

# Forecasting the Psychological Well-being of Engineering Students Utilizing Machine Learning

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**Abstract**—The increasing global prevalence of mental health disorders, coupled with the rigorous demands of engineering curricula, underscores an urgent need for proactive mental health support among engineering students. The pressures associated with intensive coursework, high-stakes assessments, and competitive job markets profoundly affect the psychological health of this demographic. This project aimed to forecast the psychological well-being of engineering students by identifying and analyzing the most impactful influencing factors using Machine Learning (ML). A comprehensive psychological assessment was conducted via a structured questionnaire, meticulously designed in consultation with specialist psychologists. The data collected underwent extensive preprocessing, including the standardization of 67 numerical columns using Z-score normalization. For predictive modeling, a stacked ensemble learning approach was implemented, utilizing five base models. After rigorous performance comparison, the Multi-Layer Perceptron (MLP) was selected as the optimal meta-learner. Optimization and feature selection were enhanced using techniques such as ANOVA, Mutual Information, Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and Particle Swarm Optimization (PSO). The results demonstrated the efficacy of the stacked ensemble model, with the MLP meta-model achieving the highest stacking accuracy of 90.8%. Among individual classifiers, the MLP model achieved the highest overall performance with an F1 Score of 96.52%. Furthermore, feature selection through PSO yielded an accuracy of 96.33%. Key factors consistently identified as highly influential in predicting well-being included stress management, routine pattern, and engineering passion. This research highlights the practical advantage of advanced data analytics in proactively identifying and supporting stressed students, enabling targeted interventions and mitigating adverse effects on academic performance and holistic development.

**Index Terms**—Engineering, Students, Psychological Well-being, Machine Learning

## I. INTRODUCTION

The increasing global prevalence of mental health disorders highlights an immediate need for preventative mental health assistance for engineering students, in combination with the incredibly tough nature of engineering degrees. The psychological health of this demographic is influenced by the stressors associated with hardcore coursework, exhaustive assessments, and difficult job placement. This project aimed to

forecast the psychological well-being of engineering students by identifying and analyzing the most impactful influencing factors using ML. A comprehensive psychological assessment was conducted via a structured questionnaire, meticulously designed in consultation with specialist psychologists. The collected data underwent extensive preprocessing, including the standardization of 67 numerical columns using Z-score normalization. For predictive modeling, a stacked ensemble learning approach was implemented, utilizing five base models -Logistic Regression (LR), K-Nearest Neighbors(KNN), Classification and Regression Trees, Support Vector Machine (SVM), and Naive Bayes(NB). After rigorous performance comparison, the MLP was selected as the optimal meta-learner. Optimization and feature selection were enhanced using techniques such as ANOVA, Mutual Information, RFE, PCA, and PSO. Thus, the above results have successfully validated the stacked ensemble model as indicated by the highest stacking accuracy achieved by the MLP meta-model of 90.8%. Meanwhile, the MLA model had the top performance among individual classifiers as expressed by the F1 Score of 96.52%. Additionally, the PSO feature selection yielded an optimal accuracy of 96.33%. However, this feature model consumed too much time because it attempted all feature permutations. Key factors consistently identified as highly influential in predicting well-being included stress management, routine pattern, and engineering passion. This research highlights the practical advantage of advanced data analytics in proactively identifying and supporting stressed students, enabling targeted interventions and mitigating adverse effects on academic performance and holistic development.

## II. LITERATURE REVIEW

Dr. J V Gorabal's study (2023) focuses on predicting student stress levels using machine learning techniques. While it accurately predicts stress levels, it lacks in uncovering underlying relationships within psychological data. The study proposes implementing a comprehensive system to manage student stress by providing personalized suggestions. [7]

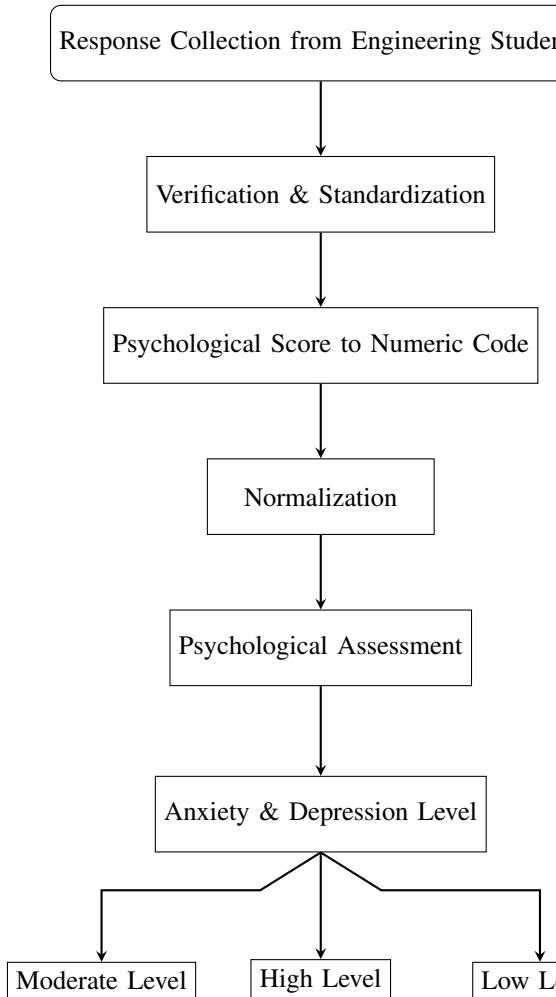


Fig. 1: Proposed Methodology for Assessing Student Psychological Levels.

Radhika R., Halde's study (2016) explores psychology-assisted prediction of academic performance using ML. While it demonstrates a 4 to 6 percent increase in prediction accuracy, limitations include focusing solely on final year students, reliance on self-reported data for variables like motivation, and failure to consider external factors influencing academic performance. "The study employs Neural Network for numeric prediction of CGPA and Decision Tree for classification of failures in the sixth semester". [4]

Zamani, M., Mohammad both focused on identifying factors and classifying mental health problems, with Mutualib finding Decision Tree (DT) to be the most accurate model for stress, depression, and anxiety. [14] Iddrisu Issah, Obed Appiah emphasized the need for a comprehensive system to predict and manage student stress, Peter Appiahene, Fuseini Inusah demonstrated the impact of student psychology on academic performance, with ML algorithm improving prediction accuracy. These studies collectively highlight the potential of ML in profiling students for career prediction, by considering their mental health and academic performance. [6]

The work of Mutualib, Sofianita (2021) addresses the same issue of forecast mental health problems of students using ML models. DT, SVM, and Neural Network show the highest accuracy for stress, depression, and anxiety, respectively. The methodology involves collecting survey data, applying various MLA and evaluating model performance based on accuracy, sensitivity, specificity, and precision. DT and SVM perform best for stress and depression, while Logistic Regression and Neural Networks yield fair results for anxiety. [9]

Nor Safika Mohd Shafiee's study (2020) examines mental health issues among higher education students and reviews existing ML techniques for prediction. It discusses contributing factors to these problems but does not address specific challenges in their identification [14].

Jetli, Chung's study (2022) discusses ML approaches for predicting mental health problems applied to psychological profiling for the career prediction of students. The paper provides a systematic literature review, analyzing challenges and limitations with potential opportunities. Limitations include small sample sizes and a lack of validation from external sources. A search of reliable databases was conducted using the PRISMA methodology, and identified articles were categorized. SVM, Random Forest, and ANN were applied. [2].

Marouf's study (2019) uses machine learning to predict psychological behavior and stress reactions in undergraduate students with around 70 percent accuracy. It highlights limitations in sample specificity and potential bias from self-reported data. The Sequential Minimal Optimization (SMO) and KNN classifier models achieve the maximum accuracy. Data collection involved 150 participants, assessing personality traits and stress levels, and employing nine machine learning models for evaluation [8].

Ravinder Ahuja's study (2019) focuses on detecting mental stress in university students using MLA. Despite limitations such as data limited to one institute and a small sample size of 206 students, Support Vector Machine achieves the highest accuracy. The study analyzes stress before exams and during internet usage, correlating it with online time. It highlights the importance of addressing factors like exam pressure and recruitment stress. Methodology involves applying four classification algorithms and enhancing accuracy through 10-Fold Cross-Validation. Identified research gaps include the impact of exam pressure and recruitment stress on mental stress levels and the correlation between stress factors and internet usage time. [1]

Rahman (2022) makes use ML algorithm random forest and adaptive boosting in order to identify the traits of negative mental well-being among college students using their health behavior data. Key findings include the identification of important predictors such as body mass index, sports activities per week, GPA, sedentary hours, and age. The study confirmed that random forest was superior compared to other classifiers like KNN, NB. Limitations include a cross-sectional design, bias caused by self-reporting, and data unavailable because of the regulation of intellectual property. This study emphasizes the need for more sophisticated methods such as natural

language processing and points out the scarcity of similar studies conducted on Asian populations. [12]

Chiyue Wang's study shows at the (2023) AIKIE conference delves into mental health conditions of college students using MLA. The research underscores the necessity for tailored intervention strategies based on personal background, gender, academic year. While successful in analyzing mental health data and identifying critical factors, the study acknowledges limitations in generalizability and potential biases introduced by machine learning algorithms. Despite not detailing specific interventions, the study aims to inform the development of targeted mental health programs. Methodologically, the research employs various machine learning algorithms and advanced techniques to dissect large-scale data, ultimately contributing insights for crafting effective interventions in educational settings. [19]

Yutao Sun's study presented at the 2021 IEEE conference addresses the potential of machine learning for analyzing and warning about college students' psychological data, aiming to enhance mental health education. Identified limitations include the absence of comparative studies on machine learning algorithms, lack of established algorithm evaluation metrics for practical problems, and the need for further exploration into the application of training models in real-world scenarios. The study collected real datasets from a Chinese university and tested ten widely used MLA to determine the optimal model for mental health screening. Methodologically, the research involved testing various algorithms on collected datasets and designing a prototype system for early warning of mental health issues. Despite limitations in real-world implementation and potential contextual restrictions. [18]

Akash D'S proposed a system for predicting stress levels among college students using MLA. This system not only identifies stress but also provides solutions for alleviating it. Akash D identifies shortcomings in existing stress management methods and institutional approaches to tracking and mitigating student stress, stressing the need for improved solutions. The study employs ML algorithms like KNN,NB,DT, along with the SVM technique and Bayes classifier, for stress assessment and solution provision. Methodologically, data is collected through survey forms, and techniques like SVM and Bayes classifier are used for data classification and analysis. It shows the potential benefits of ML-based stress prediction and solutions in reducing student stress levels. However, the study suggests further research to analyze the relative efficiency of different algorithms and conduct a comparative study. [3]

In the 2023 CyMaEn conference paper by Pornrat Nison et al., the ML approach is presented to detect depression in college students. It utilizes general information without direct mental health questions and addresses class imbalance with resampling methods. The approach achieves an average predicting accuracy of up to 0.66, indicating progress in machine learning-based depression screening for college students. [10]

Yang Zhen's 2023 conference paper presents a model to predict college students' mental health based on status data. This study applies an Apriori algorithm and an XGBoost model,

optimized by the SMOTE+ENN method, in order to obtain highly effective accuracy, recall, F1 score, and AUC. The proposed compared to other traditional ML, model performs better. deep learning approaches and a precision of 0.87, recall of 0.86.an F1 score of 0.86, and an AUC of 0.89. Methodologically, the features are extracted from students' status data, the Apriori algorithm with a pre-pruning is applied, and then the optimized XGBoost model using SMOTE+ENN is used for prediction. [20]

In the 2022 ASSIC conference paper by Minakshi Roy et al., multimodal machine learning approaches for career prediction are explored. The study utilizes MLA including ADABOOST, SVM, RF, and DT to predict students' career choices. Results indicate that SVM achieves the highest accuracy of 98 percent , outperforming other algorithms. However, the study lacks discussion on limitations associated with computational approaches and does not specify limitations for the algorithms used. Methodologically, the dataset is trained and tested with the aforementioned algorithms to predict career choices. [13]

In the 2020 paper published in the IJRTE, the use of MLA for predicting student performance and career paths is discussed. The study highlights limitations including a limited dataset obtained from a single university, which may not represent the entire student population, and need for future research to collect data from multiple universities for better generalization. Methodologically, various MLA such as Linear Regression, Logistics Regression, SVM, NM-Classifier, and K-means Clustering are applied to predict student career paths, with their efficiencies compared using real data from university students. [16]

The Journal of Advanced College of Engineering and Management 2023 has presented the development of a Career Guidance System by Subiddhya Panthee et al. using MLA to guess suitable career paths for the students based on their skills, interests, and personality traits. Web-based questionnaires are used to gather data for predicting the Big Five personality traits and VAK learning types that the users fall under, making predictions with the use of algorithms such as SVM, RF, KNN, K-Means Clustering, and Artificial Neural Networks. Methodology: Through the application of data mining techniques and preprocessing, it enhances the decision of choosing a career with quite a few limitations regarding the quality of the dataset the authors depend on for the VAK learning model and overfitting to the age-training datasets. [11]

M. Srividya's study (2018) utilizes MLA to predict mental health states in various groups, including students, for career prediction purposes. The study emphasizes the importance of positive mental health for productivity and potential realization. Methodology involves applying machine learning algorithms, including SVM, DT, and NB classifier, to identify mental health states in different target groups. Cluster labels are validated using the Mean Opinion Score, and classifiers for mental health prediction are built. [17]

Based on our literature review, we identified the following issues that must be addressed:

- i. Reliance on self-reported data from one institute limits generalizability and may introduce bias.
- ii. Limited focus on final year students and specific stressors overlooks broader mental health concerns.
- iii. Failure to consider external factors and reliance on self-reported data may affect accuracy.
- iv. Absence of intervention assessment and limited discussion on long-term implications.
- v. Small sample size and variability in algorithm performance impact reliability.
- vi. Challenges in applying machine learning to real-world practices require further research and improvement.
- vii. Lack of discussion on computational limitations and unspecified drawbacks of the utilized algorithms.
- viii. Limited by the absence of direct mental health questions and potential biases due to class imbalance.

In conclusion, addressing the identified issues is imperative for advancing the understanding and support of mental health among students. Overcoming limitations such as reliance on self-reported data, narrow focus on specific stressors, and small sample sizes will enhance the generalizability and accuracy of research findings. Furthermore, evaluating interventions and considering long-term implications are essential for developing effective strategies. Continued research to improve the application of machine learning in real-world settings is necessary to provide comprehensive support for student mental health.

Below is the revised methodology section for your research paper, focusing on forecasting the psychological well-being of engineering students using an ensemble learning-based machine learning model. The section has been reviewed for sequence, accuracy, coherence, and proper information

### III. METHODOLOGY

#### A. Introduction

Mental health remains an important strand of a healthy life, and it is such a vital factor, especially among students pursuing challenging academic programs such as engineering. The rigorous nature of engineering curricula, coupled with various personal and social factors, can contribute to heightened stress levels and potential mental health issues. However, many students may not be aware of their mental health condition or lack the necessary resources to assess these concerns effectively.

This project aims to conduct a comprehensive psychological assessment among engineering students, focusing on identifying the most impactful factors influencing their mental health. By analysing these factors, the study seeks to determine whether a student is experiencing stress or other mental health challenges. The ultimate goal is to provide engineering students with valuable insights and a better understanding of their mental well-being.

Recognizing the significance of mental health in academic and personal life, this project endeavours to offer a tailored and accessible approach to psychological assessment, catering specifically to the unique needs and challenges faced by

engineering students. By shedding light on this crucial aspect, the study specifies the awareness and understanding of mental health among engineering students.

#### B. Data collection

TABLE I: Demographic Information of Engineering Students

Age in Years	Gender	Year of Engineering	Location
18-23	Male (62.8%) Female (37.2%)	1st Year (16.8%) 2nd Year (57.2%) 3rd Year (22%) Final Year (4%)	Rural (53.2%) Urban (46.8%)

TABLE II: Academic Engagement & Career Readiness

Risk Factors	Response in Percentages (%)
Academic satisfaction	Very satisfied: 45% Neutral: 30% Not satisfied: 25%
Extracurricular participation	Yes, frequently: 20% Occasionally: 45% No: 35%
Intellectual level	Advanced: 40% Intermediate: 30% Beginner: 30%
Fear of success	Yes: 25% No: 75%
Job flexibility	Choose another field: 35% Stick with engineering: 65%

To gather comprehensive data for this psychological assessment, a structured questionnaire was meticulously designed in consultation with specialist psychologists and peer counselors. The questionnaire aimed "Capture a wide range of factors Potentially influencing the mental health of engineering students, including psychological aspects, background information, interests, engagement levels, interactions and academic-related elements." [15]

The questionnaire encompassed questions pertaining to student' psychology, exploring their thought processes, emotional states, and coping mechanisms. Additionally, it delved into their personal backgrounds, seeking insights into familial, social, and environmental factors that might contribute to their overall well-being.

In addition, the questionnaire surveyed students' perceptions about academic performance, perceived pressure, expectations, and engagement related to their studies in engineering programs. This approach allowed for a holistic understanding of the cooperation between academic demands and mental health.

To ensure a diverse and representative sample, the questionnaire was distributed as a Google Form to students across all academic years and departments within the engineering school. Participation was voluntary, and all questions were mandatory, ensuring that each respondent provided comprehensive and candid responses.

By adopting this data collection approach, the study aimed to capture raw and authentic responses from engineering students, reflecting their genuine experiences, challenges, and

TABLE III: Survey Responses on Various Risk Factors

Risk Factor	Response in Percentages (%)
1. Financial Stability	Yes: 20.8% No: 79.2%
2. Loneliness	Same city: 20.1% Different district: 75.6% Different state: 3.4% NIR: 0.9%
3. Stress/Depression	Rarely: 16.4% Sometimes: 50.3% Frequently: 33.3%
4. Overall Feelings	Mostly good: 32.5% Okay: 49.8% Mostly bad: 13.9% Really bad: 3.8%
5. Career Backup Plan	Yes: 69.2% No: 30.8%
6. First in Family to College	Yes: 27.1% No: 72.9%
7. Enjoyment of Coursework	A lot: 40.4% Somewhat: 50.5% Not at all: 9.1%
8. Abandoning Hobbies	Yes: 44.4% No: 55.6%
9. Engineering Isolation	Frequently: 30.4% Occasionally: 69.6%
10. Mental Health Challenges	Yes: 79.4% No: 20.6%
11. Coping with Stress	Exercise: 21.4% Talking: 60.6% Ignoring it: 18%
12. Pride in Accomplishments	Yes: 52.8% So-so: 47.2%
13. Regular Physical Activity	Yes: 59.9% No: 40.1%
14. Pursuing Postgraduate	Yes: 42.2% Undecided: 57.8%

perspectives. This naturalistic approach was crucial to obtain an accurate and unbiased understanding of the mental health landscape among the target population.

The collected responses were securely stored in Excel spreadsheets, ensuring data integrity and facilitating further analysis and interpretation.

### C. Data Prepossessing

The data collected through the Google Form responses constituted the initial dataset for this study. However, before proceeding with further analysis, several prepossessing steps were undertaken to ensure the data integrity, completeness, and suitability for subsequent modelling and interpretation. Firstly, the dataset contained a mix of categorical and numerical data. To facilitate analysis, categorical data were converted into numerical form using an encoding technique. In consultation with counsellors and psychologists, certain questions and responses deemed irrelevant or repetitive were excluded from the dataset to eliminate redundancy and enhance data quality.

Subsequently, the dataset was thoroughly examined for missing values, and appropriate strategies were employed to address them. If a column or feature had a substantial number of missing values, rendering it insignificant for the analysis, it was removed from the dataset. Columns with a relatively low proportion of missing values were retained for analysis.

Furthermore, to transform the raw data into a meaningful and interpretable form, feature engineering was performed. In close collaboration with counsellors and psychologists, the questions and responses were carefully analysed, and appropriate labels were assigned to each feature, ensuring meaningful and descriptive representations. This process involved grouping related questions and responses into coherent features that could effectively capture the underlying psychological constructs and mental health aspects.

By these steps of data preprocessing, initial raw Dataset was transformed into a structured and refined dataset, ready for further analysis and modelling. The involvement of counsellors and psychologists throughout the process ensured that the data retained its psychological relevance and integrity, facilitating accurate insights into the mental health of engineering students.

### D. Normalization

In our dataset of 67 numerical variables, normalization was central to the standardization of the data range and distribution to further analyze it. The preprocessing was done in detail before normalization so that missing values and outliers were addressed and that integrated the integrity of our data. Using the Z-score normalization method, every numerical column was standardized separately to obtain a value of 0 as the mean and 1 as standard deviation. The steps in this process were removing the means of each column and dividing them with the standard deviation. After the normalization, the distribution and statistical Characteristics of the data were assessed using such visualizations as histograms and box plots, which confirmed the success of the normalization. Normalization helped to reduce the effects of varying scales and variances between features, thus allowing more meaningful comparisons and explanations of the data, and providing a strong base to further analyses and insights.

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (\text{Scaling})$$

### E. Model Selection

After exploring various machine learning models, we decided to use a stacked ensemble for our project. We chose the stacked ensemble because it holds the strengths of each individual model, the ensemble offers a powerful and flexible approach to predicting mental health outcomes, a perfect fit for our research needs.

Understanding Stacked Ensemble Model Imagine you have a group of friends, each with their own expertise. You might ask one friend for advice on sports, another for help with cooking, and so on. Similarly, a stacked ensemble model

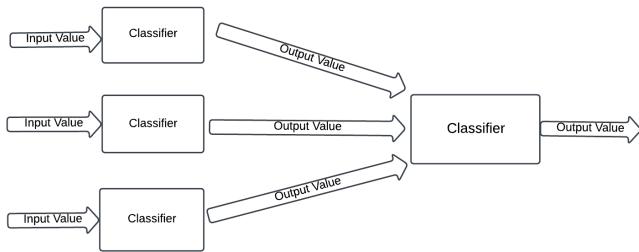


Fig. 2: System Architecture Diagram

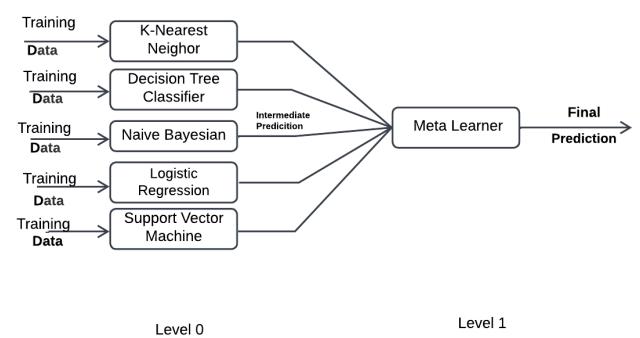


Fig. 3: Model Diagram: Stack Ensemble

combines the predictions of different machine learning models, each specialising in its own area, to make a smarter decision.

#### How Stacked Ensemble Works

Think of the stacked ensemble like a team of models. Each model (or base learner) has their own unique strengths (or machine learning algorithm). When faced with a challenge, the models combine their abilities to deal with issues (or make a prediction). But there's also a leader (or meta learner) who coordinates each and every decision and decides the best course of action based on their input.

#### Key Advantages of Stacked Ensemble

- Teamwork: By bringing together different models, the stacked ensemble can solve problems that no single model could tackle alone. Strength in Diversity: The ensemble benefits from the varied approaches of its base learners.
- Adaptability: The ensemble can adjust its strategy based on the situation, making it versatile and effective in different scenarios.
- Easy to Understand: Despite its complexity, the concept of combining predictions is intuitive and easy to grasp.

#### F. Model analyzing and training

In the beginning, we created a powerful model by combining different types of algorithms, like Logistic Regression, KNN, DT and others. This combined model is called a stacked ensemble, which is like having a team of experts working together to solve a problem.

We used SVM to oversee how these different algorithms work together and make the final predictions. Think of SVM as the meta-learner who decides on the best strategy based on everyone's input.

After training our stacked ensemble model, we carefully checked how well it performed. We wanted to make sure it gave accurate predictions, so we tested it thoroughly using different methods.

During testing, we realised we could improve our model even more by trying different strategies for the team captain role. We looked at other algorithms like DT, Logistic Regression, and MLP. After comparing their performance, we found that MLP was the best choice. It showed the most promise in making accurate predictions.

The evaluation of potential meta-learning architectures, we have formally adopted a MLP as the designated meta-learner

for our proposed framework. This determination represents a pivotal milestone in our study, as it concludes the extensive model selection and architectural design phase.

With the foundational components of the model now definitively established, the focus of the research transitions from model configuration to performance optimization. The subsequent stage will involve a systematic and meticulous fine-tuning process. This process will be dedicated to optimizing the model's hyperparameters to maximize its predictive accuracy, enhance its generalization capabilities, and ensure overall model efficacy.

#### G. Optimization and Feature Selection Techniques

We applied both statistical and optimization methods in the feature selection to identify and be able to select the most relevant features of ML. We first started by employing some statistical techniques: ANOVA, MI, and RFE. Analysis of variance, popularly known as ANOVA, is a statistical test used for analyzing the differences between more than two groups of data. In feature selection, ANOVA helps identify features that exhibit significant variations across classes or groups and thus are likely to be relevant for predicting the target variable.

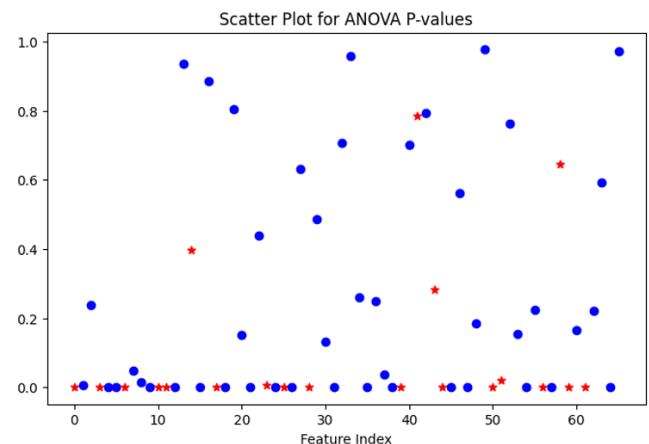


Fig. 4: Scatter Plot ANOVA

Mutual Information (MI) is another statistical measure that has been used in this paper for dependence analysis between two variables, following the approach of measuring information gain about one variable from knowing the other. MI computes the information gain about each feature concerning the target variable and thus locates the features carrying the most relevant information for prediction.

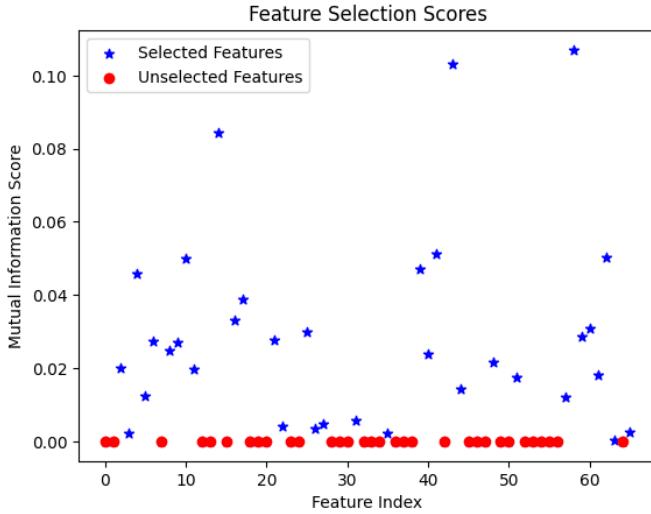


Fig. 5: Feature Selection Score

RFE is an iterative technique that systematically removes the least important features from the dataset. RFE typically utilises a machine learning model to evaluate feature importance iteratively. It removes features with the least contribution to the model's performance, retaining only the most informative features for prediction.

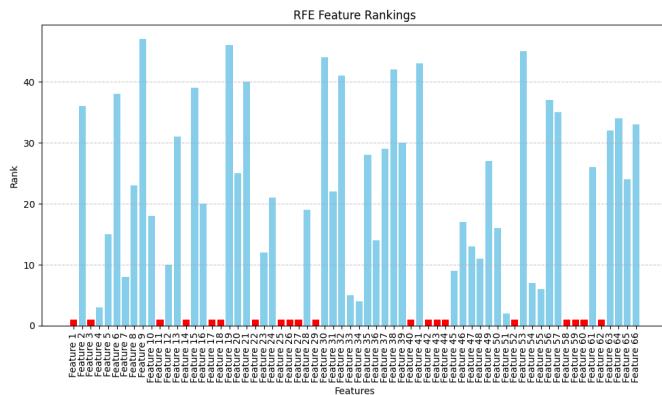


Fig. 6: RFE Feature Ranking

Optimization methods were used to maximize further our feature selection algorithm. PCA is a dimensionality reduction method of converting high-dimensional data into a dimensional space and retaining most of the significant information. PCA determines orthogonal axes, which are referred to principal components, which is the maximum variance in the data. The designation of features that relate to these principal can

be used to select features. PCA helps to reduce the dimensions of the dataset without losing its important information.

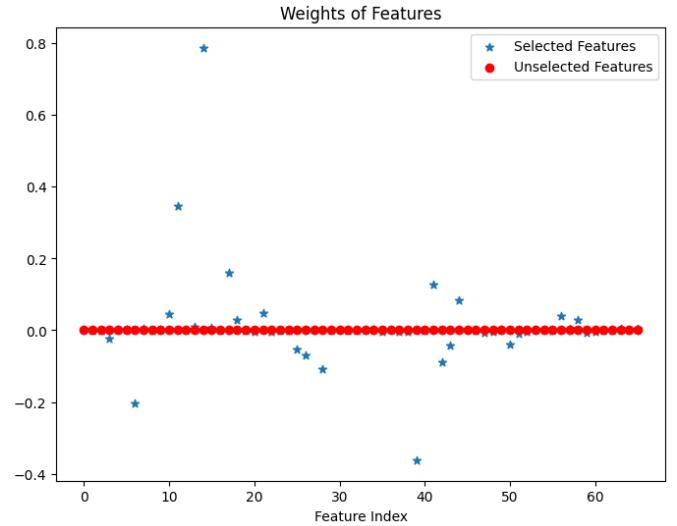


Fig. 7: Weights of Features

Another optimization technique we used in this work is PSO. PSO is a population-based optimization algorithm that replicates the social behavior of birdflocking or fish schooling. During each iteration, it updates a swarm of candidatesolutions, represented by particles, to discover the subset of features that maximizes a predefined fitness function. The convergence behaviour and exploration-exploitation trade-off of PSO depend on several parameters like the swarm size, inertia weight, and acceleration coefficients.

Different techniques employed By employing these techniques in our feature selection process, we aimed to find the most relevant features for our predictive modelling task by improving the model's Performance and interpretive ability.

To determine which factor most greatly impacts the level of stress. Among engineering students, different analysis techniques were used to assess the importance of several features. These features include the student's passion for engineering, their role in internships, development of future skills, ability to manage stress, feelings of being overwhelmed by college, aspirations for higher studies, ability to deal with arguments, real-time agitation, feelings of pride, impact of recession, routine patterns, and self-care practices. The resulting table gives the feature importance as determined by the different techniques employed.

## IV. RESULTS AND DISCUSSION

### A. Outcomes

In this study, a stacked ensemble model was employed to forecast the psychological well-being of engineering students. The ensemble comprised five base models: LR, KNN, Classification and Regression Trees (CART), SVM, and Naive Bayes. Five different meta-models were utilized: SVM, DT Classifier, Logistic Regression, MLP, and Gradient Descent. The table

TABLE IV: Percentage of Important Features

Feature	Percentage
engg_passion	16%
Internship_role	16%
future_skill_development	13%
stress_management	13%
college_overwhelmed	13%
higher_studies	12%
argument_deal	11%
realtime_agitate	10%
proud_feeling	10%

below summarizes the base model accuracies and stacking accuracies for each of the meta-Models:

TABLE V: Accuracy of Base Models and Meta Models

Models	SVM	DT	LR	MLP	GD
Logistic Regression	83.5%	83.5%	83.5%	83.3%	83.3%
K-Nearest Neighbours	83.6%	83.6%	83.6%	83.6%	83.6%
CART	68.4%	68.8%	68.8%	68.8%	68.8%
<b>SVM</b>	<b>90.7%</b>	<b>90.5%</b>	<b>90.5%</b>	<b>90.7%</b>	<b>90.7%</b>
Naive Bayes	82.4%	82.7%	82.7%	82.4%	82.4%
<b>Stacking Acc.</b>	<b>90.5%</b>	<b>87.0%</b>	<b>87.0%</b>	<b>90.8%</b>	<b>90.2%</b>

Note: DT is Decision Tree, LR is Logistic Regression, MLP is Multi-Layer Perceptron, GD is Gradient Descent, CART is Classification and Regression Trees.

Among the five meta-models evaluated, MLP meta-model achieved the highest stacking. An accuracy of 90.8%, indicating the effectiveness in integrating the predictions of the base models. The SVM meta-model and base model consistently exhibited the highest individual accuracy of 90.7% across all meta-models. However, when combined with the MLP meta-model, the stacking accuracy further improved to 90.8%, surpassing the individual SVM model's performance. The Decision Tree Classifier and Logistic Regression meta-models both yielded a stacking accuracy of 87.0%, which, although lower than the top-performing meta-models, still demonstrated substantial improvements over the individual base models. Overall, the results highlight the efficacy of the stacked ensemble approach, particularly with the MLP and Gradient Descent meta-models, in accurately forecasting the psychological well-being of engineering students by effectively combining the predictions of multiple base models.

The table below represents the performance metrics for the SVM, CART, LR, Gradient Boosting (GB), and MLP models used for classification.

TABLE VI: Performance Evaluation of Classification Models

Model	Recall (%)	Precision (%)	Accuracy (%)	F1 Score (%)
SVM	96.22	96.22	96.00	96.23
CART	92.45	93.03	92.33	92.74
LR	96.22	96.22	96.00	96.22
GB	94.33	95.54	94.66	94.93
<b>MLP</b>	<b>96.22</b>	<b>96.83</b>	<b>96.33</b>	<b>96.52</b>

Among these, the highest performance was provided by the MLP model, which achieved a 96.52% F-score, while

the SVM and LR models achieved F-scores of 96.23% and 96.22%, respectively. The GB model demonstrated good performance (F-score: 94.93%), while the CART model had the lowest performance (F-score: 92.74%). The high F-scores of the top-performing models indicate their effectiveness in accurately classifying instances related to forecasting the psychological well-being of engineering students.

### B. Hyper-parameters

TABLE VII: Hyperparameter Tuning

Classifier	Hyperparameter	Value
KNN	n_neighbour	5
LOGISTIC REGRESSION	max_iter	10000
	C	1.0
	solver	lbfgs
SVM	kernel	rbf
	C	1.0
	gamma	scale
DECISION TREE CLASSIFIER	max_depth	None
	min_samples_split	2

Like n\_neighbors in KNN affects local pattern sensitivity, max\_iter and C in LR control optimization iterations and regularization strength, kernel, C, and gamma in SVM determine kernel type, regularization, and kernel coefficient respectively. For decision trees, max\_depth limits tree depth and min\_samples\_split governs node splitting. Adjusting these hyperparameters tunes the model behavior for better performance.

- In this project, it explored various feature selection techniques, including ANOVA, MI,RFE,PCA,PSO to optimize the performance of our stacked ensemble model.
- ANOVA and MI: Utilizing statistical techniques, it identified relevant features, achieving accuracies of 90.33% and 92.33% respectively.
- RFE (Recursive Feature Elimination): Employing an iterative approach based on feature ranking, RFE yielded an accuracy of 90.33%. Interestingly, the selected features overlapped significantly with those from ANOVA and MI.
- PCA and PSO: holding optimization techniques, PCA and PSO demonstrated remarkable effectiveness, with accuracies of 92.33% and 96.33% respectively. These methods showcased their ability to discern the most appropriate features for model training, reinforcing the importance of optimization in enhancing performance.

TABLE VIII: Feature Selection Technique Evaluation

Feature Selection Technique	Accuracy
ANOVA	90.33%
Mutual Information	92.33%
RFE	90.33%
PCA	92.33%
PSO	96.33%

Across all feature selection techniques, certain features consistently stood out as highly influential. Notable examples include stress\_management, routine\_pattern,

and engg\_passion, underscoring their significance in predicting outcomes.

It utilized a heatmap to visualize pairwise correlations among the selected features. It helps identify strong positive and negative correlations, clusters of correlated features, and potential redundancies. This aids in identifying key features, detecting multicollinearity, and guiding feature engineering efforts. Most Impactful Features: Across all feature selection techniques, certain features consistently stood out as highly influential. Notable In the context of engg\_passion, internship\_role, Future\_skill\_development, stress\_management, College\_overwhelmed, higher\_studies, argument\_deal, Realtime\_agitate, proud\_feeling, recession\_impact, routine\_pattern, and selfcare are important aspects to consider. underscoring their significance in predicting outcomes. We utilized a heatmap to visualize pairwise correlations among the selected features. It helps identify strong positive and negative correlations, clusters of correlated features, and potential redundancies. This aids in identifying key features, detecting multicollinearity, and guiding feature engineering efforts.

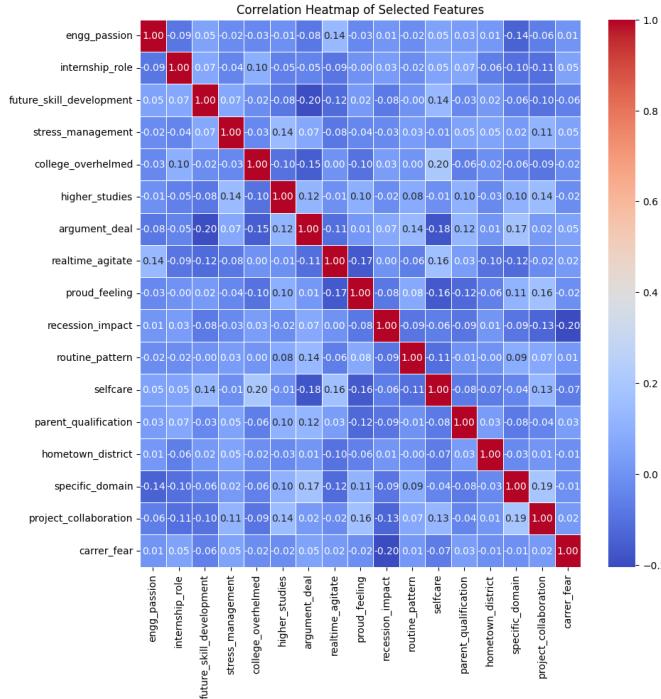


Fig. 8: Heatmap

### C. Confusion Matrix Analysis:

The confusion matrix is a detailed record of the model's Performance. In this case, it correctly classified 136 instances of Class 0, Negative, but missed 5 whereby they were classified as Positive, while it correctly classified 153 instances of Class 1, Positive, but again missed 6 which were wrongly classified as Negative. These incidences indicate where the model might be improved to ensure robustness. [5]

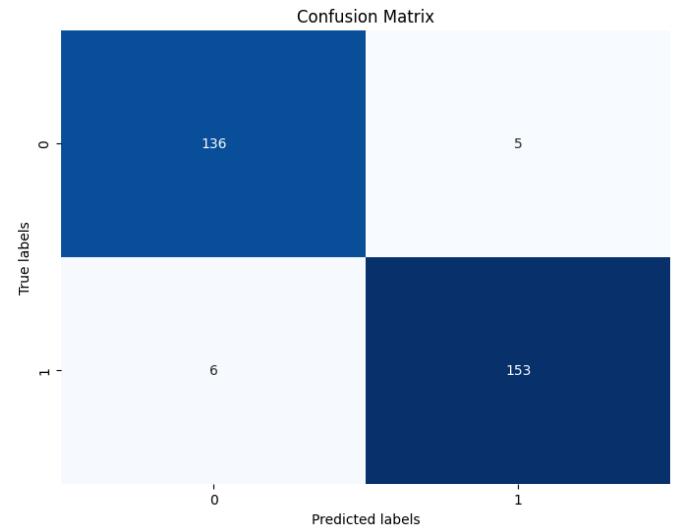


Fig. 9: Confusion Matrix

Overall, the combination of diverse feature selection methods and a stacked ensemble model enabled comprehensive analysis and robust predictive performance, laying a solid foundation for effective decision-making based on the dataset.

## V. CONCLUSION

This project looked at how engineering students are doing mentally by studying different factors that affect their well-being. It collected data, cleaned it up, and used fancy math to build a model that predicts how students are feeling. By using smart techniques, it found important factors like stress management and routine habits. It also checked how well our model worked and saw where it could do better.

This study explores how accurately it can understand stress in engineering students. Traditional methods, like assessments conducted by psychologists, may fall short and complicated when students are too stressed to provide accurate responses. Statistical methods also have limitations in accuracy. The study explains the potential of improved data analytics in determining influential stressors. This approach offers benefits in practice of identifying and supporting proactively stressed students, which will allow making targeted interventions and rehabilitation efforts to reduce the negative impact of stress on academic performance and well-being at large.

Overall, this research can assist us in knowing more about student mental health. recommends how they can be assisted in college.

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