Regularised Encoder-Decoder Architecture for Anomaly Detection in ECG Time Signals

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***Abstract*—Electrocardiography(ECG) is a procedure to record the electrical activity of the human heart. The recorded time series ECG signal are often used by medical professionals to detect any arrhythmia the subject may have. Work has been done to automate the task by modelling the problem as anomaly detection using encoder-decoder based techniques, training on just normal data and using distribution of loss to predict normal or abnormal data. We argue that normal encoder-decoder with just reconstruction loss suffers from two problem : 1. Latent vector is not smooth and continuous, which might lead to memorising signals 2. Network is prone to outliers as mean squared error is used for reconstruction loss. We propose a regularised encoder-decoder based architecture with KL divergence as regulariser for latent vector which solves the above two problem. The regulariser will enforce the network to minimise the distance between latent vector distribution and normal distribution, hence making latent vector smooth and continuous, at the same time as diverse as possible. We have experimented with various architectures such as Multilayer Perceptrons, Recurrent Neural Networks, Long Short Term Memory Networks, 1D Convolutional Neural Networks for encoder and decoder and found that regularised network outperforms normal network in all the cases. More specifically our regularised network with F1-score of 0.90 outperformed the current state of art for ECG anomaly detection which uses Long Short Term Memory networks for both encoder and decoder, resulting in F1-score of 0.88. As a result we present a regularise encoder-decoder network in this paper which outperforms current techniques for anomaly detection on ECG data.**

***Index Terms*—Anomaly detection, Heart diseases, Lifestyle diseases, Medical expert system, Encoder, Decoder, Regularisation**

I. Introduction

Electrocardiography(ECG) [1] is the process of recording the electrical signal in the heart of a patient by putting electrodes in the heart over a period of time. As this technique is non-invasive, painless and harmless with quick results, this has been used extensively by doctors to measure the health of human heart and detect any problem. Each beat of the heart is triggered by the special cells in the upper right chamber of the heart called as pacemaker cells. If there is any irregularity in the rhythm of signal during the test time (which is usually a few minutes), the doctor recognises it and proceeds accordingly.

It is worth paying attention to the fact that cardiovascular diseases are the cause for about one-third of all deaths around the globe [2]. Therefore accurate and low-cost diagnosis of arrhythmic heartbeats is highly desirable [3].To address this problem many machine learning based techniques have been proposed for ECG classification [4], [5]. It has been observed that neural network based techniques generally outperform the traditional handcrafted feature based techniques [6]- [11]. But most of them approach the problem as classification task which needs data for both normal and abnormal classes. But data for patients having different heart diseases are not readily available. Also there may be certain heart disease which will be discovered in the future, for which data is not available till date. As a result it is wise to model the problem as outlier or anomaly detection.

Anomaly detection is the process of detecting rare event of data among non anomalous data. The methods for anomaly detection varies from problem to problem [12]. In the case of ECG data the records for healthy subjects will be considered as non-anomalous data whereas records related to unhealthy subject having any kind of heart diseases will be considered as anomalous data. In the case of ECG data, anomaly detection is bit challenging task because of the amount of data available, variation in the time sequence pattern for different timescales. Many people have already approached this problem using time series analysis and wavelet transform [13], [14]. Most of them used manual feature extraction which takes many assumptions about the signal.

The machine learning problems aim is to extract out knowledge from the given training data set, in order to predict the answer for queries which are similar to the ones in the training data set. Using the same technique a lot of classification and regression problems have already been solved. A common technique is the neural network that imitates the human brain. The problem with the technique is that the features need to be manually extracted, which has a large human bias. The selection of the wrong features for the problem can give very poor results. The feature engineering can take a significant toil of time.

Deep learning is seen as an advancement of the

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traditional machine learning approaches. The motivation is to have the machine learn the encoding representing good features for the problem. This takes place by appending multiple layers to make the entire network. Every layer attempts to extract the maximum information with the least data reduction. The convolution networks do the same by applying convolution operation to every input with feature maps, while using maximum pooling and sub-sampling of the generated outputs to produce a lower dimensional data. The recurrent neural networks deal with the sequential data like time, and the deep learning variant commonly used is the Long Short Term Memory network. The network learns a representation from the temporal data so as to maintain a balance between the more recent as well as the older items in the temporal sequence.

Deep learning based methods are much more effective because of automatic feature extraction and minimal assumptions about data [15]. As ECG data inherits property of a time series signal, using deep learning techniques which utilises this property may work better than normal neural network. Long short term memory(LSTM) [16] networks are one such class of networks which works exceedingly well on time series data. 1-D Convolutional Neural Networks(CNN) [17] are another class of networks that performs really well on time series data. Few experiments have been done to utilises such networks for anomaly detection on time series data [18], [19]. As the data is unlabelled, the model has to be trained in unsupervised way.

Autoencoders [20] are a class of methods which uses reconstruction loss to train model in unsupervised way, eliminating the need for labelled data. The networks consists of two parts Encoder and Decoder. The Encoder network takes the higher dimensional input data and encodes it to lower dimensional latent vector. The latent vector is the representation of the input data in lower dimension. The Decoder network takes the encoded latent vector and decodes it back to data similar to input data. As the latent vector needs to retain all the information for reconstruction, the network might simply memorise the input data as there is no constraint over the representation of input data. As a result the latent vector needs to be diverse. Also decoder networks samples from latent vector, as a result latent vector needs to be smooth and continuous so as to have uniform sampling.

Kullback-Leibler Divergence (KL Div.) is a statistical measure of how one probability distribution is different from second. The measure has been successfully used in autoencoders to measure the distance between latent vector and normal distribution [21]. Quantitatively a value of 0 for KL Div. means two samples are exactly same and any other value describes how different two distributions are. Regularisation is a way to limit the complexity of the model and constraint the parameter representation in order to avoid the risk of overfitting, where overfitting happens when the model gets too flexible and can represent noise as effectively as normal data, reducing the validation accuracy.

In this paper we are using ECG signal data and modelled the problem of classifying healthy and unhealthy subjects as anomaly detection with healthy subjects as non-anomalous data. Encoder Decoder based network is used to model the problem in unsupervised way using reconstruction loss as optimisation objective.

The novelty of our work is the regularisation factor for the latent vector inside the encoder decoder which helps learning smooth, continuous and diverse latent vector making the network learn better representation of the input signal, whereas adding the regularisation loss to the reconstruction loss helps the network with outliers.

II. Related Work

Malhotra *et al.* [18] used LSTM based encoder-decoder network for learning the distribution of data. The network learns to model normal time series behaviour and thereafter uses reconstruction error to detect anomaly. Although this method is effective on most of the time series data, ECG data needs better sampling and preprocessing methods before using any algorithm. Also the network doesn't do anything for outliers which is frequent with time series signals.

Agarwal *et al.* [19] proposed similar method utilising LSTM based-encoder decoder for learning data distribution. But they used whole time sequence for learning the pattern and then reconstructed full signal in reverse. Using complete time sequence does helps in learning better representation, but the method again lacked the preprocessing steps required for ECG based signal.

Inspired from the previous papers Chauhan *et al.* [25]handcrafted LSTM based encoder-decoder specifically for ECG signals with preprocessing as well. They used stacked LSTM instead of single layer and reconstructed the full signal. Since they used only reconstruction error for detecting anomaly, their methods are more prone to outliers, which might be an explanation for their low recall rate. Also the latent vector learnt by the network is not smooth and diverse.

Few people successfully made use of neural networks for ECG classification. Most notably Kachuee *et al.* [11] utilised Residual based Deep Convolutional Networks on MIT database and tried transfer learning on PTB dataset. Again this method is problematic as it requires data from all the classes - healthy subjects as well as unhealthy subjects.

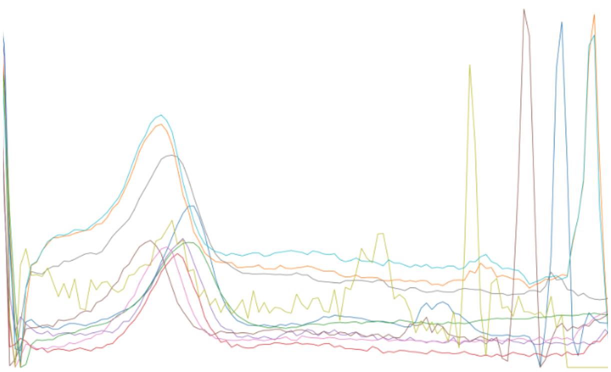
In all these papers there was a common problem that latent vector representation is not smooth and continuous which results in poor representation of the input signal. Along with this they all used only reconstruction loss for learning which is prone to outliers. We propose to regularise the latent vector for better representation of input signal. Along with this adding KL Divergence to overall loss function also helps with the outlier problem which is very significant with time series signals, that no one handled specifically.

III. Methodology

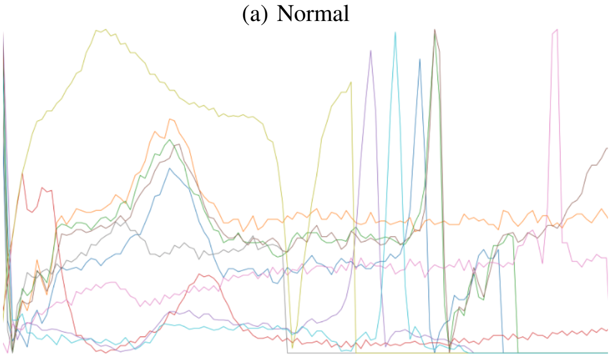
A. *Preprocessing*

The ECG signal for each subjects is around 2-3 minutes. We extracted 10s windows from each sample. We have not assumed anything about the morphology or spectrum of the signal and hence do not do any cleaning or conversion of the sample. Only preprocessing we do is extracting R-R signal [11]. The method used is very simple and effective without taking any assumption about the signal. All the signals are converted into fixed size of 188 with label 1 and 0 for anomalous and non-anomalous signal respectively.

Fig. 1 shows 1-beat R-R peak signal for normal and abnormal subjects. As clear from the figure the normal signal follows a general pattern whereas abnormal signal has no such visible pattern. This factor gives a motivating reason for using anomaly detection for ECG signals.



(a) Normal



(b) Abnormal

Fig. 1: Extracted 1-beat R-R Signal [11]

B. *Architecture*

Let's define input data as x, hidden representation as z and output signal as $\hat{x}$. The **encoder** is a network than takes as input x and encoders the signal into latent vector z using parameters θ. The **decoder** network takes as input the latent vector z and output reconstructed signal $\hat{x}$ using parameters ϕ. A representation of simple encoder-decoder is shown in Fig. 2.

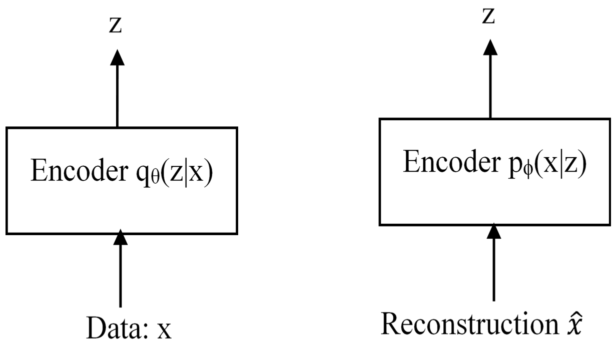


Fig. 2: Enocder - Decoder Architecture

A simple encoder-decoder suffers from two problems :

- Latent distribution z is not smooth and continuous as there is no constraint over the space in which the latent vector is represented.
- Mean squared error for reconstructed signal $\hat{x}$ is prone to outliers as the signal might contain irreugular spikes.

To cater this problem we propose a regularised encoder-decoder where we enforce the network to learn smooth and continuous latent vector z by imposing gaussian constraint on the latent vector - the learned representation of latent vector z should follow normal distribution $\mathcal{N}$ with *zero* mean(μ) and *unit* variance(σ).

Essentially we minimise the distance between latent vector z and normal distribution $\mathcal{N}$ defined in (1)

$$z \sim \mathcal{N}(x|\mu, \sigma^2) \tag{1}$$

Where gaussian distribution $\mathcal{N}$ with mean(μ) and variance(σ) is defined as :

$$\mathcal{N}(x|\mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \tag{2}$$

C. *LSTM Network*

Since the signal is a time series data, RNNs are used for both encoder and decoder network. As normal RNNs suffer from vanishing gradient problem, LSTMs are being used in place of standard RNN. Fig. 3 shows the architecture of regularised encoder decoder. The input is the ECG signal x which is passed through the encoder network. The networks encode the input into latent vector z. We impose the gaussian constrain over the latent vector z. The decoder networks takes the latent vector z as input and constructs the output signal $\hat{x}$ which have to be similar to input signal x.

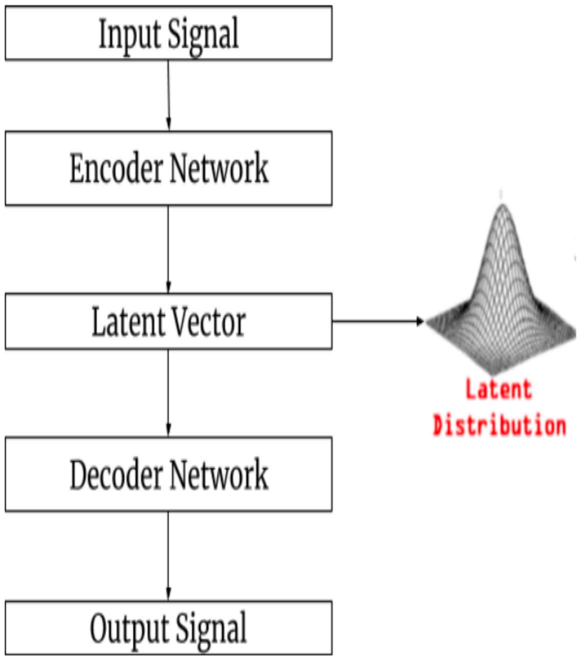


Fig. 3: Architecture of Regularised Encoder-Decoder

D. Loss Function

For reconstruction error between input signal x and output signal $\hat{x}$, Mean Squared Error(MSE) defined in (3), is used.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(x-\hat{x})^2 \tag{3}$$

MSE has the advantage that they are differentiable, symmetric and quadratic, so suitable for gaussian noises.

For latent vector KL Divergence is used as it is a standard metric for measuring the difference between two distribution. Let's assume P as latent vector distribution and Q as Normal distribution described by (3). KLD between the distribution P and Q is defined in (4)

$$KLD = D_{\mathrm{KL}}(P||Q) \tag{4}$$

Where D_{KL} is defined as :

$$D_{\mathrm{KL}}(P||Q) = -\sum_{x\sim X} P(x)log(\frac{P(x)}{Q(x)}) \tag{5}$$

Overall loss function is combination of both reconstruction loss(MSE) and divergence loss(KLD) given by equation :

$$Loss function = MSE + KLD \tag{6}$$

IV. Experiments

A. Implementation Details

Pytorch library is used for implementing all the codes. Adam optimiser is used in all the experiments with learning rate, $\beta1$ and $\beta2$ as 0.001,0.9 and 0.99 respectively, where $\beta1$ and $\beta2$ are exponential decay rates for moment values associated with the optimisers. All the models are trained on Nvidia V100 GPU with 16GB RAM. Training LSTM based regularised encoder-decoder took around 2 hours, while 1D CNN and MLP took approximately 1 hours each.

B. Dataset

In this paper, we use Physionet MIT-BIH Arrhythmia and PTB Diagnostic ECG Database [21]–[23] as data source.

The MIT-BIH Arrhythmia dataset contains ECG records for 47 subjects sampled at the frequency of 360Hz with 11 bit resolution. Each record was annotated by 2 or more cardiologists. As per the annotation provided, the dataset is divided into 5 classes (paper reference daal de). All the 5 classes belongs to subject having some heart problems.

The PTB Diagnostic ECG Database contains records for 290 subjects sampled at frequency of 1000Hz with 16 bit resolution. Out of 290 subjects : 148 diagnosed as Myocardial Infarction, 52 healthy subjects and rest diagnosed with 7 different disease.

We divided the whole dataset into two classes : anomalous and non-anomalous. For non-anomalous class we took records for 52 healthy subjects from PTB dataset, while for anomalous class we sampled records for 47 unhealthy subjects from MIT-BIH dataset belonging to 5 different diseases and records for 238 subjects from PTB dataset belonging to 8 different disease. Since we only want to predict whether the records are anomalous and not the type of disease, we combine data for unhealthy subjects from PTB and MIT-BIH into single anomalous class.

C. Training

The data is divided into non-anomalous (train), non-anomalous (test) and anomalous (test). The encoder-decoder was trained on non-anomalous(train) data for 1000 epochs. LSTM is used for both encoder and decoder network unfolding in the time dimension.The trained networks is then used to test on dataset having combination of non-anomalous and anomalous data using distribution of reconstruction error. The error is normalised between (0-1) for uniformity.

D. Validation

An optimal error threshold was selected by maximising F Score, where F_β score is defined as:

$$F_\beta = (1+\beta^2)\frac{Precision \times Recall}{(\beta^2 \times Precision) + Recall} \tag{7}$$

where ,

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{8}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \tag{9}$$

The F score varies with β as follows:

- $\beta > 1$: Higher weight to recall over precision.
- $\beta < 1$: Higher weight to precision over recall.

As we values both precision and recall equally for the anomaly detection case, we took β = 1 in all the cases. Using the optimal F1 score as threshold ECG sample was classified as anomalous or non-anomalous. The validation set contained equal number of samples for both anomalous and non-anomalous signal and all the metrics was calculated on the same.

V. Results

We evaluated the network on MIT-BIH Arrhythmia and PTB Diagnostic ECG database.We took 120 samples of healthy subjects from PTB dataset and 20 samples each from 6 different category of unhealthy subjects (1 from PTB and 5 from MIT-BIH). As a result we have 120 samples each from healthy and unhealthy subjects for testing, on which network has not been trained yet. Since we value precision and recall equally, we present our results as F1 Score.

Table 1 shows the improvement in F1 score achieved by adding KL Divergence loss to different architectures. The result is compared with all the standard architectures. Table 2 shows the improvement of F1 score of our method over other relevant methods in the literature. Theoretically we proved that adding regulariser helps learning better representation of the latent vector, making it smooth and continuous at the same time as diverse as possible. Better representation of latent vector eventually leads to better reconstruction of the input signal. Experimentally we show from the results that adding regularise does helps in the learning better representation and increasing overall accuracy of the model.

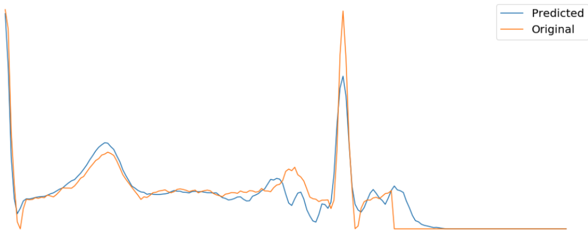
TABLE I: Comparison of ECG Anomaly detection task

Work	Approach	F1 Score
Proposed	**LSTM (MSE + KL Div.)**	**0.90**
Chauhan et al. [25]	LSTM (MSE)	0.88
Kiranyaz et al. [8]	1D CNN (MSE)	0.85
Rai et al. [15]	MLP (MSE)	0.85

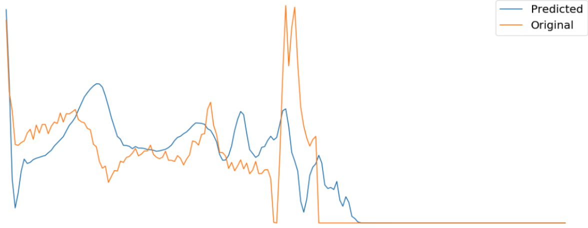
TABLE II: Improvement in F1 score using regularised loss

Work	F1 Score (MSE)	F1 Score (MSE + KL Div.)
LSTM	0.88	**0.90**
1D CNN	0.85	**0.88**
MLP	0.85	**0.86**

Fig. 4 shows the output(reconstructed) signal for normal and abnormal signals using regularised encoder-decoder architecture. As clear from the figure the reconstructed signal for normal subject is quite precise as compared to the abnormal subject which is way deviated from original signal.



(a) Normal



(b) Abnormal

Fig. 4: Reconstructed Signals

All the codes are available on github.[1]

VI. Conclusion

Electrocardiography (ECG) signals can be used to detect unhealthy human heart and this process can be automated using Machine Learning based techniques. Since there can be multiple heart diseases, and getting ECG data for each type of subjects can be difficult, it's better to model the problem as Anomaly detection, which takes only healthy subject data as input for training. As Anomaly detection is unsupervised task, Encoder-Decoder based networks which learns using reconstruction loss are best alternative.

But simple encoder-decoder suffers from non-continuous and non-uniform latent distribution along with reconstruction loss suffering from outliers. As a result we propose a regulariser based on KL Divergence to cater the problem. The regularisation factor imposes constrain over the latent vector and minimises the distance between latent vector and normal distribution.

It is evident from the results that *regularised encoder-decoder* works better than any previous methods on *ECG Signal* data achieving highest F1 score. We also experimented with various architectures for encoder and decoder and found LSTMs work better than other architecture as the data is time series signal. Furthermore we visualised the reconstructed signals for normal and abnormal signals and found the network is able to reconstruct normal signals almost perfectly whereas not so perfectly for abnormal signals giving different loss distribution for normal and abnormal signals.

[1] https://github.com/ashukid/anomaly-detection-in-ecg-signal

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