Detection of Cardiac Arrhythmias in Electroc Ardiograms Using Deep Learning

Amenah Alwan Salman
Department of Information Technologies
Altinbas University
Istanbul, Turkey
203721091@ogr.altinbas.edu.tr

Abdullahi IBARAHIM
Department of Computer Engineering
Altinbas University
Istanbul, Turkey
abdullahi.ibrahim@altinbas.edu.tr

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***Abstract*— Medical diagnostic support systems based on automatic learning algorithms, called machine learning, represent a form of artificial intelligence (AI) that improves the performance, quality, and speed of health care. Improvements in embedded machine learning applications have led to the design of many medical monitoring devices. The latter are equipped with biological signal sensors to measure the activity of the target organ of a subject. The essential objective of these devices is to record, save and analyze the acquired signals to establish an appropriate diagnosis and/or identify the signs of pathological symptoms. The work of this paper falls within this context and has the main objective of implementing new strategies for the analysis and diagnosis of Electrocardiogram (ECG) signals, focused on the detection of episodes of cardiac arrhythmia.**

***Keywords*— UAV, ML, DL, ANN.**

I. INTRODUCTION

Cardiovascular disease (CVD) is one of the most pressing health concerns. CVD is the leading cause of death worldwide. According to the World Health Organization (WHO), CVD causes 17.9 million deaths worldwide each year, or 31% of all deaths [10], CVD is the second cause of death after cancer, with around 150,000 deaths per year and 400 deaths per day. Myocardial infarction, also called heart attack, is the deadliest form of CVD in the world. It causes 18,000 deaths per year, or 10% of total mortality [11]. In this thesis, we are interested in CVD, and more specifically in one of its main causes, namely cardiac arrhythmias. Arrhythmia is an abnormality of cardiac conduction that can be accompanied by various often fatal complications. An arrhythmia can occur when the electrical impulses that coordinate the heartbeat no longer work properly, causing the heartbeat to speed up, slow down, or become irregular [12–14]. In the elderly, atrial fibrillation (AF) is the most common form of arrhythmia [12, 13].

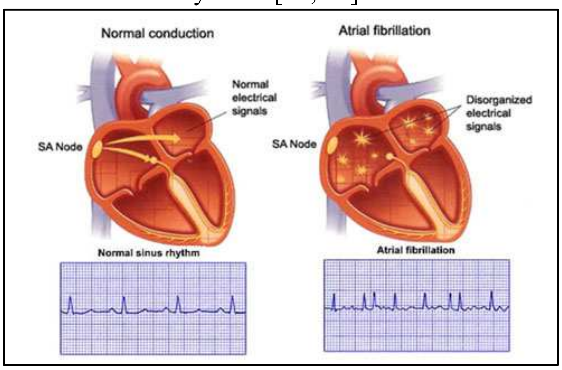

Fig..1 atrial fibrillation (AF) a common cardiovascular disease (CVD) shown in an ECG.

The diagnosis of AF is a delicate task because of its silent clinical forms and the paroxysmal form of AF [12]. Current recommendations are to use a 24-48 hour Holter electrocardiogram (ECG) to detect the presence of paroxysmal AF when it is suspected, but the recognition rate remains low [15]. In cardiology, ECG is a common practice for the detection of many forms of arrhythmias due to its non-invasive and inexpensive nature. Conventional diagnosis of arrhythmia consists of examining the ECG tracing, including its intervals and waves, generated by the various heart tissues, and checking its morphological conduction. The main morphological characteristics used to identify arrhythmias are the absence of P waves, the irregularity of the R-R intervals, or the waveform of the ECG tracing[21]. Conventional analytical methods for the diagnosis of arrhythmia by visual inspection of Holter ECG recordings are costly in terms of time and money. In addition, the presence of permanent ectopic beats, motion artifacts, and noise superimposed on ECG waveforms significantly complicate the interpretation and identification of signs associated with cardiac arrhythmias. Given these constraints and the enormous time invested in manual analyzes of Holter ECG signals, doctors have favored the use of automated systems to help diagnose arrhythmia. These systems are designed to facilitate arrhythmia diagnosis[22], overcome decision-making difficulties, and reduce evaluation time. Noble gas brain protection was studied using an in vitro hypoxic-ischemic rat hippocampus damage model. 37 Krypton, neon, helium, and other noble gases are neuroprotective after brain injury or cardiac arrest.

II. RELATED WORKS

The researchers evaluated two neuroprotective medicines on rat hippocampus cells subjected to anoxia and glucose deprivation. Given the in vitro nature of the study, these results are consistent with past studies about the neuroprotective advantages of these noble gases, yet their therapeutic value remains unknown. Manning, we employed selective aortic arch perfusion to explore noncompressible thoracic hemorrhage. 38 HBOC-201 may enhance ROSC in trauma studies. This trial compared HBOC-201 to fresh whole blood perfusion. 38,39 HBOC-201 was compared to fresh whole blood, ECLS was converted, and selective aortic-arch perfusion was used to address systemic derangements. Even in a systolic animal, ROSC was equivalent utilizing blood or HBOC-201. Extracorporeal transfer was expected.[23]

Both groups had similar physiologic derangements owing to ischemia reperfusion injury, with HBOC-201 having higher pulmonary hypertension. HBOC-201 can achieve ROSC, but pulmonary hypertension and administration issues may preclude its widespread usage until additional research are performed and reperfusion damage is avoided more commonly.[24]
Intervention arm pigs showed higher mean arterial pressure and lower cardiac output, but no improvement in post-arrest myocardial dysfunction. Similar results were seen in phase III cyclosporin studies. Gazmuri et al. found that blocking NHE-1 may delay cardiac cell death. Interrupting cytosolic and mitochondrial calcium accumulation has only been studied in clinical studies financed by pharmaceutical companies for myocardial infarction and coronary bypass grafting. Five PRO papers were included. In resource-intensive conditions like cardiac arrest, neurologic outcome prediction is a priority.
Jentzer and his colleagues observed that SCAI-high individuals were more likely to have a heart attack in the hospital. A meta-analysis of 23 studies indicated that persons over 60, men, active malignancy, and chronic renal disease increased mortality following cardiac arrest. 44 Endotracheal intubated patients had a worse survival rate, but further research is needed owing to the variety of studies included, the risk of confounding factors, and the retrospective study methodology.

UN10 Rule predicts hospital mortality after cardiac arrest. 45 Petek and colleagues assessed 95,000 patients using the AHA Get with the Guidelines Registry. Despite the ease and convenience of the three-component approach, this group deemed the 6% false-positive rate insufficient for wide application.
Procalcitonin was linked to sepsis-related inflammation last year. Shin and colleagues discovered that high procalcitonin levels in the first 48 hours of admission increased mortality and brain prognosis. Lopez Soto et al. reviewed 44 post-arrest imaging studies. MRI and CT anoxic damage predicts poor neurologic outcomes.
Neuroimaging using CT or MRI following cardiac arrest may be another useful neurologic prognostic tool; nevertheless, there are still knowledge gaps concerning conventional imaging collection intervals and procedures for measuring hypoxic-brain injury load.

The main motivation of this work is based on the analysis of data obtained by electrocardiograms (ECG). These tests contribute to the study of heart diseases, as they record information about the heart's functioning through the electrical activity of each beat. An arrhythmia is a disturbance of the heart rhythm. It is usually not possible to perceive the heartbeat of our heart, however, it is possible to feel small rhythm irregularities. As a rule, these cases are not a sign of heart disease, however if their frequency increases or if they appear accompanied by other symptoms (dizziness, fainting, tiredness, chest pain, shortness of breath), they may be manifestations of arrhythmias. more severe

III. METHODOLOGY

In this section, the design of the solution will be presented, starting with an analysis of the data set that will be used in its development. Next, the approach considered to solve the presented problem will be presented. Still in this chapter, it is possible to visualize the implementation of the proposed solution that contains the details about each of the procedures carried out to solve the problem.

A. *Dataset*

For the development of this project, a dataset available in a contest will be used. These data were recorded using the AliveCor device and donated to this challenge. The recordings were made by people who purchased the single-channel ECG device from this entity, AliveCor The dataset comprises a total of 12,186 ECG recordings, of which 8,528 would be used for training purposes and 3,658 for testing. However, the recordings corresponding to the test set are not available to the public, for the purpose of scoring the participants during the challenge period. Thus, only the recordings provided for training the classification models will be used in this project. These recordings have an interval of 9 to 61 seconds in length, approximately, having been made from 2 electrodes, one in each hand at 300Hz

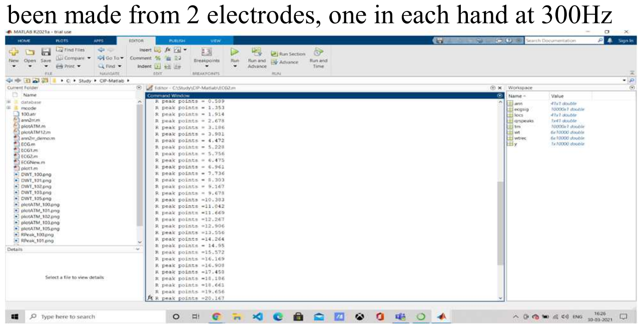

Fig. 2 - Examples of ECG waveforms

B. *Approach*

To solve the problem presented, two approaches of possible methodologies are exposed, for the analysis and classification of ECG signals.
In the first approach, represented in Fig. 2 the most common methodology is displayed, consisting of the following steps:

- **Signal Acquisition**- the signal is acquired, and at this point it may be necessary to carry out some pre-processing of the data, such as applying filters to reduce possible noise, for example.
- **Attribute Extraction**- extraction of attributes from the dataset and consequent creation of a new dataset, composed of the extracted attributes.
- **Classification**- use classification algorithms, such as Random Forests or SVM
- **Evaluation**– obtain the results of the classification of ECG signals, and evaluate these results, according to some evaluation measures,

In the second approach, a deep learning methodology is presented, using convolutional neural networks (or CNN).As in approach 1, it has the signal acquisition stage, where it may be necessary to carry out some pre-processing of the data as well as the evaluation stage, where the results of the classification of the signals are obtained, evaluating them afterwards. .

CNN's attribute detection layer implicitly learns from training data, thus avoiding explicit attribute extraction and classification. That is, using CNN it is possible to directly map the input signal to obtain the results As previously mentioned, the second approach represents the methodology that will be followed to develop the resolution of the problem, using ML library to create the CNNs.

1) Development Process

Fig. 3 shows the activity diagram that generally represents the solution development process.

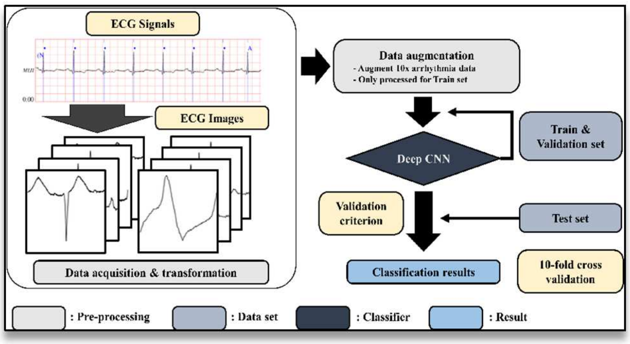

Fig. 3 Representation of the proposed method

C. *Implementation*

In this subchapter, the procedures carried out, sequentially, for the implementation of the previously suggested design will be presented and detailed. During the implementation phase, different approaches were followed, both in the pre-processing of the data and in the definition of the model's architecture, always with the objective of improving the results. In the technical description of the implementation, these approaches will be presented, in general, and more detail will be given on the final model implemented.

1) Pre-Processing

of this document, the datasets used to carry out this project were made available in a competition As was also mentioned, only 8,528 records were available for the development of this project, since the remaining 3,658 records were deprived of the contest, for the purpose of validation of results. These records are stored in .mat files, and there is also a “REFERENCEv3.csv” file, also provided by the competition, along with the records, where the mapping of the records with the respective associated classes is.Two-dimensional CNN requires images as input data. Therefore, in the first stage, the pre-processing stage, the data sets (ECG signals) were transformed into images. Two approaches were followed, whose final result (the generated images) proved to be quite different between them. Both solutions were implemented using the MATLAB language, also using external libraries, which will be presented in the description of the approaches.

In the first approach, external libraries numpy and scipy were used to manipulate data (ECG signals) and record them in images, respectively. The execution of this solution included all records (8528 records), transforming them into .bmp images. the records are not all the same size, having a range of approximately 9 to 61 seconds in length. For each 1-second segment, approximately 300 signals are covered, thus making up an interval of 2,700 to 18,300 signals between the various records. In this transformation, each signal originates a pixel in the image, which is differentiated by color depending on its value (using bytescale).

Fig. 4 - Approach 2: Record A00001 converted to image A00001.png

model, which must be passed in the execution of the model, defining the number of records of each class that must be taken into account in the training of the network, and ignoring the others. This parameter is used in the phase of obtaining the images that will be part of the CNN input, not allowing a number of records per class to be higher than the same. For example, when setting the parameter to the value 100, the model will be executed with a maximum of 400 training records, which correspond to 100 examples of each of the four classes. This measure was used to determine the possibility of distinguishing the classes in an equilibrium scenario. Although this is a different problem from the original, it allows us to assess the extent to which a lack of results is due to class imbalance.

In this way, it is possible to guarantee that the data is 100% balanced, with the same number of records for each class.

2) Selection of images by segments

the records (of the dataset) are not all the same size, there are records with an interval of 9 to 61 seconds in length, approximately. However, the images were all generated at the same size, 512x512 resolution. An image that corresponds to a 60-second recording has twice as much information (signals) as an image that corresponds to a 30-second recording, however, both images will have the same resolution. It is possible to foresee that the image related to the 60-second recording will be more distorted than that of the 30-second recording.

In Fig. 5, three images are displayed, which correspond to three records with different lengths of time (10, 30 and 60 seconds).

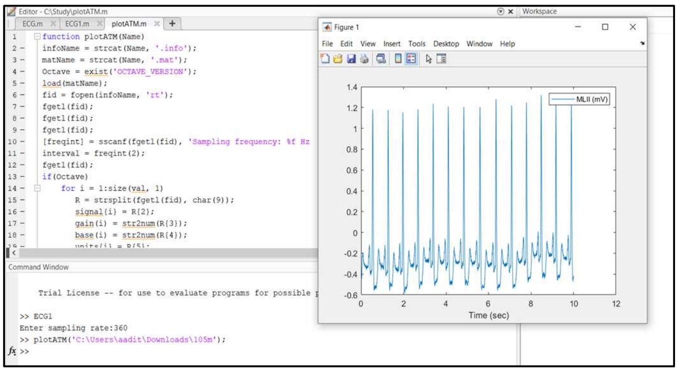

Fig. 5 - records with different time intervals

As you can see, the first image (corresponding to register A00592) is much sharper than the second (register A00001), which in turn is sharper than the third image (register A00003). This is due to the lengths of time that the registers have, and consequently the amount of signals that each register

An image selection method was defined by segments, that is, during the selection phase of the images that will be part of the CNN input, only images from the same segment (same lengths of time) will be able to enter.Looking at the number of records of each segment, in Table 4.2, it is possible to verify that most of the records (about 70%) correspond to 30-second recordings. This segment of records proves to be a great dataset for training the network.

3) Splitting images by segments

Using the segmental image selection technique and after some experiments carried out on the models using this pre-processing technique, the idea arose of implementing a method that would divide the images into small time windows. (10s being defined as the time window).

The implementation of this pre-processing action can offer great advantages to the arrhythmia detection process, such as:

- **equity in data**: the learning process of a model is fed only with images with the same time window;
- **Quality in the data**: the learning process of a model is fed with clearer images, which may lead to a greater ability to extract attributes by the algorithm;
- ***Data-Augmentation***: This technique of dividing images into segments is also part of the data-augmentation technique Using this technique, a recording of 30 seconds generates 3 images (of 10 seconds).

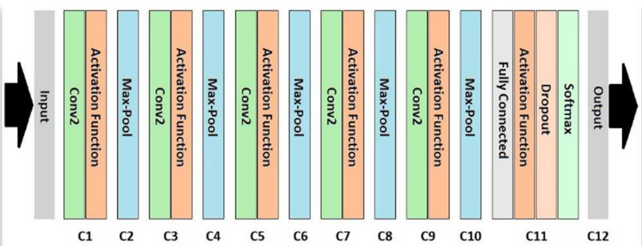

Fig. 6 - Architecture of the neural network

The neural network architecture is composed of 12 layers: 5 convolutional layers (C1, C3, C5, C7 and C9), where the activation function is always performed after convolution. After each convolutional layer, a pooling layer (max-pooling) follows, making a total of 5 layers as well (C2, C4, C6, C8 and C10).The penultimate layer (C11) is fully connected, being responsible for classifying the features obtained after the convolutional layers. This classification is followed by the dropout, which helps to avoid over-fitting the training data, and is then submitted to the softmax algorithm, which is responsible for producing the distribution over the various classes. It is also important to mention that the neural network uses an optimization function (training function) in order to update the parameters of the neural network and thus minimize the loss rate.

IV. RESULTS

If we compare the results of the average of the F-Measure measure of the 4 classes with the results of the F-Measure of the RECALL class (Fig. 7), it is possible to observe that the values of the FMeasure of this class are much higher than the values of the average. These data indicate that the models are more successful in classifying this class, that is, in detecting cardiac arrhythmias, compared to the other classes.

In Fig. 8 and Fig. 9, two graphs can be seen that present a summary of the best results obtained by each of the binary classification models tested, for the AVG evaluation measures F-Measure and F-Measure RECALL, respectively.

		PREDICTED classification				
	Classes	a	b	c	d	Total
ACTUAL classification	a	5	23	17	17	62
	b	10	540	21	14	585
	c	166	96	436	110	808
	d	1	2	5	87	95
	Total	182	661	479	228	**1550**

Fig. 7 - Best results for F-Measure average - Binary Classification

		PREDICTED classification			
	Classes	a	b	c	d
ACTUAL classification	a	TN	FP	TN	TN
	b	FN	TP	FN	FN
	c	TN	FP	TN	TN
	d	TN	FP	TN	TN

Fig. 8 - Best results for F-Measure RECALL - Binary Classification

Table 1 presents the results of some solutions developed by other authors to solve this problem, using the same dataset. The approaches followed by these authors can be seen in Table 1.The results are presented through the evaluation measure F-Measure, since this was the measure used in the

contest to classify the solutions and thus define the ranking of the participants' results.
It should be noted that the results presented by these authors are the result of a test with 3,658 records, private to the tender (not available to the public), which were intended for testing Furthermore, in this work, data balancing techniques were applied, such as the selection of only a few records of each class, ignoring the others, in order to solve the large imbalance of the classes. When comparing the results obtained, this change to the initial problem must be taken into account. Therefore, due to these two conditions, these participants' results should be seen only as indicators, and cannot be directly compared with the solution developed within the scope of this dissertation.

Table 1 - Results of other solutions

Authors	**Classification Algorithm**	**Result**
(Zabihi et al., 2017)	*random*forest	0.826%
(Xiong et al., 2017)	CNN	0.82%
(Zihlmann et al., 2017)	CRNN	0.82%
(Smolen, 2017)	RNN and GBM	0.81%
(Warrick et al., 2017)	CNN and LSTM	0.80%
Proposed	CNN with segmentation	0.87%

Fig. 8 :Comparison of Results with Other Works

V. Conclusion

The main objective of the work presented in this dissertation is to contribute to the development of a methodology capable of classifying signals resulting from the ECG, for the detection of cardiac arrhythmias in humans. In this way, this system can be used by health technicians, offering support in the decision on patient diagnoses, thus providing an improvement in their quality of life. In this document, a methodology was presented for the treatment of data obtained from electrocardiograms, using pre-processing techniques, and then applying and evaluating the different approaches of suggested classification models (using deep learning, more specifically Convolutional Neural Networks)The results obtained by the classification models show that the 2nd approach implemented obtains the most consistent results over the different experiments. This superiority on the part of the 2nd approach is achieved both in the multiclass model (referring to the original 4-class problem) and in the binary model (an alternative to improve arrhythmia detection results, this being the main objective). The application of the techniques of selecting images by segments or dividing images by segments in these models of the 2nd approach, still demonstrate a substantial improvement in the results. Several analyzes were carried out on the results obtained, namely with the measures of hit rate, ACCURACY and F-Measure. The best results obtained, Finally, considering all the work developed and the results obtained, we believe that this methodology could serve as a useful support for the development of systems for the detection and prediction of cardiac arrhythmias on ECG.

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