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ScienceDirect

Procedia Computer Science 207 (2022) 3473–3481

Procedia Computer Science

www.elsevier.com/locate/procedia

26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)

ECG-Based Arrhythmia Classification using Recurrent Neural Networks in Embedded Systems

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Abstract

Cardiac arrhythmia is one of the most important cardiovascular diseases (CVDs), causing million deaths every year. Moreover it is difficult to diagnose because it occurs intermittently and as such requires the analysis of large amount of data, collected during the daily life of patients. An important tool for CVD diagnosis is the analysis of electrocardiogram (ECG), because of its non-invasive nature and simplicity of acquisition. In this work we propose a classification algorithm for arrhythmia based on recurrent neural networks (RNNs) that operate directly on ECG data, exploring the effectiveness and efficiency of several variations of the general RNN, in particular using different types of layers implementing the network memory. We use the MIT-BIH arrhythmia database and the evaluation protocol recommended by the Association for the Advancement of Medical Instrumentation (AAMI). After designing and testing the effectiveness of the different networks, we then test its porting to an embedded platform, namely the STM32 microcontroller architecture from ST, using a specific framework to port a pre-built RNN to the embedded hardware, convert it to optimized code for the platform and evaluate its performance in terms of resource usage. Both in binary and multiclass classification, the basic RNN model outperforms the other architectures in terms of memory storage (~117 KB), number of parameters (~5 k) and inference time (~150 ms), while the RNN LSTM-based achieved the best accuracy (~90%).

Keywords: Recurrent neural network (RNN); electrocardiogram (ECG); cardiovascular disease (CVD); arrhythmia; classification; microcontroller; embedded system; wearable sensor.

1. Introduction

Cardiovascular diseases (CVDs), such as myocardial infarction, myocarditis and arrhythmia, are among the leading causes of death worldwide, accounting for more than 17 million deaths every year, representing 32% of all global deaths, according to the World Health Organization [1].

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10.1016/j.procs.2022.09.406

Cardiac arrhythmia is one of the most important CVDs. Arrhythmias are irregularities in the heartbeat, causing it to be too fast or too slow, due to improper intracardiac conduction or to erroneous pulse formation. While arrhythmia can often be a mild condition, it can affect the whole heart functionality and lead to more severe diseases, even resulting in sudden death. To complicate the diagnosis, arrhythmias can occur intermittently, especially in early stages of the problem; it is thus difficult to detect them in a short time window, requiring instead continuous patient monitoring in daily life [2].

Electrocardiogram (ECG) plays a central role in clinical diagnosis of CVDs, including arrhythmia [3–6]. The ECG signal records the electrical activities of the heart, reflecting the physiological state of various parts of the organ. Cardiologists can detect several CVDs or other anomalies by visually inspecting the waveforms from ECG recordings.

However, due to the intermittent nature of arrhythmias, the diagnosis in this case requires examination of large amount of data, thus highlighting the importance of automated analysis techniques, that have shown to generally be reliable and accurate in classification of patients affected by arrhythmia [7–16].

Such automated techniques can possibly be implemented in wearable devices [17–21], directly carried on the patient's body in order to acquire data over long periods of time, a crucial requirement for arrhythmia detection.

In particular, computer-aided multi-class classification of pathological beats is of paramount importance to perform correct diagnosis as reported in recent works [13, 22–35] where several methods for automatic classification of ECG signals have been used to this end.

A first set of algorithms can be grouped in the category of statistical machine learning (ML). Specific classification algorithms that have been used in this category include support vector machine (SVM) [8, 28, 30–32, 36–38], k-nearest neighbors (k-nn) [39], as well as powerful dynamical models such as Bayesian networks [40, 41] and hidden Markov models [42, 43]. Signals are directly elaborated in time-domain, or specific features can be extracted, for example in the frequency domain or through wavelets [44, 45].

A second category of algorithms is deep learning, using deep neural networks (DNNs) to classify input data through a network previously trained on a similar set of inputs with associated output information, in the process known as supervised learning [23, 24, 46–48], possibly combined with other techniques, like hybrid neuro-fuzzy systems [49–51]. In particular, recurrent neural networks (RNNs) have shown to be especially effective for time-based data series, being able to model temporal dependencies intrinsic in dynamically variable signals [18, 52, 53]. To this end, an RNN contains special layers that can keep track of the previous input data at a given time, unlike other layers reacting to the current state only, thus implementing a memory of the signal trend.

In this article we propose an RNN-based classification algorithm for arrhythmia operating directly on ECG data, exploring the effectiveness and efficiency of several variations of the general RNN, in particular using different types of layers implementing the network memory.

After designing and testing the effectiveness of the different networks, we then test its porting to an embedded platform, namely the STM32 microcontroller architecture from ST, using a specific framework to port a pre-built DNN to the embedded hardware, convert it to optimized code for the platform and evaluate its performance in terms of resource usage.

The article is organized as follows. In Section 2 we describe the ECG dataset we used, the architecture of the RNNs and the hardware and software used. Section 3 reports the experimental results on both the desktop and the embedded platform. Finally some conclusions are drawn in Section 4.

2. Material and Methods

2.1. Dataset

The dataset used is the MIT-BIH arrhythmia database [54, 55], a publicly available database provided by PhysioNet [56].

The MIT-BIH arrhythmia database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. 23 recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

2.2. RNN Architecture

The RNN used in this paper is depicted in Figure 1, and is based on architectures commonly used with time-based sensor data [57, 58, 53].

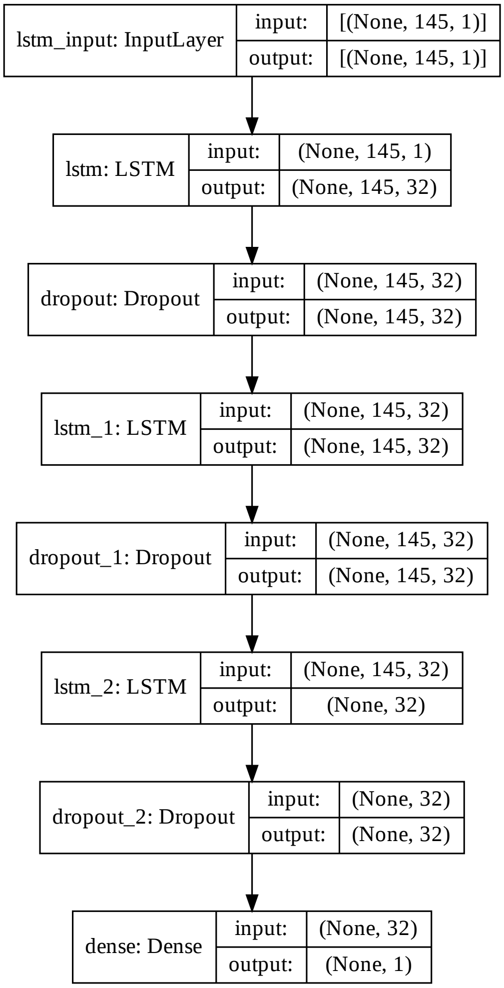

Fig. 1. Network architecture using LSTM as RNN layers.

We used TensorFlow with Keras to build and run the network (see Section 2.3). The core of the network is represented by three cascaded RNN cells, each followed by a dropout layer randomly discarding part of the input in order to reduce overfitting.

The last component is a fully connected (dense) layer with a sigmoid/softmax activation function for binary/multiclass classification respectively, performing the final classification of the input sample.

As part of the experiment, four kinds of RNN layers have been tested, all of them available in the software framework, specifically:

- *Simple RNN*: Basic RNN block where the output from previous timesteps is to be fed to next timestep.
- *GRU*: Gated Recurrent Unit, first proposed in Cho et al. [59].
- *LSTM*: Long Short-Term Memory, first proposed in Hochreiter & Schmidhuber [60].
- *Bidirectional LSTM*: A variant of LSTM that not only processes sequence from start to end, but also backwards.

2.3. Hardware and Software

For the desktop part, the RNNs were developed with TensorFlow 2.4.0 and Keras 2.4.0, on the Google Colaboratory platform.

For the embedded part, we tested the RNNs on a Cloud-JAM L4 board [61] which, for its small form factor and integrated Wi-Fi, can represent a valid prototyping base for an hypothetical wearable system. Moreover it allows testing the RNN on a real hardware and evaluating its performance in terms of memory and execution time. The classification of test data is done in real time by providing input data to the board from the test set via a serial interface. This also ensures reproducibility of the results with respect to the other tests.

The board features an STM32L476RG microcontroller, with an ARM 32-bit Cortex-M4 CPU + FPU, frequency up to 80 MHz, 1 MiB flash memory, 128 KiB RAM and about 3 mA of CPU current consumption at full speed.

The porting of the neural network to the STM32 architecture is made possible by a software framework from ST, named "STM32Cube.AI" [62] (version 7.0.0), integrated in the STM32Cube IDE. The software is a complete solution to import a TensorFlow/Keras model, test its compatibility and memory requirements and convert it to an optimized C implementation for the target architecture. The generated network can then be evaluated with test input data, both on the computer and the actual device, to get various metrics like execution time, number of specific hardware operations and accuracy.

3. Experimental Results

3.1. Testing on Desktop

The experiments were made with 4 different variations of the RNN layers (see Section 2.2) with the following parameters:

- size of the recurrent states: 32
- dropout rate: 0.2
- batch size: 64
- training epochs: 30

The MIT-BIH dataset was split as follows: 75% for traininig, 5% for validation during training, 20% for independent testing of the resulting network, considering different subjects for each set. A window of 200 ms (145 samples) containing the annotated beat was extracted for each ECG record, obtaining a tensor of $n \times 145 \times 1$ as input of the RNNs, where n represents the number of observations for training, validation or testing. Thus, the input of the RNNs is a time series divided into windows of a given duration (event-based).

A binary and a multiclass classification have been carried to detect abnormal from normal beats and to classify different types of arrhythmias.

The binary classification has been performed grouping the original 15 classes of the MIT-BIH database in 2 classes, dividing all the abnormal beat records (A) from the normal beat one (N). In this first case, the MIT-BIH dataset (47 subjects) was split in 34 subjects for traininig (75%), 3 subjects for validation (5%), 10 subjects for testing (20%) and thus have a consistency of: 82080 observations for training (56670 for N and 25410 for A), 5558 observations for validation (3485 for N and 2073 for A) and 21837 observations for testing (14884 for N and 6953 for A).

Following the Association for the Advancement of Medical Instrumentation (AAMI) recommended practice [63], the MIT-BIH heartbeat types are grouped into 5 heartbeat classes: normal beat (N), supraventricular ectopic beat (SVEB), ventricular ectopic beat (VEB), fusion (F) and unknown beat type (Q), as shown in Table 2. Therefore, multiclass classification has been performed grouping the original 15 classes of the MIT-BIH database into 5 classes.

In addition, as recommended by the AAMI, the records with paced beats were not considered, namely 102, 104, 107, and 217. In this second case, the resulting 43 subjects of the MIT-BIH dataset were split in 31 subjects for traininig (75%), 3 subjects for validation (5%), 9 subjects for testing (20%) and thus have a consistency of: 75256 observations for training, 5422 observations for validation and 20036 observations for testing.

Table 1 shows the result of the binary classification, comparing the use of the four different kinds of RNN layers. The table shows, for every experiment, the memory occupation of the resulting model, the number of trainable parameters, the classification accuracy of the training, validation and testing phases respectively, the corresponding loss value for every phase and the inference time for the testing phase, averaged on a single input.

It can be seen from the results that the LSTM layer reaches the best accuracy, in particular an accuracy of 90.62% for the independent testing set, at the cost of a bigger complexity in terms of memory and number of parameters.

Table 1. Comparison of different RNNs trained on the MIT-BIH arrhythmia database in terms of storage cost, accuracy, loss and inference time, best results are displayed in bold - Binary classification - Performance on Desktop.

Model	**Storage cost [KB]**	**Parameters number**	**Accuracy**			**Loss**			**Inference time [ms]**
			Train	Val	Test	Train	Val	Test	
RNN	**114.062**	**5281**	0.7208	0.6531	0.7871	0.5664	0.6248	0.4984	**0.505**
GRU	245.234	16065	0.9822	0.9518	0.8248	0.0563	0.1473	0.4418	0.846
LSTM	303.680	21025	0.9847	0.9291	**0.9062**	0.0540	0.2527	**0.2686**	1.374
BiLSTM	778.812	58433	0.9822	0.9225	0.8627	0.0574	0.2114	0.4832	1.653

Table 2. MIT-BIH labelling according the standard AAMI classes.

AAMI	Classes	MIT-BIH labels
Normal	N	N, L, R
Supraventricular Ectopic Beat	SVEB	e, j, A, a, J, S
Ventricular Ectopic Beat	VEB	V, E
Fusion	F	F
Unknown Beat	Q	/, f, Q

Table 3 shows the results obtained using the different architectures to solve the multiclass classification task. Also in this case, the basic RNN model outperforms the other architectures in terms of memory storage, number of parameters and inference time, while the RNN LSTM-based achieved the best accuracy.

3.2. Testing on the Embedded Platform STM32L4 Cloud-JAM L4

In order to implement a wearable sensor able to detect arrhythmia disease using RNNs, we ported the models described in Table 1 and Table 3 on the embedded device Cloud-JAM L4, based on an STM32 microcontroller, which requires a modest computational power and memory resources.

The porting of the neural networks to the STM32 architecture has been performed as follow. Once the model has been trained to a satisfactory accuracy, it must be converted to an executable code that runs on the embedded device. This can be a complex process, but STM32Cube IDE offers the STM32Cube.AI converter for this purpose, that converts the TensorFlow/Keras model in C code and generates the firmware for the chosen platform. The generated

Table 3. Comparison of different RNNs trained on the MIT-BIH arrhythmia database in terms of storage cost, accuracy and inference time, best results are displayed in bold - Multiclass classification - Performance on Desktop.

Model	Storage cost [KB]	Parameters number	Accuracy			Loss			Inference time [ms]
			Train	Val	Test	Train	Val	Test	
RNN	**116.273**	**5413**	0.9272	0.9495	0.8698	0.2722	0.1894	0.3220	**0.821**
GRU	245.984	16197	0.9642	0.9698	0.8664	0.1461	0.1027	0.4776	1.660
LSTM	305.602	21157	0.9609	0.9187	**0.9019**	0.1522	0.2086	**0.3093**	1.590
BiLSTM	782.305	58693	0.9713	0.9056	0.8888	0.1032	0.3759	0.3617	2.262

network can then be evaluated with test input data, both on the computer and the actual device, to get various metrics like execution time, number of specific hardware operations and accuracy. Figure 2 resumes the described procedure.

Table 4 reports the results achieved by the implemented on board RNNs in terms of testing accuracy, MACC (multiply-accumulate operation), ROM Bytes, RAM Bytes, and inference time, for binary and multiclass classification respectively.

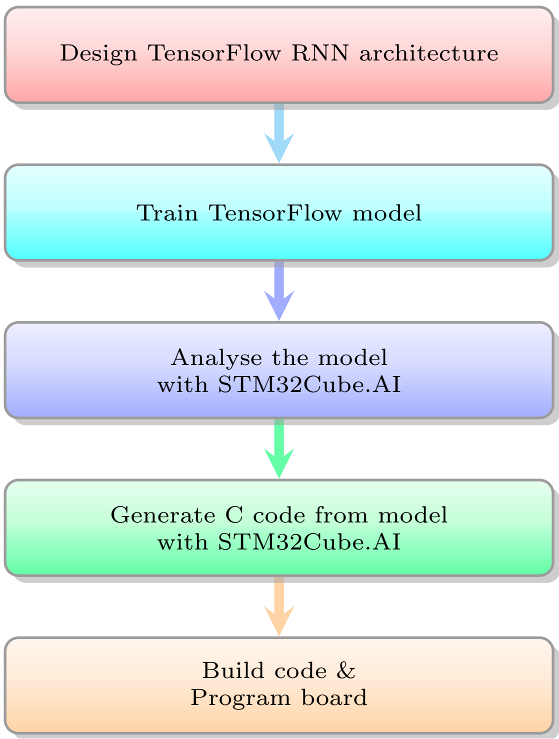

Fig. 2. Process of integrating the RNN into the STM32L4 Cloud-JAM L4 board with STM32Cube.AI.

Table 4. Details of the LSTM model on the MIT-BIH arrhythmia database analyzed with X-CUBE-AI - Binary classification - Performance on the embedded platform STM32L4 Cloud-JAM L4.

	Model	Test Accuracy	MACC	ROM Bytes	RAM Bytes	Inference time [ms]
Binary Classification	RNN	0.7871	761003	21124	37960	149.792
	GRU	0.8248	2269003	64260	38472	427.620
	LSTM	0.9062	3057803	85252	38600	659.160
	BiLSTM	0.8627	8491275	236036	75720	1640.590
Multiclass Classification	RNN	0.8698	761200	21652	37976	148.536
	GRU	0.8664	2269200	64788	38488	426.806
	LSTM	0.9019	3058000	85780	38616	665.863
	BiLSTM	0.8888	8491600	237076	75736	1642.146

4. Conclusions

In this work, several variations of RNNs have been applied to detect arrhythmia in ECG signals. The primary aim was to perform a binary and a multiclass recognition, classifying both normal/abnormal beats and different types of arrhythmia. The effectiveness, accuracy and capabilities of ECG arrhythmia detection through RNNs is demonstrated and a comparisons with different RNN models have been carried out. Moreover, in order to perform the arrhythmia detection directly on an embedded device, a porting of the implemented RNNs has been made in a low cost, low power microcontroller, ensuring the required performance in terms of accuracy and low complexity. Both in binary and multiclass classification, the basic RNN model outperforms the other architectures in terms of memory storage (∼117 KB), number of parameters (∼5 k) and inference time (∼150 ms), while the RNN LSTM-based achieved the best accuracy (∼90%).

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