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Category-Aware Chronic Stress Detection on Microblogs

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ABSTRACT: People nowadays have hectic lives. Long-term chronic stress is more dangerous than acute stress and may induce or aggravate a variety of major health conditions, including high blood pressure, heart disease, chronic pain, and mental illnesses. With social media becoming an increasingly important part of our everyday lives for information sharing and self-expression, it is now feasible to identify category-aware long-standing chronic stress from a vast number of historical open postings made by social media users. In this work, we create a data set of 971 chronically stressed individuals with a total of 54 546 open Sina microblog posts from July 5, 2018 to December 1, 2019, and build two approaches for category-aware chronic stress detection: (1) a stress-oriented word embedding based on an existing pre-trained word embedding, with the goal of improving the sensibility of stress-related expressions for linguistic post analysis; (2) a multiattention model with three layers (category-attention layer, posts self-attention layer, and category-specific post attention layer), with the goal of capturing inter-relevance from a sequence of posts and inferring long-term stress categories and stress levels. The experimental findings demonstrate that the proposed multi-attention model equipped with the stressoriented word embedding can identify category-aware stress levels with an accuracy of 80.65%, chronic stress levels with an accuracy of 86.49%, and chronic stress categories with an accuracy of 93.07%. The study's limitations and ramifications are also mentioned towards the conclusion of the report.

Keywords *– Chronic stress detection, social media, attention mechanism.*

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1. INTRODUCTION

We are all subjected to stress in our daily lives. Acute stress and chronic stress are the two types of stress. Acute stress refers to short-term stress, while chronic stress refers to long-term stress. Any stress that we experience for a brief amount of time, such as a traffic delay, a disagreement with our spouse, or criticism from our advisor, is an example of acute stress. Acute stress is a natural component of life that keeps our stress response system alert. However, if we are frequently exposed to the same or a variety of stressors over an extended period of time, we are vulnerable to the detrimental consequences of chronic stress. Chronic stress progressively raises our resting heart rate, blood pressure, breathing rate, and muscular tension levels, requiring our bodies to work harder to keep us operating properly [1]. Long-term chronic stress will ultimately lead to a slew of health issues, including high blood pressure, heart disease, persistent pain, and depression [2]. In truth, chronic stress causes or influences the majority of health issues. To avoid issues, we must first recognise long-standing stress and then use appropriate stress management strategies. The purpose of this research is to identify chronic stress in the areas of study, job, family, interpersonal relationships, self-cognition, peer relationships, and life. We use social media to identify chronic stress based on the two factors listed below. To begin with, social media has become an indispensible component of our everyday lives. They provide interactive computer-mediated technologies that enable the exchange of information, opinions, and expressions via unrestricted storage and a powerful network.

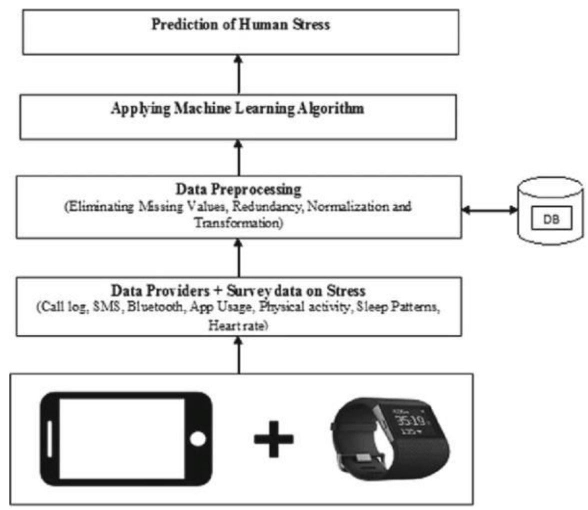

Fig.1: Example figure

The vast number of historical recordings provided by social media users allows us to detect their long-term chronic stress. Second, as compared to systems that use questionnaires or other physical sensors to detect physiological signs, social media are non-contact, labor-inefficient, and have a large reach. We may learn certain stress categories, in particular, from users' linguistic social media postings. In order to make the greatest use of social media resources, we

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conducted a category-aware chronic stress detection task in this research. That is, we propose to identify user's chronic stress levels in stress categories of study/work, family, intimate connection, self-cognition, peer relation, and life over the period using a list of user's daily postings, each of which comprises a series of linguistic words.

2. LITERATURE REVIEW

Effects of stress on heart rate complexity-A comparison between short-term and chronic stress:

This research compared the effects of chronic and short-term stress on heart rate variability (HRV) in 50 healthy people, comparing time, frequency, and phase domain (complexity) assessments. Chronic stress was measured using the hassles frequency subscale of the combined hassles and uplifts scale (CHUS). A speech task was used to test short-term stressor reaction. Surface electrocardiograms(ECG) were used to evaluate HRV. Because the rate of breathing decreased throughout the speech task (p.001), this research investigated the impact of respiration rate alterations on the effects of interest. Short-term stress lowered HR D2 (measured using the pointwise correlation dimension PD2) (p.001), but raised HR mean (p.001), standard deviation of R-R (SDRR) intervals (p.001), low (LF) (p.001), and high frequency band power (HF) (p =.009). Short-term stress had no effect on respiratory sinus arrhythmia (RSA) or the LF/HF ratio. HR D2 was linked with chronic stress (r =.35, p =.019) when the partial correlation was adjusted for respiration rate. Chronic and short-term stress had different impacts on many HRV metrics. HR D2 dropped under both stress circumstances, indicating that the cardiac pacemaker was less functioning. The findings support the usefulness of complexity measures in contemporary HRV stress studies.

Chronic stress, acute stress, and depressive symptoms

Although life events remain the primary focus of stress research, current results show that chronic stress should be prioritised. Data from a large community survey of married men (n = 819) and women (n = 936) are used to evaluate this topic. In all but one life area, the results demonstrate that chronic stress is more significantly connected to depressed symptoms than acute stress. Chronic and acute stress interaction patterns are mostly related with lower levels of depression than indicated by a main effects model. This trend implies that persistent stress may mitigate the emotional impacts of acute stress. Although the mechanisms behind this impact are unknown, it is hypothesised that anticipation and reassessment lower the stressfulness of an event by making its meaning more benign. The implications for future study on the effects of chronic and acute stress are highlighted.

A survey of affective computing for stress detection: Evaluating technologies in stress detection for better health

Affective computing is becoming increasingly popular as people become more aware of the link between emotional moods and physical health. Emotional computing detects a person's affective state using both hardware and software technologies. It is a dynamic study topic with significant advancements in technology focused toward affective state analysis. Dr. Rosalind Picard of the Massachusetts Institute of Technology (MIT) is credited with coining the term in her 1995 work on affective computing [1]. Since then, it has evolved into a contemporary discipline of computer science for human-computer interactions [2], [3]. This branch of computer science is divided into two sections: 1) detection and identification of emotional information and 2) simulation of emotion in computational systems. The present study focuses on the detection and identification of emotions as affective states.

Towards a microblog platform for sensing and easing adolescent psychological pressures

Adolescent mental health cannot be overlooked, and psychological strain is one of today's most pressing issues for teens. Because of its unique equality, freedom, fragmentation, and individuality characteristics, micro-blogging, as the most important information exchange and broadcast tool in today's society, is becoming an important channel for teenagers' information acquisition, inter-interaction, self-expression, and emotion release. This poster depicts a micro-blog platform that will (1) detect psychological stressors in teens' tweets and (2) let them relieve their tension through micro-blog. A strategy for identifying psychological stressors in teens' tweets is detailed in detail. Our early experimental findings on real-world data confirm the approach's validity. At the conclusion of the poster, we also explore strategies to help teens vent their stress via micro-blogging.

Detecting adolescent psychological pressures from micro-blog

Adolescents are subjected to a variety of psychological stresses as a result of their studies, communication, attachment, and self-recognition. If these psychological stresses are not appropriately addressed, they may manifest as mental issues, which may have catastrophic implications. Due to a lack of timeliness and variety, traditional face-to-face psychological diagnosis and therapy cannot satisfy the need of

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totally easing teens' stress. With micro-blogging becoming a popular media channel for teenagers' information acquisition, interaction, self-expression, and emotion release, we envision a micro-blogging platform that can detect psychological pressures in teenagers' tweets and help teenagers release their stress through micro-blogging. We study a variety of variables that may indicate teens' stress levels from their tweets and then evaluate five classifiers for pressure identification (Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier). We also show how to aggregate single-tweet detection findings in time series to see how teens' stress fluctuates over time. The Gaussian Process Classifier provides the best detection accuracy because to its resilience in the face of a high degree of uncertainty that may be met with previously unreported training data on tweets, according to experimental findings. Among the elements, the tweet's emotional degree, which combines negative emotional terms, emojis, exclamation and question marks, is crucial in detecting psychological strain.

3. METHODOLOGY

Acute stress is a natural component of life that keeps our stress response system alert. However, if we are frequently exposed to the same or a variety of stressors over an extended period of time, we are vulnerable to the detrimental consequences of chronic stress. Chronic stress progressively raises our resting heart rate, blood pressure, breathing rate, and muscular tension levels, requiring our bodies to work more to keep us operating properly. Long-term chronic stress, if not addressed promptly, will ultimately lead to a slew of health issues, including high blood pressure, heart disease, chronic pain, and depression. In truth, chronic stress causes or influences the majority of health issues.

Disadvantages:

1. Long-term chronic stress, if not addressed promptly, may ultimately lead to a slew of health issues, including high blood pressure, heart disease, chronic pain, and depression.
2. In truth, chronic stress causes or influences the majority of health issues.

The purpose of this research is to identify chronic stress in the areas of study, job, family, interpersonal relationships, self-cognition, peer relationships, and life. We use social media to identify chronic stress based on the two factors listed below. To begin with, social media has become an indispensable component of our everyday lives. They provide interactive computer-mediated technologies that enable the exchange of information, opinions, and

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expressions via unrestricted storage and a powerful network. The vast number of historical recordings provided by social media users allows us to detect their long-term chronic stress. Second, as compared to systems that use questionnaires or other physical sensors to detect physiological signs, social media are non-contact, labor-inefficient, and have a large reach. We may learn certain stress categories, in particular, from users' linguistic social media postings. In order to make the greatest use of social media resources, we conducted a category-aware chronic stress detection task in this research. That is, we propose to identify user's chronic stress levels in stress categories of study/work, family, intimate connection, self-cognition, peer relation, and life over the period using a list of user's daily postings, each of which comprises a series of linguistic words.

Advantages:

1. The proposed multi-attention model with stress oriented word embedding can identify category-aware stress levels with high accuracy, chronic stress levels with high accuracy, and chronic stress categories with high accuracy.
2. A multi-attention model was then developed to collect inter-relationships from a series of user postings, with the goal of estimating users' long-term category-specific stress levels.

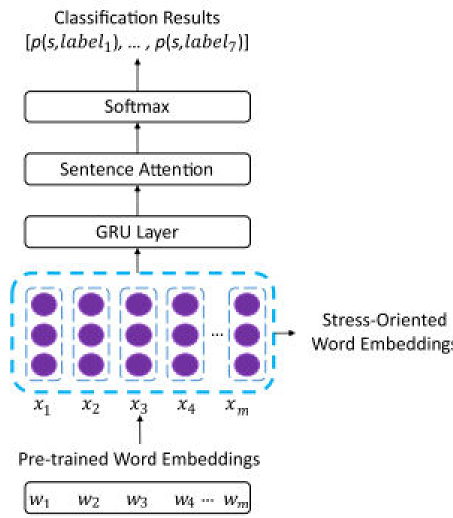

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Splitting data into train and test: Using this module, data will be separated into train and test models.
- Attention Model - MAM - BERT - Cross AutoEncoder - CNN + LSTM - SVM -

HIS - Logistic Regression for ElasticNet Classification - SVM - Voting Classifier (Extension) - RNN - LSTM - Guassian Process TeenSensor. Calculated algorithm accuracy.

- User signup and login: Using this module will result in registration and login.
- User input: Using this module will result in predicted input.
- Prediction: final predicted shown

4. IMPLEMENTATION

ALGORITHMS:

Attention Model – MAM:

Attention models, also known as attention mechanisms, are neural network input processing strategies that enable the network to concentrate on certain parts of a complicated input one at a time until the whole dataset is classified. The idea is to divide complex activities into smaller regions of focus that are processed sequentially. Similar to how the human mind handles a new issue by breaking it down into smaller tasks and tackling them one at a time.

BERT:

BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model in which every output element is linked to every input element and the weightings between them are dynamically determined depending on their relationship.

Cross AutoEncoder:

An autoencoder is a form of artificial neural network that uses machine learning to learn efficient codings of unlabeled input (unsupervised learning). [1] By trying to recreate the input from the encoding, the encoding is checked and enhanced. By training the network to disregard inconsequential input ("noise"), the autoencoder learns a representation (encoding) for a collection of data, generally for dimensionality reduction.

Logistic Regression for ElasticNet Classification:

The logistic model (or logit model) is a statistical model that represents the likelihood of an event occurring by making the event's log-odds a linear combination of one or more independent variables. Logistic regression[1] (or logit regression) in regression analysis is used to estimate the parameters of a logistic model (the coefficients in the linear combination). In binary logistic regression, there is a single binary dependent variable, coded by an indicator variable, with two values labelled "0" and "1," and the independent variables might be binary

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variables (two classes, coded by an indicator variable) or continuous variables (any real value).

SVM:

Support Vector Machine, or SVM, is a prominent Supervised Learning technique that is used for both classification and regression issues. However, it is mostly utilised in Machine Learning for Classification difficulties. The SVM algorithm's purpose is to find the optimum line or decision boundary for categorising n-dimensional space so that we may simply place fresh data points in the proper category in the future. A hyperplane is the optimal choice boundary.

Voting Classifier (Extension):

A voting classifier is a machine learning estimator that trains many base models or estimators and predicts by aggregating their results. Aggregating criteria may be coupled voting decisions for each estimator output.

RNN - LSTM :

Unlike traditional feedforward neural networks, LSTM has feedback connections. A recurrent neural network (RNN) of this kind may analyse not just single data points (such as photos), but also complete data sequences (such as speech or video).

5. EXPERIMENTAL RESULTS

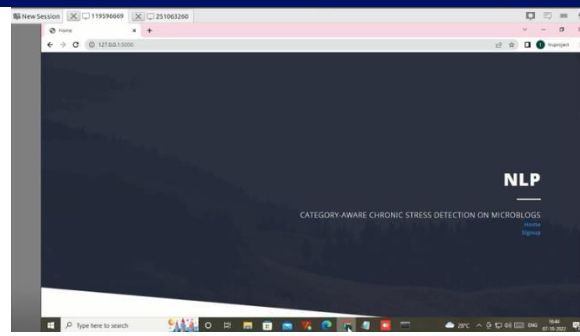

Fig.3: Home screen

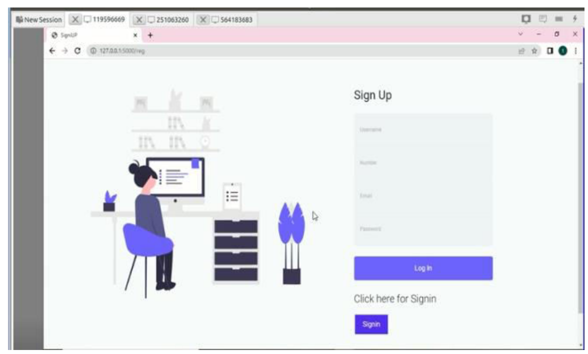

Fig.4: User registration

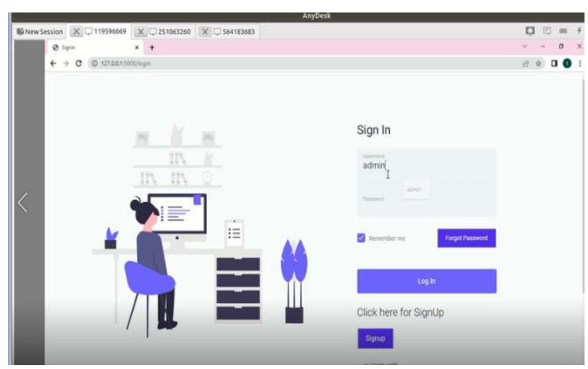

Fig.5: user login

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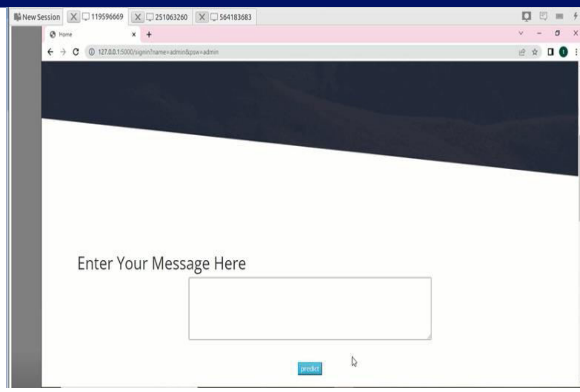

Fig.6: Main screen

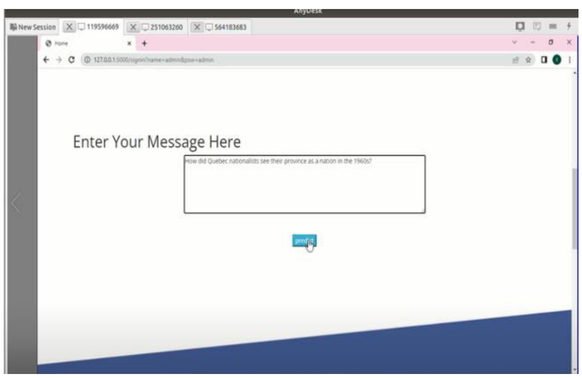

Fig.7: User input

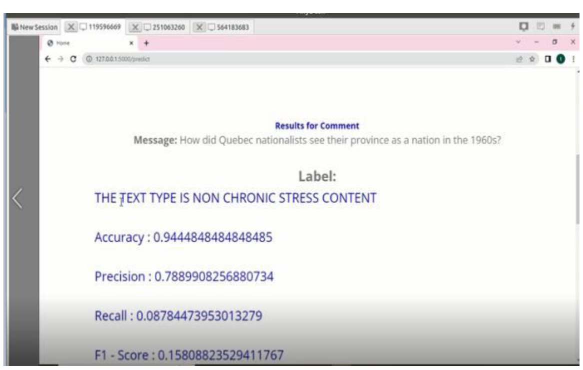

Fig.8: Prediction result

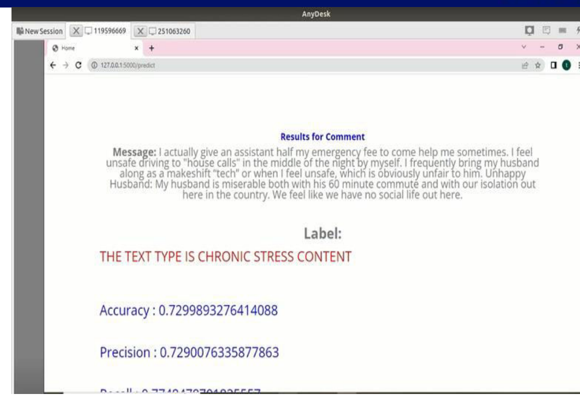

Fig.9: Negative prediction result

6. CONCLUSION

We developed a stress-oriented word embedding to improve the sensitivity of stress-related phrases for linguistic postanalysis in social media-based category-aware chronic stress detection. A multi-attention model was also developed to collect inter-relationships from a series of user postings, with the goal of inferring users' long-term category-specific stress levels. The proposed multi-attention model integrated with the stress-oriented word embedding can achieve 80.65% accuracy in category-aware chronic stress detection when tested on 971 microblog users (392 severely stressed and 579 lightly stressed). We want to evaluate and infer user kinds from social media in the future for customised fine-grained chronic stress detection.

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