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A Fast and Accurate Myocardial Infarction Detector

Harold Martin
Department of Electrical and Computer Engineering
Florida International University
Miami, FL, USA
hmart027@fiu.edu

Walter Izquierdo
Department of Electrical and Computer Engineering
Florida International University
Miami, FL, USA
wizqu003@fiu.edu

Ulyana Morar
Department of Electrical and Computer Engineering
Florida International University
Miami, FL, USA
uwill002@fiu.edu

Mercedes Cabrerizo
Department of Electrical and Computer Engineering
Florida International University
Miami, FL, USA
mcabreriz@fiu.edu

Anastasio Cabrera
Manatee Memorial Hospital
Bradenton, FL, USA
akbrera99@yahoo.com

Malek Adjouadi
Department of Electrical and Computer Engineering
Florida International University
Miami, FL, USA
adjouadi@fiu.edu

***Abstract*—We propose a novel pipeline for the real-time detection of myocardial infarction from a single heartbeat of a 12-lead electrocardiograms. We do so by merging a real-time R-spike detection algorithm with a deep learning Long-Short Term Memory (LSTM) network-based classifier. A comparative assessment of the classification performance of the resulting system is performed and provided. The proposed algorithm achieves an inter-patient classification accuracy of 95.76% (with a 95% Confidence Interval (CI) of ±2.4%), a recall of 96.67% (±2.4% 95% CI), specificity of 93.64% (±5.7% 95% CI), and the average J-Score is 90.31% (±6.2% 95% CI). These state-of-the-art myocardial infarction detection metrics are extremely promising and could pave the wave for the early detection of myocardial infarctions. This high accuracy is achieved with a processing time of 40 milliseconds, which is most appropriate for online classification as the time between fast heartbeats is around 300 milliseconds.**

Keywords—Myocardial Infarction, Machine Learning, LSTM, Real-time

I. Introduction

Heart attacks (myocardial infarctions/MIs) and heart disease are the leading cause of death in the United States, accounting for 24.2% of all male deaths and 21.8% of all female deaths in 2017 [1]. Furthermore, over 800 thousand Americans suffer heart attacks every year [2], that is roughly a heart attack every 39.42 seconds. Of these, around 75% are first-time heart attacks and 25% happen to people who have had at least another one in the past. Of all MIs, about 20% are silent and happen without warning or symptoms [2]. Overall, close to 50% of Americans are at risk of any of the many heart diseases in existence that could potentially lead to a myocardial infarction, costing an average patient $11,664 on medical expenses [3, 4]. Therefore, because they have significant possible complications [5], their early and accurate diagnosis is of extreme importance.

However, physicians have a powerful tool in electrocardiograms (ECGs) to diagnose and track the progress of MIs. These non-invasively recorded signals can help clinicians and researchers assess the health and fitness of the hearth through the characteristics of its electrical activity [6]. As a result, numerous research papers have been written on the use of ECGs to diagnose and monitor multiple cardiac conditions, including myocardial infarctions [7-19].

Across all these publications, the methods used to achieve classification vary wildly, from simple classifier that rely on prior expert knowledge like KNNs to deep-learning approaches that deduce the relevant features from the inherent statistics of the recorded data. Just as important are the standards followed in conducting the training and testing phases on these recorded datasets. Therefore, special attention should be given to the type of classifier used and the testing metrics considered before any meaningful comparison could be conducted on these different approaches, especially when it comes to delineating the data that is seen in the training phase from unseen data in the testing phase.

In this study, we propose a novel and complete pipeline for the online real-time classification (40 milliseconds) of myocardial infarctions. We do so by using an Independent Component Analysis (ICA) R-spike detection method, to identify and localize the occurrence of ventricular depolarization events, alongside a multilayer LSTM network, to detect and classify infarcted heartbeats. We particularly use LSTM neurons for their long track record of positive results at classifying time-varying signals such as speech, text, and video. The resulting real-time classifier could be of great value to the population at risk of MI and as a monitoring tool for gauging disease progression.

II. Data

We use the popular Physikalisch-Technische Bundesanstalt (PTB) diagnostic ECG database [20, 21]. This dataset is composed of 549 12-lead ECG records from 209 men and 81 women. There are multiple different diagnoses in the dataset, but

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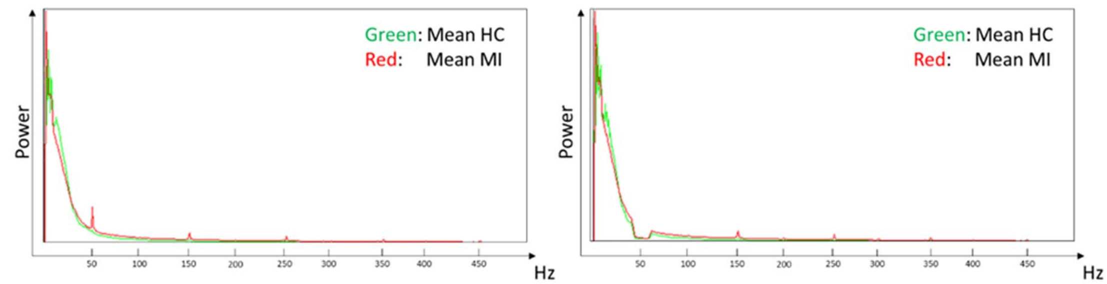

Figure 1: Frequency Power Spectrum of unfiltered (left) and filtered (right) data

for our study we only use patients with myocardial infarctions (MI) and the healthy controls (HC), this brings the patient count to 200 patients from the original 290. Furthermore, we only use records from those patients that were recorded no more than 5 days after the infarction date, except for the first electrocardiogram taken at admission, as after admission to the hospital, patients are given treatment and the heart's electrical activity responds to it.

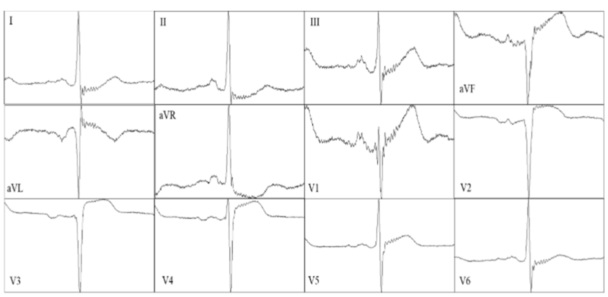

Figure 2: Sample Filtered and Centered Heartbeat

The data is filtered using a 50Hz band-stop cascade IIR filter to remove any powerline interference that might be left over after the initial recording, and a 500 milliseconds moving average filter to remove baseline wander as an inherent ECG artifact. Frequency spectrums of the signal are shown in Fig. 1 before and after the filtering step. After filtering, we apply the real-time R-peak detection algorithm described in [22] to produce near instantaneous ventricular depolarization detection. Heartbeats are segmented into 1-second samples, centered at the R-peaks, and separated into training and testing datasets. We have followed the Patient-Split dataset generation procedures as the performance metrics obtained from it on the testing dataset will most closely resemble those of the system's deployment in real-unseen data. That is, we have taken special care to ensure that any data from patients seen during training is not used for testing. A segmented sample of a processed heartbeat can be seen in Fig. 2.

III. Methods

The simplified system architecture of the proposed system for online and real-time diagnosis of myocardial infarctions is shown in Fig. 3. The first step is to filter the incoming data to remove undesired frequency components and noise. Subsequently, the ICA R-Spike detector is used to identify the center of the ventricular depolarization event and to use it as a reference for segmenting and centering samples to be passed to the MI classifier.

The proposed architecture continuously generates classification outputs for each detected heartbeat. The filter and the R-Peak detection stage run non-stop seeking out new samples to be processed. While the classifier produces a classification label (MI/HC) for every point in the input sample, only the last 80ms are used. This is because the classification does not become valid until the classifier has had a chance to look at the complete heartbeat (after the T wave).

For our classifier we use a deep LSTM neural network with five layers. The size of the network is chosen so that the network is big enough to accommodate a significant number of features and dropout is used during training on every other layer to minimize overfitting. A more detailed view of the network architecture can be seen in Fig. 4. This neural network architecture is particularly suited for this problem as it can handle time-varying data, does not require prior expert knowledge of the signal at hand, and is simpler than other previously proposed architectures. Furthermore, its simplicity makes it less prone to overfitting and yields low inference times.

The proposed model is built with Graves' LSTM [23] units and initialized using Glorot and Bengio's proposed

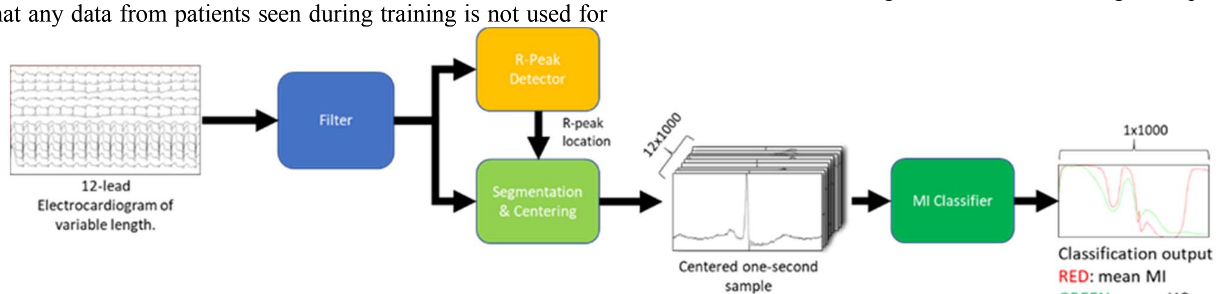

Figure 3: Simplified System Architecture

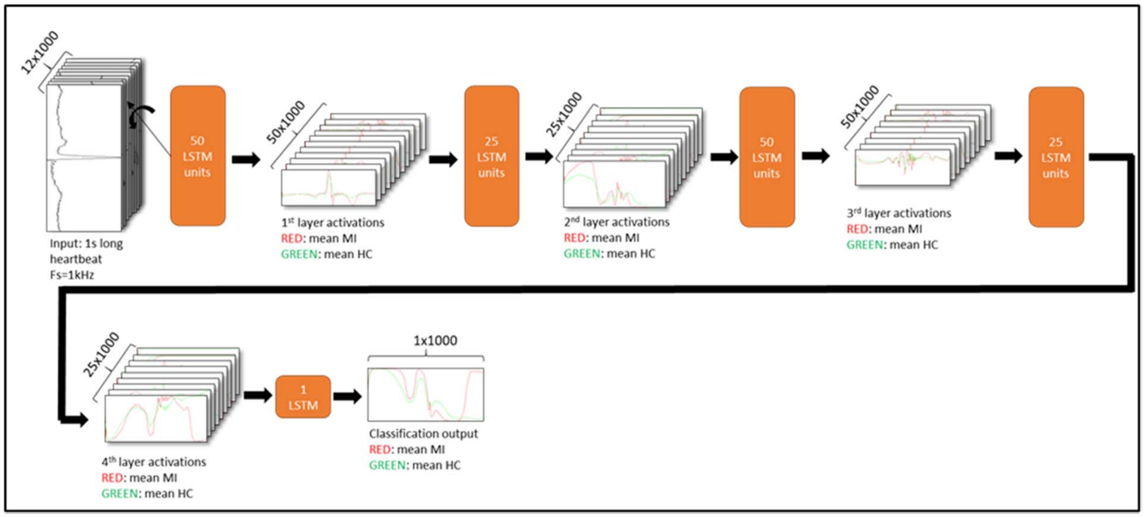

Figure 4: Classifier Architecture

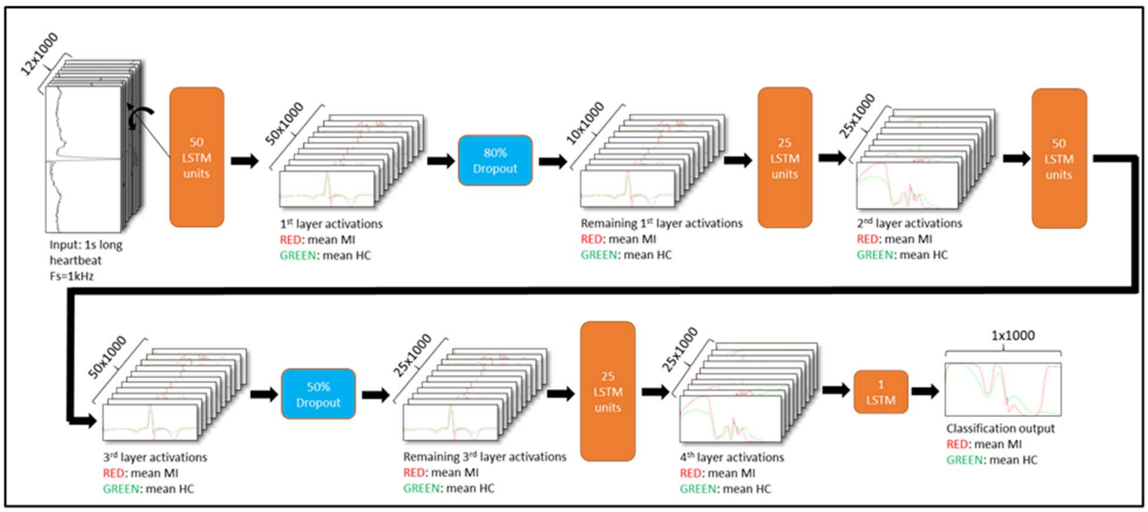

Figure 5: Classifier Architecture during Training

initialization [24]. It uses stochastic gradient decent with L2 regularization [25], RMSProp [26] as the optimizer, and gradient clipping to avoid exploding gradients due to excessive weight updates. A more detailed view of the network's training behavior and the influence of dropout can be appreciated in Fig. 5, where the first and third layer implement different dropout rates. By using dropout during training, we force the network to prioritize and create redundant copies of important latent features in large layers. We do so by randomly zeroing out, or dropping, the outputs of 80% of the neurons in the first layer and 50% of the neurons in the third one, thereby effectively reducing the amount of data available to the subsequent layers.

IV. Results

The network is trained using early stopping, where after 10 epochs of no performance improvements we stop training and back up to the best set weights. A 10-fold cross validation approach is performed to avoid reporting on a particularly beneficial or detrimental dataset split due to their small sizes. We train the model in a 64-bit Windows 10 PC with an AMD FX-8350 Eight-Core Processor, 32 GB of DDR3 RAM, and an NVIDIA GeForce GTX1070 graphics card. The system proposed herein was implemented and deployed using Java and DeepLearning4J version 0.9.1 as the machine learning library.

Performance was measured by using the following standard metrics: Accuracy, F1-Score, Precision, Recall, Specificity, and Youden's J statistic (J-Score/J-Measure) as defined in (1) through (6).

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$F1 = \frac{2*TP}{2*TP+FP+FN} \quad (2)$$

$$Prec = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$Spec = \frac{TN}{TN+FP} \quad (5)$$

$$J = Recall + Spec - 1 \quad (6)$$

TABLE I: PERFORMANCE RESULTS OF TWO TRAINING SCENARIOS

	Accuracy	F1	Precision	Recall	Specificity	J	Train Epochs
Max Acc	0.9576 (±0.024)	0.9673 (±0.021)	0.9686 (±0.027)	0.9667 (±0.024)	0.9364 (±0.057)	0.9031 (±0.062)	19.44 (±18.9)
Max J	0.9566 (±0.025)	0.9664 (±0.022)	0.9713 (±0.028)	0.9627 (±0.026)	0.9438 (±0.055)	0.9064 (±0.06)	21.33 (±17.5)

**Values in parenthesis represent the 95% confidence interval*

Where TP represent true positives (patients with MI diagnosed as MI), TN as true negatives (HC diagnosed as HC), FP as false positives (HC diagnosed as MI), and FN as false negatives (MI diagnosed as HC).

We trained our system seeking two important measures and report these values in Table 1: highest classification accuracy and highest J-Score.

The forward inference time, the time required for the network to process a sample, is 12.3 milliseconds on average, while the whole system requires around 40 milliseconds to process a sample when accounting for preprocessing time. Training took on average 5 hours and covered around 30 thousand 1-second samples per epoch (a single run through all training instances). From Table 1, the maximum number of training epochs was 50 for the slowest converging training fold and 3 for the fastest, with an average of 19.44 epochs when looking for the maximum accuracy and 21.33 when looking for the best balance between specificity and sensitivity. The average accuracy across the 10-fold cross validation is 95.76% with a 95% confidence interval (CI) from 93.36% to 98.16% and the average J-Score is 90.31% with a 95% CI from 84.11% to 96.51%.

V. Comparison and Discussion

Although the literature on myocardial infarction detection and classification is abound, the way in which they create their training and testing datasets are not uniformly consistent, resulting in intra- and inter- patient classifiers that are not directly comparable. Therefore, in this section we will attempt to compare our results to those from other methods that most closely resemble the data splitting method we use, that is inter-patient classifiers. We will also explain why we believe that the proposed method is not directly comparable to some of the references we consider in this section.

As can be appreciated from Table 2, our proposed method has some of the highest metrics in comparison to other approaches. These are methods that use the same number of Electrocardiogram leads (12) and are trained on the same database (although not specifically the same dataset). However,

TABLE II: COMPARATIVE ASSESSMENT OF THE PROPOSED METHOD

Study	Dataset	# Leads	Sample Length	Method	Accuracy	Recall	Specificity	J
[27]	**PTB** 52 HC (10,646 samples) 128 MI (48,690 samples)	12	0.6 seconds	MFB-CNN	98.79%	98.73%	99.35%	98.08%
[28]	**PTB** 52 HC (10,638 samples) 148 MI (53,712 samples)	12	0.6 seconds	CNN and BLSTM	93.08%	94.42%	86.29%	80.71%
[29]	**PTB** 52 HC (6,945 samples) 113 MI (17,212 samples)	12	4 seconds	ML-ResNet	95.49%	94.85%	97.37%	92.22%
[30]	**PTB** 52 HC (5,373 samples) 148 MI (28,213 samples)	12	4 seconds	PCA, SVM	92.69%	80.96%	80.96%	61.92%
[31]	**PTB** 52 HC (1,886 samples) 148 MI (11,355 samples)	12	5 seconds	DWT-PCA-ANN	98.21%	99.40%	98.22%	97.62%
[31]	**PTB** 52 HC (1,886 samples) 148 MI (11,355 samples)	12	5 seconds	Deep Residual CNN	100%	100%	100%	100%
Proposed	**PTB** 52 HC (10,296 samples) 148 MI (24,664 samples)	12	1 second	Deep LSTM	95.66%	96.27%	94.38%	90.64%

not all the methods covered in this table are directly comparable as detailed below.

Liu et al., in [27], introduce a Multiple-feature-branch CNN classifier, that produces a particularly good inter-patient MI classifier, but they use data from the patients in the testing set during training (the first 32 beats of each patient), effectively contaminating it and no longer producing a pure inter-patient classifier and rather something that is somewhat in between intra- and inter- patient.

In [28], Liu et al. expand on their previous work on multiple-feature-branch CNN classifiers and add bidirectional LSTMs, producing an MFB-CBRNN. This time around, they avoided contamination of their training sets and did produce a truly inter-patient MI classifier. Their approach classifies single heartbeats, just like ours, but produces less accuracy, 93.08% compared to 95.66% for ours, and lower J-Score, 80.71% vs. ours at 90.64%.

Han and Shi produced two good classifiers in [29] and [30], however, even though they claim to produce inter-patient classifiers, it is unclear from their dataset generation descriptions that they took special care to ensure that data from patients seen during training was not used for testing. It appears that their dataset generation method resembles that of a File-Split instead. They also require particularly long sample sizes that encompass more than a single heartbeat.

Perhaps the best classifier in terms of accuracy is reported by Jafarian et al.[31], achieving 100% accuracy in their end-to-end deep neural network model, but their method requires five (5) second samples and is perhaps resource intensive to deploy. Nevertheless, they do take particularly good care to avoid cross-contamination of their training and testing sets, yielding truly inter-patient classifiers.

VI. Conclusions

We have put forward a novel pipeline for the real-time online detection of myocardial infarction from a single heartbeat of a 12-lead electrocardiogram. Our pipeline combines a real-time R-spike detector with a novel deep LSTM classifier to produce highly accurate and fast detection results (40 milliseconds when accounting for preprocessing time). The proposed system achieves state-of-the-art performance with an accuracy of 95.76% (with a 95% Confidence Interval of ±2.4%) and a balance between specificity and recall of 90.31% (±6.2% 95% CI). The uses and benefits of the proposed system are far reaching as they can have significant societal and clinical impacts in the lives of not only at-risk patients but also the population at large.

However, as mentioned before in the literature, the true benefits of any MI detector would depend on the numbers of at-risk individuals. Because a significant portion of MI's mortality is due to the lack of awareness to the condition and therefore the lack of immediate medical attention. Consequently, such an approach could significantly improve the odds of detecting silent MIs by monitoring at risk individuals and providing them with an early diagnosis. Determining the early sign of MI could help in the planning of early treatment and extending the time available for doctors to plan ahead on an individual basis in case of an emergency.

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