# University student's mental stress detection using machine learning

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## ABSTRACT

University students are especially susceptible to the negative effects of mental stress in today's environment, which is a serious issue overall. A great deal of pressure is now being placed on a period of life that was traditionally considered to be the most carefree. People in today's culture are exposed to increasingly high levels of mental stress, which has been related to a broad variety of health problems, such as depression, suicide, heart attacks, and strokes. Because of this, in order to primarily extract, for the purposes of this research, the mental stress ratings of university students, we applied a total of six distinct machine learning methods. The Decision Tree Classifier, the Random Forest Classifier, the SVC, the KNN Classifier, the Multinomial NB, and the K-Nearest Neighbors Regressor are only some of the machine learning algorithms that are available. This investigation's principal objective is to determine the percentage of students who are struggling to deal with emotional pressure in their lives. The dataset was put together by hand with paper and manual information obtained from a survey. Out of the six distinct classification strategies, the Decision Tree Classifier and the Random Forest Classifier both achieved a test result of 0.99, which is the maximum score that can be achieved.

**Keywords:** Mental stress, depression, university student, automatic detection, machine learning, accuracy.

## 1. INTRODUCTION

Mental stress is a kind of human disturbance, which deteriorates the normal condition of people. Because of the subjectivity of self-reporting and the unique differences across people, it may be challenging to accurately assess stress and other human psychological dynamics. With the invention of cell phones, it is now possible to keep track of a variety of human behaviours, including [1]. Stress is a sense of being put under excessive strain that stems from several facets of daily living. Since stress is a leading source of substantial chronic health issues in the contemporary world, stress management is necessary to regulate stress levels and prevent health risks [2]. Stress is a major factor in the lives of tens of millions of individuals. Therefore, it is essential to provide the individual with a warning about their risky lifestyle before any serious issues develop [3]. The mental stress of university students can come in different ways. It is critical to investigate the current degree of mental stress among university students [4,7]. Mental stress has evolved into social problems and may contribute to a functional impairment at a regular job. Multiple disorders of a psychophysiological nature may have stress as a contributing cause. Diseases including cardiac arrest, heart attack, stroke, and depression are all made more likely by stress [5]. Similar to emotions, stress is a fleeting state of being, and both emotions and stress share a significant physiological component. The different unpleasant emotions are simply signs of extreme stress [6].

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Nowadays, mental stress has become a significant factor among youngsters. College students experience mental stress at various times in their lives. The sometimes-unnoticed impact of test stress or recruiting stress on the student. The impact of these elements on a student's mental state and the relationship between stress and online time were examined. [7]. The term "stress" refers to the heightened psychophysiological condition the body goes through in response to a stressful scenario or event. Environmental stressors are referred to as stressors. Multiple stresses working together may have a negative impact on a person's mental and physical health over time, exacerbating any pre-existing conditions. Continuous monitoring is the only approach to detecting stress-related disorders in their early stages. Keeping a close watch on stress Wearable Technology's continual and real-time data collecting makes it possible to monitor one's own stress levels. They combine machine learning algorithms and wearable sensors to identify stress. The methods for stress detection are based on sensory devices like wearable sensors, Electroencephalograms (EEG) [9], Electrocardiograms (ECG)[10], and Photoplethysmography (PPG), as well as in different environments like those encountered while studying, driving, and working[8]. Stress detection is one of the key areas of research in biomedical engineering. Information about the respiratory signal can also be found in the ECG which has a separate sensor system for measuring respiration known as EDR (ECG Derived Respiration). This is significant because effective stress detection may prevent many psychological and physical difficulties, such as arrhythmia or abnormal heart rhythm, from occurring [10]. Numerous studies have already looked into physiological signals as continuous and quantitative indicators of stress. The field's emphasis has recently switched from the laboratory to the ambulatory setting. Prioritization of physiological sensing modalities such as electrocardiograms [10], skin conductance, and electromyograms, as well as the most efficient machine learning approaches [11].

According to study, experiencing extreme stress related to academic work not only decreases our motivation to finish the task, but it also has a negative impact on our overall academic performance and may increase the percentage of students who drop out of university. Not to mention the adverse effects on one's health, which might include feelings of sadness, inability to sleep, usage of substances, and anxiety.

## 2. LITERATURE REVIEW

In this paper, using a machine learning method, we will identify mental stress in university students for research purposes primarily. We read many papers and gained knowledge by analysing them and took their works very seriously.
An important concept of mental stress that is gradually receiving research attention in the fields of neuroscience, medicine, psychology, and related disciplines like sentimental computing is stress [12, 13]. We are researching the mental stress of university students [7]. In order to characterise the inter- and intra-individual changeability in the connotation between produced stress levels and environmental occurrences, a cognitive-evaluative component has recently been included to the stress mechanism [14,15]. University students, from studying to family pressure, many times because of the number of members of the family is more, students have to bear the expenses of the family and her. Also, there are many other issues of mental stress. We basically did a survey on these. In this study, we will use machine learning algorithms to detect signs of mental stress among university students and estimate the proportion of individuals who experience it.

In this paper [16], for creative design, we provide a conceptual approach. The theoretical framework for this investigation is based on the following two postulates: (a) design thinking is a nonlinear, potentially chaotic dynamic; and (b) designer stress and creativity have an inverse U-shaped connection. To demonstrate how this theoretical model may be used to investigate design phenomena, the functions of sketching in design are interpreted. The EBD Descriptive design model was utilized in this work. Creative design assistance is widely recognised as one of the most essential elements that will be included in the subsequent generation of CAD systems used in engineering design. This study [17] aimed to determine whether the risk of thrombotic events might be reduced in high-risk groups by lowering stress-induced hypercoagulability using pharmaceutical and behavioural treatments. Acute mental stress may have a role in the pathophysiology of the clinical presentation of acute thrombotic events, and this study aims to offer a concise summary of the current knowledge of haemostatic alterations in response to acute mental stress. Prothrombotic response modulators under acute psychological stress. The ability of the acute prothrombotic stress response to predict the risk of an incident and recurring thrombotic events in both healthy individuals and patients with pre-existing vascular disease requires prospective investigations. An fNIRS-EEG study and canonical correlation analysis are both used in this work. In this work, we suggest utilising the canonical correlation analysis (CCA) technique to assess the effect of mental stress on prefrontal brain activity [18]. Using inter-subject covariances to calculate a linear relationship between two sets of data, the CCA is a statistical method. The experiment's findings demonstrated that this group of participants' mental stress was sub regionally exclusive to the right ventrolateral PFC subregion. These point to the right ventrolateral PFC as a potential candidate for the extraction of biomarkers as indications of neurofeedback training's effectiveness in teaching stress management. We suggest this approach because it has the ability to both uncover discriminative sets of features and eliminate duplicate information from within the features. University students contribute significantly to the development of a nation's educational infrastructure. In that case, the students of Bangladesh will definitely work for the development of this country. But for university students, mental stress has become a major cause of harm. They are getting into a bad disease like stress due to family, friends, relationships, exam results, and various other personal reasons. And due to this stress, they need help to focus on their studies. That is why the education nation of Bangladesh is going to face a significant threat. University students are more stressed due to various reasons. So, that's why we did a survey on the mental stress of university students. Then we will collect the data through the survey form on the mental stress of university students. Our study's primary objective is to develop a machine learning algorithm for identifying signs of mental stress among university students.

## 3. METHODOLOGY

Conducting an interview in conjunction with the collection of data from a survey is one of the most direct and productive ways to gain a respondent's trust and cooperation. This method also ranks among the most effective. In most cases, an online survey technique is one of the most common forms of survey methods that people use. Because people can more easily connect themselves with online methods, we get more immediate responses when we use this method. This is why we choose it. The topic at hand is "University Students Mental Stress Detection." Although we didn't quite reach 1632 people, we did receive a lot of responses from people who were interested in our survey and contributed a lot of information that was helpful to our work.

Following the completion of our analysis, we came to the conclusion that our dataset was not balanced. Because of this, we decided to employ the oversampling approach to create a more equitable dataset. After completing the balancing process on our data collection, we found a total of 2116 entries. Dataset balancing shown in figure 1.

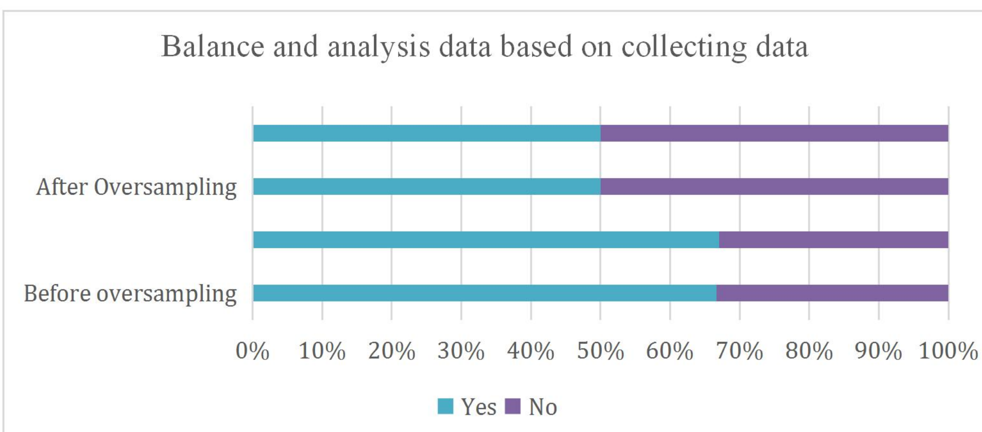


Figure 1. Dataset balancing.

Finally, Decision Tree Classifier, Random Forest Classifier, SVC, K-Nearest Neighbors Classifier, Multinomial NB, and K-Nearest Neighbors Regressor are only some of the six most common algorithms employed in our dataset.

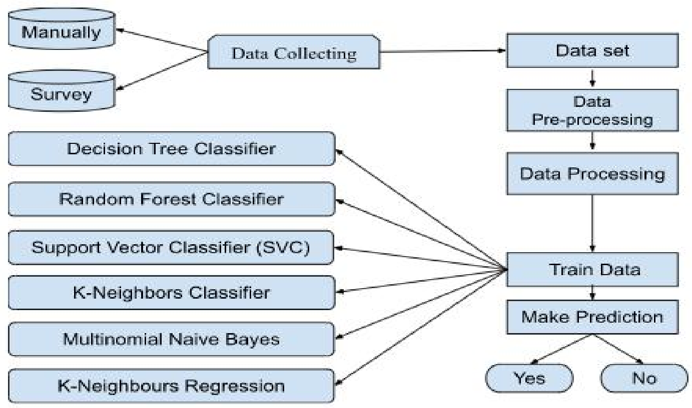


Figure 2. Overall Methodology.

Here, we try to show it in Figure 2. The overall process of our work is what we did. Firstly, we collect data in two ways. After collecting data, we preprocess the data, then label the data for application in six different algorithms. We predict our decisions according to the algorithms.

### 3.1 Description of features

Our dataset total is about 2116. In order to get individuals to respond to the survey, we first came up with a wide range of questions. Eventually, we settled on approximately 11 questions. To read the student's hidden thinking more effectively, each inquiry is highly beneficial. Here, I mostly gathered the data manually and using a google form. Out of this, 1098 data were gathered via a Google form, and 534 were gathered manually. After considering the challenges faced by a wide variety of university students, we settled on the following inquiry. Here, we got 1632 data. We defined each survey's questions very carefully which is described in table 1.

Table 1. Features of prediction.

| Features | Remarks | Features | Remarks/Evidence |
|---|---|---|---|
| Unhappy with the money get per month from family | [19] | Any problems or breakups | [27] |
| Try to recover if short of money | [20] | Loved one fear to leaving | [27] |
| unhappy with CGPA | [21] [22] [23] | In the last 3 weeks, have any negative thoughts about yourself or your future? | [28] |
| Unhappy with friends CGPA | [23] | Lately, do you have any food aversions? | [19] |
| Start a task and worry about it until finish | [24] | Are you addicted to any drug, or smoke frequently? | [29] |
| Unable to sleep properly at night | [25] [26] | | |

The replies that were included in the dataset indicated that there were 1544 males and 572 females. Following the analysis of their replies, 778 guys have Result values of 1, which indicate a high stress level, and 786 males have Result values of 0, which indicate a low stress level. On the other side, 300 females have a result of 1, which indicates a high degree of stress, and 272 females have a result of 0, which indicates a low level of stress. Figure 3 give the comparison of male and female responses.

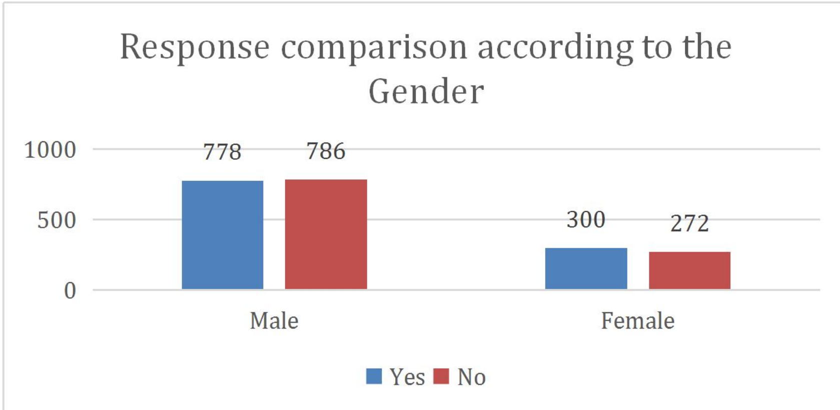


Figure 3. Male and female responses.

### 3.2 Description of dataset

For the purpose of this article, we reviewed a large number of papers and attempted to determine the primary factors that contribute to mental stress. If successful, this will allow for the identification of mental stress among students. In table 2 give the features stress detections and in table 3 give balanced value detected.

Table 2. Features Stress detection

| Features | Responses | | Remarks/ Evidence |
|---|---|---|---|
| | Yes | No | |
| Unhappy with the money get per month from family | 25.95% | 74.05% | [19] |
| Try to recover if short of money | 86.81% | 13.19% | [20] |
| unhappy with CGPA | 56.57% | 43.43% | [21][22][23] |
| Unhappy with friends CGPA | 44.47% | 55.53% | [23] |
| Start a task and worry about it until finish | 81.95% | 18.05% | [24] |
| Unable to sleep properly at night | 60.16% | 39.84% | [25][26] |
| Any problems or breakups | 42.39% | 67.61% | [27] |
| Loved one fear to leaving | 28.26% | 71.84% | [27] |
| In the last 3 weeks, have any negative thoughts about yourself or your future? | 23.49% | 76.51% | [28] |
| Lately, do you have any food aversions? | 40.76% | 49.24% | [19] |
| Are you addicted to any drug, or smoke frequently? | 22.68% | 77.32% | [29] |

Table 3. Balance value detection

| Class | Frequency |
|---|---|
| Depressed | 1058 |
| Non-Depressed | 1058 |
| Total | 2116 |

### 3.3 Data Pre-processing

Data pre-processing is a data mining approach that is used to turn raw data into a format that is more useable and productive when dealing with it. This technique is utilised when working with raw data. Data processing refers to computer-assisted data manipulation. However, it is possible to say that data processing occurs when information is acquired and put into a form that may be used. Data pre-processing is a subset of data pre-processing, which is any kind of processing done on raw data to prepare it for another data processing strategy. It has historically been a key first stage in the data mining process. Data preparation is done in

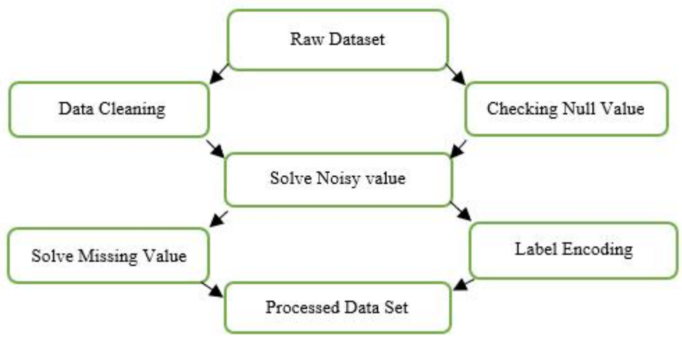


Figure 4. Data Pre-processing

seven steps: 1. Raw Data 2. Data Cleaning 3. Cleaning Null Value 4. Solve Noisy Value 5. Solve missing Value 6. Label Encoding 7. Processed Data Set which is shown in figure 4.

### 3.4 Description of algorithms used

i) Decision Tree Classifier- For both classification and regression problems, a decision tree, a non-parametric supervised learning method, may be utilised. Decision trees can be used for these kinds of problems. It is organized in a hierarchical tree fashion, with the root node serving as the starting point for the branches, internal nodes, and leaf nodes [1].

$$\text{Gini (D)} = 1 - \sum_{i=1}^{m} p_i^2 \tag{1}$$

ii) Random Forest Classifier- Random Forest is a well-known supervised machine learning technique for classification and regression. It generates decision trees from several samples, using the majority vote for classification and the average for regression. [07].

$$\text{error}(M_i) = \sum_{j=1}^{d} w_j \times err(X_j) \tag{2}$$

iii) SVC-Classification is a frequent use of the supervised machine learning approach known as the Support Vector Classifier (SVC). Data points are projected into a high-dimensional space using SVC, which then chooses the best hyperplane to act as a boundary between the two groups. C-support vector classification using libsvm as the underlying library. Sklearn is the module used by scikit-learn. Linear SVCs (Support Vector Classifiers) is designed to provide a "best fit" hyperplane that classifies your data based on the input you supply. Once you have the hyperplane, you may input it through a classifier to find out which class is "predicted" [07].

$$A \cdot B = |A| \cos\theta \times |B| \tag{3}$$

iv) K-Neighbors Classifier- K-NN algorithm retains all prior information and provides a label to a new piece of information based on it. K-Nearest Neighbors (KNN) is a data mining approach that determines the classification or label of a query by using the average label or the most frequent label from a classification (in the case of regression) [07].

$$\left(\sum_{i=1}^{k} (|x_i - y_i|)^q\right)^{\frac{1}{q}} \tag{4}$$

v) Multinomial NB - Natural language processing (NLP) often employs the Bayesian learning strategy known as the Multinomial Naive Bayes method. The computer programme generates an educated prediction as to what tag is associated with a piece of text, such as an email or a news story, using Bayes' theorem. It determines the probability that each tag will be used for a certain sample and then presents the tag with the greatest probability of usage.

$$P(A|B) = P(A) \times P(B|A) / P(B) \tag{5}$$

vi) K-Nearest Neighbour Regressor - Non-parametric to determine the association between independent variables and the continuous outcome, KNN regression employs an intuitive average of surrounding data. The KNN technique may be used to classification and regression issues, as we showed in the previous section. "Feature similarity," which is used to forecast data points that have not yet been seen, is a crucial aspect of the KNN approach. This suggests that the degree to which a new point resembles points in the training set determines how valuable it is.

$$\begin{aligned} d(p,q) &= \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \dots + (q_n - p_n)^2} \\ &= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \end{aligned} \tag{6}$$

We evaluated each algorithm's sensitivity, specificity, precision, recall, F1-score, and accuracy. Accuracy is defined as the fraction of total samples that the classifier correctly identifies. Precision is the percentage of real positive samples that the classifier correctly predicted. The percentage of positive samples that the classifier correctly identified as positive is known as recall. The harmonic mean of recall and accuracy is expressed as the F1-score. Both false positive and false negative numbers are included in the computation. Sensitivity and specificity are traits that define a test's validity.

Sensitivity: Also known as recall or true positive rate, it measures the proportion of actual positive cases that are correctly identified by the model. It is calculated by dividing the number of true positives (TP) by the sum of true positives and false negatives (FN) and then multiplying by 100%

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \tag{7}$$

Specificity: The percentage of real negative instances that the model accurately detected is what this metric measures. In order to compute it, divide the total number of false positives (FP) by the total number of true negatives (TN), then multiply the result by 100%.

$$\text{Specificity} = \frac{TN}{FP+TN} \times 100\% \tag{8}$$

Accuracy: It evaluates the model's overall accuracy. It is computed by multiplying by 100%, then dividing the number of successfully identified samples by the total number of analysed samples.

$$\text{Accuracy} = \frac{No.\ of\ correctly\ classified\ samples}{No.\ of\ tested\ samples} \times 100\% \tag{9}$$

Precision: Out of all the instances the model classified as positive, it calculates the percentage of properly detected positive cases. It is computed by multiplying by 100% after dividing the quantity of true positives (TP) by the total of true positives and false positives (FP).

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \tag{10}$$

Recall: Recall, commonly referred to as sensitivity, is a statistic used to assess how well a classification model is working. It gauges the percentage of real positive instances that the model accurately detected. The formula is -

$$\text{Recall} = \frac{TP}{TP+FN} \times 100\% \tag{11}$$

F1 score: Precision and recall have a harmonic mean. When the classes are unbalanced, it is a more useful statistic than accuracy since it takes precision and recall into consideration. In order to compute it, multiply by 100% after dividing the product of the accuracy and recall values by two.

$$F_1 score = \frac{2 \times precision \times recall}{precision+recall} \times 100\% \tag{12}$$

Table 4 gives the classifiers performance evaluations.

Table 4. Classifier performance evaluation considering the better performance

| Algorithm | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|---|---|
| Random Forest | 99 | 98 | 100 | 99 | 99 | 99 |
| Decision Tree | 98 | 98 | 98 | 98 | 98 | 98 |
| SVC | 99 | 98 | 100 | 99 | 99 | 99 |
| K-Neighbors | 96 | 96 | 94 | 96 | 96 | 96 |
| MultinomialNB | 83 | 82 | 84 | 84 | 83 | 83 |

## 4. EXPERIMENTAL EVALUATION

In this paper, the data for this research came from surveys as well as hand-collected sources. After that, the data is cleaned, which refers to the process of deleting invalid values and characters from the data. The newly collected dataset is then given labels. The conclusions are drawn from the scores that are acquired as a result of training six different machine learning algorithms on the labelled data.

In this paper, from our full data set we train 75% data and test size 0.25. After analysing 2116 data the highest test score is 0.99 which comes from Decision Tree and Random Forest Classifier. However, the K-Nearest Neighbours Regression test result is the lowest at 0.83. The results of the algorithms has shown in table 5 and graphically shown in figure 5.

Table 5. Result of the Algorithms of our work

| Algorithm | validation score | Test Score |
|---|---|---|
| Decision Tree Classifier | 0.99 | 0.99 |
| Random Forest Classifier | 0.99 | 0.99 |
| SVC | 0.99 | 0.98 |
| KNN Classifier | 0.98 | 0.95 |
| Multinomial NB | 0.86 | 0.85 |
| K-Neighbors Regressor | 0.92 | 0.83 |

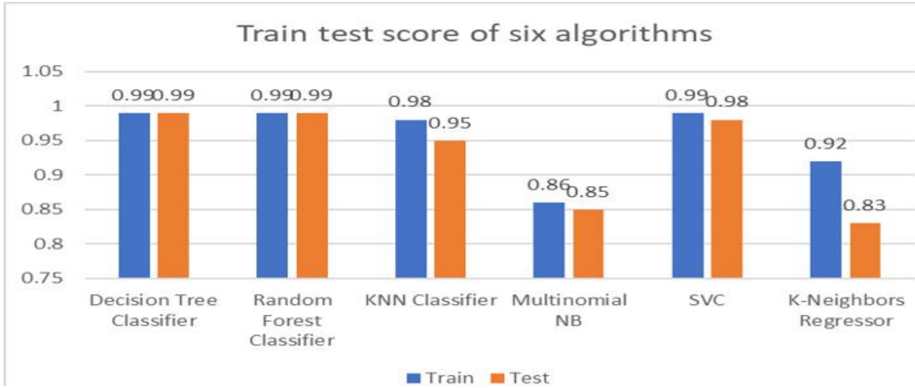


Figure 5. Train and test scores of six algorithms.

## 5. COMPARATIVE ANALYSIS

Table 6. Results of the comparison of our work and other works

| Work Done | Year | Content Of Work | Problem Domain | Algorithm | Best Accuracy |
|---|---|---|---|---|---|
| Our work | - | University mental stress detection | Detection | Decision Tree Classifier<br>Random Forest Classifier | 99%<br>99% |
| [2] | 2020 | Automatic stress detection | Detection | Support Vector<br>K-Nearest Neighbor<br>Random Forest<br>Logistic Regression | 95.98% |
| [3] | 2017 | Stress detect and predict using ML and IOT | Prediction and Detection | Logistic Regression<br>SVM | 66%<br>68% |
| [5] | 2017 | Stress detects in multiple levels using ML framework | Detection | For two-level<br>Multiple level | 94.6%<br>83.4% |
| [7] | 2019 | University students stress | Detection | SVM | 85.71% |
| [9] | 2022 | Mental stress | Detection | SVM, NB (subject wise)<br>SVM Linear (Mixed classificassion) | 98%<br>90% |
| [10] | 2019 | Biosignal based stress | Detection | Gaussian Kernel Function | 98.6% |

We compared our suggested approach to existing research in the field to determine how well it would detect mental stress in university students and shown in table 6. We carefully examined the pertinent literature on psychological stress, stress detection, and biosignal-based stress. Our goal was to compare our work to that of others using criteria including accuracy, content, problem domain, and algorithm. A summary comparison of our research and the other studies is shown in Table 6.

Heart rate has been used as a predictor of stress in people, as shown by Pandey et al. [2]. For two-level stress identification, accuracy rates by Subhani et al. [5] were 94.6%, and for multiple-level stress identification, accuracy rates were 83.4%. University students' mental stress was the subject of R. Ahuja et al.'s [7] study, which gathered data from 206 students. In

Saudi Arabia, 14 guys between the ages of 18 and 23 who were divided into control and stressed groups participated in AlShorman et al.'s [9] study on the detection of mental stress.

Comparing our suggested model to previous models that have been put forth for predicting mental stress is worthwhile given that it can achieve an accuracy of 99%.

## 6. CONCLUSION

Students' academic performance, social interactions, and emotional health may all be impacted by mental stress. Students at universities experience mental stress for a variety of reasons. By applying the machine learning method, we can determine the stress level. In this study, we utilized train and test cases to detect mental stress in a sample of 2116 students. We then employed six classification algorithms (Decision Tree Classifier, Random, Forest Classifier, SVC, KNN Classifier, Multinomial NB, and K-Nearest Neighbors Regressor) to the dataset. The highest test result of 0.99 was achieved by the Decision Tree Classifier and Random Forest Classifier, which beat the other six techniques. University students' mental health may be improved by using analysis and stress detection algorithms like Decision Tree Classifier and Random Forest Classifier with more accurate findings.

## ACKNOWLEDGEMENT

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