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Determine a Person's Susceptibility to Stress by Looking at Their Recent Tweets and Other Social Media Activity

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ABSTRACT: It's possible to describe stress as the body's attempt to manage itself in response to changes in the environment by utilising mental, physical, and emotional responses to these changes. This is what we mean when we say that stress is an attempt to control itself. When an individual is exposed to prolonged periods of severe stress, both their mental and physical health may be put in jeopardy as a result. This can have a negative effect on one's performance at work and, in the long term, can increase the risk of acquiring physical ailments such as hypertension as well as mental disorders such as anxiety disorder. The growing prevalence of persons of all ages suffering from symptoms attributable to psychological stress is a cause for concern among the world's population. It is possible that users of a system that can accurately identify acute stress and is both dependable and cost-effective will be able to better monitor and regulate their own stress, hence lowering the negative effects that stress has on their long-term health. The subject of stress is one that is gaining more and more attention, not just in academic circles but also in the social interactions of daily life. People are starting to become more aware of this issue and the consequences it has on a range of aspects of their lives, including as their health, their social lives, the jobs they have, and their general quality of life. Because of this tendency, programmes that measure and manage stress in real time, known as stress measurement and management apps for real-time monitoring and management, have grown increasingly popular. Recent scientific and technological developments, as well as the emergence of novel approaches and concepts, have contributed to the rise in interest in this topic. As part of this project, we will be developing a Windows application that makes use of the Python programming language for the detection of stress. The application will include interviewing people and collecting photographs of their faces.

-Emotion Detection, Stress Detection, Galvanic Skin Response(GSR), Electrocardiogram(ECG), Electroencephalogram(EEG).

I. INTRODUCTION

The reaction of an individual to unfavourable external circumstances that put their typical coping mechanisms to the test is what's meant to be understood as the concept of stress [1]. Negative stress (distress) encourages activation of the hypothalamic-pituitary-adrenal (HPA) axis, which controls the synthesis of hormones. Positive stress (eustress) helps an individual maintain their capacity to remain focused in the face of adversity. If the HPA axis is stimulated for a lengthy period of time, this might potentially result in a variety of disorders, both physiological and psychological [2]. [3] It has also been shown that psychological stress has an effect on physiological processes, has a negative influence on day-to-day performance at work, and is regarded to have an impact on the economy of the nation. Monitoring negative stress levels may give the opportunity to take adequate precautions in order to minimise the future disruption. This is in addition to the fact that monitoring negative stress levels provides crucial information for recognising stressors. Negative stress has two distinct effects, which can be broken down as follows: I physiological stress, which is also known as "objective" stress; and (ii) psychological stress, which is also known as "subjective" stress, which is also known as perceived stress. Both of these types of stress are characterised as follows. A shift in physiological characteristics, such as an increase in blood pressure, a faster heart rate, and heightened cortisol levels, is one of the telltale signs that an individual is experiencing objective stress. The perception of an individual who is immersed in a scenario as to whether or not the circumstance in question is stressful is an example of subjective stress. The most common approach to measuring felt stress is to make use of stress questionnaires such the DASS 21 (Depression, Anxiety, and Stress Scale - 21 Items), STAI (State-Trait Anxiety Inventory), and POMS. Cortisol and physiological signal evaluations like GSR (Galvanic Skin Response), ECG (Electrocardiogram), and EEG (Electroencephalogram) are two of the most often utilised physiological indicators for stress. Other physiological stress indicators include stress



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hormones (Electroencephalogram). In [4], we discussed a wide variety of physiological signs of stress, as well as the technologies that are now in use to evaluate stress measurements in real time. [4] In addition, we have compiled a review of the different sensors and technology that is currently on the market for the purpose of detecting stress in [5], which can be found down below. We are going to develop a Windows application for the detection of stress using the programming language Python. This application will make use of the replies to questions posed by the user as well as the user's uploaded pictures in order to determine the individual who is suffering stress.

II LITERATURE SURVEY

In this paper, in this collaborative effort, we take on the issue of developing models to detect Twitter users who attempted suicide based on their tweets sent between 30 and 182 days before the adverse event occurred, and then putting those models into practice. On the basis of a person's twitter history over a short period of time, we investigate a variety of machine learning and deep learning algorithms for predicting their suicide risk. Taking into consideration the model's real-world applicability, we make the design decision to categories tweets at the individual tweet level. Through the use of an ensemble of classifiers to vote on the suicide risk scores at the tweet level, we are able to forecast the suicidal users 30 days before the event with an 81.8 percent true-positive probability. The tweet-level voting, on the other hand, falls short when compared to the six-month-long data since the quantity of tweets with low suicidal ideation levels reduces the total strength of the suicidal signals over time. [1].

In this paper, It is our goal to construct models to detect Twitter users who attempted suicide based on tweets posted between 30 and 182 days before the adverse event happened, and then to put those algorithms into practise. Using the history of a person's tweets over a short period of time, we study several machine learning and deep learning algorithms that can be used to forecast their likelihood of suicide. Taking into account the model's real-world applicability, we make the design decision to categorise tweets at the level of the individual tweet. We are able to predict the suicidal users 30 days before the event by using an ensemble of classifiers to vote on the suicide risk scores at the tweet level. The true-positive probability for this prediction is 81.8 percent. If you compare tweet-level voting to six-month-long data, you will find that it falls short since the large number of tweets with low suicidal ideation levels diminishes the overall intensity of the suicidal signals over time.[2].

In this paper, The voters of the United Kingdom (UK) voted in 2016 to leave the European Union (EU), and the decision will be legally implemented in 2020. During this time period, people of the United Kingdom were subjected to a significant degree of uncertainty over the country's future relationship with the European Union. A large number of individuals have taken to social media sites to share their feelings about this important occasion. In recent years, sentiment analysis has been recognised as a valuable approach for detecting mental well-being in Twitter material. Because there are no specific statements indicating the sad or anxious state in political-related tweets, it is difficult to determine whether someone is experiencing psychological suffering. In order to solve this issue, this article employs a transfer learning technique for sentiment analysis in order to determine the level of non-clinical psychological discomfort present in Brexit tweets. In order to detect the distress state in Brexit tweets, the framework transfers the information gained from self-reported psychological distress tweets (source domain) to the domain of Brexit tweets (target domain). The framework makes use of a domain adaptation approach in order to reduce the impact of negative transfer across the source and target domains, respectively. In addition, the article presents a Brexit distress index, which may be used to assess degrees of psychological discomfort among individuals who have expressed themselves through Brexit tweets. We devise a study that incorporates data from both areas into its design. It has been demonstrated that the suggested model can accurately detect the presence or absence of non-clinical psychological distress in Brexit tweets with an accuracy of 66 percent on both the source and the target domains, respectively. [3].

In this paper, to automatically predict persons who would attempt suicide within (1) 30 days and (2) six months, we propose a deep learning architecture and evaluate three alternative machine learning models, utilizing the social media post data supplied in [1] and collected through the CLPsych 2021 shared task. Additionally, we develop and extract three sets of handmade characteristics for suicide risk detection, which are based on the three-stage theory of suicide as well as earlier research on emotions and the usage of pronouns among people who are expressing suicidal ideations, among others. Extensive experiments have revealed that certain classic machine learning algorithms exceed the baseline with an F1 score of 0.741 and an F2 score of 0.833 on subtask 1 compared to the baseline (see Figure 1). (Prediction of a suicide attempt 30 days prior). On subtask 2, however, the suggested deep learning technique beats the baseline with an F1 score of 0.737 and an F2 score of 0.843, respectively, compared to the baseline (prediction of suicide 6 months prior).[4].



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In this paper, the subject of suicide has grown increasingly troubling in recent years, and it has gotten a great deal of attention in today's culture. Depression is often considered to be the most prevalent contributing cause to suicides. However, there are a variety of additional factors that can contribute to poverty, including economic factors (unemployment), social factors (dowry disputes), and incurable diseases (AIDS, for example). Although artificial intelligence-based chat-bots have been developed to prevent individuals from committing suicide, their accuracy is only around 75 percent. In order to reduce the probability of suicide in the future, we employ machine learning algorithms that are capable of accurately predicting suicide attempts with high levels of precision. Early results of data analysis would provide us with information on suicide rates, the relationship between various elements, and the amount to which they contribute to the phenomenon. In order to better comprehend the trends in suicide attempts, a graphical depiction is presented. This paper discusses many existing strategies for constructing suicide prediction models, including some that are currently in use. We'll take a deeper look at the advantages and disadvantages of each strategy. An evaluation of the effectiveness of these algorithms is conducted on a comparative basis. [5].

In this paper, Suicide is a serious problem in contemporary culture. People's lives can be saved if they are identified and prevented from attempting suicide at an early stage. In addition to clinical procedures that rely on the contact between social workers or specialists and the targeted persons, machine learning techniques that use feature engineering or deep learning for automatic diagnosis of suicidal thoughts based on online social material are being developed. This work is the first survey to provide a complete introduction to and discussion of the approaches from each of the categories discussed in this research. A study of domain-specific applications of suicidal ideation detection is conducted based on the data sources used, which include surveys, electronic health records, suicide notes, and user-generated material online. A number of specific tasks and datasets are introduced and described in order to aid in future research efforts. We conclude by summarizing the limits of the present study and providing an insight on potential future paths for research. [6].

In this paper, Geographic information is useful in many data mining and social media systems because it gives significant context. Users, on the other hand, are hesitant to submit such information owing to a variety of issues, including inconvenience, privacy, and so on. As a result of this study, we want to create a deep learning-based system for predicting location information from tweets. The existing techniques have two key drawbacks: (a) it is difficult to model long-term knowledge, and (b) it is difficult to convey to end users what the model learns. These drawbacks make the current approaches ineffective. In order to overcome these concerns, our suggested model incorporates three crucial concepts. We first offer a multi-head self-attention model for text representation, which is then extended. Second, we treat the sub word as a feature in our model, which helps us get even better results in informal language. At the end of the process, the model is trained in collaboration with the city and nation to include the information gathered from various labels. In the experiment carried out on the W-NUT 2016 Geo-tagging shared task, it was discovered that our suggested model is competitive with current systems when accuracy measurements are used, while at the same time providing a superior distance measure than the existing techniques. [7].

In this paper, the fields of mental health and social media have long been considered to be closely intertwined. In this study, a novel model, the anxious depression prediction model, is presented for the prediction of anxious depression in real-time tweets. It is generally related with irregular mental processes, restlessness, and insomnia in those suffering from this mixed anxiety-depressive condition. Based on language signals and user posting habits, a 5-tuple vector is used to build the feature set, which includes the following elements: word, timing, frequency, sentiment, and contrast. An anxiety-related lexicon is being developed in order to detect the presence of anxiety-related markers. The time and frequency of tweets are examined for anomalies, and the analysis of opinion polarity is carried out in order to detect discrepancies in posting behaviour. The model is trained using three different classifiers (multinomial naive bayes, gradient boosting, and random forest), and majority voting is performed using an ensemble voting classifier to determine the winner. For tweets from a sample of 100 users, preliminary findings are analysed and the suggested model is shown to have an accuracy of 85.09 percent in classifying the tweets. [8].

III. SYSTEM ARCHITECTURE

The project will be developed as a windows application using python programming language. Stress will be detected using the question answering between system and user. The efficiency of the system depends upon the information fed to the system ie question and answer. Also as we are going to use the laptop web camera we have to compromise the accuracy while detecting user's emotions. The complete module working is divided into the two mode:



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1. Training Module

2. Testing module

In the Training Module consists are Phase-I&II.

Phase-I :We have refers that data set (data set details are mentioned in the Data Structure) for preprocessing each attribute and check the field is valid or invalid. also check the features of each attribute is valid or not. In this processing we have processed the all fields and check the value of each field.

Phase-II: Here we have trained all data set by using different algorithm like Decision Tree, KNN & SVM and calculate the performance of each algorithm with accuracy calculation.



Figure 3.1: Architecture Diagram

IV. RESULT

In proposed system, the project will be developed as a windows application using python programming language. Stress will be detected using the question answering between system and user. The efficiency of the system depends upon the information fed to the system i.e. question and answer. Also as we are going to use the laptop web camera we have to compromise the accuracy while detecting user's emotions. Stress detection system have wide range of applications and scope as in this today's fast life no one has time to concentrate on the mental health. Today 99.99 percent people suffer from stress and depression. So stress detection system will have a wide range of applications and scope. We start with results, and then we move on to decision tree algorithms.fig.4.1 shows.



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V. CONCLUSION

We have implemented a system for stress detection. The project has been designed as an application that is based on android. The emotions, such as sadness, happiness, or fear, will be identified using straightforward equations, and the level of stress will be assessed using a question-and-answer approach. In order to accomplish this goal, we will make use of SVM, linear regression, KNN, NB, and decision trees.

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