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Research Article

Classification of Cardiovascular Diseases Using Electronic Nose Dataset with Artificial Neural Network Classifier

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Abstract

Cardiovascular diseases are one of the leading reasons for mortality worldwide. With the rise of cardiovascular diseases and their effect on lives, it becomes crucial to have accurate and fast diagnosis results.
Nowadays, machine learning techniques are widely used to interpret and classify information or different measurement techniques for various diseases. Cardiovascular diseases are among the most time and accuracy-sensitive cases as even the minutes are essential, especially for myocardial infarction.
In many cases, a diagnosis of myocardial infarction can be made by simply looking at an electrocardiogram. But in some cases, physicians may not be able to determine the myocardial infarction condition by an electrocardiogram test; therefore, a blood test becomes a necessity which takes 40-60 minutes to complete. In order to overcome the current time-consuming process in one of the previous studies, an electronic nose has been used to classify MI, stable coronary artery disease and healthy individuals, which is a promising fast result method.
In this study, we focused on the classification algorithm using the dataset used in the study mentioned above. We noticed that there might be room for classification accuracy performance improvement while reducing the complexity of the process, which has the potential to affect the clinical results. The proposed algorithm results indicate that it is possible to achieve improved overall classification accuracy. At the same time, the complexity of the process is reduced by using an appropriate shallow neural network, even with a single classification step.

Keywords: Myocardial infarction, Stable coronary artery disease, Machine Learning, Neural Network, Classification

Yapay Sinir Ağı Sınıflayıcıyla Elektronik Burun Veri Seti Kullanarak Kardiyovasküler Hastalıkların Sınıflandırılması

Öz

Kardiyovasküler hastalıklar dünya çapında ölümlerin önde gelen nedenlerinden biridir. Kardiyovasküler hastalıkların artması ve yaşam üzerindeki etkileri ile birlikte doğru ve hızlı tanı sonuçlarına sahip olmak çok önemli hale gelmektedir.
Günümüzde makine öğrenme teknikleri, çeşitli hastalıklar için bilgileri veya farklı ölçüm tekniklerini yorumlamak ve sınıflandırmak için yaygın olarak kullanılmaktadır. Kardiyovasküler hastalıklar, özellikle miyokard enfarktüsü için dakikalar bile önemli olduğundan, zamana ve hassasiyete en duyarlı vakalar arasındadır.

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Çoğu durumda, sadece bir elektrokardiyograma bakarak miyokard enfarktüsü teşhisi konulabilir. Ancak bazı durumlarda doktorlar bir elektrokardiyogram testi ile miyokard enfarktüsünün durumunu belirleyemeyebilirler; bu nedenle, tamamlanması 40-60 dakika süren bir kan testi bir zorunluluk haline gelir. Önceki çalışmalardan birinde mevcut zaman alıcı sürecin üstesinden gelmek için, umut verici hızlı sonuç yöntemi olan MI, stabil koroner arter hastalığı ve sağlıklı bireyleri sınıflandırmak için elektronik bir burun kullanılmıştır. Bu çalışmada, yukarıda bahsedilen çalışmada kullanılan veri seti kullanılarak sınıflandırma algoritması üzerinde durulmuştur. Klinik sonuçları etkileme potansiyeline sahip olan sürecin, karmaşıklığını azaltırken, sınıflandırma doğruluğu performansını arttırmanın mümkün olabileceği görülmüştür. Önerilen algoritma sonuçları, geliştirilmiş genel sınıflandırma doğruluğu elde etmenin mümkün olduğunu göstermektedir. Aynı zamanda, tek bir sınıflandırma adımıyla bile, uygun bir sığ sinir ağı kullanılarak sürecin karmaşıklığı azaltılmıştır.

Anahtar Kelimeler: Miyokard enfarktüsü, Stabil koroner arter hastalığı, Makine Öğrenmesi, Sinir Ağı, Sınıflandırma

1. Introduction

As we all witnessed in the last decades, many different technologies and methods have been developed and used to analyse medical information to assist physicians with their diagnoses. One of which is electronic nose systems that analyse the odour information as well as volatile organic compounds (VOCs) gathered from individuals (Tozlu et al. 2021, Pauling et al. 1971)

With the help of machine learning techniques, those kinds of complex data can be interpreted as a diagnosis decision aid for physicians if the study is adequately designed, which we know from their high accuracy results (Tozlu et al. 2021, Pauling et al. 1971, Behera et al. 2019, D'Amico et al. 2010, Dragonieri et al. 2009, Ergün & Aydemir 2018)

Also, electronic nose systems offer an easy application and fast response compared to many other methods. In addition, it provides a non-invasive and low-cost application which is one of the main reasons for the focus. The analysis could be made in a couple of minutes without any blood work and special tools by simply collecting exhaled breaths from individuals.

The study provides the dataset (Tozlu et al. 2021), which we used in this paper, which offers a well-designed approach that tries to identify several cardiovascular diseases along with healthy individuals using an electronic nose. In order to gather information from exhaled breath and determine cardiovascular diseases, there should be some VOCs inside the exhaled breathing air related to the condition of the subject or patient. Hopefully, this phenomenon has been proven by many other studies (Pauling et al. 1971, Behera et al. 2019, D'Amico et al. 2010, Dragonieri et al. 2009), especially using the gas chromatography method (Pauling et al. 1971). Although most of the previous studies are focused on lung and lung-related diseases (Behera et al. 2019, D'Amico et al. 2010, Dragonieri et al. 2009), the study (Tozlu et al. 2021) is focused on cardiovascular diseases. Mentioned study (Tozlu et al. 2021) is based on the theory that a released protein during myocardial infarction (MI) called Troponin should be found in exhaled breath of patients, even if a significant portion of it is eliminated by renal and hepatic clearance. Suppose the physician could not determine the MI condition by looking at electrocardiogram (ECG) results (ECG without ST elevation MI condition (ESC Committee for Practice Guidelines (CPG), et al. 2012)). In that case, blood work becomes a necessity that takes approximately an hour which might be the difference between life and death.

The other coronary artery disease studied (Tozlu et al., 2021) is stable coronary artery disease (SCAD) which has a different diagnosis approach. Mainly medical imaging techniques are used to diagnose SCAD, as stated in (Tozlu et al. 2021) (Joseph et al. 2018). However, electronic nose classification performance on SCAD seems promising as well.

With this approach, 19 different gas sensors have been used to form the data set with four features (EQs. 1-4) for each sensor (Tozlu et al., 2021). We have used the same data set with the same four base features (EQs. 1-4) to be able to compare our results with (Tozlu et al. 2021) correctly. Also, four additional features (EQs. 5-8) are proposed in this study to improve the classification accuracy.

Since the focus of this study is on the classification performance of the same data used in (Tozlu et al. 2021), we designed a neural network (NN) with one hidden layer, with all features from all sensors as input and all classes in the data set as the outputs. Results indicate that the breath of MI patients, SCAD patients and healthy subjects can be separated more accurately using the proposed method even with a single classification process.

2. Design of Neural Network

Since we focused on improving the performance of the classification process, this section provides the details of the NN used in the study. More detailed information for the rest of the setup can be found in (Tozlu et al. 2021), such as patient demography, electronic nose setup, sensors used in electronic nose and the breath collection methods etc.

Although there are existing methods such as those (Üstün 2009), the hyperparameters of the network used in this study were determined mostly after some preliminary tests based on experience. The fact that some results show 100% classification performance indicates that a more complex parameter determination process, such as (Üstün 2009), is unnecessary. All trials have been performed with a shallow network, including one input layer, one hidden and one output layer. The number of inputs depends on the chosen features, as the number of features was limited to a minimum of 4 and a maximum of 8. If four features were used, the input size of the network becomes $4x19 = 76$; if eight were used, it becomes $8x19 = 152$. All the features used in this study are given with eq. 1-8. Eq. 1-4 are the features used in (Tozlu et al. 2021), while eq. 5-8 provide the equations for the additional features we proposed. Combining all the features helps to improve overall performance a little bit further, as one can compare from Table 1- 4 in the results section.

In our preliminary runs, we tested networks with several combinations for different hidden layer sizes, mini-batch sizes, activation functions and optimiser methods to determine other network parameters.

Preliminary tests were performed with the hidden layer size varying between 50 and 100 to find the optimum size for the problem. Several activation functions have also been tested, which were Rectified Linear Unit (ReLU), Leaky ReLU, Exponential Linear Unit (ELU), logistic sigmoid; and the tested optimisers were Adam, RMSprop, AdaDelta (Ruder 2017, Kingma & Ba 2014, Bircanoğlu & Arıca 2018). We used the softmax activation function for the output layer in all tests and the chosen model, thereby using the cross-entropy loss as the network error (Wan et al., 2013).

We obtained the best neural network parameters with the "8 features" configuration listed in eq. 1-8 as inputs, "80 hidden neurons", "ReLU activation function" (for the hidden neurons), "Adam optimizer" and the "mini-batch size of 8" (Li et al. 2014). The above parameters obtained all of the performance values provided in this study. We also choose the same data percentages as in (Tozlu et al. 2021) for test and training as %34 and %66, respectively.

$$\mathrm{Mean} = \frac{1}{L}\sum_{i=1}^{L}(x_i) \quad (1)$$

$$\mathrm{Skewness} = \frac{\frac{1}{L}\sum_{i=1}^{L}(x_i - \bar{x})^3}{\left(\sqrt{\frac{1}{L}\sum_{i=1}^{L}(x_i - \bar{x})^2}\right)^3} \quad (2)$$

$$\mathrm{Kurtosis} = \frac{\frac{1}{L}\sum_{i=1}^{L}(x_i - \bar{x})}{\left(\frac{1}{L}\sum_{i=1}^{L}(x_i - \bar{x})^2\right)^2} \quad (3)$$

$$\mathrm{VD} = \frac{1}{L}\sum_{i=1}^{L}(\dot{x}_i - \bar{\dot{x}})^2 \quad (4)$$

$$\text{Sum of derivatives} = \sum_{i=1}^{L}\dot{x}_i \quad (5)$$

$$\text{Log Detector} = e^{\left\{\frac{1}{L}\sum_{i=1}^{L}\log(|x_i|)\right\}} \quad (6)$$

$$\mathrm{Median} = x_{(n+1)/2} \quad \text{odd}$$
$$\mathrm{Median} = \frac{x_{(n)/2} + x_{(n/2)+1}}{2} \quad \text{even} \quad (7)$$

$$\mathrm{VSD} = \frac{1}{L}\sum_{i=1}^{L}(\ddot{x}_i - \bar{\ddot{x}})^2 \quad (8)$$

We used classification accuracy (CA)(eq. 9), sensitivity (SE)(eq. 10) and specificity (SF) (eq. 11) metrics to evaluate the performance of classifiers and to illustrate a proper comparison with (Tozlu et al. 2021),

$$\mathrm{CA} = \frac{\mathrm{CCT}}{\mathrm{TT}}\mathrm{x}100 \quad (9)$$

$$\mathrm{SE} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}\mathrm{x}100 \quad (10)$$

$$\mathrm{SF} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}\mathrm{x}100 \quad (11)$$

Here; CCT: Correctly Classified Trials

TT: Total number of considered Trials

TP: True Positive samples

TN: True Negative samples

FP: False Positive samples

FN: False Negative samples

3. Results

In this study, we classified the MI, SCAD and healthy subjects using an electronic nose database provided by the authors of (Tozlu et al. 2021) using NN based classifier. The database includes 119 breaths from 33 MI patients, 132 breaths from 22 SCAD patients and 111 breaths from 26 healthy individuals in total. Two different classification approaches have been performed; 1) single step and 2) decision tree based. NN models are applied to the whole dataset in a single step, including MI, SCAD, and Healthy classes. In the decision-tree-based NN, the training process includes two steps like the work (Tozlu et al., 2021). In the first step, the NN model is applied to the data that includes two classes - Non-MI and MI and then, in the second step, the model is applied to the Non-MI data, i.e., SCAD and Healthy.

Confusion matrices of the proposed single-step classification approach for 4 and 8 features are given in Table 1 and Table 2, respectively. From these tables, one can see the performance improvement brought by the additional four features. Table 3 also provides the performances of the proposed decision tree-based NN classification. Although Table 1 and Table 2 cannot illustrate an exact comparison for classification accuracies with the study (Tozlu et al. 2021), Table 4 can be synthesised via these tables, including Table 3.

Table 1. Confusion matrix using eight features (Eq.1-8) obtained by NN-based single-step classification method. (%)

	SCAD	MI	Healthy
SCAD	93.85	0.00	6.15
MI	0.00	100	0.00
Healthy	10.91	1.82	87.27

Table 2. Confusion matrix using four features (Eq.1-4) obtained by NN-based single-step classification method. (%)

	SCAD	MI	Healthy
SCAD	90.77	0.00	9.23
MI	0.00	100	0.00
Healthy	10.91	3.64	85.45

One can see from Table 4 (first line of 8 features) that the proposed single-step NN-based classification method has a reduced CA performance by 4% for MI vs Others classification while having improved CA performance for SCAD vs Healthy classification by 10% compared with the results in (Tozlu et al. 2021).

Table 3. Confusion matrix obtained by proposed decision tree NN-based classification method. (%)

	MI	Others	SCAD	Healthy	
MI	100	0.00	-	-	**Eight features**
Others	0.83	99.17	-	-	
SCAD	-	-	92.53	7.47	
Healthy	-	-	5.56	94.44	
MI	100	0.00	-	-	**Four features**
Others	0.00	100	-	-	

SCAD	-	-	94.03	5.93
Healthy	-	-	11.11	88.88

This concludes that with single-step NN-based classification, the proposed method has a 6% performance improvement overall compared with (Tozlu et al. 2021). Additionally, the proposed decision tree NN-based classification method using eight features (last line in Table 4) indicates a 2% and 14% CA performance improvement for MI vs Others and SCAD vs Healthy classifications, respectively. Although a previous study has already performed a NN classifier with one hidden layer that includes 100 neurons. Table 4 indicates that selected hyperparameters would yield better performance.

Table 4. Comparison of all results with the same performance metrics (CA, SE, SF). (%)

	MI vs Others			**SCAD vs Healthy**			
	CA	SE	SF	CA	SE	SF	
4 Features	91.19	100	98.41	89.83	90.76	88.68	**Single Step NN-Based Classification**
8 Features	93.08	100	99.09	91.59	91.04	92.30	
Results in (Tozlu et al. 2021)	97.19	93.37	99.07	81.48	82.56	80.19	**Decision Tree NN-Based Classification**
4 Features	100	100	100	91.73	91.30	92.30	
8 Features	99.37	100	99.16	95.76	92.53	94.44	

Figure 1 shows the training and test accuracy obtained by applying the proposed NN model to the whole dataset. The blue and orange lines illustrate the corresponding accuracy of the network performed with four features; the green and red illustrate the same metrics obtained using eight features. Each plot in the figure is the median value of the corresponding accuracy obtained by 50 independent runs. As seen from the figure, the training performance of the models sharply reaches 100%. However, the network that uses four features could never reach the testing accuracy of the network that uses eight features during the training.

Figures 2 and 3 show the same metrics. The plots in the figures show the training and testing performance of the Non-MI and MI classification task and SCAD and Healthy classification task. Like in Figure 1, the plots in Figures 2 and 3 are also the median values of 50 independent runs. Figure 2 illustrates the accuracy results of the 4-feature-NN, while Figure 3 shows the corresponding results of the 8-feature-NN.

As one can see from the plots, the 4-feature-network is slightly better than the 8-feature-network in Non-MI vs MI classification task; however, both perform well by reaching quickly 100% and 99.37% testing accuracy, respectively. When we look at the test results of the SCAD vs Healthy classification task in the figures, it is clear that the 8-feature-network is superior to the 4-feature-network in terms of fast convergence, stability and accuracy rate.

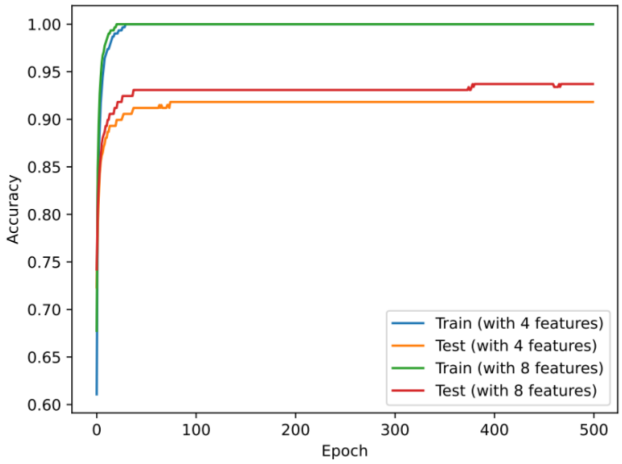

Figure 1. *Accuracy of NN-based single-step classification (4 and 8 features).*

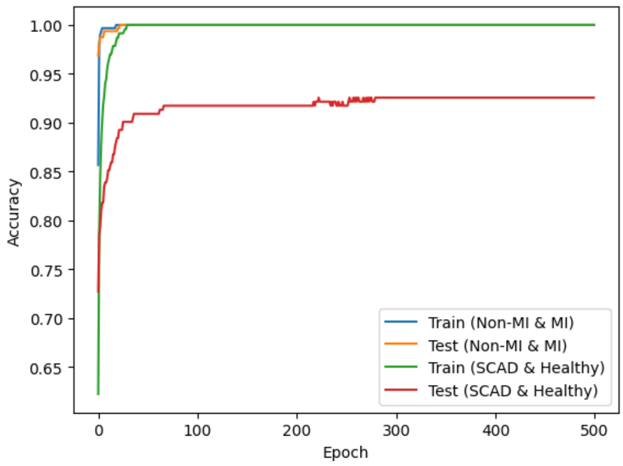

Figure 2. *Accuracy of MI vs Others and SCAD vs Healthy*

classes using NN-based decision tree classification (4 features).

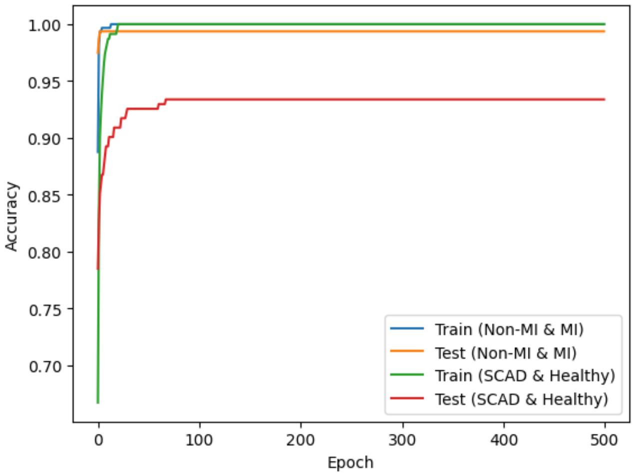

Figure 3. *Accuracy of MI vs Other and SCAD vs Healthy classes using NN-based decision tree classification (8 features).*

4. Conclusions

In this study, we proposed a single-step neural network decision tree-based classification approach to an existing data set (Tozlu et al., 2021) that includes exhaled breath measurements obtained via an electronic nose system. Results indicated that with the better-determined hyperparameters of the NN, better classification accuracies could be obtained, along with a reduction in design complexity provided by a single-step classification approach rather than a decision tree structure. Also, proposed additional features help improve classification accuracy's performance a little further.

We believe that a more extensive data set and a deep neural network structure would become much more effective since the data set provides only 362 breath trials. Nevertheless, this study has improved average classification accuracies by an average of 8% per cent with respect to the previous study (Tozlu et al., 2021).

5. Author contribution statement

In this study, author 1; writing the article, hardware design and production, extraction and classification of features, author 2; design and implementation of the classifier model, extraction, classification of features and evaluating the results, author 3; generating the main idea, producing the hardware and recording the data, author 4; determining the classification problem, extracting the features and evaluating the results, author 5; contributed to the recording of the data.

6. Ethics committee approval and conflict of interest statement

"There is no need for an ethics committee approval in the prepared article"

"There is no conflict of interest with any person/institution in the prepared article"

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