Deep learning in the classification and recognition of cardiac activity patterns

Łukasz Jeleń, Piotr Ciskowski, and Konrad Kluwak

Abstract—Electrocardiography is an examination performed frequently in patients experiencing symptoms of heart disease. Upon a detailed analysis, it has shown potential to detect and identify various activities. In this article, we present a deep learning approach that can be used to analyze ECG signals. Our research shows promising results in recognizing activity and disease patterns with nearly 90% accuracy. In this paper, we present the early results of our analysis, indicating the potential of using deep learning algorithms in the analysis of both one-dimensional and two–dimensional data. The methodology we present can be utilized for ECG data classification and can be extended to wearable devices. Conclusions of our study pave the way for exploring live data analysis through wearable devices in order to not only predict specific cardiac conditions, but also a possibility of using them in alternative and augmented communication frameworks.

Keywords—ECG signal; deep learning; arrhythmia; signal processing; ECG classification

I. INTRODUCTION

AS defined by the World Health Organization (WHO), cardiovascular diseases stand among the primary causes of mortality worldwide. According to the Organization, it causes approximately 19.9 million deaths per year. In this paper, a pattern recognition approach to ECG signal analysis is described. This strategy achieves one of the key WHO objectives in the prediction and prevention of cardiovascular disease, allowing adequate medical care and preventing early deaths. The proposed methodology ensures the most accurate depiction of the ECG waveform based on data similar to that of many primary health facilities.

In 2018 Lyon *et al.* [1] described a study that proposes the use of ECG signals for the prediction of cardiovascular diseases as a crucial stage in the diagnostic procedure. Electrocardiography examination is a clinical procedure that registers and quantifies the heart's electrical activity within a defined time frame. A trained physician, based on such a recording, is able to detect an abnormal heart function that can be induced by different circumstances.

A review of the literature shows that ECG recordings, aside from the determination of heart diseases, have multiple potential applications [2]–[4]. In recent years, the classification of

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emotions became one of the most often mentioned applications of ECG recording usage [5], [6]. Agrafioti *et al.* [7] demonstrated that their system is able to perform accurate valence classification of ECG shapes with an accuracy of 89%. Selvaraj *et al.* [6] reported that it is possible to classify emotions with about 82.88% accuracy, where "neutral" emotions provided the highest accuracy of 92.87%. This research classified popular emotions including anger and sadness.

In 2018, Liu *et al.* proposed a system that combines an accelerometer and a wearable monitoring device to track activity based on ECG recordings [8]. The researchers reported 96.92% total accuracy of the proposed framework for the data from 13 volunteers within the age range from 5 years to 68. Investigators suggested that outcomes of their research could be applied for user activity and behavior monitoring. The proposed approach could potentially be used in healthcare framework. One among the most deprived areas is interaction with individuals who struggle with capability of spoken or written communication. Such an interaction is a challenging, and has led to the development of an alternative and augmented communication system (AAC). People with impairments need to acquire a particular communication form that could be easier when a signal from wearable devices is incorporated for activity recognition tasks.

This paper outlines a deep learning approach that can be used to analyze ECG signals. We present the initial results of such an analysis on the arrhythmia dataset, and in the end, we draw promising conclusions about the deep learning architectures and their application to signals recorded with a wearable device.

II. THEORY

In the realm of modern healthcare and medical diagnostics, the integration of technology and data science has ushered in a new era of precision and efficiency. Among the myriad applications of these technological advancements, the analysis of electrocardiography (ECG) signals using deep learning techniques has risen as a transformative force. The electrocardiogram (ECG) provides a wealth of information about the electrical activity of the heart over time. However, these raw data often require extensive processing and interpretation, a task where deep learning excels.

In this section, we explore the intersection of ECG and deep learning that holds great promise for the future of cardiology

and healthcare. In Section II-A, an overview of ECG measurements is described that focuses on its essential role in the diagnosis of cardiac disorders and the understanding of heart function. Section II-B presents the intricate processes involved in harnessing the deep learning methodology for ECG data analysis.

A. ECG signals recording and measurements

Physiologically, the heart's electrical activity is a direct result of several physiological phenomena. Electrocardiography aims to register graphs of the voltage change in time that resembles that process. The concept of using sensors to measure heart's electrical activity dates back to the late 19th century. Willem Einthoven was the first to suggest the use of the PQRST symbol of the electrocardiography signal to record the heartbeat. This symbol is still used today to differentiate between various methods of ECG signal capturing. An example of such measurements is graphically depicted in Fig. 1. In the figure, one can see the representation of all the ECG peaks as well as the R–R interval which is on of the widely recognized measurements.

ECG registration is based on the capturing of a signal from electrodes placed on different parts of the human body. In medical diagnosis, the prevailing clinical standard is the 12 lead system that is in common use in hospitals. The system uses 10 electrodes that are installed on arms and legs as well as on the chest. Sometimes, when other standards are in use, a lower number of electrodes, e.g., 3, 4, or 6 electrodes are utilized. Furthermore, depending on patients' diagnostic needs, different measurements are used. These measurements include measurement of rest with the 12-lead system, Holter electrocardiography or a long-term physical activity. All of these measurements require a pre–processing of electrical signals [9].

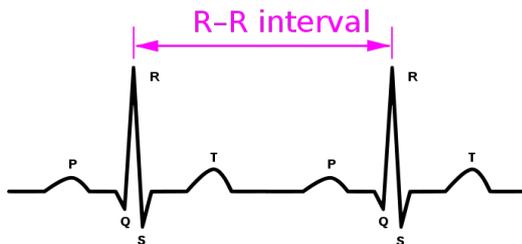Measurements shown in figure 1 are typically employed for

Fig. 1. R-R interval and other peaks of one heart cycle activity, taken from [10]

the heart rate variability (HRV) analysis. HRV is the variation in time between successive heartbeats, specifically the intervals between R waves in an electrocardiogram (ECG) signal. In the most popular wearable devices, readings come from an optical sensor, and therefore, the R–R interval is the only calculated parameter. More advanced and certified devices utilize entire electrical signals for analysis. The majority of them are then calculated from a continuous ECG recording over a specific period, such as a 5-minute recording. Typically, these measurements are as follows:

- SDNN – Standard Deviation of Normal-to-Normal (R-R) intervals– statistical measure used in the analysis of heart rate variability. It quantifies the general variability in R-R intervals and is often used as a marker of the activity of the autonomic nervous system. A higher SDNN value typically indicates greater heart rate variability, which is generally considered a sign of better cardiovascular health and adaptability to different physiological and environmental conditions.

- RMSSD – square Root of the Mean from the Sum of Squares of Differences between adjacent NN intervals – is a time-domain HRV parameter that quantifies the variability in the duration of successive R-R intervals (normal-to-normal intervals) of the heartbeats. It is calculated according to eq. 1

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{1}^{N}(RR_i - RR_{i-1})^2} \quad (1)$$

RMSSD is commonly used as a marker of parasympathetic nervous system activity. Higher RMSSD values are typically associated with increased heart rate variability and are considered indicative of better cardiovascular health and greater adaptability to different physiological and environmental conditions.

- PNN50 – Proportion of NN50 adjoining NN intervals greater than 50ms – a heart rate variability parameter used to assess short-term variability in heart rate. It is often used as a marker of parasympathetic nervous system activity. A higher value of pNN50 indicates greater variability in heart rate and is generally considered a sign of better cardiovascular health and adaptability to different physiological and environmental conditions.

- SDANN – standard deviation of the 5-minute mean NN intervals – calculated by dividing a continuous ECG recording into nonoverlapping 5-minute segments. Then, for each of these 5-minute segments, the average normal-to-normal or R-R intervals are calculated. Finally, the standard deviation is computed from these 5-minute average NN intervals. The calculated value reflects the day-to-day variations in heart rate over the recording period. It is a valuable metric for understanding how heart rate patterns change over extended time intervals and can provide information on circadian rhythms and long-term cardiovascular health.

- SDSD – Standard Deviation of Successive Differences – quantifies the variability in the duration of successive R-R intervals of the heartbeats. It is calculated as the standard deviation of the differences between consecutive R-R intervals. In other words, it measures how much each R-R interval differs from the next in a continuous ECG recording. This measure is used to assess the short-term variability in heart rate. It can provide insight into the autonomic nervous system activity and cardiac health.

- TP – total power; HF, LF, VLF – high-, low-, and very low-frequency power; these HRV frequency domains are often calculated using power spectral analysis techniques, such as the Fast Fourier Transform (FFT), which de-

composes the HRV signal into its constituent frequency components. Analyzing these frequency components can provide valuable information on the autonomic nervous system activity and general cardiovascular health.

- Poincaré plots – also known as scatter plots or Lorenz plots – are a graphical representation used in the analysis of heart rate variability (HRV) derived from an ECG (Electrocardiogram) signal. These plots are particularly useful for visualizing the dynamics and patterns of heart rate data. Poincaré plots are useful for both visual interpretation and quantitative analysis of HRV

In this paper we would like to stress out the ability of wearable device utilization in the analysis of ECG signals. One of the most popular and widely available devices is a Polar H10 sensor. As noted in the literature, it provides a reliable method of measuring heart rates [11], [12]. These studies describe tests of the Polar device against Holter medical devices. The outlined research has shown that Polar sensors are just as accurate for low- and moderate-intensity activities in healthy individuals and even more accurate for strenuous activities. In Figs. 2 and 3 one can see that these signals are very similar. From the literature, we can see that many investigations have been conducted to compare different wearable devices, and these have confirmed the accuracy of techniques based entirely on measurements and heart rate (HR) computations of the R–R interval [12]–[14]. These papers collectively provide insights into the classification of ECG signals using wearable devices. Hua *et al.* proposes a compressive domain approach that reduces energy consumption while achieving high precision in the classification of heartbeats from the ECG [14]. Saadatnejad *et al.* introduces a lightweight LSTM–based algorithm that meets the timing requirements for continuous monitoring on wearable devices [15]. Azariadi *et al.*, on the other hand, focuses on ECG analysis and classification using wearable devices from the Internet of Things, achieving high precision [13]. In 2015, Krishnan and Maneesha addressed a very important issue of electrode misplacement detection in wearable ECG devices with immediate feedback to patients and therefore reducing the risk of misdiagnosis [16]. In our approach, we intend to use the ECG signal data as described by Plawiak [17], and the Polar H10 sensor captured through the available API. In light of this, a dedicated mobile application was designed to seamlessly gather data from the Polar device (see Fig. 2).

B. ECG signal analysis with deep learning methods

In the this section, we take the domain of ECG signal analysis into the realm of cutting-edge deep learning methodologies. Our research is devoted to exploring innovative approaches to extract valuable insights from ECG data and to harness the power of artificial intelligence, paving the way for advanced cardiac diagnostics and healthcare applications.

From the literature review, one can notice that different approaches are provided for the classification of ECG arrhythmias [18]–[21]. Zeybekoglu and Mehmed used Artificial Neural Networks (ANN) to classify five types of ECG signals with 82% accuracy [21]. In 2017, Teijeiro *et al.* introduced
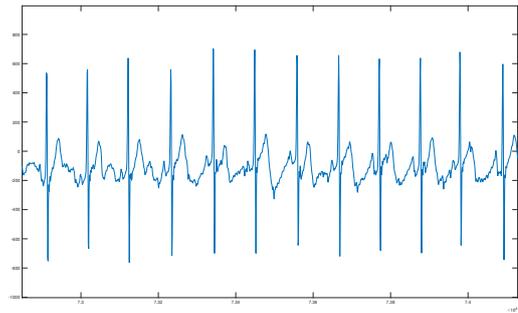

Fig. 2. Raw ECG signal obtained with Polar H10 sensor

a method that combines high-level features and a Recurrent Neural Network to classify ECG records into four target classes, achieving 83% accuracy [19]. Kadbi *et al.* introduced a method based on wavelet transform and artificial neural network to accurately classify multiple types of arrhythmias with an overall precision greater than 90% [18]. In 2018, Plawiak performed an extensive study on the application of classical classification methods, including probabilistic neural networks (PNN), radial basis function networks (RBF), support vector machines (SVM) and k–nearest neighbors (kNN) [17]. Additionally, the author describes several preprocessing and feature extraction methods, such as 3 types of normalization, periodogram generation with Welch's method, discrete Fourier transform with Hamming window, series of logarithms of signals, and genetic algorithms. Recent study of Surowiec *et al.* uses deep neural networks with preprocessing based on downsampling, passband Butterwoth filter, wavelet transform, division into one-cycle samples (approx. 1.25 seconds in length) based on the Pan-Thompkins method. The authors report that the signals were converted into two-dimensional 160x30-pixel images. The images were then classified with the highest accuracy of 93.6%. These results were compared with a one-dimensional signal classification to learn a signal representation for deep neural networks.

This research aimed to identify the most suitable architecture for managing upcoming measurements. To carry out the analysis, we sought a signal representation that would be most suitable for distinguishing different ECG signals, either one-dimensional vector or two-dimensional image. Contrary to previous studies, the preprocessing of the ECG signal was minimized. Such an approach resulted in larger architectures for both classification and feature learning, what conforms with the main assumption of deep learning.

The preprocessing stage involved sampling of the original 10 second long signals at 360 Hz. This led to the creation of 3600 samples in the range of 400–1800 mV. The signals were normalized to range 0–1 or standard normal variate (mean 0, std. dev. 1). Subsequently, the signals were converted to two-dimensional images with Matlab *plot* function and then resized to 750x250 pixels. Example of the signals used in the described study are shown in Figs. 3 and 4, respectively. Such signals were presented as inputs to 2-dimensional con-
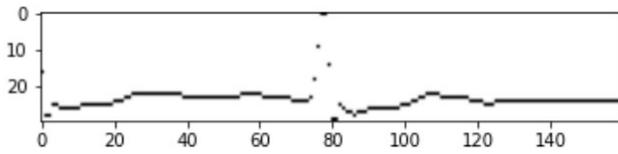
Fig. 3. Two–dimensional ECG signal representation [4]

Fig. 4. Two–dimensional normal ECG signal representation used in this study

volutional neural networks. To be able to conform with the aim of this research, we have compared several classification methods. Based on the results described in sec. III we were able to perform a comparative study of a suitable architecture for ECG data analysis. Methods employed in our study include several traditional algorithms, as well as deep learning neural networks. Traditional methods include

- **Random Forest (RF)** – is a method that integrates multiple decision trees for the decision making process. It is commonly used to handle complex datasets due to its robustness. When used in classification tasks, it outputs the class based on majority voting among individual trees.
- **Support Vector Machine (SVM)** – is a method that calculates a hyperplane that best separates data points belonging to different classes. This algorithm aims to maximize the margin between the classes.
- **k–Nearest Neighbors (kNN)** – is an effective and simple machine learning algorithm used for classification and regression tasks. Given a set of point, it makes decisions based on the majority class among their k–nearest neighbors in the feature space.

In recent years, deep learning algorithms have achieved remarkable success in various domains, including computer vision and signal processing. These networks attempt to mimic the architecture of the human brain to process and learn from large volumes of data. Recently, the most popular deep learning architectures include Convolutional Neural Networks (CNNs) for image analysis, and recurrent neural networks (RNNs) for sequential data. In this paper, we compared the following base architectures:

- **Long Short-Term Memory (LSTM)** – is a type of RNN architecture that is designed to effectively model and process sequential data. It can capture long-range dependencies and mitigate the problem of vanishing gradients during training.
- **Convolutional Neural Networks (CNNs)** – are a type of deep learning model specifically designed for processing and analyzing grid-like data, such as images and

videos. CNNs learn hierarchical representations through the repeated application of convolutional and pooling layers. Convolutional layers extract low-level features such as edges, textures, and simple shapes. Deeper layers capture more abstract and complex features, eventually recognizing high-level concepts such as object parts or entire objects. The final prediction or classification is based on these high-level features.

C. ECG Database

In this section, an overview of the database used in our study is presented. The experiments were carried out on the ECG signal database described by Plawiak [17]. This collection consists of 1000 signals from the *MIT-BIH Arrhythmia Database*. The data was obtained from 45 patients and divided into 17 classes: normal and pacemaker rhythm and 15 types of cardiac dysfunction.

Many studies mentioned earlier used the original *MIT* long time-series with approx. half-hour recording for each patient. Furthermore, they were also used in a time-series-style approach, as continuous signals presented to recurrent neural networks. These signals are typically divided into single heartbeat cycles, usually centered around the R peak.

The database for this study was carefully selected based on the uniqueness of the length of the ECG signal. Plawiak's [17] database introduces a different approach where 10 second long signals are used. This choice corresponds approximately to the scope of a signal considered by an expert physician who analyzes ECG recordings. Here, only the MLII lead is used. Furthermore, examination of the class distributions of the classes allowed us to gain valuable insights about the composition of the dataset. Such an analysis showed a high-class imbalance in the original data. Since data imbalance can have a negative influence on classification, we chose only a subset of classes that contained at least 45 signals. For classification purposes, we have used the following 8 classes for which the distribution is presented in Fig. 5:

1 NSR - Normal Sinus Rhythm,
2 APB - Atrial premature beat,
4 AFIB - Atrial fibrillation,
7 PVC - Premature ventricular contraction,
8 Ventricular bigeminy,
14 LBBBB - Left bundle branch block beat,
15 RBBBB - Right bundle branch block beat and
17 PR - Pacemaker rhythm.

III. EXPERIMENT

In this section, we explore the experiments on ECG classification. These experiments were designed to harness the power of machine learning and deep learning techniques to create robust and accurate models capable of automatically identifying and categorizing cardiac arrhythmia from ECG data (see sec. II-C). Through a comprehensive exploration of model selection, and performance evaluation, we aim to gain deeper understanding of the architectures that provide high accuracies.
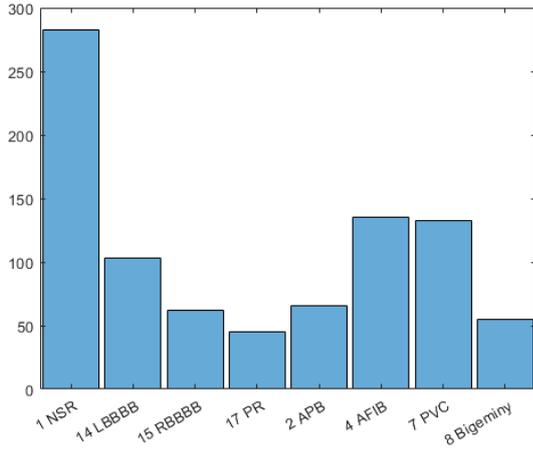
Fig. 5. Distribution of used classes from MIT-Arrythmia database

TABLE II
DETAILS OF THE HYBRID NEURAL NETWORK ARCHITECTURE

No.	Type	Activations	Learnable Properties
1	Sequence Input	1(C) x 1(B) x 36(T)	-
2	1-D Convolution	64(C) x 1(B) x 1(T)	Weights: 36 x 1 x 64 Bias: 1 x 64
3	Batch Normalization	64(C) x 1(B) x 1(T)	Offset: 64 x 1 Scale: 64 x 1
4	ReLU	64(C) x 1(B) x 1(T)	-
5	Dropout	64(C) x 1(B) x 1(T)	-
6	1-D Global Max Pooling	64(C) x 1(B)	-
7	LSTM	16(C) x 1(B)	InputWeights: 64 x 64 RecurrentWeights: 64 x 16 Bias: 64 x 1
8	Fully Connected	8(C) x 1(B)	Weights: 8 x 16 Bias: 8 x 1
9	Softmax	8(C) x 1(B)	-
10	Classification Output	8(C) x 1(B)	-

Table II and the achieved results are summarized in Table I. From the table, one can notice that the recorded accuracy is approaching almost 89%. From the above results, we can see that our experiments demonstrate a significant insights on the architectures that provide promisig results when applied to real-world data, at the same time showcasing their potential for practical applications in ECG signal analysis.

A. Signal Analysis

In the initial phase of the depicted study, we performed a comparative analysis of various deep neural network architectures operating on one-dimensional ECG signals. These signals were pre-processed as described in sec. II-B, resulting in sequences of 3600 samples scaled in the range of 0-1. Based on the pre–processed signals, various configurations of long-term memory networks (LSTM) have been studied, including structures with single hidden and double LSTM layers of up to 128 neurons. In addition, deep four-lstm-level architectures were also investigated. Table I provides the summary of the investigated networks. From these results, one can notice that the best results obtained with the network types mentioned above were as low as 34%.

The second group of architectures examined included one-dimensional convolutional neural networks. These networks were tested with the same signals as in the previous experiment. This setup included networks with one or two convolutional layers, with filters ranging from 32 to 128 and sizes between 36 and 72. Throughout the experiment, it was determined that the optimal filter length is 36 samples, which corresponds to 1 second of the ECG signal. The results for the two best 1-dimensional networks are presented in Table I as No. 3 and 6. Hybrid neural networks were another intriguing architectural approach. These networks consist of a series connection of one-dimensional convolutional layers and recurrent LSTM layers. The convolution layers served as feature extractors creating an input vector for the subsequent LSTM layers. A summary of such a structure is depicted in

B. Image–based Signal Analysis

Beyond the initial set of experiments, we introduce an image–based approach to signal analysis that allows further exploration and validation of our hypothesis. These complementary experiments are designed to provide a more comprehensive view of ECG signal classification.

The presented methodology is based on the examination of several machine learning algorithms to classify images of signals from MIT databases representing all 17 classes (see II-C). For the purpose of this study, we compared three traditional machine learning methods (see sec. II-B) using the Orange Data Mining Framework [22]. These methods were trained on a feature vector calculated with a convolutional neural network named SqueezeNet. SqueezeNet is a compact yet effective model trained on ImageNet. To accurately assess the performance and generalization ability of proposed models, a Stratified 5-fold Cross-Validation was used. Based on the cross-validation, we determined 5 classification metrics. These results are summarized in Table III and the ROC curve is depicted in Fig. 6. From the results one can notice that the best classification accuracy of 82.5% and AUC of 97.5% was obtained for the SVM classier whilst Random Forest model provided the lowest classification precision of 71.5% and AUC of 93%. The kNN algorithm showed a satisfactory result of 80% and an AUC of 94.9%. Based on these results we can note that SVMs

TABLE I
RESULTS FOR SELECTED NEURAL NETWORK ARCHITECTURES

No.	Architecture	Configuration	Additional Info	Accuracy (%)
3	1x Conv. 1D	64 filters	Filter length: 36	89.39
6	2x Conv. 1D	64 + 32 filters	Filter length: 36	89.39
13	Hybrid Smaller	CNN-1D: 64 LSTM: 16	Filter length: 36	88.64
17	1x LSTM	128 nodes		34.09

TABLE III
IMAGE–BASED SIGNAL ANALYSIS RESULTS

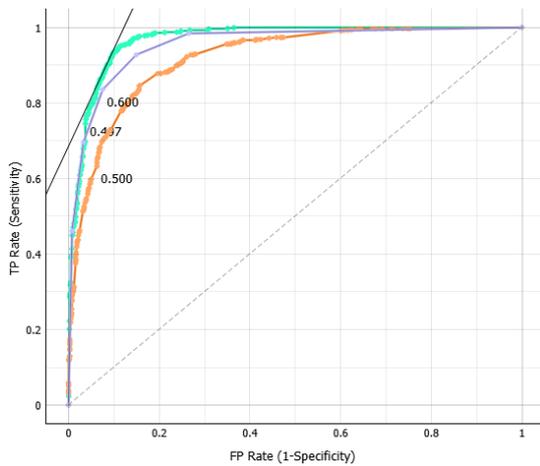| Model	AUC	CA	F1	Precision	Recall
kNN	0.949	0.800	0.788	0.787	0.800
SVM	0.975	0.825	0.810	0.824	0.825
Random Forest	0.930	0.715	0.695	0.708	0.715

Fig. 6. Image–based Signal Analysis ROC Curve

and kNN provided the high model reliability. Other metrics confirm our findings about the models and their classification abilities. The calculated Precision (P) and Recall (R) metrics provide insight into how well a model is performing in terms of correctly identifying positive and negative instances within a dataset. In our investigation, the best P and R were obtained for the SVM model at levels of 82.4% and 82.5%, respectively. For kNN precision recorded at 78.7%, while the recall was 80%. At the same time, RF provided the worst level at 70.8% and 71.5%, respectively. Furthermore, the F1 score was calculated that combines precision and recall into a single value. Observations of the F1 ranges also confirm our previous finding, where SVMs provided the best rate of 81%, signifying a well-balanced relationship between Precision and Recall. For kNN, the score of 78.8% indicates a balanced harmonic mean of P and R. In the case of Random Forests, the F1 score was the lowest recorded value (F1 = 69. 5%), still demonstrating a reasonable balance of Precision and Recall.

The results described in this section reveal that the SVM model outperformed other models in all evaluated metrics, firmly establishing its effectiveness in accurately classifying ECG images within the signal analysis context. The kNN model also delivered credible results, showcasing its capability as a robust classifier. Although the Random Forest model demonstrated its usefulness, it showed comparatively lower performance in all various evaluation metrics. These findings not only highlight the strengths of the SVM and kNN models, but also offer valuable insights for selecting the most suitable model for future image–based signal analysis tasks in ECG signal processing contexts.

IV. Conclusions

The aim of this study was to determine the most appropriate architecture for managing ECG measurements and to explore the potential of the neural networks to analyze these signals. In Section III we present and discuss the classification results. From this discussion, several interesting conclusions were drawn. The first conclusion is that for simple recurrent neural networks with at most a few LSTM layers, we were unable to obtain satisfactory results.

More promising results were obtained when the one–dimensional convolutional layers were added to the network architecture. Our research showed that the optimal size of convolutional layers is 64 filters with a length of 36, which corresponds to 1 second of the analyzed signal. All these hybrid networks provided a high accuracy of 88-89%. These findings lead to the conclusion that neither simple architectures nor recurrent networks alone provide satisfactory results. Only by adding additional layers we are able to obtain high classification precision. Despite the addition of extra layers, these structures remain relatively simple, allowing for rapid processing and making them suitable for the analysis of data from wearable devices.

We may also conclude that convolutional neural networks, in combination with traditional algorithms, offer even more promising results in processing two-dimensional images of ECG signals. The presented results clearly show that the SVMs outperformed other traditional classification algorithms. The computational complexity of this approach is still acceptable for future practical implementation.

The insights gained from this study provide valuable contributions to the analysis of ECG signals, offering opportunities for further applications to cardiac analysis, as well as augmented and alternative communication frameworks based on wearable devices.

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