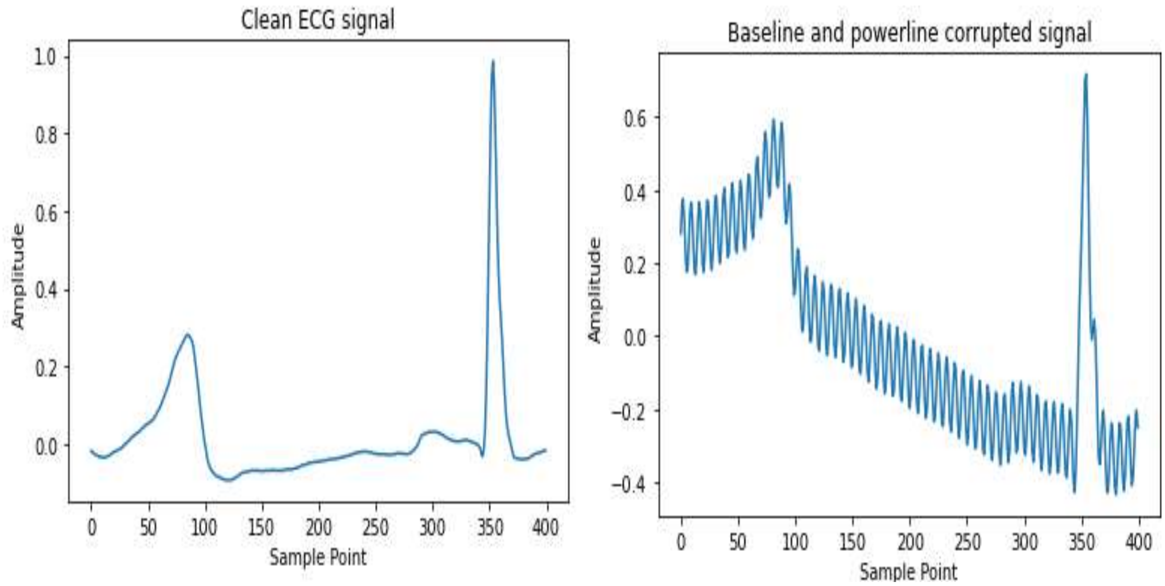

**(a)** **(b)**

**Figure 6: (a) Clean ECG signal and (b) ECG signal corrupted with 50Hz powerline noise**



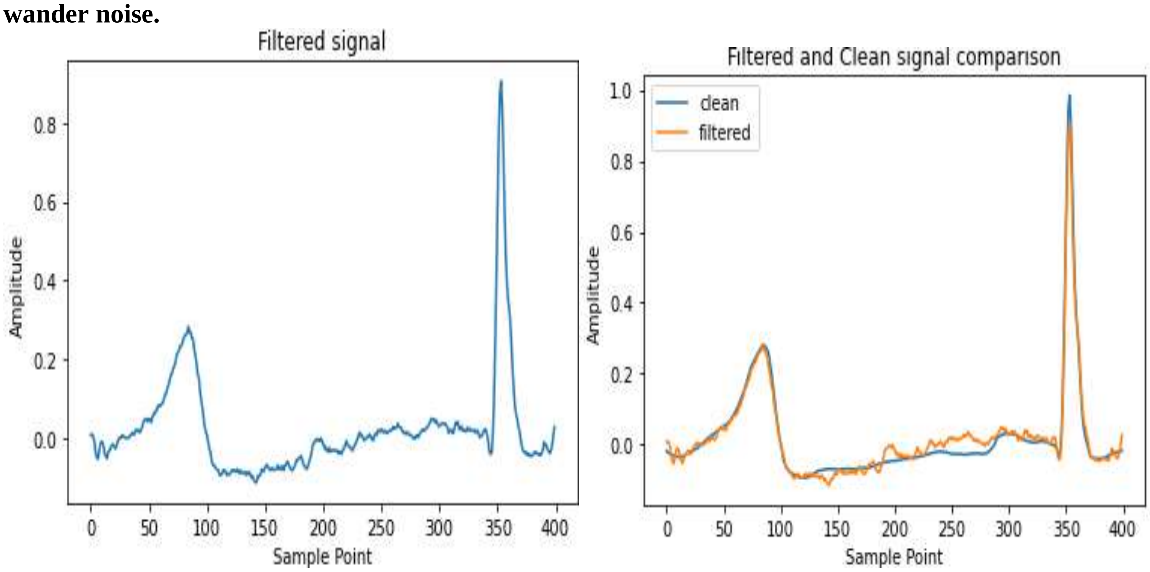

**(a)** **(b)**

**Figure 7: (a) ECG signal record2 filtered from powerline noise (b) Comparison of Clean ECG signal and ECG signal filtered from 50Hz powerline noise.**




**(a)** **(b)**

**Figure 8: (a) Clean ECG signal and (b) ECG signal corrupted with 50Hz powerline noise and 0.5Hz baseline wander noise.**




**(a)** **(b)**

**Figure 9: (a) ECG signal record3 filtered from powerline noise and baseline wander noise (b) Comparison of Clean ECG signal and ECG signal filtered from powerline noise and baseline wander noise.**

**Table 1: ECG Signal Filtered with the UBLSTM Recurrent Neural Network.**

| **ECG Signal (record 1 – record 3)** | **SNR(dB) before filtering** | **SNR(dB) after filtering with UBLSTM Recurrent Neural Network.** $SNR = 10 * \log \left[\frac{\frac{1}{N}\sum_{n=0}^{N-1}[S_f(n)]^2}{MSE}\right]$ |
|---|---|---|
| record 1 | 2.36 | 22.8 |
| record 2 | 6.3 | 22.1 |
| record 3 | 1.45 | 20.2 |

Observation from the waveform of filtered ECG signals with UBLSTM recurrent neural network as presented in Figures 5, 7 and 9 shows that the proposed model has successfully filtered the ECG signal corrupted with baseline wander noise, 50Hz powerline noise and ECG signal corrupted with baseline wander noise and powerline noise. From Table 1 it was obvious that the signal to noise ratio of the three ECG signal records considered in this work before filtering were 2.36dB, 6.3dB and 1.45dB and it was improved to 22.8 dB, 22.1 dB and 20.2 dB after filtering.

## 4.0. Conclusion

This research work has successfully implemented a unidirectional and bidirectional LSTM (UBLSTM) neural network for filtering 50Hz powerline noise and baseline wander noise in ECG signal. This was built using LSTM layer, a bidirectional layer and a dense layer. Validating the model with the test data set as presented in Figures 5, 7 and 9 showed clearly that the proposed model has successfully filtered the ECG signal corrupted with powerline noise and baseline wander noise. The results presented in Table 1 showed that UBLSTM model displayed an improved SNR of 22.8dB, 22.1dB, 20.2dB for the three ECG signal records considered in this work. Thus, it was concluded that UBLSTM recurrent neural network model has successfully filtered the noisy ECG signal.

## 5.0 Recommendation

The UBLSTM model proposed in this work can be apply in processing other signals like EEG and EMG signals to examine its effectiveness in processing the signals.

## References

Anthony, A., 2007. *SinusRhythm*. Available from: https://en.wikipedia.org/wiki/File:SinusRhythmLabels.svg.

Aswathy, V., Soniya, P., 2016. *Noise analysis and different denoising techniques of ECG signal*. Journal of electronics and communication engineering (IOSR-JECE) e-ISSN: 2278-2834, p- ISSN: 2278-8735, 40-44.

Bommadevara, L.H., Rao, B.S.P., Kumar, P.R., 2011. *Interference reduction in ECG using digital FIR filters* .International journal of electronics and communication technology (IJECT). Vol. 2, 76-80.

Corneliu T.C., Arsene, Richard, H., Hujun, Y., 2019. *Deep learning models for denoising ECG Signals*. 27th European Signal Processing Conference (EUSIPCO), 1-5.

Duong, T.L., Nguyen, D. T., Dang, H.H., 2015. *Removal of power line interference from electrocardiograph (ECG) using proposed adaptive filter algorithm*. Global journal of computer science and technology: C software & data engineering, Volume 15, Issue 2.

Fatemeh, B., Nafiseh ,G., Fariba,B., 2013. *Electrocardiogram (ECG) signal modeling and noise reduction using Hopfield neural networks*. ETASR - Engineering, technology & applied science research .Vol. 3, 345-348.

Goldberger, A.L., Amaral, L.A.N., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K., Stanley. H.E., 2000. *PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals*, Circulation 101(23):e215-e220 http://circ.ahajournals.org/cgi/content/full/101/23/e215.

Imteyaz, A., Ansari, F., Dey, U.K., 2015. *Power line interference noise removal in ECG-A comparative study*. International journal on computer Science and engineering (IJCSE). Vol. 7, 13-18.

Kadam, G., Bhaskar, P.C., 2012. *Reduction of power line interference in ECG signal using FIR filter*. International journal of computational engineering research (IJCER), Vol. 2, 314-319.

Karol, A., 2018. *Deep recurrent neural networks for ECG signal denoising*. Institute of Computer and Information Systems, Military University of Technology, 1-8.

LeCun, Y., Bengio,Y., Hinton, G., 2015. *Deep learning.* Nature, Vol. 521, 436–444. Available from: http://dx.doi.org/10.1038/nature14539

Narwaria, R.P., Verma, S., Singhal, P.K., 2011.*Removal of Baseline wander and powerline Interference from ECG signal* - A survey approach" International journal of electronics engineering, 3 (1), 107–111.

Mbachu, C. B., Anumaka M. C., 2013. *Removal of power line interference in ECG signal with height adjustable triangular (HAT) window-based digital FIR filter*. IRACST – International journal of advanced computing, engineering and application (IJACEA), Vol. 2, 107-111.

Rosiek, A., Leksowsk, K., 2016. *The risk factors and prevention of cardiovascular disease: the importance of electrocardiogram in the diagnosis and treatment of acute coronary syndrome*. Therapeutics and Clinical Risk Management Dove press open access to scientific and medical research: 1223-1229.