FOUNDATIONS OF MACHINE LEARNING ALGORITHMS (MA-722)

Project Title:

Stress Detection from Social Media using Machine learning

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1. INTRODUCTION

Stress is a feeling of emotional or physical tension. It can come from any event or thought that makes you feel frustrated, angry, or nervous. According to the World Health Organization (WHO), stress affects the brain and body. Little stress is good for performance and protection, but too much stress will be overwhelming to fight, flight, and freeze, depending on how individuals react to it [1]. A considerable amount of stress can lead to depression. So detection of stress at early stages becomes important.

In the ever-evolving landscape of social media, individuals find diverse avenues for self-expression. From crafting text-based updates on Facebook and WhatsApp to composing captions for Instagram posts, or engaging in lively discourse on Twitter and subreddits, we leave digital breadcrumbs of our thoughts and emotions. By analyzing the underlying semantic structure of these textual artifacts, a fascinating possibility emerges: the ability to predict a person's mental state, specifically, their level of stress.

By delving into the linguistic choices, sentence structure, and even the use of emojis, sophisticated algorithms can potentially learn to identify patterns indicative of stress, offering a glimpse into the emotional undercurrents swirling beneath the surface of seemingly mundane online interactions. This opens up a world of possibilities for mental health interventions, allowing for early detection and support for individuals struggling with stress, ultimately contributing to a more informed and compassionate online environment.

2. PROBLEM STATEMENT

Stress detection on social media poses a unique set of challenges due to the diverse ways individuals express themselves online. The sheer volume of data, coupled with the nuanced nature of language, necessitates sophisticated tools for accurate identification of stress indicators. The crux of the problem lies in developing a machine learning model that can navigate the intricacies of language, context, and individual expression to reliably detect signs of stress in social media posts.

Furthermore, the impact of stress on individuals' lives is multifaceted, making its detection even more challenging. Users may not explicitly state their emotional state, and stress indicators can manifest in various linguistic forms, including subtle nuances and implicit expressions.

This project aims to explore the potential of Natural Language Processing (NLP) and Machine Learning (ML) for detecting stress from social media posts. NLP techniques can be used to analyze the language used in social media posts, such as the chosen words, the sentence structure, and the use of emojis. ML algorithms can then be trained on this data to learn to identify patterns that are indicative of stress.

3. LITERATURE REVIEW

Several studies have been done to detect stress through machine learning with different kinds of methods. The following are some research papers we studied.

A. “Stress Detection with Machine Learning and Deep Learning using Multimodal Physiological Data”

Authors: Pramod Bobade and Vani M (Department of Computer Science and Engineering, National Institute of Technology- Karnataka Surathkal, India).

Published Year: 2020

Methodology: The proposed methodology uses diverse machine learning and deep learning techniques on the WESAD dataset for effective stress detection. Leveraging a multimodal wearable sensor dataset, it addresses various stress-related health issues. A simple feed-forward deep learning neural network is applied for classifications, providing a robust analysis.

Drawbacks: The proposed methodology uses diverse machine learning and deep learning techniques on the WESAD dataset for effective stress detection. Leveraging a multimodal wearable sensor dataset, it addresses various stress-related health issues. A simple feed-forward deep learning neural network is applied for classifications, providing a robust analysis.

B. “Stress detection using natural language processing and machine learning over social interactions”

Authors: Tanya Nijhawan, Girija Attigeri and T. Ananthakrishna

Published Year: 2022

Methodology: The proposed system enhances stress detection by analyzing sentiment and emotion in social media posts. Using large tweet datasets, machine learning and the BERT model classify sentiments. Additionally, Latent Dirichlet Allocation identifies patterns in documents for a comprehensive understanding. The approach aims to assess stress through social media interactions.

Drawbacks: The effectiveness of sentiment analysis and emotion detection models heavily depends on the training data. If the training data is biased or not representative of diverse user sentiments, the model may not generalize well to real-world scenarios.

C. "Detecting Stress Based on Social Interactions in Social Networks"

Authors: Huijie Lin, Jia Jia, Jiezhong Qiu, Yongfeng Zhang, Guangyao Shen, Lexing Xie, Jie Tang, Ling Feng, and Tat-Seng Chua

Published Year: 2017

Methodology: The researchers introduced a hybrid model, combining a factor graph model with a Convolutional Neural Network, to detect stress by analyzing tweet content and social interactions. They define stress-related attributes from textual, visual, and social aspects. Additionally, their analysis revealed intriguing phenomena, such as stressed users having social structures with sparse connections, indicating less complexity compared to non-stressed users.

Drawbacks: The model is intricate, combining a variety of components such as CNN, CAE, and factor graph model. The complexity might pose challenges in terms of interpretability, making it harder to understand the model's decisions. Clear explanations or visualizations of the model's internal workings could enhance its transparency.

D. "Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits"

Authors: Andrey Bogomolov, Bruno Lepri, Michela Ferron, Fabio Pianesi and Alex Pentland.

Published Year: 2014

Methodology: The proposed system aims to detect daily stress using non-intrusive measures such as mobile phone activity, weather conditions, and personality traits. It utilizes behavioral metrics from phone usage, app interactions, and communication frequency. The model is efficient for multimedia applications with a reduced low-dimensional feature space for computational efficiency (32 dimensions).

Drawbacks: The model proposed has limitations in generalizing across diverse user populations. It might perform well for certain demographic groups but may not be as effective for others. The success of stress detection systems relies on user acceptance. If users find the system intrusive or perceive it as a threat to their privacy, it might lead to low adoption rates.

E. “Multimodal mental health analysis in social media”

Authors: Amir Hossein YazdavarI, Mohammad Saeid Mahdavinejad, Goonmeet Bajaj , William Romine and Amit Sheth.

Published Year: 2018

Methodology: The proposed multimodal framework improves depressive behavior detection on Twitter using visual, textual, and user interaction data. It explores the relationship between demographic information and mental health for targeted interventions. Empirical evaluations show a 5% improvement in the F1-Score compared to state-of-the-art approaches.

Drawbacks: The findings and models developed in this study may not generalize well to diverse populations or individuals who do not express their mental health struggles on social media. The sample may be biased towards those who are more open about their mental health. The absence of a gold standard or clinical validation for the identified depressed individuals on Twitter raises questions about the accuracy of the model's predictions. It's crucial to validate these predictions against clinical assessments for robustness.

4. DATASET

The dataset employed for this project was sourced from Kaggle. It contains data posted on subreddits related to mental health. **Reddit** is a social media website where users post in topic-specific communities called subreddits, and other users comment and vote on these posts. The lengthy nature of these posts makes Reddit an ideal source of data for studying the nuances of phenomena like stress.

It is inferred from the statistics that the dataset is balanced; abstaining us to perform any class imbalance modifications. It is a labeled dataset, where the target variable is represented with numbers 1 and 0, where **1 indicates the post depicting 'stress'** and **0 depicting 'nonstress'**; this also signifies that the computational models built would be of binary classification. It also includes some of the basic details of every post such as post id, sentence range, time, and date during which the post was online and alike.

Any fault bound to these parameters would not have any effect on the experimentation since our focus is to understand and analyze from social media posts if the user has symptoms of stress or not.

Scenario	Total	Percentage (%)
Stress	1488	52.43
Non-Stress	1350	47.57
Total	2838	100

Table 1: Statistics of Balanced Dataset

This dataset has 2838 posts posted by people [3]. It has 116 columns. Out of these 116, only 2 columns are relevant for us. First is "text" which indicates the posts collected from different subreddits and the second is "label" which tells where that post is labeled as 0 (no stress) or 1 (stress).

The first 3 posts and labels are shown in Table 2.

Text	Label
He said he had not felt that way before, suggeted I go rest and so ..TRIGGER AHEAD IF YOUI'RE A HYPOCONDRIAC LIKE ME: i decide to look up "feelings of doom" in hopes of maybe getting sucked into some rabbit hole of ludicrous conspiracy, a stupid "are you psychic" test or new age b.s., something I could even laugh at down the road. No, I ended up reading that this sense of doom can be indicative of various health ailments; one of which I am prone to.. So on top of my "doom" to my gloom..I am now f'n worried about my heart. I do happen to have a physical in 48 hours.	1
Hey there r/assistance, Not sure if this is the right place to post this.. but here goes =) I'm currently a student intern at Sandia National Labs and working on a survey to help improve our marketing outreach efforts at the many schools we recruit at around the country. We're looking for current undergrad/grad STEM students so if you're a STEM student or know STEM students, I would greatly appreciate if you can help take or pass along this short survey. As a thank you, everyone who helps take the survey will be entered in to a drawing for chance to win one of three $50 Amazon gcs.	0
My mom then hit me with the newspaper and it shocked me that she would do this, she knows I don't like play hitting, smacking, striking, hitting or violence of any sort on my person. Do I send out this vibe asking for it from the universe? Then yesterday I decided to take my friend to go help another "friend" move to a new place. While we were driving the friend we are moving strikes me on my shoulder. And I address it immediately because this is the 4th time I have told him not to do these things, then my other friend who is driving nearly gets into an collision with another car i think because he was high on marijuana and the friend we are moving in the backseat is like "you have to understand I was just trying to get your attention" you know the thing 5 year olds do to get peoples attention by smacking them, this guy is in his 60's.	1

Table 2: Top 3 posts and labels in the dataset

5. METHODOLOGY

The flow of the project is shown in the following figure.

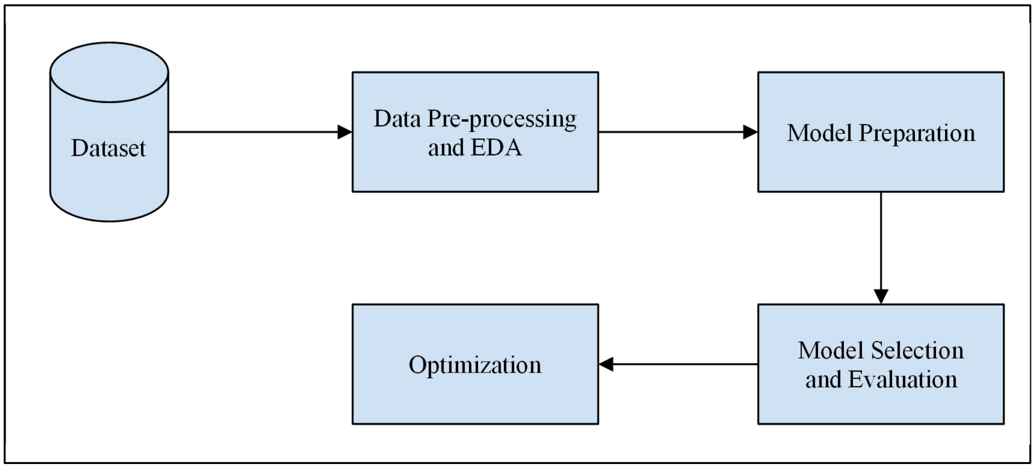

Fig 1: Flow Chart Methodology

We propose some machine learning models by training the dataset of posts. The dataset preparation and model development are discussed thoroughly in the following subsections:

5.1 DATASET

We have already discussed the dataset earlier in section 4.

5.2 PRE-PROCESSING AND EXPLORATORY DATA ANALYSIS

The initial phase of the project involves preparing the raw data for analysis. This is achieved through comprehensive pre-processing and Exploratory Data Analysis (EDA). Here's a concise overview of the crucial steps undertaken during this phase:

A. Lowercase Conversion and Removal of Punctuations

a. Convert all text to lowercase to ensure uniformity.

b. Eliminate punctuation to facilitate accurate tokenization.

B. Tokenization

a. Break down full-length texts into smaller, manageable chunks.

b. Enhances the understanding of sentence structure and word relationships.

C. Stopwords Removal

a. Exclude common words like 'the,' 'is,' 'in,' etc., which do not significantly contribute to the analysis.
b. Improves the efficiency of subsequent processes.

D. Lemmatization

a. Transform words into their base forms.
b. Distinguishes between words of the same root, providing a nuanced understanding.
c. Unlike stemming, lemmatization considers the context, preserving the meaning of words.

These steps collectively form a robust pre-processing framework, ensuring that the data is cleansed of unnecessary elements and is ready for in-depth exploratory analysis.

Before	After
He said he had not felt that way before, suggeted I go rest and so ..TRIGGER AHEAD IF YOUI'RE A HYPOCONDRIAC LIKE ME: i decide to look up "feelings of doom" in hopes of maybe getting sucked into some rabbit hole of ludicrous conspiracy, a stupid "are you psychic" test or new age b.s., something I could even laugh at down the road. No, I ended up reading that this sense of doom can be indicative of various health ailments; one of which I am prone to.. So on top of my "doom" to my gloom..I am now f'n worried about my heart. I do happen to have a physical in 48 hours.	say felt way suggeted go rest .. trigger ahead youi 're hypocondriac like decide look `` feel doom `` hope maybe get suck rabbit hole ludicrous conspiracy stupid `` psychic `` test new age b.s something could even laugh road end reading sense doom indicative various health ailment one prone .. top `` doom `` gloom .. f'n worried heart happen physical 48 hour

Table 3: Raw data vs Pre-processed data

5.3 MODEL PREPARATION

With the dataset thoroughly pre-processed, the next phase involves preparing it for the machine learning models. This step encompasses the transformation of text data into a format suitable for training and testing models.

We used the **CountVectorizer** tool for the feature extraction and convert text data into matrix form suitable for machine learning models. The prepared dataset sets the stage for the subsequent model selection and training phases.

5.4 MODEL SELECTION AND TRAINING

In this pivotal stage, the choice of machine learning models is crucial. For our project, we employed three machine learning models: Decision Tree (**DT**), Naive Bayes (**NB**), and Support Vector Machine (**SVM**).

We utilized our pre-prepared dataset to train and validate these models. To assess the performance of each model, we employed relevant metrics such as the following-

A. **Accuracy:** The proportion of correctly predicted instances out of the total instances.
B. **Precision:** The ratio of correctly predicted positive observations to the total predicted positives.
C. **Recall:** The ratio of correctly predicted positive observations to all actual positives.
D. **F1-score:** The harmonic mean of precision and recall, providing a balanced measure of a model's performance.

5.5 OPTIMIZATION

Following the evaluation of our initial models, we naturally progressed to the optimization phase. We explored techniques like **n-grams** and **TF-IDF** to improve the performance of our models. After implementing these techniques, we re-evaluated the results to assess their effectiveness.

6. RESULTS AND DISCUSSION

We evaluated the performance of three classifiers: Decision Tree (DT), Naive Bayes (NB), and Support Vector Machine (SVM). Their accuracy, precision, recall, and F1 scores are presented in Table 4.

Classifier	Accuracy	Precision	Recall	F1-Score
DT	59%	61%	63%	62%
NB	**74%**	**74%**	**81%**	**77%**
SVM	72%	76%	70%	73%

Table 4: Performance of Models

From Table 4 we can conclude that the **Naive Bayes classifier gives the best result.**

To improve model performance and achieve higher accuracy, we incorporated bigrams into the feature set, alongside the previously used unigrams. The updated performance metrics obtained for each model are now presented in Table 5.

Classifier	Accuracy	Precision	Recall	F1-Score
DT	61%	64%	63%	63%
NB	73%	74%	79%	76%
SVM	72%	76%	71%	73%

Table 5: Model Performance with Unigrams and Bigrams as Features

Upon integrating unigrams and bigrams as features, the accuracy of the decision tree rose to 61%. In contrast, the accuracy of naive Bayes declined. This discrepancy arises from the observation that the efficacy of using n-grams as features is not universally associated with accuracy improvement; rather, its performance is contingent on the characteristics of individual datasets.

To enhance optimization, we propose employing TF * IDF as the feature value, as opposed to solely relying on term frequency (TF). The performance metrics resulting from the implementation of TF * IDF are presented in Table 6.

Classifier	Accuracy	Precision	Recall	F1-Score
DT	61%	63%	65%	64%
NB	73%	71%	86%	78%
SVM	73%	77%	72%	74%

Table 6: Performance metrics upon using TF * IDF as feature values

After incorporating TF-IDF, the performance metrics exhibited a slight increase.

7. SUMMARY AND CONCLUSION

The ever-evolving field of stress detection motivates our research in developing machine learning models for predicting stress from social media data. In this project we used DT, Naive Bayes and SVM and compared their performance.

Experimental results demonstrate the effectiveness of SVM, achieving an accuracy of 73%, precision of 77%, recall of 72% and F1 score of 74% in predicting stress levels, where Naive Bayes also performed equally good with an accuracy of 73%, precision of 71%, recall of 86% and F1 score of 78%. While these outcomes are promising, we acknowledge the need for continuous improvement in personality prediction models.

Further improvements in performance might be achieved through the utilization of advanced algorithms such as BERT, coupled with sophisticated language processing methods. Additionally, expanding the scope of this research beyond binary classification to multi-class classification could unlock deeper insights. This would enable the prediction of not only stress presence, but also its intensity, ranging from extreme stress to extreme joy and all points in between.

We believe that ongoing research and development in this area are crucial for unlocking the full potential of stress detection from social media. By embracing innovative approaches and exploring new techniques, we can strive towards more accurate and reliable personality prediction models.

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