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3D Vectorcardiographic Machine Learning for Classification Cardiovascular Disease

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Abstract— **This study aims at comparing the performance of computational intelligence methods to classify ECG data in normal (NORM), myocardial infarction (MI), and ST-T change (STTC) groups using the XYZ ECG coordinates as input. The ECGs of 7146 patients were randomly selected from the PTBXL Database to produce a balanced dataset. The multi-layer perceptron model achieved 99.99% accuracy during the training and 99.80% in testing. The convolutional neural network model achieved 96.07% accuracy during the training and 83.26% in testing. The long short-term memory (LSTM) model achieved 99.90% accuracy during the training and 89.00% during the test. Also, the LSTM model applied to 10-fold produced an average accuracy of 94.03 ± 1.83%. In conclusion, this study provides an effective framework for the automated detection of MI and STTC on ECG. Specifically, it classifies NORM, MI, and STTC with more than 94% accuracy and hence can be employed in clinical settings.**

Keywords— **Vectorcardiography, Myocardial Ischemia, Artificial Neural Networks.**

I. Introduction

The electrocardiogram (ECG) is a non-invasive tool to assess a patient's overall heart condition and is therefore the first-line test for any diagnosis of cardiac disease (CVD) [1]. The 3D vectorcardiogram (VCG) signal is considered to add value to ECG analysis, as it provides different information and allows the calculation of parameters that cannot be calculated from separate ECG leads [2]. The VCG represents the sum of all instantaneous electrical vectors generated in the heart by myocardial cells and is designed to display a multidirectional view of cardiac electrical activity in space-time [3].

The use of this tool allows the development of different markers, such as the assessment of ventricular repolarization heterogeneity, which is due to intercellular differences in depolarization times and action potential morphology [4]. Furthermore, a recent study showed that QT dispersion is largely determined by T-loop morphology, expressed by T-loop amplitude and width, while an older study reported a widened QRS-T angle in patients with left ventricular failure [5]. The QRS-T angle reflects the deviations between ventricular depolarizations. Spatial and frontal QRS-T angles are two different ways to measure the QRS-T angle [5].

However, these previously developed VCG morphology descriptors are insufficient to fully characterize the complex three-dimensional morphology of the VCG loop [5]. Analysis of the QRS loops of the VCG morphology can help define abnormal electrophysiological substrate in patients with life-threatening ventricular arrhythmias [5]. The morphology of the VCG loop can be characterized by the direction and amplitude of the initial instantaneous [5] and maximum peak and average spatial vectors of the loop [5]. In addition, deep learning-based artificial intelligence (AI) algorithms have recently achieved cutting-edge performance in multiple domains [6]. An advantage of deep learning is the automatic learning of features and relationships from certain data without a domain [6].

This study investigated AI algorithms based on deep learning to detect myocardial infarction (MI) and ischemic ST-T changes (STTC) through 3D VCG loop morphology to compare their performance with conventional methods in the literature. The approaches were the MLP, which consists of a minimum of three layers of nodes and uses the back-propagation technique for its training, which is part of the supervised learning methods [7]. The convolutional neural network (CNN) was another model studied. CNN is a non-linear statistical model and attempts to identify optimal linear combinations of the input variables and then model the result as a nonlinear function of these covariates [7]. This deep learning framework is able to distinguish data that is not linearly separable. Another model used was long-term memory networks (LSTM) [7-8] that have been used in the classification of ECG signals [7-8]. An important approach widely used in recent deep learning studies.

Objective: compare the performance of the MLP, CNN and LSTM classifiers in separating the NORM, MI and STTC groups using the XYZ ECG coordinates as input features for classification. In particular, our study investigated the ability of XYZ ECG coordinates to discriminate between MI, STTC and NORM patients using deep learning models.

II. MATERIALS AND METHODS

Dataset: We used a dataset available for free in the Physionet repository [9]. They followed the research procedures that were conducted in accordance with the Helsinki Decla-

ration [9]. The PTBXL dataset comprises 21837 clinical 12-lead ECG records o 10 s in length from 18885 patients, where 52 % were male and 48 % were female. The data presented a hierarchical organization into five coarse superclasses (NORM: normal ECG, CD: conduction disturbance, MI: myocardial infarction, HYP: hypertrophy, and STTC: ST-T changes) [9]. Only the classes NORM, MI, and STTC were investigated, by randomly selecting 2382 patients for each group (total 7146 subjects). The PTBXL has a rich set of ECG annotations and further metadata, which turns the dataset into an ideal resource for training and evaluating machine learning algorithms [9].

Preprocessing: Twelve-lead ECG signals were low-pass filtered by a Butterworth, 2nd-order filter with 35 Hz cutoff frequency. R-wave detection was carried out on digitized ECG signals by the Pan & Tompkins algorithm [10]. A software implemented in Python 3.9 [11] was developed to perform ECG and 3D vectorcardiographic analysis.

Twelve-lead vectorcardiogram: The Kors matrix was used to transform 12-lead ECG into XYZ ECG coordinates for all ECG signals [12]. After that, each XYZ ECG coordinate was averaged considering R-wave as reference. The XYZ coordinates (X, Y, Z, superclass) were used for analysis. The data were organized in a matrix (2501100 x 4), where every 350 samples represent a patient (2501100/350 = 7146 patients). For each group, 2382 patients were randomly allocated. After, the dataset was split into two non-overlapping sets: training (70%; n = 5002) and testing (30%; n = 2144).

For the MLP the data were organized in a matrix (7146 x 1050) to have (X, Y, Z, superclass) side by side. The data were organized in a matrix (7146 x 350 x 3) to fit the expected structure [samples, timesteps, features] required by the LSTM and CNN algorithms to classify in 3D structure.

The MLP, LSTM, and CNN models were created using the Keras framework on top of TensorFlow 2.1.

The first layer for these three models was an embedding layer. The LSTM network consisted of two bidirectional LSTM layers followed by two fully connected layers [14]. The CNN network consisted of a convolutional layer, an average pooling layer, a convolutional layer, a global average pooling layer, and two fully connected layers [14]. The number of layers and the number of epochs were empirically determined on a single training set with the original distribution of NORM, MI and STTC groups.

For each step, the models were trained multiple times using the above-mentioned temporary training sets with different sizes and prevalence. The number of epochs was empirically determined by a test run, resulting in 20 epochs for the MLP/LSTM/CNN models.

Evaluation: Model performance was evaluated by assessing sensitivity and specificity. The predictive accuracies of the models were compared by the area under the receiver operator curve (AUC). As the goal of screening is to identify all individuals with the prevalent cardiovascular disease (CVD), the target was to maximize the test's sensitivity. The validation of the CVD detection performance was made in the independent dataset by measuring AUC and assessing the sensitivity and specificity of the selected at the previous step threshold.

The sliding windows and the LSTM models were developed using Python 3 (Libraries: Keras, Numpy, Pandas and Scikit learn) [11] and executed in Google Colab notebooks is a cloud service based on Jupyter notebooks, which is a service linked to a Google Drive account, and free of charge.

The age and VCG parameters were compared using a one-way ANOVA based on a 95% confidence interval.

III. RESULTS

Table 1 shows the data (mean + standard deviation) for the patient age, the QRS-T angle, the magnitude of the spatial ventricular gradient (SVG), and the elevation angle of the SVG (EL-SVG). There was no significant difference in age between the groups. However, significant differences were observed for VCG parameters (Table 1).

Table 1 - The average and standard deviation for age, QRS-T angle, SVG and EL-SVG

	NORM	**MI**	**STTC**	**p-value**
Age	51.88 ± 17.16	63.97 ± 12.68	64.80 ± 14.44	0.2341
QRS-T angle	55.87 ± 45.46	86.39 ± 46.05	89.11 ± 49.07*	< 0.0001
SVG	1226.57 ± 390.69	1017.34 ± 351.23	1083.05 ± 340.76*	<0.0001
EL-SVG	66.55 ± 14.05	72.15 ± 11.549	65.10 ± 13.77*	<0.0001

The comparison of classifier performance indices (Table 2) indicated MLP model as the cutting-edge performance. One additional test was performed to LSTM model, using the K-fold approach with 10 folds. This increased the performance, reaching 94.03 ± 1.83% average accuracy.

Table 2 - Comparison of classifier performance indices

	MLP		**CNN**		**LSTM**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
AUC	0.99	0.99	0.96	0.83	0.99	0.89
Categorical accuracy	0.99	0.97	0.89	0.69	0.97	0.77
Precision	0.99	0.96	0.89	0.69	0.97	0.77
Recall	0.99	0.99	0.89	0.68	0.97	0.77

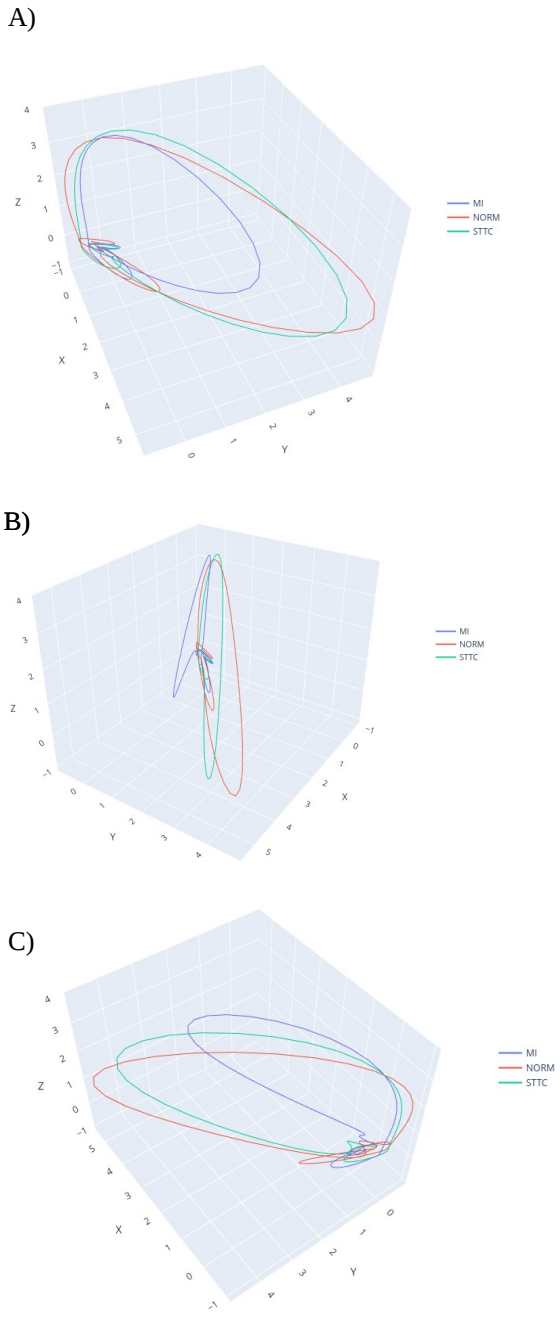

Figure 1 - Average VCG for MI, STTC, and Normal patients from different views (A, B, and C).

IV. DISCUSSION

Our goal was to compare the performance of the MLP, CNN, and LSTM classifiers in separating the NORM, MI, and STTC groups using the XYZ ECG coordinates as input features for classification. To the best of our knowledge, this study is the first to assess VCG morphology using an AI algorithm, which prevents any comparison with literature.

The best results were produced by the classical MLP model, using three layers. An excellent performance was obtained with the 3D ECG samples, without needing any segmentation on the ECG or fiducial point measurements. The results found are overcoming the limits indicated for classification for this type of cardiac disease [6-8][13].

However, CNN and LSTM models underperformed with similar results. This can not be used to point out MPL as the best tool since any classification model has a set of configuration parameters that could be explored. For example, only rearranging the VCG data in a k-fold approach allowed improving the LSTM performance to values similar to other methods in the literature.

In converting the 12-lead ECG to the VCG, much redundant information is removed, however, some relevant characteristics may be lost by the mathematical method used to extract the XYZ coordinates. Even so, we were able to achieve important results for the classification of heart diseases such as MI and STTC.

V. Conclusions

This study provides an effective framework for the automated detection of MI and STTC on short segments of XYZ ECG. Specifically, it is able to classify NORM, MI and STTC with an accuracy of more than 94% and hence can be employed in clinical settings. In future studies, the performance evaluations of the proposed model will be done on the different MI and STTC datasets.

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Conflict of interest

There are no conflict of interest.

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