Wearable devices for ECG as an accessible way for Subject Identification using Deep Learning Techniques

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Abstract—**The electrocardiogram (ECG) is not only a very useful diagnostic tool for clinical purposes, but also is a potential new biometric tool for human identification. Combined with new wearable device technologies, and the development of Deep Learning, allows a high degree of accessibility and accuracy in terms of usability and data processing. There has recently been increased interest in the use of the electrocardiogram in the context of subject identification, leading to the development of various neural networks, which are increasingly high-performance. In this paper, different types of neural networks (Feed Forward, Recurrent and Convolutional Neural Network) are analyzed with the aim of being able to classify subjects uniquely by using Polar H10, an electrocardiogram chest band. In addition to a resting situation, the subjects will also be subjected to a physical task so that they can be better characterized and the performance of the wearable and Neural Networks can be tested with a signal corrupted by increased noise and motion artifacts. The spectrogram of the ECG signal on rest dataset was also considered in the CNN Network. The best results were obtained with the RNN network (93% test accuracy rest dataset, 92% test accuracy task dataset) suggesting a robust way to perform subject identification. The best compromise between complexity and performance were in FFNN, especially for the rest dataset (93% test accuracy rest dataset, 81% test accuracy task dataset). The 2D-CNN network led to disappointing results (55% test accuracy), but it can be a starting point for further investigation of time-frequency analysis of ECG in terms of subject identification.**

Index Terms—**ECG, Subject Identification, Wearable, Feed-Forward Neural Networks, Recurrent Neural Networks, Convolutional Neural Networks.**

I. Introduction

The science of bio-metric recognition makes use of statistical techniques to leverage physical and behavioral characteristics to uniquely identify persons. It mainly helps to solve access control issues by offering effective and secure alternatives for traditional authentication methods. The ECG signal is an excellent candidate for this application due to its characteristics, the ease with which it can be obtained via wearable technology and the expanding application of neural networks as a tool for highly subject-specific employment.

Subject identification can be achieved using several human discriminants such as retinal structure, fingerprint, face, etc. Some of them are more reliable than others, but in order to correctly represent a single human, they all need to be tamper-proof, timeless, and unique. However, each one of them exhibits different issues related to technologies and instruments used to collect them. There are many investigation in literature about the ECG as a promising personal identification attribute, due to his nature as a signal with many subject-dependent 'features'. In addiction, recent developments in wearable technologies have paved the way for monitoring the electrocardiogram (ECG) signal without the need for any laboratory settings, enhancing the accessibility of the data acquisition. Also, Deep Neural Network (DNN) architectures as a 'tool' for a wide range of medical tasks, can provide us an accurate ECG discrimination based on individual unique features, without requiring a specialist medical evaluation.

In this paper, we will propose the usage of a wearable sensor Polar H10 to perform a high-accessible acquisition of ECG data with the purpose of subject-identification among a group of person, comparing many DNN architectures. The use of the wearable sensor allowed us to take full advantage of the portability and accessibility of the object, that enable us to acquire ECG data quickly but at the same time reliably, without necessarily bring the patient to a specialized center, thus expressing the full potential that these technologies offer in terms of accessibility. In addition to this, the use of ECG signal, confirmed as a very promising biometric trait for identification and authentication purpose, permit us to explore new implementation of Neural Network, considering not only the most promising network such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) with pre-processed data, but also evaluating manual extraction of new features such as the *Spectrogram* of the signal given to the DNN.

Here the structure of the report. In *Section II* we describe the state of the art about the fundamental topic; The processing pipeline, the data handling and the models are presented in *Sections III*; in *Section IV* we will go deep in technical details. The proposed Neural Networks are in *Section V*

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and its performance evaluation is carried out in *Section VI*. Concluding remarks are provided in *Section VII*.

II. Related Work

In terms of physical security and cybersecurity, biometrics is one of the most dependable and robust methods of identifying individuals. It is a global technique designed to determine a person's identity by measuring one of his physical traits. Biometrics may be divided into two broad categories: physiological biometrics measure biological traits, for instance, characteristics of a fingerprint or iris. Behavioral biometrics measure how users perform certain actions, such as speaking or writing. While the first cannot change, behavioral biometrics naturally change with the action that is performed [1]. Researches based on physiological signals are gaining tremendous attentions and showed a high efficiency [2], giving us the characteristic of an trustworthy subject-related representation, expressed as numeric data which applied for identification purposes [3]. Previous attempts to summarise ECG-based recognition techniques can be traced back in [4]–[6] . Comparing to common commercial biometric systems, such as fingerprints, hand geometry and face recognition, ECG identification has a several advantages [7], [8]:

1) It is more fraud resistant, because of its internal biometric nature, which makes imitation more complicated than in case of external biometrics systems.
2) Possibility to provide fresh biometric reading continuously.
3) Good accuracy even in abnormal cases, low sensitivity to noise.
4) It is relatively easy to acquire: ECG signals acquisition can be made with the fingers and hand palms using one lead sensor or textile electrodes.

Multi-lead ambulatory ECG devices have served as the gold standard but there are multiple alternative devices, mainly based on single-lead ECG, more convenient and practical for measuring the signal. Recent HR monitors using a chest strap for ECG detection are in prominence for its simplicity in usage, and they enable the data to be recorded in situations in which it was not previously feasible with lab-based or even ambulatory ECGs [9]. Recently, several validation studies in different populations have compared the RR intervals (Fig.1) obtained by ECG devices and Heart Rate (HR) monitors [10]. Their results demonstrated good agreement in the recordings of HR monitors. However, the majority of these investigations were conducted using data obtained during resting activities, such as lying down, sitting, or standing still. In contrast, the signal quality obtained during exercise might be in a less favorable context with regard to the HR monitor movements inducing noise in the measured electric signal [11], but giving a new perspective in terms of characterization of the signal and subject-dependencies. An example of the usage of a non-ambulatory ECG sensors to collect the signal, coupled with the development and use of a feed-forward neural network model, can be found in [3], in particular an Arduino Uno, a micro controller board for programming, extended with an e-Health Sensor Platform V2.0 to implement biometric and medical applications. Because of the Polar H10 claims to offer relevant performance in the HR measurements, and the product series has been widely used as a reference for wearable HR measurement systems [12], [13], it suits for us to generate trustworthy data to use in deep learning to perform subject identification with the advantages of a wearable sensor. Depending on database characteristics, nature of the problem

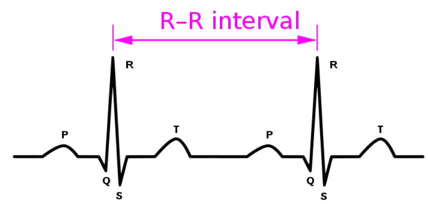

Fig. 1: *QRS complex of an ECG: in evidence RR interval*

and model usage peculiarities, the classification algorithm can be chosen from a variety range of possible options. *HM.Lynn et al.* in [8] performed a study on the generation of potentially numerous segmentation signals from a source signal for a training data set and on the integration of the 2-layer neural network with retro propagation of the gradient to manage the many identification classes. Precisely, were identified 20 classes with 5066 raw ECG-ID record, reaching 94% of accuracy. In *Y.Li et al.* [14] the use of RNN for feature extraction and subsequent subject identification is proposed, achieving accuracy of 94.3% using five public datasets. Another deep Feed-Forward Neural Network was used as a basic architecture in [3], and every various combination tested has reached an accuracy over 84% within 18 classes. Each of them addressed feature extraction from the data using different approach based on Deep Learning, thus as an alternative to canonical waveform recognition methods, all of them compared in [4].

By providing more information to the networks due to data collection in situations of physical movement of the patient, with the usage of wearable sensors that are easier to manage but with the need for adequate signal cleaning, would bring the process of subject identification to a more user-friendly situation and more easily implementation providing appropriate accurate networks for these devices.

III. Processing Pipeline

It was possible to achieve the ultimate goal of subject identification through several steps, starting with the collection of data via the wearable with a precise design , the development of a pipeline for ECG cleaning, the preparation of data and its use in various Deep neural network configurations, and the subsequent comparison. The main steps that led to the complete design of the experiment will be sequentially exposed (Fig. 2); details are reserved for the following Sec. *IV. Signal and Features*. The two dataset were collected with the *Polar H10* wearable band chest, one with the subject at *rest*,

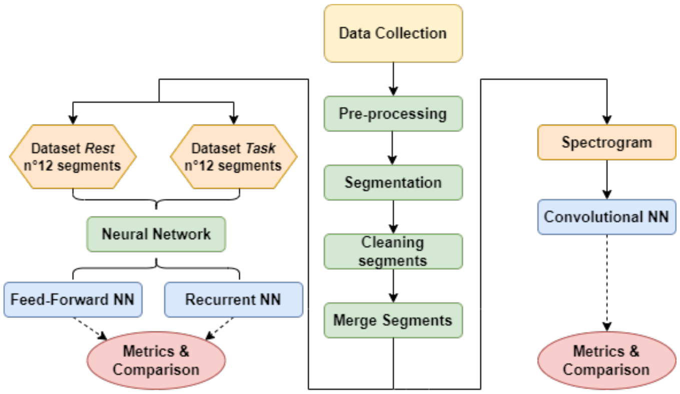

Fig. 2: *Study Design*

the second asking to do a specific *task* to the subject. This is suppose to give us more information compared with previous works, where the dataset were generally collected during subject's rest. All of them were undergone Pre-processing steps, leading to a quality segmentation of the data. This step was relevant to identify segments that where subject to an high level of impairment, allowing us to delete them to have a more clear signal. The next step is to combine the individual segments to form a signal of consistent length; composition of No. 12 segments were considered. The two data-sets were, then, organized to be an input in the different Neural Networks. Specifically, the networks that will be presented are FFNN and RNN, both of which are used for the rest and task data-sets. The spectrogram was, in addition, applied to the concatenated signal from the *rest* dataset, so that the information could be analyzed from a 2-dimensional point of view, with the appropriate Neural Network, which in this case will be a 2-Dimensional CNN. At last, all the Networks were compared wit several performance metrics (accuracy, F1, precision and recall), considering also the model complexity, learning and response time.

IV. Signals and Features

In this section we will go into the details of the experimental design and signal processing, all the way to the Neural Network.

A. Dataset collection

In this work, we aimed to build a personalized system for biometric identification based on ECG signals, collected during situations of *rest* and assigning the subject a short physical *task* to diversify the variability of the signal that can characterized the subject. We collect the data from 17 subject, age 23 ± 3, 8 men and 7 women, none of them with past history of cardiovascular disease. For each of them, the ECG was collected by the usage of Polar H10, placing the sensor around the chest; the sensor communicates with an Android Phone thanks to an App developed by the *UNIPD, Department of Mathematics, Human Data Analytics course* via Bluetooth. An acquisition was made with the subject at rest sitting for 2 minutes, then was asked to the subject to do *Jumping jacks*, an high intensity exercise, following this pattern: 60 second seated rest, 30 second of task and 60 second seated rest (2:30 minutes overall). It is observed that for each subject the duration of the experiment was never perfectly adhered to, thus generating signals longer than 2 minutes for the rest and 2:30 for the task. It was decided not to truncate the signals in order to have uniform length in the data-set, as the signal would still be subject later to the segmentation, cleaning and segment merging steps, creating further randomness in the number of segments recognized for each subject, which is strictly dependent on the recognition from the number of peaks in the signal that vary according to the pulse of each subject. At the beginning of the data collection we encountered some difficulties by placing the chest band during the task section: we recommend to place properly and firmly the band, so that to prevent the movement during the task and the acquisition of a signal with many motion artifacts. No. 2 subjects where excluded from the study because their sample where too affected by the bad placement of the band, generating the artifacts cited above; the work will then proceed using 15 subjects, which are associated with the same number of classes for subject identification.

B. Pre-processing of the ECG Signal

Firstly, we observed that the data had been sampled at different frequencies, and more in detail the signal had a non-uniform time axis; we suppose that this may be due to both the instrument and the communication process taking place between the wearable and the smartphone. So, a *Linear Interpolation* was done on the data, considering the lowest sample frequencies in the two dataset.

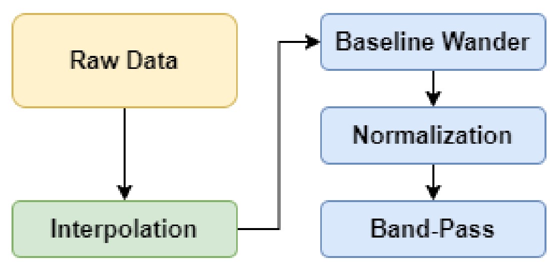

Fig. 3: *Pre-processing step*

Pre-processing was carried out following [15] as a reference and adapting them to our situation; *Baseline Wander removal, Normalization and Band-Pass Filtering* were the main operations performed on the raw signal, described in the same order as their execution (Fig. 3). *Baseline wander* is a low-frequency artifact in the ECG that arises from several factors, such as breathing, electrically charged electrodes, or subject movement. In the ECG signal, it can be seen as a low-frequency trend, which is not related to the heart activity and should be removed. We use two median filters, one with 0.2 seconds and one with 0.6 seconds window size, to estimate the baseline, and then remove it from the signal. *Normalization* is a further critical stage. The quality of the electrical connection between the electrodes, the subject, the subject's skin resistivity, and many other factors can all have a significant impact on the ECG's amplitude. For this, we simply estimate the signal amplitude using the 99th and 5th percentiles and normalize with respect to this value. Because we are interested in the shape, the process was applied on each trace independently, in order to make them comparable. Lastly, a *Feed-Forward Band-pass Filter* was applied to the signal, with *0.667-65 Hz* cut-off frequencies, *order = 8*. The feed-forward application allow us to clear the phase-shift generated by the filtering process, and the pass-band deletes all the frequencies components not relatives to the ECG signal, such as heartbeat, breathing and noise [15]. No *power-line* component was found, so it was unnecessary to apply a notch filter to remove it. Overall, this process allows us to have a clear signal, removing all the non-informative frequencies. The Fig.4 represents the final results of the cleaning process of a portion of the ECG signal.

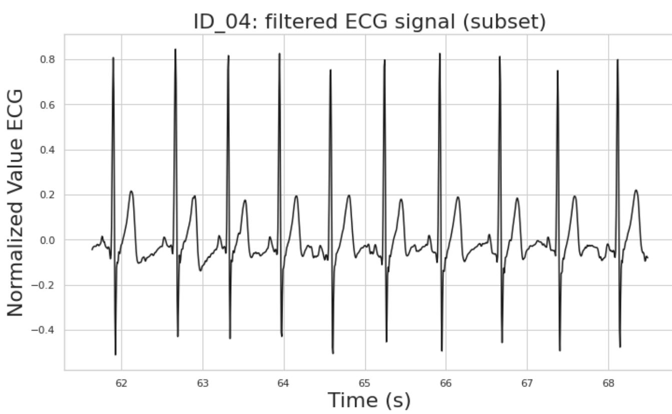

Fig. 4: Portion of the filtered ECG signal

C. Segmentation, Cleaning and Merging

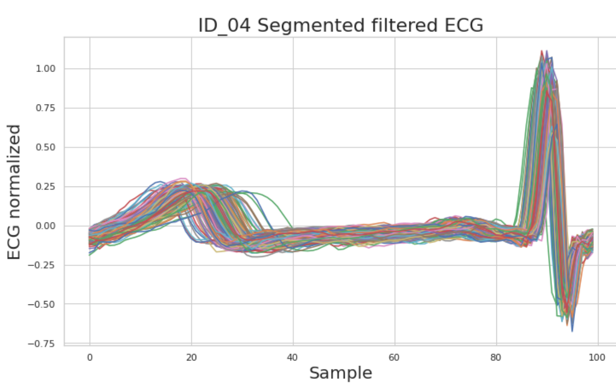

Fig. 5: *ECG segmented*

Once the signal has been processed, we go on to evaluate the individual segments.The segmentation algorithm involves recognizing the peaks of the signal and then dividing it into segments, of fixed length to be set (which for us will be No. 100 samples). An example, Fig.5. The segments were subjected to visual inspection, and thanks to the normalization process it was found that the amplitudes of the correctly collected segments remain within a well-defined range. It was chosen to eliminate any segment that had inconsistent amplitudes: in particular, in the first part of the signal (until the 79th sample) the values should be contained within a maximum amplitude of 0.3. In the second part of the signal, precisely where the peak is present, the amplitudes should be contained within 1.3. Any individual segment that did not meet these values was removed from the data set. In Fig.6 the resume of the operation: there will therefore be 15 classes with unbalanced data, and will betaken into account during the models training and the evaluation.

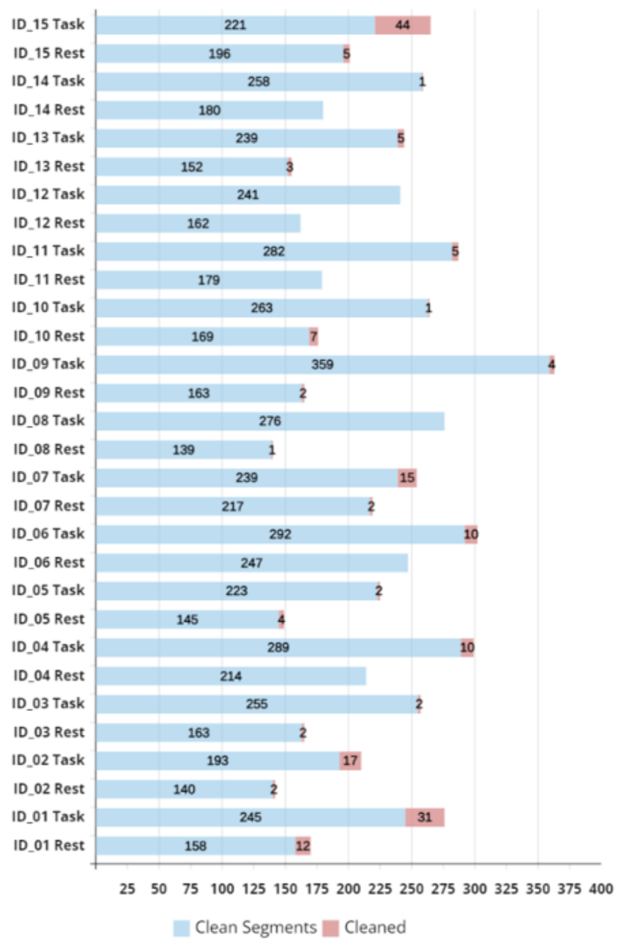

Fig. 6: *Resume of Cleaning operation for each subject, for both Dataset*

Once the segments have been cleaned, we merge them: starting with the first one, we create a single signal by joining a predefined number of them subsequently in time . Groups of 12 segments were considered: this number corresponds to a sampling time ranging from *1* to *2 seconds*, depending on whether the subject is at rest or performing an activity. It was considered a valid and accessible time, allowing for a possible action of quickly collecting the ECG data for the subject identification task, without the risk of missing relevant

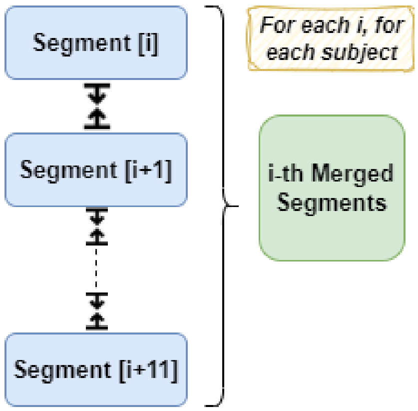

Fig. 7: *Flow chart of merging operation.*

information. So in a subject having n segments, we will have n-11 signals. To clarify, starting from the i-th segment of the subject in question, a single trace will be created by joining the segments from i-th up to i+11 (Fig.7).

The next trace will start from i+1 to i+12. The fact that we had eliminated some segments, could have generated discontinuities when we went to connect them. This was remedied by a *Moving Average* function applied at the joining points of them, through a 5-sample wide window starting from the last 10 samples of the segment moving to the first 10 of the next one.

D. Dataset Structure 1D

For each dataset, the data were splitted, in *Train Set* to 60%, *Test Set* to 25% and *Validation Set* to 15%, Tab.1. Instances of each of the 15 subjects are uniformly distributed within each dataset, for credibility of the proposed evaluation metrics.

TABLE 1: Train, Test, Validation set.

	Dataset Rest	**Dataset Task**	***Percentage***
Train Set	1471	2222	*60%*
Test Set	620	932	*25%*
Validation Set	368	556	*15%*
Total	2459	3710	*100%*

These datasets, thus including their subdivision just described, will be used for FFNN and for RNN.

E. Dataset Structure Spectrogram

An additional dataset was created by computing the *Spectrogram* on the *rest* signals: a *Tukey* window (dimension=100, alpha=0.2, overlap=20) was used to compute them. This type of dataset will be used for the *2D-CNN*

V. Learning Framework

Once the ECG segments for each subject are extracted, cleaned and concatenated, deep learning models can be applied. In this study, three architectures have been examined:

1) *Deep Feed-Forward Neural Network* as simplest basic architecture;
2) *Recurrent Neural Network* in order to take advantage of temporal correlation between samples that characterize an ECG signals.
3) *2-Dimensional Convolutional Neural Network* applied on the Spectrogram, as an alternative to 1D signals.

A. Feed forward neural network

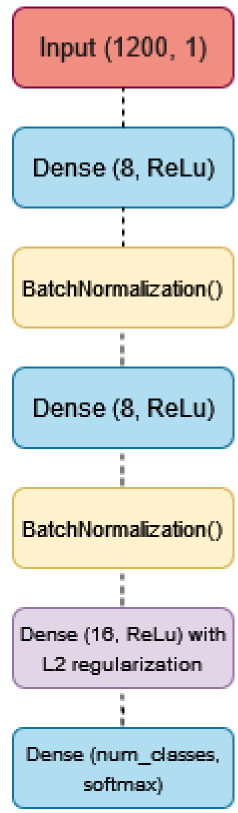

Fig. 8: FFNN model

It is fully-connected neural network architecture, without internal states. The architecture is provided in Fig. 9. The issue of zero gradients during back propagation is avoided by using ReLU activation function after both of the Dense Layers. Batch normalization layers were introduced to speed up the training process and make it more stable, performing the standardizing and normalizing operations on the input of a layer coming from a previous layer. The L2 Regularization was introduced to avoid overfitting of the model. As output, we provide the *Softmax* activation for the classification purpose.
The model was trained for 40 epochs with an *Adam Optimizer*, learning rate = 1e-2, dividing the train set in mini-batches of 32; Accuracy was our Weighted metrics to be evaluated by the model during training and testing, taking into account the unbalanced classes; The loss function was computed as Categorical Cross-entropy. Stopping criteria was based on evaluating the *Validation Loss*, through a patience parameter equals to 5 epochs.

B. Recurrent Neural Network

In this architecture we want to enforce the time-dependecies of the ECG signal, trough a Recurrent layer with memory, the *Gated Recurrent Unit (GRU)*, that also provides for the problem of the gradient vanishing. The overall network is provided in Fig.9. The GRU layer was provided by a *tanh* activation function, and a *Dropout=0.1* regularization to avoid overfitting. Dense layer were provided with a Relu activation function with an L2 regularization. As output, again *Softmax* activation for classification.
The model was trained at the same way as the FFNN, apart from the *Adam* optimizer being set with a learning rate = 5e-4.

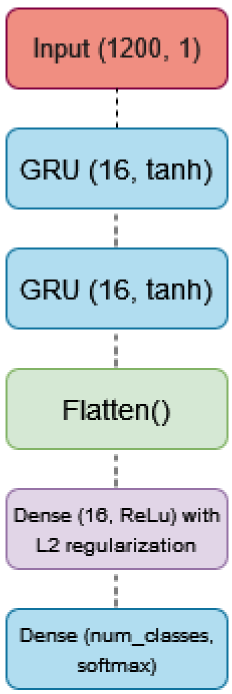

Fig. 9: RNN model

C. Convolutional neural network (2D)

The performance of this network will be tested with the dataset proceeds from the Spectrogram images of size (42,42) from ECG Rest data.

The 3 convolutional layers have increasing size, allowing the extraction of more and more abstract features as the network advances. Each of these layers is followed by a Batch normalization layer, provided by a *Relu* activation, and a Maxpooling Layer, that provides a pooling operation calculating the maximum value for patches of fixed size from a feature map, and uses it to create a downsampled (pooled) feature map. Usually used after a convolutional layer,it adds a small amount of translation invariance, meaning that translating the image by a small amount does not significantly affect the values of most pooled outputs. The *Flatten* layer reshape the 2D features from the convolutional layer to a 1-Dimensional size. The lasts two layers provide a *Dropout=0.6* regularization and a Dense layer with *Softmax* activation. The global architecture is shown in Fig.10.
The model was trained for 60 epochs with an *Stochastic Gradient Descend Optimizer (SGD)*, learning rate = 1e-4 with momentum=0.01, dividing the train set in mini-batches of 8. Unlike previous networks, *Adam optimizer* led to a sub optimal solution, not allowing the model accuracy to increase, stopping the train process in a local minimum. As well as above, accuracy was our Weighted metrics and the loss function was computed as Categorical Cross-entropy. Stopping criteria was based on evaluating the *Validation Loss*, but this time the patience was set to 8 epochs.

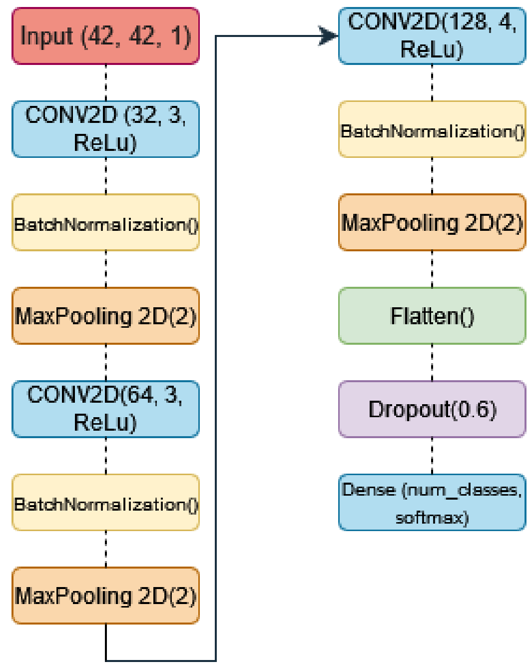

Fig. 10: CNN (2D) model

VI. Results

In this section the results of the above mentioned architectures are presented. Experiments were made in Python using Colab GPU with 16Gb (*Nvidia Teslak80*). Following frameworks and libraries were used: numpy, sci-kit learn, TensorFlow and matplotlib. For each network are reported:

1) *Learning curves*;
2) Table with *Weighted Evaluation metrics*
3) *Time of training*.

A. FFNN Results

It is possible to appreciate the Learning curves for the rest Dataset, Fig.11; less performing results were found in the case of the Task dataset, but quietly apprecciable, considering the FFNN as the simplest one (Tab.2). In fact, the timing of training and the number of parameters are the lowest. The number of effective training Epochs never reached the maximum, stopping around No.30 for both rest and task. For

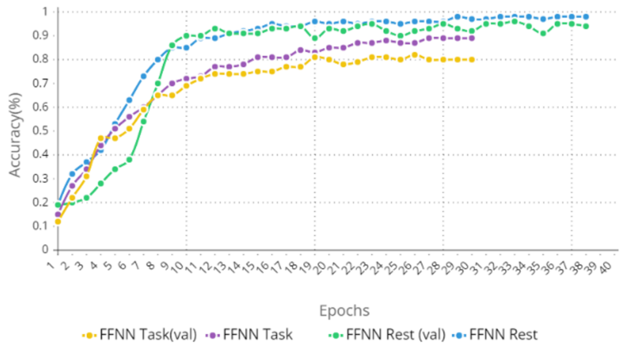

Fig. 11: FFNN learning curves

the subjects *01, 02, 03 and 14* in the test set, for both rest and task, the classification accuracy were the worst.

TABLE 2: FFNN rest and task

	FFNN rest	FFNN task
Test accuracy	0.93	0.81
Average f1	0.93	0.81
Average precision	0.93	0.82
Average recall	0.93	0.81
Training time	20.2 s	19.0 s
No. parameters	10.143	10.143

B. RNN results

The RNN performs comparably between the two datasets; in Fig.12 the learning curve for the task dataset. This result suggests that in the case where the subject is moving, a network structure that takes into account the correlation of the time series between samples is preferable. Comparable metrics are shown in Tab.3. Lastly, the network presents a greater complexity than the FFNN, and higher timing of training. The number of effective training Epochs never reached the maximum, stopping around No.21 for rest dataset and No.32 for task dataset. In the test set, subjects *01, 02 and 14* and *01, 14* presents the worst accuracy respectively for rest and task dataset.

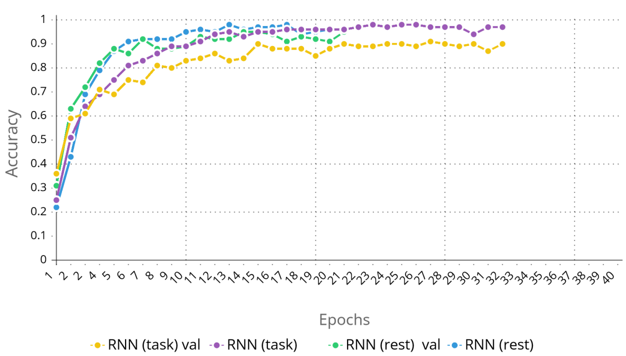

Fig. 12: RNN learning curves

C. 2D CNN results

More complex was the learning curve of the 2D convolutional network. As mentioned in the previous section, an *Adam* optimizer was not used, as opposed to the other networks, because the network training process always led to results compromised by local minima. A sub-optimal solution was to use a *Stochastic Gradient Descend* with *momentum*. This lead to a validation accuracy curve that oscillates too much, Fig.13. However, the result is reported as it is believed that the learning process can be improved, so that it can then be compared to other networks, possibly bringing a novelty in terms of the type of feature extracted from an ECG signal. The metrics are reported in Tab.4. The number of effective training Epochs never reached the maximum, stopping around No.38. For the test set, half of the subject weren't classified right.

TABLE 3: RNN rest and task

	RNN rest	RNN task
Test accuracy	0.93	0.92
Average f1	0.92	0.92
Average precision	0.93	0.92
Average recall	0.92	0.92
Training time	75.3 s	163.9 s
No. parameters	310.015	310.015

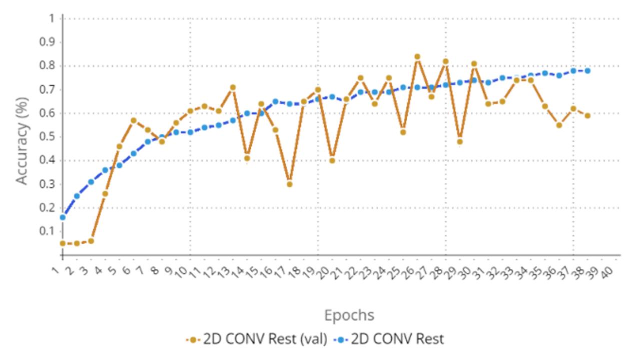

Fig. 13: 2D-CNN rest dataset Learning curves

TABLE 4: CONV-2D rest

	CONV-2D rest)
Test accuracy	0.55
Average f1	0.51
Average precision	0.61
Average recall	0.56
Training time	72.1 s
No. parameters	997.647

VII. Concluding Remarks

In this project, the problem of subject identification was addressed starting from an ECG signal collected with a wearable, the *Polar H10* in situations of rest and movement of 15 subjects. Two main architectures, the FFNN and the RNN were trained and tested on the pre-processed dataset, previously divided into train, test and validation set. An additional 2D Convolutional network was tested on the rest dataset, to which the spectrogram was computed instead of the ECG signal, to check if the information provided by the

two domanin (temporal and frequencies) could bring us to satisfying results. The first architectures have achieved comparable results: FNN 93% test accuracy rest dataset and 81% test accuracy on rest dataset; RNN 93% test accuracy rest dataset and 92% test accuracy task dataset. This highlights how an ECG signal from a moving subject is more easily interpreted by a network with recurrent layer, where performance is good for both datasets. On the other hand, it is highlighted how a simple FNN allows for very good results with the subject at rest, performing less in motion situations but having low complexity to its advantage. The comparison between the networks applied to the rest and task datasets allows us to state how pre-processing of the raw ECG signal is necessary to have comparable performance. In a future perspective of identification provided by Wearable tools, even less complex and even more accessible and everyday than a chest band, it is essential to have good results even when the subject is moving. The Convolutional network applied to the spectrogram did not lead to relevant results compared to the previous network, but its training process requires more attention before excluding it as an alternative for more accurate subject identification than the one carried out with the ECG signal in the time domain.It could be a starting point to address the problem in the spatio-temporal domain of the ECG in order to characterize it even better.
Concluding, an evaluation in terms of network performance and complexity allows us to say that the FFNN turns out to be the simplest and least complex, easier to adapt on a wearable device. However, the most reliable turns out to be the RNN, which continues to perform even in the case where the subject is moving, making the identification process more accurate in everyday-likely situations. 2D-CNN requires more investigation.

A. *Future Works*

1) Evaluating advanced architectures to obtain better performance.
2) Using architectures to extract other features (e.g. PCA, Autoencoder).
3) ECG data collection with different tasks to evaluate the performance with rough data.
4) Evaluating multimodal data provided by other wearables, such as PPG signal from smartband.
5) Taking advantage of the chest band during competitive sports for prevention and diagnosis.

B. *What was learned*

This project allowed the authors to have the first application of Deep Learning, specifically with biomedical data, which were studied for the entire Master of Science in Bioengineering for Neuroscience degree program. In particular, it was intriguing to work from scratch with networks, allowing us to understand what are the fundamental components that lead to excellent results, thus emphasizing the union between the application of theory and the critical spirit in evaluating the results.
Other technical aspects learned:

1) Common deep learning architectures and their application
2) Practice building learning curves,
3) Working with tensorflow API,
4) Enabling regularization techniques,
5) Tracking metrics and time resources,
6) Paying attention to diverse metrics.
7) Paying attention on how the data set-up influence the Network

C. *Difficulties encountered*

1) First approach to Python
2) First approach to Deep Learning
3) How to deal with Wearable sensor
4) Deal with large dataset
5) Optimizing parameters
6) Deal with a Network that's no good

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