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IOT BASED ECG: HYBRID CNN-BILSTM APPROACH FOR MYOCARDIAL INFARCTION CLASSIFICATION

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Abstract. *Cardiovascular disease such as ischemic heart disease and stroke are the most dangerous diseases in the WHO stats. Myocardial Infarction (MI), an ischemic disease of the heart, occurs due to a sudden blockage in the coronary arteries that supply blood to the heart causing a lack of oxygen and nutrients. The MI patient needs continuous monitoring using electrocardiography, the latter is always at risk of developing complications such as arrhythmias. As a solution, we proposed an internet of things (IoT) based ECG system for monitoring, the application layer was reserved for the detection of MI and arrhythmias using artificial intelligence so that the patients can keep being monitored even outside health facilities. For this purpose, this paper proposed a hybrid Convolutional Neural Network (CNN) – Bidirectional Long Short-Term Memory (BiLSTM) approach to classify ECG signals and evaluates its performance by using raw and preprocessed data, and comparing the results to related studies. Two datasets have been used in this classification. The results were promising, the model has scored 99.00% accuracy on raw data classifying 4 classes, and 99.73% accuracy on a larger preprocessed data for 3 classes classification. The proposed model is suitable to serve in our monitoring task.*

Keywords: electrocardiography, deep learning, Internet of Things, convolutional neural network (CNN), Bidirectional Long Short-Term Memory (BiLSTM)

EKG OPARTE NA IOT: HYBRYDOWE PODEJŚCIE CNN-BILSTM DO KLASYFIKACJI ZAWAŁÓW MIĘŚNIA SERCOWEGO

Streszczenie. *Choroby układu krążenia, takie jak choroba niedokrwienna serca i udar mózgu, to najniebezpieczniejsze choroby według statystyk WHO. Zawał mięśnia sercowego (MI), choroba niedokrwienna serca, występuje w wyniku nagłego zablokowania tętnic wieńcowych dostarczających krew do serca, powodując brak tlenu i składników odżywczych. Pacjent po zawale serca wymaga ciągłego monitorowania za pomocą elektrokardiografii, gdyż zawsze istnieje ryzyko wystąpienia powikłań w postaci arytmii. Jako rozwiązanie zaproponowano system monitorowania EKG oparty na Internecie rzeczy (IoT), którego warstwa aplikacyjna została zarezerwowana do wykrywania zawału serca i arytmii z wykorzystaniem sztucznej inteligencji, dzięki czemu pacjenci mogą być monitorowani nawet poza placówkami służby zdrowia. W tym celu w artykule zaproponowano hybrydowe podejście oparte na konwolucyjnej sieci neuronowej (CNN) i dwukierunkowej długiej pamięci krótkotrwałej (BiLSTM) do klasyfikacji sygnałów EKG i oceny ich działania przy użyciu surowych i wstępnie przetworzonych danych oraz porównaniu wyników z powiązanymi badaniami. W tej klasyfikacji wykorzystano dwa zbiory danych. Wyniki były obiecujące, model uzyskał 99,00% dokładności w przypadku surowych danych klasyfikujących 4 klasy i 99,73% dokładności w przypadku większych, wstępnie przetworzonych danych w przypadku klasyfikacji 3 klasy. Zaproponowany model nadaje się do realizacji postawionego zadania monitorowania.*

Słowa kluczowe: elektrokardiografia, uczenie głębokie, Internet rzeczy, konwolucyjne sieci neuronowe (CNN), dwukierunkowa długa pamięć krótkotrwała (BiLSTM)

Introduction

From WHO (World Health Organization) reports, in the fact sheets, cardiovascular disease tops the list of leading causes of death with both ischemic heart disease and stroke claiming more than 15 million lives, responsible for 27% of all deaths worldwide in 2019 [4]. Ischemic heart disease, mentioned in this report as the world's biggest killer, has the largest increase in deaths, increased by more than 2 million deaths from 2000, it is a critical public health problem. Commonly known as coronary artery disease, it is a noncommunicable disease, it occurs when the heart's blood vessels that supply the heart with oxygen and nutrients are blocked or narrowed [18] due to a build-up of fatty substances that reduce blood flow to the organ and leading to atherosclerosis.

After feeling pain in the chest, discomfort or shortness of breath, the patient must seek medical attention immediately, and describe the symptoms to the doctor in order to perform an ECG (electrocardiogram). It is a diagnostic non-invasive test used to extract signals from the heart by putting electrodes on the chest, arms and legs. It detects and records the electrical impulses of each beat. The diagnosis is made by analysing the recorded patterns and waveforms by a doctor or cardiologist. The graphical representation this activity consists of a series of waves and segments that provide valuable information about the heart's condition [22]. T wave and ST segment carry a lot of valuable information, the changes either elevation or depression of the segment and the flattening or the inversion of the wave can indicate some heart conditions such as myocardial infarction or ischemia, myocarditis, pericarditis [20].

In this paper, our main goal is to classify Myocardial Infarction and arrhythmias in order to use it in the application layer of our IoT wearable device [12] (Fig. 1). This device facilitates remote consultation between the ischemic patient and his doctor, allowing him to receive care without leaving his home resolving the mobility issues. It consists on extracting the ECG signal of the patient, processing it and send it via network to the healthcare provider, the latter will be aided by our diagnosis based on this classification as a second opinion, the interpretation and the analysis will be made by the doctor or the cardiologist in the context of the patient's clinical history and other diagnostic tests.

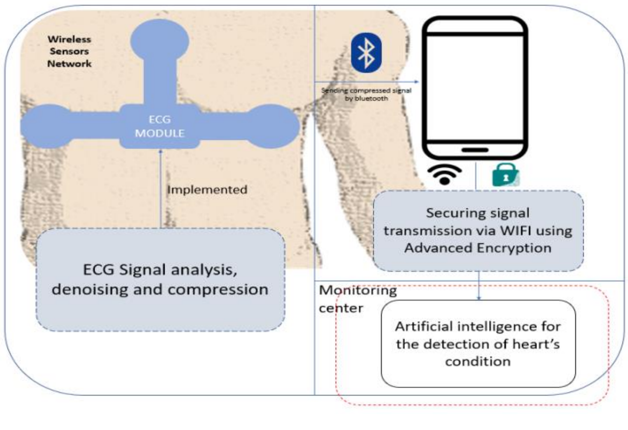

Fig. 1. IoT wearable device scheme

Recently, deep neural networks are applied widely in ECG signals classification, especially convolutional neural networks (CNNs), they've showed good accurate results. Mengze Wu et al. [23] proposed a 12-layer CNN model with 4 sets of convolutional layers. After each set, they reduce the number of filters and increment the kernel size by 2 beginning with kernel size of 13, and using average pooling layers, and adding in the end a dropout layer and 2 fully-connected layers.

The dataset utilized in this model is MIT-BIH Arrhythmia Database (MITDB) with 5 classes and pre-processing it by using some filters. They scored an overall accuracy rate of 97.41%. Acharya et al. [1] implemented a 9 layers CNN model based on 3 convolution layers with kernel size of 3, 4 and 4 respectively, and Max-pooling layer came after and at the end there are 3 fully connected layers. This model is deployed to classify 5 classes of ECG abnormalities, they reached an accuracy of 94.03% and 93.47% in original and denoised dataset respectively. In the other hand, Long Short-Term Memory LSTM is also widely used to classify ECG signals, it's a type of RNNs architecture used to overcome the disadvantages of RNNs such as vanishing gradients problems applied on sequential data. Yildirim et al. [24] used deep bidirectional LSTM to identify and classify ECG signals, the model starts with a wavelet-based layer WS for ECG signal sequences, followed by 2 BLSTM set of layers 64 and 32 respectively, then 2 fully connected layers. The model is also used to classify 5 classes and the outcome was a good performance of 99.39%. Singh et al. [21] also implemented an LSTM model for their 5 classes classification, the model contains 3 LSTM layers with 64, 265 and 100 neurons respectively followed each by a dropout layer of 0.2 and at last a sigmoid activation with MSE as the loss function. The model showed an accuracy of 88.1%. Depending on the complexity and the amount of data and resources, we can determine the architecture of our model, and since we can't rely on guess, the number of layers to use, especially in CNN, is often determined through experimentation. Deeper CNNs can learn more complex features, but eventually they require more data.

This paper's focus is the classification of myocardial infarction and some arrhythmias combined using deep learning approaches, we used the combination of 2 datasets from Physionet [10], MIT BIH Arrhythmia Database (MITDB) [17,19] and PTB Diagnostic ECG Database (PTBDB) [6], 3 classes to classify, normal class, MI class and Arrhythmia class. In this paper, we will apply our proposed model based on CNN and BiLSTM to raw and preprocessed Data. In the following section Proposed research method, we dive more in the architecture of our proposed model, the description and the preprocessing of the dataset and the evaluation metrics to evaluate the model. Section 2 is reserved for experimental results and discussion followed by conclusion in section 3.

1. Methodology

Our proposed model has been applied on a combination of 2 Physionet datasets, using the wanted categories to serve our main purpose. To evaluate the model's architecture efficiency, we used the training and testing on raw and preprocessed data separately. The first training was based on raw data using 4 classes of annotations from MITDB. The second training has been applied on a preprocessed data, based on [13] method, only 3 classes this time, but they carry more data, MITDB and PTBDB were both used. All operations have been done on a I5-8th gen processor laptop, 8 GB ram and Nvidia GeForce GTX 1050, including the GPU made the training/validation faster with an average of 37 seconds per epoch in preprocessed data training and 6 seconds per epoch in raw data.

1.1. Data preprocessing

In this paper, we use Physionet MITDB and PTBDB. In accordance with our main project, only ECG Lead II has been used. PTBDB contains 549 records sampled at 1000 Hz frequency, 148 subjects from 290 diagnosed with MI and 52 healthy subjects, these 2 classes are the only classes we need. MITDB contains records extracted from 47 subjects digitized at 360 Hz sampling frequency. Beats were annotated by 2 cardiologists who worked on them independently. We used these annotations to create 4 classes based on mappings between them and AAMI EC57 [3], see table 1.

Authors in [13] used a simple yet an effective method for pre-processing the data, they followed these steps to extract the beats from it:
1) Splitting the signal into 10sec window.
2) Normalisation of the amplitude values [0 1].
3) Finding all local maximums.
4) Applying a 0.9 threshold to find the R-peaks.
5) Finding the median time intervals of R-R.
6) Selecting signal parts with the length of 1.2 T for the R-peaks.
7) Filling the selected parts with zeros to make it equal to the predefined length.

After following these steps, we got beats of the length of 187 samples each, applied on both datasets, the distribution of beats in each class were as follow in table 2 and its distribution (Fig. 2). A balancing method is needed, in order to not delete useful information, we use oversampling over under-sampling, although oversampling duplicates or creates new synthetic examples in the minority class that can lead to overfitting [7]. The data shape now is (271767x187).

Table 1. AAMI EC57 chosen categories

Class	Annotations
F	Fusion of ventricular and normal
N	Normal
S	Aberrant Atrial premature Atrial premature Nodal premature Supra-ventricular premature
V	Premature ventricular contraction Ventricular escape

Table 2. Beats distribution per class

Class	Number of beats
Normal	90589
Arrhythmia	18857
Myocardial Infarction	10506

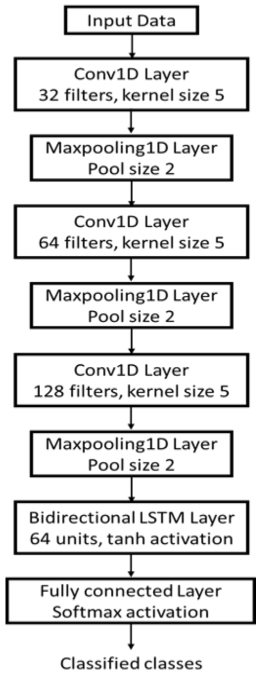

Fig. 2. Proposed model architecture

1.2. Hybrid CNN-BiLSTM approach

In this section, the model has been first built with a set of 3 convolution layers (Fig. 2), the first layer has 32 filters, the second has 64 and the third has128 filters, each layer has a kernel size of 5 with a ReLu activation function. The kernel size calculates the sliding window's size that moves along the input data to extract features [5], a kernel size of 5 would be suitable and large enough to capture meaningful patterns in the signal, with experimentation, we will verify if it's optimal. The 3 convolution layers are followed by Max-pooling layer each, to reduce the dimension of the output data and to increase the efficiency of the network and thus avoiding over-fitting phenomenon [16].

In the other hand, LSTM is known for capturing long-term dependencies in sequential data [25]. Since we have a large dataset, BiLSTM can perform better than a regular LSTM, it processes the input sequence in both backward and forward directions (Fig. 3), one from past to future and one in the opposite way using the 2 hidden states combined preserving information from both future and past rather than just future in LSTM. To increase the complexity of the model, we add after the convolution set a BiLSTM layer of 64 hidden units using tanh activation function to calculate the activation of the LSTM cells in both directions backward and forward. At the end, we add a Fully-Connected layer stacked with softmax activation.

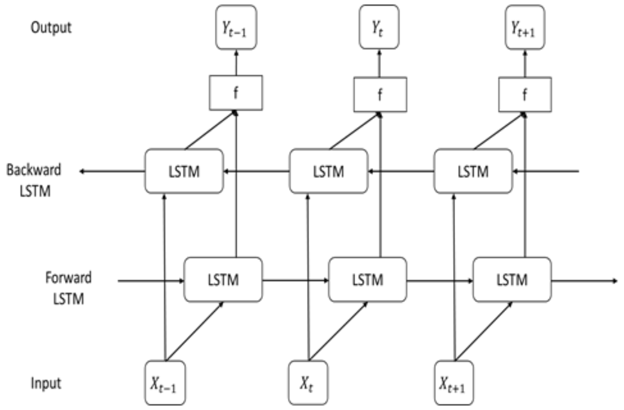

Fig. 3. BiLSTM Network architecture

1.3. Evaluation metrics

In order to evaluate how well our model is doing, we use the evaluation metrics. They indicate how a model is doing on the unseen data and its ability to make accurate predictions [15]. In this paper, we used accuracy (1), it calculates the match between the actual and the predicted class. Precision (2), it focuses only on the positives, TP and FP. Sensitivity (3) has the same principal as the precision, except it focuses on FN.

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

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

$$Sensitivity = \frac{TP}{TP + FN}$$

2. Results and discussion

2.1. Results on raw data

In this section, only MIT-BIH Arrhythmia dataset was used, no preprocessing was made, the long signals were segmented to 720 samples per portion, 4 classes of table 1 have been classified by our model, the dataset is imbalanced table 3. The compilation was based on Adam optimizer, and a batch size of 128. The data was split to 80% training and 20% testing. The validation took 20% from the training data. The training was made in 40 epochs. The model reached 99.15% training accuracy (Fig. 4) alongside with a 99.00% testing accuracy and a loss of 0.039 (Fig. 5). The minor class 4 has playing role in decreasing the overall accuracy as shown in the classification report (Table 4) due to the shortage of data in comparison with other classes.

Table 3. Number of portions per class

Class	Number of portions
N	7000
S	2700
V	7000
F	800

Table 4. Classification report based on the prediction of the testing data of the first training applied on raw data

Class	Precision %	Sensitivity %	Accuracy %
N	99.81	99.77	99.89
S	99.64	99.68	99.69
V	99.72	99.53	99.75
F	97.00	96.72	96.67

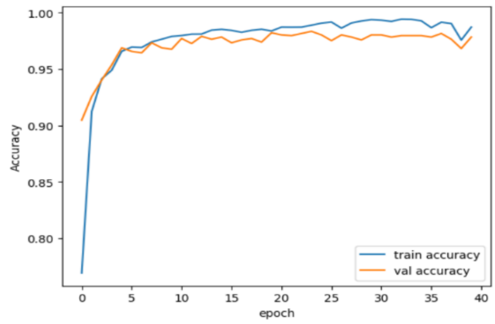

Fig. 4. Accuracy curve during training and validation applied on raw data

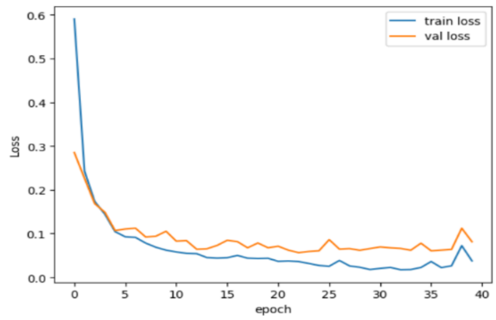

Fig. 5. Loss curve during training and validation applied on raw data

2.2. Results on preprocessed data

Unlike the previous section, both MITDB and PTBDB were used. This time the dataset is balanced, 3 classes with more data than the other one. The same parameters were used, with only 20 epochs this time. The results were very satisfying, the model achieved a training accuracy of 99.78% (Fig. 6) and a test accuracy of 99.73% and a training loss of 0.0063 (Fig. 7). The comparison of evaluation metrics of the 2 operations is in table 5. The classification report was as close as perfect (table 6).

Table 5. Proposed model performances in %

Input Data	Accuracy	Sensitivity	Precision
Raw Data (4 classes)	99.00	98.93	99.04
Preprocessed Data (3 classes)	99.73	99.80	99.80

Table 6. Classification report based on the prediction of the testing data of the first training applied on preprocessed data

Class	Precision %	Sensitivity %	Accuracy %
N	99.86	99.54	99.60
Arrhythmias	99.57	99.92	99.66
MI	99.97	99.94	99.94

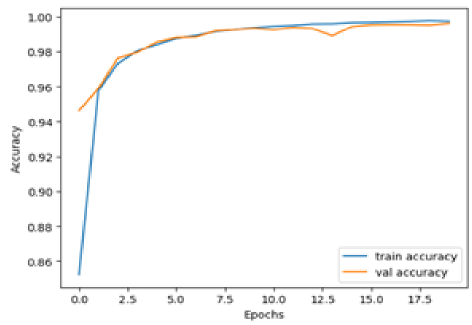

Fig. 6. Accuracy curve during training and validation applied on preprocessed data

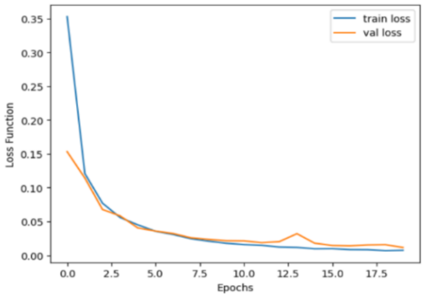

Fig. 7. Loss curve during training and validation applied on preprocessed data

2.3. Discussion

In this paper, we introduced our proposed approach applied to raw and pre-processed datasets. Our main goal is to classify myocardial infarction, but we had to experiment our model on a raw data to make sure that the pre-processing method is efficient and we can rely on it even in the main project (Fig. 1). The results were quite satisfying, the over-sampling has done well by balancing the data to ensure that the model won't take only the oversampled major classes. In the other hand, in the first experiment applied to raw data, the sensitivity of the fourth class was low in comparison with other classes (table 4), which decreases the overall performance of the classification, and that's due to the imbalanced data phenomenon.

In this experiment, we had to add and remove several layers, and adjust the parameters each time to get the best combination and results. Combining CNN with its extracting features nature and BiLSTM for sequential data proved to be a good match to this kind of data and classification. In the classification report (table 6), all the classes scored a good result. Comparing our model performance with the state-of-the-art, our proposed model outperforms a lot of other approaches with an accuracy of 99.73%, table 7. In the literature, many studies were bases on MIT-BIH arrhythmia database to provide their approaches, but not in the same manner or classes, but they give useful ideas as they work in ECG signals. Yildirim et al. [24] designed a DULSTM-WS and DBLSTM-WS for 5 classes classification from MITDB, the results show the effectiveness of the BiLSTM, moving forward and backward, reaching an accuracy of 99.39% as DULSTM-WS scored a 99.25% accuracy, and in the same time, adding WS layer outperforms by far the other standard models. For the same classes' classification, Mengze Wu et al. [23] proposed a 12-layer CNN with a data pre-processing based on wavelet transform, achieving 97.41% accuracy. Acharya et al. [1] proposed CNN model composed from 9 layers to classify the same classes, reaching 94.03%. Acharya et al. [2], to classify MI beats, they achieved 95.22% accuracy using CNN model. CNNs, through the literature, have shown good performance on ECG signals, though adding LSTM and BiLSTM improve their performances and make them more efficient. A pre-processing is always needed to get better results, we can't just rely fully on CNN ability of extracting features, also using an imbalanced data may decrease the performance if the gap is huge between the minor and the major class.

Table 7. Performance of the proposed model compared to state-of-the-art studies

Study	Database	Number of classes	Number of beats	DL Technique	Results
[23]	MITDB	5	32422	CNN	Denoising: Acc = 97.41%, Sen = 97.05%, Ppv = 97.21% Raw: Acc = 97.02%, Sen = 96.57%, Ppv = 96.84%
[1]	MITDB	5	109449	CNN	Acc = 94.03%, Spec = 91.54%, Sen = 96.71%,
[2]	PTBDB	2	110094	CNN	Noised: Acc = 93.53%, Ppv = 98.03%, Sen = 93.71% Denoised: Acc = 95.22%, Ppv = 98.43%, Sen = 95.49%
[14]	MITDB	5	83648	CNN	Acc = 99%, Ppr = 90.6%, Sen = 93.9% - **VEB** Acc = 97.6%, Ppv = 63.5%, Sen = 60.3% - **SVEB**
[24]	MITDB	5	7326	DULSTM-WS DBLSTM-WS	Acc = 99.25% Acc = 99.39%
[26]	MITDB	8	93371	LSTM, Focal Loss	Acc = 99.26%, Sen = 99.26%, Spec = 99.14%
[9]	MITDB CINC Challenge Dataset	3	8249	CNN	Balanced data: Acc = 85% , F1 = 84% Imbalanced data: Acc = 87%, F1 = 85%
[8]	MITDB Supraventricular Arrhythmia Database	5	289666	CNN	Acc = 93.71%, Spec = 94.77%, Sen = 91.25%, - **VEB** Acc = 93.61%, Spec = 96.40%, Sen = 62.70%, - **SVEB**
[11]	MITDB	5	100389	CNN	Acc = 92.7%
Proposed model	**MITDB** **MITDB+PTBDB**	**4** **3**	**17500** **119952**	**CNN-BiLSTM**	**Acc = 99%, Ppv = 99.04%, Sen = 98.93%** **Acc = 99.73%, Ppv = 99.80%, Sen = 99.80%**

3. Conclusion

We have presented in this paper our proposed model, fulfilling the objective of the application layer of our IoT ECG based, to provide continuous monitoring to MI patients, from arrhythmias to the disease itself. Combining CNN and BiLSTM has shown good results achieving 99.73% accuracy and takes place among the best approaches in the state-of-the-art. The preprocessing used on the data will be also used after extracting the signal from the patient, segmenting the signal to beats which can point directly to the change occurred on the ECG waves and intervals. The results were very good and satisfactory, serving our main objective. We won't stop on just MI, we will try to include other anomalies that needs monitoring as well, and saving lives thanks to the early diagnosis.

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