Journal of Theoretical and Applied Information Technology
15th October 2024. Vol.102. No. 19

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MACHINE LEARNING-BASED CLASSIFICATION AND PREDICTION OF STUDENT STRESS LEVELS: A COMPARATIVE STUDY OF ALGORITHMS

G. DEENA[1*], A. SANDHYA[2], K. RAJA[3]

[1*,2,3]Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, TamilNadu, India.

Corresponding Author: deenag@srmist.edu.in, [2]sandhyaa@srmist.edu.in, [3]rajak1@srmist.edu.in

ID 55239 Submission	Editorial Screening	Conditional Acceptance	Final Revision Acceptance
02-08-2024	10-08-2024	13-09-2024	30-09-2024

ABSTRACT

Stress is an increasing issue because of its adverse impacts on students' academic achievement, psychological health, and general well-being. The current research examines the classification and prediction of student stress levels with machine learning algorithms. The objective is to create models that can precisely classify and predict stress levels using a well selected dataset intended to capture elements contributing to student stress. Given the global increase in student stress levels, it is imperative that we deal with this issue to avert serious consequences. This work proposes a machine learning algorithm that measures students' stress levels in classroom environments by leveraging recent advances in computer science, especially in the field of healthcare. The examination examines personal attributes and significant stressors, encompassing academic demands, psychological states, and social engagements. Several machine learning algorithms—Support Vector Machines, Logistic Regression, Naive Bayes, Decision Trees, and Random Forest—are examined, with Naive Bayes identified as the most effective model. It attains a prediction accuracy of 90% and an F1 score of 90%, excelling other classifiers. The model accurately predicts stress levels, enabling early intervention in educational settings, demonstrating the potential of machine learning for monitoring mental health in students.

Keywords: *Stress Level, Machine Learning, Mental Health, Classifiers, Naïve bayes, Logistic Regression*

1. INTRODUCTION

Stress is defined as a kind of mental suffering which sometimes becomes life threatening [1]. Stress is a ubiquitous aspect of daily existence that the majority of individuals encounter on diverse occasions. But, enduring chronic stress, or experiencing a significant level of stress, will impede our well-being and interrupt our daily routines. Early detection of mental stress can effectively mitigate several health complications linked to stress. Stress is a term commonly used equivalently with negative valuable experiences or life circumstances. Multiple studies have demonstrated that feelings of unease and being in a high-pressure situation can result in various health problems and psychological disorders. Legitimate inquiry on tension and unease presents diverse viewpoints on the subject [2]. It is imperative for individuals to manage pressure constraints as stress can result in various health complications such as obesity, mental melancholy, diabetes, heart troubles, respiratory problems, and poor sleep. School kids today endure substantial stress from a variety of sources, which leads to the negative influence on their academic performance, mental health, and overall well-being. A few major causes of stress for students include pressure from their studies, social issues, life transitions, family problems, and mental health issues. Excessive stress can have negative impacts or greatly impact an individual's daily life [3]. Psychological stress has emerged as a significant problem in society and can result in diminished productivity in the workplace [4]. The academy has established programs and interventions to address students' lack of attention under academic. machine learning algorithm as a practical and easy-to-deploy model that can provide actionable insights and decisions regarding students' academic stress [5].

1.1 Cause for the stress

Academic Pressure: Students frequently experience great pressure to achieve academically, retain excellent marks, and strive with others in their class. The responsibilities of classwork, tests, and other school-related tasks can become exhausting. For an instance a high-school pupil who is facing significant pressure to uphold a perfect 4.0 grade point average in order to get acceptance into a prestigious university. The individual in question dedicates extensive hours to studying, sacrificing social activities and sleep, with the aim of achieving exceptional scores. Example: an elementary school student experiencing difficulty in a particular subject, such as math, and expressing fear about upcoming assessments and tests in that class. The apprehension of experiencing failure can serve as a significant source of stress.

Social issues: Students may experience a great deal of stress when navigating pressure from others, bullying, and social connections, particularly in their early teens. An instance would be a student who is subjected to bullying by their peers, either in the form of physical aggression or through cyberbullying. The persistent apprehension and distress of coming across the tormentor can have a detrimental impact on one's mental and emotional well-being. A student who is attempting to learn about the complex relationships of groups and peer networks at a new educational institution. The pressure of attempting to assimilate and establish new social bonds might be overpowering.

Transition Periods: Major changes, which include joining a new school, can be especially stressful as students adjust to unfamiliar surroundings and responsibilities.
An individual commencing secondary school following a favourable encounter at a tiny, tightly-knit middle school. The heightened external circumstances, increased workload, and necessity to form a fresh social circle can induce significant levels of stress.
An individual who is affiliated with the military and is required to change schools because of a parent's relocation to a different duty station. Adapting to a fresh syllabus, professionals, and peers can cause considerable stress.

Family Issues: Domestic challenges, such as financial difficulties, divorce, or other familial disputes, can exacerbate student stress. An individual is currently undergoing a highly contested separation from their parents. The domestic upheaval and ambiguity over the future can have an adverse effect on their capacity to concentrate on their academic pursuits. An example would be a student who assumes major responsibility for caring for an ill or disabled family member. The additional obligations and psychological burden can disrupt their academic performance and social interactions.

Mental Health Concerns: Prolonged stress can lead to mental health issues such as anxiety, depression, post-traumatic stress disorder, substance abuse, sleep disturbances, and personality abnormalities.

By comprehending the stress patterns of a certain student, machine learning algorithms can suggest customized approaches to managing stress, like mindfulness exercises, enhancements in sleep hygiene, or referrals for counselling. A person struggling with generalized anxiety disorder frequently experiences physical symptoms like elevated heart rate and sweating before every exam or public speaking event. A depressed student is increasingly struggling to find the drive to attend classes or complete assignments. The general public may suffer from anxiety disorders, which are extremely common mental illnesses that can lead to long-lasting symptoms and a significant risk of mortality [6].

The World Health Organization (WHO) recognizes anxiety as a prevalent condition that individuals commonly experience. Students identify anxiety as the primary cause of disease and impairment [7]. The Pan American Health Organization (PAHO) 2018 report reveals that anxiety ranks as the second most prevalent mental disorder causing significant disability, warranting urgent treatment in the region.[8]. Stress is a concern both for the health of people who suffer from it as well as for the emotional aspects of their lives [9]. Stress is also a major cause of several health issues, including heart disease and mental illnesses [10-11]. Severe stress reduces job productivity and contributes to various illnesses and negative feelings. Persistent stress causes harm to multiple internal organs, leading to the development of numerous illnesses. These issues lead to epithelial, gastrointestinal, musculoskeletal, cardiovascular, and mental illnesses [12]. Psychological stress is commonly defined as a condition that involves mental or emotional stress and anxiety [13] that can impact several essential biopsychological processes, such

Journal of Theoretical and Applied Information Technology
15th October 2024. Vol.102. No. 19

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

as attention [14], decision-making [15], and cognitive growth [16], [17]. Adaptation emphasizes the usefulness of active learning methodologies in enhancing the precision of machine learning models for student anxiety prediction.

2. LITERATURE SURVEY

The objective of the study described in reference [18] is to detect stress levels in individuals in order to prevent health problems associated with stress. This is achieved by analysing a dataset called WESAD and determining whether a person is now feeling stress or not. The findings indicated that the machine learning methods attained an accuracy of 81.65% and 93.20% for multiclass and binary classifications, respectively.

In [19], Jacqueline and her colleagues undertook a study with the objective of identifying mental stress by utilizing wearable sensors to analyse physiological signals. The signals comprised an electrocardiogram (ECG), skin conductance, breathing, and electromyography (EMG). By employing Fisher's Least Square Linear Classifier, researchers attained an accuracy rate of 80% in accurately differentiating between stress and non-stress states in individuals. These findings indicate that integrating physiological signal measures and machine learning approaches has the potential to effectively identify mental stress.

The authors in [20] employed a decision tree method to analyse the data gathered from the two tests and concluded that these tests were inadequate. The study examined the level of stress experienced by students at the beginning and end of each academic term or semester. The study shows that students' stress levels were lower at the start of the semester and increased as the course progressed.

In [21], Utilizing sensors, extracted data features such as the electrocardiogram (ECG) and galvanic skin response (GSR). These data are then processed. By utilizing supervised machine learning techniques such as support vector machines (SVM), K-Nearest Neighborhood (KNN) on the SWELL-KW dataset.

The researchers in [22], used KNN and SVM algorithms to classify the stressors into three distinct categories: high, low, and medium. The researchers gathered a total of 78 data features with the goal of identifying the most optimal feature that could yield the highest level of accuracy.

A multitude of studies endeavoured to forecast the level of stress experienced by an employee or student at a distinct university by using machine learning algorithms. Our proposed system aims to classify and predict a stress level at a school. We have categorized the stress level as low, medium, and high using the available data. To assess the amount of stress, we obtained the dataset from Kaggle in order to assess the amount of stress.

P. Madhan Mohan et al. proposed a study that uses heart rate variability data to assess an individual's stress level [22]. Researchers can use the optical sensor known as photoplethysmography (PPG) to predict HRV. The researchers classify the heart rate into three categories: very low frequency, low frequency, and high frequency. One can infer an individual's level of stress from variations in their LF and HF ratios.

In [23], Jie Zhang et al. seek to identify the amount of stress. utilizing the cardiovascular rate parameter. The RR interval values were derived from the electrocardiogram (ECG) data. It utilizes them to determine the precise positive as well as negative rates. Employed an SVM classifier to categorize instances as either positive or negative.

Author Jorn Bakker [24], and colleagues offered a work in which GSR data obtained from wearable watch-style stress monitoring is used to identify the stress pattern. Its goal is to identify the connection between the outside variables influencing stress and its appearance.

In [25], R. A. Rahman et al. suggested using datasets, machine learning algorithms, and a way to pull out features to look at how to identify mental health in OSNs. Keyword searches were conducted to review the research pieces, and the CASP checklist was used in this systematic review to rate a number of method-focused papers. The survey showed that OSNs have a lot of promise to help find mental health problems by collecting data.

Ahuja et al. assessed the mental tension levels of students in [26]. one week prior to the examination. The tension level was assessed using a PSS test. The inquiries pertain to prevalent circumstances. The queries necessitated responses from the participants. The accuracy of SVM was the highest at 85.7%. The research conducted by Rao et al. examined the mental well-being of engineering students in South India. It assessed their understanding of the COVID-19 epidemic and measured their levels of depression, worry, and stress in [27].

The importance of familial histories of illness and the provision of mental health employee benefits by a manager outweighs other factors when determining an individual's susceptibility to developing mental health problems as suggested by [28].

Previous studies mentioned in the literature review explored the use of different physiological and environmental factors to predict stress levels. As an examples, the use of Heart Rate Variability (HRV) and sensor data was common in past research. The current study builds on these findings but shifts focus towards psychological, academic, and social factors. Combining this with the current results, the study shows that while physiological factors are important, psychological attributes like anxiety and bullying also play a crucial role in predicting stress.

2.1 Objectives and Intentions:

Classifying or predicting the stress level of student can have many substantial implications for students' well-being, academic achievements, and entire learning experiences. Educators and counselors can identify at-risk students by predicting stress levels and providing timely support. They can also design personalized interventions like counseling, stress management workshops, or relaxation techniques. Reduced stress can optimize learning outcomes by enhancing students' focus, retention, and cognitive abilities, resulting in improved academic achievement and heightened engagement and involvement in classroom activities. Chronic stress can result in psychological conditions such as anxiety, depression, and burnout. However, the timely identification and intervention can be effective in averting these problems by establishing a nurturing atmosphere within educational institutions. Predictive models provide empirically-based insights that can guide policy decisions and the creation of student support programs, allowing schools to optimize resource allocation by focusing interventions on areas with the greatest need. The research problem focuses on the growing concern about student stress, its negative effects on well-being and academic performance, and the potential for Machine Learning (ML) algorithms to predict and classify stress levels based on relevant factors. The study findings justified the research problem effectively by employing multiple ML classifiers to analyze and predict stress levels. The comparison among classifiers showed that Naïve Bayes was the most effective algorithm with an accuracy of 90%, confirming its ability to handle categorical data well. This high accuracy supports the research problem's goal of identifying a reliable ML model for early stress detection and intervention.

3. METHODOLOGY

The classification and prediction of students' stress levels can have many significant implications for their well-being, academic achievements, and entire educational journey. The process of classifying and predicting student stress using machine learning entails several crucial stages. Here is a comprehensive method to tackle this issue. Numerous studies have attempted to classify and predict student stress levels, but more research is required to refine the necessary features or factors. The most crucial factors are involved in this process, and the current work focuses on determining these key factors for effective stress prediction. The primary contribution of the work is the collection of the dataset, the analysis of its features, the extraction of these features using a variety of techniques, the training of the data, and the implementation of the machine learning model. Figure 1 presents the proposed work process. We divide the work flow into four phases: the initial phase involves data collection, followed by data cleaning and normalization, and the third phase involves model training and testing. The final phase involves evaluating the trained model to classify and predict the student's stress level.

3.1 Initial Phase

Data Collection: The dataset initially consists of 21 factors that are affecting stress levels, including internal psychological moods, physical well-being, external environmental conditions, academic pressures, and social interactions. Scale value is used to rate the value in each factor. In proposed system, stress levels are classified as low, medium, and high. Additional factors such as procrastination, smartphone usage, peer friends, and leisure length were included in the dataset. Based on the factors in the dataset, the students were classified into any one of these levels. The students have reported that there are additional elements that contribute to the increase in stress levels. In this connection, new factors were incorporated to the dataset which used for the work progress.

3.2 The second phase:

Preprocessing: In the machine learning, the basic steps is to remove the unwanted factors. It is the crucial stage that involves the process of removing discrepancies from the data, dealing with any missing information, and converting features to the correct scale or to the specified format. Preprocessing has been done by adding or remove any missing values, if any categorical variables are present in this dataset, they must be encoded, even though the majority of the data appears to be numerical. Normalization or standardization may be required to ensure that all features are brought to a consistent scale.

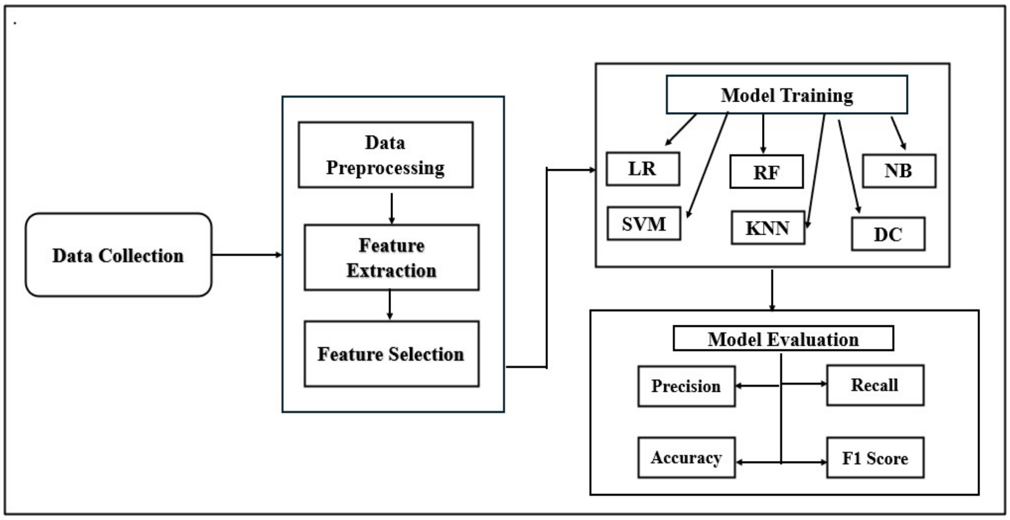

Fig 1. Architecture Diagram Of Proposed Work

Identifying the features and target variables:

Independent variables- It also known as features, are the input variables utilized to forecast the target variable. These factors provide the necessary data for the model to identify trends and generate forecasts. Target Variable are also known as dependent Variable. The target variable is the output variable that the model aims to predict the output. It is dependent on the factors and is the primary variable of interest in the prediction task. Our dataset has the following target variable such as "Stress_level" This is the variable that wants to predict based on the other features. i.e., to measures the stress level of the student**.** Initially, the 'stress_level' column is removed from the dataset to create the feature set X, representing input data. Subsequently, the target variable y, which consists solely of the 'stress_level' column, is extracted from the original dataset. In supervised, a model is trained using X features to predict or classify y outcomes.

This partitioning enables the utilization of X features to train machine learning algorithms while referencing corresponding y values for training purposes.

Correlation association:

A correlation study implies considerable connections between components. The symbol 'r' represents the Pearson's association coefficient. It determines the strength and direction of a linear relationship between two variables. Pearson's correlation coefficient calculated as mentioned in equation (1),

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}$$

---------------- eqn. (1)

x_i and y_i are the individual data points. $\bar{x}$ and $\bar{y}$ represent the average values of x and y, respectively. data point represented by 'n'. when r=1 it represents the perfect positive linear correlation, when r=-1 it represents the perfect negative linear correlation and when r=0 represent there is no correlation between the factors.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

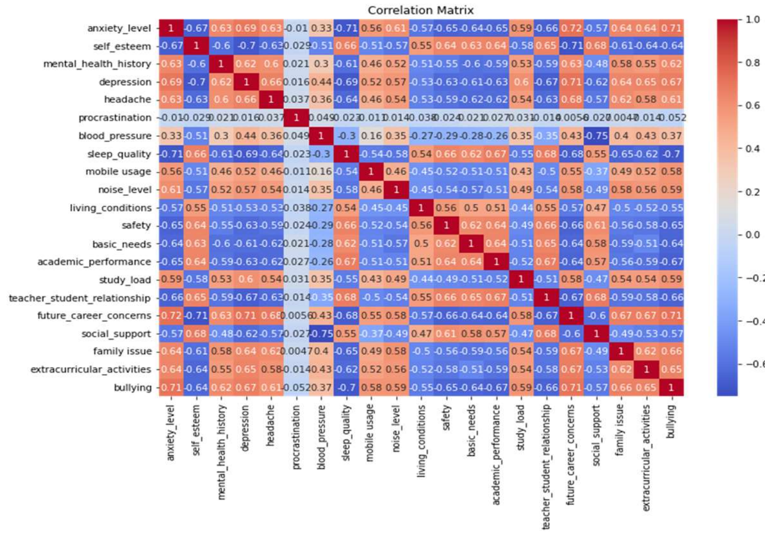

Fig 2. Correlation Matrix

Correlation associations are quantitative measures of the proportional connection between two variables. The coorelation between the factors from the dataset is given in the figure 2, where proposed system gives the positive associations between the factors anxiety, bullying, career concerns, and depression. Depression closely correlates with bullying and career worries. Anxiety, depression, and bullying were all associated with future career concerns. Finally, bullying is strongly associated with anxiety. Each factors influences the others, given the interconnectedness of anxiety, future career concerns, and bullying.

3.3 Features Selection

Univariate selection is a feature selection method that assesses each characteristic separately to establish its correlation with the target variable. By assessing each component separately, obtain insights into whether features have a robust individual correlation with the outcome. By conducting an independent analysis of each characteristic can able to acquire an understanding of which features have a significant individual association with the variable that is being targeted. To analyse the relationship between each factor from the dataset and the target variable, conduct a chi-square test for independence.

The Chi-Square ($\chi 2$) test quantifies the correlation among two categorical variables, aiding in the identification of the most influential aspects of the target variable. It is used to determine if there is a significant correlation between categorical variables by comparing actual event frequencies with predicted frequencies. The chi-square test determines if category variables are significantly related. The Chi-Square statistic is crucial for selecting features in the analysis of categorical information. This method excels in categorical data analysis, enabling the classification of variable frequencies into groups as given in equation 2.

$$\chi 2 = \frac{\Sigma(Oi - E\ )2}{Ei} \text{ ---------------------- eqn. (2)}$$

as a result, the top five selected features, extracted from the dataset using chi-square are anxiety_level', 'self_esteem', 'depression', 'sleep_quality', 'bullying', and 'depression'.

The aforementioned characteristics are the root cause of a student's stress level. The comparison has been made between the selected features as shown in figure 3. The discussion is given as, for Anxiety level, the level of stress experienced with high stress levels indicating higher anxiety, low stress levels indicating lower anxiety, and average stress levels indicating moderate anxiety.

In Self-Esteem, low stress levels are associated with higher self-esteem, high stress levels with lower self-esteem, and average stress levels with moderate self-esteem. In Sleep_quality, High stress levels are associated with worse sleep quality, low stress levels are associated with better sleep quality, and average stress levels are associated with moderate sleep quality.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

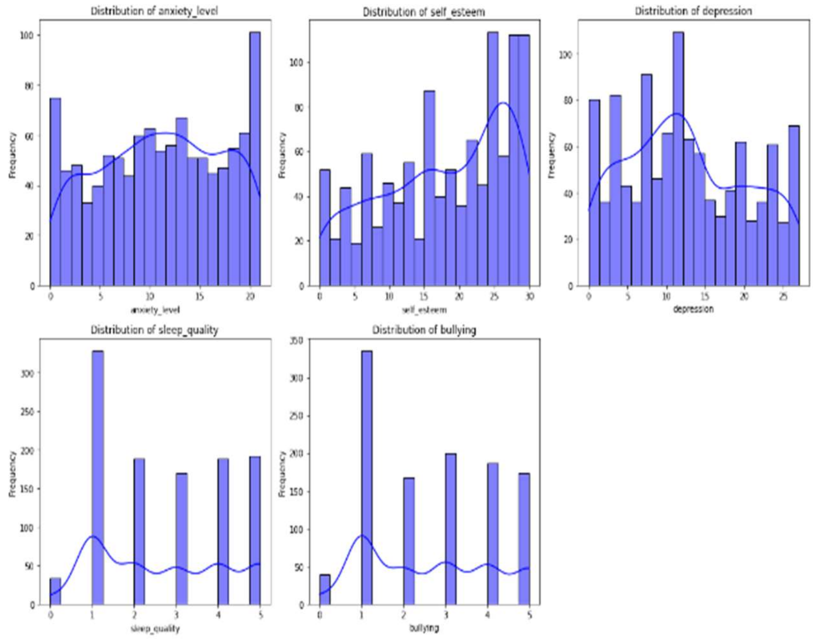

Fig 3. Selected Features From The Dataset

In depression, Higher depression scores are associated with high stress levels, lower depression scores are associated with low stress levels, and moderate depression scores are associated with average stress levels.

In bullying, High stress levels are associated with higher bullying scores; low stress levels are associated with lower scores; and average stress levels are associated with moderate bullying scores. In depression, Higher depression scores are associated with high stress levels, lower depression scores are associated with low stress levels, and moderate depression scores are associated with average stress levels. In bullying, High stress levels are associated with higher bullying scores; low stress levels are associated with lower scores; and average stress levels are associated with moderate bullying scores.

All the conclusion about the about stress level and selected features were given in figure 4 represent the conclusions about stress level and selected features.

4. TRAINING AND TESTING

Partitioning data into separate training and testing sets enables the proper evaluation of machine learning models. Random partitioning ensures impartial representation, whereas maintaining the class distribution in both subsets ensures the model's dependability and applicability. Where the input and output are given in X and y variables. ‘X’ represents the feature matrix or input data and the ‘y’ represents the target variable or output data. In the proposed work, size of the test data 0.2 which specifies that 20% of the data will be allocated to the testing set, while the remaining 80% will be used for training. Once the data has been divided, you may proceed to train your machine learning model using X_train and y_train. Subsequently, you can assess its performance by utilizing X_test and y_test. This division enables you to evaluate the model's ability to apply its learned knowledge to new, unknown data by measuring its performance on the testing set.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

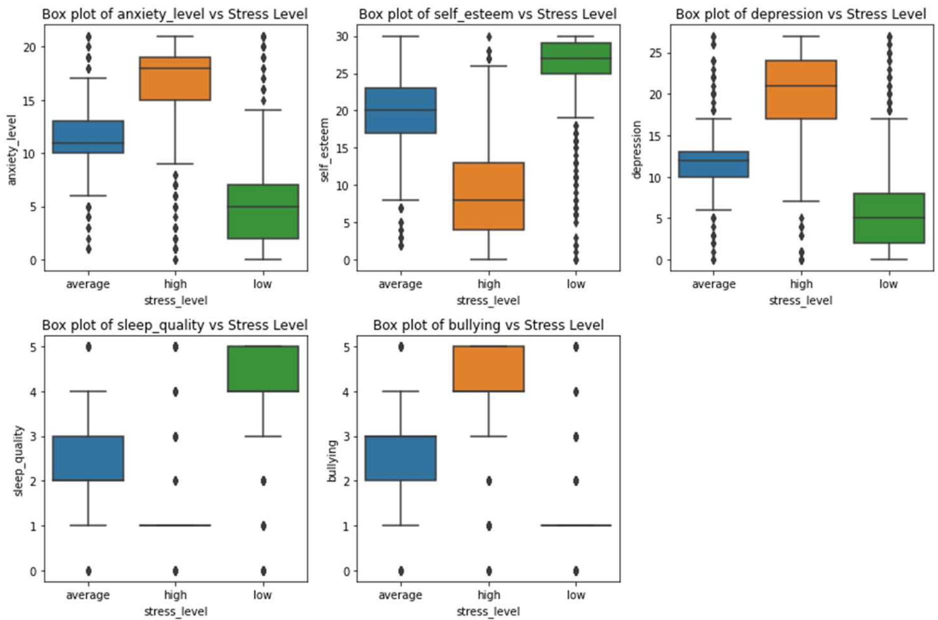

Fig 4. Representation Of Stress Level In Primary Features

4.1 Various Machine Learning Model:

Machine learning classifier models are algorithms that learn from data, designate labels, or predict outcomes for new, unseen data. In supervised learning, the algorithm learns from labelled training data to make predictions or decisions about future data points. A machine learning model's effectiveness is assessed by contrasting its predictions with the actual values found in the testing dataset. Various metrics and methodologies are available for assessment, contingent on the nature of the issue. Different algorithms were implemented to classify the test data.

4.1.1. Logistic Regression

Logistic Regression is a supervised machine learning approach used for binary or multiclass classification problems. Logistic regression predicts the likelihood that an instance falls into a specific class or category. The Logistic Regression model estimates the probability of the target variable as stress level belonging to one of three classes like low, high or average using the input features. The model employs the logistic function, commonly referred to as the sigmoid function, to convert the linear combination of the input data into a probability ranging from 0 to 1. Subsequently, this likelihood can be utilized to categorize the data point into one of the two classes by implementing a decision threshold. The representation of logistic regression is given in equation 3.

$$P(Y = 1 \mid X) = 1 / (1 + e^{\wedge} (-\beta_0 - \beta_1 X_1 - \beta_2 X_2 - \dots - \beta_n X_n)) \text{ -----------------------eqn. (3)}$$

The Logistic Regression model calculates the optimal coefficient values for training data using optimization methods like gradient descent or maximum likelihood estimation. The trained model predicts stress levels based on input features, outputs the probability of high stress levels, and can be compared to a decision threshold to classify data as high, average and low stress levels.

4.1.2 Random Forest Classifier

The Random Forest (RF) technique is widely utilized in machine learning for both classification and regression tasks. It is a technique in machine learning that utilizes ensemble learning by combining numerous decision trees to generate predictions. It is a supervised machine learning algorithm used for classification and prediction. It creates decision trees based on data samples, with each tree providing one prediction. The best solution is selected by voting. RF is an ensemble method, as many uncorrelated models outperform a single model due to their protection from errors. Attribute selection and pruning methods are crucial for decision tree design, with the Gini Index method being the most commonly used.

Journal of Theoretical and Applied Information Technology
15th October 2024. Vol.102. No. 19

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$\sum\sum (f(C_i, T)/|T|)\, f(C_j, T)/|T|)$ ----------------eqn. (4)

from equation (4), numerator represent the probability of a selected case belonging to class C_i is calculated. The RFC generates a prediction model by defining two parameters: desired number of classification trees and predicting variables used in each node. It consists of N decision trees, which choose their class based on the maximum votes from N.

4.1.3 Naïve Bayes Classifier

The Naive Bayes classifier is a probabilistic algorithm used for classification tasks, assuming independence among predictors or features. It is particularly relevant in predicting depression in the medical domain, as it relies on probabilities and assumes statistical independence among different features, allowing specific features to exist autonomously. Here, features are conditionally independent based on the class label, simplifying the calculation of probabilities as given in [29].

$$P(C|X) = \frac{P(X|C).\ P(C)}{P(X)} \quad \text{------------------eqn. (5)}$$

P(C|X) is the posterior probability of class C given features X. P(X|C) is the likelihood of observing features X given class C. P(C) is prior probability of class C, P(X) known as the evidence which is the probability of observing features X.
To predict the new student, Naïve bayes calculate for each possible class C and selects the class with the highest probability as given in equation 6,

$$C' = \text{argmax}_C\ P(C|X) \quad \text{------------------- eqn. (6)}$$

4.1.4 Support Vector Classifier

Support vector classifier (SVM) is a machine learning approach used for classification and regression problems, handling continuous and categorical data. It categorizes data points into two groups based on similar properties. The dataset is represented as p-dimensional vectors separated by p-1 planes called hyper-planes, which set boundaries between data groups based on the distance between two classes. In multi class, for each class, SVM creates a distinct binary classifier, with each classifier distinguishing one class from the others. In our dataset, 3 classes are given so three classifiers are built like

- Classifier 1: low vs. (medium + high)
- Classifier 2: medium vs. (low +high)
- Classifier 3: high vs. (low + medium)

The linear kernel is suitable for linearly separable data as our dataset has classes that are linearly separable as given in the below equation 5, and Maximum-margin hyper-plane of SVM is given in equation 8.

$$(a'_1, b_1) \ldots \ldots \ldots (a'_1, b_n) \quad \text{-------------eqn. (7)}$$

Where b_1 represent the class of a_1.

$$v^1, a^1, -c = 0, \quad \text{------------ eqn. (8)}$$

Where v is a normal vector and $b/|v^1|$if offset of hyper plane. Finally, the linear kernel is used the dot product to calculate the value as given in equation 9.

$$K(a, a_i) = sum(a * a_i) \quad \text{---------- eqn. (9)}$$

4.1.5 K-Nearest Neighbors Classifier

K-Nearest Neighbors (KNN) categorizes data into groups based on feature distance within a dataset, with close groups forming groups and far groups forming many groups. The k-Nearest Neighbor algorithm is a non-parametric method that classifies objects based on a majority vote of their k nearest neighbors in which k is positive integer. The 'k' value was adjusted to determine the match class between training and testing data, with a value of 1 assigning the object to the nearest neighbor class. Euclidean distance is the common distance metric as shown below in equation 10.

$$d(p,q) = \sqrt{(p_1 - q_1)2 + (p_2 - q_2)2} \quad \text{---- eqn. (10)}$$

4.1.6 Decision Classifier

Decision trees are built from a root node using entropy and information gain. Entropy measures randomness of a variable, while information gain calculates the difference between entropy values before and after splitting, indicating impurity in class elements. Here, these criteria were used to classify stress levels in a dataset. To calculate the entropy of an attribute, use the equation 11,

$$E(S) = \sum_{i=1}^{c} -p_i \log_2 p_i \quad \text{------------- eqn. (11)}$$

The term E(S) refers to the entropy of attribute S, whereas pi represents the probability of event i or the percentage of class i in a node of S. The equation defines the information gain (IG), which allows each node in the tree to produce the most data possible in each division. The algorithm converts categorical variables like productivity and study-time into factors and assigns them as integers, preprocessing them before splitting the training and testing data into a decision tree classifier.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5. EXPERIMENTAL ANALYSIS

This section showcases the empirical findings obtained by employing different classifiers to forecast stress levels. The analysed classifiers consist of Logistic Regression, Random Forest, Decision Tree, SVM, Naive Bayes, and KNN. Here, evaluated the classifiers using criteria like accuracy, precision, recall, and F1-score. We partitioned the dataset into training and testing sets using an 80-20 ratio, and used the Select Best method with the chi-square test to identify the top 5 attributes or features from the stress Level Dataset. Each classifiers output is evaluated using the accuracy, precision, recall and F1-Score for the three class label values as mentioned as low, high and average as mentioned in [30-32].

The study used various evaluation metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of different ML models. These criteria are critical as they provide insights into how well the model can generalize (accuracy), handle positive cases (precision), identify true positives (recall), and balance between precision and recall (F1-score). The choice of these evaluation metrics is significant because stress detection, particularly among students, requires minimizing false negatives to ensure that no highly stressed student is overlooked

Accuracy: Accuracy measures the percentage of correctly classified instances out of all instances.

Accuracy = correctly classified count/ total count

Precision: Precision is defined as positive prediction accuracy. Precision is defined as the ratio of accurately predicted positive observations to the total expected positive observations.

$$\text{Precision} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Positive})}$$

Recall: Recall measures the percentage of positives predicted accurately.

$$\text{Recall} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})}$$

F1-score

The F1-score is a mathematical average that combines precision and recall, resulting in a single metric that achieves a balance between both measures.

$$\text{F1 score} = \frac{2.\ \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})}$$

The analysis criteria used for different models (SVM, Naïve Bayes, Decision Tree, etc.) are similar in that they all focus on the same set of evaluation metrics. However, the performance outcomes differ. For example, Naïve Bayes and SVM achieved similar accuracy (around 90%), but Naïve Bayes excelled in handling categorical features like stress levels, outperforming other models in terms of precision and recall

5.1 Logistic regression

The accuracy of logistic regression was 89.09%. The classification report provides specific information on the performance of the model. It shows that the "high" stress level class has a high precision of 89.85% and recall of 87.32%, resulting in an F1-score of 88.57%. The class with a "low" stress level demonstrated a precision of 94.37%, recall of 88.16%, and an F1-score of 91.16% and graphical representation is shown in figure 5

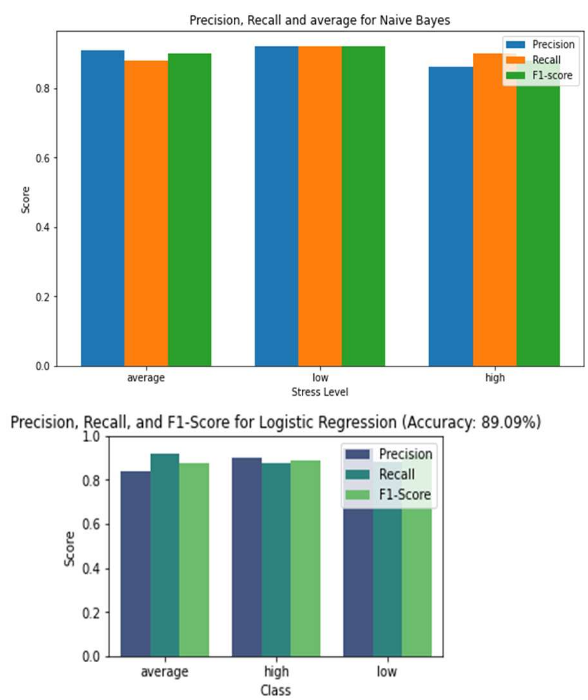

Fig 5. Performance Of Logistic Regression Classifier

5.2 Random Forest

The Random Forest classifier attained an accuracy rate of 89.09%. The "high" stress level class achieved a precision of 90%, a recall of 89.32%, and an F1-score of 89.11%. For the "low" stress level class, precision, recall, and F1-score were 87.50 which mentioned in the figure 6.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

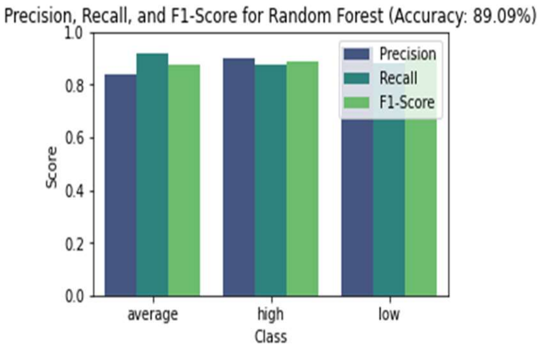

Fig 6. Performance Of Random Forest Classifier

5.3 Naïve Bayes Classifier

Figure 7, shows the performance of Naive Bayes model achieved a 90% accuracy rate, with a detailed classification report providing a comprehensive analysis of performance across various stress level categories.

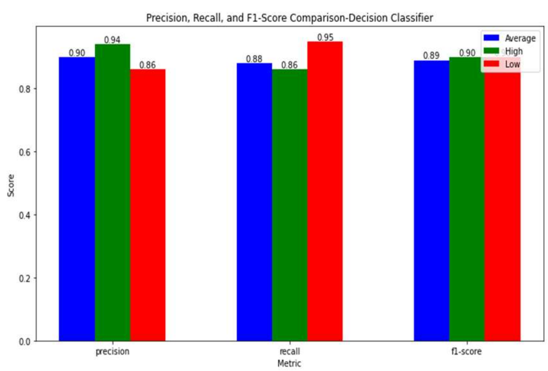

Fig 7. Performance Of Naïve Bayes Classifier

The model achieved a precision of 0.91, recall of 0.88, and an F1-score of 0.90 for the average stress level class. The low stress level class achieved the highest performance among the three courses, with precision, recall, and an F1-score of 0.92. The class with the highest stress level scored the lowest precision, recall, and F1-score of 0.88, surpassing the performance of the other two classes. The model regularly demonstrates high performance across different stress levels, achieving precision, recall, and F1-score values of 0.90. It precisely classifies occurrences, with classes that have low stress levels producing the best outcomes. The categorization report and comparison graph offer a thorough comprehension of the model's abilities and areas that need enhancement.

5.4 Support Vector Machine

The findings indicate that the SVM model demonstrated robust performance in categorizing the stress levels within this dataset. Achieving an accuracy rate of 89.55%, the model successfully forecasted the stress levels. In the "high stress level" class, the model obtained a precision of 88.88%, a recall of 87.32%, and an F1-score of 88.09%. The "low stress level" class achieved even better metrics, with a precision of 95.65%, a recall of 86.84%, and an F1-score of 91.03%. Figure 8, shows the summary which indicate that the SVM model is an appropriate and robust technique for accurately forecasting the stress levels of the research participants using the provided data.

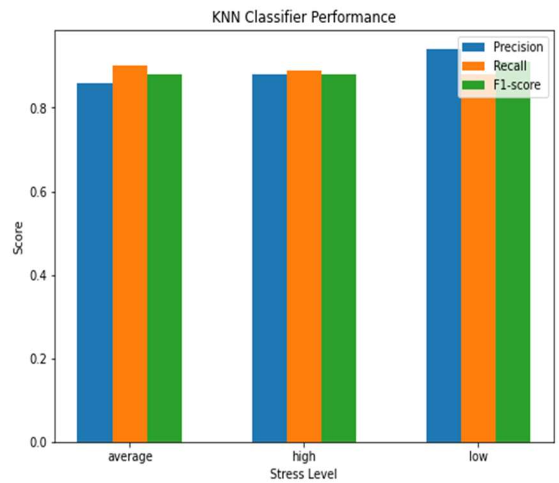

Fig 8. Performance Of SVM Classifier

5.5 Decision Classifier

The decision tree classifier exhibited a uniformly strong performance across the various stress level categories, achieving F1-scores of approximately 90% for each of the three classes. This indicates that the model successfully captured the patterns and accurately differentiated between the different stress levels in the dataset. The Decision Tree classifier demonstrated an accuracy rate of 88.18%. The "high" stress level class demonstrated a precision of 89.71%, recall of 85.92%, and an F1-score of 87.77%. The class with a "low" stress level achieved an accuracy of 82.35%, a sensitivity of 92.11%, and an F1-score of 86.96%.

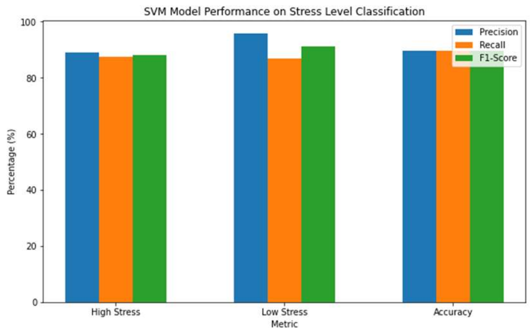

Fig 9. Performance Of Decision Classifier

Above figure 9, shows the performance of decision classifier that categorizing the stress levels in the provided dataset. Both the high overall accuracy and the fact that the metrics are the same for each class show that the decision tree model is a good fit for this stress level assignment. The results instill confidence in the model's capacity to precisely forecast the stress levels of individuals using the provided characteristics.

5.6 KNN Classifier

The KNN classifier used in this study demonstrated strong and consistent performance in accurately classifying stress levels in the dataset. It achieved an overall accuracy of 89.09% and F1-scores ranging from 88% to 91% across different stress level categories. The performance of KNN classifiers given in figure 10 from these results inspire confidence in the model's ability to accurately predict stress levels based on the given variables. Extended periods of stress can have a significant impact on an individual's mental well-being, leading to ailments such as anxiety, depression, post-traumatic stress disorder, substance abuse issues, sleep disturbances, and personality abnormalities.

Fig 10. Performance of KNN classifier

6. RESULT AND CONCLUSION

The three classification algorithms that performed the best, Naive Bayes, SVM, and Decision Tree, each achieved an accuracy of 90%, demonstrating their effectiveness in classifying the stress levels of students. K-Nearest Neighbors (KNN) exhibited the highest precision (0.94) in detecting low-level stress, making it particularly useful for identifying students with minor stress.

The Decision Tree classifier demonstrated outstanding performance in identifying high-level stress, achieving a precision score of 0.94. Both Naive Bayes and SVM classifiers were very good (0.90) at predicting average levels of stress, which means that students who are experiencing moderate stress can trust the predictions they make. The results demonstrate the potential use of machine learning models for stress detection and management, as well as their potential to enhance students' mental health. Figure 11 depicts the comprehensive performance of these classifiers.

The outcome, where Naïve Bayes emerged as the most accurate model, can be justified by its probabilistic nature. The dataset includes separate, independent features such as stress level, anxiety, and self-esteem, which Naïve Bayes can handle efficiently. Additionally, the F1-score of 90% indicates that the model balances well between precision and recall, which is crucial in a sensitive domain like stress detection, where both false positives and false negatives have significant consequences

7. FUTURE ENHANCEMENT

Future machine learning methods, like gradient boosting, AdaBoost, XGBoost, and neural networks, can classify student stress levels as low, high, or medium. It is critical to assist students in managing their stress by providing time and stress management skills, as well as implementing necessary measures to improve stress detection accuracy.

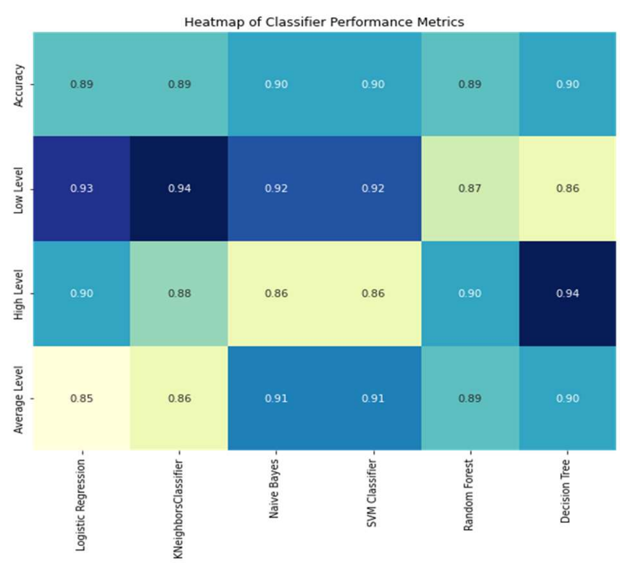

Fig *11. Comparison Of Different Algorithm*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

REFERENCES

[1]. Y. Jung and Y. I. Yoon, "Multi-level assessment model for wellness service based on human mental stress level," “Multimedia Tools and Applications”, vol. 76, no. 9, pp. 11305-113, 2017.

[2]. "Predicting stress levels of secondary school students using machine learning approaches," “Test Engineering and Management”, vol. 83, pp. March-April, 2020.

[3]. L. Xin, C. Zetao, Z. Yunpeng, et al., "Stress state evaluation by an improved support vector machine," “Neurophysiology”, vol. 48, pp. 86-92, 2016.

[4]. Ghaderi, J. Frounchi, and A. Farnam, "Machine learning-based signal processing using physiological signals for stress detection," in “2015 22nd Iranian Conference on Biomedical Engineering (ICBME)”, Tehran, Iran, 2015, pp. 93–98.

[5]. R. Rois, M. Ray, A. Rahman, and S. K. Roy, "Prevalence and predicting factors of perceived stress among Bangladeshi university students using machine learning algorithms," “Journal of Health Population and Nutrition”, vol. 40, pp. 1-12, 2021.

[6]. K. A. Armstrong and N. G. Khawaja, "Gender differences in anxiety: an investigation of the symptoms, cognitions, and sensitivity towards anxiety in a nonclinical population," “Behavioral and Cognitive Psychotherapy”, vol. 30, pp. 227-231, 2002.

[7]. Daza, "Systematic review of machine learning techniques to predict anxiety and stress in college students," “Informatics in Medicine Unlocked”, vol. 43, 2023.

[8]. Pan American Health Organization, "The burden of mental disorders in the region of the Americas," “PAHO”, 2018. [Online]. Available: https://iris.paho.org/handle/10665.2/49578.

[9]. M. C. Pascoe, S. E. Hetrick, and A. G. Parker, "The impact of stress on students in secondary school and higher education," “International Journal of Adolescence and Youth”, vol. 25, no. 1, pp. 104-112, 2020. [Online]. Available: https://doi.org/10.1080/02673843.2019.1596823.

[10]. World Health Organization, "Investing in mental health," “WHO”, 2003. [Online]. https://apps.who.int/iris/bitstream/handle/10665/42823/9241562579.pdf.

[11]. Y. T. Xiang, Y. Yang, W. Li, L. Zhang, Q. Zhang, and T. Cheung, "Timely mental health care for the 2019 novel coronavirus outbreak is urgently needed," “The Lancet Psychiatry”, vol. 7, no. 3, pp. 228-229, 2020.

[12]. G. P. Chrousos, "Stress and disorders of the stress system," “Nature Reviews Endocrinology”, vol. 5, no. 7, pp. 374-381, June 2009.

[13]. J. T. Le Pelley, D. Watson, L. Begg, L. Albertella, and M. E. Le Pelley, "Physiological and subjective validation of a novel stress procedure: The simple singing stress procedure," “Behavior Research Methods”, vol. 53, no. 4, pp. 1478-1487, Aug. 2021.

[14]. J. Sänger, L. Bechtold, D. Schoofs, M. Blaszkewicz, and E. Wascher, "The influence of acute stress on attention mechanisms and its electrophysiological correlates," “Frontiers in Behavioral Neuroscience”, vol. 8, p. 353, Oct. 2014.

[15]. M. Mather and N. R. Lighthall, "Risk and reward are processed differently in decisions made under stress,"“Current Directions in Psychological Science”, vol. 21, no. 1, pp. 36-41, Feb. 2012.

[16]. P. Kim, et al., "Effects of childhood poverty and chronic stress on emotion regulatory brain function in adulthood," “Proceedings of the National Academy of Sciences of the United States of America”, vol. 110, no. 46, pp. 18442-18447, Nov. 2013.

[17]. K. G. Noble, et al., "Family income, parental education, and brain structure in children and adolescents," “Nature Neuroscience”, vol. 18, no. 5, pp. 773-778, May 2015.

[18]. P. Bobade and Vani, "Stress detection with machine learning and deep learning using multimodal physiological data," in “Second International Conference on Inventive Research in Computing Applications”, 2020.

[19]. J. Wijsman, B. Grundlehner, and H. Liu, "Towards mental stress detection using wearable physiological sensors," in “2011 IEEE International Conference on Data Mining Workshops”, Vancouver, Canada, 2011.

[20]. N. Sulaiman, "Determination and classification of human stress index using nonparametric analysis of EEG signals," Ph.D. dissertation, Universiti Teknologi MARA, 2015.

[21]. S. Sriramprakash, V. D. Prasanna, and O. R. Murthy, "Stress detection in working people," “Procedia Computer Science”, vol. 115, pp. 359-366, 2017.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[22]. P. Madhan Mohan, et al., "Stress measurement from wearable photoplethysmographic sensor using heart rate variability data," in “International Conference on Communication and Signal Processing”, 2016, ISBN: 978-1-5090-0396-9.

[23]. J. Zhang, et al., "Recognition of real-scene stress in examination with heart rate features," in “International Conference on Intelligent Human-Machine Systems and Cybernetics”, 2017, ISBN: 978-1-5386-3022-8.

[24]. J. Bakker, et al., "What’s your current stress level? Detection of stress patterns from GSR sensor data," in “2011 11th IEEE International Conference on Data Mining Workshops”, Vancouver, Canada, 2011, ISBN: 978-0-7695-4409-0.

[25]. R. A. Rahman, K. Omar, S. A. Mohd Noah, M. S. N. M. Danuri, and M. A. Al-Garadi, "Application of machine learning methods in mental health detection: A systematic review," “IEEE Access”, vol. 8, pp. 183952-183964, 2020.

[26]. R. Ahuja and A. Banga, "Mental stress detection in university students using machine learning algorithms," “Procedia Computer Science”, vol. 152, pp. 349-353, 2019.

[27]. S. Rao, K. Pushpalatha, R. Sapna, and H. Monika Rani, "An analysis of the psychological implications of COVID-19 pandemic on undergraduate students and efforts on mitigation," in “Communications in Computer and Information Science”, 2022, pp. 133-147.

[28]. U. Reddy, A. Thota, and A. Dharun, "Machine learning techniques for stress prediction in working employees," in “2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)”, 2018.

[29]. Thotad, et al., "Diabetes disease detection and classification on Indian demographic and health survey data using machine learning methods," “Diabetes and Metabolic Syndrome: Clinical Research and Reviews”, vol. 17, 2023.

[30]. G. Deena and K. Raja, "Keyword extraction using latent semantic analysis for question generation," “Journal of Applied Science and Engineering”, vol. 26, no. 4, pp. 501-510, 2023.

[31]. G. Deena and K. Raja, "Objective type question generation using natural language processing," “International Journal of Advanced Computer Science and Applications”, vol. 13, no. 2, pp. 539-548, 2022.

[32]. G. Deena, et al., "Developing the assessment questions automatically to determine the cognitive level of the e-learner using NLP techniques," “International Journal of Service Science Management Engineering and Technology”, vol. 11, no. 2, pp. 95-110, 2020.