QUANTITATIVE ASSESSMENT AND CLASSIFICATION OF PERCEIVED STRESS -A STATISTICAL AND MACHINE LEARNING APPROACH USING PSS-10 SCALE

A Thesis Submitted
in Partial Fulfilment of the Requirements for the
Degree of

MASTER OF TECHNOLOGY
in
SOFTWARE ENGINEERING

by
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CANDIDATE'S DECLARATION

I, Pavitra Rani Gautam, 2K23/SWE/23 student , hereby certify that the work which is being presented in the thesis entitled **"Quantitative Assessment and Classification of Perceived Stress - A Statistical and Machine Learning Approach using PSS-10 Scale "** in partial fulfilment of the requirement for the award of the Degree of MASTER OF TECHNOLOGY in SOFTWARE ENGINEERING, submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my own work carried out during my degree under the supervision of Professor Ruchika Malhotra.

The matter presented in this report/thesis has not submitted by me for the award of any other degree of this or any other Institute/University.

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CERTIFICATE

I hereby certify that the Project Dissertation **"Quantitative Assessment and Classification of Perceived Stress - A Statistical and Machine Learning Approach using PSS-10 Scale",** submitted by Pavitra Rani Gautam, Roll No 2K23/SWE/23, to the Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirements for the award of the Degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

This thesis outlines stress factors that affect military personnel’s and student’s performance in various situations. The present thesis comprises two objectives, Objective 1: identified the different factors in military context that contribute to military suicide, taking into account psychological, personal, social, behavioral and administrative issues. Under this author, we identify the key factors leading to the surprisingly high suicide rate among soldiers. Gaining understanding of these elements is essential to improve the welfare, security and efficiency of military personnel. The study compares the results and findings of all selected studies to identify the most crucial factors. It was also found that there is no significant difference in stress levels between the different ranks of officers and soldiers in the military. Under Objective 2: We examine the performance of machine learning algorithms which help in early prediction of stress among university students using the best prediction model. The dataset was taken from postgraduate (Master of Technology) students using Google form , it consisted of 57 students data. We have applied 6 types of classification algorithms: Logistic (75.00%), KNN (83.33%), SVM (66.67%), the Decision Tree (92.00%), Random Forest (92.00%)and Naive Bayes’ (91.67%) and also we calculated their accuracy with the help of confusion matrix. In this study, Decision Tree algorithm and Random Forest algorithm shared an equal and highest accuracy of 92.00% as compared to other algorithms. Objective 3: Construct validity of the perceived stress scale (PSS-10) in a sample of university student’s dataset. The result of our study showed that the PSS-10, as a two factor model with good reliability and validity, may accurately measure the stress levels among university students.

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ABBREVIATIONS

Machine Learning	ML
Decision Tree	DT
Random Forest	RF
K-Nearest Neighbors	KNN
Linear Regression	LR
Perceived Stress Scale-10	PSS-10
Standard Deviation	SD
Support Vector Machines	SVM

CHAPTER 1
INTRODUCTION

1.1 Understanding Stress

The terminology **stress** was first coined by Hans Selley in the 1930s. The Selyes General Indication Syndrome (GAS) model define total three stages of stress response as alarm, resistance and fatigue [1]. This framework remains fundamental in stress research, demonstrating how chronic exposure to stressors can drain individuals' physical and emotional resources. Since the early studies of Sely's research, many psychological models have expanded their understanding of stress. In particular, the transaction model developed by Lazarus and Faulkman highlights the role of cognitive assessment and coping strategies in communicating stress responses [2].

Stress has become an increasingly prominent subject of academic, clinical, and social discourse due to its significant impact on individual well-being and public health. Defined broadly, stress is the individual body's defensive reaction to any pressure or challenge that ruin its equilibrium, whether physical, emotional, or psychological. It is more essential than ever to get understand the causes, effects, and nature of stress in today's world, where frequent changes, high standards, and continual stimulation are the norm. Stress broadly categories as acute or chronic, external or internal, and may be due to events such as loss of job, academic performance pressure, interpersonal conflict, or health issues. Internal factors consists perfectionism, negative thought, and lack of control etc. Furthermore, a person's response is mostly depending the way he perceives a situation rather than by the stressor itself. Two people behave totally different in same situation just because of their individual resilience, support networks, personality, and past experiences.

Stress has all over the body effect including psychological, physiological, and behavioral of a person and many more things. Anxiety, depression, irritability, and cognitive impairments all are linked to stress even poor memory concentration is also associated with it. Physically heart related problems, weakened immunity, hormonal imbalances, and sleep disturbances are primarily caused by prolonged stress.

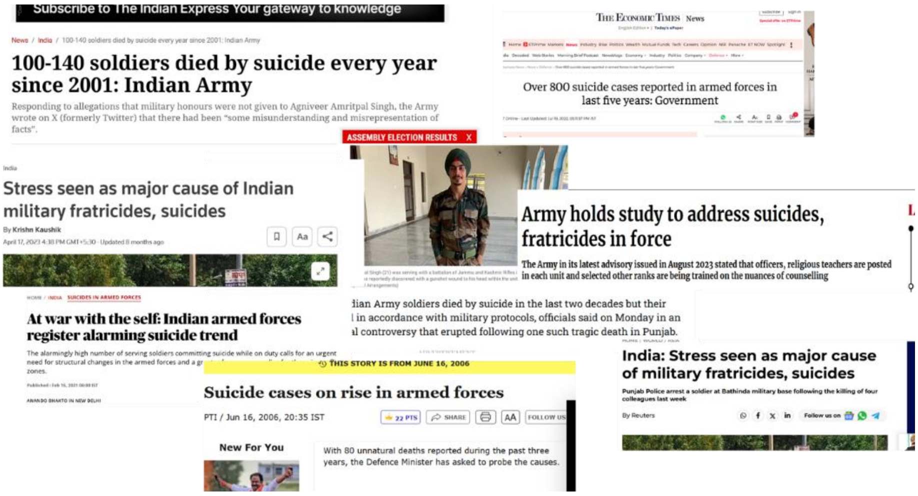
Stress management is a hot topic of research in fields ranging from psychology and neuroscience to public health and education because of its complexity and its wide effects. Understanding stress is very important not only to addressing individual well-being but also for developing institutional and societal frameworks that foster resilience and psychological safety.

1.2 Stress in Soldier life

The ministry of Defence released a report according to this report one member it can be from army, air force or navy committed suicide in every three days which is very disturbing. This report as prepared by compiling data from 1st January 2014 to 31st March 2017. This report state that 348 soldiers died by suicide while they were on duty [3].

The huge increase in suicide rates in armed forces is a grave concern that demands urgent concern or attention and comprehensive understanding of the causes for this act. This research aims to identify important factors influencing suicidal tendencies within the armed forces by shedding light on this critical issue that shoul be adopted for the well-being of our military personnel’s. This also checks whether there’s any difference in stress level or not in all ranks. Combat exposure, post-traumatic stress disorder (PTSD), posting- related stress, interpersonal conflicts, and access to lethal means all are the main factors which contribute to the elevated suicide rates. However, reasons for all these elements remains poorly understood.

By undertaking and performing systematic investigation, this project seeks to uncover the circumstances surrounding armed forces cause suicidal cases. Any methods as surveys, interviews, and data analysis are used to discern patterns, commonalities, and outliers within the demographic, psychological, and environmental aspects of armed forces personnel. The results provide insightful information about the root causes an also serves as a foundation for developing focused intervention strategies and support mechanisms. Ultimately, this research contribute to the overall well-being of armed forces personnel by fostering a better knowledge of the factors impacting suicide rates. Since the year 2003 to 2022 total 2932 soldiers committed suicide which is a huge number.



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News / India / 100-140 soldiers died by suicide every year since 2001: Indian Army

100-140 soldiers died by suicide every year since 2001: Indian Army

Responding to allegations that military honours were not given to Agniveer Amritpal Singh, the Army wrote on X (formerly Twitter) that there had been "some misunderstanding and misrepresentation of facts".

THE ECONOMIC TIMES News

Over 800 suicide cases reported in armed forces in last five years: Government

ASSEMBLY ELECTION RESULTS X

India

Stress seen as major cause of Indian military fratricides, suicides

By Krishn Kaushik

April 17, 2023 4:38 PM GMT+5:30 · Updated 8 months ago

Army holds study to address suicides, fratricides in force

The Army in its latest advisory issued in August 2023 stated that officers, religious teachers are posted in each unit and selected other ranks are being trained on the nuances of counselling

dian Army soldiers died by suicide in the last two decades but their

in accordance with military protocols, officials said on Monday in an

controversy that erupted following one such tragic death in Punjab.

HOME / INDIA SUICIDES IN ARMED FORCES

At war with the self: Indian armed forces register alarming suicide trend

The alarmingly high number of serving soldiers committing suicide while on duty calls for an urgent need for structural changes in the armed forces and a gr

zones.

ANANDO BHAKTO IN NEW DELHI

THIS STORY IS FROM JUNE 16, 2006

Suicide cases on rise in armed forces

PTI / Jun 16, 2006, 20:35 IST

New For You

With 80 unnatural deaths reported during the past three years, the Defence Minister has asked to probe the causes.

India: Stress seen as major cause of military fratricides, suicides

Punjab Police arrest a soldier at Bathinda military base following the killing of four colleagues last week

By Reuters

Figure 1.1: News of suicide in armed forces

As per the report of Deccan Herald (DH) in every three days one of the soldier is committing suicide. Year wise distribution is given in Table 1.

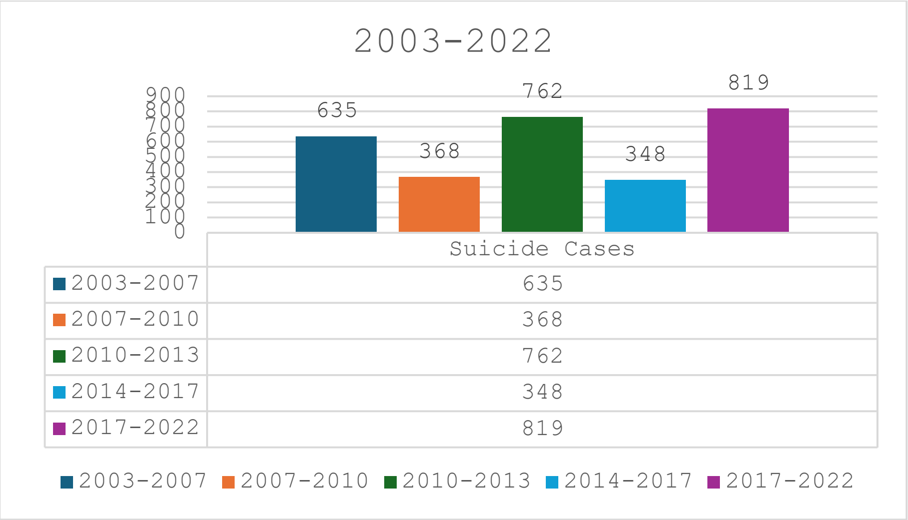


Figure 1.2 : Year wise suicide cases among military personnel

This need to be addressed and worked upon it for well being of our national support system.

1.3 Stress in student life

Student life is the best phase of an individual life and considered as a golden period in one's life. It is full of opportunities for learning, personal growth, and preparation for the future. Stress is less discussed issue instead of the excitement and academic difficulties in student life. Stress among students is global problem from their school to college level. It can be caused by a number of things, such as personal struggles, economic constraints, social expectations, and academic pressures. To protect the overall health of the future generations, educators, elected officials, and society at large must have a thorough understanding of student stress, including its causes, effects, and management techniques.

Define Student Stress?

Stress is the anyone’s natural response to obstacles or requirements, and while it can sometimes motivate students to perform better, prolonged or excessive stress adversely effects on their mental, emotional, and physical well being. Student stress refers specifically to the stressors and pressures associated with academic life [19]. It is a multi-faceted phenomenon influenced by various internal and external factors, such as rigorous study schedules, competition, parental expectations, and the transition to new environments like college or university.

Figure 1.3 : Impact of Stress on a Student

(Source:https://www.linkedin.com/pulse/managing-student-stress-promoting-well-being-insights-)

While occasional stress can be beneficial for performance, chronic stress often leads to burnout, anxiety, depression, and other health issues. For students, these challenges can manifest in difficulty concentrating, poor performance in study, strained relationships, and even long-term mental health issues.

1.3.1 Causes of Student Stress

Stress among students is not a singular problem but a culmination of various factors that differ by individual, age, and circumstances. Below are some of the most common causes:

Academic Pressure: One of the primary contributors to student stress is academic expectations. The pressure to perform well in exams, achieve high grades, and meet deadlines can be overwhelming. In this highly competitive environment, the constant demand to excel often leads students to feel low or overloaded.

Parents Expectations: Students are frequently face their parents' high standard expectations along with society pressure in order to maintain family reputations, excel academically and financially. These demands can increase his fear of failing.

Peer Pressure: Competitive feeling with fellow students has significant impact on their life. Pressure to fit in all dimensions including academically, achievements with classmates etc. increases stress and feeling of isolation. This is particularly found in adolescents and young adults navigating social dynamics in schools and universities.

Financial Struggles: Economic constraints are a major cause of stress in higher education system. Maintaining academic performance is made more difficult by the reality that many students balance between tuition, student loans, and part-time jobs.

Technological and Digital Stress: As digitization s the backbone of today's world so the use of technology in education increasing day by day. It has both positive and negative impact on students. It can be used for gaining opportunities and can also be a stressor if used unwisely.

Transition and Adjustment: : For many students, it is the case when they have to move from one place to another if their parents have transferable job. This movement to a new environment can also be a significant cause of stress for the students.

Personal and Emotional Challenges: Stress level frequently get worsen with personal struggles such as family issues, relationship problems etc. Many students may also face mental health issues , such as anxiety hyper tension ,depression , sadness, which go unnoticed or untreated.

1.3.2 Impacts of Student Stress

The consequences of unmanaged stress are far-reaching, affecting students' academic, physical, and emotional well-being. Below are some key impacts:

Academic Performance: Chronic stress can impair cognitive functions like memory, focus, and problem-solving, leading to a decline in academic performance. Procrastination, missed deadlines, or exam anxiety are common outcomes[20].

Physical Health: Stress manifests physically through symptoms such as tiredness, headaches, fatigue, sleeplessness disturbances, and weakened immunity. Long-term stress increases the risk of conditions like hypertension, heart disease, and gastrointestinal issues.

Mental Health: Student stress is associated to mental health problems like anxiety, helplessness, , depression, and lack of energy. In extreme cases, it can lead to suicidal thoughts or action, emphasizing the necessity for urgent intervention.

Social Relationships: Stress often impacts students' interpersonal relationships. It can lead to withdrawal from friends and family, irritability, or difficulty maintaining social bonds.

Reduced Quality of Life: When stress becomes overwhelming, students may experience a diminished sense of purpose, reduced motivation, and difficulty enjoying life, all of which affect their overall quality of life.

1.3.3 . Coping Mechanisms and Stress Management

Understanding how to manage and mitigate stress is critical for students to lead balanced, fulfilling lives. Effective stress management involves a combination of individual practices, institutional support, and societal awareness.

Time Management: Better time management is one of the most critical skills for students. Assign priority to tasks, setting of doable goals, and avoiding delay or laziness can help reduce the overwhelming nature of academic responsibilities.

Physical Activity and Health: With adequate sleep if you do regular physical activity and have balance diet you can beat stress as it is a natural stress reliever.

Mindfulness and Relaxation Techniques: Techniques like mindfulness meditation, yoga, and regular deep breathing exercises, dhyan can help students in managing stress in better way. This will develop a high sense of self-awareness.

Social Support : A strong and solid support system that can have friends, family, or counselors, is crucial for managing stress. Open communication can alleviate feelings of isolation and provide perspective on problems.

Professional Help : Counseling services play a vital role in helping students address stress-related issues. Schools and universities should prioritize accessible mental health support and regular counselling sessions for students who need it.

Institutional Measures : Educational institutions can implement stress-reduction programs as a part of study. The can also reduce excessive academic workloads, and create environments that has student well-being over everything .

Digital Detox: Limiting screen time and practicing digital detox can help students avoid the stress associated with social media and excessive information consumption.

1.3.4 . Societal and Institutional Role in Addressing Student Stress

While individual efforts are essential, tackling student stress requires a collective approach involving families, schools, governments, and society at large. Key initiatives include:

a. Raising Awareness

Promoting awareness about the causes and impacts of stress is vital for early intervention. Campaigns, workshops, and seminars can educate students and parents about recognizing and managing stress.

b. Mental Health Integration

If mental health education should be included into school curriculum. There should be all tools to manage stress and promote resilience from childhood.

c. Policy Changes

Governments and policymakers must address systemic issues that contribute to stress, such as educational inequities, financial burdens, and the overemphasis on standardized testing.

d. Creating Safe Spaces

Schools and colleges should create environments where students feel safe to express their concerns without fear of judgment or punishment.

1.4 Objectives and Hypothesis

Objective 1: “Identify the variations in stress level among the various army ranks officials”

Null Hypothesis (H_0):

The stress level of different rank officials in military personnel’s is equal.

Alternate Hypothesis (H_1):

There is a significant difference in stress level of different rank officials in military personnel’s

Objective 2: “Identify the best ML model for stress prediction: Model efficiency Comparison”

Null Hypothesis (H_0):

All Machine learning algorithms have same accuracy for predicting the stress levels in university students based on the given dataset.

Alternate Hypothesis (H_1):

All Machine learning algorithms have significant difference in their accuracy for predicting the stress levels in university students based on the given dataset.

Objective 3: “Validation of the perceived stress scale (PSS-10) in a university student”

1.5 Scope of The Research

1. **Identification of Stress Factors**
    - Examine academic, social, personal, and environmental stressors impacting university students.
    - Collect and analyse data related to physical, emotional, and behavioural indicators of stress.
2. **Data Collection**
    - Gather data from university students through surveys, questionnaires, or academic records.
3. **Application of Machine Learning Algorithms**
    - Implement supervised and unsupervised machine learning techniques to examine or evaluate stress levels.
    - Evaluate models like SVM, Decision Trees, N, Random Forests, etc.
4. **Model Evaluation**
    - Performance metrics are used assess model performance . There are many metrics like accuracy, precision, recall etc.
    - In order to ensure the model's generalizability, cross-validation is performed if required.
5. **Prediction and Classification**
    - Develop a model capable of predicting stress levels (e.g., low, moderate, high) .
6. **Future Directions**

    - Explore the scalability of the system to larger populations or different educational settings.
    - Investigate the inclusion of additional parameters like cultural or regional factors

7. **Ethical and Privacy Considerations**
    - Ensure data privacy and security during data collection and analysis.
    - Obtain informed consent from participants and follow ethical research practices. (if applicable)

This scope outlines a structured approach to investigating, predicting, and addressing stress levels in university students using ML, with potential for practical applications and future expansion.

CHAPTER 2

LITERATURE REVIEW

2.1 FACTORS ASSOCIATED WITH MILITARY SUICIDE CASES

Suicide is common in the general public as well as in the military. In the general scenario, not much research has been done in the military. This could be due to the limited access to the data, or there could be some other administrative or political reasons. We searched the online databases and found that 58 articles were found using key words such as military suicide and factors. After removing duplicates, we left with 36 papers. We applied the inclusion and exclusion criteria as follows: (1) free full text; (2) comparable statistics; (3) focus on military personnel as subjects; (4) year of publication: 2010–2024; and (5) factors and reasons in the body of the papers.. Figure 4 shows the flow char for this.

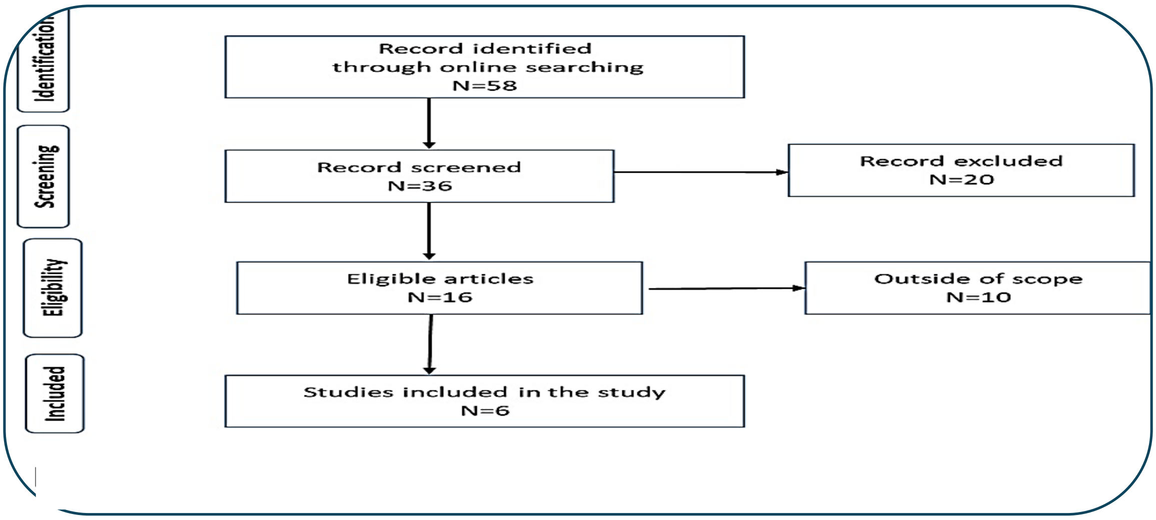
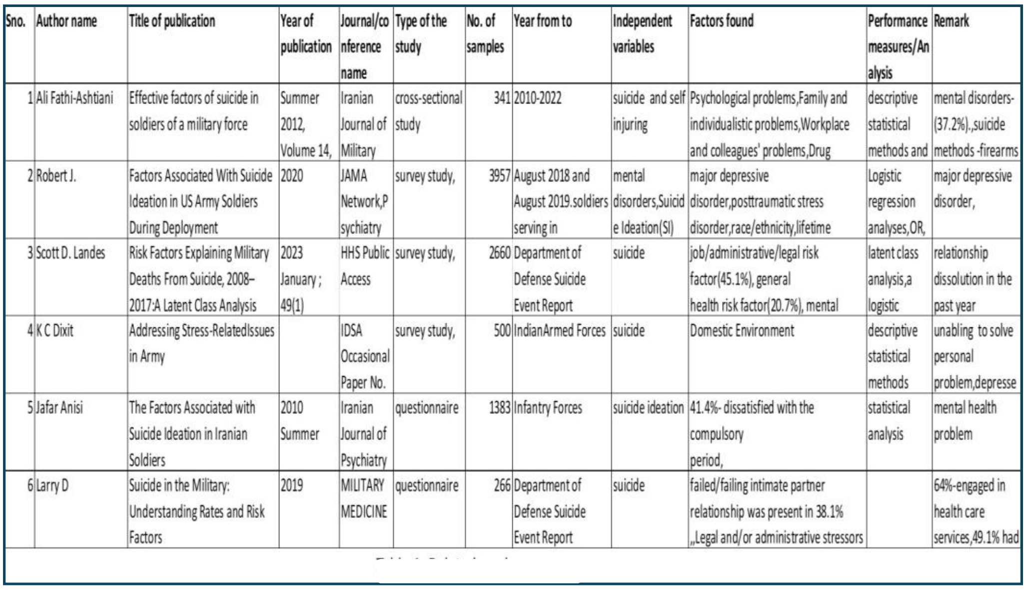


Figure 2.1: Prisma Flow Chart :military studies

Related work in the area has been reviewed. After the main information about the factors, their reasons, what their significance is, how much they influence the suicide rate, what are the statistics used to conclude the results, and in which year the publication has been made, all the necessary information is included in Table 1: Comparison of Related Work.



Sno.	Author name	Title of publication	Year of publication	Journal/conference name	Type of the study	No. of samples	Year from to	Independent variables	Factors found	Performance measures/Analysis	Remark
1	Ali Fathi-Ashtiani	Effective factors of suicide in soldiers of a military force	Summer 2012, Volume 14,	Iranian Journal of Military	cross-sectional study	341	2010-2022	suicide and self injuring	Psychological problems,Family and individualistic problems,Workplace and colleagues' problems,Drug	descriptive statistical methods and	mental disorders-(37.2%).,suicide methods -firearms
2	Robert J.	Factors Associated With Suicide Ideation in US Army Soldiers During Deployment	2020	JAMA Network,Psychiatry	survey study,	3957	August 2018 and August 2019.soldiers serving in	mental disorders,Suicide Ideation(SI)	major depressive disorder,posttraumatic stress disorder,race/ethnicity,lifetime	Logistic regression analyses,OR,	major depressive disorder,
3	Scott D. Landes	Risk Factors Explaining Military Deaths From Suicide, 2008–2017:A Latent Class Analysis	2023 January ; 49(1)	HHS Public Access	survey study,	2660	Department of Defense Suicide Event Report	suicide	job/administrative/legal risk factor(45.1%), general health risk factor(20.7%), mental	latent class analysis,a logistic	relationship dissolution in the past year
4	K C Dixit	Addressing Stress-RelatedIssues in Army		IDSA Occasional Paper No.	survey study,	500	IndianArmed Forces	suicide	Domestic Environment	descriptive statistical methods	unabling to solve personal problem,depresse
5	Jafar Anisi	The Factors Associated with Suicide Ideation in Iranian Soldiers	2010 Summer	Iranian Journal of Psychiatry	questionnaire	1383	Infantry Forces	suicide ideation	41.4%- dissatisfied with the compulsory period,	statistical analysis	mental health problem
6	Larry D	Suicide in the Military: Understanding Rates and Risk Factors	2019	MILITARY MEDICINE	questionnaire	266	Department of Defense Suicide Event Report	suicide	failed/failing intimate partner relationship was present in 38.1% „Legal and/or administrative stressors		64%-engaged in health care services,49.1% had

Table 2.1: Selected studies

Ashtiani, Ali Fathi-et al. (2012) [4]. In their cross-sectional investigation, [1] found that 44% of the participants had a history of self-mutilation or suicide. Mental illnesses accounted for the majority of the background factors associated with suicide and self-mutilation (37.2%). difficulties with coworkers and the work environment (13.8%), as well as family issues (36.7%). Winter was the season when most suicides were committed. usage of guns (49.9%), stabbing (25.2%), drug usage (18.5%), hanging (4.4%), consuming oil and hand soap (1.2%), and jumping from a height (0.9%) were the means of suicide. For his research, he employed analytical tests like the Chi-Square test and descriptive statistical techniques.

Using a survey study, Robert J. et al. (2020) [5] discovered that 44.2% of people had major depressive disorder (MDD). Aside from this post-traumatic stress disorder, other indicators include race or ethnicity, lifetime noncombat trauma, interpersonal issues, legal issues, or the illness or death of a friend or family member.

Scott D. Landes et al. (2023) [6] used a survey study in their procedures. While conducting the study, they used latent class analysis and a logistic regression model and found that job/administrative/legal risk factors (45.1%), general health risk factors (20.7%), mental health risk factors (47.7%), and relationship dissolution in the past year (51.1%) were the major factors for suicide among soldiers.

K. C. Dixit et al. (2011) [7] conducted a survey in the Indian Army in 2011 to find out the factors contributing to suicidal attempts. They performed descriptive statistics and concluded that the domestic environment is the main factor. The study stated that the majority of soldiers were unable to solve personal problems and were depressed, which motivated them to make suicidal attempts.

Jafar Anisi et al. (2010) [8] showed that psychological factors, poor and negative family background, environmental surroundings and assigned work issues, and sociodemographic problems were significantly associated with suicide ideation: 41.4% of people were dissatisfied with the compulsory period, while 25.2% were not satisfied with their seniors officers in charge, and 11.9% of the subjects showed feelings of worthlessness in their work environment.

Using DoDSER data reports, Larry D. et al. (2019) [9] found that 49.1% of the population had a history of having at least one behavioral health condition or issue. Twenty-six percent (24.6%) received a diagnosis of substance addiction or dependence. The second most common diagnosis, found in 23.2% of cases, was adjustment disorder. In 12.5% of cases, major depression was found, and in 8.3% of cases, post-traumatic stress disorder was diagnosed.

2.2 LITERATURE REVIEW: STRESS IN UNIVERSITY STUDENT: FACTORS

Numerous studies have been undertaken regarding stress, particularly among college students. **Cheng Ding, Yuhao Zhang, and Ting Ding [10]** proposed a combined model called hybrid model (HB) which was the fusion of random forest along with gradient boosting machine (GBM) model. Soft voting criteria will be used to merge these models, and the final projection will be based on the prediction probability of each model. With 100% accuracy, the suggested model is noteworthy when compared to the most sophisticated techniques. They carried out a 10 fold cross validation using the suggested model to demonstrate the importance of the suggested method, and the suggested HB model performs better with a mean accuracy of 1.00 and a SD of +/- 0.00. Ultimately, They used a statistical T-test to demonstrate the importance of the suggested strategy when compared to different approaches.

Disha Sharma Sumit Chaudhary [11] Stress is an issue which is getting worse day by day and also has an impact on the personal physical and psychological well-being of an individual. The classification methods we have utilized Naive Baye's, Logistic Regression, Multilayer perceptron in prediction. The accuracy of different techniques are calculated and compared by using Weka tool, . This paper noticed Baye's Net classifier provides the longest accuracy of 88 %. They examine 220 undergrad and postgraduate students. The data was collected by google dox.

Garima Verma*, Sandhya Adhikari, [12] These days, a startling percentage of teenager and young adult people suffer from anxiety and despair. One of the primary cause is Mental strain. Finding the variables that influence mental health conditions including anxiety, stress, and depression in college students—particularly in engineering schools was the goal of this research. To forecast the pupils' stress levels, two machine learning models Logistic and (SVM) were put forth. 513 individuals enrolled in graduation-level engineering programs in northern India made up the dataset for this study. Both online and offline surveys were used to gather the data. The models performance is measured by using performance metrics such as accuracy, precision, recall, and curve performance. The SVM obtained 86.84% accuracy, whereas the logistic regression achieved 67%.

Ishrak Jahan Ratul ,2023 [13] , This study create a trustworthy prediction model based on ML for predicting perceived stress and validate it with actual data gathered from an online survey completed by 444 college students of various ethnic backgrounds. Supervised ML algorithms were used to design the machine learning models. The chi-squared test and Principal Component Analysis (PCA) were used as feature reduction methods. Additionally, genetic algorithms (GA) and grid search cross-validation (GSCV) were used for hyperparameter optimization (HPO). The results showed that approximately 11.26% of people had significant levels of social stress. Comparatively, it was shown that about 24.10 percent of participants having high psychological stress, which is concerning for the mental health of students. Additionally, the ML models' prediction results showed the most impressive recall value (0.826), F1 score (0.890), accuracy (80.5%), and precision (1.000). Combining the Multilayer Perceptron model with GSCV for HPO and PCA as a feature reduction technique yielded the highest accuracy.This study's convenience sampling method solely takes self-reported data into account, which could lead to biased and non-generalizable conclusions .mobile devices and support the welfare of students in times of stress, such as pandemics. Future studies should examine a sizable data set and concentrate on monitoring the long-term effects of therapies and coping mechanisms. The findings of this study can be utilized to create plans to lessen the negative consequences of excessive mobile device use and support students' wellbeing in times of stress, such as pandemics..

Joey Man Yee KWOK & Douglas Kei Shing[14] This study analyzes Hong Kong students. In Open University of Hong Kong total 337 student data points were gathered. The Perceived Stress Scale 10 (PSS-10) was used in this study is a 10-point scale that is used to measure perceived stress levels. The questionnaire also included

BAI scale to evaluate the convergence validity of PSS-10 scale . General scales of self-efficacy (GSE) and subjective lucky scales (SHS) used to assess the different validity associated with each other. It reveled that , stress levels in individuals in age group between 18 and 29 years had an average of 19.02, which was greater than normal values values (M = 14.2; SD = 6.2) .

Ms. Ancy Paul1, Ms. Resija P R2 et all [15], The study's objective was to detect the different stress levels among students .The main goal is to estimate the levels of stress using use ML algorithms. The 954 student data was obtained from a private college named Vimala College through online survey form. This study used supervised ML classification techniques. Total data was divided into three groups or classes as acute , episodic and chronic. Author trained it with 9 algorithms with satisfying accuracy. Random forest and logistic regression got higher accuracy as compared to others. . Author applied random forest technique in testing phase to precisely detect the stress level and display the class of stress and its level. They used pie chart to show level of stress with 99 percentage of testing accuracy.

Prakruthi Manjunath, Twinkle S et all [16], The author suggested an educational institution system that allows responsible officials to track the stress level of every student. Students are allowed to fill out a questionnaire that determines the causes of their anxiety and mental distress. The survey data gathered are used as input for a pre-trained machine learning model that predicts the stress level of every student. This model carries out a binary classification to establish if a student is stressed or not, and then classifies stressed students into three groups: low, medium, and high. Depending on their level of stress and the probable causes determined, all stressed students are provided with customized solutions and feedback by the educational institution. Through these solutions, students can strive to minimize their stress and improve their mental health. The machine learning model employs the KNN classification algorithm.

Ravinder Ahuja, Alisha Banga [17] Stress causes to many heath issues like feeling of depression , suicide thoughts, heart attack in many cases, and stroke many times. In this study author analyzed the mental stress just one week prior the exam and while using internet . The main goal was to study stress at various stages of student's life .The is lots of pressure that goes unnoted during the time of recruitment and exam . The total 206 college students data points was collected from Jaypee Institute of Information Technology for this research. Four classification algorithms LR, Naïve Bayes, RF, and SVM were used.After that author calculated performance parameter as sensitivity, specificity, and accuracy . The accuracy and performance of data were further improved by applying 10 fold cross validation for correctness . SVM showed highest accuracy of 85.71%

Reshma Radheshamjee Baheti, Supriya Kinariwala [18], A person health is harmed by psychological stress. In today's environment stress is identified in person interview, conversation or any additional technique, where more than two people are examined by another. This suggests a system architecture for detecting user psychological tension strain or stress level by using weekly social sites and media data, tweet ,social interactions etc. Each word in this has a word dictionary grading

from -5 to +5 . This study implemented SVM and second NB algorithm. To increase the result accuracy, the Word Sense Disambiguation by using n-gram and Skip-gram model is used. Using WSD and Ngram SVM yields 65% and 67% precision and recall respectively.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 PROPOSED APPROACH

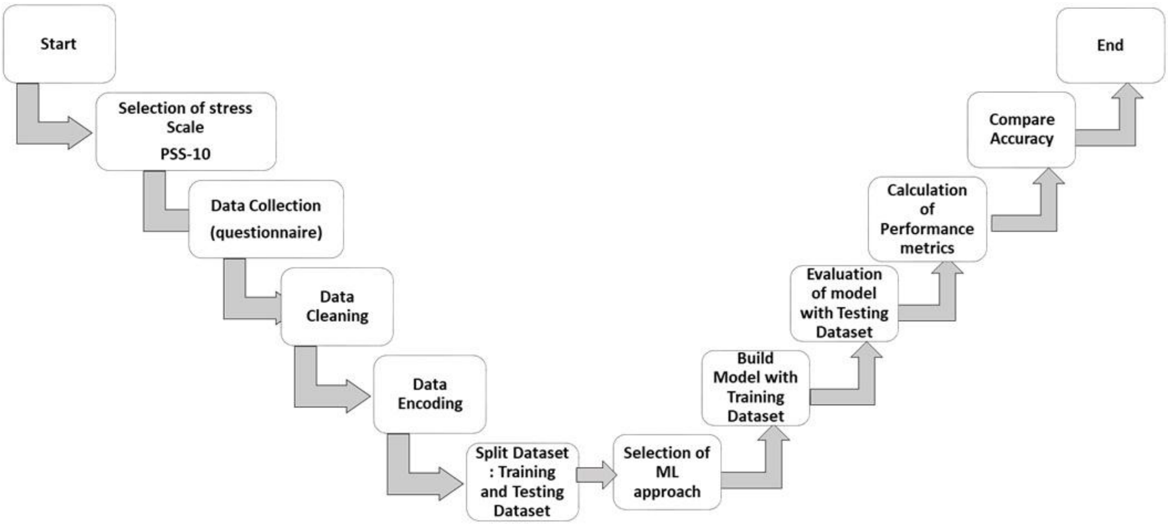


Figure 3.1: Methodology

The steps shown in the above figure ere followed during the research.

3.2 STATISTICS

Statistics is a field of mathematics that deals with the data gathering, analysis with different methods, interpretation of results, presentation of findings, and organization of data in managed way. It facilitates the user essential methods , software and resources for making valuable decisions which are influenced by empirical evidences. In both academic research and real-world applications, statistics play a critical role in understanding patterns, testing hypotheses, and making insightful conclusions or decisions from datasets.

The importance of statistics has grown significantly in recent decades, especially with the rise of data-driven decision-making in fields such as healthcare, economics, education, psychology, and business. By applying statistical methods, researchers can analyze large datasets to uncover trends, measure relationships, assess variability, and evaluate the reliability of findings. Descriptive statistics help summarize data through measures such as mean, median, mode, and standard deviation, while inferential statistics allow researchers to make predictions and generalizations about a population based on a sample.

Key concepts of statistics such as confidence intervals, significance levels, and p-values enable a researcher to evaluate the strength of their findings and reduce the percentage of errors by meeting standards.

If we talk about academic research, statistics provide a rigorous a solid framework for testing hypotheses and validating the results of the research. Whether conducting experiments, surveys, or observational studies, researchers rely on statistical tools to ensure the accuracy and credibility of their work. Proper use of statistical methods enhances the reliability and validity of methods and scientific investigations

3.2.1. Descriptive Statistics

Descriptive statistics is primarily used to provide crucial insights inside the data for understanding it and making intelligent decision. It summarizes large datasets by using measures like mean, median, and mode. It also used in finding the hidden patterns, trends, and central tendencies within the datasets. Descriptive statistics is very important in various fields, from finance to healthcare for risk assessment, resource distribution in various sectors, and performance evaluation. Moreover, descriptive statistics is the backbone of advanced analyses, guiding researchers towards relevant hypotheses and methodologies.

3.2.2. Inferential Statistics

Inferential statistics go beyond merely describing data. They help in making predictions, testing hypotheses, and drawing conclusions about a larger population based on a sample. It help in better understanding of your data.

Key features of inferential statistics are as :

Use in **Hypothesis testing** many test as T-tests, chi-square tests, ANOVA etc are used for this.

Confidence intervals used in Estimating population parameters with a particular level of confidence that can be 95% or 99% as per user requirements.

Regression and correlation analysis: Understanding positive or negative relationships between variables

Probability distributions: Normal distribution, binomial distribution, etc.

Example: Conducting a survey of 100 people to estimate the average income of an entire city or testing whether a new drug is more effective than an existing one

3.3 MACHINE LEARNING TECHNIQUES.

Categorical data often requires specialized machine learning algorithms or preprocessing techniques to handle its discrete nature. Here are brief descriptions of a few key algorithms used in the study [22].

3.3.1. Decision Trees (DT): Decision trees work well with categorical data as they partition the data based on feature values at each node. They handle non-linear relationships effectively, can process mixed types of data, and are intuitive to interpret. Overfitting can occur, but this can be mitigated with pruning techniques or ensemble methods.

3.3.2. Naive Bayes: It is a probabilistic algorithm that assumes that the features are independent. It is particularly suitable for categorical data because it calculates the likelihood of each class given the feature values. Despite its simplicity, it often performs well in text classification and spam detection tasks.

3. K-Nearest Neighbors (KNN): KNN can work with categorical data by using distance metrics such as the Hamming distance. It classifies new incoming instance based on the maximum instances closest neighbors class. While simple to implement, it is expensive when used on large datasets.

3.3.4. Logistic Regression: Logistic regression is applicable for the classification of categorical data in both binary and multiclass scenarios. Through the implementation of the sigmoid function, it forecasts the probabilities for the various classes. Categorical variables often need to be encoded using techniques like one-hot encoding or label encoding before being used [23].

3.3.5. Random Forests (RF): Random forests is a collective method based on decision trees. They are resistant to overfitting and perform well on categorical data.

By averaging or voting across multiple trees, random forests reduce variance and improve predictions.

3.3.6. Support Vector Machines (SVM): Although primarily designed for continuous data, SVMs can handle categorical data through kernel tricks or appropriate encoding. This technique is particularly effective particularly in scenarios where the data cannot be separated linearly.

PERFORMANCE MEASURES.

There are many performance measures we can use to compare the performance of ML models. Performance measurers are calculated using confusion metric elements as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) [24].

Accuracy: It is the ratio of correct prediction (all positive and negative prediction) to the total predictions. Formula used to calculate the accuracy is:

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{All predictions}}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: It is the proportion of rightly positive to all positive predictions. Formula used to calculate the precision is:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall: It represents the proportion of accurately identified positive predictions to the overall count of actual positive occurrences. The formula used to determine recall is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-score : It is defined as the harmonic mean of precision and recall. Formula used to calculate the F1score is

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

ENCODING TECHNIQUES

- **Label Encoding**:
    - Assigns a unique integer to each category.
    - Example: `["orange", "Berry", "Mango"]` → `[0, 1, 2]`.
    - Works well with ordinal data but can introduce artificial order in nominal data.
- **One-Hot Encoding**:
    - Creates columns of 0 and 1 entry for each category.
    - Example: `["orange", "Berry", "Mango` ill be encoded as `[1, 0, 0], [0, 1, 0], [0, 0, 1]`.
    - Avoids ordinal bias but increases dimensionality.
- **Ordinal Encoding**:
    - Encodes categories with a meaningful ordinal relationship.
    - Example: `["Low", "Medium", "High"]` → `[1, 2, 3]`.

- **Target Encoding**:
    - In this mean is placed at the place of each category of the target variable Can introduce leakage if not handled properly with cross-validation.

3.4 PYTHON

Python is a driving force behind Machine Learning because of its simplicity, readability, and rich library ecosystem. It gives developers and scientists the freedom to work on the problem of ML instead of coping with the baroque syntax of other languages. Python supports data acquisition and cleaning, model learning, evaluation, and deployment as well. Python's flexibility makes it perfect for rapid prototyping and experimentation. It is easily compatible with other technologies and has good community support, which guarantees constant updates and plenty of learning materials. Some of the key libraries that make Python so powerful for ML are:

- NumPy and Pandas: Necessary for data manipulation and numerical calculations.
- Matplotlib and Seaborn: is used to performing exploratory data analysis.
- Scikit-learn: is imported for for standard ML algorithms such as classification, regression, and clustering. ETC

3.5 PERCEIVED STRESS SCALE-10 (PSS-10)

The PSS-10 is one of the most popular psychological tests of stress. In the literature, there is evidence of its reliability and validity across different populations and cultures. PSS-10 was developed by Cohen et al. (1983) and it is used to evaluate s stress by self-reported questionnaires focusing on the individual’s life experiences within the previous month passed. Responses gathered from person are measured by using five-point scale from ‘never means 0 ’ to ‘very often means 4’ with maximum score of 40. Higher the scores greater the stress.

Among youth aged 12 and above, this scale is appropriate for use. Additionally, PSS-10 captures perceived stress from two main perspectives: helplessness—negatively phrased items—and self-efficacy—positively framed, reverse-scored items. Although PSS-10 is not a clinical diagnostic tool, it remains useful for assessing general stress levels across different groups and populations. The scale is commonly utilized within clinical frameworks aiming to evaluate stress and measure the subsequent effectiveness of applied interventions. Its non-specific approach allows it to be utilized within many demographic and cultural settings.

The PSS-10 – Stress Indicators:

Measuring and assessing the stress, the (PSS-10) is among the most prevalent psychological stress measuring instruments.

Development and Purpose

The PSS-10 was created in response to the need for a general measure of perceived stress that could be easily administered to population samples with at least a junior high school above age 11. Unlike stress inventories that focus on specific events or diagnoses, the PSS-10 identify the extent to which respondents find their lives measirable, uncontrollable, and overburden -three core dimensions associated with psychological stress [25].

The scale was designed to be general and not limited by age, occupation, or specific life circumstances, making it suitable for use in diverse populations and research contexts.

Structure and Scoring

The PSS-10 having of 10 questions related to stress, each item is assigned 5-point Likert scale ranging from 0 to 4, here 0 indicates never and 4 indicated very often [26]. Respondents are asked to reflect on how often they have experienced certain feelings or thoughts in the past month. The sum of all or I must say score lies between 0 to 40, higher scores means greater perceived stress level.

Six questions (1, 2, 3, 6, 9, 10) are positively feeling based questions hence points are summed directly .While Four questions (4, 5, 7, 8) are reverse-scored so for them reverse scaling done and after that final sum is calculated.

The PSS-10 is suitable for individuals aged 12 and above, making it appropriate for use with adolescents and adults. Its simplicity and general wording ensure that it is accessible to people from varied educational and cultural backgrounds. The scale has been conveted and validated in many other languages to help the all community.

Limitations

While the PSS-10 is a robust tool, it has some limitations:

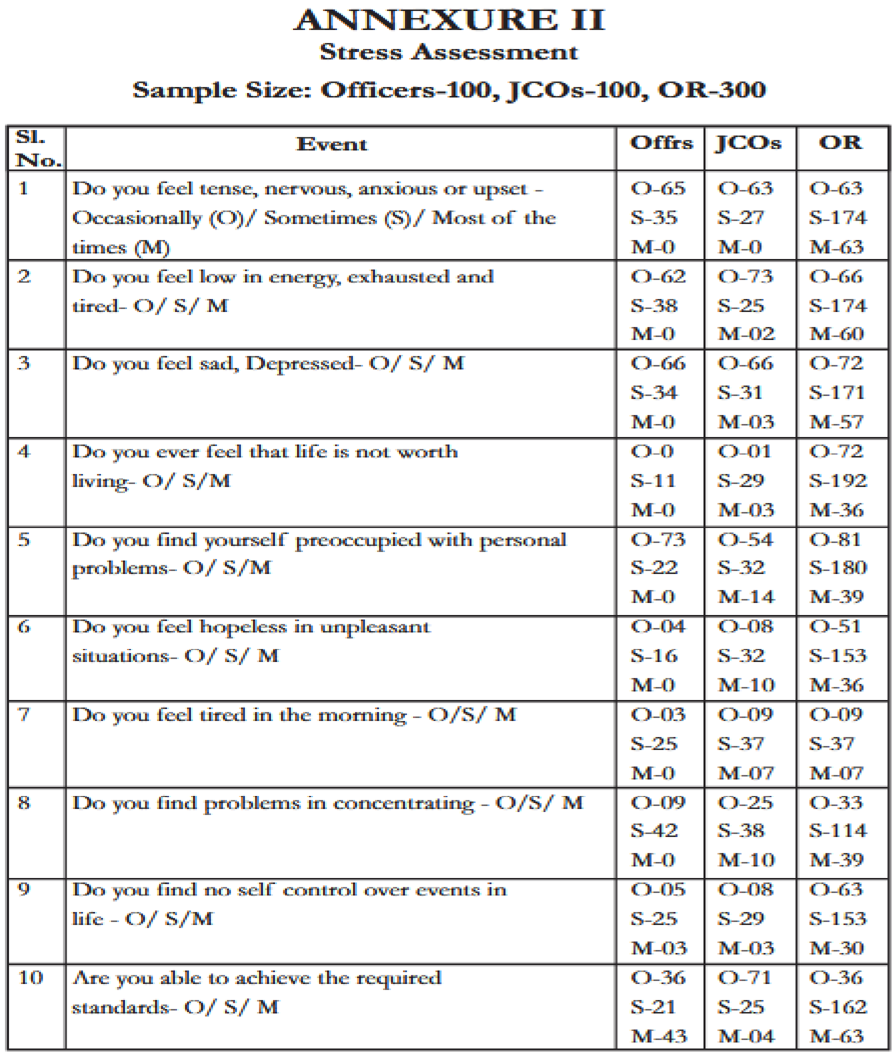
It measures perceived, not objective, stress-capturing subjective appraisal rather than specific stressors or physiological responses.

Predictive validity declines beyond four to eight weeks, so it is best used for assessing recent stress.

3.6 DATASET DISCRIPTION

3.6.1 Dataset 1 : Military Data

K. C. Dixit et al. Institute for Defence Studies and Analyses, New Delhi Addressing Stress-Related Issues in Army, IDSA Occasional Paper No. 17 (Appendix-II)

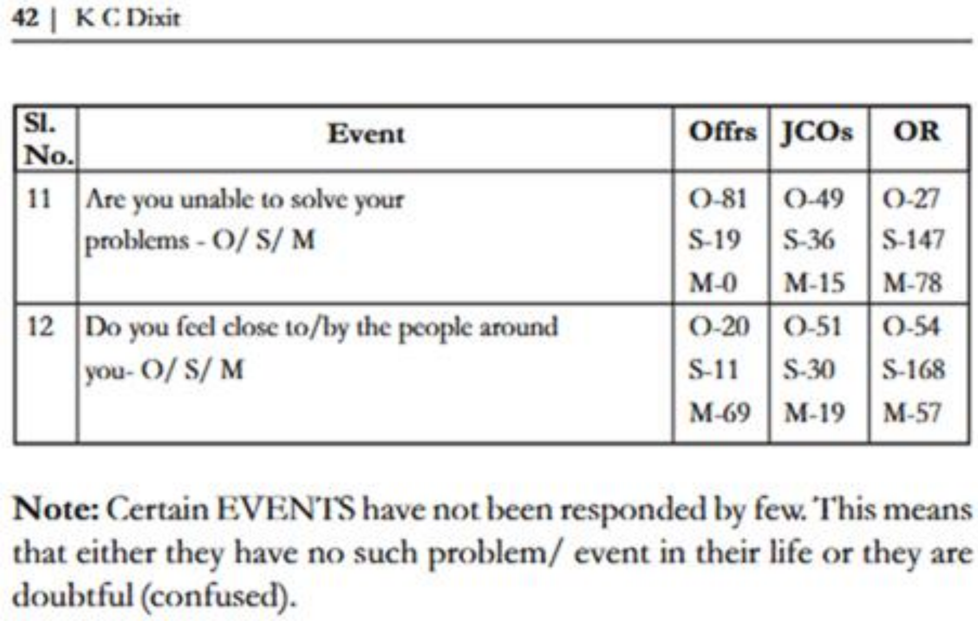


ANNEXURE II

Stress Assessment

Sample Size: Officers-100, JCOs-100, OR-300

Sl. No.	Event	Offrs	JCOs	OR
1	Do you feel tense, nervous, anxious or upset - Occasionally (O)/ Sometimes (S)/ Most of the times (M)	O-65 S-35 M-0	O-63 S-27 M-0	O-63 S-174 M-63
2	Do you feel low in energy, exhausted and tired- O/ S/ M	O-62 S-38 M-0	O-73 S-25 M-02	O-66 S-174 M-60
3	Do you feel sad, Depressed- O/ S/ M	O-66 S-34 M-0	O-66 S-31 M-03	O-72 S-171 M-57
4	Do you ever feel that life is not worth living- O/ S/M	O-0 S-11 M-0	O-01 S-29 M-03	O-72 S-192 M-36
5	Do you find yourself preoccupied with personal problems- O/ S/M	O-73 S-22 M-0	O-54 S-32 M-14	O-81 S-180 M-39
6	Do you feel hopeless in unpleasant situations- O/ S/ M	O-04 S-16 M-0	O-08 S-32 M-10	O-51 S-153 M-36
7	Do you feel tired in the morning - O/S/ M	O-03 S-25 M-0	O-09 S-37 M-07	O-09 S-37 M-07
8	Do you find problems in concentrating - O/S/ M	O-09 S-42 M-0	O-25 S-38 M-10	O-33 S-114 M-39
9	Do you find no self control over events in life - O/ S/M	O-05 S-25 M-03	O-08 S-29 M-03	O-63 S-153 M-30
10	Are you able to achieve the required standards- O/ S/ M	O-36 S-21 M-43	O-71 S-25 M-04	O-36 S-162 M-63



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Sl. No.	Event	Offrs	JCOs	OR
11	Are you unable to solve your problems - O/ S/ M	O-81 S-19 M-0	O-49 S-36 M-15	O-27 S-147 M-78
12	Do you feel close to/by the people around you- O/ S/ M	O-20 S-11 M-69	O-51 S-30 M-19	O-54 S-168 M-57

Note: Certain EVENTS have not been responded by few. This means that either they have no such problem/ event in their life or they are doubtful (confused).

3.6.2 Dataset 2: University College Students

We have used statistician random sampling for data collection. The data collection process yielded information from 57 students total of 106 final year students pursuing M-Tech degrees in CS, IT, SWE, and DS, conducted via a Google Form. The questioner designed for stress prediction is having 14 questions out of which 10 questions are of PSS-10 scale and four questions focuses on kindness for exploring the perceived kindness with stress in our study. The dataset consists of three targeted classes low, moderate and high in alignment with the prescribed standard defined by well-established and validated PSS-10 scale. We have used label encoding for converting the categorical data values to the numerical data . The dataset further partitioned into training set ith 20 percent and testing set with 80% for Machine Learning model training and evaluation. Accuracy, precision, recall and confusion matrix are used to compare the performance along accuracy of a classification model.

In this study , jupyter notebook and python libraries (pandas, numpy, matplotlib, sklearn) are used for metric calculation model selection, data preprocessing , descriptive statistics of machine learning algorithms and data. Details of Dataset used in this study are:

Total Students=106 (M.Tech(DS,IT,SWE and CS))

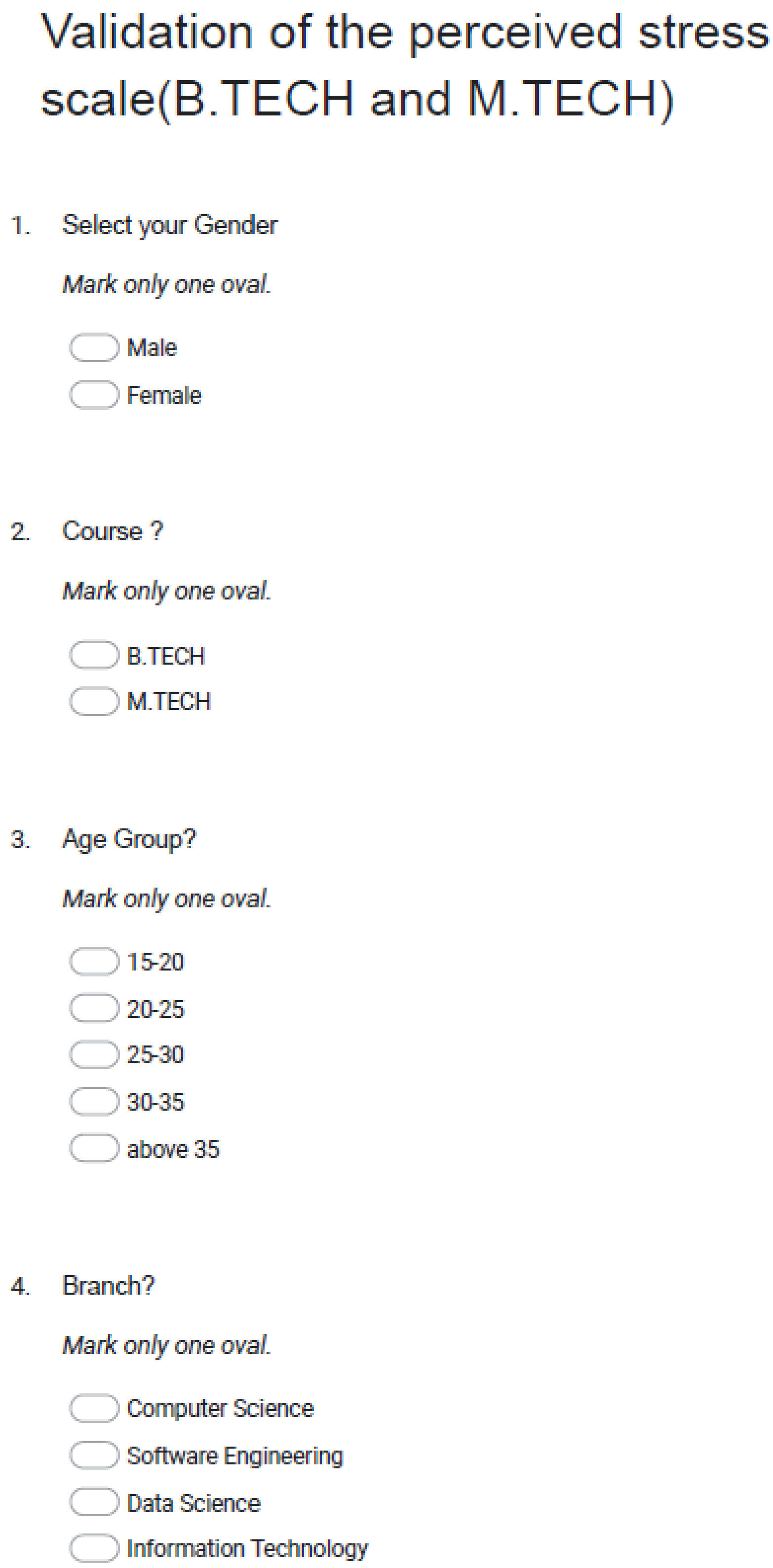
Data collected=57

Stress Scale used=PSS-10

Data Collection Technique=Random Sampling

Data collection method=questionnaire

3.7 SURVEY QUESTIONNAIRE



Validation of the perceived stress scale(B.TECH and M.TECH)

1. Select your Gender

   Mark only one oval.

   ○ Male
   ○ Female

2. Course ?

   Mark only one oval.

   ○ B.TECH
   ○ M.TECH

3. Age Group?

   Mark only one oval.

   ○ 15-20
   ○ 20-25
   ○ 25-30
   ○ 30-35
   ○ above 35

4. Branch?

   Mark only one oval.

   ○ Computer Science
   ○ Software Engineering
   ○ Data Science
   ○ Information Technology

5. Staying?

Mark only one oval.

○ In Hostel
○ PG
○ Day scholar

6. Q1. In the last month, how often have you been upset because of something that happened unexpectedly?

Mark only one oval.

○ Never
○ Amost Never
○ Sometimes
○ Fairly Often
○ Very Often

7. Q2. In the last month, how often have you felt that you were unable to control the in important things in your life?

Mark only one oval.

○ Never
○ Almost Never
○ Sometimes
○ Fairly Often
○ Very Often

8. Q3. In the last month, how often have you experienced kindness from others?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

9. Q4. In the last month, how often have you felt nervous and stressed?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

10. Q5. In the last month, how often have you felt confident about your ability to handle your personal problems?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

11. Q6. In the last month, how often have you felt that things were going your way?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

---

12. Q7. In the last month, how often have you felt the desire to support the greater good?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

13. Q8. In the last month, how often have you found that you could not cope with all the things that you had to do?

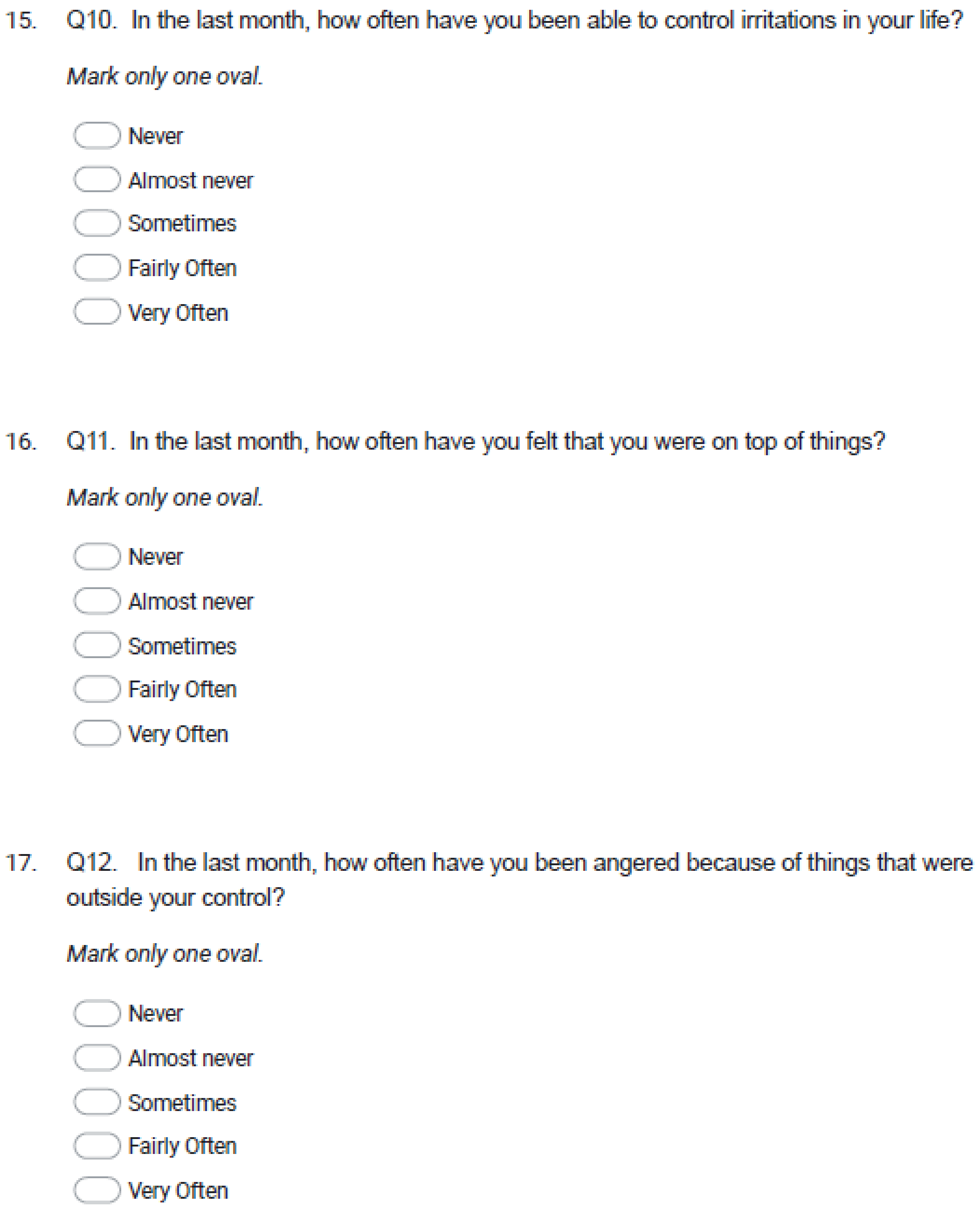
Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

14. Q9. In the last month, how often have you been kind to others?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often



15. Q10. In the last month, how often have you been able to control irritations in your life?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

16. Q11. In the last month, how often have you felt that you were on top of things?

Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

17. Q12. In the last month, how often have you been angered because of things that were outside your control?

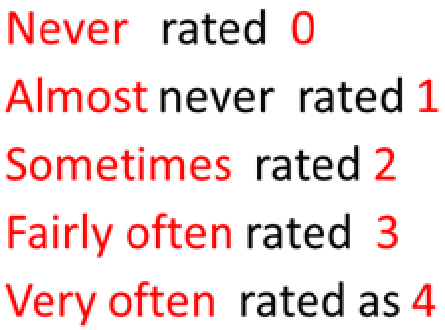
Mark only one oval.

○ Never
○ Almost never
○ Sometimes
○ Fairly Often
○ Very Often

Preprocessing:

1) Encoding
2) Remove missing value data
3) Reverse as per PSS-10 (4,5,7,8)
4) Total

The PSS-10 is a set of questions where 10 questions are there, each item is measured by using 5-point Likert scale. It lies from 0 to 4 .Responders are queried how frequently they have experienced particular feelings or thoughts in the past month.



Never rated 0
Almost never rated 1
Sometimes rated 2
Fairly often rated 3
Very often rated as 4

After that

we need to reverse the responses for questions (4, 5, 7 and 8) means if it is 0 convert it to 4 , 1 to 3, 2 to 2, and 4 to 0.

The PSS score is then obtained by summing all the responses across all the items. The total pss 10 score ranges from 0 to 40, with higher scores indicating greater perceived stress.

. The stress level is detected based on the total of PSS score as below:

1. PSS<= ***13****,* *it denotes* ***low stress.***

2. 13<PSS<=26 ***between 14 to 26****, it implies* ***moderate stress.***

3. 26 <PSS <=40 ***between 27-40****, it indicates* ***high level of stress.***

CHAPTER 4

RESULTS

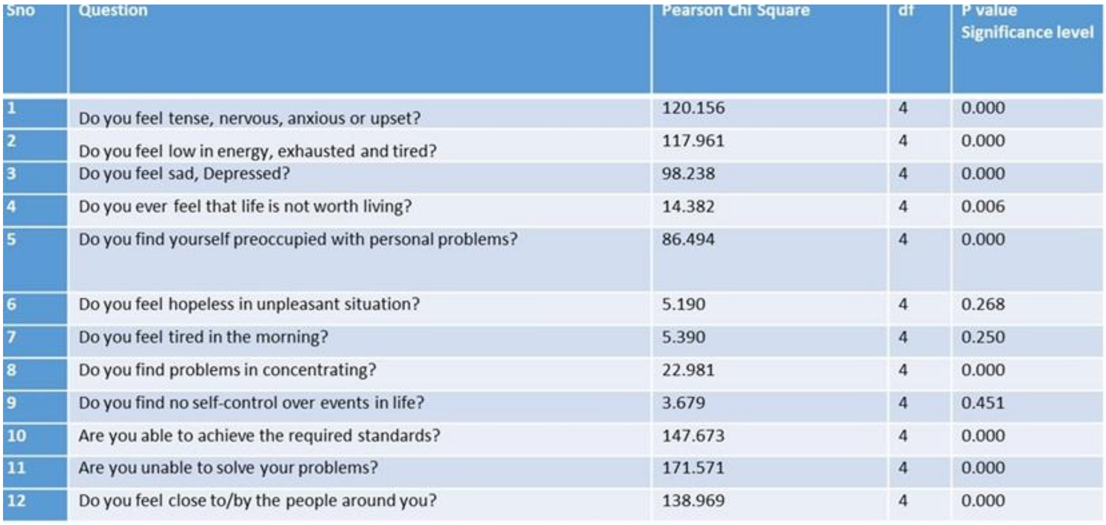
4.1 Risk Factors for Suicide in The Military

Suicide is a complex and very important issue need to be addressed in the armed forces or military, there exists many key factors that may have crucial role in elevating suicide rates in this community. It's essential to remember that these risk factors are not deterministic, and individuals may experience a combination of factors it depends person to person. Additionally, the military has implemented various programs for prevention and to support the soldiers to address these issues. Some of the key **factors for suicide in the serving forces** include:

- ✓ Deployment and Combat Exposure:
- ✓ Post-Traumatic Stress Disorder (PTSD
- ✓ Mental Health Issues
- ✓ Substance Abuse
- ✓ Access to Firearms
- ✓ Relationship Issues
- ✓ Financial Strain
- ✓ Legal Issues
- ✓ Stigma and Barriers to Help-Seeking
- ✓ Lack of Social Support
- ✓ Demographic Factors

Data collection

"K C Dixit" [2] is the base study, this study focuses on two main points (1). Evaluation of Org and Domestic Environment and (2) Stress Assessment. We took stress assessment where there were 12 questions for all three groups (Officers, JCOs, and OR). we also try to find out which cadre officers, JCOs or other rank who is more stressed or more depressed that motivates them to suicide attempt. We choose Chi square test as we have categorical dataset for analyzing the stress level difference. Each question analyzed separately for all three groups. It is found a significant difference with p value ($p<0.05$) in level of stress for all three group.



Sno	Question	Pearson Chi Square	df	P value Significance level
1	Do you feel tense, nervous, anxious or upset?	120.156	4	0.000
2	Do you feel low in energy, exhausted and tired?	117.961	4	0.000
3	Do you feel sad, Depressed?	98.238	4	0.000
4	Do you ever feel that life is not worth living?	14.382	4	0.006
5	Do you find yourself preoccupied with personal problems?	86.494	4	0.000
6	Do you feel hopeless in unpleasant situation?	5.190	4	0.268
7	Do you feel tired in the morning?	5.390	4	0.250
8	Do you find problems in concentrating?	22.981	4	0.000
9	Do you find no self-control over events in life?	3.679	4	0.451
10	Are you able to achieve the required standards?	147.673	4	0.000
11	Are you unable to solve your problems?	171.571	4	0.000
12	Do you feel close to/by the people around you?	138.969	4	0.000

Table 4.1: List of questions with their Significance Level and degree of freedom=04.

For questions (1,2,3,4,5,8,10,11,12), the null hypothesis is ruled out and alternate hypothesis has been agreed or accepted which concludes that there is a difference in the stress level among the three group. While looking at question 6 ,7 and 9 results there is no difference in the responses of all three groups, they are behaving in similar way. They feel hopeless in unpleasant situation, they feel tired in the morning and sometime they even find no self-control over some events. After looking all data and results of all questions Other Ranks personnel are found more stressed.

4.2 Performance Analysis of ML Algorithms for Classification of Stress using PSS-10 scale of University Postgraduate Students

In this study , jupyter notebook and python libraries (pandas, numpy, matplotlib, sklearn) are used for metric calculation model selection, data preprocessing , descriptive statistics of machine learning algorithms and data. Details of Dataset used in this study are:

Total Students=106 (M.Tech(DS,IT,SWE and CS))

Data collected=57

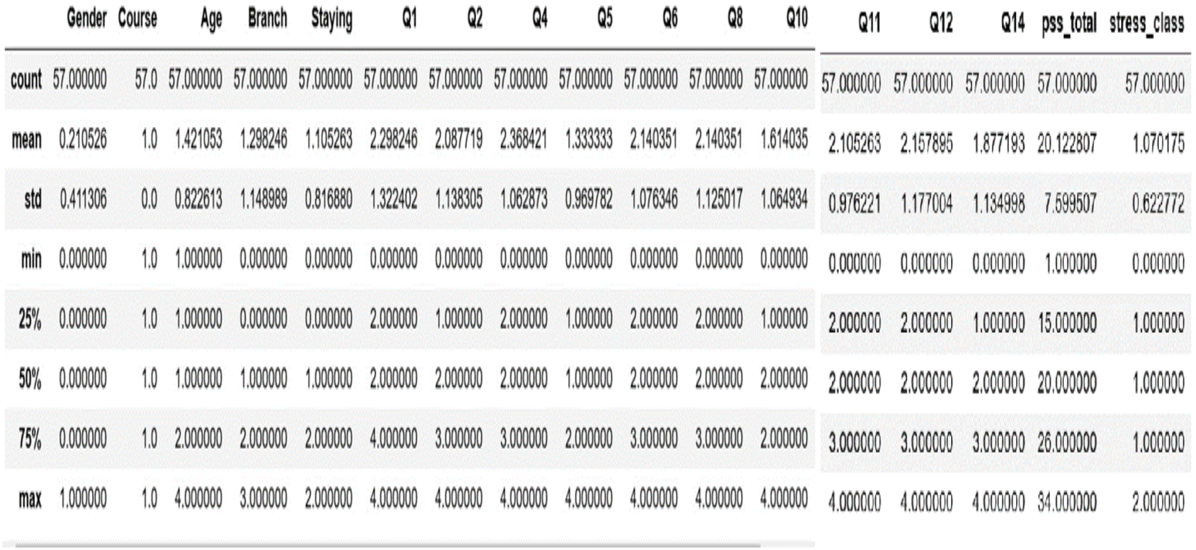
Stress Scale used=PSS-10

Data Collection Technique=Random Sampling

Data collection method=questionnaire

After preprocessing, mean, median, SD, MIN, MAX ,and interquartile range for all parameter of the data are calculated as shown in Table 1.

Table4.2: Detailed Descriptive statistics measures of the dataset



	Gender	Course	Age	Branch	Staying	Q1	Q2	Q4	Q5	Q6	Q8	Q10	Q11	Q12	Q14	pss_total	stress_class
count	57.000000	57.0	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000
mean	0.210526	1.0	1.421053	1.298246	1.105263	2.298246	2.087719	2.368421	1.333333	2.140351	2.140351	1.614035	2.105263	2.157895	1.877193	20.122807	1.070175
std	0.411306	0.0	0.822613	1.148989	0.816880	1.322402	1.138305	1.062873	0.969782	1.076346	1.125017	1.064934	0.976221	1.177004	1.134998	7.599507	0.622772
min	0.000000	1.0	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000
25%	0.000000	1.0	1.000000	0.000000	0.000000	2.000000	1.000000	2.000000	1.000000	2.000000	2.000000	1.000000	2.000000	2.000000	1.000000	15.000000	1.000000
50%	0.000000	1.0	1.000000	1.000000	1.000000	2.000000	2.000000	2.000000	1.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	20.000000	1.000000
75%	0.000000	1.0	2.000000	2.000000	2.000000	4.000000	3.000000	3.000000	2.000000	3.000000	3.000000	2.000000	3.000000	3.000000	3.000000	26.000000	1.000000
max	1.000000	1.0	4.000000	3.000000	2.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	34.000000	2.000000

Table 4.2 :Descriptive statistics

As per the analysis maximum students are found at moderate level of stress, which is pre-stage to the high level of perceived stress. In a group of 57 students, 9 are identified as having low stress levels, 35 are assessed to be at a moderate level of stress, while

13 students are classified as experiencing high perceived stress levels as shown in Figure6.

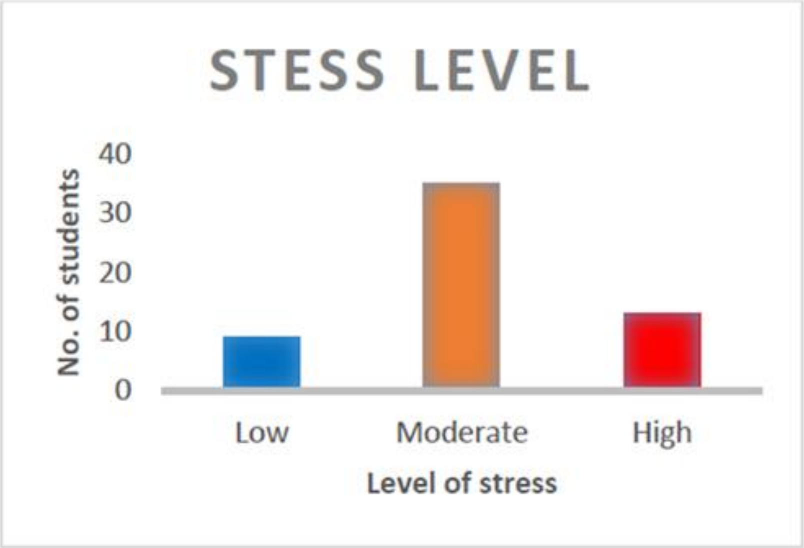
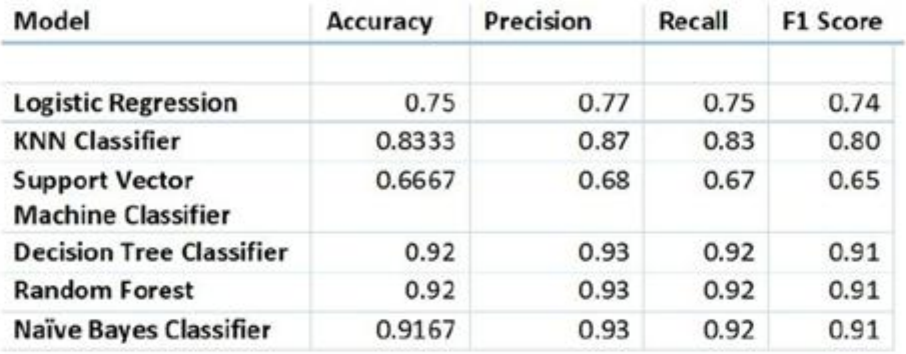


Figure 4.1: Stress Level overview



Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.75	0.77	0.75	0.74
KNN Classifier	0.8333	0.87	0.83	0.80
Support Vector Machine Classifier	0.6667	0.68	0.67	0.65
Decision Tree Classifier	0.92	0.93	0.92	0.91
Random Forest	0.92	0.93	0.92	0.91
Naïve Bayes Classifier	0.9167	0.93	0.92	0.91

Table 4.3: Model Efficiency Comparison on student dataset

With the help of accuracy and model we have generated accuracy percentage graph shown in Figure 4.2.

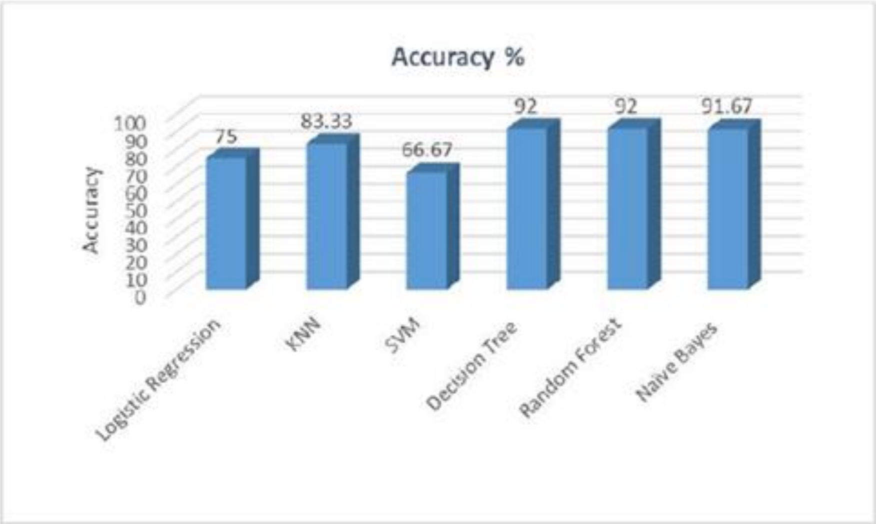
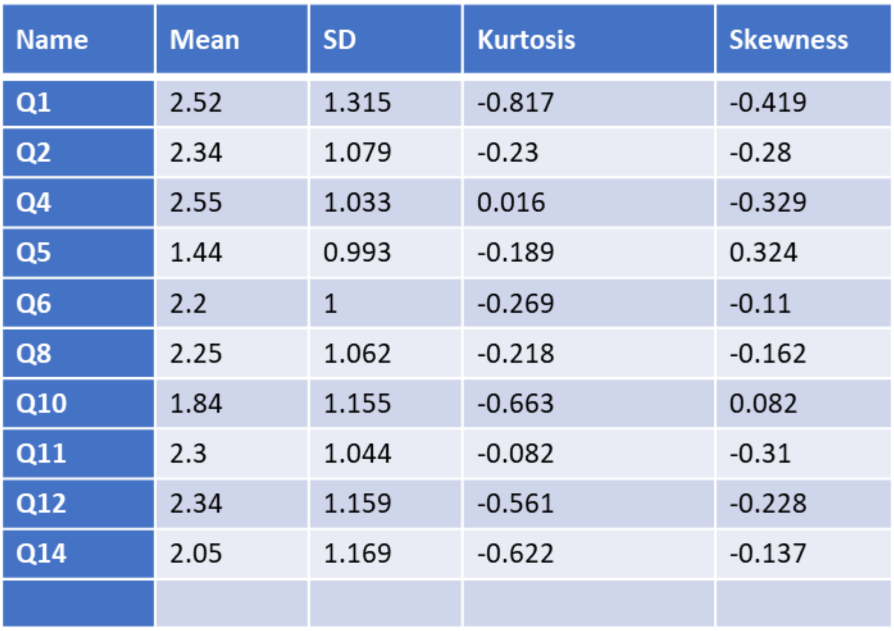


Figure 4.2: Accuracy percentage bar chart

The word or expression “Stress” is a typically used with negative unfavorable events of life , this impacting individual wellbeing’s [23]. Stress is identified as one of the leading health issues faced by individuals today. It is a primary contributor to numerous other health problems, highlighting the importance of its careful and effective management. In our research, we utilized six machine learning algorithms to assess their predictive accuracy: Logistic Regression (75.00%), K-Nearest Neighbors (83.33%), SVM (66.67%), DT (92.00%), RF (92.00%), and Gaussian Naive Bayes (91.67%). Among these, the DT and RF algorithms demonstrated the highest levels of accuracy in predicting stress, outperforming the other classifiers.

4.3 PLS-SEM ANALYSIS

To perform PLSSEM e have used SmartPls 4 softer and perform various analysis result are shown below



Name	Mean	SD	Kurtosis	Skewness
Q1	2.52	1.315	-0.817	-0.419
Q2	2.34	1.079	-0.23	-0.28
Q4	2.55	1.033	0.016	-0.329
Q5	1.44	0.993	-0.189	0.324
Q6	2.2	1	-0.269	-0.11
Q8	2.25	1.062	-0.218	-0.162
Q10	1.84	1.155	-0.663	0.082
Q11	2.3	1.044	-0.082	-0.31
Q12	2.34	1.159	-0.561	-0.228
Q14	2.05	1.169	-0.622	-0.137

Table-4.4 : Descriptive statistics of PSS-10: University College Student Dataset

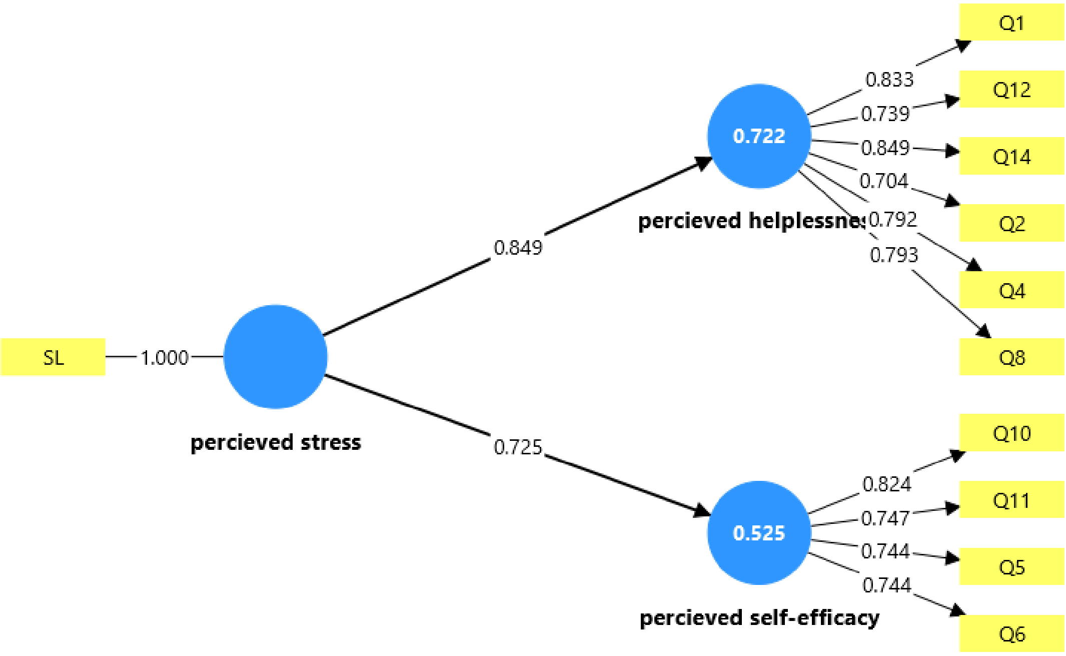
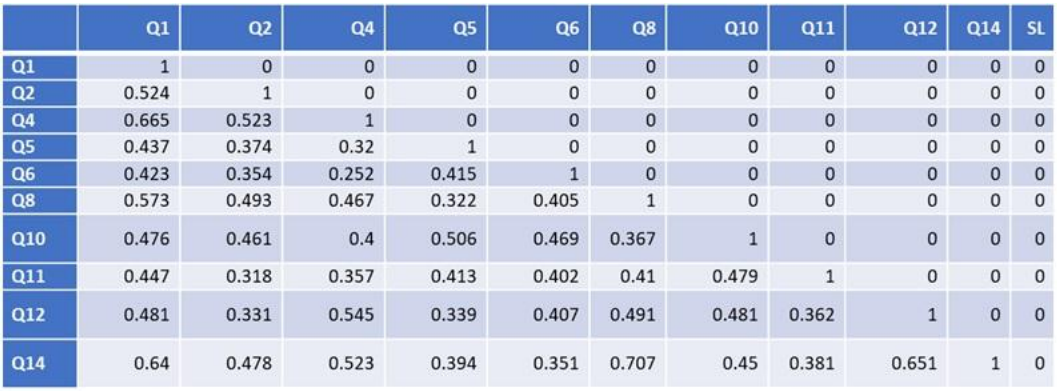
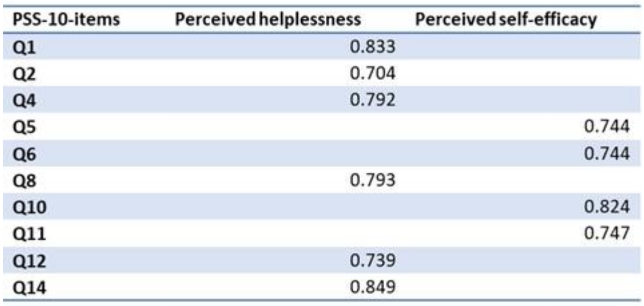


Figure 4.3 : Factor Loading for to factor model of PSS-10 in DTU university students



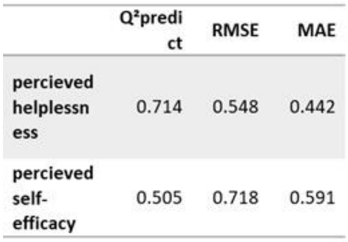
	Q1	Q2	Q4	Q5	Q6	Q8	Q10	Q11	Q12	Q14	SL
Q1	1	0	0	0	0	0	0	0	0	0	0
Q2	0.524	1	0	0	0	0	0	0	0	0	0
Q4	0.665	0.523	1	0	0	0	0	0	0	0	0
Q5	0.437	0.374	0.32	1	0	0	0	0	0	0	0
Q6	0.423	0.354	0.252	0.415	1	0	0	0	0	0	0
Q8	0.573	0.493	0.467	0.322	0.405	1	0	0	0	0	0
Q10	0.476	0.461	0.4	0.506	0.469	0.367	1	0	0	0	0
Q11	0.447	0.318	0.357	0.413	0.402	0.41	0.479	1	0	0	0
Q12	0.481	0.331	0.545	0.339	0.407	0.491	0.481	0.362	1	0	0
Q14	0.64	0.478	0.523	0.394	0.351	0.707	0.45	0.381	0.651	1	0

Table 4.5 : Correlation between entire items of PSS-10



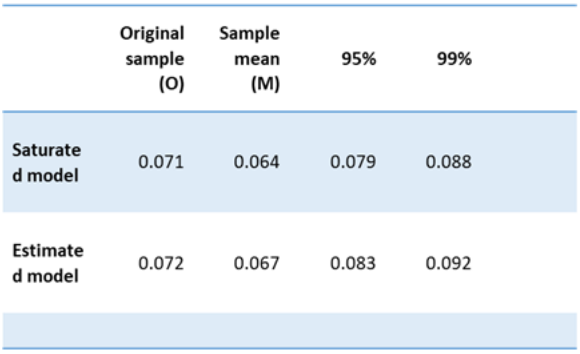
PSS-10-items	Perceived helplessness	Perceived self-efficacy
Q1	0.833	
Q2	0.704	
Q4	0.792	
Q5		0.744
Q6		0.744
Q8	0.793	
Q10		0.824
Q11		0.747
Q12	0.739	
Q14	0.849	

Table 4.6 : Standard Factor loading



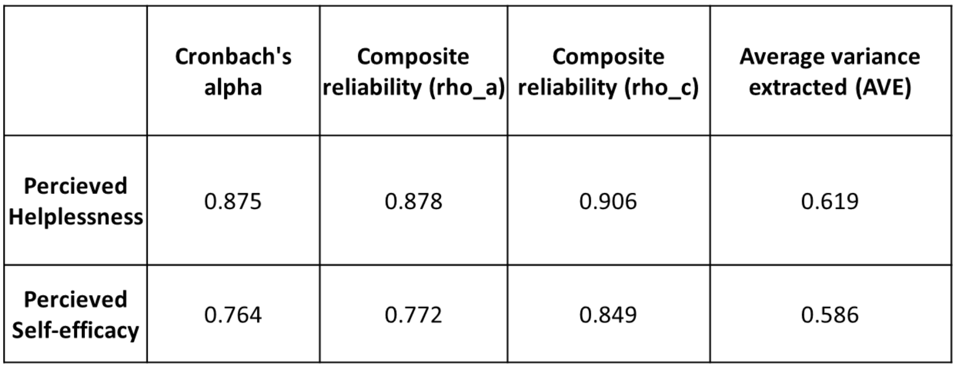
	Q^2predict	RMSE	MAE
percieved helplessness	0.714	0.548	0.442
percieved self-efficacy	0.505	0.718	0.591

Table 4.7: RMSEA



	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0.071	0.064	0.079	0.088
Estimated model	0.072	0.067	0.083	0.092

Table 4.8 : SRMR



	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Percieved Helplessness	0.875	0.878	0.906	0.619
Percieved Self-efficacy	0.764	0.772	0.849	0.586

Table 4.9 : Reliability and Validity

After Analyzing collected student dataset, we found that mean of each question varies between 1.44 to 2.55 while SD ranged from 0.99 to 1.32. Kurtosis and Skewness is less than 1 which shows that items followed normal distribution. SRMR <0.08 and RMSEA <0.08 which indicated that model we constructed is fit for two factors with the factor loading 0.849 for perceived helplessness and 0.725 for perceived self-efficacy. By calculating Reliability and Validity parameter we found Cronbach alpha exceeds minimum threshold value that is 0.7 while for AVE got above 0.5 which indicated that model is reliable and valid.

The result of our study showed that the PSS-10, with a two factor model may accurately measure the stress levels among university students with good reliability and validity,

CHAPTER 5

DISCUSSION AND CONCLUSION

OBJECTIVE1 Discussion and Conclusion:

Suicidal incidents continue to rise despite attempts to cope with mental /psychological health issues in the military, such as campaigns to raise awareness and de-stigmatize asking for help. This highlights or pinpoint the critical need for more rigorous support networks and interventions. It is imperative that mental health specialists, legislators, and military leadership work together to identify risk factors, improve preventive measures, and offer service members who are experiencing mental health problems with appropriate treatment alternatives. Further, lowering the suicide rate and protecting the wellbeing of individuals who commit their life to serving their country can be achieved by cultivating an environment of transparency, empathy, and support inside the armed forces. The importance of the armed services' resilience and mental health cannot be overstated as the country struggles with this urgent problem.

OBJECTIVE 2 and 3: Discussion and Conclusion:

Expression “Stress” is a frequently used for unpleasant and difficult life events, this harm wellbeing of an individual [14,23] in many dimensions. Stress is identified as one of the leading health issues faced by individuals today. It is a primary contributor to numerous other health problems, highlighting the importance of its careful and effective management. In our research, we utilized six machine learning algorithms to assess their predictive accuracy: Logistic Regression (75.00%), KNN (83.33%), SVM (66.67%), DT (92.00%), RF (92.00%), and Gaussian Naive Bayes (91.67%). Among these algorithms, the Random Forest and Decision Tree algorithms demonstrated the greatest levels of accuracy in predicting stress, as compared to the other classifiers. In future we can validate the PSS-10 stress model and conduct sequential modeling to gain deeper insights from data. Additionally, we have the option to integrate several additional variables while performing PCA factor analysis. PLSEM results shows that the proposed bimodal is reliable and valid. There are various approaches that the university can implement to address stress management, ensuring that students remain free from stress, depression or anxiety and are able to deal with stress in a positive and efficient manner Periodic counselling and mindfulness practice sessions will be best to detect stress before it gets severe. The mentor assigned to the student should be in touch with the student and must have periodic sessions with them to understand their current state of mind to avoid unwanted consequences.

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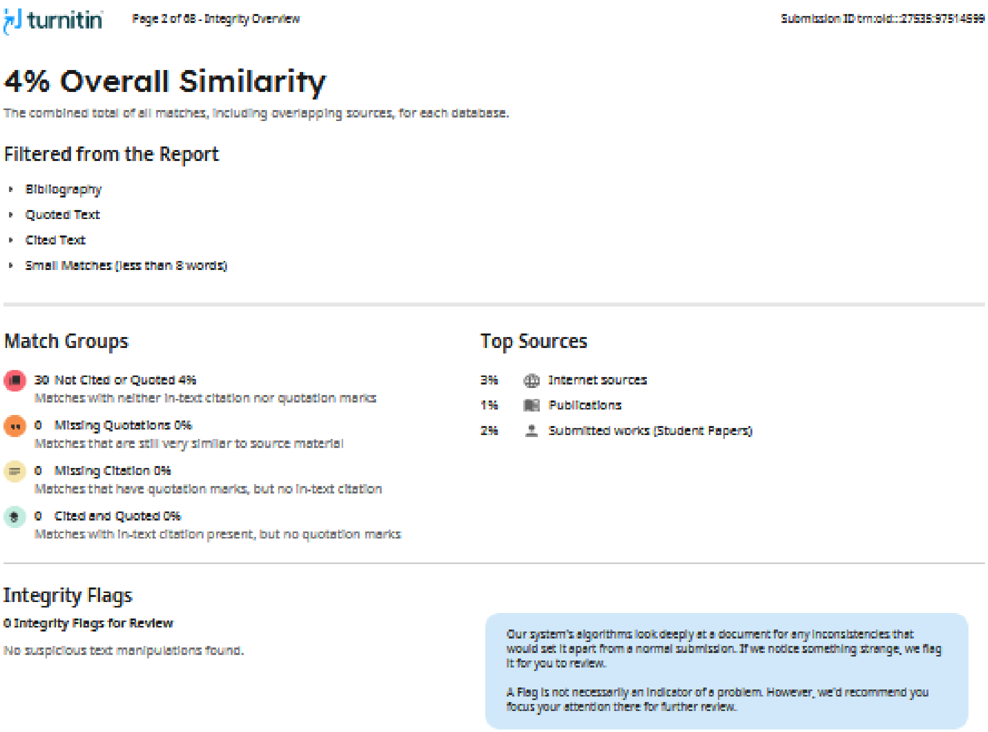

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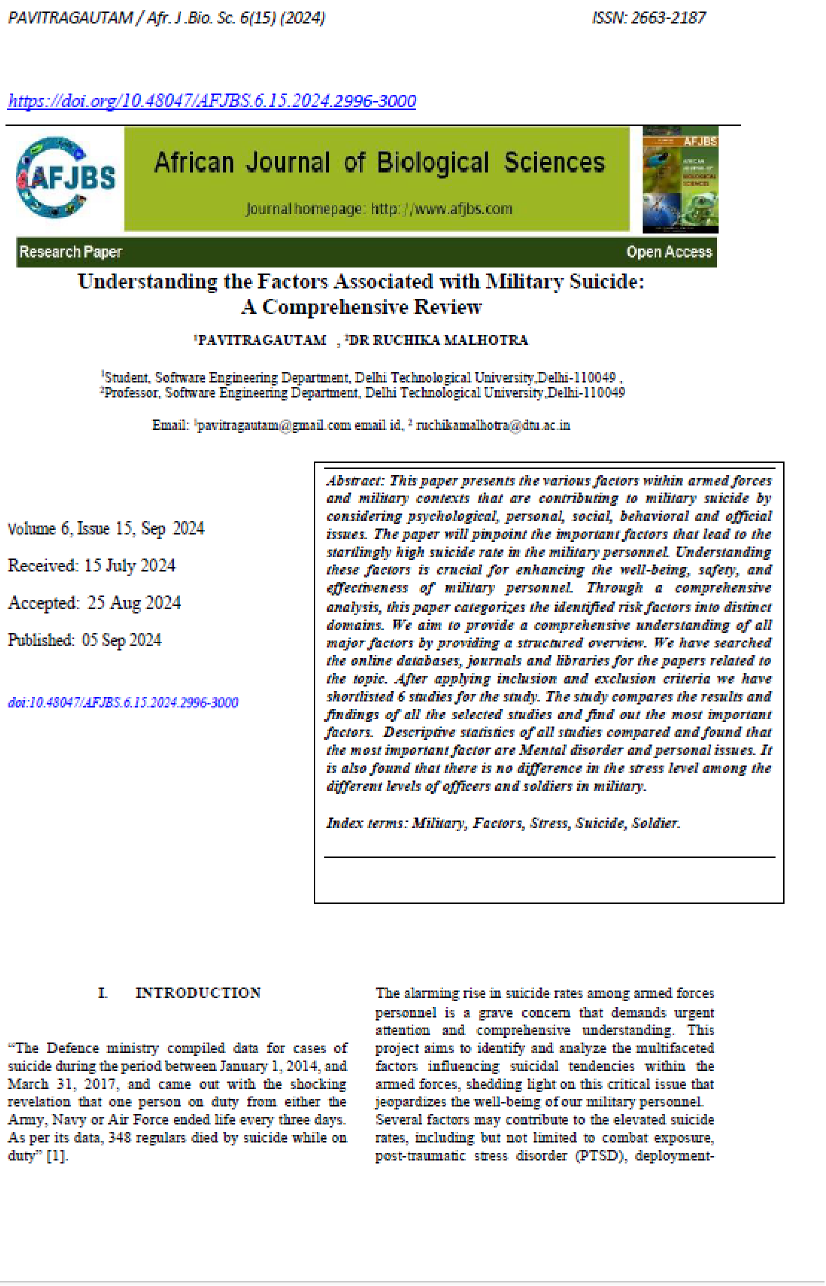
2.	Title: ***Performance Analysis of Machine Learning Algorithms for Classification of Stress using PSS-10 scale of University Postgraduate Students*** Journal Name: Journal of Information Systems Engineering and Management ISSN: 2468-4376	Published (Proof enclosed)

APPENDIX -I

Published Papers : Paper 1



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Understanding the Factors Associated with Military Suicide: A Comprehensive Review

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***Abstract:** This paper presents the various factors within armed forces and military contexts that are contributing to military suicide by considering psychological, personal, social, behavioral and official issues. The paper will pinpoint the important factors that lead to the startlingly high suicide rate in the military personnel. Understanding these factors is crucial for enhancing the well-being, safety, and effectiveness of military personnel. Through a comprehensive analysis, this paper categorizes the identified risk factors into distinct domains. We aim to provide a comprehensive understanding of all major factors by providing a structured overview. We have searched the online databases, journals and libraries for the papers related to the topic. After applying inclusion and exclusion criteria we have shortlisted 6 studies for the study. The study compares the results and findings of all the selected studies and find out the most important factors. Descriptive statistics of all studies compared and found that the most important factor are Mental disorder and personal issues. It is also found that there is no difference in the stress level among the different levels of officers and soldiers in military.*

Index terms: Military, Factors, Stress, Suicide, Soldier.

I. INTRODUCTION

"The Defence ministry compiled data for cases of suicide during the period between January 1, 2014, and March 31, 2017, and came out with the shocking revelation that one person on duty from either the Army, Navy or Air Force ended life every three days. As per its data, 348 regulars died by suicide while on duty" [1].

The alarming rise in suicide rates among armed forces personnel is a grave concern that demands urgent attention and comprehensive understanding. This project aims to identify and analyze the multifaceted factors influencing suicidal tendencies within the armed forces, shedding light on this critical issue that jeopardizes the well-being of our military personnel.
Several factors may contribute to the elevated suicide rates, including but not limited to combat exposure, post-traumatic stress disorder (PTSD), deployment-

related stress, interpersonal conflicts, and access to lethal means. However, the complex interplay of these elements remains poorly understood.

By undertaking a systematic investigation, this project seeks to unravel the intricate web of circumstances surrounding armed forces suicides. Through surveys, interviews, and data analysis, we aim to discern patterns, commonalities, and outliers within the demographic, psychological, and environmental aspects of armed forces personnel. The findings will not only provide valuable insights into the root causes but also serve as a foundation for developing targeted intervention strategies and support mechanisms. Ultimately, this research endeavors to contribute to the overall well-being of armed forces personnel by fostering a deeper understanding of the factors influencing suicide rates, paving the way for evidence-based policies and initiatives to address this pressing concern.

Since the year 2003 to 2022 total 2932 soldiers committed suicide which is a huge number. As per the report of Deccan Herald (DH) in every three days one of the soldier is committing suicide. Year wise distribution is given in Table 1.

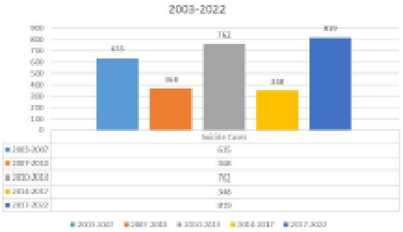


Figure 1:Year wise suicidal cases in armed forces

This concerning rise in self-inflicted fatalities among military personnel has raised significant alarms within both the armed forces and the broader society. While the exact reasons behind this surge are multifaceted and complex, several underlying factors have been identified. Among them are the intense operational tempo, prolonged separation from families, inadequate mental health support systems, and the stigma surrounding mental health issues within the military culture. The demanding nature of military service often exposes personnel to high-stress environments, traumatic experiences, and prolonged deployments, all of which can take a toll on one's mental well-being. Furthermore, the hierarchical structure of the armed forces may deter individuals from seeking help for fear of being perceived as weak or unfit for duty.

II. MATERIALS AND METHODS

Descriptive statistics encapsulate data succinctly, providing crucial insights for understanding and decision-making. By summarizing large datasets into manageable measures like mean, median, and mode, they unveil patterns, trends, and central tendencies. Such statistical snapshots facilitate easy comprehension and comparison across different groups or periods. They're indispensable in various fields, from finance to healthcare, aiding in risk assessment, resource allocation, and performance evaluation. Moreover, descriptive statistics lay the groundwork for advanced analyses, guiding researchers towards relevant hypotheses and methodologies. Without them, navigating through data complexities would be daunting, hindering effective problem-solving and informed decision-making essential for progress in diverse domains.

Suicide is common in the general public as well as in the military. In the general scenario, not much research has been done in the military. This could be due to the limited access to the data, or there could be some other administrative or political reasons. We searched the online databases and found that 58 articles were found using key words such as military suicide and factors. After removing duplicates, we left with 36 papers. We applied the inclusion and exclusion criteria as follows: (1) free full text; (2) comparable statistics; (3) focus on military personnel as subjects; (4) year of publication: 2010–2024; and (5) factors and reasons in the body of the papers.. Figure 2 shows the flow char for this.

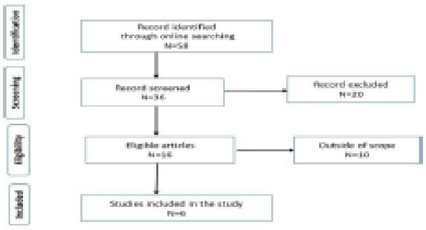


Figure 2: Prisma flow chart of included studies

Related work in the area has been reviewed. After the main information about the factors, their reasons, what their significance is, how much they influence the suicide rate, what are the statistics used to conclude the results, and in which year the publication has been made, all the necessary information is included in Table 2: Comparison of Related Work.

Sno.	Author name	Title of publication	Year of publication	Journal/its reference name	Type of the study	No. of samples	Year from-to	Independent variables	Factors found	Performance measures/Analysis	Remark
1	Ali Fathi-Ashtiani	Effective factors of suicide in soldiers of a military force	Summer 2012, Volume 14	Iranian Journal of Military	cross-sectional study	[illegible]	2002-2012	suicide and self-injuring	Psychological problems, family and individualistic problems, Workplace and colleagues' problems, Drug	descriptive statistical methods and	mental disorders (37.2%), suicide methods: Firearms
2	Robert J.	Factors Associated With Suicide Ideation in US Army Soldiers During Deployment	2020	JAMA Network [illegible]	survey study,	[illegible]	August 2008 and August 2009 soldiers serving in	mental disorders, Suicide Ideation(SI)	major depressive disorder, posttraumatic stress disorder, race/ethnicity, lifetime	Logistic regression analyses, OR,	major depressive disorder,
3	Scott D. Landes	Risk Factors Explaining Military Deaths From Suicide, 2008–2017: A Latent Class Analysis	2023 January, 49()	HHS Public Access	survey study,	[illegible]	Department of Defense Suicide Event Report	suicide	job/administrative/legal risk factors(45.1%), general health risk factors(20.7%), mental	latent class analysis, logistic	relationship dissolution in the past year
4	K. C. Dixit	Addressing Stress Related Issues in Army		DSA Occasional Paper No.	survey study,	[illegible]	Indian Armed Forces	suicide	Domestic Environment	descriptive statistical methods	unable to solve personal problem, depressi
5	Jafar Anisi	The Factors Associated with Suicide Ideation in Iranian Soldiers	2010 Summer	Iranian Journal of Psychiatry	questionnaire	[illegible]	Military Forces	suicide ideation	41.4% dissatisfied with the compulsory period,	statistical analysis	mental health problem
6	Larry D.	Suicide in the Military: Understanding Rates and Risk Factors	2019	MILITARY MEDICINE	questionnaire	[illegible]	Department of Defense Suicide Event Report	suicide	Failed/failing intimate partner relationship was present in 38.1% , Legal and/or administrative stressors		49% engaged in healthcare services, 49.1% had

Table 1: Related work

III. DISCUSSION

- Ashtiani, Ali Fathi-et al. (2012). In their cross-sectional investigation, [1] found that 44% of the participants had a history of self-mutilation or suicide. Mental illnesses accounted for the majority of the background factors associated with suicide and self-mutilation (37.2%). difficulties with coworkers and the work environment (13.8%), as well as family issues (36.7%). Winter was the season when most suicides were committed. usage of guns (49.9%), stabbing (25.2%), drug usage (18.5%), hanging (4.4%), consuming oil and hand soap (1.2%), and jumping from a height (0.9%) were the means of suicide. For his research, he employed analytical tests like the Chi-Square test and descriptive statistical techniques.
- Using a survey study, Robert J. et al. (2020) [2] discovered that 44.2% of people had major depressive disorder (MDD). Aside from this post-traumatic stress disorder, other indicators include race or ethnicity, lifetime noncombat trauma, interpersonal issues, legal issues, or the illness or death of a friend or family member.
- Scott D. Landes et al. (2023) [3] used a survey study in their procedures. While conducting the study, they used latent class analysis and a logistic regression model and found that job/administrative/legal risk factors (45.1%), general health risk factors (20.7%), mental health risk factors (47.7%), and relationship dissolution in the past year (51.1%) were the major factors for suicide among soldiers.
- K. C. Dixit et al. (2011) [4] conducted a survey in the Indian Army in 2011 to find out the factors contributing to suicidal attempts. They performed descriptive statistics and concluded that the domestic environment is the main factor. The study stated that the majority of soldiers were unable to solve personal problems and were depressed, which motivated them to make suicidal attempts.
- Jafar Anisi et al. (2010) [5] revealed that psychological factors, negative family background, environmental and task-related problems, and sociodemographic problems were significantly associated with suicide ideation: 41.4% were dissatisfied with the compulsory period, 25.2% were not satisfied with those officers in charge of soldiers, and 11.9% of the subjects showed feelings of worthlessness in their work environment.
- Using DoDSER data reports, Larry D. et al. (2019) [6] found that 49.1% of the population had a history of at least one behavioral health condition. Twenty-six percent (24.6%) received a diagnosis of substance addiction or dependence. The second most common diagnosis, found in 23.2% of cases, was adjustment disorder. In 12.5% of cases, major depression was found, and in 8.3% of cases, post-traumatic stress disorder was diagnosed.

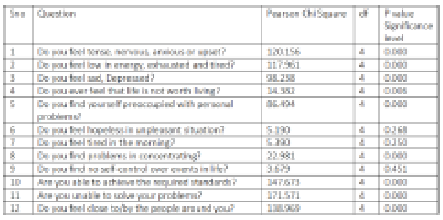
Suicide is a complex and multifaceted issue, and in the military, there are unique risk factors that may contribute to the elevated rates of suicide compared to the general population. It's important to note that these risk factors are not deterministic, and individuals may experience a combination of factors. Additionally, the military has implemented various prevention programs and support systems to address these issues. Some of the risk factors for suicide in the military include:

1. **Deployment and Combat Exposure:** Military personnel who have experienced combat or multiple deployments may be at higher risk due to the stress, trauma, and challenges associated with these experiences.
2. **Post-Traumatic Stress Disorder (PTSD):** Exposure to traumatic events during military service can lead to the development of PTSD, which is associated with an increased risk of suicide.
3. **Mental Health Issues:** Pre-existing mental health conditions, such as depression, anxiety, or bipolar disorder, can contribute to an elevated risk of suicide.

4. Substance Abuse: Substance abuse, including alcohol and drug misuse, is a significant risk factor for suicide. Military personnel may be at risk due to the availability of substances and the stressors associated with their profession.
5. **Access to Firearms**: The availability of firearms, often a standard issue in the military, increases the lethality of suicide attempts.
6. **Relationship Issues**: Difficulties in personal relationships, including family problems, divorce, or social isolation, can contribute to emotional distress.
7. **Financial Strain**: Financial difficulties, such as debt or economic instability, may contribute to stress and increase the risk of suicide.
8. **Legal Issues**: Legal problems, including disciplinary actions, criminal charges, or court-martial proceedings, can be significant stressors for military personnel.
9. **Stigma and Barriers to Help-Seeking**: Concerns about stigma, career impact, or perceived weakness may discourage military personnel from seeking help for mental health issues.
10. **Lack of Social Support**: Feeling isolated or lacking a strong social support system can contribute to emotional distress and increase the risk of suicide.
11. **Demographic Factors**: Certain demographic factors, such as age, gender, and rank, may influence suicide risk. For example, younger enlisted personnel may face different challenges than older officers.

IV. RESULT

Comparing all the studies selected, it is found that mental disorders are the first main factor and personal problems are the second main factor of suicidal among soldiers. Method of suicide also explored and it is found that availability of the firearms is the main method of suicide in most of the cases. Taking the study of "K C Dixit" [2] as a base study, in this study that focuses on two main points (1). Evaluation of Org and Domestic Environment and (2) Stress Assessment. We took stress assessment where there were 12 questions for all three groups (Officers, JCOs, and OR). we also try to find out which cadre officers, JCOs or other rank who is more stressed or more depressed that motivates them to suicide attempt. We choose Chi square test as we have categorical dataset for analyzing the stress level. Each question analyzed separately for all three groups and found a significant difference ($p<0.05$) in stress level of all three groups Table 2.



Sno	Question	Pearson Chi Square	df	P value Significance level
1	Do you feel tense, nervous, anxious or upset?	120.156	4	0.000
2	Do you feel low in energy, exhausted and tired?	117.961	4	0.000
3	Do you feel sad, Depressed?	98.238	4	0.000
4	Do you ever feel that life is not worth living?	14.382	4	0.006
5	Do you find yourself preoccupied with personal problems?	86.494	4	0.000
6	Do you feel hopeless in unpleasant situation?	5.190	4	0.268
7	Do you feel tired in the morning?	5.390	4	0.250
8	Do you find problems in concentrating?	22.981	4	0.000
9	Do you find no self-control over events in life?	3.679	4	0.451
10	Are you able to achieve the required standards?	147.673	4	0.000
11	Are you unable to solve your problems?	171.571	4	0.000
12	Do you feel close to/by the people around you?	138.969	4	0.000

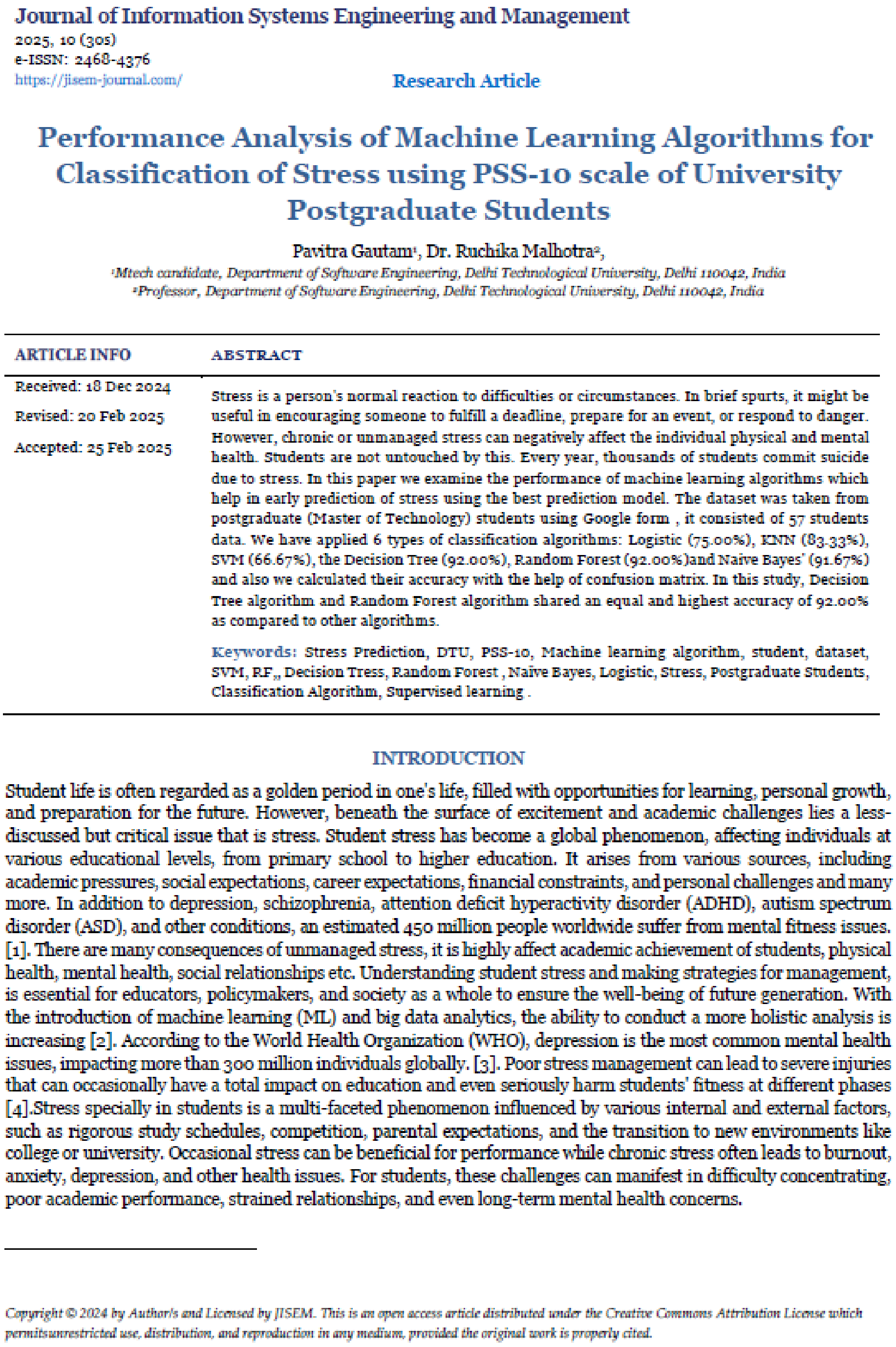
Table 2: List of questions with their Significance Level and degree of freedom=04.

for questions (1,2,3,4,5,8,10,11,12). Thus, the null hypothesis is rejected and alternate hypothesis accepted for these questions and concludes that there is a difference in the stress level among the three group. While looking at question 6 ,7 and 9 results there is no difference in the responses of all three groups, they are behaving in similar way. They feel hopeless in unpleasant situation, they feel tired in the morning and sometime they even find no self-control over some events. After looking all data and results of all questions Other Ranks personnel are found more stressed.

V. CONCLUSION AND FUTURE WORK

Suicidal incidents continue to rise despite attempts to address mental health issues in the military, such as campaigns to raise awareness and de-stigmatize asking for help. This highlights the critical need for more extensive support networks and interventions. It is imperative that mental health specialists, legislators, and military leadership work together to identify risk factors, improve preventive measures, and offer service members who are experiencing mental health problems with appropriate treatment alternatives. Further, lowering the suicide rate and protecting the wellbeing of individuals who commit their life to serving their country can be achieved by cultivating an environment of transparency, empathy, and support inside the armed forces. The importance of the armed services' resilience and mental health cannot be overstated as the country struggles with this urgent problem.

Published Papers : Paper 2



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Research Article

Performance Analysis of Machine Learning Algorithms for Classification of Stress using PSS-10 scale of University Postgraduate Students

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ABSTRACT

Stress is a person's normal reaction to difficulties or circumstances. In brief spurts, it might be useful in encouraging someone to fulfill a deadline, prepare for an event, or respond to danger. However, chronic or unmanaged stress can negatively affect the individual physical and mental health. Students are not untouched by this. Every year, thousands of students commit suicide due to stress. In this paper we examine the performance of machine learning algorithms which help in early prediction of stress using the best prediction model. The dataset was taken from postgraduate (Master of Technology) students using Google form , it consisted of 57 students data. We have applied 6 types of classification algorithms: Logistic (75.00%), KNN (83.33%), SVM (66.67%), the Decision Tree (92.00%), Random Forest (92.00%)and Naive Bayes' (91.67%) and also we calculated their accuracy with the help of confusion matrix. In this study, Decision Tree algorithm and Random Forest algorithm shared an equal and highest accuracy of 92.00% as compared to other algorithms.

Keywords: Stress Prediction, DTU, PSS-10, Machine learning algorithm, student, dataset, SVM, RF,, Decision Tress, Random Forest , Naive Bayes, Logistic, Stress, Postgraduate Students, Classification Algorithm, Supervised learning .

INTRODUCTION

Student life is often regarded as a golden period in one's life, filled with opportunities for learning, personal growth, and preparation for the future. However, beneath the surface of excitement and academic challenges lies a less-discussed but critical issue that is stress. Student stress has become a global phenomenon, affecting individuals at various educational levels, from primary school to higher education. It arises from various sources, including academic pressures, social expectations, career expectations, financial constraints, and personal challenges and many more. In addition to depression, schizophrenia, attention deficit hyperactivity disorder (ADHD), autism spectrum disorder (ASD), and other conditions, an estimated 450 million people worldwide suffer from mental fitness issues. [1]. There are many consequences of unmanaged stress, it is highly affect academic achievement of students, physical health, mental health, social relationships etc. Understanding student stress and making strategies for management, is essential for educators, policymakers, and society as a whole to ensure the well-being of future generation. With the introduction of machine learning (ML) and big data analytics, the ability to conduct a more holistic analysis is increasing [2]. According to the World Health Organization (WHO), depression is the most common mental health issues, impacting more than 300 million individuals globally. [3]. Poor stress management can lead to severe injuries that can occasionally have a total impact on education and even seriously harm students' fitness at different phases [4].Stress specially in students is a multi-faceted phenomenon influenced by various internal and external factors, such as rigorous study schedules, competition, parental expectations, and the transition to new environments like college or university. Occasional stress can be beneficial for performance while chronic stress often leads to burnout, anxiety, depression, and other health issues. For students, these challenges can manifest in difficulty concentrating, poor academic performance, strained relationships, and even long-term mental health concerns.

Numerous studies have been undertaken regarding stress, particularly among college students. ***Cheng Ding, Yuhao Zhang, and Ting Ding [5]*** in their research authors introduced a hybrid model that integrates two approaches: a random forest model and a gradient boosting machine (GBM), achieving an accuracy rate of 100%. They carried out a 10-fold cross validation and statistical T-test with suggested model to demonstrate the importance of the suggested method over other techniques, This paper showed that HB model performs better with a mean accuracy of 1 and a standard deviation of +/- 0 .

Disha Sharma, Sumit Chaudhary [6] , stress is the main cause that have high impact on mental and physical health of students. In this research they have applied number of classification techniques as Naive Baye's, Logistic Regression, Multilayer perceptron technologies for the prediction of stress in professional students. They have used Weka tool, the accuracy measures of various techniques are calculated and compared in this study. Authors investigate 220 undergraduate and postgraduate understudies and observed that Baye's Net classifier gives the longest accuracy of 88 % by using Kappa, statistic F-measure, MCC, mean absolute error, ROC area, false positive, true positive etc.

Garima Verma*, Sandhya Adhikari, [7] ,the objective of the paper was finding the variables that influence mental health conditions including anxiety, stress, and depression in college students—particularly in engineering school. The size of the dataset was 513 individuals enrolled in graduation-level engineering programs in northern India. Data was gathered using both online and offline surveys. The machine learning models used in this model are Logistic and second Support Vector Machine (SVM) resulting accuracy of 67% and 86.84% respectively.

Ishrak Jahan Ratul a, Mirza Muntasir Nishat [8] , This study was to develop a reliable machine learning-based prediction model aimed at forecasting perceived stress and to validate it against real-world actual data. To achieve feature reduction, the authors employed the chi-squared test along with Principal Component Analysis (PCA). Two approaches one genetic algorithms (GA) and grid search cross-validation (GSCV) were used for important phase that is hyper parameter optimization (HPO) to control the learning process. The results showed that approximately 11.26% of people had significant levels of social stress. 24.10 % of participants had extremely high psychological stress. Additionally, the ML models' prediction results showed the most impressive recall value (0.826), F1 score (0.890), accuracy (80.5%), and precision (1.000).

Joey Man Yee KWOK & Douglas Kei Shing[9], This study analyzed 337 undergraduate students at the Open University of Hong Kong . Perceived Stress Scale-10 (PSS-10) along with The Beck Anxiety Inventory (BAI) scale was used as the measure of perceived stress level and evaluating the convergent validity of PSS-10 respectively. The General Self-Efficacy (GSE) Scale and the Subjective Happiness Scale (SHS) were employed to assess the associated divergent validity. The primary results indicated that, the stress level of the participants in age group of 18-29 had an average score of 19.02 which was considered to be higher than the standard score (M = 14.2; SD =6.2), and thus undergraduate students who belonged to this age group were found to present a potential higher stress level among those participants.

Ms. Ancy Paul1, Ms. Resija P R2 et all[10], The objective of the study was to detect the different level of stress among students of Vimla College. Data from 954 students was gathered online. Nine algorithms were trained across three categories: a) chronic, b) episodic, and c) acute, achieving satisfactory accuracy levels. Among the nine algorithms, two models demonstrated superior accuracy: the RF classifier and logistic regression. Subsequently, the random forest classifier was used during the testing phase of the model development, effectively identifying the level of stress and categorizing, achieving an accuracy rate of 99% for both the classifers.

Prakruthi Manjunath, Twinkle S et all [11], A solution was suggested for the educational institution that enables authorities to monitor the anticipated stress levels of each enrolled student. The input for this process consists of survey data, which is utilized by a pre-trained machine learning model to estimate the stress percentage for every student. The model performs a two-tier classification of stress levels, determining whether a student is stress-free or experiencing stress. Additionally, among those identified as stressed, a further categorization is made regarding the severity of their stress, classifying it as low, medium, or high. The underlying framework of the ML model is based on the KNN classification algorithm with the accuracy of 94.50%.

Ravinder Ahuja, Alisha Banga [12] , In this study, the authors assessed the mental stress experienced by students one week prior to examinations and during their internet usage. The aim was to evaluate stress levels among college students at various stages of their academic journey. Data was collected from 206 students at the Jaypee Institute of Information Technology. Four machine learning classification algorithms were applied with resulting accuracy as Random forest (83.33 %), Naïve Bayes (71.42 %), SVM (85.71%) and KNN (55.55%). Utilizing 10-fold cross-validation led to a notable enhancement in the accuracy and performance of the data. The analysis revealed that the support vector machine exhibited the highest performance among the four algorithms, attaining an accuracy of 85.71%.

Reshma Radheshamjee Baheti, Supriya Kinariwala [13], In this research, the author introduced a system framework designed to identify users' psychological stress levels through the analysis of weekly social media data. A word dictionary was employed, assigning ratings from -5 to +5 for each term. To classify and predict the data, the study utilized Support Vector Machine (SVM) and Naive Bayes (NB) algorithms. Additionally, two models, n-gram and Skip-gram, were implemented to enhance the accuracy of the results, incorporating Word Sense Disambiguation. Support Vector Machine with WSD and Ngram gives 65% precision and 67% recall.

MATERIALS AND METHODS

Dataset and preprocessing

We have used statistician random sampling for data collection. The data collection process yielded information from 57 students total of 106 final year students pursuing M-Tech degrees in Computer Science, Information Technology, Software Engineering, and Data Science, conducted via a Google Form. The questioner designed for stress prediction is having 14 questions out of which 10 questions are of PSS-10 scale and four questions focuses on kindness for exploring the perceived kindness with stress in our study. The dataset consists of three targeted classes low, moderate and high in alignment with the prescribed standard defined by well-established and validated PSS-10 scale. We have used label encoding for converting the categorical data values to the numerical data . The dataset further divided into training set and testing set in the ration 80:20 ration respectively for Machine Learning model training and evaluation. Accuracy, precision, recall and confusion matrix are used to evaluate the performance of a classification model.

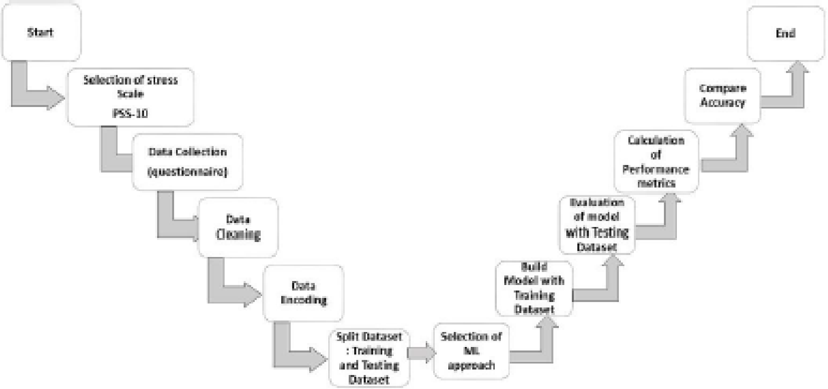


Figure 1: Methodology

The Perceived Stress Scale-10 (PSS-10)

The Perceived Stress Scale-10 (PSS-10) is a widely used psychological assessment tool designed to measure perceived stress in individuals. Formulated by Sheldon Cohen and colleagues. It consists of 10 items that are rated on a 5-point Likert scale, ranging from 0 ("never") to 4 ("very often"). The PSS-10 is valuable because it measures perceived stress over the past month, reflecting a subjective appraisal of life circumstances rather than specific stressors or their intensity. This subjective approach makes it particularly useful for comparing stress levels across diverse populations and contexts. The stress level is detected based on the total of PSSS score as below:

1. If the PSS score is between 0 to 13, it denotes that the stress level of students is low.
2. If the PSS score is between 14 to 26, it implies that the stress level of students is moderate.
3. If the PSS score is between 27-40, it indicates that the stress level of students is high.

Machine Learning Techniques.

Categorical data often requires specialized machine learning algorithms or preprocessing techniques to handle its discrete nature. Here are brief descriptions of a few key algorithms used in the study.

1. **Decision Trees** (DT): Decision trees work well with categorical data as they partition the data based on feature values at each node. They handle non-linear relationships effectively, can process mixed types of data, and are intuitive to interpret. Overfitting can occur, but this can be mitigated with pruning techniques or ensemble methods.

2. **Naive Bayes:** Naive Bayes is a probabilistic algorithm that assumes independence between features. It is particularly suitable for categorical data because it calculates the likelihood of each class given the feature values. Despite its simplicity, it often performs well in text classification and spam detection tasks.

3. **K-Nearest Neighbors** (KNN): KNN can work with categorical data by using distance metrics such as the Hamming distance. It classifies new instances based on the majority class of their nearest neighbors. While simple to implement, it can be computationally expensive for large datasets.

4. **Logistic Regression:** Logistic regression is applicable for the classification of categorical data in both binary and multiclass scenarios. Through the implementation of the sigmoid function, it forecasts the probabilities for the various classes. Categorical variables often need to be encoded using techniques like one-hot encoding or label encoding before being used.

5. **Random Forests (RF):** Random forests are an ensemble method based on decision trees. They are robust to overfitting and provide strong performance on categorical data. By averaging or voting across multiple trees, random forests reduce variance and improve predictions.

6. **Support Vector Machines (SVM):** Although primarily designed for continuous data, SVMs can handle categorical data through kernel tricks or appropriate encoding. This technique is particularly effective particularly in scenarios where the data cannot be separated linearly.

Performance measures.

There are many performance measures we can use to compare the performance of machine learning models. We have used following prime performance measurers which are calculated using True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) predictions of confusion matrix.

Accuracy: It is the ratio of correct prediction (all positive and negative prediction) to the total predictions.

Formula used to calculate the accuracy is:

ACCURACY = (TP + TN)/ (TP + TN + FP + FN)

Precision: It is the ratio of correctly positive to all positive predictions. Formula used to calculate the precision is:

PRECISION = TP/ (TP + FP)

Recall: It represents the ratio of accurately identified positive predictions to the overall count of actual positive occurrences. The formula used to determine recall is:

RECALL = TP/ (TP + FN)

F1-score : It is defined as the harmonic mean of precision and recall. Formula used to calculate the F1score is:

F1 score=2[(Precision*Recall)/(Precision +Recall)]

RESULTS

In this study , jupyter notebook and python libraries (pandas, numpy, matplotlib, sklearn) are used for metric calculation model selection, data preprocessing , descriptive statistics of machine learning algorithms and data. Details of Dataset used in this study are:

Total Students=106 (M.Tech(DS,IT,SWE and CS))

Data collected=57

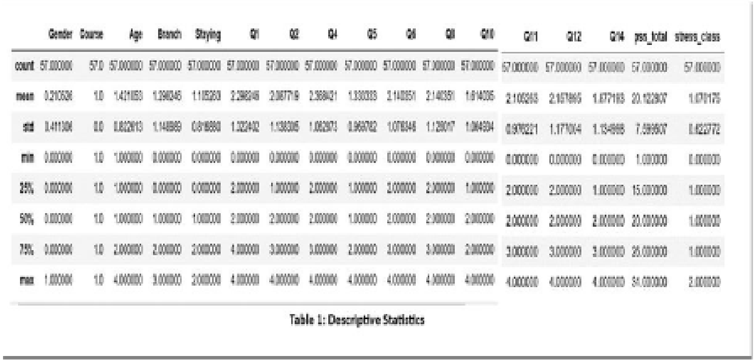
Stress Scale used=PSS-10

Data Collection Technique=Random Sampling

Data collection method=questionnaire

After preprocessing, mean, median, SD, MIN, MAX ,and interquartile range for all parameter of the data are calculated as shown in Table 1.

Table1: Descriptive statistics of the dataset



	Gender	Course	Age	Branch	Staying	Q1	Q2	Q4	Q5	Q6	Q8	Q10	Q11	Q12	Q14	pss_total	stress_class
count	57.000000	57.0	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000	57.000000
mean	0.210526	1.0	1.421053	1.298246	1.105263	2.298246	2.087719	2.368421	1.333333	2.140351	2.140351	1.614035	2.105263	2.157895	1.877193	20.122807	1.070175
std	0.411306	0.0	0.822913	1.148989	0.816880	1.322402	1.138306	1.062973	0.968702	1.078346	1.128017	1.084934	0.976221	1.177004	1.134986	7.596607	0.622772
min	0.000000	1.0	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000
25%	0.000000	1.0	1.000000	0.000000	0.000000	2.000000	1.000000	2.000000	1.000000	2.000000	2.000000	1.000000	2.000000	2.000000	1.000000	15.000000	1.000000
50%	0.000000	1.0	1.000000	1.000000	1.000000	2.000000	2.000000	2.000000	1.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	20.000000	1.000000
75%	0.000000	1.0	2.000000	2.000000	2.000000	4.000000	3.000000	3.000000	2.000000	3.000000	3.000000	2.000000	3.000000	3.000000	3.000000	26.000000	1.000000
max	1.000000	1.0	4.000000	3.000000	2.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	34.000000	2.000000

Table 1: Descriptive Statistics

As per the analysis maximum students are found at moderate level of stress, which is pre-stage to the high level of perceived stress. In a group of 57 students, 9 are identified as having low stress levels, 35 are assessed to be at a moderate level of stress, while 13 students are classified as experiencing high perceived stress levels as shown in Fig 2.

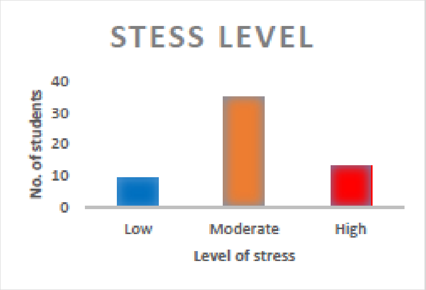


Figure 2:Stress Level

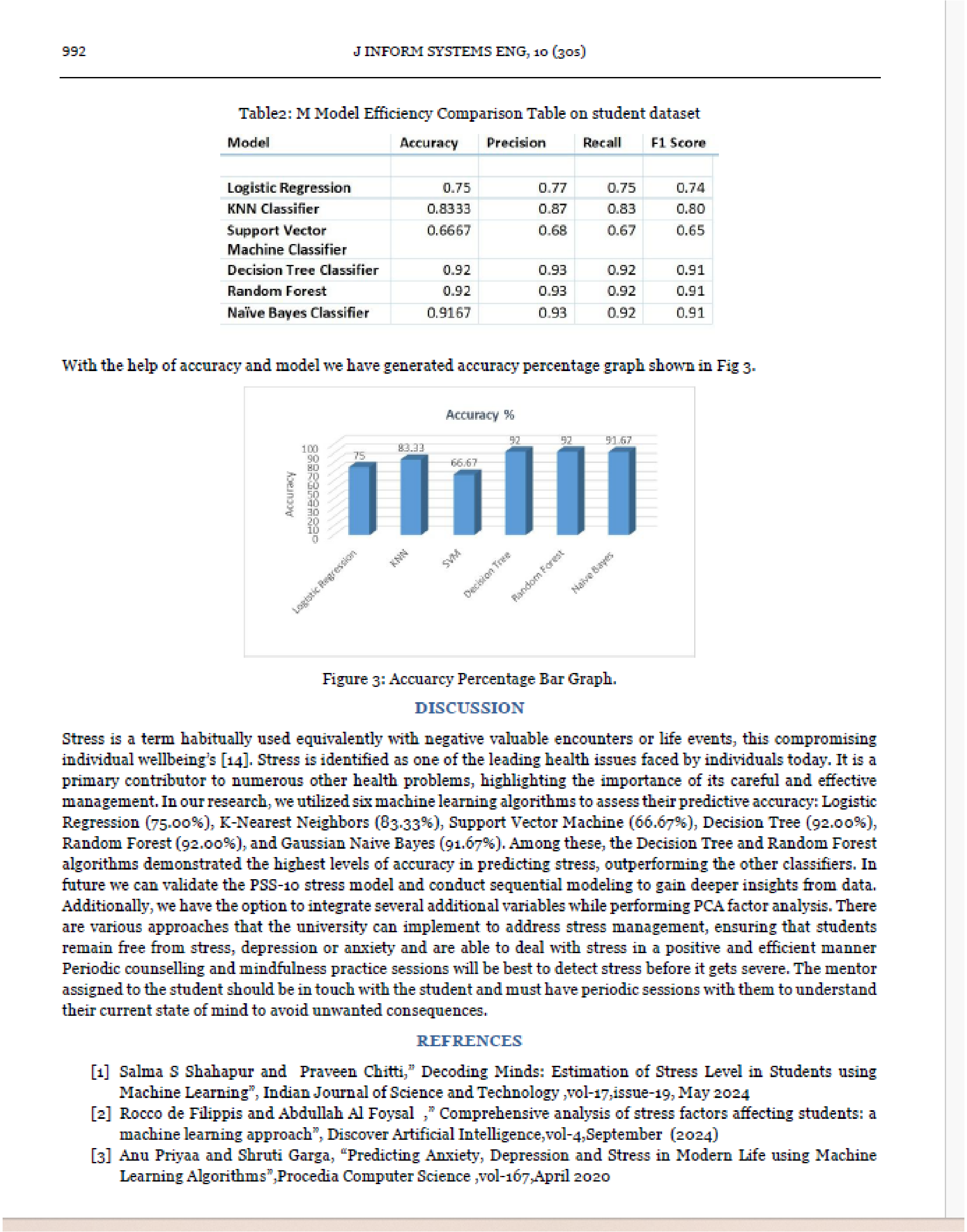


Table2: M Model Efficiency Comparison Table on student dataset

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.75	0.77	0.75	0.74
KNN Classifier	0.8333	0.87	0.83	0.80
Support Vector Machine Classifier	0.6667	0.68	0.67	0.65
Decision Tree Classifier	0.92	0.93	0.92	0.91
Random Forest	0.92	0.93	0.92	0.91
Naïve Bayes Classifier	0.9167	0.93	0.92	0.91

With the help of accuracy and model we have generated accuracy percentage graph shown in Fig 3.

Figure 3: Accuarcy Percentage Bar Graph.

DISCUSSION

Stress is a term habitually used equivalently with negative valuable encounters or life events, this compromising individual wellbeing's [14]. Stress is identified as one of the leading health issues faced by individuals today. It is a primary contributor to numerous other health problems, highlighting the importance of its careful and effective management. In our research, we utilized six machine learning algorithms to assess their predictive accuracy: Logistic Regression (75.00%), K-Nearest Neighbors (83.33%), Support Vector Machine (66.67%), Decision Tree (92.00%), Random Forest (92.00%), and Gaussian Naive Bayes (91.67%). Among these, the Decision Tree and Random Forest algorithms demonstrated the highest levels of accuracy in predicting stress, outperforming the other classifiers. In future we can validate the PSS-10 stress model and conduct sequential modeling to gain deeper insights from data. Additionally, we have the option to integrate several additional variables while performing PCA factor analysis. There are various approaches that the university can implement to address stress management, ensuring that students remain free from stress, depression or anxiety and are able to deal with stress in a positive and efficient manner Periodic counselling and mindfulness practice sessions will be best to detect stress before it gets severe. The mentor assigned to the student should be in touch with the student and must have periodic sessions with them to understand their current state of mind to avoid unwanted consequences.

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