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Unveiling Psychological Turmoil: A Deep Dive into Stress Detection and Analysis through Machine Learning Techniques

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Abstract: Abstract— Each year, millions grapple with depression, often without timely intervention. Detecting stress via social media is crucial for early intervention. This paper outlines a method to gauge stress and relaxation using Twitter data through sentiment analysis, crucial for managing mental health proactively. Leveraging the TensiStrength framework, it quantifies sentiment strength in informal English text, discerning stress and relaxation expressions on a scale from -5 to +5. By categorizing stressed sentences, it identifies stress and relaxation levels adeptly across various social media contexts.

However, while humans naturally understand nuanced meanings, machines face challenges with Word Sense Disambiguation (WSD), where a word can have multiple senses. To address this, the proposed method enhances pre-processing with parts-of-speech disambiguation and employs unigram, bigram, and trigram analysis to refine results. Employing SVM with N-gram yields promising precision (65%) and recall (67%). Yet, the primary aim remains assessing explicit and implicit stress and relaxation levels in tweets.

Keywords—Stress Detection, Data Mining, TensiStrength, word sense disambiguation.

I. INTRODUCTION

In today's world, stress burgeons rapidly, despite apparent prosperity, leaving people unhappy. Stress, a pressured sensation, can stem from emotional, physical, or mental strains, fostering a fear of failure. It pervades every facet of life, stemming from various sources like thoughts and circumstances. Its manifestations are manifold—physical, mental, and financial—exerting a profound impact on individuals. Moreover, stress can catalyse a shift in personality, inducing superiority or inferiority complexes, impeding optimal functioning. While some stress can be motivating, fostering productivity, excessive stress leads to lethargy, fear, and isolation, distinguishing between short-term situational stress and chronic, long-term stress, which poses graver risks, often being hereditary. Recognizing and managing stress early is imperative, with accessible remedies crucial for a balanced life.

Research endeavors to detect stress through diverse methods. Questionnaires, though common, suffer from limitations like subjectivity and inadequacy. Sensor-based approaches, while promising, are time-consuming and costly. Alternatively, social media analysis emerges as a novel method. By scrutinizing users' activities, reactions, and sentiments on platforms like Twitter and Facebook, professionals can discern stress levels. The brevity and informality of tweets unveil users' innermost thoughts, emotions, and stress levels, aiding in early intervention and prevention. Thus, minimizing social media usage may signal stress avoidance.

Word Sense Disambiguation (WSD) is pivotal in discerning precise word meanings, resolving ambiguities inherent in language. It involves ascertaining the appropriate word sense based on contextual cues, enhancing comprehension and communication Frequently, tweets feature words with multiple meanings [9]. Natural Language Processing (NLP) aims to extract information from human language, necessitating Word Sense Disambiguation (WSD) for accurate machine translation. While humans effortlessly discern the various senses of an ambiguous word in context, machines rely solely on programmed instructions. Take, for instance, the word "bank," which could signify a financial institution or a riverside. Such ambiguous words demand WSD to

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determine the precise sense within a given context [10]. In sentiment analysis, WSD plays a crucial role by assigning polarity to specific word senses. Traditional NLP methods for WSD rely on standardized grammar and spelling, a rarity in the realm of social media. WordNet serves as a cornerstone in WSD research, enhancing the performance of lexicon-based Stress/Relaxation detection algorithms like TensiStrength.

TensiStrength, a lexicon-based sentiment analysis algorithm, specializes in real-time Twitter content analysis. It gauges the intensity of stress and relaxation conveyed in short, informal text messages, providing a sentiment strength rating ranging from 1 to 5 for both positive and negative sentiments. This method disregards standard grammar and spelling, effectively capturing non-standard emotions expressed in social web data, such as tweets. An adaptation of the sentiment strength detection software SentiStrength, TensiStrength outperforms its predecessor, categorizing each tweet or sentence as stressed or relaxed [1].

In sentiment analysis, systems typically employ either lexicon-based or machine learning algorithms. While lexicon-based approaches excel in certain contexts, the choice between the two hinges on the nature of the text being analysed and the task's objective. Machine learning algorithms, though powerful, suffer from domain specificity, performing best on text types similar to those on which they were trained. Conversely, lexicons operate on predefined rules. However, sentiment analysis often lacks context, such as the tweet's topic or the user's identity. Consequently, performance may be contingent on the corpus used for evaluation rather than solely on Twitter data.

In the proposed system, stress detection involves employing both lexicon based TensiStrength and machine learning algorithms. Stress reduction strategies encompass various techniques, including meditation, yoga, breathing exercises, listening to music, watching relaxing videos or films, engaging in favourite subjects, hobbies, and ensuring sufficient sleep.

LITERATURE REVIEW:

Traditional Methods of Stress/Relaxation Measurement: Traditional methods of measuring stress encompass various indicative parameters such as heart rates, galvanic skin response, and pupil diameter. Additionally, questionnaires and life events serve as diagnostic tools for identifying individuals prone to stress. However, these conventional approaches necessitate continuous monitoring or assessments and may involve expensive sensors. Moreover, there is an inherent reliance on the veracity of responses provided by individuals, as they may withhold or distort information to cultivate a more favourable impression in the eyes of psychiatrists. Furthermore, there exists a discernible correlation between an individual's personality and their susceptibility to psychological stress.

2.2 Identification of Stress and Relaxation from Social Media Content Moving to Research on

As we navigate the era of technological advancement, our penchant for expressing ideas and thoughts on social media continues to grow. Through status updates and comments on current topics, we inadvertently reveal our mental state, whether it be "Stressed" or "Relaxed". Emotion detection at the tweet level not only captures immediate sentiments but also offers insights into mental health disorders such as depression and post-traumatic stress disorder (PTSD).

In a study by Mike Thelwell [1], a Word Sense Disambiguation (WSD) technology was implemented as a pre-processing step, enhancing the accuracy of lexicon-based stress or relaxation detection methods like TensiStrength. Utilizing a dataset of "1000" tweets containing the word "Fine," which exhibits ambiguous meanings in various sentence contexts, redundant words such as prepositions, conjunctions, interjections, and articles were eliminated. The remaining words were categorized on a scale of -5 to +5 based on dictionary indications.

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Another study [2] explores the correlation between users' psychological stress states and their social interactions, employing a unified hybrid model integrating factor graph modelling with convolutional neural networks (CNNs). This approach leverages the CNN's ability to derive unified latent features from multiple modalities and the factor graph model's aptitude for modelling correlations. By designing a CNN with cross autoencoder (CAE) and utilizing a partially labelled factor graph, stress detection based on user-level social interactions was achieved. The study compared results using datasets from Twitter and Sina Weibo, employing various comparison methods such as logistic regression, Support Vector Machines (SVM), gradient boosted decision trees, and deep neural networks.

In emphasizing the significance of TensiStrength, Mike Thelwell [3] underscores its effectiveness as a lexicon-based algorithm for detecting stress and relaxation in social media text messages. When compared with generic machine learning approaches, TensiStrength outperforms in certain contexts, with its applicability contingent upon the nature of the analysed text and the task at hand. Despite the relatedness of sentiment and stress/relaxation detection tasks, they are not synonymous. TensiStrength's results exhibit a reasonable level of accuracy compared to human coders, surpassing sentiment analysis programs but falling short of machine learning methods trained and optimized on the same data.

Another paper [5] delves into using social media to detect and diagnose depression, leveraging its characteristic features to discern positive or negative traits. By analysing Twitter data and employing questionnaires as primary tools for crowd workers, the study identifies behavioural patterns indicative of depression. Machine learning techniques, particularly Support Vector Machines (SVM), are employed to predict depression based on user behaviour and activity patterns.

In a study on sentiment strength detection [6], the effectiveness of SentiStrength, an algorithm for informal English text, is examined. Despite the challenges posed by spelling and grammar variations in social media communication, SentiStrength's robustness is evident, demonstrating superior performance compared to standard machine learning methods.

In another paper [7], the focus shifts to SentiStrength's newly invented algorithm, which excels in identifying sentiment and sentiment strength from informal English text. The algorithm's ability to disregard spelling and grammar intricacies while capturing abbreviations, emotions, and truncated sentences underscores its relevance in sentiment analysis on social media platforms.

Similarly, research [8] highlights the role of social media in self-expression and information sharing, albeit at the expense of face-to-face communication. By analysing Twitter conversations, researchers aim to detect stress, albeit facing challenges in identifying users who are stressed but less active on social media.

A survey paper [9] explores Word Sense Disambiguation (WSD) and its applications, particularly in machine translation. With a focus on accuracy across various languages, the study categorizes WSD into knowledge-based, supervised, and unsupervised methods, emphasizing the importance of language dictionaries and corpora in achieving accuracy.

Furthermore, a unified model for word sense representation and disambiguation is proposed [10], leveraging large knowledge bases like WordNet and Wikipedia. By utilizing these resources, words can be represented differently based on their senses, with the model employing the k-nearest neighbour algorithm for classification. However, a major drawback lies in the evolving senses of words over time, necessitating continuous adaptation.

Lastly, stress detection in spoken English is explored [11], with a focus on vowel quality features and machine learning methods like Support Vector Machines (SVM) and decision trees. Hand-labelling vowels as stressed or unstressed, researchers aim to classify each vowel segment accordingly.

In addressing the challenge of machine translation, another paper [12] focuses on Word Sense Disambiguation (WSD), employing cosine similarity and supervised learning methods. By extracting features and converting paragraphs into feature values, the study aims to accurately choose the correct meaning of multi-meaning words based on context.

Proposing a novel model for WSD, Andrew Trask [13] advocates for supervised NLP labelling of data over unsupervised clustering methods. By analysing ambiguous words and assigning specific labels, this approach enhances accuracy while reducing computational complexity. Evaluation techniques like subjective baseline assessments are employed to validate the effectiveness of the model.

Part of Speech Disambiguation,

Consider the word "apple," which can represent either the noun denoting the fruit or the proper noun indicating the company.

Similarly, in sentiment disambiguation, part of speech tagging is utilized to label adjectives with positive or negative sentiment. For instance, "bad" is recognized as the negative counterpart of "good."

Through the analysis of these diverse techniques, disambiguated embeddings have the potential to enhance the accuracy of various syntactic dependency parsing tasks in a language.

PROPOSED SYSTEM ARCHITECTURE

Stage I: Upload Input Data

The system operates on textual data, where users upload conversations, tweets, sentences, or blogs. Stress detection relies on analysing the content of these interactions.

Upon input, whether it is a .txt file, a single sentence posted on a wall, or a blog formatted as a paragraph, the system undergoes a preprocessing phase to prepare the data for analysis.

Stage II: Pre-Processing Phase

Data Cleaning and Preprocessing:

Remove Non-Alphabetic Characters:

In this initial step, the system filters out non-alphabetic characters, restricting input to readable formats comprising only letters from 'A-Z' and 'a-z', along with certain special symbols. Numeric characters '0-9' are excluded as they do not contribute to identifying stress-related emotions.

Remove Special Symbols:

The preprocessing phase targets the elimination of unwanted special symbols commonly found in Twitter

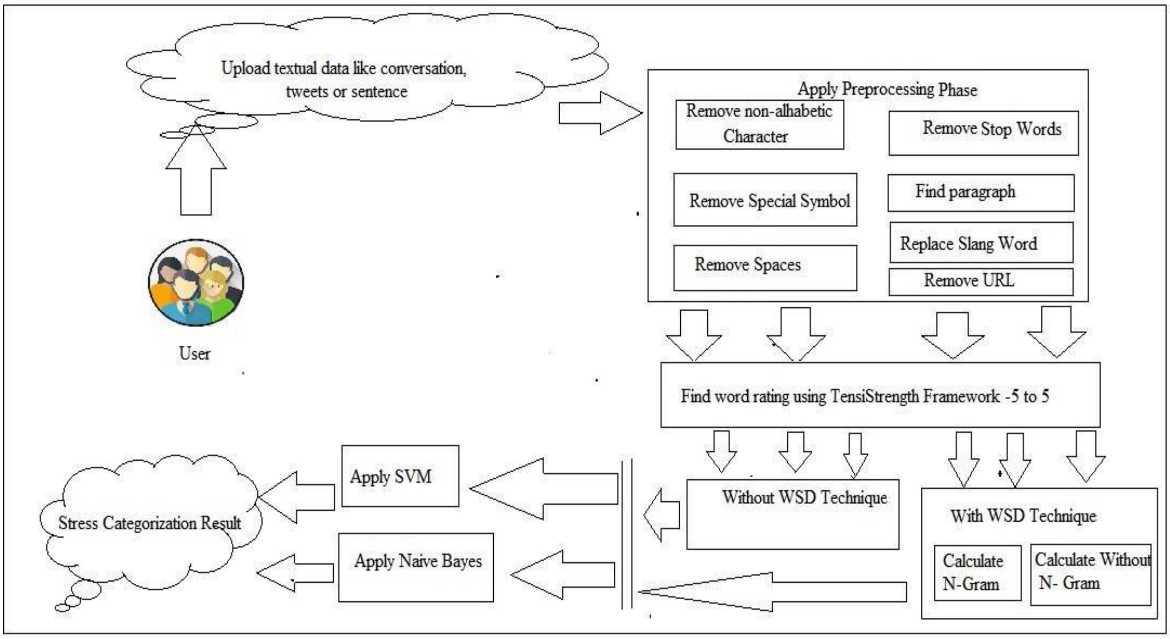

Figure 3.1: Architecture of Proposed System

datasets. While these symbols may convey information concisely, they pose challenges for algorithmic analysis. Symbols such as “! @, #, $, %, &" are thus removed to facilitate efficient processing.

Remove Spaces:

Erroneous spaces or lines inadvertently added to handwritten or human-coded text are removed to ensure accuracy in subsequent analysis. Eliminating these extraneous spaces enhances the system's ability to interpret the given data accurately.

Remove Stop Words:

Common stop words in the English language, such as "I," "am," and "she," which do not alter sentence meaning or convey stress-related emotions, are filtered out. This step involves referencing a stop word list (stopword.txt) to exclude these words from the text.

Replace Slang Words:

To address the presence of slang words that offer abbreviated versions of expressions, the system replaces them with their full-form equivalents. This substitution ensures that the sentiment analysis accurately captures the intended meaning of the sentences, especially in cases where slang conveys negation or opposition.

Remove URLs:

The preprocessing phase includes the removal of website links or URLs ("http" and "https") to streamline the input data for subsequent analysis. By excluding these extraneous elements, the system focuses solely on textual content relevant to stress detection.

Identify Paragraphs:

As part of the preprocessing workflow, the system distinguishes between tweets, individual sentences, and longer blog entries or paragraphs. Paragraphs, denoted by special symbols "<!!>", are identified based on their opening and closing tags. This enables the system to differentiate between single sentences and multi-sentence content, facilitating clearer data segmentation.

By implementing these various operations during preprocessing, the system refines the input data, ensuring that it is concise, relevant, and optimally prepared for subsequent phases of analysis within the architecture.

STAGE III: Word Sense Disambiguation:

Without WSD Technique:

In instances where the input sentence contains words with singular meanings, the system employs a straightforward approach known as skip gram. By leveraging the WordNet dictionary (version 2.1), this technique considers only synonyms of a word to identify similar meanings in the dictionary. Thus, words with comparable meanings receive ratings, even if they are not explicitly listed in the dictionary.

With WSD Technique:

When the pre-processed data includes ambiguous words or words whose meanings vary based on their position in a sentence, the system proceeds to this phase. Here, the approach integrates parts of speech (POS) tagging, n-gram analysis, and the skip gram model to resolve ambiguities.

POS Tagging:

This initial step categorizes the sentence into different parts, focusing on nouns, verbs, adverbs, and adjectives essential for further processing. Other parts of speech are excluded to streamline the data. This yields clear and precise words for comparison with dictionary entries.

N-Gram:

After POS tagging, the system analyses the position of words using uni-, bi-, and trigram concepts. Based on the POS tagging, nouns are identified, and their adjacent words are used to calculate uni-, bi-, and trigrams. The choice between uni-, bi-, or trigrams depends on the context of the sentence. This approach ensures accurate disambiguation by considering the surrounding context of each word.

Skip-Gram:

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Similar to the technique applied without WSD, skip gram is utilized to identify words with synonymous meanings, enhancing the specificity of word classification for identifying stressed or relaxed tweets/sentences.
This stage plays a pivotal role in ensuring the precise identification of words, thereby facilitating the accurate classification of tweets or sentences as stressed or relaxed.

STAGE IV: Find Word Rating

In the WSD phase, the system seamlessly integrates with the TensiStrength framework to extract word ratings. These ratings, ranging from -5 to +5, are crucial for assessing the sentiment of the text. Leveraging a standard dictionary like AFINN, which encompasses over 2500 words along with their corresponding ratings, allows for comprehensive analysis. Within this framework, each word is assigned a rating indicative of its impact on stress levels, with -5 denoting extreme stress or depression, while +5 signifies a state of profound relaxation. These ratings are derived from words identified in the preceding stages of the architecture, providing valuable input for subsequent stages of analysis.

STAGE V: Apply Algorithm

In this stage, the extracted ratings are utilized for classification and prediction purposes, requiring them to be categorized into distinct classes such as Happy, Depressed, and others. This crucial step involves employing both Support Vector Machine (SVM) and Naïve Bayes algorithms to perform the classification and prediction tasks effectively. By leveraging these algorithms, the system can accurately assign each rating to its corresponding emotional category, facilitating comprehensive sentiment analysis.

Naïve Bayes: Naïve Bayes is mostly used in sentiment In this final stage of analysis, the classifier employs the Bayes theorem for its predictive tasks. This algorithm operates by categorizing or predicting text based on the frequency of words within the document, making it particularly effective for document classification in various real-world scenarios. Notably, the Naïve Bayes classifier demonstrates efficiency with minimal training data required to estimate the essential parameters and boasts rapid processing speeds compared to alternative methods. On the other hand,

Support Vector Machine (SVM): SVM serves as a discriminative classifier, adept at establishing a hyperplane to separate data points. While SVM initially operates as a linear classifier, it can efficiently conduct non-linear classifications by implicitly mapping points into high-dimensional feature spaces. This process necessitates training the system with a dataset for subsequent testing, with the accuracy of results contingent upon the quality of the training data. Ultimately, this stage yields the final categorization results, providing valuable insights into the sentiment analysis conducted by the system.

Stage VI: Output

This stage is final and last step of the architecture. It concludes (gives final result of a) tweet, sentence or blogs in category like Happy, Stressed, Depressed and Non-identified.

3. PERFORMANCE ANALYSIS:

3.1 Experimental Setup:

This concluding stage represents the final step in the architecture, providing definitive categorizations for tweets, sentences, or blogs. The system assigns each piece of text to categories such as Happy, Stressed, Depressed, or Non-identified based on the sentiment analysis conducted throughout the process. Through this stage, the system generates conclusive categorizations, offering valuable insights into the sentiment conveyed by the analysed text.

Table 4.1 Overall Results of category wise classification for all five Test Cases

The categorization is as:

Algorithm Applied	Depression	Stress	Normal	Relax	Happy	Other
SVM	7	47	20	19	4	1
NB	16	37	13	26	4	1
SVMWSD	7	39	22	17	3	10
NBWSD	14	33	17	21	3	10
SVMNgram	7	39	21	17	3	10
NBNgram	14	33	17	21	3	10

Upon completion, the system discerns whether the user is experiencing depression, utilizing a rating dictionary like AFFINN, which encompasses over 2500 words. Additionally, a stop-word list is incorporated to filter out irrelevant data, enhancing the accuracy of the analysis. Leveraging WordNet 2.1 for Word Sense Disambiguation (WSD) and skip gram models further refines the process. This algorithm accepts input in the form of blogs or sentences and outputs probabilistic values, which are then utilized to ascertain the emotional state conveyed by the text—whether it reflects depression, stress, normalcy, happiness, or relaxation. This application of sentiment analysis holds relevance across various fields, particularly in instances where social media data is abundant. Unlike traditional data mining methods, social media platforms offer vast quantities of data, presenting a highly viable resource for accurate analysis.

3.2 Experimental Results:

Machine learning algorithms, including Support Vector Machine (SVM) and Naïve Bayes (NB), are deployed both with and without Word Sense Disambiguation (WSD) and Ngram techniques on test data. Tweets are categorized into distinct emotional states such as Stress, Depression, Normal, Relax, Happy, and others that remain unidentified by the system. The results of these classifications are organized and expressed through various test cases, allowing for comprehensive analysis across different datasets. The average performance across five distinct test cases is then summarized and presented in a table format, providing a clear overview of the system's effectiveness in sentiment analysis.

3.2.1 Performance Analysis:

In assessing performance, both SVM and NB algorithms are employed on the test files, incorporating the WSD and Ngram techniques.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

3.2.2 Precision and Recall:

Precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved.
for enhanced accuracy. The evaluation of performance is facilitated through the utilization of a confusion matrix. Precision and recall metrics are pivotal in this evaluation process, where precision denotes the proportion of retrieved instances that are relevant, while recall signifies the proportion of relevant instances that are retrieved. In information retrieval contexts, precision and recall serve as crucial performance measures, providing insights into the completeness and quality of the results. Precision, also known as the positive predictive value, indicates the relevancy of the outcomes, whereas recall, or sensitivity, measures the true positive rate for the class. Precision reflects the percentage of relevant results among the retrieved instances, while recall indicates the percentage of total relevant results that are correctly identified by the algorithm. Mathematically, precision (P) is defined as the ratio of true positives to the sum of true positives and false positives.

Recall (R), also known as the sensitivity, is calculated by dividing the number of True Positives (TP) by the sum of true positives and false negatives (FN).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

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Precision and Recall values for the five test cases are summarized in Figure 4.2. Similarly, the extensive dataset is partitioned into smaller segments comprising 100 records each. Various machine learning algorithms, including SVM, NB, SVMWSD, NBWSD, SVMNgram, and NBNgram, are then applied to these partitions of data. The subsequent results and their analysis are presented in this Performance Analysis section.

Figure 4.2: Overall classification for all five Test Cases

The number of False Positives (FP). The formula is as follows: $\text{Precision} = \dfrac{\text{TP}}{\text{FP} + \text{TP}}$

Conclusion:

The Precision and Recall values for the five test cases are depicted in Figure 4.2. Likewise, the expansive dataset is divided into smaller segments, each containing 100 records. Following this partitioning, a range of machine learning algorithms, such as SVM, NB, SVMWSD, NBWSD, SVMNgram, and NBNgram, is employed on these data segments. The subsequent outcomes and their analysis are detailed within this section dedicated to Performance Analysis.

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