Iron Oxide-Au Magneto-Plasmonic Heterostructures: Advances in Their Eco-Friendly Synthesis

A neural network approach for the prediction of arrhythmic events in patients with Brugada syndrome via ECG features analysis

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***Abstract*—Brugada syndrome is an inherited cardiac electrical disorder associated with elevated risks of ventricular fibrillation and sudden cardiac death. Determining the optimal approach for asymptomatic individuals remains uncertain. Precise evaluation of the risk of arrhythmic events could prevent premature deaths and unnecessary interventions. This research uses neural networks to analyze electrocardiograms (ECGs) to assess their effectiveness in differentiating between subjects with and without documented arrhythmic events. The study involved 265 ECGs on which fourteen ECG features were independently measured by three cardiologists. The classification performances were evaluated by considering: accuracy, positive and negative predictive values, specificity, sensitivity, and AUC. Also, univariate statistical tests were performed to select the most significative features. Results show the capability of neural networks for risk stratification in patients with Brugada syndrome, achieving satisfactory performance in both validation (93% *accuracy*, 93% *AUC*) and test (88% *accuracy*, 90% *AUC*) sets, proving the ability of AI-based ECG analysis in giving assistance in clinical decision-making.**

***Index Terms*—Neural networks, Brugada syndrome, Cardiac disease, Risk stratification, Electrocardiography, ECG, feature selection**

I. Introduction

Since Pedro and Josep Brugada introduced the Brugada syndrome (BrS) as a new clinical entity in 1992 [1], it has gained significant attention due to its elevated risk of sudden death. In recent years, there has been a significant increase in reported cases, accompanied by an escalation of literature aimed at clarifying the clinical, genetic, and molecular aspects of the syndrome [2] [3]. Approximately 10% of patients exhibiting the typical BrS pattern experience symptoms such as cardiac arrest or syncope, often occurring during periods of rest, especially after a substantial meal or during sleep. Diagnosis involves recording an electrocardiogram (ECG) and identifying the distinctive pattern in the right precordial leads [4]. However, these anomalies may not be consistently detectable, and in some cases, the administration of specific drugs may be necessary to reveal these unique ECG signs if they are not naturally present [5].

Electrocardiography is an essential diagnostic tool for clinicians. Through the measurement of voltage changes over time during the cardiac cycle, the ECG effectively records the electrical activity of the heart. Precisely, the 12-lead ECG provides a detailed understanding of the heart performance, utilizing six limb leads strategically positioned on the arms and legs, and six precordial leads placed at specific locations on the chest.

Several recent studies have shown promising results by employing AI-based ECG analysis across various clinical settings, since electrocardiography is a widely adopted and cost-effective cardiological tool. For instance, deep learning techniques, employing various neural network architectures, are applied to estimate arterial blood pressure based on photoplethysmography (PPG) and electrocardiogram (ECG) signals, offering a noninvasive approach to blood pressure measurement [6] [7]. In addition, convolutional neural models have undergone optimization and customization for the automatic detection and classification of arrhythmias [8] [9].

The employment of artificial intelligence for the detection of the Brugada pattern in ECGs has been recently validated [10]. Despite this significant advancement, the challenge of risk stratification persists, primarily due to the rarity of patients with documented arrhythmic events. This study aims to

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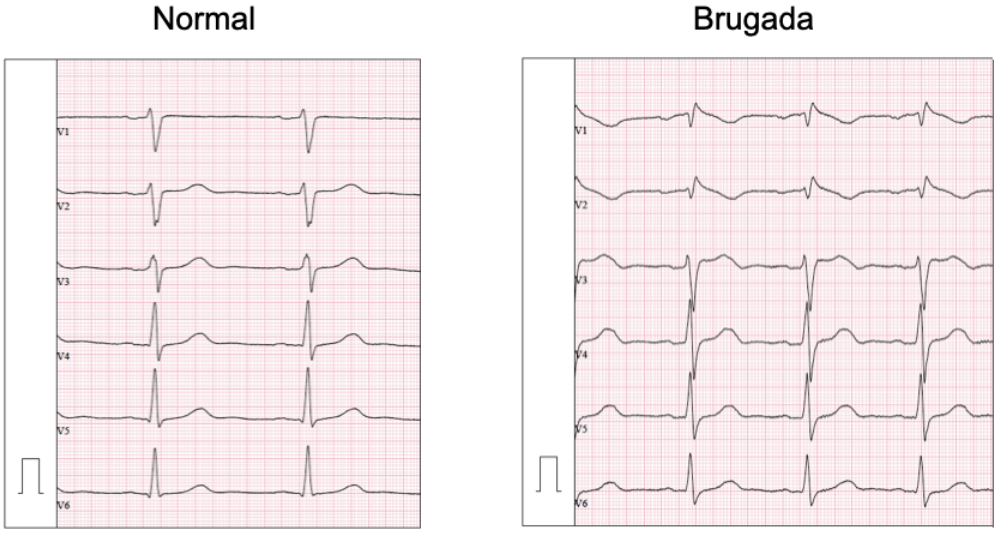

Fig. 1. Comparison between the six precordial leads of a normal ECG with the precordial lead exhibiting a Type 1 Brugada pattern.

address this critical gap by conducting an analysis of ECG features from individuals diagnosed with Brugada syndrome. At this purpose, a dataset of 265 ECGs has been extracted from the Piedmont Brugada register [11], with 97 ECGs belonging to patients who experienced arrhythmic events, while the remaining ones serve as a control group.

In section II, an overview of the main characteristics of Brugada syndrome is provided, emphasizing the challenges associated with diagnosis and risk stratification. Section III details the ECG dataset, the population distribution across the two classes taken into account ("*event*" and "*no event*"), and describes the neural network models considered for the experiments. Section IV presents the results obtained from the experiments, including those achieved by using the same models but considering a subset of features selected based on univariate statistical tests. Finally, Section V summarizes the principal contributions of the present work.

II. Brugada Syndrome

A consensus report [12] outlined specific diagnostic criteria and three ECG patterns for Brugada syndrome. Type 1 is characterized by a coved-shaped ST-segment elevation (>2 mm in one or more right ventricular precordial lead V1-V3), followed by a negative T wave, and represents the only electrocardiographic abnormality for potential diagnosis (see Fig. 1). Types 2 and 3 are not diagnostic patterns but are considered suspicious for Brugada ECG. When these suspicious patterns are present, especially with a family history of sudden cardiac death (SDC) at less than 45 years old, syncope or nocturnal agonal respiration, patients should undergo a pharmacological test with sodium-channel blocking drugs.

A positive test is indicated by the occurrence of a Type 1 ECG pattern during drug administration. Among patients with the Brugada ECG pattern, less than 20% are symptomatic, and implantable cardioverter defibrillator (ICD) insertion is generally recommended. The primary concern lies with asymptomatic individuals, where the identification of patients at risk of major arrhythmic events is crucial because cardiac arrest or sudden death often manifest as initial symptoms. For asymptomatic patients with spontaneous Type 1 ECG pattern, an electrophysiological (EP) study is suggested to identify higher-risk patients requiring therapy [13]. However, even a negative EP study result does not eliminate the possibility of major arrhythmic events. Consequently, a predictive system capable of anticipating fatal arrhythmic events in asymptomatic patients is interesting for the clinical community.

III. Methods

A. Dataset description

This study assembles a comprehensive dataset consisting of 265 12-lead ECGs. Within this dataset, 97 instances were associated with patients who experienced arrhythmic events, specifically sustained ventricular tachycardia (VT), ventricular fibrillation (VF), or sudden cardiac death (SCD). This class will be denoted as the *event* class throughout our analysis. Arrhythmic syncope was excluded from this category due to the inherent challenge of distinguishing it from vasovagal syncope, which is unrelated to Brs syndrome.

The remaining portion of the dataset includes patients exhibiting spontaneous Type 1 Brugada ECG but without any documented arrhythmic events. This class will be simply referred to as the *no event* class.

For each experiment, the testing set comprises 20% of the entire dataset while maintaining a proportional representation of both the *event* and *no event* classes. This splitting is maintained across all different models considered to compare their performance.

B. Data pre-processing and ECG features

A fundamental preprocessing step involved the standardization of the dataset, ensuring that the data across different features have a mean of 0 and a standard deviation of 1. This step is imperative for various machine learning algorithms, as it helps prevent features with larger scales from influencing the model.

All relevant features were independently measured by three expert cardiologists and all measurements were conducted using a caliper.

The selected features are representative of a comprehensive set of key aspects associated with the Brugada pattern. These include J point elevation, duration of S wave, QRS complex characteristics, QT interval, and QRS fragmentation. In addition to these Brugada-specific parameters, the feature set incorporates other essential ECG metrics such as heart rate and PR interval. The complete set of features is summarized in Table I.

TABLE I
DETAILED LIST OF FEATURES CONSIDERED IN THE EXPERIMENTS

Features	**Description**
HR (bpm)	Heart rate
PRint (ms)	PR interval
QRSdurDII (ms)	QRS complex duration in the second peripheral lead (DII)
QRSdurV6 (ms)	QRS complex duration in the sixth precordial lead (V6)
QRSdurV6 (ms)	QRS complex duration in the sixth precordial lead (V6)
QTintV5 (ms)	QT interval in the fifth precordial lead (V5)
QTintV2 (ms)	QT interval in the second precordial lead (V2)
cQTintV5 (ms)	QT interval corrected in the fifth precordial lead (V5) using Bazett's formula QTc = $QT/\sqrt{RR}$
cQTintV2 (ms)	QT interval corrected in the second precordial lead (V2) using Bazett's formula QTc = $QT/\sqrt{RR}$
TpeakTendV2 (ms)	interval between the peak of T wave and its end (adopting tangential method) in the second precordial lead (V2)
JTendV2 (ms)	interval between the J point and the peak of T wave in the second precordial lead (V2)
JelevV1 (mV)	elevation of J point above the baseline in the first precordial lead (V1)
JelevV2 (mV)	elevation of J point above the baseline in the second precordial lead (V2)
SdurDI (ms)	duration of S wave in the first peripheral lead (DI)
fQRS	if the fragmented QRS is present (the value is 0 in the absence of fragmentation, on the contrary, it is 1)

Lastly, any missing values (NaN) for each parameter were imputed using the median value.

C. Neural network models

In this section, a detailed descriptions of the models employed for the experiments is provided. Each model serves as a distinctive approach in the classification task.

At first, a boosted decision tree (BDT) model was used [14], employing the logit function for decision making. The model was configured with 30 splits per tree, 40 learners, and a learning rate set to 0.1. Then, several algorithms were considered to asses the classification performance, in order: discriminant analysis (DA) in both linear (DALin) and quadratic (DAQuad) forms [15]; the Naive Bayes (NB) model with the Gaussian method for classification [16]; and support vector machines (SVM) with both linear (SVMLin) and Gaussian (SVMGauss) kernels [17].

Finally, a multilayer perceptron (MLP) [18] was designed, made of a fully connected layer comprising 40 hidden units and utilizing a sigmoid activation function. To booster model stability, batch normalization was applied. The final output was provided by a classification layer with softmax activation. During training, a learning rate of 0.01 was employed, along with a dropout rate of 0.2 to mitigate overfitting. The Adam optimizer was utilized over 30 epochs, with a batch size set at 32.

All models were implemented using the MATLAB toolbox, except for the MLP, which was implemented in Python including the scikit-learn library that facilitates the selection of optimal features for classification and the evaluation of metrics.

D. Metrics

To compare the performance of various neural network models, a comprehensive set of metrics was considered:

1) **accuracy** (acc.): calculates the ratio of correctly predicted samples to the total number of samples.
2) **positive predictive value** (PPV): quantifies the accuracy of positive predictions by evaluating the ratio of true positive predictions to the sum of true positive and false positive predictions.
3) **negative predictive value** (NPV): quantifies the accuracy of negative predictions by evaluating the ratio of true negative predictions to the total number of negative predicted examples.
4) **specificity** (spec.): calculates the percentage of negative samples correctly predicted by the classifier and measures the model capability to correctly identify negative instances.
5) **sensitivity** (sens.): represents the ability of the model to identify the positive instances in a corrected way by evaluating the percentage of positive examples correctly predicted by the classifier.
6) **area under the receiver operating characteristic** (ROC) **curve** (AUC): it is the probability that the model randomly assigns a higher score to a positive example than to a random negative example and it is evaluated by estimating the area under the ROC curve that plots the true positive rate against the false positive rate at different classification thresholds.

IV. RESULTS

In this study, the performance of multiple models, that were previously described, was rigorously evaluated through a 5-fold cross-validation on the training data. Subsequently, the

models were tested on independent testing data (20% of the entire dataset), and a set of metrics, as detailed in the preceding section, was used for evaluation.

As can be noted, looking at the cross-validation results (see Table II), the boosted decision tree model performed better than other models in terms of accuracy. It showed strong classification abilities for both classes. This good performance has been confirmed when the model was tested on new, unseen data, validating its effectiveness (see Table III).

TABLE II
RESULTS OF THE DIFFERENT MODELS IN 5-FOLD CROSS-VALIDATION

Models	acc.	PPV	NPV	spec.	sens.	AUC
BDT	0.93	0.89	0.96	0.93	0.94	0.93
DALin	0.86	0.90	0.84	0.96	0.69	0.82
DAQuad	0.90	0.86	0.92	0.92	0.86	0.89
NB	0.92	0.93	0.92	0.96	0.86	0.91
SVMLin	0.87	0.90	0.86	0.96	0.73	0.84
SVMGuass	0.88	0.89	0.88	0.94	0.77	0.86

TABLE III
RESULTS OF THE DIFFERENT MODELS ON THE TEST SET

Models	acc.	PPV	NPV	spec.	sens.	AUC
BDT	0.88	0.73	1.00	0.79	1.00	0.90
DALin	0.75	0.67	0.80	0.82	0.63	0.73
DAQuad	0.89	0.88	0.89	0.94	0.79	0.86
NB	0.85	0.79	0.88	0.88	0.79	0.83
SVMLin	0.75	0.64	0.84	0.76	0.74	0.75
SVMGuass	0.75	0.65	0.82	0.79	0.68	0.74

To further optimize feature selection, a subset of five features was identified using the chi-squared test [19]. The selected features were as follows: *JelevV1, JelevV2, QRSdurV6, QRSdurDII, SdurDII*. These experiments were conducted excluding the MLP model, where a different feature selection technique was employed. Tables IV and V show the results using this subset of feature selected with the chi-squared test.

TABLE IV
RESULTS OF THE DIFFERENT MODELS IN 5-FOLD CROSS-VALIDATION WITH FIVE FEATURES SELECTED

Models	acc.	PPV	NPV	spec.	sens.	AUC
BDT	0.90	0.86	0.92	0.92	0.87	0.89
DALin	0.84	0.91	0.82	0.96	0.69	0.80
DAQuad	0.89	0.90	0.88	0.95	0.78	0.86
NB	0.91	0.94	0.90	0.97	0.82	0.89
SVMLin	0.86	0.89	0.85	0.95	0.72	0.83
SVMGuass	0.89	0.95	0.86	0.97	0.73	0.85

It can be observed that accuracy across models remained largely unchanged, with the boosted decision tree continuing to demonstrate strong overall performance. However, it can be noted a small reduction in sensitivity, indicating a shift towards more accurate predictions for the *no event* class. Nevertheless, it can be stated that this set of features embeds the key information essential for the classification task.

TABLE V
RESULTS OF THE DIFFERENT MODELS IN TESTING WITH FIVE FEATURES SELECTED

Models	acc.	PPV	NPV	spec.	sens.	AUC
BDT	0.89	0.76	1.00	0.82	1.00	0.91
DALin	0.87	0.87	0.86	0.95	0.73	0.84
DAQuad	0.90	0.94	0.89	0.97	0.79	0.88
NB	0.89	0.84	0.91	0.91	0.84	0.88
SVMLin	0.89	0.78	0.96	0.85	0.95	0.90
SVMGuass	0.85	0.82	0.86	0.91	0.74	0.82

In an attempt to refine the feature set, a subset of five features was identified through mutual information analysis for the MLP model. The specific features chosen are: *JelevV1, JelevV2, QRSdurV6, QRSdurDII, SdurDII*. Then, the MLP model was retrained on this subset and the accuracy in cross-validation results mirrored the previous experiments, as shown in Table VI. However, also in this case, a decrease in sensitivity was observed.

The number of selected features was then increased to seven (JelevV1, JelevV2, QRSdurV6, QRSdurDII, SdurDII, *PRint and cQTintV2*) but the accuracy remained consistent. Furthermore, the sensitivity improved, and this positive change was also reflected in the testing results (see Table VII).

TABLE VI
RESULTS IN 5-FOLD CROSS-VALIDATION WHEN THE MLP IS CONSIDERED. MLP-k STANDS FOR THE EXPERIMENT COMPUTED WITH A SUBSET OF FEATURES WITH k ELEMENTS

Models	acc.	PPV	NPV	spec.	sens.	AUC
MLP	0.86	0.90	0.85	0.95	0.72	0.83
MLP-5	0.87	0.95	0.85	0.97	0.70	0.84
MLP-7	0.88	0.94	0.87	0.97	0.83	0.86

TABLE VII
MAIN METRICS IN TESTING WHEN THE MLP IS CONSIDERED. MLP-k STANDS FOR THE EXPERIMENT COMPUTED WITH A SUBSET OF FEATURES WITH k ELEMENTS

Models	acc.	PPV	NPV	spec.	sens.	AUC
MLP	0.79	0.68	0.87	0.79	0.79	0.79
MLP-5	0.88	0.95	0.85	0.97	0.70	0.82
MLP-7	0.81	0.66	0.96	0.74	0.95	0.84

V. CONCLUSION

In conclusion, this research explored deep learning models as alternative methods for risk stratification in patients with Brugada syndrome.

Different neural network models were employed to analyze ECG features, aiming to identify individuals with documented arrhythmic events. The study involved 265 ECGs and 14 features were independently measured by expert cardiologists. The boosted decision tree model demonstrated superior accuracy in both cross-validation and testing, together with the

Naive Bayes model and the quadratic discriminant analysis. Feature selection was further optimized by identifying subsets using the chi-squared test and mutual information analysis, confirming the selected featured map key information for the classification task.

In the case of the MLP model, after feature refinement, consistent accuracy was maintained, but there was a decrease in sensitivity. However, by increasing the number of selected features, accuracy remained stable, and sensitivity improved, as validated in testing results.

Expanding the dataset by including more ECGs is expected to enhance the performance of neural network models, especially when accompanied by the incorporation of additional ECG features.

Overall, this study points out that ECG signals from individuals with Brugada syndrome carry valuable information for identifying those at a high risk of fatal events. The application of AI-based ECG analysis holds promise in assisting clinical decision-making processes and decrease the number of deaths among this category of patients.

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