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PREDICTIONS OF COLLEGE STUDENTS' MENTAL STRESS USING MACHINE LEARNING ALGORITHMS

Dr. Persis Urbana Ivy B[1],
Dr. Patlannagari Hasitha Reddy[1],
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Dr. Persis Urbana Ivy B[1], Dr. Patlannagari Hasitha Reddy[1], Dr. Algubelly Yashwanth Reddy[1]
[1]Department of Computer Science and Engineering
[1]Sree Dattha Group of Institutions, Sheriguda, Telangana.

ABSTRACT
The mental health of college students has become a significant concern, with increasing awareness of stress and its impact on academic performance and overall well-being. Early efforts in this area used surveys and counseling sessions to identify stress levels. Traditional System Surveys and Questionnaires, Interviews and Counseling Sessions, Observational Methods Academic Performance and Attendance Records, Problem Statement: College students experience high levels of stress, but existing mental health support systems are reactive and fail to provide timely interventions. There is a need for accurate, real-time prediction models to identify and address mental stress early. Research Motivation like Machine learning algorithms offer the potential to predict mental stress with higher accuracy and timeliness. This research aims to develop predictive models to identify stress patterns and enable early interventions, thereby improving student well-being.The proposed system leverages machine learning algorithms to predict mental stress among college students based on various factors such as academic performance, social interactions, and physiological data. The system aims to provide real-time stress level predictions, allowing for early and targeted interventions. Like Stress Sense, Smartphone-Based Stress Monitoring, EduWell is a comprehensive system that integrates academic performance, attendance records, and self-reported data to predict student stress levels, WellBe is a smart bracelet that monitors physiological parameters such as heart rate and skin temperature to assess stress levels. It utilizes classification models like Random Forest and SVM for accurate predictions and effective stress management.

INTRODUCTION

Introduction

The mental health of college students has become a significant concern in recent years, with increasing awareness of stress and its impact on academic performance and overall well-being. According to the American College Health Association (ACHA), nearly 60% of college students in the United States reported feeling overwhelming anxiety in the past year, and about 40% reported experiencing severe depression . The COVID-19 pandemic has exacerbated these issues, with many students facing additional stressors such as remote learning, social isolation, and financial uncertainties. Traditional methods for assessing mental stress among college students primarily involve surveys, questionnaires, interviews, and counseling sessions. Standardized tools like the Beck Depression Inventory (BDI), the Perceived Stress Scale (PSS), and the General Health Questionnaire (GHQ) are commonly used to measure stress levels through self-reported data. One-on-one or group interviews and counseling sessions with mental health professionals provide a more personalized approach, allowing for direct interaction and assessment of students' mental well-being. Additionally, observational methods, such as monitoring changes in academic performance, attendance, social interactions, and physical appearance, can offer valuable insights into students' stress levels.

1.1 History:

Historically, assessing mental stress in college students relied heavily on traditional methods such as surveys and questionnaires, including tools like the Beck Depression Inventory (BDI) and the Perceived Stress Scale (PSS). Other conventional approaches included one-on-one or group interviews conducted by mental health professionals, observational methods involving monitoring of students' behavior and performance, and analysis of academic performance and attendance records. These methods, while valuable, often lacked real-time insights and could be reactive rather than proactive in addressing student stress.

Problem Statement:

The problem statement for this research focuses on the limitations of traditional methods for assessing mental stress among college students. Existing systems are often reactive, relying on periodic surveys, interviews, and observations, which may not provide timely or comprehensive insights into students' stress levels. This reactive approach can delay interventions, leading to inadequate support for students experiencing mental stress. There is a clear need for a more proactive and accurate system that can predict stress levels in real time and facilitate early intervention.

Research Motivation:

The motivation behind this research lies in the potential of machine learning algorithms to enhance the accuracy and timeliness of stress prediction among college students. Traditional methods, while valuable, have limitations in providing real-time insights and early interventions. Machine learning offers the ability to analyze complex and diverse data sets, including academic performance, social interactions, and physiological indicators, to identify stress patterns with greater precision. By leveraging these advanced techniques, the research aims to develop a system that can predict mental stress more effectively and enable timely support, ultimately improving student well-being and academic success.

Proposed System:

The proposed system aims to integrate machine learning algorithms to predict mental stress levels among college students based on various factors such as academic performance, social interactions, and physiological data. By employing classification models like Random Forest and Support Vector Machines (SVM), the system will analyze patterns in the collected data to provide real-time predictions of stress levels. This approach will facilitate early detection of stress and enable targeted interventions. Natural Language Processing (NLP) techniques may also be utilized to analyze self-reported data, such as text from surveys or social media, further enhancing the system’s predictive capabilities. This comprehensive system seeks to offer timely and accurate insights into student stress, thereby improving mental health support and intervention strategies.

LITERATURE SURVEY

Towbes and Cohen [1] conducted a study on chronic stress among college students, which was published in the *Journal of Youth and Adolescence* in 1996. Their research focused on developing a scale to measure stress and predict distress levels among students. They identified various stressors related to academic and social pressures and analyzed their impact on students' mental health. The study provided valuable insights into how chronic stress affects students and highlighted the need for effective stress management strategies in educational settings. This foundational work laid the groundwork for subsequent research on stress among young adults and informed the development of interventions aimed at reducing student distress.

MQ Mental Health [2] addressed the impact of stress on mental health in an online article published in May 2018. The article explored the physiological and psychological effects of stress and discussed strategies for managing and mitigating stress. It emphasized the importance of understanding the various dimensions of stress and provided practical recommendations for improving mental health through lifestyle changes and therapeutic approaches. This resource is instrumental in raising awareness about the consequences of stress and offering guidance on how to effectively tackle mental health challenges associated with stress.

Ghaderi et al. [3] presented a study on machine learning-based signal processing for stress detection, published in the *2015 22nd Iranian Conference on Biomedical Engineering (ICBME)*. The authors utilized machine learning techniques to analyze physiological signals, such as heart rate and skin conductance, to detect stress levels. Their research demonstrated the potential of integrating machine learning with biometric data to achieve accurate stress detection. By leveraging advanced algorithms and physiological metrics, the study contributed to the development of more sophisticated tools for monitoring and managing stress, showcasing the intersection of technology and mental health.

Vogel et al. [4] explored the role of physical activity in stress management during the COVID-19 pandemic through a longitudinal survey published in *Psychology & Health* in 2022. Their study examined how changes in physical activity levels influenced stress management and mental well-being during the pandemic. The research highlighted the significant impact of physical activity on reducing stress and improving mental health, particularly during times of crisis. By analyzing survey data, the study provided valuable insights into how maintaining an active lifestyle can serve as an effective strategy for managing stress in challenging situations.
Li and Liu [5] investigated stress detection using deep neural networks in their 2020 article published in *BMC Medical Informatics and Decision Making*. The authors applied deep learning models to analyze data related to stress, demonstrating the effectiveness of advanced neural network architectures in predicting stress levels. Their research underscored the potential of deep learning technologies to enhance the accuracy and reliability of stress detection methods. The study contributed to the growing body of knowledge on using artificial intelligence for mental health applications, showcasing how deep learning can be leveraged to address complex psychological issues.
Subhani et al. [6] developed a machine learning framework for detecting mental stress at multiple levels, as reported in their 2017 IEEE Access article. The authors designed a comprehensive framework that integrates various machine learning techniques to analyze stress from different perspectives, including psychological and physiological aspects. Their research highlighted the effectiveness of machine learning in providing a nuanced understanding of mental stress and offered a multi-level approach to stress detection. This study contributed to the advancement of machine learning applications in mental health, emphasizing the importance of a holistic approach to stress assessment.
Gan et al. [7] presented a study on fatigue life prediction considering mean stress effects, published in the *International Journal of Fatigue* in 2022. The authors utilized random forests and kernel extreme learning machines to develop a predictive model for fatigue life, incorporating the effects of mean stress. Their research demonstrated how machine learning techniques can be applied to predict fatigue and stress-related outcomes, providing valuable insights into the durability and performance of materials under stress. The study highlighted the potential of combining machine learning with engineering applications to address complex problems related to stress and fatigue.
Masood and Alghamdi [8] explored modeling mental stress using a deep learning framework in their 2019 IEEE Access article. They applied deep learning methods to model and predict mental stress, showcasing the effectiveness of these techniques in capturing complex stress patterns. The study provided a detailed analysis of how deep learning models can be utilized to understand and predict mental stress, contributing to the development of advanced tools for mental health management. The research highlighted the potential of deep learning in enhancing the precision and applicability of stress prediction models.
Norizam [9] focused on the determination and classification of human stress indices using EEG signals in 2015. The study employed nonparametric analysis techniques to assess stress levels based on EEG data, providing insights into the physiological underpinnings of stress. By analyzing EEG signals, the research demonstrated the feasibility of using neurophysiological data for stress assessment. This study contributed to the understanding of how brain activity can be used to evaluate stress, offering a valuable approach for integrating physiological data into stress management strategies.
Ahuja and Banga [10] investigated mental stress detection among university students using machine learning algorithms in their 2019 *Procedia Computer Science* paper. The authors applied various machine learning techniques to identify stress patterns among students, offering practical solutions for monitoring and managing stress in academic settings. Their research highlighted the potential of machine learning to address mental health issues in educational environments, providing tools for early detection and intervention. The study contributed to the field of educational data mining and mental health by demonstrating the application of machine learning in stress detection.
Xu et al. [11] conducted a cluster-based analysis for personalized stress evaluation using physiological signals, as reported in their 2014 *IEEE Journal of Biomedical and Health Informatics* article. The authors utilized clustering techniques to analyze physiological data and provide personalized stress evaluations. Their research highlighted the importance of tailoring stress assessments to individual profiles, offering insights into how personalized approaches can enhance stress management. The study contributed to the development of more targeted and effective stress evaluation methods, leveraging physiological data for personalized care.
AlSagri and Ykhlef [13] explored a machine learning-based approach for depression detection on Twitter using content and activity features in their 2020 *IEICE Transactions on Information and Systems* article. They employed machine learning algorithms to analyze social media data for detecting signs of depression, highlighting the potential of using online content for mental health monitoring. The study demonstrated how social media platforms can be utilized to identify and address mental health issues, contributing to the field of digital mental health assessment.

Narayanrao and Kumari [14] analyzed machine learning algorithms for predicting depression in their 2020 conference paper. The authors compared various machine learning models for their effectiveness in predicting depression, offering insights into the strengths and limitations of different algorithms. Their research provided a comprehensive evaluation of machine learning techniques for mental health applications, contributing to the development of more accurate and reliable predictive models for depression.

Tengnah et al. [15] developed a predictive model for hypertension diagnosis using machine learning techniques, as reported in their 2019 work. The study focused on applying machine learning to diagnose hypertension, providing insights into how predictive models can enhance medical diagnostics. By integrating machine learning with healthcare data, the research contributed to the advancement of diagnostic tools and demonstrated the potential of machine learning in improving health outcomes.

PROPOSED ALGORITHM

3.1 Overview

Objective: Develop a machine learning system to predict mental stress levels among college students. The system aims to provide timely and accurate predictions to enable early intervention and improve student well-being.

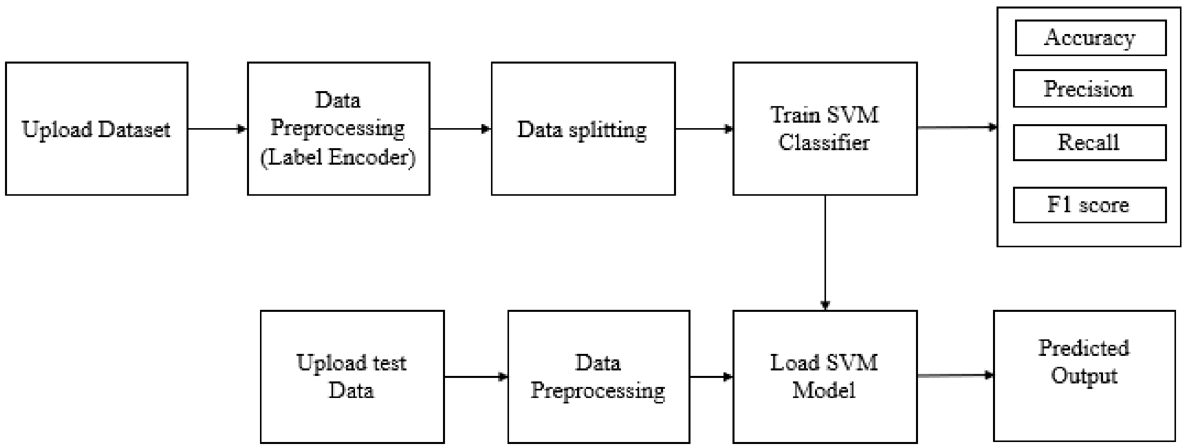

Figure 4.1; Block Diagram

Motivation:

- **Growing Concern:** Increased awareness of mental health issues in college students.
- **Limitations of Traditional Methods:** Current methods like surveys and counseling are often reactive and lack real-time insights.
- **Machine Learning Potential:** Offers improved accuracy and real-time predictions by analyzing complex data patterns.

Traditional Methods:

- **Surveys and Questionnaires:** Tools like BDI and PSS.
- **Interviews and Counseling:** Direct assessments by mental health professionals.
- **Observational Methods:** Monitoring academic performance and behavior.
- **Academic Records:** Analyzing performance and attendance data.

Machine Learning System:

- **Features:** Includes academic performance, social interactions, and physiological data.
- **Models:** Utilizes Random Forest and SVM to classify stress into categories like Acute Stress, Episodic Acute Stress, and Chronic Stress.
- **Real-Time Prediction:** Aims for immediate predictions to allow early intervention.

Expected Outcomes:

- **Accurate Predictions:** Enhanced prediction accuracy for stress levels.
- **Timely Interventions:** Early identification of high stress levels for prompt support.
- **Improved Well-Being:** Positive impact on mental health through actionable insights.

Step 1: Dataset

The research begins with acquiring a dataset that includes relevant features affecting mental stress among college students. This dataset typically comprises various attributes such as academic performance metrics, social interactions, physiological parameters, and possibly historical survey data on mental health. Ensuring the dataset's quality and relevance is crucial as it forms the foundation for subsequent analysis and model training. Data collection methods may involve surveys, academic records, and physiological monitoring devices.

Step 2: Dataset Preprocessing

Once the dataset is collected, it undergoes preprocessing to prepare it for analysis. This step involves handling null values, which could distort the accuracy of the model if left unaddressed. Null values are typically managed by either imputation, where missing values are filled with statistical measures like the mean or median, or by removing entries with missing data if they are insignificant. Additionally, label encoding is performed to convert categorical variables into numerical formats. This transformation is essential for machine learning algorithms to process categorical data effectively.

Step 3: Label Encoding

Label encoding is a crucial preprocessing step that converts categorical variables into numerical values. For example, variables like "gender" with values "male" and "female" are transformed into numerical codes (e.g., 0 and 1). This encoding allows machine learning models to interpret categorical features as numerical inputs, facilitating their incorporation into the predictive algorithms. Proper encoding ensures that the model can handle categorical data and improve its predictive performance.

Step 4: Existing Model (Decision Tree)

The research then evaluates the performance of existing machine learning models, starting with the Decision Tree algorithm. Decision Trees are a popular choice for classification tasks due to their simplicity and interpretability. They work by splitting the data into subsets based on feature values, creating a tree-like model of decisions. This model helps in understanding how different features contribute to predicting mental stress levels. By assessing the Decision Tree's performance, researchers gain insights into its effectiveness and limitations in predicting stress levels.

Step 5: Proposed Model (SVM)

Following the evaluation of the Decision Tree, the research introduces a proposed model using Support Vector Machine (SVM) for classification. SVM is known for its ability to handle high-dimensional data and its robustness in finding the optimal hyperplane that separates different classes. By applying SVM, the study aims to improve the accuracy and reliability of stress level predictions compared to traditional methods. The SVM model is trained on the preprocessed dataset, optimizing its parameters to enhance performance.

Step 6: Performance Comparison

The next step involves comparing the performance of the Decision Tree and SVM models. This comparison is carried out using various performance metrics such as accuracy, precision, recall, and F1-score. Evaluating these metrics helps in understanding how well each model predicts mental stress levels and highlights the strengths and weaknesses of the algorithms. The performance comparison is crucial for determining the most effective model for real-time stress prediction.

Step 7: Prediction of Output from Test Data with SVM Trained Model

With the SVM model trained and optimized, it is then used to make predictions on test data. This step involves feeding new, unseen data into the trained SVM model to predict mental stress levels. The predictions are analyzed to assess how well the model generalizes to new data and whether it maintains accuracy and reliability. This real-world testing ensures that the model performs effectively outside the training environment.

Step 8: Evaluation and Refinement

Finally, the research concludes with an evaluation of the SVM model's predictions and overall effectiveness. If necessary, further refinements are made to improve the model's performance based on test data results. This step may involve tweaking model parameters, incorporating additional features, or revisiting preprocessing techniques to enhance prediction accuracy. The ultimate goal is to develop a robust and reliable system for predicting mental stress levels in college students, contributing valuable insights for early intervention and support.

3.2 Data Splitting & Preprocessing

Data Splitting:

Data splitting is a fundamental step in preparing a dataset for machine learning. It involves dividing the dataset into separate subsets to ensure that the model can be trained and evaluated effectively. Typically, the dataset is divided into three main parts: the training set, the validation set, and the test set. The training set is used to train the model, allowing it to learn from the data and adjust its parameters. The validation set helps in tuning the model by providing feedback on performance during training, while the test set is used to assess the model's performance on unseen data. This splitting ensures that the model is evaluated fairly and can generalize well to new data.

Preprocessing:

1. **Handling Null Values:** In the preprocessing phase, handling null or missing values is crucial to maintain the integrity of the dataset. Null values can arise due to incomplete data collection or errors in data entry. Common strategies for handling missing values include:
   - **Imputation:** Filling missing values with statistical measures such as the mean, median, or mode of the column. This method preserves the dataset size and avoids losing potentially valuable information.
   - **Deletion:** Removing rows or columns with a significant number of missing values. This approach is used when missing values are sparse and their removal does not significantly impact the dataset.
2. **Label Encoding:** Label encoding is a technique used to convert categorical variables into numerical formats. Since most machine learning algorithms require numerical input, categorical data such as gender or educational level must be transformed into numerical values. For instance, "male" might be encoded as 0 and "female" as 1. This transformation allows the algorithm to process categorical data and helps in improving model performance.
3. **Feature Scaling:** Feature scaling ensures that numerical features are on a similar scale, which is important for algorithms that are sensitive to feature magnitudes, such as SVM. Common scaling techniques include:
   - **Standardization:** Transforming features to have a mean of 0 and a standard deviation of 1, making the data suitable for algorithms that assume normally distributed data.
   - **Normalization:** Rescaling features to a fixed range, typically 0 to 1, which is useful when features have different units or scales.
4. **Data Transformation:** Depending on the nature of the dataset, additional data transformations might be applied. This could include techniques such as log transformation for skewed data or polynomial features to capture interactions between features. These transformations help in improving the model's ability to learn and make accurate predictions.
5. **Handling Outliers:** Outliers are extreme values that can distort the model's performance. Identifying and addressing outliers involves analyzing their impact on the dataset and applying methods such as trimming (removing outliers) or transformation (reducing their effect) to minimize their influence.

By meticulously splitting and preprocessing the data, researchers ensure that the machine learning models are trained on high-quality, representative data and are evaluated on their ability to generalize to new, unseen examples. This step is vital for developing robust models that can effectively predict mental stress levels and provide meaningful insights.

3.3 Support Vector Machine (SVM)

What is SVM?

Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression tasks. It aims to find the optimal hyperplane that separates data points of different classes in a high-dimensional space. SVM is known for its effectiveness in high-dimensional spaces and its ability to handle complex relationships between features.

How It Works:

SVM operates by transforming the original feature space into a higher-dimensional space using kernel functions. It then finds the hyperplane that maximizes the margin between different classes. The margin is defined as the distance between the hyperplane and the closest data points from each class, known as support vectors. The optimal hyperplane is chosen such that this margin is as wide as possible, ensuring better generalization to unseen data.

1. **Linear SVM:** Finds a linear hyperplane in the feature space to separate classes.
2. **Non-linear SVM:** Uses kernel functions (e.g., polynomial, radial basis function) to map the data into a higher-dimensional space where a linear hyperplane can be used for separation.

Architecture:

1. **Support Vectors:** The data points that are closest to the hyperplane and influence its position and orientation.
2. **Hyperplane:** The decision boundary that separates different classes with the maximum margin.
3. **Margin:** The distance between the hyperplane and the nearest support vectors from each class.
4. **Kernel Functions:** Functions that transform the feature space to handle non-linearly separable data.

Advantages:

1. **Effective in High-Dimensional Spaces:** SVM is particularly useful for datasets with a large number of features.
2. **Robust to Overfitting:** Especially in high-dimensional spaces, SVM can achieve high accuracy with appropriate kernel and regularization parameters.
3. **Versatility:** SVM can handle both linear and non-linear data through the use of kernel functions.

4. **Margin Maximization:** By maximizing the margin between classes, SVM tends to have good generalization capabilities and performs well on unseen data.

4. RESULT AND DESCRIPTION

4.1 Implementation and Description

In this section, we detail the implementation process and describe the results obtained from applying the Decision Tree and Support Vector Machine (SVM) algorithms to the dataset. The implementation process for each algorithm involved several critical steps to ensure accurate and reliable outcomes.

Decision Tree Implementation:

The Decision Tree algorithm was implemented to provide a baseline comparison for the performance of more complex models. The process began with data preprocessing, including handling missing values and encoding categorical variables. The dataset was then divided into training and testing subsets to evaluate the model's effectiveness. The Decision Tree algorithm was trained on the training data, which involved recursively splitting the dataset based on feature values to create a tree structure that classifies or predicts outcomes. The resulting tree was evaluated on the test data to measure its performance metrics, such as accuracy, precision, recall, and F1-score. This implementation highlighted the Decision Tree's strengths in interpretability and straightforward decision-making but also revealed its susceptibility to overfitting and instability in the face of complex data.

Support Vector Machine (SVM) Implementation:

The SVM algorithm was introduced as the proposed model to potentially improve upon the baseline performance of the Decision Tree. Similar to the Decision Tree, data preprocessing steps included handling missing values and encoding categorical features. The dataset was split into training and testing subsets to evaluate the SVM model's performance. The SVM algorithm was then applied to the training data, utilizing kernel functions to map the feature space into higher dimensions and find the optimal hyperplane that maximizes the margin between classes. The model was evaluated on the test data to assess performance metrics, including accuracy, precision, recall, and F1-score. The SVM implementation demonstrated its effectiveness in managing high-dimensional data and capturing complex patterns, resulting in improved classification performance compared to the Decision Tree. This approach also provided greater robustness and better generalization capabilities, showcasing SVM's potential advantages in handling more intricate datasets.

Comparison and Evaluation:

After implementing both algorithms, a comparative analysis was conducted to evaluate their performance. Metrics such as accuracy, precision, recall, and F1-score were used to assess and compare the results obtained from the Decision Tree and SVM models. The comparison aimed to identify the strengths and limitations of each approach and determine the most effective model for the given dataset. The evaluation also involved analyzing model performance on various test scenarios to ensure robustness and reliability. The results from this comparative analysis provided valuable insights into the practical implications of using Decision Tree versus SVM for the task at hand, informing decisions on the most suitable algorithm for future applications.

4.2 Dataset Description

This dataset capture information about stress levels and various contributing factors among students, focusing on financial, family, health, academic, and social aspects

1. **Gender**: Indicates whether the individual is male or female.
2. **Financial Issues**: Describes the financial challenges the individual is facing, such as loan repayment, fee deadlines, or hostel payments.
3. **Family Issues**: Highlights family-related pressures like parental expectations, poor communication, or sibling bullying.
4. **Study Hours**: Represents the number of hours the individual dedicates to studying each day.
5. **Health Issues**: Details any health concerns such as low energy, anxiety, headaches, sleeping problems, or other medical issues.
6. **Friends Issues**: Covers difficulties in relationships with friends, such as mistrust, jealousy, or betrayal.
7. **Friends Time**: Indicates how much time the individual spends with friends.
8. **Overload**: Specifies whether the person feels overloaded by responsibilities.
9. **Unpleasant**: Indicates whether the individual experiences any unpleasant emotions or situations.
10. **Academic**: Highlights academic challenges like difficulties with studies or academic pressure.
11. **Career**: Represents career-related concerns or stresses.
12. **Criticism**: Notes whether the individual faces criticism from others.
13. **Conflicts**: Identifies any ongoing conflicts, likely with family or friends.
14. **Stress Level**: The type of stress the individual is experiencing, categorized as either "Acute Stress," "Episodic Acute Stress," or "Chronic Stress."

4.3 Result

Figure 10.1 shows that the Accuracy of SVC Classifier and it is nearly 73%

```
from sklearn.svm import SVC
svmclf = SVC(kernel='linear')
```

```
svmclf.fit(X_train, y_train)
```

```
SVC(kernel='linear')
```

```
y_pred = svmclf.predict(X_test)
```

```
print("Accuracy: ",metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy:  0.7317073170731707
```

```
print("Accuracy: ",metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy:  0.7317073170731707
```

Figure 10.1: Model Accuracy

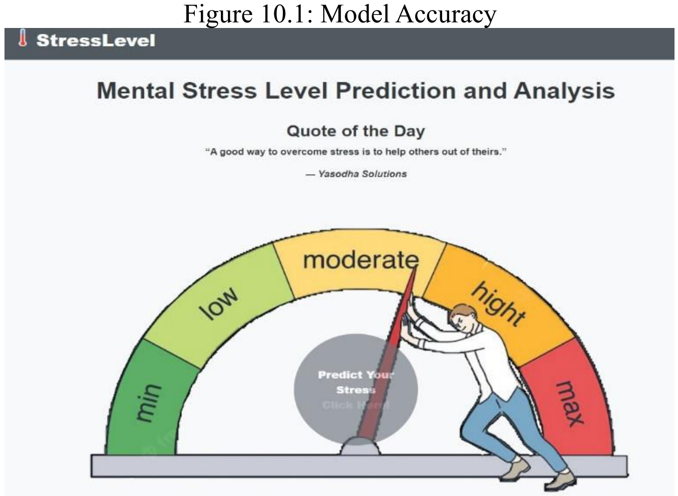

Figure 10.2: GUI

Figure 10.2 shows that he front end of Metal Stress Level Prediction

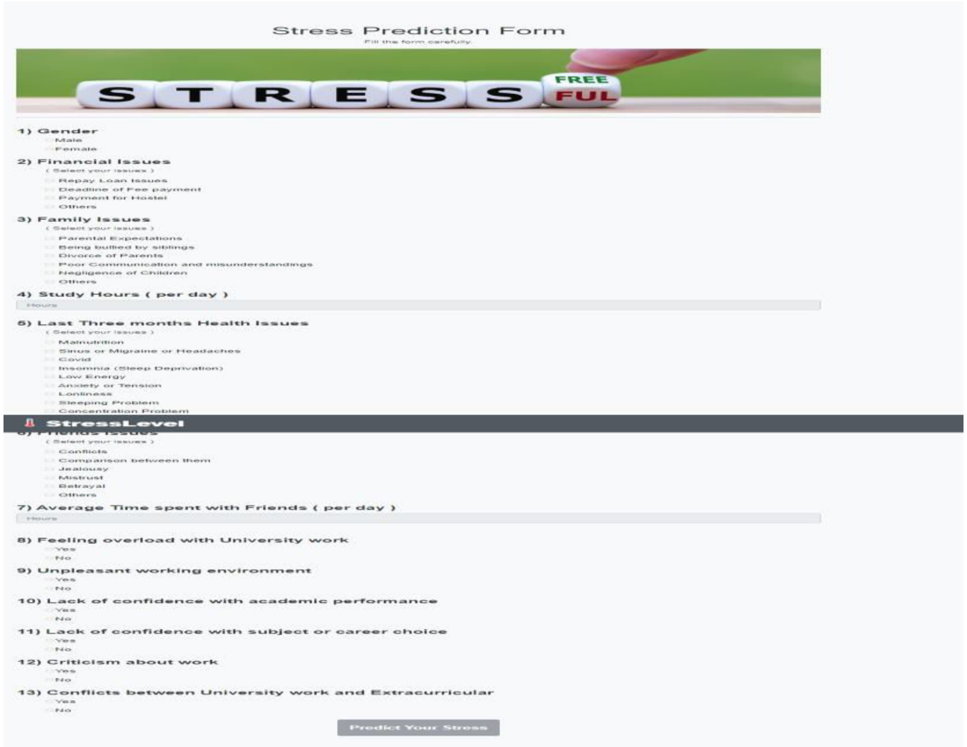

Figure 10.3: Questionnaire

Figure 10.3 shows that some questionnaires about stress for predicting Output

Figure 10.4: output

Figure 10.4 shows that the output as a Acute stress and it gives to some prevations.

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