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Automatic classification of migraine and tension-type headaches using machine learning methods

Soroor Shafieizadegan Esfahan
Department of Electrical and Computer Engineering
Isfahan University of Technology
Iran
s.shafeizadegan@gmail.com

Arezoo Haratian
Department of Electrical and Computer Engineering
Isfahan University of Technology
Iran
arezo.h1992@gmail.com

Azadeh Haratian
Department of Psychology
Islamic Azad University
Science and Research Branch
Iran
azadeh.h1990@gmail.com

Farzaneh Shayegh
Department of Electrical and Computer Engineering
Isfahan University of Technology
Iran
f.shayegh@iut.ac.ir

Soroor Kiani
Department of Psychology
Islamic Azad University
Arak Branch
Iran
soroorkiani@gmail.com

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***Abstract*— Migraines and tension-type headaches (TTH) are the more prevalent types of primary headaches. Usually, the diagnosis of these types of headaches is imprecise. Meanwhile, emotional and cognitive dysfunctions are associated with these disorders and have potential diagnostic power. This paper aims to classify patients with TTH and migraines using machine learning methods. It uses psychological questionnaires and demographic data as features for the classification. The Boruta algorithm is applied to select the most relevant features, and various machine learning models are compared to find the best one. In this study, 79 patients with migraine headaches and 81 with TTH referring to the two neurology clinics in Isfahan City, Iran, from 2019 to 2020 completed the cognitive emotion regulation questionnaire and perseverative thinking questionnaire. Results show that random forest (RF) and naïve Bayes achieve the highest accuracy, sensitivity, and specificity in distinguishing TTH and migraine. In fact, RF and naïve Bayes outperformed other classifiers in training and testing sets with a slight difference. The TTH and migraine were classified with 98% accuracy, 100% sensitivity, and 96% specificity in the testing set. Applying machine learning algorithms to distinguish TTH and migraine using these disorders' psychological roots helps significantly in the more accurate diagnosis and treatment of these two disorders.**

Keywords—machine learning, migraine, tension-type headache, psychological distress, feature selection

I. Introduction

Headache is a common neurological symptom that affects people's quality of life. More than 90% of the population report a lifetime history of headaches [1]. According to the International Headache Society (IHS), headaches can be classified into primary and secondary headaches [2]. Primary headaches include migraines, tension-type headaches (TTH), and cluster headaches. Migraine, TTH, and coexisting migraine and TTH are the most prevalent types of primary headaches, accounting for two-thirds of all headaches [3], [4]. The diagnosis of these types of headaches is based on specific criteria established by the IHS, as well as physical and neurological examinations and sometimes specialized tests such as magnetic resonance imaging, tomography, and electroencephalogram [5]. TTH is characterized by a mild to moderate feeling of pressure around the forehead or back of the head and neck, lasting from 30 minutes to several days. It is associated with various somatic and emotional signs. Migraine is a recurrent headache with moderate to severe intensity, usually affecting one side of the head. It can be accompanied by nausea, photophobia, and phonophobia, and lasts for 4 to 72 hours. Migraine has a higher prevalence in women than in men worldwide (9.7% in men and 20.7% in women) [2], [6], [7], [8], [9], [10].

The correct diagnosis of headache type is the first and most crucial step for headache treatment [11]. However, the diagnosis of TTH and migraine is often imprecise. Moreover, these types of headaches are associated with psychiatric comorbidity of depression and anxiety, as well as psycho-affective, emotional regulation problems and cognitive aspects such as repetitive negative thinking (RNT) [12], [13], [14]. These psychological factors may have diagnostic value for distinguishing TTH and migraine, as they may differ in their levels and impacts on each type of headache. However, there are limitations in the assessment and intervention of these factors in clinical settings for headache treatment [15]. Therefore, machine learning methods, which have recently been widely used to create decision support systems that can increase diagnosis accuracy, may be useful to take advantage of these factors for classifying TTH and migraine [16], [17], [18], [19], [20]. Previous studies have used machine learning models such as logistic regression, support vector machine (SVM), decision tree, random forest (RF), gradient boosting, XGboost, and neural network to classify different types of headaches based on physical symptoms such as headache course, intensity, photophobia, and phonophobia. These studies have achieved impressive results in terms of accuracy, sensitivity, and specificity [16], [17], [18], [21], [22], [23]. They obtained an accuracy of 93% using this model with the RF classification model. A similar attempt to use the RF model to classify three types of migraine, TTH, and cluster headache using the Migbase dataset has reached 99% accuracy [23]. However, to the best of our knowledge, none of these studies have used psychological factors as features for the classification. These factors are easy to access compared to other expensive and complex tests such as EEG [24]. Moreover, by creating and interpreting machine learning models to predict headache types based on psychological factors, we can gain insight into the role of these factors in each type of headache. This insight can help adjust the psychotherapy protocols for the treatment of TTH and migraine accordingly.

In this study, we propose the automatic classification of subjects with TTH from migraine based on psychological factors. We use psychological questionnaires and demographic data as features for the classification. We apply the Boruta algorithm to select the most relevant features, and we compare various machine learning algorithms to identify the best classification model to distinguish TTH from migraine.

II. Method and Materials

A. Participants

Our study was performed on patients with TTH and migraine referring to the neurology clinics of Askarieh Hospital and Samen Medical Center in Isfahan City, Iran, from 2019 to 2020. Difficulties in emotional regulation and RNT were measured by the Cognitive Emotion Regulation Questionnaire (CERQ) and Perseverative Thinking Questionnaires (PTQ). Diagnosis of migraine and TTH disorders was made by a neurologist based on the IHS criteria [2], [14]. In addition, we obtained written informed consent from all subjects.

To increase the reliability of the study, patients who had other primary or secondary headaches or combined headaches according to the IHS criteria or neurologic disorder were excluded from the study; moreover, migraine and TTH patients experienced the first headache attack at least one year before being included in the study; finally, 160 participants including 79 patients with migraine headache and 81 patients with TTH completed the study questionnaires for research. Demographic information for each group is shown in Table I.

B. Questionnaires Used in Research

1) Cognitive Emotion Regulation Questionnaire (CERQ)

The first questionnaire is developed to assess cognitive emotion regulation strategies about thinking after experiencing life-threatening or stressful events and includes 9 subscales from the 36 items. Participants rate each item on a scale from 1 (Almost never) to 5 (Almost always), how often this item is applied in the process of their emotion regulation strategies [25].

2) Perseverative Thinking Questionnaire (PTQ)

The PTQ is a measure to assess trait repetitive negative thinking and includes 3 subscales from the 15 items. Participants rate each item on a scale from 0 (never) to 4 (almost always) on how often the item applies to their thinking process [26].

C. Feature Selection

In order to determine which features were most predictive of migraine or tension headache classification, we used a feature selection method, Boruta [27]. The Boruta relies on the RF algorithm to determine relevant features; This trains an RF classifier and provides Z-scores of mean decrease accuracy measure to evaluate the importance of each feature. Finally, Boruta confirmed/rejected features that are strongly/weakly relevant to the target variable. Our feature selection has been performed using the Boruta package in the R programming language. Our features include nine subscales for positive and negative cognitive emotion regulation strategies, three subscales for repetitive negative thinking, and two demographic information which are listed in Table II.

D. Classification Algorithms

In the current study, five supervised machine learning algorithms containing RF, SVM, K-Nearest Neighbors (KNN), logistic regression, and Naïve Bayes were chosen to evaluate and find the best model for diagnosing and classifying migraine and TTH. Moreover, we split the entire dataset randomly into a training set (70% of data) and a test set (30% of data). The classification was performed using Python (version 3.10.8) and Scikit-learn.

1) Naïve Bayes

Naïve Bayes is a probabilistic classifier based on applying Bayes' theorem. There are different Naïve Bayes classifiers due to the various assumptions for likelihood distribution. In the current study, we used a Naïve Bayes classifier with a Gaussian distribution. Model parameters are estimated using maximum likelihood. One advantage of this classifier is that it requires a small amount of training data to estimate parameters. Indeed, in this method, a new object belongs to a class with the highest posterior probability [28].

2) RF

RF is an ensemble learning method based on bagging and the decision tree classifier. It consists of an ensemble of tree classifiers that generate a forest, and this forest can make better decisions than a tree. Independently, each tree is constructed using a bootstrap of input data, meaning samples have been chosen randomly with replacements from the original dataset. Bootstrapping is beneficial for RF since it decreases the bias in the analysis. Finally, the prediction of the forest is the class that received the most votes from the trees in the forest [29].

TABLE I. Demographic characteristics for each of the migraine and tension-type headache groups.

Characteristic	Groups (160)		p-value
	Migraine Headache (79)	*Tension Headache (81)*	
Age (year)	37.56±11.86[c] (18-72)	37.75±10.85 (18-63)	0.913[a]
Gender (male/female)	27/52	25/56	0.655[b]
Education (Less than Diploma/Diploma/Bachelor's degree/Master's degree or higher level)	13/42/19/5	11/47/20/3	0.948[b]

a. The p-values were based on a two-sample t-test.
b. The p-value was obtained based on a chi-square test.
c. Mean± SD.

TABLE II. List of features.

Number	Name	Description and value	Migraine Headache (n=79)	Tension Headache (n=81)
PTQ				
1	P1	The core characteristics of RNT, Numeric	18.72±6.78	22.16±5.72
2	P2	Perceived unproductiveness of RNT, Numeric	6.23±2.29	7.53±2.2
3	P3	RNT capturing mental capacity, Numeric	7.33±2.73	8.3±2.43
CERQ				
4	C1	Acceptance, Numeric	26.57±6.34	17.15±3.71
5	C2	Refocus on planning, Numeric	16.66±4.22	10.1±2.37
6	C3	Positive refocusing, Numeric	8.73±2.12	7.14±1.99
7	C4	Positive reappraisal, Numeric	11.61±2.4	7.44±2.03
8	C5	Putting into perspective, Numeric	26.24±6.2	16.81±3.66
9	C6	Self-blame, Numeric	8.75±1.82	7.56±1.86
10	C7	Other blame, Numeric	14.1±4.17	18.86±4.23
11	C8	Rumination, Numeric	11.68±2.59	14.72±2.99
12	C9	Catastrophizing, Numeric	11.91±2.35	16.73±8.51
Demographic				
13	Age	Patient's age, Numeric	37.56±11.86	37.75±10.85
14	Gender	Patient's gender, Binary, (man=0, woman=1)	-	-
Target variable				
15	Type	Diagnosis of headache type, Binary, (TTH =1, migraine=0)	-	-

3) Logistic Regression

Logistic regression is a generalized linear model used to solve binary classification problems. It takes continuous or discrete features as input and uses a logistic or sigmoid function to predict the probability or odds of a specific class [30].

4) SVM

SVM classification is one type of supervised learning algorithm. Features are independent variables that describe an observation called vectors. SVM fits the optimal multidimensional hyperplane for separating data into different classes. The vectors near the hyperplane are called support vectors. The distance between the support vectors is called the margin. The purpose of SVM is to find a hyperplane that maximizes the margin and minimize the number of misclassification simultaneously. SVM uses a kernel function to map data into the high dimensional space where a hyperplane can separate the different classes [31]. Regarding data, we can use various kernel functions; In the current study, Linear, Radial Basic Function, Sigmoid, and Polynomial kernels were evaluated using GridsearchCV.

5) KNN

KNN is a non-parametric method used for classification. Assume K is a positive integer and x_0 is a test observation. First of all, the KNN classifier identifies the K points (observations) in training data that are nearest to the x_0, and all those points are represented by N_0, then the conditional probability for x_0 which belongs to the class j, is as follows:

$$\Pr(\mathrm{Y} = \mathrm{j} \mid \mathrm{X} = x_0) = \frac{1}{K} \sum_{i \in N_0} I(Y_i = j) \quad (1)$$

Finally, an observation classifies to a class with the highest estimated probability [32], [33].

E. Model performance evaluation

The selected features were used to train the classifiers. We applied leave-one-out (LOO) and 3-fold cross-validation on the training set for evaluating the performance of classification models. Also, we used the GridsearchCV method, which searches over specified the classifier parameters values to find the best classification model parameters within each classification method. Then, the trained classifiers were assessed on the testing set. We computed three measures containing accuracy, sensitivity, and specificity to evaluate the quality of the classifiers for the testing set; in addition, mean accuracy was estimated for reporting the performance of models on the training set.

III. Results

A. Selection of Most Informative Features

Features with regard to their rank and importance are shown in Fig.1. Among features Gender, Age, P3 rejected and discarded; therefore, 11 features are selected among 14 features and fed to classifiers; moreover, the top four prominent features for classification of TTH and migraine are C2, C5, C1, and C4; as displayed in Table II, the mean value of these features was significantly reduced in TTH patients compared to migraine patients.

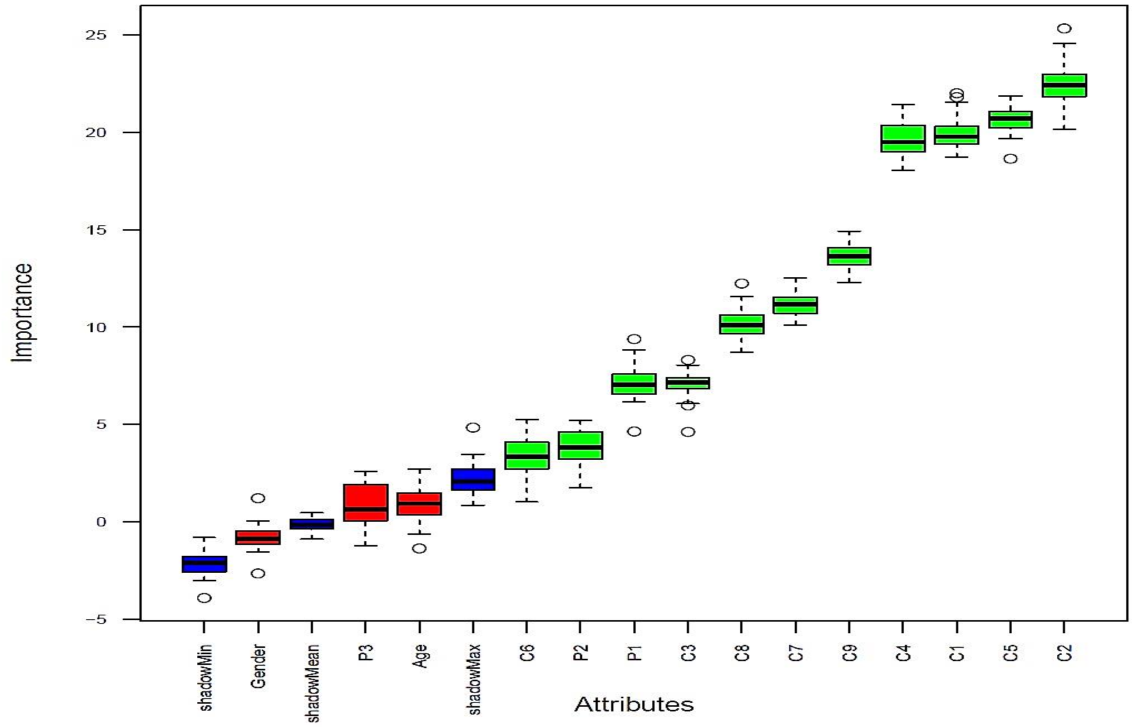

Fig. 1. The Boruta result for each feature. Green boxplots depict the Z-score of confirmed attributes, and red ones represent the Z-score of rejected attributes; Blue boxplots correspond to the minimal, average, and maximum Z-scores of a shadow attribute.

B. *Comparison of classifiers performance*

To confirm the reliability of the results of LOO cross-validation, we repeated the classification process using 3-fold cross-validation; because the classification performance might be biased by overfitting the LOO method [34]. The performances of the classifiers for both training and testing sets were assessed. The results of LOO and 3-fold cross-validation schemes were the same in the testing set. High accuracy was achieved through several machine-learning algorithms. As depicted in Table III, two classification algorithms, including RF and Naïve Bayes had the highest mean accuracy (99.1%) in the training set using 3-fold cross-validation. However, four classification algorithms, RF, KNN, Naïve Bayes, and logistic regression had the highest accuracy (97.92%) in the testing set (see, Fig.2). The sensitivity of all classification methods was 100% in the testing set, which revealed that all TTH subjects were diagnosed correctly (see, Fig.3). The highest specificity in the testing set was 95.65% for all classifiers except SVM (see, Fig.4). Generally, most of the classifiers performed better in diagnosing TTH than migraine. Although there were slight differences in the classifiers' performances, results revealed that RF and Naïve Bayes outperformed the other classifiers in both training and testing sets.

IV. Discussion

Migraine and tension headache, like many neurologic disorders, have a strong aspect of psychological problems, that are involved in the severity and risk of these disorders. On the other hand, cognitive emotional regulation strategies and repetitive negative thinking, are two important components involved in psychological problems. As a result, the indicators measured in the questionnaires of cognitive emotional regulation strategies and repetitive negative thinking help to create a diagnostic model to distinguish these two disorders.

The rejected features in our feature selection step include age, gender, and P3 (RNT capturing mental capacity). The low relevance of age and gender to headache type is in line with the results of previous studies [16, 17]. All the other factors detected have a high relevance to the target variable, and the selected set of features achieved an acceptable accuracy in the detection of headache type in comparison to other models that used physical symptoms. These results confirm the potential of CERQ and PTQ questionnaires in differential diagnosis of headache types. A detailed comparison between the models developed to classify the headache types in present and previous studies is represented in Table IV. Only one of the previous studies considered the impact of psychological factors on these disorders by including the depression, and anxiety in their model features.

In current study, the centers considered for data collection are concentrated in one region of the province, which can be representative of a specific area and society, and so the impact of a different culture has been ignored. Generally, increasing the number of subjects under study and having data from diverse communities, cultures, ages, genders, and the like lead to more accurate and reliable results in the headache classification.

V. Conclusion

TTH and migraine headaches are disorders that have serious psychological roots and can be considered as interdisciplinary problems in neurology, psychology, and psychiatry. However, the diagnosis and treatment of these disorders are often one-dimensional and neglect psychological factors. There are few studies that explore the diagnostic value of psychological risk factors in headache disorders. This study aims to use machine learning models to classify TTH and migraine based on psychological factors. We compare different classification models and achieve 98%

accuracy, 100% sensitivity, and 96% specificity to distinguish TTH from migraine using RF, naïve Bayes, logistic regression, and KNN models.

This is a remarkable performance using only psychological factors, compared to the models that used the physical symptoms and obtained accuracies between 76% to 96%. Moreover, these results suggest that adding psychological factors to the current decision support systems will improve detection accuracy. The differential diagnosis of TTH and migraine is crucial for the treatment of these disorders. A differential diagnosis method based on psychological factors, either alone or in combination with physiological methods, can enhance the diagnostic accuracy of these two headache disorders. This method can be a useful tool for neurologists and psychologists who deal with psychosomatic patients. Using the psychological factors along with the physiological symptoms to train the machine learning models can also help improve the decision support systems. Further research can apply this method to other physical disorders with psychological roots and increase the diagnostic accuracy in psychosomatic and conversion disorders.

TABLE III. Evaluation of various classifiers for training set using 3-fold cross-validation.

Classification Method	RF	SVM	Logistic regression	Naïve Bayes	KNN
Mean accuracy (%)	**99.1**	98.2	97.3	**99.1**	96.4

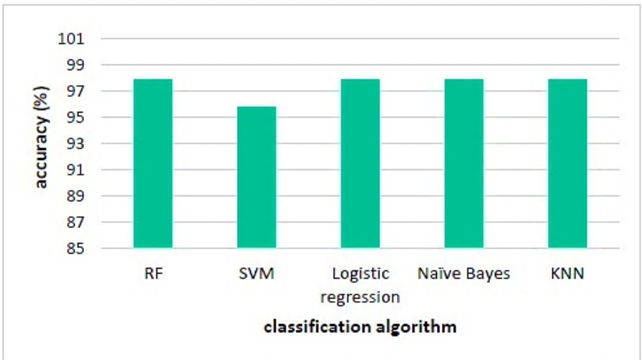

Fig. 2. Classification accuracy of different classifiers for testing set

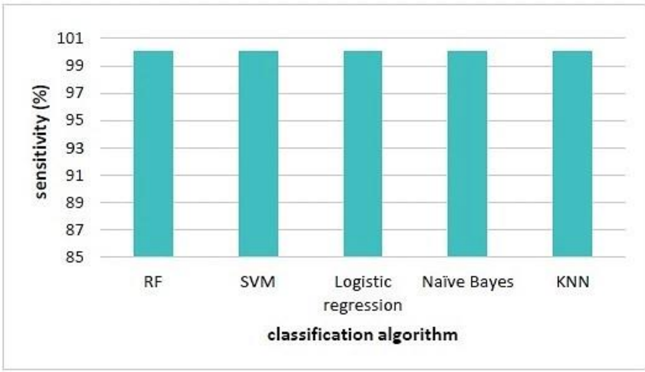

Fig. 3. Classification sensitivity of different classifiers for testing set

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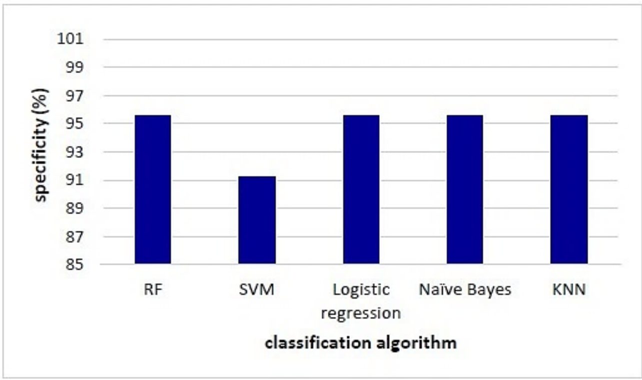

Fig. 4. Classification specificity of different classifiers for testing set

TABLE IV. Comparison of features, model type, and efficiency of the models created to diagnose types of headaches.

Study	Physical symptoms	Psychological parameters	Model	Accuracy
F. Liu, et al. [16]	yes	no	Logistic regression, SVM, RF, Decision tree, and Gradient boosting	72-84%
J. Kwon, et al. [21]	yes	yes	XGBoost	81%
P. A. Sanchez-Sanchez, et al.[22]	yes	no	Neural network	98%
A. Qawasmeh, et al.[17]	yes	no	RF, Naïve Bayes, Multilayer perception, etc.	54-93%
Present work	no	yes	Logistic regression, SVM, RF, Naïve Bayes, and KNN	96-98%

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