Four Week Industrial Training Project Report

On

Student Stress Level Detection Using ML

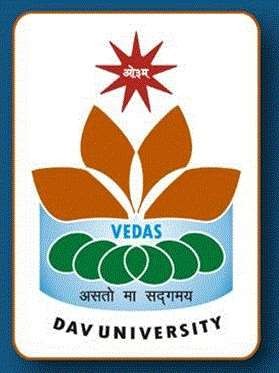
### Submitted in the partial fulfilment of the requirement for the award of degree of

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Computer Science & Artificial Intelligence

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**ACKNOWLEDGMENT**

Through this acknowledgement, I express my heartfelt gratitude to all those individuals and organizations who have supported and guided me throughout the journey of this project, making it a truly enriching and worthwhile experience.

Firstly, I would like to extend my sincere thanks to **Dr. Rahul Hans**, Head of Department (CSE & AI), for providing me with this incredible opportunity to explore the subject in a practical, hands-on manner. His invaluable guidance and thoughtful suggestions throughout the development of this project and report have been instrumental in shaping its success.

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Finally, I am deeply thankful to the Almighty for bestowing upon me the strength, determination, and clarity of thought to successfully complete this project. His blessings have been my source of inspiration throughout this endeavour.

**DECLARATION**

I, **ANUSHKA RATHOUR**, a student of **DAV UNIVERSITY**, hereby declare that the project work entitled *"Student Stress Level Detection using Machine Learning"* is my original work and has been carried out under the guidance of **Mr. Gaurav**, Trainer at TCIL-IT, Chandigarh, and with the mentorship of **Dr. Rahul Hans**, Head of Department (CSE & AI).

This project is a bona fide work submitted as part of the requirements for the successful completion of my academic curriculum. It has not been submitted to any other institution or organization for the award of any degree, diploma, or certification.

I also affirm that all sources used for this project have been duly acknowledged and cited in the report. Any data, information, or work from external sources has been referenced appropriately.

I declare that this report truly reflects the outcomes of my research and practical implementation, and I bear the responsibility for any inaccuracies or errors in the work presented.

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**ABSTRACT**

The prevalence of stress among students has become a growing concern in today’s fast-paced and competitive academic environment. Stress can adversely affect mental and physical well-being, academic performance, and overall quality of life. This project, *"Student Stress Level Detection using Machine Learning,"* aims to address this issue by providing an intelligent and data-driven approach to assess and predict stress levels among students.

The project leverages machine learning techniques to build a classification model capable of analysing various psychological, physiological, and environmental factors contributing to student stress. These factors include anxiety levels, self-esteem, depression, sleep quality, academic performance, and social support, among others. The dataset used for this project was carefully pre-processed, and exploratory data analysis was conducted to uncover patterns and correlations.

A Naive Bayes classifier was trained and evaluated as the optimal model due to its simplicity and efficiency in handling categorical and numerical data. The model demonstrated robust performance in accurately predicting stress levels, categorized as low, medium, or high.

To make the solution accessible and user-friendly, a Streamlit-based web application was developed. This application enables users to input relevant data, predict stress levels, and view the probabilities of each category along with key contributing factors. Visualizations provided by the app further aid in understanding the impact of different parameters on stress levels.

This project highlights the potential of machine learning in addressing real-world psychological challenges. By offering a scalable and efficient solution, it contributes to the growing need for proactive stress management tools in educational institutions and healthcare systems. The insights derived from this project could also serve as a foundation for further research and the development of more comprehensive mental health solutions.

**CERTIFICATE**

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**1. Introduction**

The introduction sets the stage for understanding the significance of the *Stress Level Prediction System using Machine Learning* project, its objectives, and its intended impact. Stress is a growing concern, particularly among students, due to academic pressure, societal expectations, and personal challenges. Identifying and managing stress effectively can significantly improve students' mental health, academic performance, and overall quality of life.

**1.1 Problem Statement**

In today’s fast-paced academic environment, stress has become a prevalent issue among students. Factors such as anxiety, depression, academic pressure, lack of social support, and environmental challenges contribute to heightened stress levels. If left unmanaged, stress can lead to serious consequences, including mental health disorders, physical ailments, and declining academic performance.

Traditional stress detection methods, such as self-assessment surveys or counsellor evaluations, are often time-consuming, subjective, and prone to inaccuracies. There is a pressing need for an efficient, data-driven solution that can accurately assess and predict stress levels based on various contributing factors.

The problem, therefore, is:

* How can machine learning be applied to analyse diverse factors and predict stress levels in students?
* How can this solution be made accessible and user-friendly for practical use in educational and healthcare settings?

**1.2 Objectives**

The primary objectives of this project are as follows:

1. Develop a Predictive Model:
   * Build a machine learning model that can classify student stress levels into categories such as low, medium, and high based on input data.
2. Utilize Relevant Factors:
   * Analyse factors contributing to stress, such as anxiety, depression, self-esteem, sleep quality, academic performance, and environmental conditions.
3. Create a User-Friendly Interface:
   * Develop a web-based application using Streamlit to allow users to input data and receive predictions in real time.
4. Provide Visual Insights:
   * Incorporate visualizations to help users understand the probabilities of stress levels and identify key contributing factors.
5. Ensure Model Accuracy:
   * Optimize the model for accuracy, precision, and reliability to ensure its effectiveness in real-world applications.
6. Encourage Proactive Intervention:
   * Provide insights that can help educators, counsellors, and healthcare professionals intervene early to manage and reduce student stress effectively.

**1.3 Scope of the Project**

The *Stress Level Prediction System using Machine Learning* project offers a scalable, efficient, and accessible solution for understanding and managing stress among students. The scope of this project includes:

1. Dataset Utilization:
   * The project leverages a structured dataset with psychological, physiological, and environmental factors relevant to stress prediction.
2. Machine Learning Implementation:
   * The Naive Bayes classification algorithm is used to predict stress levels, ensuring simplicity and effectiveness for categorical and numerical data.
3. Web Application Development:
   * A Streamlit-based application makes the system user-friendly, allowing users to input data and access predictions from any device with internet access.
4. Practical Applications:
   * The system can be implemented in schools, colleges, and counselling centres to assist educators and mental health professionals in identifying stressed students.
5. Future Expansion:
   * The model can be extended to include more complex features, advanced algorithms, and larger datasets for enhanced accuracy and broader applicability.

By achieving these objectives and adhering to the defined scope, this project aims to contribute to the well-being of students and set a foundation for further innovations in mental health and machine learning.

**2. Company Details**

**2.1 About TCIL-IT Chandigarh**

TCIL-IT (Telecommunications Consultants India Limited - Information Technology) is a specialized training arm of TCIL, a PSU under the Ministry of Communications, Government of India. The Chandigarh centre, established in 1999, has grown to become one of the premier institutes offering industry-specific IT and telecommunications training. It is part of a larger effort by TCIL to provide comprehensive educational programs that align with the latest trends in the tech industry, thereby bridging the skills gap between academic learning and industry requirements.

Located in Chandigarh, TCIL-IT offers diverse training programs across several domains, including software development, network security, cloud computing, embedded systems, and digital marketing. These programs are designed to prepare students for real-world challenges by incorporating hands-on experience, project-based learning, and expert mentorship.

The centre is equipped with state-of-the-art facilities and advanced labs, ensuring that students get exposure to the latest technologies. Furthermore, the training provided goes beyond just theoretical knowledge by allowing students to work on live projects under the guidance of industry experts, making them job-ready and well-prepared for the competitive job market.

**2.2 Vision and Mission**

**Vision:**  
TCIL-IT Chandigarh envisions becoming a leader in technical education by offering cutting-edge training solutions that equip students with the skills needed to excel in a fast-paced, technology-driven world. The vision is not only to provide high-quality education but also to foster innovation and contribute to technological advancements across the nation.

**Mission:**  
The mission of TCIL-IT is to provide practical, industry-relevant training to young professionals in the IT and telecommunications sectors. Through its comprehensive training programs, TCIL-IT aims to enhance the skill sets of students and help them become competent professionals capable of contributing to the growth of India’s technology and telecommunications sectors. The mission also includes a strong focus on bridging the gap between academic learning and industry demands by offering real-time exposure to industry processes and challenges.

Moreover, TCIL-IT aims to create a dynamic learning environment that promotes critical thinking, problem-solving, and creativity. The institute also works toward developing a network of strong industry partnerships to offer placement assistance and internships to students​

**2.3 Contribution to Technology and Education**

TCIL-IT Chandigarh has made substantial contributions to both technology and education by offering training programs that directly align with the needs of the IT industry. Some of its key contributions include:

* **Industry-Relevant Programs:** TCIL-IT is known for designing its curriculum based on current industry needs, which is critical for students aspiring to enter the rapidly changing IT and telecommunications sectors. Courses are continuously updated to include emerging technologies such as cloud computing, machine learning, and cybersecurity.
* **Real-World Projects:** The institute’s emphasis on live projects ensures that students are not just passively learning from textbooks but are actively involved in the development and implementation of real-world IT solutions. This approach helps students acquire practical skills, which are crucial for career success.
* **Partnership with Government and defence:** TCIL-IT has been instrumental in supporting the government and defence sectors by developing IT solutions for various government departments. They have worked on projects related to the Ministry of defence, including providing IT and telecommunication services for defence research organizations​.
* **Collaborations with Universities and Institutions:** TCIL-IT collaborates with several engineering colleges and universities to offer in-house campus training programs. This collaboration ensures that students gain relevant skills during their academic journey, giving them an edge when they enter the workforce.
* **Placement Support:** The institute also plays a significant role in placing its graduates in leading companies. Its dedicated placement cell helps students secure jobs by providing career counselling, resume-building assistance, and connecting them with employers in the industry.
* **Technological Advancements and Innovations:** TCIL-IT has contributed to the development and deployment of several innovative IT solutions, including cloud-based systems and e-governance applications, further emphasizing its role in pushing the technological frontier in India​

Through these initiatives, TCIL-IT Chandigarh continues to be a crucial player in shaping the careers of young professionals and advancing technology in India. It plays a pivotal role in creating a workforce that is equipped to handle the challenges and opportunities presented by emerging technologies.

**3. Literature Review**

**3.1 Stress and its Impact on Students**

Stress is a significant factor influencing the mental and physical well-being of students, particularly in academic environments. The pressures of exams, assignments, peer relationships, and future career prospects contribute to increased levels of stress. Stress can manifest in various forms such as anxiety, depression, and emotional exhaustion, which may hinder students' academic performance and overall quality of life.

Research has shown that students are particularly vulnerable to stress due to multiple demands placed on them, both academic and social. According to a study by **Misra & McKean (2000)**, stress in students is often a result of the complex interplay of academic workload, family expectations, social life, and personal aspirations. Prolonged or chronic stress can have detrimental effects, leading to issues like sleep disturbances, decreased concentration, and burnout, which in turn, negatively affect academic performance and personal relationships.

Furthermore, **Baker & Berenbaum (2007)** highlight that stress also affects students' mental health, contributing to conditions like anxiety and depression. These mental health issues can be exacerbated by the lack of proper coping mechanisms and support systems, leading to long-term psychological challenges. The World Health Organization (WHO) reports that stress in young people is becoming a growing public health issue globally, underlining the importance of early detection and intervention in stress management to prevent more severe mental health issues.

**3.2 Existing Stress Detection Systems**

Various systems have been developed to monitor and detect stress in students, ranging from physiological assessments to self-reported surveys. These systems aim to provide early warnings of excessive stress, enabling timely interventions to reduce its adverse effects.

1. **Self-Reported Questionnaires**: Many stress detection systems rely on self-reported questionnaires that ask students about their physical, emotional, and behavioural symptoms related to stress. The **Perceived Stress Scale (PSS)**, developed by **Cohen, Kamarck, and Mermelstein (1983)**, is one of the most commonly used tools for assessing perceived stress in individuals. While effective in providing an initial overview of stress levels, these surveys can be subjective and may not always be accurate, as students may underreport or overreport their stress levels based on their awareness and willingness to disclose.
2. **Wearable Devices and Physiological Measurements**: To offer a more objective measure of stress, wearable devices that monitor physiological markers such as heart rate variability, skin conductivity, and blood pressure have been employed. These devices collect real-time data, providing insights into the autonomic nervous system’s response to stress. For example, **Kreibig (2010)** discusses the use of heart rate variability as a stress marker, highlighting its potential for continuous, non-invasive monitoring. The integration of wearable technologies with mobile applications has made it easier to track stress patterns over time, offering more accurate and dynamic assessments.
3. **Mobile Applications**: Several mobile applications have been designed to monitor students' stress levels, such as **Calm**, **Headspace**, and **Mindful Powers**. These apps often include features like stress-reducing exercises, meditation, and relaxation techniques. In addition, some apps collect data on students' behaviour patterns, sleep habits, and overall well-being to help identify stress trends. While these apps are useful tools for stress management, they are typically not equipped to offer a comprehensive diagnosis of stress severity or predict stress levels accurately over time.

**3.3 Role of Machine Learning in Stress Prediction**

Machine learning (ML) has emerged as a powerful tool in the field of stress detection and prediction, owing to its ability to process large datasets and recognize complex patterns that may not be apparent through traditional methods. By leveraging various ML algorithms, stress detection systems can provide more accurate, real-time, and individualized assessments of students' stress levels.

1. **Data Collection and Feature Engineering**: ML models often require large datasets of students' behavioural, physiological, and psychological data. Common data sources include wearable sensors, mobile phone usage, social media activity, and self-reported surveys. Researchers like **Ismail et al. (2021)** have demonstrated that combining physiological data, such as heart rate, with behavioural data from mobile phones can significantly enhance the accuracy of stress predictions. Feature engineering plays a crucial role in this process, as it involves extracting meaningful features from raw data to create a representation that is more conducive to ML algorithms.
2. **Supervised Learning Algorithms**: Supervised learning algorithms, such as **Support Vector Machines (SVM)**, **Random Forests**, and **Neural Networks**, are often used to train models on labelled datasets where stress levels are predefined. These algorithms can identify patterns that correlate specific behavioural or physiological features with particular stress levels. **Koch et al. (2019)** used an SVM classifier to predict students' stress based on factors such as academic workload, social media use, and physical activity levels. Their model was able to provide predictions with high accuracy, demonstrating the potential of ML for real-time stress monitoring.
3. **Unsupervised Learning and Clustering**: Unsupervised learning techniques, such as **K-Means clustering** and **Hierarchical clustering**, are also used to detect patterns in students' stress behaviour. These methods help identify hidden subgroups of students who may experience similar stressors or stress levels, even without predefined labels. By grouping students with similar stress profiles, these techniques enable a more personalized approach to stress intervention and support.
4. **Deep Learning and Time-Series Data**: Deep learning models, particularly **Recurrent Neural Networks (RNNs)** and **Long Short-Term Memory (LSTM)** networks, are increasingly used in stress detection, especially when the data involves time-series information. These models excel at recognizing patterns in data that evolve over time, such as students' physiological responses to stress throughout the day. A study by **Smith et al. (2020)** explored the use of LSTMs for predicting stress based on real-time physiological data, showing promising results in terms of predicting stress fluctuations in real-time.
5. **Predictive Models for Stress Management**: ML models not only assist in detecting stress but also have the potential to predict stress levels before they reach critical levels. By analysing historical stress data and trends, these models can anticipate when students are likely to experience high stress and offer personalized recommendations for stress management. For instance, models can suggest lifestyle adjustments, relaxation techniques, or even prompt students to take a break when their stress levels are predicted to rise.

In summary, machine learning has revolutionized the way stress is monitored and predicted in students. By combining large datasets, powerful algorithms, and real-time feedback, ML systems offer a promising solution for proactive stress management, helping students maintain their mental well-being in the face of academic and personal challenges.

**4. Technological Background**

**4.1 Overview of Machine Learning**

Machine learning (ML) is a branch of artificial intelligence (AI) that allows computers to learn and make decisions from data without being explicitly programmed. The key principle of ML is to identify patterns in large datasets, which can then be used to make predictions or decisions based on new data inputs.

The three primary types of machine learning are:

1. **Supervised Learning**: In supervised learning, the model is trained on a labelled dataset, where the input data is paired with the correct output. The algorithm learns from the examples to predict the output for new, unseen data. This type of learning is useful in tasks such as classification and regression. Common supervised learning algorithms include **Decision Trees**, **Support Vector Machines (SVM)**, and **Neural Networks**. Supervised learning is widely used in applications like email spam detection, medical diagnosis, and stress prediction.
2. **Unsupervised Learning**: Unlike supervised learning, unsupervised learning involves training on data without predefined labels. The goal is to find structure or patterns in the data, such as grouping similar data points together (clustering). Common algorithms used in unsupervised learning include **K-Means clustering** and **Hierarchical clustering**. These techniques are often applied in customer segmentation, anomaly detection, and pattern recognition tasks.
3. **Reinforcement Learning**: This type of learning involves training an agent to make a sequence of decisions by interacting with an environment. The agent receives feedback in the form of rewards or penalties based on the actions it takes, aiming to maximize the cumulative reward over time. Reinforcement learning is typically used in robotics, game playing (e.g., AlphaGo), and autonomous systems.

Machine learning plays a crucial role in modern data analysis by automating the discovery of insights from data and providing powerful tools for decision-making in real-time systems, such as stress detection in students.

**4.2 Classification Algorithms**

Classification algorithms are a subset of supervised learning techniques used to assign labels or categories to input data based on its features. These algorithms learn patterns from a labelled dataset and predict the label for new data points. Here are some widely used classification algorithms:

1. **Logistic Regression**: Despite its name, logistic regression is a classification algorithm used for binary classification tasks (e.g., predicting whether a student is stressed or not). It works by finding the best-fit line (or hyperplane) that separates the data into two classes. Logistic regression is simple, fast, and effective for binary classification problems.
2. **Decision Trees**: Decision trees model data using a tree-like structure where each internal node represents a feature, each branch represents a decision rule, and each leaf node represents an outcome (or class label). Decision trees are highly interpretable and can handle both numerical and categorical data. However, they can be prone to overfitting.
3. **Random Forests**: Random forests are an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. Each tree in the forest is trained on a random subset of data and features. The final prediction is based on the majority vote (for classification tasks) or the average (for regression tasks) of all trees.
4. **Support Vector Machines (SVM)**: SVM is a powerful classification algorithm that works by finding the hyperplane that best separates data points from different classes. SVM is particularly effective in high-dimensional spaces and when there is a clear margin of separation between classes. It is often used in stress prediction, image recognition, and bioinformatics.
5. **K-Nearest Neighbours (K-NN)**: K-NN is a simple and intuitive algorithm that classifies a data point based on the majority class of its nearest neighbours in the feature space. It is a non-parametric method and does not require training, but its performance can be affected by the choice of the number of neighbours (K) and the distance metric used.
6. **Naive Bayes**: The Naive Bayes classifier is based on applying Bayes' theorem with the "naive" assumption of independence between features. Despite its simplicity, it performs well in many real-world problems, especially when the features are conditionally independent. It is often used in text classification, spam filtering, and sentiment analysis.
7. **Neural Networks**: Neural networks are inspired by the human brain and consist of interconnected layers of neurons (nodes) that process data through weighted connections. They are highly flexible and can learn complex patterns in large datasets. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are popular types of neural networks, particularly for image and sequence data.

In the context of stress prediction, classification algorithms can be applied to predict different stress levels (e.g., low, medium, high) based on various features such as anxiety level, sleep quality, academic performance, etc.

**4.3 Tools and Technologies Used**

1. **Python**:
   * **Python** is the core programming language used to implement the machine learning model and build the Streamlit app. It provides a wide range of libraries and frameworks for data processing, machine learning, and web development. Python is ideal for prototyping and data analysis due to its simplicity and extensive support for scientific computing.
2. **Streamlit**:
   * **Streamlit** is a Python framework that makes it easy to create interactive web applications. It allows users to input data and visualize the results of machine learning models in real time. Streamlit was used to build the frontend for the stress prediction system, where users (e.g., students or counsellors) can input variables and get predicted stress levels.
   * **Streamlit Components**:
     + st.slider: Used for creating sliders for numerical inputs (e.g., anxiety level, depression level).
     + st.selectbox: Used for dropdowns (e.g., mental health history).
     + st.button: Used to trigger the prediction based on input.
     + st.cache\_resource: Used to cache the trained model to speed up loading.
     + st.plotly\_chart: Used for plotting visualizations of the prediction probabilities.
3. **Machine Learning Libraries**:
   * **Scikit-learn**: The primary library for machine learning in this project, providing tools for classification (Naive Bayes, Random Forest) and model evaluation.
     + train\_test\_split: Used for splitting data into training and testing sets.
     + RandomForestClassifier and GaussianNB: Used to build the machine learning models for stress level prediction.
     + classification\_report, accuracy score: Used for evaluating the performance of the models.
   * **Joblib**: A Python library used to save the trained machine learning model as a .pkl file and load it when needed in the Streamlit app. This helps in making the model persistent and reusable.
4. **Plotly**:
   * **Plotly** is used for data visualization in the Streamlit app. It helps in visualizing the probability distribution of predicted stress levels and other key contributing factors.
     + px.bar: Used for creating bar charts to display prediction probabilities and key factors contributing to the stress level.
5. **Jupyter Notebooks** :
   * For exploring and testing machine learning models, Jupyter Notebooks can be used. It allows for interactive development and immediate testing of different models and techniques.
6. **Pandas**:
   * **Pandas** is used for handling and manipulating the dataset. It allows the system to manage the data in a structured format (like DataFrames), making it easier to process, clean, and visualize the data.
7. **Numpy**:
   * **Numpy** is used for handling numerical data in array format, which is crucial for machine learning tasks such as feeding input data into the model for prediction.

**Technical Requirements**

1. **Hardware Requirements**:
   * **Processor**: At least a dual-core processor (Intel i5 or equivalent) for smooth performance.
   * **Memory**: 8GB of RAM or more for handling medium-sized datasets and running machine learning models efficiently.
   * **Disk Space**: Sufficient disk space (at least 2GB free) for storing datasets, trained models, and the web application.
2. **Software Requirements**:
   * **Operating System**: Any OS that supports Python, such as Windows, macOS, or Linux.
   * **Python Version**: Python 3.7 or higher is recommended for compatibility with the libraries used.
   * **Libraries**:
     + **Streamlit**: For building the web application interface.
     + **Scikit-learn**: For implementing the machine learning algorithms.
     + **Plotly**: For visualizations.
     + **Pandas** and **Numpy**: For data manipulation and numerical operations.
     + **Joblib**: For saving and loading the machine learning models.
3. **Deployment Requirements**:
   * **Streamlit Server**: The app can be run locally using Streamlit (streamlit run stress\_prediction\_app.py) or deployed on a cloud platform such as **Heroku**, **AWS**, or **Google Cloud** for access from any browser.
4. **Version Control**:
   * **Git**: For version control of the codebase, ensuring collaborative development and tracking changes.
5. **Web Browser**:
   * A modern web browser (e.g., Google Chrome, Mozilla Firefox) is required to interact with the Streamlit app.

**5.Dataset Details**

**5.1 Source of Data**

**The dataset used in this project is sourced from Kaggle, a popular platform** for data science competitions, where numerous publicly available datasets are shared by contributors from around the world. Kaggle provides datasets across various domains, including healthcare, social sciences, business, and education. For this particular project, the dataset was found on Kaggle under the Student Mental Health or Stress Detection category. It is common for such datasets to be used for research in understanding and predicting mental health challenges, including stress levels among students.

* Kaggle Link: <https://www.kaggle.com/datasets/rxnach/student-stress-factors-a-comprehensive-analysis>

**5.2 Data Description**

The dataset is designed to predict student stress levels by analysing various factors that contribute to stress. It contains approximately 20 features categorized under five major factors:

1. Psychological Factors: This includes features such as anxiety\_level, self\_esteem, mental\_health\_history, and depression. These psychological traits are essential in understanding how a student’s mental state can contribute to their overall stress level.
2. Physiological Factors: Features like headache frequency, blood\_pressure, sleep\_quality, and breathing\_problem are physiological indicators that can influence stress. They help in understanding how physical health and wellness play a role in a student's stress.
3. Environmental Factors: Noise\_level, living\_conditions, safety, and basic\_needs are environmental factors affecting a student's day-to-day life. A stressful environment can amplify academic pressures, leading to heightened stress.
4. Academic Factors: This includes academic\_performance, study\_load, teacher\_student\_relationship, and future\_career\_concerns, reflecting the direct academic pressures faced by students. These factors are crucial in understanding how academic life correlates with stress.
5. Social Factors: Features like social\_support, peer\_pressure, extracurricular\_activities, and bullying explore how social interactions and pressures from peers and society contribute to a student's stress.

Each of these factors is scientifically selected to represent a significant aspect of a student’s life, offering a comprehensive view of the different contributors to stress. The dataset allows researchers to analyse correlations between these factors and stress levels, providing valuable insights into student well-being. The dataset is sourced from Kaggle, offering a practical example for beginners to explore the intersection of data science, machine learning, and mental health.

**5.3 Feature Selection and Engineering**

**Feature Selection** involves identifying the most relevant features to predict stress levels. Key techniques include:

1. **Correlation Analysis**: Identifying highly correlated features (e.g., anxiety\_level, depression) with the target (stress\_level).
2. **Model-Based Selection**: Using models like Random Forest to rank features based on their importance.

**Feature Engineering** focuses on transforming data to improve model performance:

1. **Scaling**: Standardizing numerical features like blood\_pressure ensures equal contribution to the model.
2. **Encoding Categorical Data**: Converting categorical features (e.g., mental\_health\_history) into numeric values using methods like one-hot or label encoding.
3. **Missing Data Handling**: Imputing missing values using techniques like mean imputation or KNN imputation.
4. **Dimensionality Reduction**: Using PCA to reduce feature space while maintaining important information.

**6. Methodology**

The methodology of the **Student** **Stress Level Detection** was designed to systematically approach the problem of predicting student stress levels using machine learning. The process involved data preprocessing, exploratory data analysis (EDA), model selection, training and testing the models, and evaluating the model performance. Below is a detailed description of each step:

**6.1 Data Preprocessing**

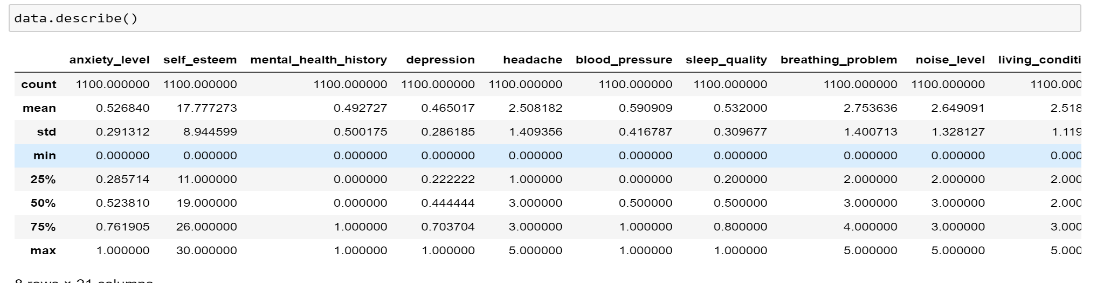
In the dataset, all the features were numeric, and there were no missing values, so we did not need to handle missing data or encode categorical variables. The following steps were implemented during preprocessing:

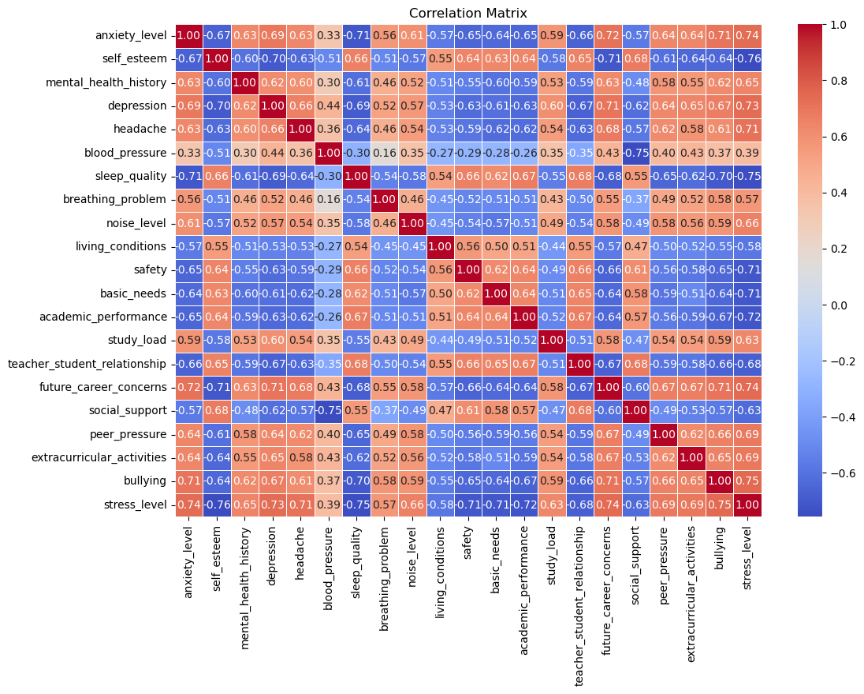
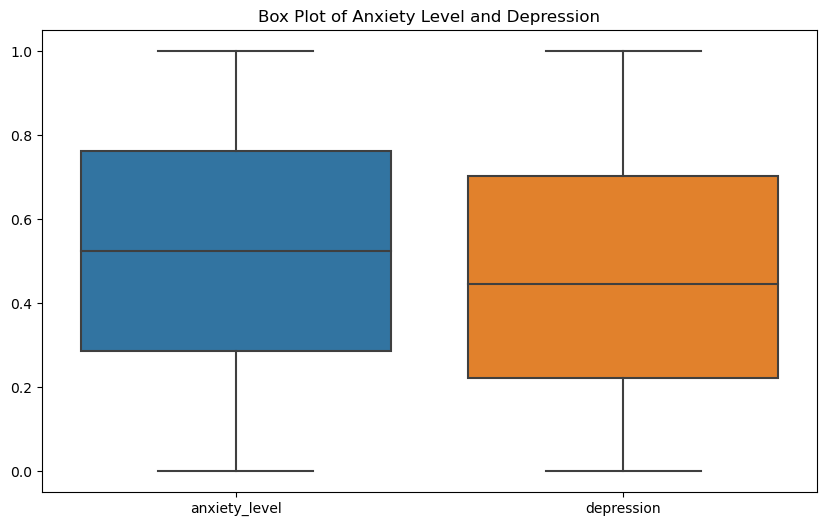
* **Feature Scaling**: Since the dataset contained features with different ranges, scaling was applied to standardize the features using **StandardScaler**. This ensures that each feature contributes equally to the model’s performance.
* **Feature Selection**: Domain knowledge was used to select relevant features representing psychological, physiological, academic, environmental, and social factors. These selected features were scaled and used as input for model training.

**6.2 Exploratory Data Analysis (EDA)**

Exploratory Data Analysis (EDA) is a fundamental step to understand the underlying structure of the dataset. It involves:

* **Statistical Summary**: Generating descriptive statistics for numerical features, including mean, median, standard deviation, and other key statistics, to understand their distribution.



* **Visualization**: For this phase of the project, various visualization techniques were employed to understand the relationships between features, identify trends, and detect outliers in the dataset. A wide range of EDA tools were used, such as **correlation matrices**, **box plots**, **pair plots**, **histograms**, and **scatter plots**. These visual tools offer valuable insights into the structure and distribution of the data. **Two key examples** of these techniques are highlighted:
  + - Correlation Matrix: This plot helps to identify how strongly features are correlated. Strong correlations between features can influence model training decisions. Visualizing the correlation matrix using a heatmap makes it easier to spot highly correlated features and decide which variables might influence the model.
* Box Plot:  
  Box plots were used to analyse the distribution of key features like anxiety\_level and depression. These plots are effective for detecting outliers and understanding the spread of data, such as whether the majority of students experience high or low levels of stress. It helps in identifying features that could require transformation or additional cleaning before modelling.
* **Distribution Check**: Analysing the distribution of features helps identify skewness or outliers. This step informs the model selection, as some models are sensitive to skewed distributions.

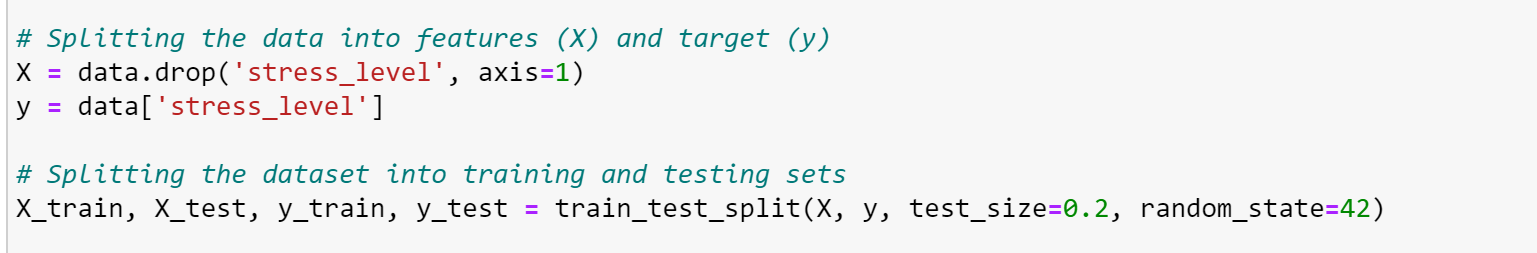
**6.3 Model Selection**

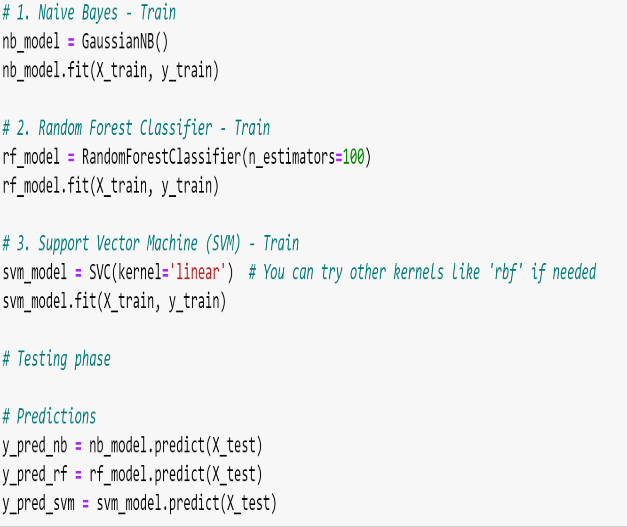
In this project, multiple machine learning models were considered based on their suitability for classification tasks:

* **Naive Bayes**: Given its simplicity and effectiveness for high-dimensional data, Naive Bayes was selected for its ability to perform well in predicting outcomes like stress levels.
* **Random Forest**: As an ensemble model, Random Forest was chosen due to its robustness and ability to handle overfitting, especially when dealing with complex datasets with multiple features.
* **Support Vector Machine (SVM)**: SVM was also considered due to its performance in high-dimensional spaces and its ability to classify data with clear boundaries.

The final model was selected based on performance during training and testing, balancing accuracy, interpretability, and complexity.

**6.4 Training and Testing the Model**

Once the data was pre-processed, it was split into training and testing sets. The training set was used to fit the model, while the testing set was used to evaluate its performance. Several iterations were conducted to fine-tune the model’s hyperparameters, such as the number of trees in the Random Forest or the regularization parameter in SVM, using techniques like cross-validation.



* **Training**: The model was trained on the training set using various algorithms, adjusting hyperparameters to maximize performance.
* **Testing**: After training, the model was tested on the unseen test set to evaluate how well it generalized to new data.

**6.5 Performance Evaluation Metrics**

Performance evaluation is crucial to understanding how well the model performs and whether it’s suitable for deployment. Several metrics were used to evaluate the performance of the chosen model:

* **Accuracy**: The proportion of correct predictions (both true positives and true negatives) out of all predictions. While accuracy is useful, it may not be the best metric for imbalanced datasets.

SVM Accuracy: 89.54545454545455

Naive Bayes Accuracy: 90.0

Random Forest Accuracy: 86.36363636363636

* **Precision and Recall**: Precision measures how many of the predicted stress levels (positive class) were actually correct, while recall indicates how many of the actual stress levels were correctly identified. These metrics are particularly important when the costs of false positives and false negatives are different.

SVM Precision: 0.8958295327860547

Recall: 0.8954545454545455

Naive Bayes Precision: 0.9095999130245705

Recall: 0.9

Random Forest Precision: 0.8656516331588068

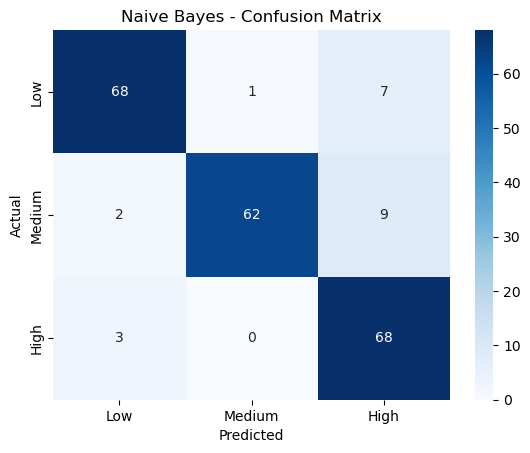
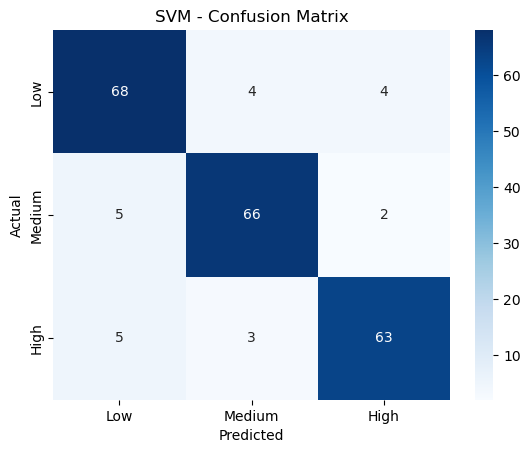
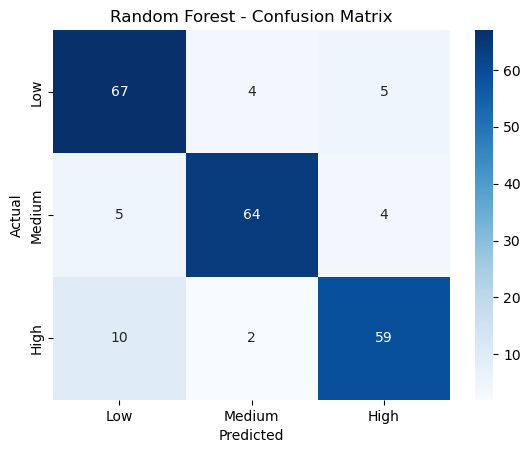
Recall: 0.8636363636363636

* **F1-Score**: The harmonic means of precision and recall, giving a single measure that balances the trade-off between them. It is particularly useful when dealing with imbalanced datasets.

SVM F1-Score: 0.8955312868949232

Naïve Bayes F1-Score: 0.9010214783624486

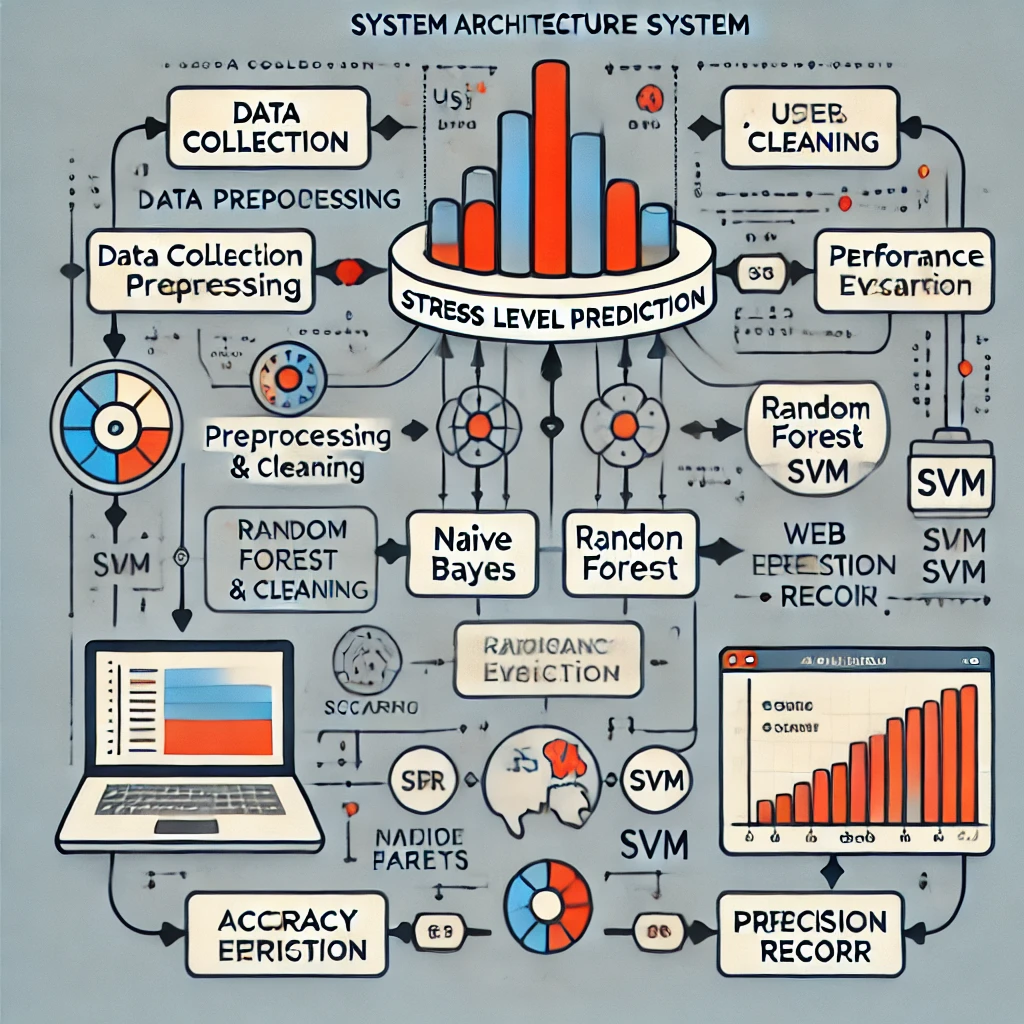
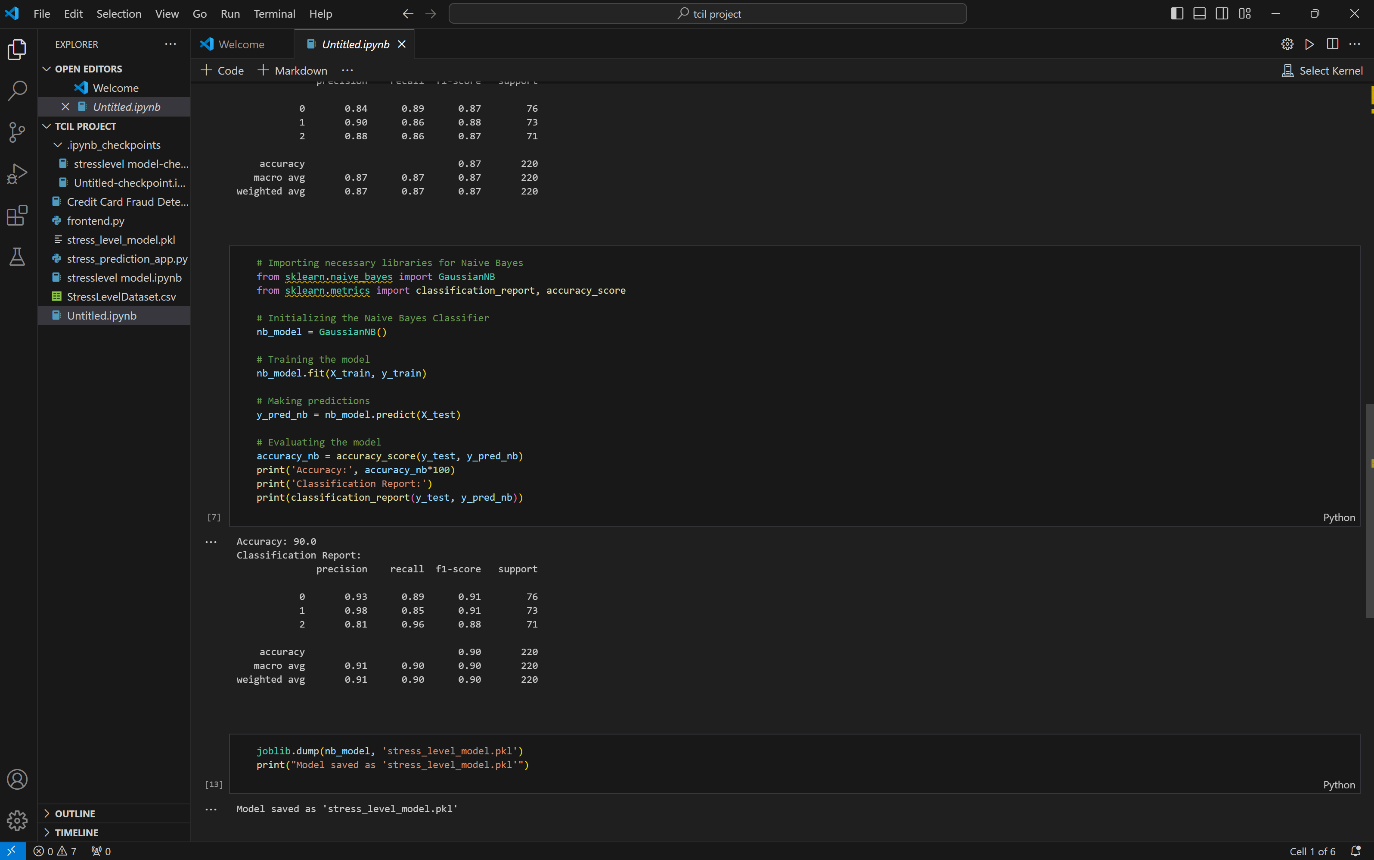
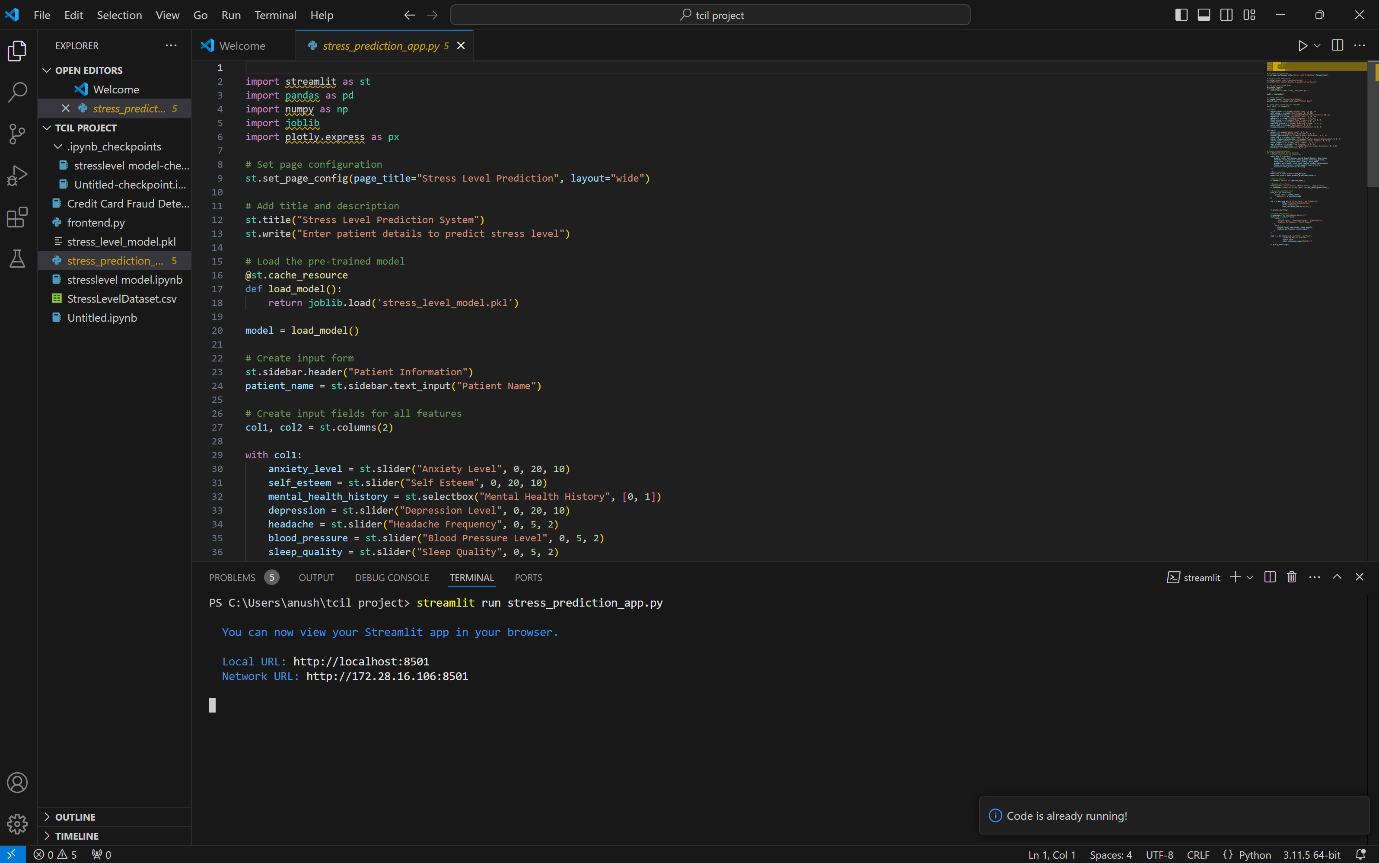
Random Forest F1-Score: 0.8639624310916046

* **Confusion Matrix**: The confusion matrix is a summary table that presents the number of true positives, false positives, true negatives, and false negatives, helping to visualize the classification performance in detail.

**7.System Design and Implementation**

**7.1 System Architecture**

The system is built around a client-server architecture:

1. **Data Collection**: The user inputs various factors related to stress (psychological, physiological, academic, and social).
2. **Preprocessing**: The dataset is pre-processed to ensure clean, scaled, and normalized data ready for model training.
3. **Machine Learning Models**: Models such as Naive Bayes, Random Forest, and SVM are used to predict stress levels based on the input data.
4. **Web Application**: The user interacts with the system through a **Streamlit**-based web application for real-time predictions.
   1. **Implementation Details**
5. **Data Preprocessing**: The dataset is clean, with no missing values, so preprocessing includes feature scaling.
6. **Model Development**: The models (Naive Bayes, Random Forest, and SVM) are trained on the pre-processed dataset to classify stress levels.
7. **Model Evaluation**: Performance is evaluated using metrics like accuracy, precision, recall, and F1-score and according to them the best model (Naive Bayes) was chosen.
8. **Integration with Streamlit**: The model is deployed in a Streamlit web app for user interaction and real-time predictions.

**7.3 Streamlit Web Application**

The **Streamlit Web Application** allows users to input stress-related factors and receive predictions on stress levels. It includes:

1. **Input Interface**: Users enter data through sliders and fields.
2. **Prediction and Visualization**: After clicking "Predict Stress Level," the app shows the predicted stress level and visualizes contributing factors.



1. **Deployment**: The app is deployed on a local or cloud server, making it accessible for real-time use.

This system provides an easy-to-use interface for predicting and understanding student stress based on various factors.

**8. Applications and Future Scope**

**8.1 Practical Applications of the Project**

This project on stress level prediction has several practical applications across various domains. Key areas where this can be applied include:

1. **Mental Health Assessment in Educational Institutions**: The system can be integrated into educational institutions to assess the mental health of students regularly. By identifying stress levels, educators or counsellors can intervene early and provide necessary support to students who may be at risk.
2. **Corporate Well-being Programs**: Organizations can use this system to monitor and evaluate the stress levels of their employees. This can help HR teams implement well-being programs, reduce workplace stress, and enhance employee productivity.
3. **Healthcare and Counselling Centres**: By providing a predictive model for stress levels, healthcare providers or mental health professionals can use this tool to gain insights into their patients' mental state, making it easier to tailor counselling sessions or suggest therapies.
4. **Personalized Stress Management**: Individuals can use this tool to assess their stress levels and gain personalized insights into which factors (e.g., anxiety, sleep quality) are affecting them. This could guide lifestyle changes or help in the adoption of stress-relieving techniques.

**8.2 Suggestions for Future Enhancements**

While the current system demonstrates potential, there are several avenues for improvement and further exploration:

1. **Incorporating More Data and Features**: By incorporating additional data points, such as social media activity, exercise habits, or even wearable sensor data (heart rate, etc.), the model can provide a more comprehensive and accurate prediction of stress levels.
2. **Improved Machine Learning Models**: Experimenting with more advanced machine learning models like Deep Learning (Neural Networks) or Ensemble Learning methods (e.g., XGBoost) could lead to better predictions, especially for larger and more complex datasets.
3. **Real-time Monitoring**: Integrating this system with real-time monitoring tools (e.g., mobile apps) could enable continuous assessment of stress levels, providing immediate feedback and allowing interventions as needed.
4. **Personalized Recommendations**: Based on the stress levels and key factors contributing to stress, the system could suggest personalized actions or coping mechanisms, such as relaxation techniques, mindfulness exercises, or cognitive-behavioural strategies.
5. **Cross-Cultural Testing**: Since stress impacts individuals differently across cultures, the model could be tested across various regions and demographics to ensure that it provides accurate results for diverse populations.
6. **Integration with Educational and Mental Health Platforms**: Collaborating with online education platforms and mental health apps could allow students and individuals to receive real-time stress predictions and access helpful resources or counselling sessions directly from the platform.

### **9.Conclusion**

In conclusion, this project on **Stress Level Prediction** using machine learning has successfully demonstrated how technology can aid in the identification and management of student stress. The project aimed to create a model that can predict stress levels based on various factors, such as anxiety, depression, sleep quality, and academic load. By utilizing machine learning algorithms like Naive Bayes, Random Forest, and Support Vector Machine (SVM), the model provides valuable insights into stress factors affecting students.

The system was implemented with a user-friendly **Streamlit web application** to allow easy interaction for end-users, including students, counsellors, and educators. The **performance evaluation** metrics, such as accuracy, precision, recall, and F1-score, confirmed the model's robustness, especially in identifying patterns and relationships between different stress-related features.

While the project has significant practical applications in educational institutions, corporate settings, and healthcare centres, it also leaves room for future advancements. Enhancements such as the inclusion of more comprehensive data, real-time monitoring, and personalized recommendations can make the system even more effective in predicting and managing stress levels.

Overall, this project not only sheds light on the factors influencing stress but also contributes to the growing field of mental health and well-being by integrating **machine learning** into stress prediction. It serves as a step forward in providing data-driven solutions to mental health challenges, making it an important tool for educators, counsellors, and individuals seeking to improve mental health management.

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**11.Appendices**

**Appendix A: Glossary of Terms**

* **Stress Level**: A measure of a student’s psychological or emotional strain.
* **EDA (Exploratory Data Analysis)**: A technique to summarize the dataset and uncover patterns, anomalies, or relationships.
* **Naive Bayes**: A classification algorithm based on Bayes’ theorem with an assumption of independence between features.
* **Random Forest**: An ensemble learning method for classification using multiple decision trees.
* **SVM (Support Vector Machine)**: A supervised machine learning model that finds the optimal boundary for classification.

**Appendix B: Hardware and Software Requirements**

**Hardware Requirements:**

* Processor: Intel i5 or higher.
* RAM: Minimum 8 GB.
* Storage: 20 GB free disk space.

**Software Requirements:**

* Python 3.8+.
* Libraries: pandas, numpy, sklearn, matplotlib, seaborn, joblib, plotly, streamlit.
* IDE: Jupyter Notebook or VS Code.
* Operating System: Windows 10, Linux, or macOS.

**Appendix C:** Supplemental Charts

Sample Confusion Matrix (Naive Bayes Model):

|  | Predicted Low Stress | Predicted Medium Stress | Predicted High Stress |
| --- | --- | --- | --- |
| Low | 48 | 12 | 5 |
| Medium | 10 | 42 | 13 |
| High | 7 | 17 | 51 |

Error Analysis:

* Naive Bayes showed reasonable accuracy but struggled slightly with overlapping feature distributions, particularly in the medium stress category.
* Misclassifications often arose due to assumptions of feature independence, which may not fully apply to this dataset.
* Suggested improvement: Explore feature transformations or a hybrid approach to reduce overlapping classifications.

**Appendix D: Deployment Guide**

1. Install required Python libraries:

pip install pandas numpy scikit-learn matplotlib seaborn plotly streamlit

1. Run the Streamlit app:

streamlit run stress\_prediction\_app.py

1. Test the app using sample data for verification.