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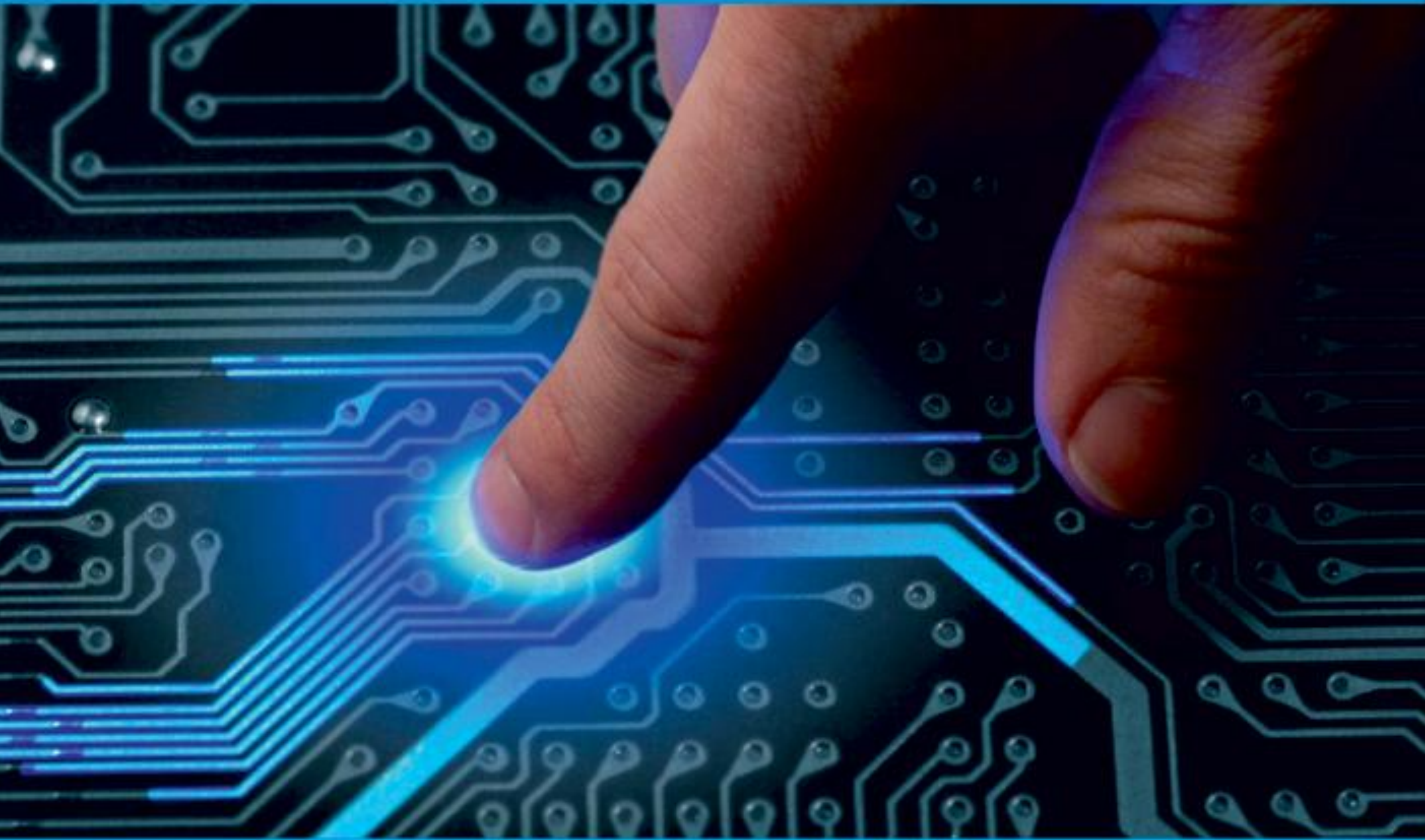

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Predicting Perceived Stress Related to the Covid-19 Outbreak through Stable Psychological Traits and Machine Learning Models

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ABSTRACT: The COVID-19 pandemic has caused widespread devastation throughout the world. In addition to the health and economic impacts, there is an enormous emotional toll associated with the constant stress of daily life with the numerous restrictions in place to combat the pandemic. To better understand the impact of COVID-19, the proposed a framework that utilizes public tweets to derive the sentiments, emotions and discussion topics of the general public in various regions and across multiple timeframes. Using this framework, we study and discuss various research questions relating to COVID-19, namely: (i) how stress level identified during the pandemic? (ii) How sentiments/emotions change in relation to global events? And (iii) what are the common topics discussed during the pandemic?. The stress score for each tweet is calculated as a sum of the stress scores for words in the tweet. A net positive overall stress score indicates a positive statement, a net negative overall stress score indicates a negative statement and a net overall stress score of zero indicates a neutral statement.

KEYWORDS: COVID-19; stress; personality; public health; mental health; coping

I. INTRODUCTION

The study has various implications for academicians as it adds to the existing knowledge pool. The findings provide guidance to the policy makers to tailor their support policies in response to the stress state of their people and also assists the marketers to tailor the communication strategies in the light of the stress state of the target people. Emotional Features: The emotion of depressed people is usually different from no depressed people, which influences their posts on social media. In this work, we studied user positive and negative emoji in each tweet to represent emotional features. Furthermore, users in social media often use a lot of slang and short words, which also convey positive and negative emotions. In this study, positive and negative emotion features are also extracted based on slang and short words.Stress is defined as an adaptive psycho-physical reaction to a physical, social or psychological stimulus, called a stressor. Stress-related responses may be cognitive, emotional, behavioral, or physiological. Depending on the type, timing, and severity of exposure to a stressor, the resulting stress may become a risk factor for a number of illnesses, including those of a psychiatric or cardiovascular nature [28–32]. An emergency such as the COVID-19 outbreak might rightly be considered a severe stressor, as it is a new and unexpected situation with a potentially serious impact on health (experienced both personally and through loved ones) that also involves social restrictions.Coping is one of the most widely studied dispositional traits, and it has been found to be significant in modulating responses to stressful events. Coping is defined as the effort to solve personal and interpersonal problems in an attempt to master, minimize, or tolerate stress and conflict.

II. RELATED WORK

The recent Coronavirus Infectious Disease 2019 (COVID-19) pandemic has caused an unprecedented impact across the globe. We have also witnessed millions of people with increased mental health issues, such as depression, stress, worry, fear, disgust, sadness, and anxiety, which have become one of the major public health concerns during this severe health crisis. Depression can cause serious emotional, behavioral, and physical health problems with significant consequences, both personal and social costs included. This article studies community depression dynamics due to the COVID-19 pandemic through user-generated content on Twitter. A new approach based on multimodal features from tweets and term frequency-inverse document frequency (TF-IDF) is proposed to build depression classification models. Multimodal features capture depression cues from emotion, topic, and domainspecific perspectives. We study the problem using recently scraped tweets from Twitter users emanating from the state of New South Wales in Australia. Our novel classification model is capable of extracting depression polarities that may be affected by COVID-19 and

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related events during the COVID-19 period. THE RESULTS FOUND THAT PEOPLE BECAME MORE DEPRESSED AFTER THE OUTBREAK OF COVID-19. THE MEASURES IMPLEMENTED BY THE GOVERNMENT, SUCH AS THE STATE LOCKDOWN, ALSO INCREASED DEPRESSION LEVELS.

III. PROPOSED ALGORITHM

The process of Covid-19 Stress analysis involves taking the pool of words that have been identified from the pre-processing steps and comparing them to lexicons to determine their stress or polarity. We observe that the stress surprisingly makes up a consistently higher proportion of tweets as compared to other stress levels. Additionally, the stress makes up for a consistently lower proportion of tweets as compared to others. These results are surprising because a pandemic is usually associated with devastation and it would be natural to assume a greater prevalence of negative stress. The proposed method methods consider a word or collection of words to make inferences about the feelings. Such approaches are described as keyword based approaches. In this method emotion detection on related keywords are used. Keywords are matched with predefined stress keywords. There are many ways of data collection in the proposed system for stress analysis on social media. Social media websites like twitter have user tweets for the public and that are accessible for analysis. One can directly import tweets from twitter website. Twitter's API allows to perform complex queries like pulling every tweet about a certain topic and have used a dataset available on twitter binder. A code is written to remove tabs, blank spaces, links etc. Further data is pre-processed to remove stop words like determiners (e.g the, a, an), conjunctions etc. Hash tags which are generally used by twitter users are also removed from data for analysis purpose. It is observed that many social media users make use of special characters like "#"(hashtag) and "@" at in their tweets. which need to be removed for lexical processing with dictionary words.

IV. RESULTS

```
------Accuracy------
('Support Vector Machine Accuracy:', 79.10000000000001, '%')

------Classification Report------
              precision    recall  f1-score   support

         0.0       0.61      0.68      0.64        41
         1.0       0.92      0.82      0.87       600
         2.0       0.08      0.50      0.13         2
         3.0       0.29      0.25      0.27         8
         4.0       0.42      0.62      0.50         8
         5.0       0.39      0.73      0.51        56
         6.0       0.85      0.83      0.84       149
         7.0       0.74      0.73      0.73       136

   micro avg       0.79      0.79      0.79      1000
   macro avg       0.53      0.65      0.56      1000
weighted avg       0.83      0.79      0.80      1000

[[ 28   7   0   1   1   3   0   6]
 [  4 492   1   2   0   6  12  20]
 [  1   2   1   2   0   2   4   1]
 [  2   2   0   2   0   1   0   0]
 [  0   2   0   0   5   0   4   1]
 [  2  53   0   0   0  41   4   6]
```

Fig 1: Accuracy of support vector machine

```
('NAIVE BAYES Accuracy:', 67.0, '%')

------Classification Report------
              precision    recall  f1-score   support

         0.0       0.35      0.48      0.41        33
         1.0       0.87      0.72      0.79       645
         2.0       0.15      0.29      0.20         7
         3.0       0.29      0.33      0.31         6
         4.0       0.00      0.00      0.00         0
         5.0       0.21      0.31      0.25        72
         6.0       0.88      0.68      0.76       188
         7.0       0.27      0.73      0.39        49

   micro avg       0.67      0.67      0.67      1000
   macro avg       0.38      0.44      0.39      1000
weighted avg       0.77      0.67      0.70      1000


Confusion_matrix
[[ 16  11   1   2   0   8   3   5]
 [  3 465   1   1   0  38  26   3]
 [  3   2   2   0   0   0   5   1]
 [  3   2   0   2   0   0   0   0]
 [  0   1   0   0   0   0  11   0]
 [  5  75   0   0   0  22   3   1]
```

Fig 2: Accuracy of Naïve Bayes

```
('DECISION TREE Accuracy:', 66.10000000000001, '%')

------Classification Report------
              precision    recall  f1-score   support

         0.0       0.22      0.38      0.28        26
         1.0       0.80      0.78      0.79       557
         2.0       0.23      0.25      0.24        12
         3.0       0.00      0.00      0.00        10
         4.0       0.25      0.14      0.18        21
         5.0       0.38      0.44      0.41        91
         6.0       0.65      0.73      0.69       129
         7.0       0.59      0.51      0.55       154

   micro avg       0.66      0.66      0.66      1000
   macro avg       0.39      0.40      0.39      1000
weighted avg       0.67      0.66      0.66      1000


Confusion_matrix
[[ 10  13   1   2   0   2   4  14]
 [  7 432   2   5   2  38  12  39]
 [  1   6   3   0   1   1   1   0]
 [  1   3   0   0   0   1   0   2]
 [  0   3   0   0   3   1   4   1]
```

Fig 3: Accuracy of Decision Tree

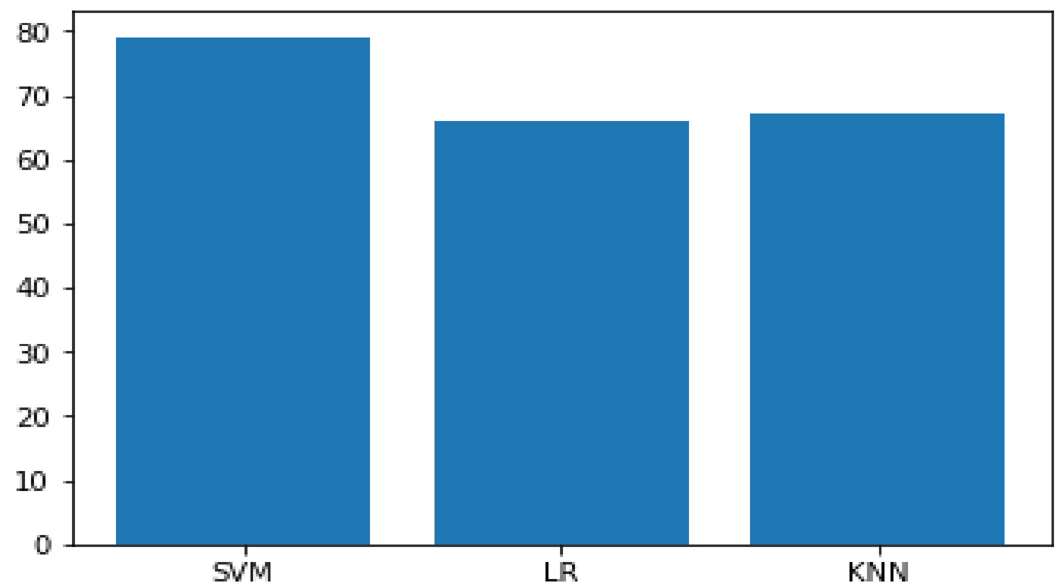

Fig 4: Combined Accuracy of Algorithms

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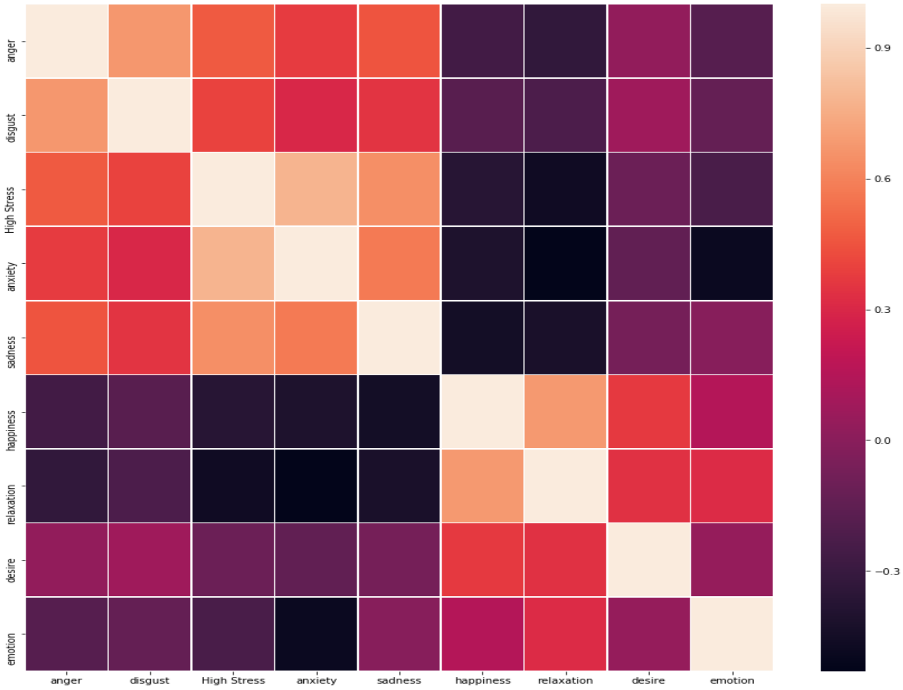

Fig 5: Heat Map of Algorithms

V. CONCLUSION AND FUTURE WORK

The present study measured the impact of the COVID-19 emergency on perceived levels of stress, taking into account sociodemographic variables and stable psychological traits. The results confirmed that participants perceived the COVID-19 crisis as a stressful experience; in the present sample, the level of perceived stress was higher than that of the general population in a non-emergency condition. Indeed, almost 20% of the sample scored above the results from the normative data on measures of perceived stress. These results are in line with the findings of recent studies on the psychological impact of COVID-19 [10] and the international literature on epidemic outbreaks. The mean values of the single items of the PSS-10 suggest that, in addition to nervousness and stress, feelings of being unable to control one's personal life accounted for the majority of participants' perceived stress. This suggests that the unpredictability and uncontrollability of the pandemic may play a significant role in determining levels of perceived stress during the crisis. Moreover, it may reflect participants' attitudes toward the significant lifestyle changes demanded of them due to the lockdown and other restrictive measures.

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