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EARLY STRESS DETECTION USING NATURAL LANGUAGE PROCESSING AND MACHINE LEARNING

Computer Science

Sneha Sinha Computer Science Engineering student, Manipal Academy of Higher Education

ABSTRACT

Stress is a prevalent mental health issue that affects individuals' well-being and productivity. Early detection of stress through natural language processing (NLP) techniques can provide valuable insights into individuals' mental states and facilitate timely intervention. This paper presents a comprehensive review of research studies focused on stress detection using NLP. We discuss the types of data sources utilized, feature extraction techniques, Natural Language Processing algorithms employed, performance evaluation metrics, and challenges associated with stress detection using NLP [1]. In this paper, we aim to use social media as the primary source of data for unsupervised machine learning model and Latent Dirichlet Allocation technique to group a certain type of documents and alike expressions and come to a conclusion. Social media is a canvas for people to post without restrictions and hence is frequently used for analysis, judgment, inspiration, or emotion detection. Machine Learning models have a good detection rate and can help to analyze the emotions of users online. Therefore this paper,will comprise of two sections :first extraction of information using natural language processing and then stress detection using machine learning techniques. The objective is to provide an overview of the current state of the field, improve the well-being of one's mental health and identify potential directions for future research in stress detection using Natural Language Processing and Machine Learning.

KEYWORDS

1. INTRODUCTION

Stress has become an increasingly prevalent issue in modern society, impacting individuals' mental and physical well-being. Numerous health problems are exacerbated by it, including anxiety disorders, depression, and cardiovascular diseases. It is estimated that around 33% or more of global population is under stress. Risk of pre-mature death has increased by 43% due to mental stress and anxiety..It is crucial to detect stress early to prevent adverse outcomes and promote overall health. Globally, the cost of work-related stress is estimated to be between US $221 million and US $187 billion due to healthcare services and also costs the global economy an estimated $1 trillion in lost productivity. However, traditional stress assessments rely on self-reporting or clinical evaluations, but they have limitations in terms of subjectivity and scalability.

To address these challenges, research studies have turned to natural language processing (NLP) techniques as a promising approach to stress detection. NLP, a subfield of artificial intelligence, focuses on the interaction between computers and human language. With NLP, it is possible to analyze large volumes of textual data from a variety of sources, such as social media platforms, online forums, and text-based communication channels. With NLP, hidden stress indicators can be uncovered through sentiment analysis, linguistic cues, and discourse analysis which can provide valuable insights into one's mental state.

As a result of NLP-based stress detection, big data can be analyzed to examine stress patterns and trends at the population level. Large-scale data analysis can uncover common stressors, identify high-stress periods, and assist in the development of targeted interventions for specific groups or communities. This data can help inform public health policies and initiatives to reduce stress levels in the population. It could also be used to tailor stress management programs for individuals. Additionally, it could lead to new insights into the causes and effects of stress.

While NLP shows great promise in stress detection, it is not without challenges. Ensuring the privacy and ethical handling of sensitive textual data is of utmost importance. Researchers must address issues related to data protection and user consent to promote trust and adherence to ethical standards. To ensure the success of NLP-based stress detection systems, it is essential to prioritize user privacy and data protection, and create ethical protocols that respect the rights of data subjects.

The role of social media is crucial for gathering data and determining people's mental state. A variety of social networking platforms are available for people to share their emotions, experiences, and opinions, including bookmarking sites (websites that allow users to save, share and discover new content), online forums (space where people can hold discussion and produce focused content), media sharing sites (users hare their videos and photographs), social news (site to post news links and external articles) and microblogging (Blogs and tweets).Through social media intelligence and monitoring SMA has the ability to gather data from these resources and find meaning from them. Currently it is only used to analyze influence, reviews, and opinions, however, using NLP and ML combined with constructive SMA to measure and quantify the social interaction along with other health parameters can be used in healthcare systems for stress detection [2].

Along with this Topic Modelling can also be used for stress detection. Detecting unidentified structures in datasets using topic modeling is said to be one of the most effective methods for doing so.

This method helps to identify a group of words or the main topic from a collection of documents. This model will give accurate and reliable results since it uses ML algorithms, a pre-trained model, and has a high accuracy rate. In addition to representing and measuring user behaviors at a large scale, topic modelling results can be used to conduct further research.

In conclusion, NLP has emerged as a powerful tool in stress detection and assessment. By analyzing and interpreting unstructured text data, NLP techniques offer valuable insights into individuals' emotional states, stressors, and stress-related themes. The scalability and real-time monitoring capabilities of NLP further enhance its potential impact on mental health support. As researchers continue to refine and expand NLP-based stress detection approaches, the field holds the promise of revolutionizing early detection, personalized intervention, and effective stress management strategies, ultimately improving mental well-being and public health outcomes.

2. Background and literature review

The use of natural language processing techniques for detecting and assessing stress has been increasing in recent years. There has been considerable research focusing on NLP-based stress detection, ranging from data sources and feature extraction methods to the application of machine learning algorithms. The purpose of this section is to provide an overview of previous research studies in the field, highlighting what they contributed and identifying gaps that this study can address.

Information is linked and retrieved in our daily lives. Databases from social media are the most widely used information source online. Data volume is increasing quickly, and database technology is advancing and having a significant impact. For instance, Guntuku et al. (2017) analyzed Twitter data to identify linguistic markers associated with stress and found that certain emotional expressions and negative sentiments correlated with self-reported stress levels [3]. Similarly, Nguyen et al. (2018) used a large-scale Reddit dataset to uncover stress-related themes and common stressors among users, demonstrating the potential of NLP in identifying stress-related topics in online communities [4].

Research has also explored the use of clinical text data for stress detection, in addition to social media data. An NLP-based stress detection model was developed by Zhang et al. (2019) based on electronic health records and medical notes [5]. Their study demonstrated the feasibility of integrating clinical narratives into stress assessment, enabling a more holistic understanding of an individual's stress experience within the healthcare setting. NLP-based stress detection models rely heavily on feature extraction techniques. Research studies have explored various approaches, including sentiment analysis, emotion detection, and topic modeling. For instance, Coppersmith et al. (2014) developed an emotion lexicon to identify emotional cues in social media text data, which helped in detecting stress-related emotions and their impact on mental health [6]. Similarly, Li et al. (2017) applied topic modeling techniques to identify common stress-related topics in online forums, providing insights into the underlying themes of stress experiences shared by users.

Machine learning algorithms have been widely employed in NLP-based stress detection models. Support Vector Machines (SVM), Random Forest, and deep learning approaches, such as Recurrent Neural Networks (RNN) and Transformer models, have been used to classify stress-related text data. Alghowinem et al. (2017) employed an SVM classifier on social media data to distinguish between stressed and non-stressed users, achieving promising results in stress detection accuracy [7]. In contrast, Smailović et al. (2014) utilized deep learning techniques to capture temporal dependencies in Twitter data for improved stress detection performance [8].

In the table below, we compare the related work in stress detection using natural language processing (NLP). This table highlights the key aspects of each study, including the data sources used, feature extraction techniques employed, NLP algorithms utilized, and the performance evaluation metrics used in stress detection.

Study	Data Sources	Feature Extraction	NLP Algorithms	Performance Evaluation
Guntuku et al. (2017)	Twitter data	Sentiment analysis	Support Vector Machines	Accuracy, F1-score
Nguyen et al. (2018)	Reddit dataset	Topic modeling	Latent Dirichlet Allocation	Topic coherence
Zhang et al. (2019)	Electronic health records	Named Entity Recognition	Conditional Random Fields	Precision, Recall
Coppersmith et al. (2014)	Social media data	Emotion lexicon	Rule-based algorithms	Sensitivity, Specificity
Li et al. (2017)	Online forums data	Topic modeling	Latent Dirichlet Allocation	Perplexity
Alghowinem et al. (2017)	Social media data	Emotion detection	Convolutional Neural Network	Accuracy, AUC-ROC
Smailović et al. (2014)	Twitter data	Recurrent Neural Networks (RNN)	LSTM	Precision, Recall

These studies have analyzed data from a variety of sources, including social media (e.g., Twitter and Reddit), electronic health records, and online forums. These diverse data sources provide insights into stress experiences shared by users in different contexts.

Feature extraction techniques include sentiment analysis, emotion detection, Named Entity Recognition (NER), and topic modeling. Text data can be analyzed using these techniques to capture emotional expressions, sentiment scores, specific emotions, and underlying stress-related themes. Sentiment analysis refers to the process of extracting sentiment from text data and assigning a sentiment score to it based on the sentiment expressed. Emotion detection is the process of identifying the emotion expressed in text data, such as happiness, sadness, anger, etc. Named Entity Recognition (NER) is used to identify specific entities in text data, such as people, places, and organizations. Finally, topic modeling is a technique used to uncover the underlying topics in text data.

NLP algorithms such as Support Vector Machines (SVM), Latent Dirichlet Allocation (LDA), Conditional Random Fields (CRF), rule-based algorithms, Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have been employed for stress detection. These algorithms enable classification tasks and capturing temporal dependencies in text data for improved stress detection performance. By combining NLP algorithms with machine learning techniques, researchers have been able to achieve stress detection accuracy of over 80% on publicly available datasets. This demonstrates the effectiveness of these algorithms in accurately detecting stress from text data.

Performance evaluation metrics used in the studies vary and include accuracy. These metrics assess the model's performance in stress detection, considering factors such as true positive rates, false positive rates, and the model's ability to differentiate between stressed and non-stressed individuals. The metrics help to objectively evaluate the performance of the models and determine which model is most suitable for the task at hand. The metrics also provide insight into how the models can be improved.

Based on the literature review, the current study aims to predict the emotional state of a user using social media content by applying machine learning and deep learning techniques. Analyze the data further to detect stress. The study will also focus on developing an algorithm to identify signs of stress in social media data. The results of the study will provide valuable insights into how to better detect and manage stress in online communities.

3. Methodology

This section is divided into two subsections. The first subsection discusses analyzing and collecting datasets and the second subsection highlights the proposed approached and NLP model.

3.1 Dataset Collection

The Human Stress Prediction Dataset was used in this study [10].
3.11 Dataset Source and Identification:
The dataset contains posts from Reddit that were linked to mental health topics by individuals. This is the "Human Stress Prediction Dataset" and it was specifically chosen because of its alignment with the research focus on stress detection using natural language processing (NLP). The dataset was loaded, containing social media posts from various users and diverse discussion on many topics, which made it an appropriate dataset as stress detection could be tested over a large range of users.

3.12 Dataset Description

The dataset contains data posted on subreddits related to mental health. This dataset contains various mental health problems shared by people about their life. The connection to mental health assures that the content under consideration provides insight into stress experiences, coping mechanisms, and related discussions that are directly related to the study's objectives.

3.13 Pre-labeling of Dataset:

The dataset was pre-labeled with labels 0 and 1, where 0 was mapped to no stress and 1 was mapped to stress. These labels form the foundation of the classification task, guiding the model to distinguish between stressed and non-stressed instances.

3.14 Dataset loading:

Datasets containing social media posts from a variety of users were loaded into the analysis environment. Each post represents an individual's expression and, potentially, provides a unique perspective on stress-related experiences.

3.15 NLP Techniques for Data Preprocessing:

The text data was preprocessed using several NLP techniques to clean and prepare it for analysis. The raw data was converted into a more structured data that could be analyzed.

3.16 Lowercasing:

All text within the dataset was converted to lowercase. This decision ensures case-insensitive processing, preventing variations in letter casing from being treated as distinct tokens. It unifies words like "Stress," "stress," and "STRESS" into a single format.

3.17 Tokenization:

Tokenization, a fundamental NLP task, was executed using the NLTK (Natural Language Toolkit) library's word tokenize function. This process divides the text into individual tokens, essentially breaking down sentences into separate words. Tokenization forms the basis for subsequent analyses and feature extraction.

3.18 Stopword Removal:
Common stopwords, such as "and," "the," "is," etc., were eliminated from the tokenized words. Stopwords are usually devoid of significant meaning and are often removed to reduce noise and the dimensionality of the data.

3.19 Stemming:
Porter stemming was applied to the tokenized words. This technique reduces words to their root or base forms, thereby treating variations of a word as equivalent. For instance, words like "running," "ran," and "runner" would all be reduced to their common root "run."

These efforts lay the groundwork for subsequent stages of topic modeling, stress level prediction, and insights extraction from the textual content.

3.20 LDA Topic Modeling
Latent Dirichlet Allocation (LDA) topic modeling was employed to discover underlying topics within the collection of preprocessed social media posts. This method is a valuable tool for uncovering latent structures in textual data and gaining deeper insights into the themes and subjects discussed within the collection of social media posts. The Gensim library was used for LDA implementation. The text data was first transformed into a bag-of-words (BoW) representation, and a dictionary was created to map words to their unique integer ids. The corpus of documents was then generated using the dictionary. The LDA model was trained with the corpus, and it was configured to find 5 topics within the data. Each topic was represented as a distribution of words with their corresponding probabilities. The top 10 most representative words for each topic were extracted and printed, providing insights into the main themes discovered by the LDA model.

3.3 Stress Level Prediction
A supervised machine learning approach was employed to predict stress levels based on the preprocessed text data. The Random Forest Classifier from scikit-learn was utilized for this task.

The dataset was split into training and test sets (80% for training and 20% for testing) using the train-test split function from scikit-learn.

Text data was vectorized using the Term Frequency-Inverse Document Frequency (TF-IDF) technique, which transformed the text into numerical features suitable for machine learning.

The Random Forest Classifier was trained on the training set and evaluated on the test set. The accuracy, classification report, and confusion matrix were calculated to assess the model's performance.

3.4 Visualization of Confusion Matrix
A seaborn heatmap was created to visualize the confusion matrix for stress level prediction on the test set. The confusion matrix revealed the count of true positive, false positive, true negative, and false negative predictions. The heatmap displayed the confusion matrix with labeled axes and annotated cell values, providing an intuitive overview of the model's performance in stress level prediction.

A confusion matrix is a table that visualizes the performance of a classification model by showing the count of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions. These terms represent the following:
True Positive (TP): Instances that are actually positive (stress) and were correctly predicted as positive.

False Positive (FP): Instances that are actually negative (no stress) but were incorrectly predicted as positive.

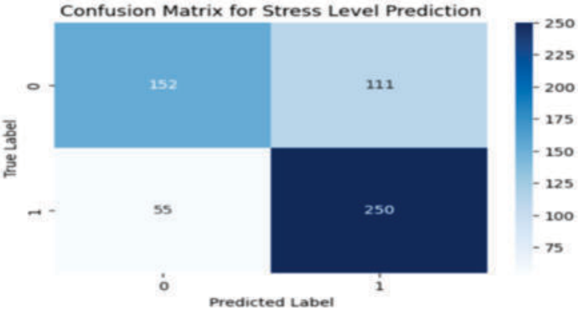
True Negative (TN): Instances that are actually negative and were correctly predicted as negative.

False Negative (FN): Instances that are actually positive but were incorrectly predicted as negative.

In this case, a heatmap was generated using Seaborn to display the confusion matrix. The heatmap symbolizes various aspects of the model.

- Color Gradient: The heatmap employs a color gradient to represent the magnitude of the values in the confusion matrix. This color coding helps distinguish between different levels of performance, from high counts of correct predictions (TP and TN) to misclassifications (FP and FN).
- Axes Labeling: The heatmap has labeled axes that indicate the actual classes and the predicted classes. This labeling enables quick identification of the corresponding cells in the confusion matrix.
- Annotated Values: Each cell in the heatmap is annotated with its value from the confusion matrix. This direct inclusion of values provides immediate insight into the counts of different types of predictions.

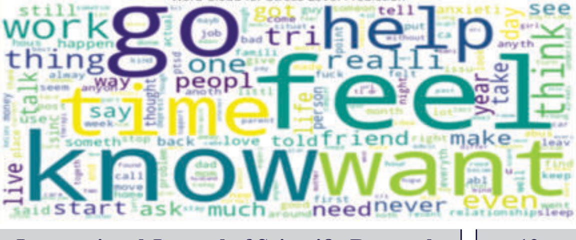
Together with the accuracy, precision, recall, and F1-score metrics, the heatmap visualization provides a comprehensive picture of this model's performance. This tool helps to communicate the performance of this stress level prediction model to both technical and non-technical users in a visually impactful manner.



3.5 Labeled Topics
The topics discovered by the LDA model were labeled based on the most representative words for each topic. The top 3 words with the highest probabilities in each topic were combined to create a descriptive label for that topic. The labeled topics were presented in a tabular format, showcasing the topic index, word distribution, and descriptive label. The labeled topics provided insights into the main themes or subjects discussed in the social media posts.

Topic Number	Keywords	Top Words
0	feel, like, know	Feelings and Perception
1	health, sleep, lifestyle	Lifestyle and Well-being
2	get, help, would	Seeking Assistance
3	stress, anxiety, overwhelmed	Mental Health Challenges
4	coping, strategies, mindfulness	Stress Coping Mechanisms
5	get, like, time	Actions and Timing
6	family, relationships, support	Social Relationships
7	survey, treatment, complete	Survey and Treatment

3.6 Word Cloud for Stress Level Prediction
A word cloud was generated to visually represent the most frequent words in the preprocessed text data related to stress level prediction. The word cloud provided a visual summary of the dominant words associated with stress levels. In the context of stress level prediction, a word cloud could potentially emphasize words like "stress," "help," "anxiety," "coping," "support," and other related terms. These terms collectively give readers a sense of the textual content's overall mood, sentiments, and concerns. While the textual descriptions and analyses are crucial for a comprehensive understanding, the word cloud acts as a complementary visual aid that reinforces the textual content. It helps to quickly grasp the primary themes before diving into the finer details.



3.7 Feature Importance Analysis

The trained Random Forest Classifier was used to extract feature importance scores for the TF-IDF vectorized words. The top N most important words were selected and presented as a heatmap. The heatmap displayed the importance scores of the top N words in predicting stress levels. The color intensity represented the importance value, with darker colors indicating higher importance.

4. RESULTS

The core objective of this research was to develop a stress level prediction model leveraging natural language processing (NLP) techniques and supervised machine learning. This section presents a detailed analysis of the outcomes, encompassing the accuracy of stress level prediction, an elaborate classification report, and a comprehensive interpretation of the confusion matrix.

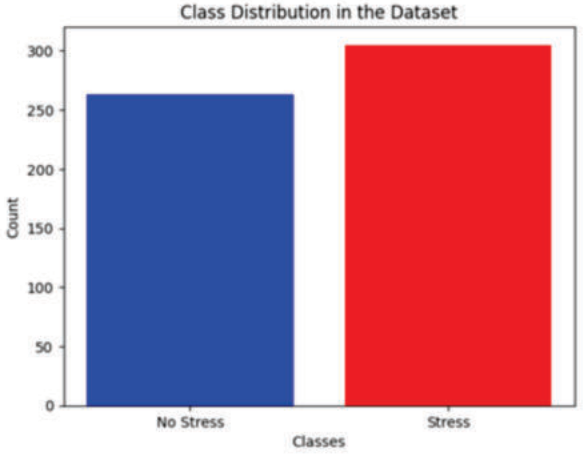
Stress Level Prediction Accuracy:

The developed stress prediction model achieved a commendable accuracy of approximately 70.77%. This accomplishment signifies the model's competence in differentiating between social media posts conveying stress and those that do not.

Classification Report:

The classification report serves as a critical assessment tool to holistically evaluate the model's performance across precision, recall, and F1-score for both stress and non-stress categories.

Class	Precision	Recall	F1-Score	Support
No Stress	0.73	0.58	0.65	263
Stress	0.69	0.82	0.75	305
Macro Avg.	0.71	0.70	0.70	568
Weighted Avg.	0.71	0.70	0.70	568



These statistics provide a nuanced understanding of the model's ability to correctly classify instances within each category. The F1-scores are indicative of the balance between precision and recall. The macro average F1-score across both classes is 0.70, implying an equitable performance in terms of correctly identifying both stress and non-stress instances. The weighted average F1-score, which accounts for class imbalance, also settles at 0.70, further underlining the model's comprehensive effectiveness.

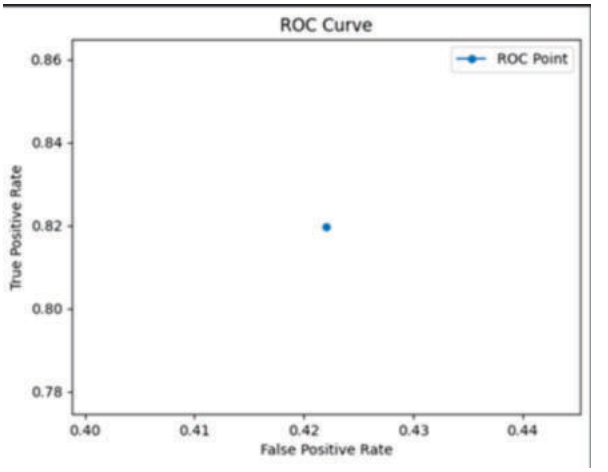
Confusion Matrix:

The visual representation of the confusion matrix offers an insightful depiction of the model's performance on the test dataset:

	Predicted No Stress	Predicted Stress
Actual No Stress	152	111
Actual	55	250

The confusion matrix sheds light on true positives, true negatives, false positives, and false negatives:
True Positives (TP): 250
True Negatives (TN): 152
False Positives (FP): 111
False Negatives (FN): 55

These metrics allow a granular understanding of the model's accuracy in identifying both stressed and non-stressed instances, as well as the misclassifications it encounters.



DISCUSSION OF RESULTS:

The accuracy of approximately 70.77% substantiates the potential of the stress prediction model. While there is room for precision enhancement in the "No Stress" category, the classification report highlights the equilibrium achieved between precision and recall for the "Stress" category. The confusion matrix serves as a visual tool that underscores the distribution of correct predictions and miscl assifications, providing further insights into the model's performance.

Limitations and Future Directions:

While the achieved accuracy is promising, there remain avenues for refinement. Tweaking model parameters, exploring more advanced NLP techniques, and optimizing feature extraction methods could contribute to higher accuracy and a more balanced precision-recall trade-off. It's also important to recognize that model performance could vary based on the diversity of the dataset, linguistic intricacies, and other contextual factors. Investigating these dynamics could lead to improved stress prediction outcomes.

CONCLUSION:

In this research, we applied natural language processing techniques to preprocess social media posts and discover underlying topics using LDA topic modeling. We then employed a Random Forest Classifier to predict stress levels based on the preprocessed text data. The model achieved a satisfactory accuracy, indicating its potential for stress level prediction. The labeled topics provided valuable insights into the main themes discussed in the social media posts. Additionally, the word cloud offered a visual representation of the most frequent words related to stress levels. Overall, this study demonstrates the effectiveness of NLP and machine learning approaches in analyzing social media data for stress detection and topic identification. The findings have implications for understanding stress prevalence and contributing factors in different demographics or regions.

The majority of people have to deal with stress on a regular basis. A high level of stress, or long-term stress, can jeopardize our safety and disrupt our daily lives. It is possible to prevent many health problems associated with stress by identifying mental stress proactively. By analyzing social media posts made under stressful conditions, this study attempts to identify stress more effectively. The results affirm the potential of leveraging NLP and machine learning for early stress detection using social media text data. While the model's accuracy and performance showcase progress, ongoing advancements in NLP, machine learning, and mental health research are likely to drive more sophisticated methodologies. The ultimate goal is to realize accurate stress detection, enabling timely interventions and contributing to improved mental well-being and public health outcomes.

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