Prediction of Iranian EFL teachers’ burnout level using machine learning algorithms and maslach burnout inventory

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Abstract
Burnout results from constantly feeling emotional, physical, and mental stress. Most of the time, it is related to one’s job and involves a sense of reduced accomplishment and loss of personal identity. Because accountability pressures, workload, and hours can increase stress, teachers are usually high achievers who like to work hard. They confront significant challenges. They must adapt curricula to a wide range of learning styles, manage to shift education policies, attend to students with special needs, and juggle administrative work. In addition, pay remains low in comparison with other graduate roles. Therefore, after prolonged exposure to poorly managed emotional and interpersonal job stress, many experience teacher burnout, resulting in employee turnover and many socio-economic problems. In this regard, accurate prediction provides essential research and decision-making benefits. To this aim, the Maslach Burnout Inventory was administered to a sample of 1433 Iranian EFL teachers. Moreover, nine different machine learning algorithms were implemented on the data set to predict burnout levels through the Python programming language. The algorithms’ performances were also investigated through accuracy. In conclusion, the results of this study demonstrate the prediction of teachers’ burnout levels to prevent the destructive consequences of the issue.

Keywords Classification algorithms · Burnout · Machine learning · Maslach Burnout Inventory · EFL Teachers

1 Introduction
Pollard and Collins [1] state, "teaching is a complex and highly skilled activity which, higher than all, needs room teachers to exercise judgment to decide the way to act." Every person in a role as a teacher has his/her particular methods, ways, and thoughts of effective teaching. The teaching method involves believing that "effective student learning is the end outcome of educational practices" [2].

Effective and successful teaching is not an easy job, and teachers need to practice hard enough to achieve effective teaching. Because effective teaching requires a high level of attention and training, it can be considered one of the most demanding and challenging professions among other professions [3]. Teachers are expected to perform a wide range of tasks and often feel that their tasks are constantly changing [3, 4]. In the past, teachers used an authoritarian discipline style to guide and teach students, and students went to class to learn the knowledge [5]. However, modern pedagogy emphasizes addressing learners’ needs and adapting the teaching style to meet those needs [5]. As the task of teachers becomes more and more difficult in the face of the general changes in educational systems, some teachers are leaving the profession. Therefore, many researchers working in teacher education have paid attention to teacher burnout, which has become one of the most critical issues in the field.

Burnout, "a series of unsuccessful attempts by an individual to cope with various perceived distress states" [6], was initially invented by Herbert Freudenberger in the 1970s and received much more empirical attention thanks to Christine Maslach [6]. Most researchers define "burnout" as an extreme reaction to some form of occupational stress [7, 8], while others believe that "work stress" and "burnout" are the same [9]. Farber [10] supposed that stress and burnout are distinct phenomena but difficult to distinguish without empirical evidence. Therefore, it can be concluded that there is a relationship between occupational stress and burnout.

In addition, some stressors can increase teachers’ workloads and lead to burnout. Call some of those stressors can
be assumed the loss of support (from control and/or colleagues), workload, disruptive students, function ambiguity, function conflict, loss of resources, stressors, environmental situations, noise, air first-rate, and temperature [11–13]. Many of us are unaware that burnout is a form of work depression. According to an evaluation posted in the Journal of Psychotherapeutics [14, 15], there may be a massive overlap between burnout and depression. Burnout ends when the teachers are feeling extra depression, which includes a lack of hobby or interest in their work, temper swings, and weariness. The more mood disorders they have, the more burnout signs they will also have. Another study published by Stress Management [16] in International Journal showed that ninety percent of participants who scored high on burnout met the standards for conditional classification as depression. Given the magnitude of this correlation, it is essential to note that burnout is an entirely different form of depression (Fig. 1).

According to the Yankee Federation of Teachers’ 2017 pedagogue Quality of labor Life Survey, sixty-one percent of teachers said their work was forever or typically stressful. Even as alarming, if no more so, fifty-eight percent of respondents cited a poor psychological state due to that stress. Since burnout is way more severe than is portrayed, it is necessary to work out how we can predict burnout in teachers, which is often our inspiration for this paper. Because of the overlap between burnout and depression, faculty who are affected by burnout may seek medical and/or psychological help to manage their (depressive) burnout symptoms. It is critical that faculty proactively address psychological issues in the workplace, as in some cases, this leads to unplanned consequences (e.g., ineffective teaching, faculty self-harm and/or suicide, and more like that.) To address this far too common problem, teachers in administration should take different approaches to prevent and treat burnout. Some strategies are presented below.

In this study, we use nine machine learning-based algorithms on the data set related to 1433 English as a Foreign Language (EFL) teachers in private institutes. With the results, we can predict the teachers’ burnout and prevent its negative effect on the education, students, or personal teachers’ life. As we know, school and teaching are a significant part of society, and making it healthier can cause a healthy society too. After observing and analyzing the results, we got that in the case of depersonalization and personal accomplishment, quadratic discriminant analysis and emotional exhaustion, linear discriminant analysis have the best prediction results and are the best methods to predict future burnout based on our data.

Thus, the current study aims to compare nine machine learning methods result of the EFL teachers’ burnout that can help predict teacher burnout in the future and prevent its negative effect on education and the teachers’ life. This paper is organized into five sections. Section 2 describes the literature review on the EFL teachers’ burnout and machine learning or computer-based burnout and stress predictions, respectively. In the next section, we describe the methodologies used in this study and how we used them to achieve our goal. Finally, based on the findings of this study, the data analysis, results and discussion, and suggestions for future studies are discussed in Sects. 4 and 5.

2 Literature review

2.1 Teacher burnout

Teacher burnout is described due to extended pressure, which is observed via means of physiological and biochemical modifications in trainers, resulting in emotional and bodily exhaustion, complaints, and continual bodily and intellectual conditions [11]. According to Maslach, Jackson, and Leiter [16], trainer burnout encompasses three major additives: emotional exhaustion, decreased personal accomplishment, and depersonalization. Emotional exhaustion is being emotionally overtired, depersonalization manifesting bad reactions to humans, and sooner or later decreased personal accomplishments with a lousy assessment of oneself. Maslach and Leiter [17] proposed a version of trainer burnout with five major organizational characteristics, personal traits of instructors, project traits, social support, political, policy, and economic context, and ecology of the school. The version shows that trainer burnout includes and is the result of exhaustion, depersonalization, and decreased accomplishment. It appears that, as in the system version of burnout, emotional exhaustion takes place first and results in the upward thrust of depersonalization, while decreased personal accomplishment develops separately. This version observes how trainer burnout affects college students’ conduct and outcomes. High tiers of trainer burnout might also bring about much less excellent remarks or more outstanding grievances of college students, which might additionally, in flip, bring about much less involvement of college students inside the classroom (Fig. 2).

Regarding empirical research on burnout, [18] investigated the affiliation between process demands, assets, burnout, and illness absenteeism. The consequences confirmed that loss of assets and the excessive process could
expect burnout, and burnout is undoubtedly associated with illness absenteeism. Furthermore, it found that dating among those variables may be around. For instance, preliminary painting engagement predicts assets that once more complement painting engagement and decrease burnout. The findings of another [19] discovered that college students’ misbehavior correlates undoubtedly and notably with three dimensions of trainer burnout (emotional exhaustion, depersonalization, and decreased personal accomplishment). Moreover, it determined that emotional exhaustion is the most correlated issue with college students’ misbehavior, depersonalization, and decreased personal accomplishment sooner or later.

Various frameworks practice straightforwardly to know how pressure and the coping function perform in dealing with pressure. These frameworks can deliver a premise to know how strategies for coping affect the extent of pressure person stories while faced with an ability stressor [20]. Research has tested that occupational pressure in instructors may be more incredible enormous than occupational pressure in particular occupations [21]. A look at via way of means by Cooper and Marshall [22] determined that teachers who placed their occupational pressure as ‘excessive’ encountered a greater noteworthy fee of coronary heart attack and stroke. It said more significant intellectual ailments than humans in particular occupations who likewise prominent their pressure stage as ‘excessive.’ Adams [23] determined that the results of trainer pressure can provide implications for their capacity to teach, their own lives, and their cooperation with their college students.

Other studies have said teacher strain is an incredible contributor to trainer burnout, making teachers lower delight with education and leave the profession [24, 25]. Work-very own circle of relative’s conflicts was one of the primary predictors of emotional exhaustion—the median length of burnout [26]. According to Corbin and colleagues [27], close to teacher–student relationships stated higher tiers of personal accomplishment, while more conflictual relationships were associated with multiplied emotional exhaustion.

### 2.2 Machine learning usage in prediction burnout and stress

Machine learning might be a massive subject of facts, and there is no single definition. The considerable know-how of device mastering refers to examining algorithms and structures that enhance their information and consequences except gaining expertise [28]. It is essential not to forget that device mastering and information mining equipment are derived from the strategies of synthetic intelligence and multidimensional statistics [29]. These days through enhancing the consequences of various devices, mastering algorithms prediction has become one of the maximum usages of device mastering algorithms. Prediction includes using a few variables to expect unknown values of different information, and supervised strategies are mainly used for this purpose [30].

Although device mastering has been advancing for numerous years, it has the simplest lately been used for behavioral sciences [31]. For instance, those algorithms are utilized in computational psychiatry to enhance the analysis of temperament disorders: strain [32], depression [33], and suicidality [34]. In addition, there are one-of-a-kind approaches to gathering information for the use of device mastering; for instance, Kaczor and colleagues [35] used device mastering strategies to come across worrying conditions the use of virtual sensors worn via way of means of emergency medicine physicians and a self-evaluation questionnaire (Fig. 3).

Lu et al. [36] proposed a device framework for real-time strain tracking and intervention. Different from present strain detecting device frameworks, we combine strain tracking and corresponding strain intervention strategies into a device. This device can assist humans with high-strain risks, including police officers and pilots, to reveal and intrude on their strain in time. [37] first extracted the functions the use of various algorithms, and they implemented device mastering algorithms to construct a type version. It is located that functions extracted the use of Heart fee, Heart fee variability, and pores and skin conductance are more significant benefits in the prediction of strain stage of a person at the same time as support vector device, random forest, and K-nearest neighbor are the simplest type algorithms. Ahuja and Banga [38] gathered a data set to come across intellectual strain in college students using device mastering. Their data set includes 206 students’ information. They used four algorithms and implemented sensitivity, specificity, and accuracy as overall performance parameters.

Predicting job burnout has many advantages for personnel and employers. In addition, through prediction, we will lessen the drain rate on company resources and the dramatic impact of burnout in the world of work. For example,
civil servants, assisting experts, caregivers, teachers, and social employees in toddler welfare practice. On the other hand, working beneath Neath’s workload pressures can result in troubles like burnout [39]. An instance is a piece by Bauernhofer et al. [40], who studied 103 sufferers clinically identified with occupational burnout. Three burnout subtypes have been identified: the burned-out, the cynical subtype, and the exhausted subtype. The results confirmed that the burned-out subtype turned into a few more depressed people than the others.

Lee et al. [41] used the k-approach on approximately 1000 nurses running in a clinical middle in Taiwan classes. Next, the convolutional neural network (CNN) deep mastering approach was implemented in the predictive version to estimate 38 parameters for the burnout pattern. Next, Kurbatov et al. [42] implemented k-approach unsupervised clustering (k-approach analysis) and supervised clustering (k-approach cluster institution) to discover and expect burnout in surgical trainees. As gathered information indicates, the strain and fitness of the respondents have been predicted. The empirical consequences confirmed that using those strategies to account for personal variations led to substantial—overall performance improvements [43]. Finally, Zhernova et al. [44] used Maslach Burnout Inventory [45] to expect early stipulations of burnout. Applying device mastering processes allowed us to expect burnout in 70% of cases successfully.

3 Methodology

3.1 Data set and pre-processing

Our proposed technique uses the device to determine type algorithms for classifying EFL instructors’ burnout levels. The participants included 1433 Iranian instructors (1042 female and 391 male) teaching English at private language institutes. The Maslach Burnout Inventory was administered [45], a psychological assessment comparing 22 symptom items regarding work-related burnout. At the moment, there are five different versions of the MBI: Human Services Survey (MBI–HSS), Human Services Survey for Medical Personnel (MBI–HSS (MP)), Educators Survey (MBI–ES), General Survey (MBI–GS), and General Survey for Students (MBI–GS [S]). The Educators Survey (MBI–ES) is the version used for this study. In the following paragraph, the used questionnaire and the method of scoring the answers are described.

The Maslach Burnout Inventory (MBI, [45]) 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 associated with emotional exhaustion, #5, #10, #11, #15, #22 are associated with depersonalization and #4, #7, #9, #12, #17, #18, #19, #21 are for reduced personal accomplishment.

Then, Statistical Package for Social Sciences (SPSS 18) was used to summarize the characteristics of a data set and to measure internal consistency reliability, Cronbach alpha (α) coefficient. As indicated in Table 1, the teachers have been divided into three groups: high-burned-out (HB), mid-burned-out (MB), and low-burned-out (LB).

3.1.1 Experimental design, materials, and methods

The facts indicate that during all classes, the maximum number of the teachers are mid-burned-out. In the non-public accomplishment and emotional exhaustion categories, a variety of high-burned-out instructors are more than low-burned-out. Nevertheless, in depersonalization classes, low-burned-out instructors are more than high-burned-out instructors. This data set analyzes the inter-correlations of teaching context, perceived occupational stress, and burnout with the mediating position of trainer resilience among Iranian EFL instructors [46].

Here is how to answer the questions. 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 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 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 a machine to gain knowledge of (ML) to perceive the teachers’ burnout level. The proposed version consists of data set collection, pre-processing, characteristic extraction, and making use of machines to gain knowledge of algorithm (decision tree, support vector machine, support vector classifier, support vector regression, multi-layer per-cep-tron, K-nearest neighbor, Gaussian Naïve Bayes, random forest, quadratic discriminant analysis, linear discriminant analysis) with the aid of using enforcing python programming language and evaluating it to 3 overall performance parameters as proven in Fig. 4.

As observable in Fig. 4, our methodology’s procedure started with data collection. To achieve this, we asked teachers to answer the MSI questionnaire; the result of its analysis will be published in another paper (Karimi & Adam, 2018). Then, for the task of machine learning, we needed some small pre-processing on data like eliminating invalid data and not answered data in the data set and analyzing the main features and essential data to extract from the data set. After that, we applied nine machine learning algorithms to the data set and then observed and discussed the results.

We have used K-fold cross-validation (CV) to boom the dimensions of the data set and enhance the performance of our version subsequently. K-fold cross-validation is a way to generalize the records conduct and grow the records’ k-fold instances, primarily based on this analysis. The manner includes dividing the data set into k-folds, after which generalizing the conduct and growing the records inputs, thereby growing the performance of our version. Due to the small data set, we carried out tenfold cross-validation in our case.

A classification Algorithm is a unique approach in records mining, in which the given records are decomposed, and a single case is taken from it. It classifies the instance into a sure magnificence with a meager error opportunity. It eliminates patterns representing vital lessons in the given records index. We have used a few class algorithms to become aware of
the strain degree of individuals. We first skilled our records, after which we examined our version at the closing records. We have three outstanding obligations predicting emotional exhaustion, depersonalization, and Personal accomplishment on teachers.

Moreover, in every aspect, we examine and are expecting the extent of burnout in 3 extraordinary ranges low, moderate, and excessive burnout. Our class assignment used (0) as excessive, (1) as moderate, and (2) as low degree of burnout. Our used machines gaining knowledge of algorithms are:

3.2.1 Decision tree

Decision tree (DT) is a non-parametric supervised getting-to-know method. That is the usage for category and regression. This category of algorithms intends to make a version that predicts the well-worth of a goal variable with the aid of easy-to-know easy selection policies inferred from the records features.

3.2.2 Support vector machine

Support vector machine (SVM) is a linear and supervised machine learning algorithm most and generally used to solve classification problems and is also referred to as support vector classification. This classifier typically works with a hyperplane. Support vector machine helps in sorting the data into two or more categories with the help of a boundary to differentiate similar categories.

3.2.3 Linear support vector classifier

Linear support vector classifier (SVC) is used to shape the data, returning a "first-rate in shape" version that divides or categorizes the data. From there, as soon as acquiring the version, it will then feed a few alternatives on the classifier to test what the "predicted" magnificence is. That makes this precise algorithmic rule as a substitute suitable for our uses, though it could be used for numerous situations.

3.2.4 Support vector regression

Support vector regression (SVR) is a support vector machine, and it helps each linear and non-linear regression issue and algorithm. The undertaking is to fit as numerous times as possible among the traces while proscribing the margin violations.

3.2.5 Multi-layer perceptron

A multi-layer perceptron (MLP) is one of the synthetic neural community algorithms. Associate diploma MLP is considered a logistical regression classifier anywhere the center is first made over using a non-linear transformation. This transformation involves the enter records into the residence wherein it turns linearly separable. This intermediate layer is said as a hidden layer. One hidden layer is enough to create MLPs as a general estimator.

3.2.6 K-nearest neighbor

A supervised machine learning algorithm (as opposed to an unsupervised machine learning algorithm) relies on labeled input data to learn a function that produces an appropriate output when given new unlabeled data. It is a classifier that specifies that data is in the A or B group. There may be no between. The statistics are split into three corporations if there are three groups. There are likewise a few compromises with the aid of using the neighbors, with the query being allocated to the magnificence, which one is its nk nearest neighbors (nk maybe a nice variety and a bit number). If k = 1, then the protest can be assigned to the magnificence of that solitary nearest neighbor.

3.2.7 Gaussian Naïve Bayes

A Gaussian Naive mathematician system might be a unique fashion of the NB algorithm. It is primarily used as soon as the alternatives have non-stop values. It is assumed that every capability follows a Gaussian distribution, i.e., conventional distribution. In the period of machine studying, naive Bayes classifiers incorporate a bunch of easy "probabilistic classifiers." The paintings upon probability are extraordinarily scalable. They want several parameters directly inside the various things (highlights/indicators) inside the studying issue.
3.2.8 Random forest

This algorithmic software considers various name bushes, consequently forming a forest. It is also called an ensemble of choice tree algorithms. That can be used for class, furthermore, as regression. This set of rules attempts to is looking for the most effective function indiscriminately amongst all the features. Our experiment used one hundred choice bushes and Gini for the impurity index.

3.2.9 Linear discriminant analysis

Linear discriminant analysis (LDA), conventional discriminant evaluation (NDA), or discriminant function evaluation can be a generalization of Fisher’s linear discriminant, a way hired in statistics, sample recognition, and opportunity fields to hunt down a linear mixture of alternatives that characterizes or separates two or additional classes of items or events. The resulting mixture may also be used as a linear classifier or, extra commonly, for spatial assets discount earlier than later classification.

3.2.10 Quadratic discriminant analysis

Quadratic discriminant analysis (QDA) is associated with LDA, and anywhere it is meant that the sports from every class are generally distributed. Now no longer like LDA, in QDA, there may be no supposition that the variance of each of the kinds is identical. As soon as the normality assumption is valid, the only ability test for the speculation that a given size is from a given magnificence is the chance quantitative relation test.

4 Results and Discussion

In this study, we used nine different machine learning algorithms that are: 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 these methods in 3 distinct elements of teachers’ burnout (predicting emotional exhaustion, depersonalization and Personal accomplish). The effects are proven in Table 2.

For the term of accuracy measurement, we used mean absolute error. In statistics, mean absolute error (MAE) is a measure of errors between paired observations expressing the same phenomenon. Examples of Y versus X and compare predicted values versus observed values, subsequent time versus initial time, or one technique of measurement versus an alternative technique. MAE is calculated as:

\[
MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}.
\]

It is proven that each quadratic discriminant strategies have higher overall performance in the assignment of predicting teacher’s burnout in phrases of emotional exhaustion, aid vector classifier and linear discriminant evaluation have the first-rate accuracy with 93% accurate prediction and in the depersonalization and private accomplish factors the quadratic discriminant evaluation has the first-rate accuracy with 100% accurate predictions. However, linear discriminant analysis, support vector classifier, and K-nearest neighbor strategies have extreme accuracy with greater than 97% accuracy (Fig. 5; Table 3, 4, 5).

5 Conclusion and future studies

We proposed a brand-new approach in the usage of 9 systems studying type algorithms (decision tree, support vector system, support vector classifier, support vector regression, multi-layer perceptron, K-nearest neighbor, Gaussian Naïve Bayes, random forest, quadratic discriminant analysis, linear...
Fig. 5 The chart of the classifier methods on the collected data set

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

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

That includes 199 low, 590 moderate, and 590 High values

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

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

That includes 173 low, 910 moderate, and 349 High values

Table 5 Result of predicting and classifying methods on the collected data set

|        | DT  | SVC | SVR | MLP | KNN | GNB | 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  |
discriminant analysis) on a data set of 1433 EFL instructors to predict their burnout level. The effects are based on three unique categories: low, moderate, and high. Due to our tiny data set, tenfold cross-validation was carried out to grow the number of statistics in our accrued data set. Teachers’ tiredness affects college students’ conduct and effects which might also bring about much less involvement of college students in the study room and reduce their fulfillment rate. Therefore, the findings of this study might also have implications for the development of instructors’ situations, consequently improving their pedagogical decision-making in particular areas.

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

Declarations

Conflicts of interest 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 materials The data are available with the request from the corresponding email address.

Ethics approval All the collected data were based on the Maslach Burnout Inventory, and all participants were aware of it.

Consent to participate All the participants were older than 18 and worked as teachers at institutes and schools.

Consent for publication In the collected and used data, the participants’ details are not needed and are not collected.

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