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Classification of ECG signals by dot Residual LSTM Network with data augmentation for anomaly detection

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***Abstract*—Classification of ECG signals is of great importance for the detection of cardiac dysfunction. Recurrent Neural Network family has been greatly successful for time series related problems. In this paper, we compare different RNN variants and propose dot Residual LSTM network for ECG classification. Here, we use extracted features both from time and frequency domain with the network to improve the classification performance. A data generation scheme was developed with Conditional variational autoencoder (CVAE) and LSTM to increase training samples. A comparative analysis was studied to assess the performance of the model. The proposed dot Res LSTM achieved maximum accuracy of 80.00% and F1 score of 0.85. Furthermore, the model achieved maximum F1 score of 0.87 with augmented data. The study is expected to be useful in automatic cardiac diagnosis research.**

***Index Terms*—RNN, LSTM, ECG Classification, CVAE, Data Augmentation**

I. Introduction

There are a lot of approaches that have been taken to analyze anomalous behavior of ECG and EEG signals. Recurrent Neural Network family has been extensively successful for bio-signal classification in recent times. In [1] authors used a stacked LSTM network to detect the deviation from normal behavior of a time series where the predictor was used to model the non-anomalous data and prediction error was used to indicate the abnormality of the time series. Authors approached a model combining Convolutional Neural Network (CNN) and LSTM networks that had the ability to learn the sequences of long-term pattern of unknown length in [2]. The model can predict the temporal sequences of cardiac arrhythmia. Researchers proposed a predictive model using Deep Recurrent Neural Network with LSTM in [3] where the probability distribution of the prediction error identified the normal and abnormal behavior of ECG signals. In [4] authors compared Deep Convolutional Neural Network (CNN) with a network combining convolutional layers and LSTM layers. The second architecture showed better performance than first one where training set was based on ECG data and testing data worked as an evaluation of effectiveness in the AF classifications. Authors proposed a Deep Neural Network based model combining auto encoder and LSTM in [5] where the model learned the ECG waveâs shape with the temporal sequences to evaluate the detection accuracy of abnormal waves. Data augmentation has been very successful in medical image and bio-signal processing domain [6]–[8]. Researchers evaluated the performances of image recognition with the shallow and deep computational models before and after data augmentation in [9]. The experimental results showed that the data augmentation is an effective way for the recognition process for limited datasets of EEG.

II. Methodology

Recurrent Neural Network family has been extensively successful for time series classification in recent times [10]–[12]. In this work, we have tried to optimize the performance by proposing dot Res LSTM network. Augmented data was generated using c-VAE, and LSTM models to increase data samples. The dot Res LSTM model was trained with both the ECG signals and the extracted features to improve classification scheme. The overall methodology of the study has been presented in Figure 1.

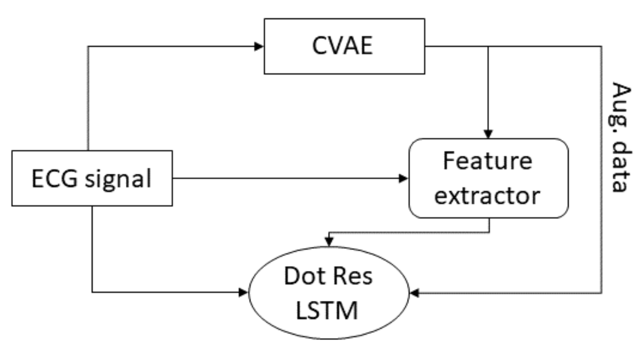

Fig. 1: Overall methodology

A. Dataset and Pre-processing

The ECG signals were collected from MIT-BIH Arrhythmia database [13]. The ECG signals were from multiple patients (19 female (age: 23-89) and 26 male (age: 32-89)). The ECG signals contained 17 classes: normal sinus rhythm, pacemaker rhythm, and 15 types of cardiac dysfunctions which were later split into two classes for binary classification. For the analysis, 1000, 10-second (3600 samples) fragments derived from one lead, the MLII, (not overlapping) were randomly selected. The ECG signals were downsampled to 905 sample points by applying multi-level wavelet transformation with 'db4' wavelet at level 2. Only the approximation coefficients were used for training.

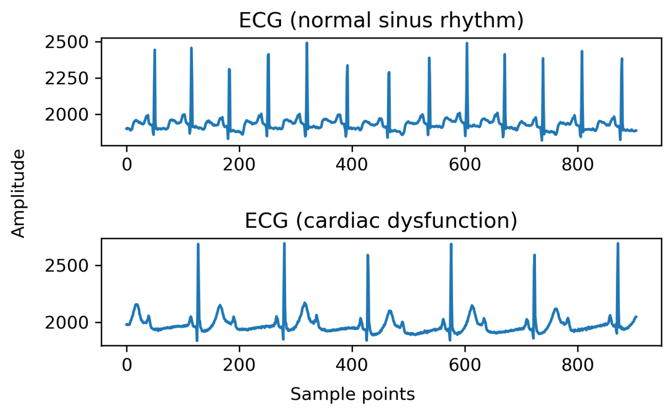

Fig. 2: ECG signals from dataset

Data scarcity is a big constraint when working with biosignals. There are many approaches to solve the data limitation problem [6], [14]–[17]. Data augmentation methods can be applied to generate new instances to increase training samples to train a better generalized model. We have used a CVAE and LSTM model to generate new ECG instances to increase training set variance.

B. CVAE and LSTM Generator

Lets consider an ECG dataset $E = \{x^{(i)}\}_{i=1}^{K}$ with K samples. We make a simplified assumption that the ECG data are generated from a random process. From a prior distribution $p_\theta(z)$, a latent variable z is drawn and from conditional distribution $p_\theta(x|z)$, we can draw a sample x, where both $p_\theta(z)$ and $p_\theta(x|z)$ are parameterized by theta. In, variational autoencoder there is a encoder-decoder architecture. The encoder maps the variable x to the approximated posterior distribution $p^*_\theta(z|x)$ and the decoder maps the latent variable z to the conditional distribution $p_\theta(x|z)$ [18], [19].

CVAE is trained so that the conditional log likelihood of x given c is maximized. The efficient training with the Stochastic Gradient Variational Bayes (SGVB) involves maximizing the variational lower bound of the conditional log likelihood [20]. Figure 2 demonstrates an overview of the data generation process of the VAE, in CVAE we also pass the label to the encoder to generate samples from multiple classes.

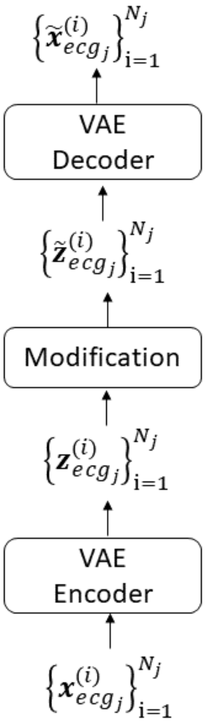

Fig. 3: VAE Data Generation

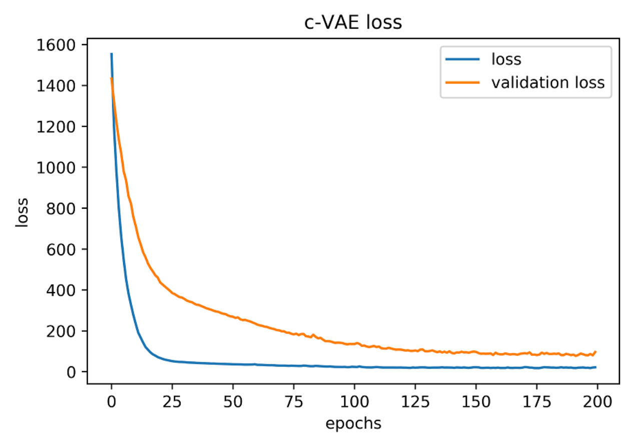

Fig. 4: Training of CVAE Generator

We have designed a simplified LSTM regression model which takes 100 samples and predicts the next 805 sample points. It consists of 2 LSTM layers, with ReLU activation. The final layer is a fully connected layer with linear activation. But, the model is limited to generate samples for only one class.

C. Model Architecture

In our model, we have incorporated the manually designed features with automatic feature learning. The learnable parameters are distributed to capture the data representation better. The features used in this experiment are: absolute energy,

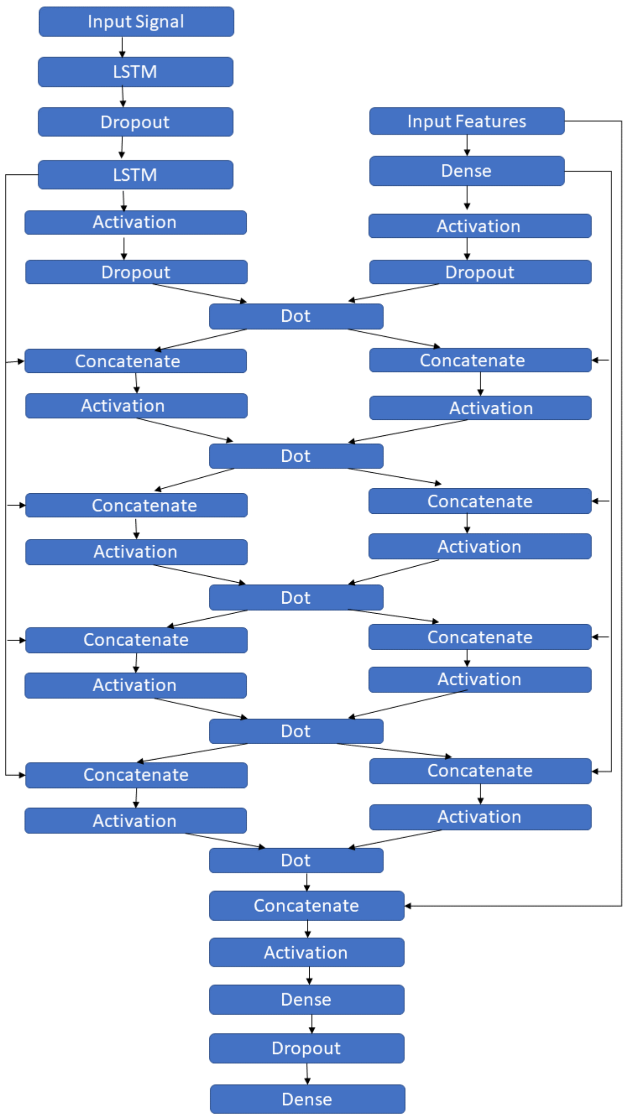

Fig. 5: Architecture of dot Res LSTM

spectral moment 2, LOG, WL, autocorrelation, binned entropy, sample entropy, AAC, time reversal asymmetry statistic, variance.

Features from both time and frequency domain were used for the network. 10 features were calculated from ECG signals and fed to dot Res LSTM model. List of features [21] with mathematical definitions are listed below:
Absolute Energy is the sum of squared values.

$$E = \sum_{i=1}^{n} x_i^2 \tag{1}$$

Spectral Moments(SM2) is a statistical approach to extract

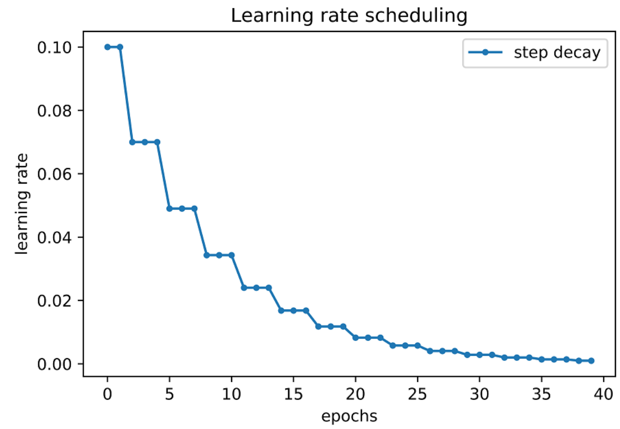

Fig. 6: Step Decay Learning Rate

power spectrum of ECG singal and it is defined as:

$$SM2 = \sum_{i=1}^{n} P_i f_i^2 \tag{2}$$

Waveform Length (WL) is used to measure the complexity of ECG signal and is defined as:

$$WL = \sum_{i=1}^{n-1} |x_{i+1} - x_i| \tag{3}$$

Binned Entropy(BE) is calculated as:

$$BE = - \sum_{k=0}^{min(max\_bins, len(x))} P_k log(p_k).where, p_k > 0 \tag{4}$$

Average amplitude change (AAC) is formulated as

$$ACC = \frac{1}{N} \sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{5}$$

Variance is the measure of how far a random variable is spread out and Time Reversal Asymmetry Statistic (TRAS) is

$$TRAS = \frac{1}{n - 2lag} \sum_{i=0}^{n-2lag} x_{i+2lag}^2 . x_{i+lag} - x_{i+lag} . x^2 \tag{6}$$

The model was shown both the signals and the features while training. We used he normal for initializing the kernels. Both L1 and L2 regularization was used. For LSTM layers, we used L2 regularization and for FC layers L1 regularization was used. To minimize the number of parameters in the network, we used multiple dot layers. These dot layers can be considered as non-learnable similarity gates which can mix features from two branches in the network [22], [23]. The network is also inspired by [24]. The residual connections are used to solve the vanishing gradient problem. The architecture of the proposed dot Res LSTM is shown in Figure 4. The model was trained with cross entropy loss and adam optimizer for 30 epochs. We used step decay learning rate which is shown in Figure 5.

TABLE I: Performance Comparison

Model	Accuracy	Precision	Recall	F1	Parameters
LSTM	0.73	0.73	0.95	0.82	50,050
Bidir. LSTM	0.73	0.72	0.96	0.82	52,322
GRU	0.71	0.70	0.98	0.82	37,570
dot Res LSTM	**0.80**	0.82	0.89	0.85	50,871
dot Res LSTM + aug. data	0.78	0.77	0.98	**0.87**	50,871

III. Result Analysis

In this work, we compared multiple RNN types with our model. We were able to achieve better classification performance while keeping the number of parameters of the proposed network almost same. The proposed dot Res LSTM outperformed other models which is shown in Table 1. The CVAE was used to generate ECG samples for two classes. The training loss is shown in Figure. In the early epochs, the model showed overfitting but eventually, converged with reasonable validation loss.

In the evaluation of the performance of the model, accuracy has been used as the preliminary parameter. Accuracy is defined as the proportion of the correct outputs that a classifier achieved. Through accuracy, we get an estimate of the correct predictions made by the model over all kinds of the predictions made.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{7}$$

Accuracy is a good metric when there are balanced data of two or multiple classes. But as the dataset is imbalanced, it is not reliable for performance evaluations. Again, accuracy considers only the correct results, does not take the incorrect results into account. It is more convenient to consider all the correct and incorrect predictions made by the model in the performance evaluation.So, we would like to allow the F1 score in our consideration. F1 score is defined as the weighted average of precision and recall which takes both false positive and false negative into account.

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{10}$$

True Positive (TP): When the ECG signal had anomaly and the model predicted it.

True Negative (TN): When the ECG signal had no anomaly and the model predicted it.

False Positive (FP): When the ECG signal had no anomaly but the model predicted that the signal had an anomaly.

False Negative (FN): When the ECG signal had anomaly but the model predicted that the signal had no anomaly.

Here, precision is the number of correct positive results over the positive prediction made by the model and Recall is the number of correct positive results over the number of all samples that should have been predicted as positive. A model in which the difference between the actual values and the predicted values is relatively small and unbiased for the training set, validation set, and testing set would be a good fitting model. We have evaluated the performance of our model through accuracy, precision, recall, and F1 score.

The embedding plot of the CVAE encoder is shown in Figure 6. It turned out to be challenging to generate distinguising samples which can be realized from the correlated plot. As a result, the performance slightly dropped after introducing samples generated by CVAE. But, it had some regularization effect which resulted in a better test F1 score.

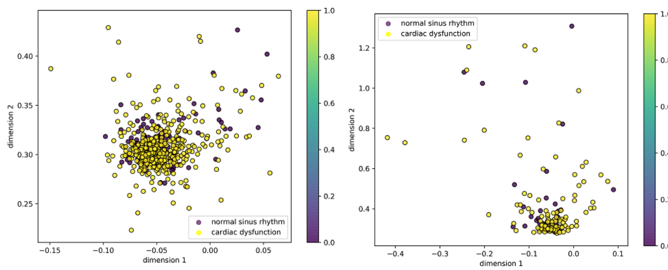

Fig. 7: Embedding plot of CVAE Encoder (training, testing)

From the training curve of Figure 7 it is evident that the model is highly regularized. The model was trained with crossentropy loss. We used adam optimizer with step decay learning rate. Initally, 800 samples were used for training and 200 samples were kept for testing. 15% data from training split was used for validation purpose. Additional 800 samples were generated by CVAE, but only 50 samples were used with training set. For all of the RNN variants, we used two recurrent layer followed by one fully connected layer with softmax activation. Overall, the dot Res LSTM model showed better performance than other RNN variants with limited training examples.

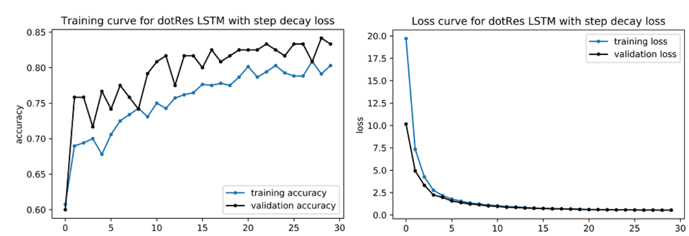

Fig. 8: Training of dot Res LSTM

IV. Conclusion

In this paper, we proposed dot Residual LSTM Network for classifying ECG signals and found that this method performs better in classification task with reduced number of parameters than other RNN variants. The main contribution of this work is that, we tried to find a method which uses both handcrafted features and learnt features in a single network to better generalize the classification task. We also experimented with data augmentation and synthetic data generation process with CVAE which improved the F1 score of the model. dot Residual LSTM showed better generalization with few trainable parameters as the hyper-parameters were chosen very carefully to train the network. We intend to improve the modelâs performance by adding more robust data generation scheme, and introducing knowledge distillation to further reduce the number of parameters, which will be an important aspect of real time automatic cardiac diagnosis.

References

[1] P. Malhotra, L. Vig, G. Shroff, and P. Agarwal, "Long short term memory networks for anomaly detection in time series," in *Proceedings*. Presses universitaires de Louvain, 2015, p. 89.

[2] P. Warrick and M. N. Homsi, "Cardiac arrhythmia detection from ecg combining convolutional and long short-term memory networks," in *2017 Computing in Cardiology (CinC)*. IEEE, 2017, pp. 1–4.

[3] S. Chauhan and L. Vig, "Anomaly detection in ecg time signals via deep long short-term memory networks," in *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 2015, pp. 1–7.

[4] M. Zihlmann, D. Perekrestenko, and M. Tschannen, "Convolutional recurrent neural networks for electrocardiogram classification," in *2017 Computing in Cardiology (CinC)*. IEEE, 2017, pp. 1–4.

[5] K. Sugimoto, S. Lee, and Y. Okada, "Deep learning-based detection of periodic abnormal waves in ecg data," in *Proceedings of the International MultiConference of Engineers and Computer Scientists*, vol. 1, 2018.

[6] Y. Luo and B.-L. Lu, "Eeg data augmentation for emotion recognition using a conditional wasserstein gan," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 2535–2538.

[7] Y. Chang, "Graph-based data augmentation approach for electroencephalogram analysis," *International Journal of Multidisciplinary Research And Studies*, vol. 1, no. 03, pp. 298–307, 2018.

[8] T. A. A. Zabir Al Nazi, "Automatic skin lesion segmentation and melanoma detection: Transfer learning approach with u-net and dcnn-svm," *International Joint Conference on Computational Intelligence (IJCCI 2018)*, 2018.

[9] F. Wang, S.-h. Zhong, J. Peng, J. Jiang, and Y. Liu, "Data augmentation for eeg-based emotion recognition with deep convolutional neural networks," in *International Conference on Multimedia Modeling*. Springer, 2018, pp. 82–93.

[10] L. Wu, L. Wang, P. Zhang, T. Li, and Y. Yan, "Space-time residual lstm architechture for distant speech recognition," in *2018 11th International Symposium on Chinese Spoken Language Processing (ISCSLP)*. IEEE, 2018, pp. 379–383.

[11] S. Singh, S. K. Pandey, U. Pawar, and R. R. Janghel, "Classification of ecg arrhythmia using recurrent neural networks," *Procedia computer science*, vol. 132, pp. 1290–1297, 2018.

[12] S. Saadatnejad, M. Oveisi, and M. Hashemi, "Lstm-based ecg classification for continuous monitoring on personal wearable devices," *IEEE journal of biomedical and health informatics*, 2019.

[13] P. Plawiak. (2017, nov) Ecg signals (1000 fragments). [Online]. Available: http://dx.doi.org/10.17632/7dybx7wyfn.3

[14] Q. Zhang and Y. Liu, "Improving brain computer interface performance by data augmentation with conditional deep convolutional generative adversarial networks," *arXiv preprint arXiv:1806.07108*, 2018.

[15] S. Haradal, H. Hayashi, and S. Uchida, "Biosignal data augmentation based on generative adversarial networks," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 368–371.

[16] Z. Zhang, F. Duan, J. Solé-Casals, J. Dinarès-Ferran, A. Cichocki, Z. Yang, and Z. Sun, "A novel deep learning approach with data augmentation to classify motor imagery signals," *IEEE Access*, vol. 7, pp. 15 945–15 954, 2019.

[17] S. D. M. F. H. Tanvir Hasan Shovon, Zabir Al Nazi, "Classification of motor imagery eeg signals with multi-input convolutional neural network by augmenting stft," in *5th International Conference on Advances in Electrical Engineering (ICAEE)*. IEEE, 2019.

[18] W.-N. Hsu, Y. Zhang, and J. Glass, "Unsupervised domain adaptation for robust speech recognition via variational autoencoder-based data augmentation," in *2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*. IEEE, 2017, pp. 16–23.

[19] T. Zhao, R. Zhao, and M. Eskenazi, "Learning discourse-level diversity for neural dialog models using conditional variational autoencoders," *arXiv preprint arXiv:1703.10960*, 2017.

[20] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," *arXiv preprint arXiv:1312.6114*, 2013.

[21] M. Christ, N. Braun, J. Neuffer, and A. W. Kempa-Liehr, "Time series feature extraction on basis of scalable hypothesis tests (tsfresh–a python package)," *Neurocomputing*, vol. 307, pp. 72–77, 2018.

[22] D. F. Specht, "Probabilistic neural networks," *Neural networks*, vol. 3, no. 1, pp. 109–118, 1990.

[23] T.-H. Chan, K. Jia, S. Gao, J. Lu, Z. Zeng, and Y. Ma, "Pcanet: A simple deep learning baseline for image classification?" *IEEE transactions on image processing*, vol. 24, no. 12, pp. 5017–5032, 2015.

[24] R. K. Srivastava, K. Greff, and J. Schmidhuber, "Highway networks," *arXiv preprint arXiv:1505.00387*, 2015.