

Review Article

Emotional Health Monitoring on Social Media

Dr. Sonia H. Bajaj¹, Sheikh Nabil², Aslam Khan³, Tanu Patle⁴, and Vedant Raut⁵

¹Research & Consultancy Coordinator, Department of Computer Science & Engineering, GH Rasoni University, Saikheda(M.P)

^{2,3,4,5}Student, Department of Computer Science & Engineering, GH Rasoni University, Saikheda(M.P)

ABSTRACT

Depression, a prevalent mental illness and a leading contributor to global disability, can tragically lead to suicides. It's estimated that over 300 million individuals worldwide grapple with depression each year. Typically, depression is diagnosed through in-person clinical assessments. However, during the initial stages, a significant portion of patients, approximately 70%, refrain from seeking medical consultation, allowing their condition to progress further. This study also seeks to determine whether a user is experiencing depression based on the content of their tweets and their network activity. Moreover, it possesses the capability to detect other mental health conditions and could serve as a foundational framework for implementing mechanisms to detect and mitigate the spread of depression within social networks.

KEYWORDS

Natural Language Analysis, Twitter, Online Social Platforms, EDA and Feature Selection, Logistics Regression, support vector machine (SVM), k-nearest neighbors(k-NN), Decision Tree Classifier, Random Forest Classifier, Neural Network, LSTM.

1. INTRODUCTION

The advent of internet and communication technologies, particularly online social networks, has transformed the way people engage and communicate electronically. Platforms like Facebook, Twitter, Instagram, and similar ones not only serve as hosts for various forms of content but also enable users to express their emotions and sentiments on various topics and issues. On the one hand, this fosters open and unrestricted contributions and responses on social networking sites. On the other hand, it presents an opportunity for healthcare professionals to gain insights into the mental state of individuals based on their reactions to specific topics.

To gain such insights, machine learning techniques can potentially provide unique capabilities for analyzing hidden communication patterns online. These techniques can process these patterns to uncover the emotional states, including 'happiness,' 'sadness,' 'anger,' 'anxiety,' and 'depression,' among users of social networks. Furthermore, there is a growing body of research that explores the impact of social networks on various aspects of social relationships, such as relationship breakups, mental health issues like 'depression' and 'anxiety,' relapses in smoking and drinking habits, incidents of sexual harassment, and even instances of suicidal ideation. The goal of this project is to implement supervised machine learning techniques in order to detect tweets containing depressive characteristics.

2. LITERATURE SURVEY

In this section, our objective is to provide a comprehensive overview of research related to identifying depression detection on social networks. Choudhury et al. [5] explored an often-overlooked mental health concern affecting a significant portion of the female population. Their focus was on using Twitter posts to create a predictive model that assesses the impact of childbirth on the emotional well-being and behavior of new mothers. They analyzed Twitter posts from 376 mothers, considering dimensions such as emotions, social interactions, linguistic style, and social network activity to detect postpartum changes. In [6], the aim was to investigate whether apprehension levels related to suicide-related tweets could be determined solely from the content of the tweets. This investigation involved both human coders and machine learning classifiers.

In the context of mental health and social media, [7] noted the increasing use of social media as a platform for sharing emotions and daily experiences. They utilized Twitter posts to construct a well-labeled dataset focusing on depression. Six feature groups were extracted, incorporating criteria related to depression from clinical and online social behaviors. These feature groups were then used to develop a multimodal depressive dictionary learning model to identify depressed users on Twitter. Examining the connection between mental wellness and social media, [8] associated anxiety and depression with irregular thought processes, agitation, and insomnia.

They proposed a real-time prediction model for anxious depression, utilizing posting patterns and linguistic cues. The feature vector included sentiment, timing, frequency, contrast, and word usage. Ensemble voting classifiers were employed for prediction. In [9], the authors employed a variety of machine learning algorithms to classify users' emotions (positive and negative) based on Twitter tweets, comparing their performance with deep learning approaches. Their findings indicated that CNN-based deep learning outperformed traditional machine learning models. Twitter posts were also leveraged in [10] to create datasets for depression classification, with classification carried out using Naive Bayes' classifier. Observing the trend of discussing depression and suicidal thoughts on social media, [11] analyzed Twitter profiles, utilizing multiple accounts and tweet-related features to detect suicidal profiles.

They evaluated the effectiveness of their approach using a dataset of individuals who had already committed suicide. In a similar vein, recent research in [12] focused on classifying depression by analyzing text messages from Reddit users. Various baseline features such as TF-IDF, bigrams, and embeddings, as well as more complex features like stylometric and morphological attributes, were considered. Authors in [13] utilized users' prior writings on Reddit to detect early signs of depression. They employed a standard bag-of-words, surface features, and linguistic-related features to build a supervised prediction model for early depression detection. [14] introduced a Feature Attention network comprising various feature networks related to depressive symptoms, sentiments, ruminative thinking, and writing style. Deep learning techniques were applied to identify depressed users. In [15], researchers explored diverse methods for early depression detection, including singleton and dual approaches using machine learning. The singleton approach utilized a random forest classifier with two threshold functions, while the dual approach employed two independent random forest classifiers, one for detecting depressed users and the other for identifying non-depressed individuals. [16] utilized two distinct methods for early symptom detection. The first method considered user-specific time and writing patterns, while the second method incorporated clues from shared text and tweets.

3. METHODOLOGY

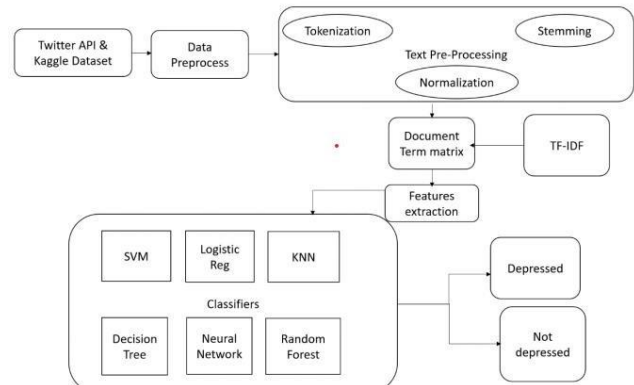
3.1 Datasets

We need two types of datasets one with tweets containing depressive characteristic which is obtained from twitter API and the other one with random tweets. Data mining more than 20K tweets by using Twitter API and Tweepy library. The raw data retrieved from Twitter can be find here. Random tweets have been extracted from the Kaggle datasets. The processed dataset used for training machine learning algorithms.

3.2 Data Preprocessing

Perform data cleaning, exploration, and preprocessing using Natural Language Processing (NLP) libraries such as NLTK or spaCy. Annotate and analyze the data to

create ground truth labels (e.g., depressed or not depressed) for supervised learning.



Methodological approach of depression detection on twitter

3.3 EDA and Feature Selection

Explore the dataset to gain insights into its characteristics and distribution. Use techniques like Count Vectorizer, TF-IDF (Term Frequency-Inverse Document Frequency), and spaCy word embedding models to extract relevant features from the text data.

3.4 Model Selection

Choose a variety of machine learning algorithms for classification, including:

- Logistic Regression
- Support Vector Machine (SVM)
- K-Nearest Neighbors (K-NN)
- Decision Tree Classifier
- Random Forest Classifier
- Neural Network
- Long Short-Term Memory (LSTM)

3.5 Model Training

Implement and train these models using Scikit-Learn, Keras/TensorFlow, or other relevant libraries. Utilize the annotated dataset with ground truth labels for supervised learning.

3.6 Inference

Evaluate model performance using metrics like F1-Score, Confusion Matrix, and ROC-AUC to assess the model's ability to classify depression. Adjust hyperparameters, algorithms, or features based on evaluation results.

3.7 Data Product

Create a Flask-based web application that integrates the deployed model. Implement a user-friendly interface where users can input text, and the application will provide predictions on whether the text suggests signs of depression.

4. CONCLUSION

This research paper addresses a binary classification problem: determining if an individual is experiencing

depression based on their Twitter activity, including tweets and profile interactions. Various machine learning algorithms are utilized, and diverse feature datasets are explored. Several preprocessing steps are carried out, including data preparation, alignment, labeling, and feature extraction and selection. The Support Vector Machine (SVM) model stands out as it achieves the most optimal combinations of accuracy metrics. It effectively transforms an inherently complex nonlinear classification problem into one that is linearly separable. Conversely, the Decision Tree (DT) model, while comprehensive and intuitive, may falter when presented with entirely new data. This study can be viewed as a pivotal step towards the development of a comprehensive social media-based platform for the analysis and prediction of mental and psychological issues, as well as the provision of solutions to affected users. The primary contribution of this study lies in the exploitation of a diverse and discriminative feature set that encompasses both the textual content of tweets and the behavioral patterns of different users. In the future, this research can be extended by incorporating additional machine learning models that are less prone to overfitting and by devising a more robust method for assessing the impact of these features.

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