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An Intelligent System for Detection of Mental Stress Using Machine Learning

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Abstract: Tens of millions of people experience depression each year, yet only a small percentage of them receive timely, effective therapy. So, it is essential to timely identify human tension and relaxation through social media. It is crucial to identify and control stress before it becomes a serious issue. Daily posts to blogs, discussion forums, and social networking sites total in millions of casual communications. This essay outlines a method for identifying stress using data from social media networking sites like Twitter. Using sentiment analysis to uncover emotions or feelings about daily life, this research proposes a method to find expressions of tension and relaxation in tweeter datasets. Sentiment analysis automatically extracts information about sentiment from text. Here, sentiment strength from the informal English language is extracted using the TensiStrength framework for sentiment strength identification on social networking sites. TensiStrength is a technology that analyzes social media text messages to identify the levels of tension and relaxation that are being conveyed. With the purpose of identifying both overt and covert signs of tension or relaxation, TensiStrength employs a linguistic approach and a set of rules. According to the strength scale from -5 to +5, this categorizes both pleasant and negative emotions. Stressed and relaxed sentences from the dialogue are both taken into consideration. TensiStrength is a robust system that may be used in a number of social media scenarios. TensiStrength's efficacy is based on the content of the tweets. Humans have the innate capacity to distinguish between the various meanings of a word in a specific situation, but machines just function as directed. Word Sense Disambiguation is the main flaw in machine translation. A single word might really have several different meanings or "senses," as the case may be. Pre-processing analyzes part-of-speech disambiguation, and the suggested technique uses unigrams, bigrams, and trigrams to get around WSD's shortcomings and get better results with ambiguous terms. SVM with Ngram provides a superior outcome in this case. Recall is 67% and Precision is 65%. But, this technique's primary goal is to identify the explicit and implicit levels of tension and relaxation reflected in tweets.

Keywords: TensiStrength, Data Mining, Stress Detection, and word sense disambiguation.

1. Introduction

Relaxation is beneficial to one's health, whereas stress is detrimental to one's health. The current state of affairs is as follows: The level of stress is rising at an alarming rate. This is the reason why individuals remain unhappy despite their material wealth. A sense of being under pressure is what stress is. The stress might manifest itself in any of three ways: emotionally, physically, or mentally. When someone is under pressure, it can either be emotionally, physically, or even mentally taxing. When someone is under a lot of stress, they get the feeling that they would be better off failing than succeeding. Whenever you look, you may find stress. It can be found in every single person's unique personality. Any idea or circumstance might

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bring on feelings of tension. But nature is different. There are several causes of stress. It affects the body, the mind, and the wallet. Any idea or circumstance might bring on feelings of anxiety. It steadily escalates in multiples whenever someone disputes it when they are under pressure.

When put in such a position, one's personality undergoes a complete transformation. Both superiority complexes and inferiority complexes contribute to the development of stress. A man who is troubled is not capable of doing much of anything properly. Stress can be beneficial, but it also frequently has negative effects. Constructive stress pushes you to put in the effort at work; it also ensures that you remain occupied, engaged, and motivated. On the other hand, damaging stress may make you lethargic and sluggish, increase your level of fear, and make you feel alone. One may classify stress as either short-term or long-term, sometimes known as chronic. [2] Based on what we know so far, we can split stress into these two categories. Stress that lasts just a short time is situational; as soon as the circumstances alter, the tension disappears or ends. Long-term stress is a condition with long-term repercussions. Because of this, engaging in it is risky.

There are occasions when chronic stress is largely caused by genetic factors or is also tied to genes. It has the potential to take the life of anyone. An unhealthy level of stress can ultimately be fatal. The first step in leading a stress-free and happy life is learning to accept stress. It is of the utmost importance to diagnose and treat stress early, before it develops into an acute condition, especially since there are effective treatments available at reasonable prices. [3].

From an extremely long time ago, research has been carried out to identify persons who are stressed. When it comes to studying stress detection, there is a significant body of material accessible. It is possible to identify persons who are under stress using both conventional and scientific means. A) A Psychiatrist will give a patient a lengthy questionnaire, and depending on how the patient responds, they will determine whether or not the patient is experiencing stress. This approach has its own set of limits and downsides, one of which is that the answers it produces are frequently not factual.

There are occasions when a few of the questions included in the questionnaire are inappropriate. B) The sensor measurement technique is the alternative to this method. This approach has the drawbacks of being both time-consuming and somewhat costly to carry out. The other option, which is also relatively new, is the use of social media to detect stress[1]. Stress detection is achievable through the use of social media. A person's write-up on social media, their reaction to a particular situation on social media, as well as their likes and dislikes, might assist detect stress. A psychiatrist can discover people who are under strain, insane, or angry after a typical subject by reading the constant writing that takes place on social media. This is another sign that you are under a lot of stress. One's mental health and way of thinking may be deduced from their use of social networking sites.

Twitter and Facebook both have a significant number of active users. Individuals talk about their own ideas, opinions, philosophies, feelings, and so on. Remarks made on social media platforms like Twitter or Facebook unmistakably reveal if the author is normal or weird. And abnormal is most certainly under some sort of strain. The statement that someone makes reveals aspects of their personality. Tweets are known for being succinct, informal, and restricted to a certain

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number of characters. Twitter is a phenomenon that defies explanation. There are 58 million tweets written every single day. Tweets have the ability to bring one's innermost thoughts, feelings, and anxieties to the surface. Tweets reveal both the material from which they are constructed and the nature of this material.

A person's tweets might quickly reveal if they are relaxed, enjoying their freedom, or feeling under strain. This is an early diagnosis of stress, which, over the course of time, will be useful in avoiding the more serious condition.

2. Related Work

A. Stress and its detection

An unhealthy amount of stress can play a role in the development of a variety of conditions, some of which can be life-threatening. The creation of a stress detection method that is both effective and economical has emerged as a significant goal for the research being done today. Existing research has been done on the topic of data collecting for the purpose of determining necessary signals and parameters for stress detection and identification. The researchers Pascual et al. [1] devised a portable non-invasive technology that measures galvanic skin reaction (GSR), body temperature, and heart rate in order to determine a person's degree of stress[2][3][4]. In the study [1], researchers monitored the levels of stress experienced by a group of students ranging in age from 19 to 26 using sensors that the participants wore on their bodies. The authors used the features extracted from the signal generated by the electrocardiogram (ECG)[2] and electrodermal activity (EDA)[2] during relax mode, oral presentation, and examination of students and found that the students who were taking the examination had the highest levels of stress. This was determined by using the features extracted from the signal generated by the ECG and EDA during the three different stages. Moreover, wearable sensors [3][4] are an excellent technique for gathering essential characteristics in order to determine whether or not a person is stressed. This was discussed in detail in the research conducted by Lakudzode and Rajbhoj [5], in which GSR [6] or galvanic skin level (SCL), HR monitor (HRM), blood pressure (BP), electrocardiogram (ECG), and electrodermal activity (EDA) data were collected. Parameters such as heart rate, skin conductance, and body temperature were examined in the research [7]. Use under a valid license is restricted to just Delhi Technical University. Retrieved from IEEE Xplore at 14:01:30 Universal Coordinated Time on April 7, 2023. There are several limitations. Using the Global System for Mobile Communications (GSM) and the Global Positioning System, temperatures were captured and analyzed at a remote location (GPS). Whereas other investigations used the physionet database to get the datasets of ECG signal, GSR, and respiration rate [8][9][10].

In the work referred to as [11], a new non-invasive electroencephalogram (EEG) measure for detecting stress was devised. In the study, there were a total of 41 healthy participants, and 9 channel electrodes were employed to capture their physiological signals. Electrodes for the electroencephalogram (EEG) and electrocardiogram (ECG) were appropriately positioned on the subject's head and chest, respectively, for the study [12]. Ghaderi et al. utilized biological data of drivers such as heart rate, electromyogram (EMG), breathing, hand GSR, and foot GSR [13]. In a similar manner, Khan and Lawo [14] develop a system to recognize the emotional states of one individual by using physiological devices such as blood volume pulse, GSR, and skin temperature to classify a person's various emotional states (such as stress, joy/happy,

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sad, normal/neutral, dislike, no-idea, positive, and negative). Following the collection of data, the following step is to process the data that was received from the various sensors in order to categorize or determine the level of stress that a person is experiencing. Previous research has made use of artificial intelligence as well as machine learning in order to classify and identify different types of stress.

The combination of GSR, systolic blood pressure, diastolic blood pressure, and heart rate was not employed as a stress detector in the research that was presented previously. In addition, there was not a single research that employed gender as a characteristic in which there was a significant difference in the levels of stress experienced by males and females. In previous research, machine learning methods were utilized; nevertheless, it should be emphasized that the best accuracy that could be reached was just 93.75%. It is suggested that this study be carried out in order to further increase the quality of the machine learning model in order to have an accurate and dependable system.

B. Stress and the pace of the heart rate

The resting heart rates of both men and women are included in Table 1. It has been demonstrated that women have a greater resting heart rate than men. Because of this, gender was included as a trait that may be used to detect whether a man or a woman is stressed or not.

C. The relationship between Stress and Blood Pressure

When stress levels are too high, it might increase the risk of developing high blood pressure, often known as hypertension, as well as other ailments. The range of a person's normal blood pressure, dependent on their age, is presented in Table 2 below. This demonstrates that various ages have varied levels of blood pressure that constitute a threshold.

D. The Relationship Between Stress and Galvanic Skin Response

The galvanic skin response (GSR) is a change in the electrical resistance of the skin that may be measured using a sensitive galvanometer. This change is produced by emotional stress and can be utilized in lie detector tests. GSR, also known as skin conductance (SC) or electro-dermal activity, is one of the most sensitive indicators for emotional arousal. Other names for GSR include: galvanic skin response (EDA). In the course of this investigation, GSR will function as either a stress detector or one of the parameters.

3. Proposed System

In this study, we employed machine learning (ML) to recognize the students' rising stress levels, anticipate their tension, and be able to prevent serious harm to their lives. Throughout the test, we assess pupils in a variety of circumstances. The undertaking execution approved the stress level. The suggested model, as seen in figure 1, covers the gathering of PSS datasets, pre-processing, feature extraction, application of machine learning algorithms (Random Forest, SVM, NB, and KNN), and comparison of these algorithms on three performance criteria.

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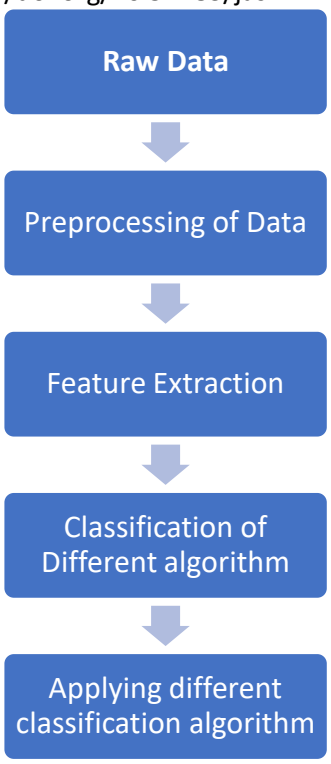

Fig. 1. Methodology

4. Performance Analysis

4.1 Experimental Setup: To train and test the system, the Standard Twitter Sentiment Analysis dataset from Kaggle is used. More than 99999 recordings are used to train the system, whether they are good or negative.Whether the user is sad or not, the categorisation is carried out. A stop-word list is placed here using the rating dictionary AFFINN, which also has more than 2500 terms, to weed out any irrelevant information. For the WSD skip gram model, WordNet 2.1 is employed. The program may use phrases or blogs as input and produce probabilistic values. The probability values are used to assess if a blog or sentence is in a state of depression, tension, normalcy, happiness, or relaxation.

There are several sectors in which sentiment analysis may be applied. Social networking site data differs from traditional data mining in several ways. Use of the vast amounts of data created on social media is quite possible. Compared to other methods, social media sites provide analysis that is more accurate.

4.2Experimental Results: SVM and NB machine learning algorithms are used to test data, both with and without WSD and Ngram, Tweets are categorized by the algorithm as Stress, Depression, Normal, Relax, Happy, and other, or unidentified. Several test cases can be used to express results. Here, five separate test scenarios are examined using various data sets, and Table 4.1 provides a summary of the average of the five examples.

Algorithm Applied	Depression	Stress	Normal	Relax	Happy	Other
NB	15	36	12	25	3	1
SVM	6	48	19	20	5	1
NBWSD	12	23	17	20	4	10
SVMWSD	6	37	23	19	5	10
SVMNgram	6	37	22	19	5	10
NBNgram	12	23	17	20	4	10

Table. 1. Results overall for the five test cases classified by category

4.3 Measuring Performance:

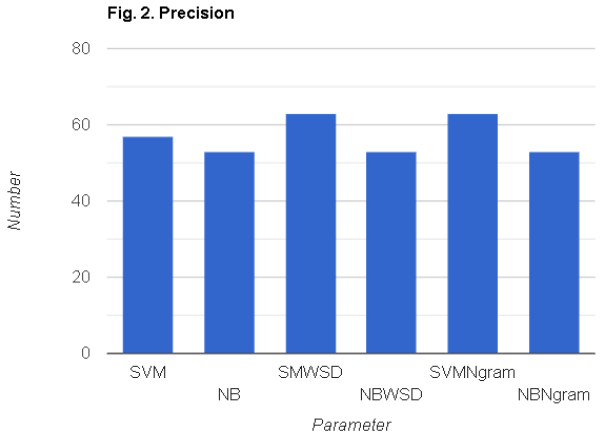

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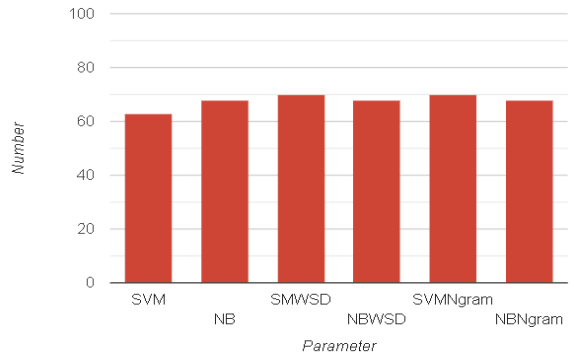
Fig. 3. Recall



Recall is the percentage of relevant instances that are found, whereas precision is the percentage of relevant examples that are found.

Precision can be seen as a metric for completeness or excellence. Recall is nothing more than the class's real positive rate.

Precision and Recall can be used to generate Performance Measures in information retrieval. They play a crucial role in assessment matrices. Where recall is a sensitivity and precision is positive predictive value. Recall is a measurement of how many really relevant results are returned, whereas precision measures the relevance of the results. Recall delivers a proportion of all relevant results that are accurately categorised by the algorithm, whereas it assesses the percentage of results that are relevant.

Five test cases' precision and recall may be summarized as shown in Fig. 4. 2 In a similar manner, a huge dataset is divided into several groups of 100 records, and the same data is then subjected to the application of SVM, NB, SVMWSD, NBWSD, SVMNgram, and NBNgram. In this Performance Analysis, the outcomes are therefore addressed.

Conclusion:

Mental tension harms one's health. With the current system, face-to-face interviews, communications, and other activities can identify stress. where another person analyzes two or more persons. In this article, a system framework for identifying users' psychological stress levels is provided. It makes use of users' social interactions and weekly social media data.

Here, each word has a dictionary grade ranging from -5 to +5. The SVM and NB algorithm were utilized to categorize and predict the data. Implemented the Word Sense Disambiguation utilizing the Skip-gram and Ngram models to increase result accuracy. WSD and Ngram combined with Support Vector Machine results in 67% recall and 65% accuracy.

By leveraging the user's daily social media interactions and other data without the user's knowledge, this system will be useful in identifying whether they are anxious or calm. In next study, smiling, like, and dislike symbols may be taken into consideration for categorizing the data that has been gathered due to their significant role in expressing sentiments.

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