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Cardiac arrhythmia classification of imbalanced data using convolutional autoencoder and LSTM techniques

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Abstract: Cardiovascular diseases (CVD) can be identified by medical professionals with the help of electrocardiogram (ECG) signals. The ECG signals shows the heart rhythm and any irregularity in heart rhythm is called arrhythmia. The arrhythmias can be broadly classified into five categories: 1) class N; 2) class S; 3) class V; 4) class F; 5) class Q. The proposed research work automatically categorises the ECG beats into one of the five classes using long short-term memory (LSTM). The ECG waveform is divided into individual ECG beats and is provided as input to the convolutional autoencoders. The compressed representation of the encoder is used as features for further classification by LSTM. The class imbalance problem in the dataset is overcome using ADASYN technique. The proposed research work gives an overall accuracy of 99.12%.

Keywords: arrhythmia; long short-term memory; LSTM; autoencoder; ADASYN; deep learning; disease classification; convolutional neural network; CNN.

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1 Introduction

World population prospect 2019 states that out of six people in the world, one person will be of age more than 65. As the age increases, the cardio vascular system gets weaker and may lead to cardiovascular diseases (CVD). High blood pressure, diabetes, smoking habit, cholesterol, physical inactivity and ethnic background are other important factors for occurrence of heart disease. The cardiovascular health status of patients can be known by medical experts with the help of ECG signals. The ECG waveform shows the rhythm of the heartbeat and the irregularity in the rhythm are known as arrhythmias. Identifying the class of arrhythmia manually is much time consuming. Hence automation in arrhythmia classification is required.

The important issues faced by researchers while classifications of cardiac arrhythmias are:

1 Imbalanced dataset – data instances of certain rare arrhythmia classes are very less compared to normal arrhythmia class. Imbalanced dataset may lead to poor performance by classification algorithms.

2 Noisy data – the ECG waveform is much noisy and requires pre-processing.

The proposed research work focuses on:

1 solving the class imbalance problem using ADASYN

2 using convolutional autoencoder for feature extraction

3 long short-term memory (LSTM) for classification.

2 Literature survey

Several research works are carried out by various researchers using machine learning and deep learning techniques for the automatic classification of cardiac arrhythmias. Support vector machine, probabilistic neural network, mixture of experts, K-nearest neighbour algorithm, discriminant classifier and random forest algorithms are some of the commonly used machine learning techniques for arrhythmia classification (Herry et al., 2015; Bouchikhi et al., 2015; Marhoon and Hamad, 2015; Kumari and Kumar, 2016; Rekha and Vidhyapriya, 2017; Sahoo et al., 2018; Chashmi and Amirani, 2022). The drawback of machine learning algorithms is that it requires feature extraction prior to classification. Deep learning technique-based classifiers do not require feature extraction to be carried out before classification.

Yildirim et al. (2019) developed a LSTM based classification model using 7,376 data samples during the training phase. They were able to classify the normal ECG beat (2,190), LBBB beat (1,870), RBBB beat (1,356), PVC beat (510) and PACE (1,450) beat with 99.39% accuracy. The drawback of the model is its high time requirement for its training and wavelet transformation. Acharya et al. (2017a, 2017b) proposed a convolutional neural network (CNN) based arrhythmia classification system using MIT_BIH arrhythmia database. They used ECG signals of two seconds and five seconds durations without QRS detection and achieved an accuracy 92.50% and 94.90%.

Zubair et al. (2016) proposed an automation method to categorise normal beat, Supraventricular ectopic beat, Ventricular ectopic beat, fusion beat and unknown beat using CNN. The overall performance of the proposed approach shows a validation accuracy of 96.4% and test accuracy of 92.7%. Kiranyaz et al. (2016) developed an ECG classification system that uses some amount of patient specific data and a model is constructed for each patient. This approach performed using CNN improves the classification rate of SVEB and VEB arrhythmia class. Acharya et al. (2017a, 2017b) developed a deep learning-based arrhythmia classification model in which CNN was used for classification. It was reported that the performance of the model improved when data samples were augmented and balanced. The performance degraded when the imbalanced dataset was used for model construction. CNN was used for arrhythmia classification by Huang et al. (2019), Abdalla et al. (2020), Salem et al. (2018) and Ullah et al. (2020).

3 Dataset used

The MIT-BIH Arrhythmia Database is used for experimentation. The database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. The recordings were digitised at 360 samples per second. As per the recommendations by ANSI/AAMI EC57:1998/(R)2008 standard, the heart beats are classified into five classes:

1 class N (normal beat)

2 class S (supraventricular ectopic beat)

3 class V (ventricular ectopic beat)

4 class F (fusion beat)

5 class Q (unknown beat).

4 Methodology

The ECG signal is segmented into individual beats using Pan Tompkins algorithm (Pan and Tompkin, 1985). This algorithm identifies the R peak of the ECG waveform and 100 samples before and after the R-peak constitutes one ECG beat. The dataset indicates the imbalance present in the number of heart beats in each category of arrhythmia class. In order to balance the data, adaptive synthetic (ADASYN) algorithm is used. This algorithm generates synthetic data based on the data density. The heart beat classes that contain lesser number of samples with low density are identified and more synthetic data is generated in that region.

4.1 Convolutional autoencoder

The ECG beat represented in 1D as a sequence of data samples are passed over a sequence of convolution and max pooling layers (Convolution 1 – max pooling 1 – convolution 2 – max pooling 2 – convolution 3). This forms the encoder part of the convolutional autoencoder. Feature maps are created with the help of convolution filters

and the size of the feature maps are reduced by max pooling. The output of the convolution 3 layer gives the latent vector representation of the input ECG signal.

The latent vector is taken as an input by the decoder part of the convolutional autoencoder architecture. The input is passed through a sequence of convolution transpose and up sampling layers. The objective is to reconstruct the original 1D representation of ECG signal from the reduced representation. The failure of the decoder to reconstruct the ECG signal that resembles the original signal is considered as loss. The weight values of the autoencoder are adjusted to reduce the loss. After few iterations, the loss gets minimised and the latent vector gives the better representation of original ECG signal with 186 samples to a vector with only 41 samples.

The encoder portion of the convolutional autoencoder inputs 186 samples with a total of 11,809 parameters. Out of the total, 11,649 parameters are trainable and 160 parameters are non-trainable. The encoder outputs a vector of size 41 and is given as input to the decoder. The decoder has a total of 12,581 trainable parameters.

Table 1 LSTM model summary

Model: 'LSTM classification'		
Layer (type)	*Output Shape*	*Number of parameters*
LSTM (Input layer)	[(None, 41.1)]	0
Lstm_2 (LSTM)	(None, 41.32)	4352
Dropout_1 (dropout)	(None, 41.32)	0
Lstm_3 (LSTM)	(None, 32)	8320
Flatten_1 (flatten)	(None, 32)	0
Dense_3 (dense)	(None, 32)	1056
Dense_4 (dense)	(None, 16)	528
Dense_5 (dense)	(None, 5)	85
	Total parameters: 14,341 Trainable parameters: 14,341 Non-trainable parameters: 0	
Model: 'classification'		
Layer (type)	*Output shape*	*Number of parameters*
Input (input layer)	[(None, 186.1)]	0
Encoder (functional)	(None, 41.1)	11,809
LSTM Classification		14,341
	Total parameters: 26,150 Trainable parameters: 25,990 Non-trainable parameters: 160	

4.2 Long short-term memory

The LSTM model is used for classification of ECG betas into one of the arrhythmia classes. The compressed representation (latent vector) of the original ECG signal is taken as input by the LSTM model. The LSTM has forget gate, input gate and output gate. The forget gate decides which information to retain and which to forget with the help of sigmoidal activation function. The sigmoidal function gives an output in the range of 0 to

1. The output nearer to '0' is forgotten by LSTM. The overfitting that may be caused in the model during training is avoided by adding dropout layers. Adam optimiser is used for weight updation in the LSTM model due to its computational efficiency. Categorical cross entropy loss function is used for loss computation. The output of LSTM layer is flattened and passed over dense layers where the input is classified into one of the five arrhythmia classes. The summary of the proposed model of LSTM classification is shown in Table 1.

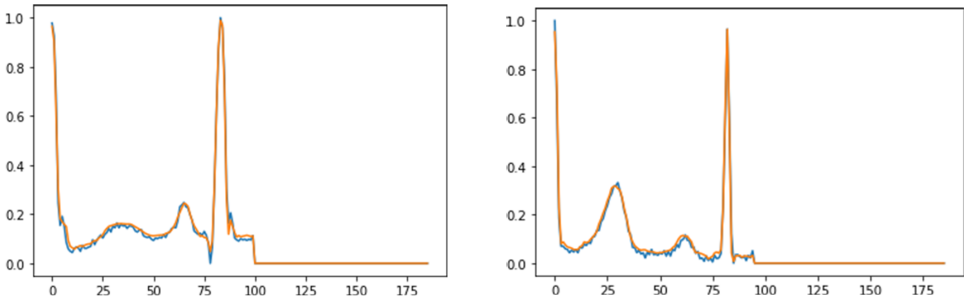
5 Experimental results

The experiments are carried out using the GPU facility provided by Google Colab. The entire dataset is divided for training and testing in the ratio of 80:20 respectively. The total dataset with 87,554 ECG beats is considered for experiment. Each ECG beat is represented with a length of 186 samples. The 187th sample represents the type of arrhythmia class. ADASYN technique is used for synthetic data generation. This helps to overcome the class imbalance. This is done by importing the ADASYN module from the python library 'imblearn. Oversampling'. The whole dataset along with class labels are passed over the ADASYN function so that minority arrhythmia classes get oversampled. The number of data instances available in each arrhythmia class before and after resampling is shown in Table 2.

Table 2 Number of data instances in each arrhythmia class before and after resampling

Class	*Before resampling*		*After resampling*	
	Training data	*Testing data*	*Training data*	*Testing data*
N	57,892	14,579	58,010	14,461
S	1,797	426	58,020	14,477
V	4,676	1,112	58,027	14,463
F	496	145	58,005	14,458
Q	5,182	1249	57,852	14,620
Total	70,043	17,511	289,914	72,479

Figure 1 Original and reconstructed signal by convolutional autoencoder (see online version for colours)



The training data of resampled dataset is given as input to convolutional autoencoder. The autoencoder architecture generates the latent vector representation of original ECG

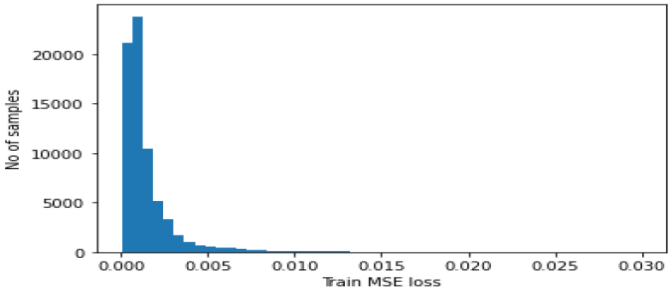
data instance through the encoder part and tries to reconstruct the original signal from the compressed representation. The output generated by the convolutional autoencoder is shown in Figure 1. The original ECG signal is shown in blue, while the reconstructed signal is shown in orange.

The inability of the convolutional encoder to reconstruct the original ECG signal from the compressed representation is measured using mean square error (MSE) loss.

$$MSE = \frac{1}{\text{No. of samples}}(\text{Original data} - \text{predicted data})2$$

The mean square error loss between the original signal and the reconstructed signal is calculated, and the result is plotted as a histogram and shown in Figure 2. The average MSE loss of all the five arrhythmia classes is 0.001455793.

Figure 2 Histogram of MSE loss of training dataset (see online version for colours)



The confusion matrices showing the classification results of arrhythmia classes using convolutional autoencoder_LSTM before resampling and after resampling is shown in Tables 3 and 4 respectively.

Table 3 Before resampling

		True label →				
		N	*S*	*V*	*F*	*Q*
Predicted label	N	14,451	132	69	30	21
	S	33	281	1	0	0
	V	29	9	1,021	10	11
	F	10	3	10	104	0
	Q	56	1	11	1	1,217

The evaluation of the performance of the model is performed using the following metrics: [TP – True positive, TN – True negative, FP – False positive, FN – False Negative].

a Accuracy = (TP + TN) / (TP + TN + FP + FN)

b Sensitivity (Recall) = (TP / (TP + FN))

c Specificity = (TN/(TN + FP))

d Precision = (TP/(TP + FP))

e F – Score = 2 * (Precision * Recall) / (Precision + Recall)

Table 4 After resampling

		True label →				
		N	*S*	*V*	*F*	*Q*
Predicted label	N	13,872	74	180	126	35
	S	488	14,384	53	11	6
	V	56	3	14,177	1	9
	F	23	16	51	14,320	1
	Q	22	0	2	0	14,569

Table 5 Arrhythmia classification results before and after resampling

Class	*Resampling*	*Total*	*TP*	*TN*	*FP*	*FN*
N	No	14,579	14,451	2,680	252	128
	Yes	14,461	13,872	57,603	415	589
S	No	426	281	17,051	34	145
	Yes	14,477	14,384	57,444	558	93
V	No	1,112	1,021	16,340	59	91
	Yes	14,463	14,177	57,947	69	286
F	No	145	104	17,343	23	41
	Yes	14,458	14,320	57,930	91	138
Q	No	1,249	1,217	16,193	69	32
	Yes	14,620	14,569	57,835	24	51

Table 6 Performance of convolutional autoencoder + LSTM without and with resampling

Class	*Resampling*	*Sensitivity*	*Specificity*	*Precision*	*F-score*	*Accuracy*
N	No	0.99	0.9	0.98	0.99	0.98
	Yes	0.98	1.0	0.98	0.98	0.99
S	No	0.61	1.0	0.87	0.72	0.99
	Yes	0.99	1.0	0.99	0.99	1.0
V	No	0.89	1.0	0.94	0.92	0.99
	Yes	0.99	1.0	0.99	0.99	1.0
F	No	0.74	1.0	0.73	0.73	1.0
	Yes	1.0	1.0	1.0	1.0	1.0
Q	No	0.98	1.0	0.96	0.97	1.0
	Yes	1.0	1.0	1.0	1.0	1.0

The TP, TN, FP, FN for the classification results obtained before and after sampling are shown in Table 5. The sensitivity, specificity, precision, F-score and accuracy obtained for the convolutional autoencoder + LSTM model without resampling and after resampling using ADASYN technique is shown in Table 6.

The model accuracy and loss for the original dataset and dataset resample using ADASYN techniques are shown in Figure 3 and Figure 4.

Figure 3 Accuracy and loss for original dataset (see online version for colours)

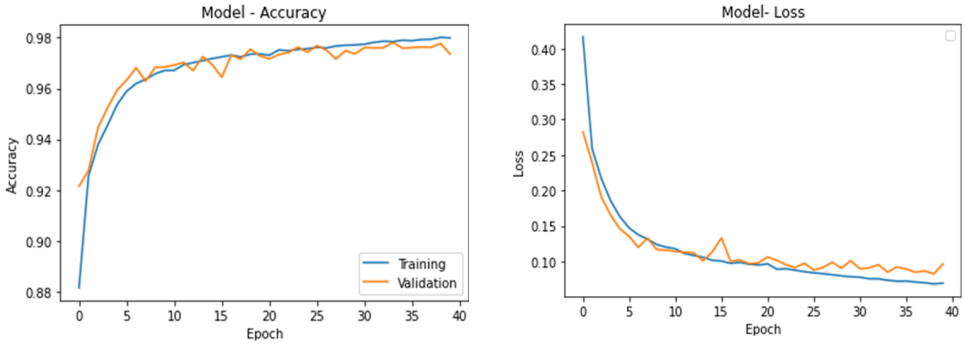
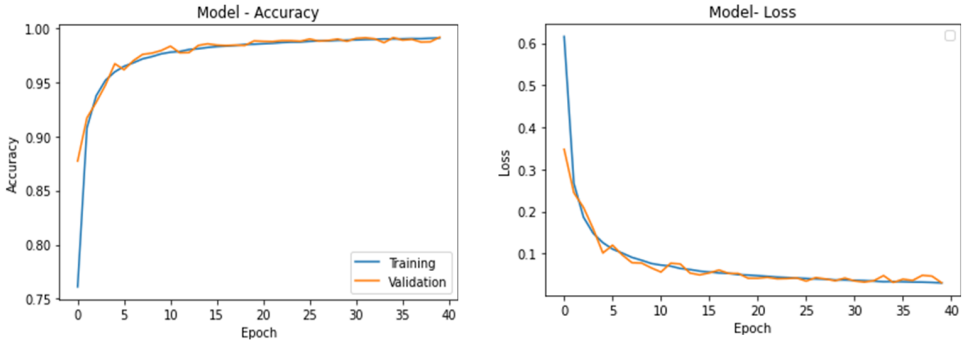


Figure 4 Accuracy and loss for ADASYN resampling technique (see online version for colours)



On comparison of the obtained results with other existing works (Yildirim, 2018; Acharya et al., 2017a, 2017b; Zubair et al., 2016; Kiranyaz et al., 2016; Rekha and Vidhyapriya, 2018a, 2018b), the proposed method gives an overall accuracy of 99.8%.

The highlights of the proposed model are as follows:

- Proposed system is fully automated.
- Noise filtering, feature extraction and selection techniques are not required.

6 Conclusions

Automation in identification of cardiac arrhythmias can help medical professionals by saving huge amount of time. The class imbalance due to lesser number of data instances in certain rare arrhythmia classes may reduce the overall performance of the arrhythmia classification system. The proposed research work overcomes this problem by resampling the minority classes with ADASYN technique. The combined use of convolutional autoencoder for feature extraction and LSTM for classification along with ADASYN improves the performance of the classification model. The average sensitivity, specificity, precision, F-score and accuracy of the proposed model is 99.2%, 100%, 99.2%, 99.2% and 99.8% respectively. The proposed work can be further extended by analysing the model with different datasets and varying the resampling technique.

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