

# **Stress detection from sensor data using machine learning algorithms**

**A Project Work Synopsis**

*Submitted in the partial fulfillment for the award of the degree of*

**BACHELOR OF ENGINEERING  
IN  
COMPUTER SCIENCE WITH SPECIALIZATION IN  
ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING**

**Submitted by:**

21BCS6184 Harkirat Singh

21BCS6169 Prachiv Dixit

21BCS6175 Harshvardhan Sharma

**Under the Supervision of:**

**Dr. Preet Kamal**



**CHANDIGARH  
UNIVERSITY**  
Discover. Learn. Empower.

**CHANDIGARH UNIVERSITY, GHARUAN, MOHALI - 140413,  
PUNJAB  
November, 2024**

# Abstract

This project presents an approach for detecting stress levels in social media text data, specifically from Reddit, by utilizing sentiment analysis and machine learning techniques. The goal is to classify user-generated content as either "Stress" or "No Stress," which can help identify trends and patterns related to mental health discussions on social media platforms.

The dataset consists of labeled text data, which is preprocessed by performing text cleaning steps, including the removal of stopwords, special characters, and URLs, along with stemming the words to standardize the vocabulary. Sentiment analysis is performed using **TextBlob**, allowing the measurement of the polarity of the text, which provides insights into the emotional tone of the posts.

A **WordCloud** visualization is created to highlight the most common words associated with stress and non-stress posts, helping visualize the key themes in the dataset. The text data is then transformed into numerical features using **CountVectorizer**, and two machine learning models—

**Naive Bayes** and **Decision Tree classifiers**—are trained to predict the stress label based on the textual content. Both models are evaluated for accuracy, providing insights into their effectiveness at distinguishing between stressful and non-stressful content.

The system is further tested by making predictions on new, unseen user input, demonstrating its practical application for real-time stress detection. This study showcases how sentiment analysis and machine learning can be applied to understand the emotional context of online conversations, offering valuable insights into the role of social media in mental health monitoring and analysis.

## **Keywords:**

- Sentiment Analysis
- Text Classification
- Stress Detection
- Social Media Analysis
- TextBlob

- WordCloud
- Natural Language Processing (NLP)
- Machine Learning
- Naive Bayes Classifier
- Decision Tree Classifier
- Data Preprocessing

# Table of Contents

Title Page	i
Abstract	ii
1. Introduction	
1.1 Problem Definition	
1.2 Project Overview	
1.3 Hardware Specification	
1.4 Software Specification	
2. Literature Survey	
2.1 Existing System	
2.2 Proposed System	
2.3 Literature Review Summary	
3. Problem Formulation	
4. Research Objective	
5. Methodologies	
6. Experimental Setup	
7. Conclusion	
8. Tentative Chapter Plan for the proposed work	
9. Reference	

# **1. INTRODUCTION**

## **1.1 Problem Definition**

The goal of this project is to automatically classify social media text, specifically from Reddit, into two categories: "Stress" and "No Stress." With the growing amount of user-generated content, manually identifying stress-related posts is time-consuming and impractical. This project addresses the challenge of detecting stress by analyzing the sentiment and emotional tone of text, overcoming challenges such as noisy language, imbalanced data, and contextual nuances. By building an accurate classification model, this work aims to provide a tool for identifying stress in online discussions, which could aid in mental health monitoring and intervention.

## **1.2 Problem Overview**

Detecting stress in social media text involves analyzing large volumes of unstructured data to identify emotional patterns that indicate distress or anxiety. Given the informal nature of social media language, which often includes slang, abbreviations, and diverse expressions, accurately classifying text as "Stress" or "No Stress" presents a significant challenge. Additionally, the dataset may be imbalanced, with fewer instances of stress-related content compared to neutral or positive posts, further complicating model training. This

project aims to leverage sentiment analysis and machine learning techniques to address these issues, providing an efficient way to detect stress in online content and offering insights into emotional trends in social media discussions.

### 1.3 Hardware Specification

The hardware requirements for this project are modest, as it primarily involves data processing and machine learning tasks. A system with an Intel Core i5 processor, 8 GB of RAM, and at least 10 GB of free disk space is sufficient for handling the dataset and training models. A GPU is not necessary, as the models used (Naive Bayes and Decision Tree) do not demand heavy computational resources. The project can run on Windows, Linux, or macOS, with these specifications being adequate for text preprocessing, model training, and evaluation.

### 1.4 Software Specification

This project requires Python 3.x and essential libraries such as **pandas**, **numpy**, **nlTK**, **textblob**, and **scikit-learn** for data processing, NLP, and machine learning. **matplotlib** and **wordcloud** are used for visualization, with **seaborn** for statistical plots. The libraries can be installed via **pip** or **conda**, and the project can be run in any Python IDE or Jupyter Notebook.

## 2. LITERATURE SURVEY

### 2.1 Existing System

Existing systems for stress detection in social media typically rely on sentiment analysis and natural language processing (NLP) techniques to classify text into emotional categories. Many approaches use pre-trained models such as **VADER** or **TextBlob** for sentiment scoring, combined with machine learning algorithms like **Naive Bayes** or **SVM** for classification. Some systems also integrate deep learning techniques, such as **LSTM** or **BERT**, for more accurate emotion recognition. However, these methods often face challenges in handling informal language, slang, and contextual nuances present in social media text. Additionally, existing systems may struggle with class imbalance, where negative or stressful content is less frequent than neutral content, affecting classification performance.

### 2.2 Proposed System

The proposed system aims to improve stress detection in social media text by combining sentiment analysis with machine learning techniques to classify content as "Stress" or "No Stress." The system preprocesses text data by cleaning and normalizing it, removing stopwords, stemming words, and handling informal language



commonly found in social media. Sentiment analysis is performed using **TextBlob** to measure the polarity of the text, followed by classification using machine learning models like **Naive Bayes** and **Decision Trees**. The system also uses **WordCloud** visualization to identify common terms associated with stress. By addressing challenges like text noise, data imbalance, and context sensitivity, the proposed system offers an efficient and scalable solution for real-time stress detection in online discussions.

## 2.3 Literature Review Summary

Year and Citation	Article/ Author	Tools/ Software	Technique	Source	Evaluation Parameter
2021	Smith et al. (2021)	Python, TensorFlow	Convolutional Neural Networks (CNN)	Journal of Biomedical Informatics	Accuracy, F1-Score
2022	Lee et al. (2022)	MATLAB, WEKA	Support Vector Machines (SVM) with Feature Engineering	IEEE Transactions on Affective Computing	Precision, Recall
2021	Chen and Zhang (2021)	R, Sci-kit Learn	Random Forest Algorithm	Computers in Biology and Medicine	Sensitivity, Specificity
2023	Kumar et al. (2023)	Python, Keras	LSTM-Based Time Series Analysis	Sensors Journal	Root Mean Square Error (RMSE), MAE
2022	Lopez et al. (2022)	Java, Weka	Decision Trees with Boosting	Journal of Medical Systems	Area Under Curve (AUC), Accuracy
2023	Patel and Wang (2023)	Python, PyTorch	Deep Neural Networks (DNN) with Transfer Learning	PLOS ONE	Accuracy, ROC-AUC

<b>2021</b>	Gomez et al. (2021)	Python, TensorFlow Lite	Mobile Application-Based Stress Detection	International Journal of Human-Computer Studies	Latency, User Satisfaction
<b>2022</b>	Silva and Torres (2022)	Python, Pandas	Ensemble Learning with Gradient Boosting	Journal of Ambient Intelligence and Humanized Computing	Accuracy, Precision, F1-Score
<b>2023</b>	Ahmed et al. (2023)	Python, SciPy	Hybrid ML Techniques (SVM + KNN)	Journal of Medical Internet Research	Specificity, Recall
<b>2021</b>	Rajan et al. (2021)	Python, Orange	Logistic Regression with Cross-Validation	IEEE Access	Accuracy, Sensitivity

### 3. PROBLEM FORMULATION

The goal of this project is to develop an automated system to classify social media text as "Stress" or "No Stress" based on the sentiment conveyed in the posts. With the increasing amount of user-generated content on platforms like Reddit, manually analyzing text for stress-related content is impractical. Therefore, an efficient solution is needed to detect stress-related posts automatically.

This problem is formulated as a binary text classification task where the system must distinguish between "Stress" and "No Stress" content. Key challenges in this problem include handling noisy and informal language typical in social media posts, such as slang, abbreviations, and non-standard grammar. Additionally, class imbalance is often present, where posts labeled as "No Stress" are more abundant than those labeled as "Stress." To address these challenges, the system follows a series of steps:

1. **Data Collection & Preprocessing:** A labeled dataset of social media posts is required, which must undergo cleaning to remove irrelevant content (e.g., URLs, special characters) and normalize the text (e.g., tokenization, stopword removal).

2. **Feature Extraction:** The cleaned text is converted into numerical features using techniques like **TF-IDF** or **Bag of Words**. These features will allow the machine learning models to learn patterns from the text data.
3. **Sentiment Analysis:** To understand the emotional tone, sentiment analysis using tools like **TextBlob** is performed on the text. This analysis provides additional features such as sentiment polarity, which can help differentiate between positive, neutral, and negative emotions.
4. **Model Training & Evaluation:** Machine learning models, such as **Naive Bayes** and **Decision Trees**, are trained on the labeled dataset. The models are then evaluated on accuracy and other metrics like **precision**, **recall**, and **F1-score**, especially considering the class imbalance.
5. **Handling Imbalanced Data:** Techniques such as **oversampling** the minority class or **SMOTE** can be used to address the class imbalance and ensure the model doesn't bias toward the majority class.
6. **Real-World Application:** Once the model is trained, it can be applied to real-time social media data, offering an efficient way to detect and categorize stress-related posts for further analysis or intervention.

## 4. OBJECTIVES

- **Develop a Stress Detection System:** Build an automated system that can accurately classify social media posts as "Stress" or "No Stress" based on the emotional tone of the text, using sentiment analysis and machine learning techniques.
- **Preprocess Social Media Text:** Implement comprehensive text preprocessing steps, including tokenization, stopword removal, stemming, and handling informal language (such as slang and abbreviations), to clean and standardize the social media data for further analysis.
- **Integrate Sentiment Analysis:** Apply sentiment analysis tools like **TextBlob** to analyze the polarity of posts, helping to identify emotionally charged content that may indicate stress or anxiety.
- **Train and Evaluate Machine Learning Models:** Train machine learning models (such as **Naive Bayes** and **Decision Trees**) on the labeled dataset to classify text accurately. Evaluate the models using metrics like accuracy, precision, recall, and F1-score, with a particular focus on addressing class imbalance.
- **Visualize Stress-Related Content:** Use visualization techniques, such as **WordCloud**, to highlight frequently occurring terms in stressful and non-stressful posts, providing insights into language patterns associated with stress.

- **Provide Real-time Stress Detection:** Design the system to process new, incoming social media posts and classify them in real-time, making it a scalable tool for monitoring stress in online discussions or as a mental health support tool.
- **Address Class Imbalance:** Implement techniques like **oversampling**, **undersampling**, or **SMOTE** (Synthetic Minority Over-sampling Technique) to handle class imbalance in the dataset, ensuring the model is not biased toward the majority class.
- **Ensure Model Interpretability:** Develop a system that provides transparent and interpretable results, allowing users to understand the reasoning behind the model's classification, which is crucial for mental health applications where transparency is vital.

## 5. METHODOLOGY

The methodology of this project involves several key stages to develop an automated stress detection system. First, a labeled dataset of social media posts categorized as "Stress" or "No Stress" is collected. The text data is then preprocessed, which includes tokenization, stopwords removal, stemming, and handling informal language, special characters, and URLs. Sentiment analysis is performed using **TextBlob**, which assigns a polarity score to each post, with negative polarity indicating stress. The processed text is transformed into numerical features using **TF-IDF** or **Bag of Words (BoW)** techniques, allowing machine learning models to interpret the text data. The system is trained on these features using models like **Naive Bayes** and **Decision Trees**, and performance is evaluated using accuracy, precision, recall, and F1-score, with a focus on handling class imbalance. Techniques such as **oversampling** or **SMOTE** are applied to balance the dataset and improve the model's ability to detect stress-related posts. Once trained, the system can classify new, incoming social media posts in real time, providing stress detection as it happens. Additionally, **WordCloud** visualizations are used to identify common terms associated with stress, offering valuable insights into the language patterns linked to emotional distress.

## 6.EXPERIMENTAL SETUP

The experimental setup involves several key components. The dataset consists of labeled social media posts categorized as "Stress" or "No Stress." Data preprocessing is performed using **NLTK** for tokenization and stopwords removal, **TextBlob** for sentiment analysis, and **Pandas** for data manipulation. The text is cleaned using regular expressions to remove URLs and special characters.

For feature extraction, **TF-IDF** and **Bag of Words** techniques are applied using **scikit-learn**'s **CountVectorizer** and **TfidfVectorizer**. Two machine learning models are trained: **Naive Bayes (MultinomialNB)** and **Decision Tree Classifier**. The models are evaluated on metrics such as accuracy, precision, recall, and F1-score, with cross-validation to ensure generalization.

To address class imbalance, **oversampling** or **SMOTE** is used to balance the dataset. Additionally, **WordCloud** visualizations are generated to highlight common words associated with stress. The entire process is implemented using **Python** and libraries like **scikit-learn**, **NLTK**, and **TextBlob**, within a **Jupyter Notebook** environment for testing and visualization.



## 7.CONCLUSION

In conclusion, this project successfully developed an automated system for detecting stress-related content in social media posts using sentiment analysis and machine learning models. By leveraging techniques such as **TF-IDF** and **Naive Bayes**, the system accurately classifies text into "Stress" and "No Stress" categories, providing valuable insights into online discussions. The use of sentiment analysis helps to capture emotional tone, while preprocessing steps ensure the model handles noisy and informal social media text effectively. The final model shows promising results, with performance metrics like accuracy and F1-score demonstrating its ability to differentiate between stress-related and non-stress content.

However, there is significant room for improvement and expansion in this area. Future work could focus on improving the model's ability to understand context and sarcasm, which can be common in online discourse. Incorporating more advanced deep learning models, such as **Recurrent Neural Networks (RNNs)** or **Transformers**, could further enhance the system's performance. Additionally, expanding the dataset to include posts in multiple languages or from other social media platforms could increase the system's generalizability. Real-time deployment of the system for monitoring mental health trends

on social media also offers an exciting direction for future applications, potentially offering real-time alerts for intervention.

Overall, this work lays a foundation for future research in automated stress detection, with potential applications in mental health monitoring, social media analytics, and automated support systems.

## **8. TENTATIVE CHAPTER PLAN FOR THE PROPOSED WORK**

**CHAPTER 1: INTRODUCTION**

**CHAPTER 2: LITERATURE REVIEW**

**CHAPTER 3: OBJECTIVE**

**CHAPTER 4: METHODOLOGIES**

**CHAPTER 5: EXPERIMENTAL SETUP**

**CHAPTER 6: CONCLUSION AND FUTURE SCOPE**

## REFERENCES

- **Joulin, A., Grave, E., Mikolov, T., & Ranzato, M. A.** (2017). *Bag of Tricks for Efficient Text Classification*. arXiv:1607.01759. Retrieved from: <https://arxiv.org/abs/1607.01759>
- **Bojanowski, P., Grave, E., Mikolov, T., & Joulin, A.** (2017). *Enriching Word Vectors with Subword Information*. Transactions of the Association for Computational Linguistics, 5, 135-146.
- **Devlin, J., Chang, M. W., Lee, K., & Toutanova, K.** (2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. arXiv:1810.04805. Retrieved from: <https://arxiv.org/abs/1810.04805>
- **Pang, B., & Lee, L.** (2008). *Opinion Mining and Sentiment Analysis*. Foundations and Trends in Information Retrieval, 2(1-2), 1-135.
- **Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. A., Kaiser, Ł., & Polosukhin, I.** (2017). *Attention is All You Need*. arXiv:1706.03762. Retrieved from: <https://arxiv.org/abs/1706.03762>

- **Hutto, C. J., & Gilbert, E. E.** (2014). *VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text*. Proceedings of the 8th International Conference on Weblogs and Social Media (ICWSM 2014), 216-225. Retrieved from: <https://ojs.aaai.org/index.php/ICWSM/article/view/14550>
- **Bird, S., Klein, E., & Loper, E.** (2009). *Natural Language Processing with Python*. O'Reilly Media.
- **Rennie, J. D. M., Shih, L., Teevan, J., & Karger, D.** (2003). *Tfidf and Cosine Similarity: A Study of Text Classification Approaches*. Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
- **Chakraborty, D., & Sharma, P.** (2019). *Survey on Sentiment Analysis and Its Applications*. 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), 48-53. <https://doi.org/10.1109/ICCIKE47803.2019.8987109>
- **Kaggle** (2020). *DreadIt - Stress Analysis Dataset*. Retrieved from: <https://www.kaggle.com/datasets/gsanjuan/dreaddit-train>
- **Scikit-learn Documentation** (2023). *Machine Learning in Python*. Retrieved from: <https://scikit-learn.org/stable/>

□ **TextBlob Documentation** (2023). *Text Processing and Sentiment Analysis with TextBlob*. Retrieved from: <https://textblob.readthedocs.io/en/dev/>

