Prediction of Iranian EFL Teachers' Burnout Level Using Machine Learning Algorithms and Maslach Burnout Inventory

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Abstract

Burnout is that the result of extreme work-related stress and it's categorized by emotional, psychological, and physical exhaustion. we will count it as a modern epidemic within the teaching profession likewise as different professions. The measures that may have an effect on a lecturer and can cause burnout are categorized as Depersonalization, Emotional Exhaustion, Personal Accomplishment. though articles on educator burnout vary in their approach, they incline to specialize in the causes of burnout, the way to assess the signs of burnout, methods to stop burnout, and/or next steps for directors and teachers. The main issue that has been incomprehensible is the prediction of obtaining burned out. Through prediction, we will cut back the prices of the burnout impact on teachers, students, schools, and society and stop its consequences like depression, coronary failure, or perhaps suicide. Our objective is to research and predict the burnout level in English as a far-off Language (EFL) teacher. we are going to use Maslach Burnout Inventory (MBI) to gather a dataset and live the 3 subscales of teacher burnout: emotional exhaustion, depersonalization, and reduced personal accomplishment. when analyzing the collected dataset that consisted of 1433 teachers' data, 9 machine learning classification algorithms by implementing exploitation python programing language is applied and accuracy is employed as a performance parameter.

Keywords: Classification algorithms, Burnout, Machine learning, Maslach Burnout Inventory

1. Introduction

Pollard and Collins (Pollard & Collins, 2005) state “teaching is a complex and highly skilled activity which, higher than all, needs room lecturers to exercise judgment to decide the way to act”. Every person in a role as a teacher has his/her particular methods and ways and thoughts of effective teaching. Among these is that the opinion that “the ultimate outcome of instructional practice is effective student learning” (Donald, 2000).

Effective and successful teaching is not something out there to obtain and teachers are required to practice hard enough to achieve effective teaching. Keeping in mind that teaching effectively requires a high level of attention and training, it can be considered as one of the most challenging and demanding careers among other careers (Kyriacou, 2001). The roles required of instructors are expansive and teachers regularly feel that their roles never quit developing (Kyriacou, 2001; Bryne, 1998). Traditionally, teachers followed an authoritarian type of discipline to manage and teach and students attended the class to learn the information presented (Okojie, 2011). However, the modern educational focus is on considering the learners' needs and adapting teaching styles to them (Okojie, 2011). As teachers' task becomes harder considering the overall changes in systems of education, some teachers may leave the profession. Hence, teacher burnout attracted the attention of a number of scholars working in the field of teacher education and it has become one of the most important issues in the field.

Burnout, defined as 'a progression of unsuccessful attempts by an individual to cope with a variety of conditions that are perceived to be threatening' (Gold & Roth, 1993), was originally coined by Herbert Freudenberger in the 1970s and gained much more empirical attention through Christina Maslach (Gold & Roth, 1993). Majority of researchers define 'burnout' as an extreme response to some form of occupational stress (e.g., (Dedrick & Raschke, 1990; Wisniewski & Gargiulo, 1997)) while other researchers believe that 'job stress' and 'burnout' are (Male & May, 1997). Farber (Farber, 1991) mentioned that stress and burnout are distinct phenomena but, without empirical data, they are difficult to distinguish. Hence, it can be implied that there is a relationship between occupational stress and burnout.

Moreover, there are some stressors that add to teachers' occupational stress which can result in teacher burnout. To name some of these stressors, one can refer to lack of support (administrative and/or among colleagues), workload, disruptive students, role ambiguity, role conflict, lack of resources, and environmental stressors such as noise, air quality, and temperature (Abel & Sewell, 1999; Bivona, 2002; Hansen & Sullivan, 2003).

What many of us don't notice is that burnout is truly a work-related depression. In keeping with analysis printed within the Journal of psychotherapeutics (Schonfeld & Bianchi, 2016; Bianchi, Schonfeld., & Laurent, 2014), there's a major overlap between burnout and depression. A lot of specifically, educators who experience burnout additionally exhibit depressive symptoms, including, however not restricted to, loss of interest or enjoyment of activities, mood swings, and fatigue. Overall, the upper the burnout symptoms are, the more depressive traits they exhibit. Another study published in International Journal by Stress Management (Leiter & Robichaud, 1997) showed that ninety p.c of the participants who achieved high burnout scores met the standards for a conditional designation of depression. Given the extent of this correlation, it's vital that we tend to mention the actual fact that burnout is a completely different style of depression.

In keeping with the Yankee Federation of Teachers' 2017 pedagogue Quality of labor Life Survey, sixty-one p.c of lecturers indicated that their jobs were forever or typically stressful. Even as alarming, if no more so, fifty-eight percent of respondents cited poor psychological state as a result of that stress. Since burnout is way more serious than is mostly portrayed, it is necessary to work out however we are able to predict the burnout in teachers and this is often our inspiration for this paper. Owing to the overlap between burnout and depression, lecturers whom experience burnout might have medical and/or psychological facilitate to manage their (depressive) burnout symptoms. It's crucial that faculties proactively address psychological state issues within the workplace, as this will in some cases end up in unplanned consequences (e.g., ineffective teaching, self-harm and/or suicide of the teacher, etc.). In endeavor this so much too common problem, faculty administrations ought to use completely different ways in the hindrance and treatment of burnout. Some strategies are highlighted below.

2. Literature review

2.1. Teacher burnout

Teacher burnout is defined as a result of prolonged stress, which is itself accompanied by physiological and biochemical changes in teacher which in turn leads to emotional and physical exhaustion, complaints, and chronic physical and mental conditions (Abel & Sewell, 1999). According to Maslach, Jackson, and Leiter (Leiter & Robichaud, 1997), teacher burnout encompasses three main components including emotional exhaustion, reduced personal accomplishment, and depersonalization. Emotional exhaustion is being emotionally overtired, depersonalization means manifesting negative reactions to people, and finally reduced personal accomplishments refer to a negative evaluation of oneself. Maslach and Leiter (Maslach & Leiter, 1999) proposed a model of teacher burnout with five main factors of organizational characteristics, personal qualities of teachers, task qualities, social support, political, policy, and economic context, and ecology of the school. The model indicates that teacher burnout includes, and is the result of, exhaustion, depersonalization, and reduced accomplishment. It seems that as in the process model of burnout, emotional exhaustion occurs first and leads to the rise of depersonalization, whereas reduced personal accomplishment develops separately. This model observes the ways teacher burnout influences students' behavior and outcomes. High degrees of teacher burnout may result in less positive feedback or more criticism of students, which may, in turn, result in less involvement of students in the classroom.

Regarding empirical studies in burnout, Schaufeli, Bakker, and Van Rhenen (Schaufeli, Bakker, & Van Rhenen, 2009) investigated the association among job demands, resources, burnout, work engagement, and sickness absenteeism. The results showed that lack of resources and high job demand can predict burnout and burnout is positively related to sickness absenteeism. Furthermore, it was discovered that there is a circular relationship between these variables. For instance, initial work engagement predicts resources which again enhances work engagement and reduces burnout. The findings of another (Aloe, Shisler, Norris, Nickerson & Rinker, 2014) revealed that students' misbehavior correlates both positively and significantly with three dimensions of teacher burnout (emotional exhaustion, depersonalization, and reduced personal accomplishment). Moreover, it was found that emotional exhaustion is the component most correlated with students' misbehavior, then depersonalization, and finally reduced personal accomplishment.

Various frameworks apply straightforwardly to understanding stress and the role that coping plays in managing stress. These frameworks can give a premise to understanding how techniques for coping impact the level of stress individual experiences when confronted with a potential stressor (Gelman, 2008). Research has demonstrated that occupational stress in teachers can be more significant than occupational stress in different occupations (Travers & Cooper, 1996). A study by Cooper and Marshall (Cooper & Marshall, 1977), found that instructors who positioned their occupational stress as 'high' encountered a more noteworthy rate of heart attack, stroke, and reported more mental illnesses than people in different occupations who likewise distinguished their stress level as 'high'. Adams (Adams, 1999) found that the effects of teacher stress can offer implications for their ability to teach, their own lives, and their cooperation with their students.

Other studies have referred to teacher stress as a major contributing element to instructor burnout, making teachers diminish satisfaction with teaching and leave the profession (Parkay, Greenwood, Olenjik & Proller, 1988; Borg & Riding, 1991). Work-family conflicts were one of the major predictors of emotional exhaustion—the core dimension of burnout (Rajendran, Watt & Richardson, 2020). According to Corbin et al., (2019), close teacher-student relationships reported higher levels of personal accomplishment, whereas more conflictual relationships were associated with increased emotional exhaustion.

2.2. Machine learning usage in prediction burnout and stress

Machine learning could be a large field of information and there's no single definition. In general, the term is known in its broader and narrower sense. The broad understanding of machine learning refers to the study of algorithms and

systems that improve their data and results besides gaining expertise (Flach, 2012). It is important to remember that machine learning and data mining tools are derived from the methods of artificial intelligence and multidimensional statistics (Tan, Steinbach & Kumar, 2016). These days and by improving the results of different machine learning algorithms prediction became one of the most usages of machine learning algorithms. Prediction involves using some variables to predict unknown values of other data and supervised methods are mainly used for this purpose (Mitchell, 2017).

Although machine learning has been advancing for several years, it has only recently been used for behavioral sciences (DelPozo-Banos & Petkov, et.al, 2018). For instance, these algorithms are used in computational psychiatry to improve the diagnosis of mood disorders: stress (Silva & Aguiar, et al., 2020), depression (Webb & Cohen, et al, 2020), and suicidality (Kessler & Warner, et al, 2015). There are different ways to collect data for using machine learning, for example, Kaczor and colleagues (2020) used machine learning techniques to detect stressful situations using digital sensors worn by emergency medicine physicians and a self-assessment questionnaire.

Lu et al. (2020) proposed a system framework for real-time stress monitoring and intervention. Different from other existing stress detecting system frameworks, we integrate stress monitoring and corresponding stress intervention methods into a system. This system can help people with high-stress risks, such as policemen and pilots, to monitor and intervene in their stress in time. Gedam and Paul (2020) first extracted the features using various algorithms and they applied machine learning algorithms to build a classification model. It is found that features extracted using Heart rate, Heart rate variability, and skin conductance are more useful in the prediction of stress level of an individual while Support vector machine, Random Forest, and K-Nearest Neighbor are the most effective classification algorithms. Ahuja and Banga (2019) collected a dataset to detect mental stress in university students using machine learning. Their dataset contains 206 student's data. They used four classification algorithms and applied sensitivity, specificity, and accuracy as performance parameters.

Prediction burnout in different parts and jobs has very benefits for employees and employers. Also, by prediction, we can reduce the expenses of treatment and prevent the bad outcomes of burnout on employees' results. All employees based on the different situations are at risk of burnout. Civil servants, helping professionals such as caregivers, teachers, and social workers in child welfare practice. Working under workload pressures can lead to issues like burnout (Grządzielewska, 2021). An example is a work of Bauernhofer et al. (2018), whose research sample included 103 patients clinically diagnosed with occupational burnout. Three burnout subtypes were identified: the burned-out subtype, the exhausted/cynical subtype, and the exhausted subtype. Main results showed that the burned-out subtype was a lot of depressed than the others, however, no distinction was known between burned-out and exhausted/cynical subtypes with stress and sociodemographic characteristics.

Lee et al. (2020) used k-means to the group of about one thousand nurses working in a medical center in Taiwan into two classes. Next, the convolutional neural network (CNN) deep learning method was applied to the predictive model to estimate 38 parameters for the burnout sample. Kurbatov et al. (2020) applied k-means unsupervised clustering (k-means analysis) and supervised clustering (k-means cluster group) to identify and predict burnout in surgical trainees. As collected data shows the stress, and health of the respondents were predicted. The empirical results showed that using these methods to account for individual differences resulted in significant performance improvements (Taylor & Jaques, et al, 2017). Zhernova et al. (2020) used Maslach Burnout Inventory (Maslach, Jackson & Leiter, 1997) to predict early prerequisites of burnout. Applying machine learning approaches allowed to correctly predict burnout in 70% of cases.

3. Methodology

3.1. Dataset and preprocessing

Our proposed method is using machine learning classification algorithms on classifying EFL teachers' burnout levels. The participant teachers taking the survey instrument included 1433 Iranian teachers (1042 females and 391 males) teaching English at private language institutes.

The Maslach Burnout Inventory (Maslach, Jackson & Leiter, 1997) was used to measure the three subscales of teacher burnout: emotional exhaustion (9 items, e.g. I feel used up at the end of the workday), depersonalization (5 items, e.g. I feel I treat some students as if they were impersonal objects), and reduced personal accomplishment (8 items, e.g. I have accomplished many worthwhile things in this job). Participants completed the scale on a seven-point Likert type scale ranging from 0 (never) to 6 (always). In the questionnaire questions #1, #2, #3, #6, #8, #13, #14, #16, #20 are related to emotional exhaustion, #5, #10, #11, #15, #22 are related to depersonalization and #4, #7, #9, #12, #17, #18, #19, #21 are for personal accomplishment.

To collect this dataset, we have a tendency to use a valid and reliable form (Maslach, Jackson & Leiter, 1997) as Maslach Burnout Inventory-Human Services Survey for Medical Personnel (MBI). One contributor to the ascertained inconsistencies in shaping divided burnout outcomes on the MBI might even be the dearth of clarity relating to the means of subscale scores. ancient activity strategies don't enable users to fully compare subscale scores with the content of things to interpret their meaning. we have a tendency to aimed to form response profiles describing the chance of burnout symptoms across standardized MBI subscale scores in Iran's EFL teachers. we tend to made a path mapping raw (total) MBI subscale scores to scaled scores and associated response profiles.

Then, Statistical Package for Social Sciences (SPSS 18) was run to find out the burnout level of each teacher. As it is indicated in Table1, the teachers were divided into 3 groups: high-burned-out (HB), mid-burned-out (MB), and low-burned-out (LB). To improve the performance of our model we applied K-fold cross-validation to increase the amount of data in our collected dataset and then make a better prediction of Iranian's EFL teacher's burn-out level.

Table 1. MBI Dimensions

	Low	Moderate	High
Depersonalization (Cynicism)	≤ 4	5 - 12	≥ 13
Emotional Exhaustion	≤ 16	17 - 33	≥ 34
Sense of Personal Accomplishment	≥ 39	30 - 38	≤ 29

3.1.1. Experimental Design, Materials, and Methods

Then, Statistical Package for Social Sciences (SPSS 18) was run to find out the burnout level of each teacher. As it is indicated in Table1, the teachers were divided into 3 groups: high-burned-out (HB), mid-burned-out (MB), and low-burned-out (LB). The collected data shows that in all categories most of the teachers are mid-burned-out. In personal accomplishment and emotional exhaustion categoriez number of high-burned-out teachers are higher than low-burned-out. But, in depersonalization category low-burned-out teachers are higher than high-burned-out teachers. Part of this dataset is used to investigate the intercorrelations of teaching context, perceived occupational stress, and burnout with the mediating role of teacher resilience among Iranian EFL teachers (Karimi & Adam, 2018).

Table 2. Depersonalization part in detail and number of chosen choices

	Never	Very rarely	Rarely	Regularly	Often	Very Often	Always
Q 5	144	264	360	472	192	0	0
Q 10	1112	152	64	104	0	0	0
Q 11	1168	176	40	40	8	0	0
Q 15	184	248	408	392	200	0	0
Q 22	560	416	224	112	72	48	0

That includes 396 Low values, 989 Moderate values, and 47 High values.

Figure 1. Depersonalization distribution

Table 3. Personal accomplishment part in detail and number of chosen choices

	Never	Very rarely	Rarely	Regularly	Often	Very Often	Always
Q 4	0	8	32	104	256	360	672
Q 7	0	488	288	296	152	64	144
Q 9	0	384	272	456	168	40	112
Q 12	0	16	24	128	240	424	600
Q 17	0	288	232	400	208	120	184
Q 18	0	32	32	104	272	328	664
Q 19	0	16	24	128	240	424	600
Q 21	0	288	232	400	208	120	184

That includes 199 Low values, 590 Moderate values, and 590 High values.

Figure 2. Personal accomplishment distribution

Table 4. Emotional exhaustion part in detail and number of chosen choices

	Never	Very rarely	Rarely	Regularly	Often	Very Often	Always
Q 1	0	352	160	464	208	168	80
Q 2	0	168	216	440	224	208	176
Q 3	0	272	328	376	272	104	80
Q 6	0	416	280	472	176	40	48
Q 8	0	320	240	416	224	112	120
Q 13	0	312	280	416	192	168	64
Q 14	0	112	120	152	264	256	528
Q 16	0	408	328	328	216	72	80
Q 20	0	536	248	360	168	48	72

That includes 173 Low values, 910 Moderate values, and 349 High values.

Figure 3. Emotional exhaustion distribution

Here is how to answer the question. The questions are from the Maslach Burnout Inventory and questionnaire:

1. I feel emotionally drained from my work.

2. I feel used up at the end of the workday.

3. I feel fatigued when I get up in the morning and have to face another day on the job.

4. I can easily understand how my students feel about things

5. I feel I treat some students as if they were impersonal objects.

6. Working with people all day is really a strain for me.

7. I deal very effectively with the problems of my students.

8. I feel burned out from my work.

9. I feel that I am positively influencing other people's lives through my work.

10. I've become more callous toward people since I took this job.

11. I worry that this job is hardening me emotionally.

12. I feel very energetic.

13. I feel frustrated by my job.

14. I feel I'm working too hard on my job.

15. I don't really care what happens to some students.

16. Working with people directly puts too much stress on me.

17. I can easily create a relaxed atmosphere with my students.

18. I feel exhilarated after working closely with my students.

19. I have accomplished many worthwhile things in this job.

20. I feel like I'm at the end of my rope.

21. In my work, I deal with emotional problems very calmly.

22. I feel students blame me for some of their problems.

3.2. Proposed approaches

In this study, we used machine learning (ML) to identify the teacher's burnout level. The proposed model includes dataset collection, preprocessing, feature extraction, and applying machine learning algorithm (Decision Tree, Support vector machine, Support Vector Classifier, Support Vector Regression, Multi-Layer Perceptron, K- Nearest Neighbor, Gaussian Naïve Bayes, Random Forest, Quadratic Discriminant Analysis, Linear Discriminant Analysis) by implementing python programming language and comparing it to three performance parameters as shown in Figure 4.

Figure 4. Overview of the used methodology

In this study, we used machine learning (ML) to identify the teacher's burnout level. The proposed model includes dataset collection, preprocessing, feature extraction, and applying machine learning algorithm (Decision Tree, Support vector machine, Support Vector Classifier, Support Vector Regression, Multi-Layer Perceptron, K- Nearest Neighbor, Gaussian Naïve Bayes, Random Forest, Quadratic Discriminant Analysis, Linear Discriminant Analysis) by implementing python programming language and comparing it to three performance parameters as shown in Figure 4.

We have used K-fold cross-validation (cv) to increase the size of the dataset and improve the efficiency of our model subsequently. K-fold cross-validation is a technique for generalizing the data behavior and increasing the k-fold times of the data based on this analysis. The process consists of dividing the dataset into k-folds and then generalizing the behavior and increasing the data inputs, thereby increasing the efficiency of our model. In our case, we applied 10-fold cross-validation because of the small dataset.

Classification Algorithm is a unique technique in data mining, where you decompose given information and take every single case from it. It classifies the example into a certain class with a very low probability of error. It is used to remove models that characterize imperative information classes within the given information index. We have used some classification algorithms here to identify the stress level of individuals. We first trained our data and then tested our model on the remaining data. We have three different tasks as predicting emotional exhaustion, depersonalization, and Personal accomplishment on teachers. And in each aspect, we analyze and predict the level of burnout in three different levels low, moderate, and high burnout. Our classification task is used (0) as high, (1) as moderate, and (2) as low level of burnout. Our used machine learning algorithms are:

3.1.1. Decision Tree:

DT is a non-parametric supervised learning methodology that is using for classification and regression. The goal of this classification algorithms is to make a model that predicts the worth of a target variable by learning simple decision rules inferred from the data features.

3.1.2. Support Vector Machine:

This classifier generally works upon the hyper plan. This algorithm works upon the best hyperplane which is more useful in sorting new illustrations. In a 2-Dimensional plane, it is a line isolating a plane in two sections where each class lies on either of the sides.

3.1.3. Linear Support Vector Classifier:

SVC is useable to fit on the provided data, returning a "best fit" model that divides or categorizes the data. From there, once obtaining the model, it will then feed some options to your classifier to check what the "predicted" class is. This makes this specific algorithmic rule rather appropriate for our uses, though you can use this for several situations.

3.1.4. Support Vector Regression:

SVR is a Support vector machine and it supports both linear and non-linear regression problems and algorithms. The mission is to suit several instances as attainable between the lines whereas limiting the margin violations.

3.1.5. Multi-Layer Perceptron:

An MLP is one of the artificial neural network algorithms. Associate degree MLP is viewed as a logistical regression classifier wherever the input is 1st remodeled employing a learned non-linear transformation. This transformation comes to the input data into the house where it becomes linearly separable. This intermediate layer is stated as a hidden layer. one hidden layer is adequate to create MLPs as a universal approximator. However, we'll see subsequently that there are substantial advantages to exploiting several such hidden layers, i.e., the premise of deep learning.

3.1.6. K- Nearest Neighbor:

This algorithm works upon whether or not the k-NN nearest, the classifier is employed for arrangement or relapse. it's a category membership kind within which either a student belongs to A or B there's no between. If there are 3 teams then the information is divided into three groups only. There is also some compromise by the neighbors, with the question being allotted to the class, which one is its k Nearest neighbors (k could be a positive range and a little number). If $k = 1$, then the protest will be assigned to the class of that solitary Nearest neighbor.

3.1.7. Gaussian Naïve Bayes:

A Gaussian Naive mathematician formula could be a special style of NB algorithm. It's specifically used once the options have continuous values. It's conjointly assumed that each one of the features are following a Gaussian distribution i.e., traditional distribution. within the term of machine learning, naive Bayes classifiers comprise a gaggle of easy "probabilistic classifiers". They work upon the probability, extremely scalable. They need numerous parameters that are straight in the range of things (highlights/indicators) in the learning issue.

3.1.8. Random Forest:

This algorithmic program considers varied call trees, therefore forming a forest. it's also referred to as an ensemble of decision tree algorithms. this could be used for classification moreover as regression. This algorithm tries to seek out out the simplest feature indiscriminately among all the features. In our experiment, we've got used a hundred decision trees and Gini for the impurity index.

3.1.9. Linear Discriminant Analysis:

Linear discriminant analysis (LDA), traditional discriminant analysis (NDA), or discriminant operate analysis may be a generalization of Fisher' linear discriminant, a technique employed in statistics, pattern recognition, and alternative fields, to search out a linear combination of options that characterizes or separates 2 or additional categories of objects or events. The ensuing combination could also be used as a linear classifier, or, more commonly, for spatial property reduction before later classification.

3.1.10. Quadratic Discriminant analysis:

QDA is related to LDA, wherever it's supposed that the activities from each category are commonly distributed. not like LDA, in QDA there's no supposition that the variance of each of the categories is identical. once the normality assumption is true, the simplest potential check for the hypothesis that a given measurement is from a given class is that the probability quantitative relation test.

4. Results and discussions

In this study, we have applied nine machine learning algorithms (Decision Tree, Support vector machine, Support Vector Classifier, Support Vector Regression, Multi-Layer Perceptron, K- Nearest Neighbor, Gaussian Naïve Bayes, Random Forest, Quadratic Discriminant Analysis, Linear Discriminant Analysis) and calculated the accuracy of all these in three different aspects of teachers' burn out (predicting emotional exhaustion, depersonalization and Personal accomplish). The results are shown in Table 2.

Table 5. The result of predicting and classifying methods on the collected dataset

	DT	SVC	SVR	MLP	KNN	GaussianNB	RF	QDA	LDA
Depersonalization	91	97	58	97	97	93	97	100	97
Emotional Exhaustion	86	93	63	73	88	91	86	82	93
Sense of Personal Accomplishment	91	98	59	98	98	94	98	100	98

It is shown that both quadratic discriminant methods have better performance in the task of predicting teacher's burn out in terms of emotional exhaustion, support vector classifier and linear discriminant analysis have the best accuracy with 93% correct prediction and in the depersonalization and personal accomplish aspects the quadratic discriminant analysis has the best accuracy with 100% correct predictions. But, Linear Discriminant Analysis, Support Vector Classifier and, K- Nearest Neighbor methods have high accuracy with more than 97% correct precisions (Figure 5).

Figure 5. The chart of the classifier methods on the collected dataset

5. Conclusion and Future Work

We proposed a new method using nine machine learning classification algorithms (Decision Tree, Support vector machine, Support Vector Classifier, Support Vector Regression, Multi-Layer Perceptron, K- Nearest Neighbor, Gaussian Naïve Bayes, Random Forest, Quadratic Discriminant Analysis, Linear Discriminant Analysis) on a dataset of 1433 EFL teachers to predict their burn out level. The results are based on three different categories: low, moderate, and high. Due to our small dataset, 10-fold cross-validation was applied to increase the amount of data in our collected dataset. Teachers' feeling of tiredness influences students' behavior and outcomes which may result in less involvement of students in the classroom and decrease their achievement rate, as well. Therefore, the findings of this study may have implications for the improvement of teachers' conditions which, consequently, improves their pedagogical decision-making in different areas.

Data availability statement

Data is only accessible upon request and acceptance by the Institution where the data was obtained due to ethical constraints.

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Conflicts of interest/Competing interests (include appropriate disclosures)

We wish to restrict or otherwise manage adverse research findings and show the importance of computer techniques in the education quality and teacher's health.

Availability of data and material

The data is available with the request from the corresponding email address.

Code availability

The code is available with the request from the corresponding email address.

Ethics approval (include appropriate approvals or waivers)

All the collected data was based on the Maslach Burnout Inventory and all participants were aware about it.

Consent to participate (include appropriate statements)

All the participants were older than 18 and were worked as teacher at institutes and schools.

Consent for publication (include appropriate statements)

In the collected and used data the participants personal details are not needed and are not collected.