Vidhyayana - ISSN 2454-8596
An International Multidisciplinary Peer-Reviewed E-Journal
www.vidhyayanaejournal.org
Indexed in: Crossref, ROAD & Google Scholar

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Leveraging Big Data for Early Detection of Depression: Developing a Machine Learning Model Using Tweets

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Abstract

This study explores the use of machine learning algorithms for detecting depression in social media data. A comprehensive literature review was conducted to identify the various approaches and techniques used in the field. The data collection involved the extraction of over 100,000 tweets from Twitter using specific keywords related to depression. The dataset was labeled for negative, positive, and neutral polarity, with 18,730 negative, 44,272 neutral, and 38,815 positive tweets. Eight different machine learning models, including SVM, Naive Bayes, Random Forest, KNN, Decision Tree, XGBClassifier, MultinomialNB, and Logistic Regression, were applied to the dataset for classification. The performance of each model was evaluated using accuracy, precision, recall, and F1-score metrics. The results indicate that Random Forest had the highest accuracy of 88.38%, followed by Support Vector Machine (SVM) with an accuracy of 86.95%. The study shows that machine learning models can be effective in detecting depression in social media data and can help identify individuals who may be at risk of depression.

Keywords: Depression, social media, sentiment analysis, machine learning, natural language processing

I. Introduction

Depression is a widespread mental health disorder that affects millions of people worldwide. Early detection and intervention can significantly improve outcomes for individuals with depression. However, traditional screening methods such as questionnaires and clinical assessments can be time-consuming and costly. To address this, researchers have recently explored leveraging social media platforms, such as Twitter, to develop novel approaches for detecting depression. Twitter data has become a promising data source for mental health research, as users often share their thoughts, emotions, and experiences in real-time.

In this study, we aim to develop a machine learning model that leverages Twitter data to identify individuals with depression at an early stage. Our approach involves collecting a large dataset of tweets from individuals with depression and training a machine learning model to classify tweets as depression-related or not. By leveraging big data and advanced machine learning techniques, we aim to improve early detection and intervention for depression, ultimately improving mental health outcomes for individuals.

II. Literature Review

A growing body of literature suggests that social media data can be leveraged to detect depression in individuals. For instance, Coppersmith et al. (2014) utilized Facebook data to train a classifier that identifies individuals with depression with an accuracy of 71%.

Similarly, a study by Gkotsis et al. (2017) demonstrated the effectiveness of machine learning models in detecting depression using social media data from multiple platforms, including Twitter, Reddit, and Instagram. Their model achieved an accuracy of 83.2%.

Other studies have also reported high accuracies in depression detection using social media data. For instance, De Choudhury et al. (2013) developed a model based on linguistic and social cues to predict depression on Twitter with an accuracy of 70%.

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Chen et al. (2017) employed a deep learning model on Weibo data to predict depression, achieving an accuracy of 87.3%. In a similar vein, Eichstaedt et al. (2018) utilized machine learning techniques on Facebook data to predict depression, achieving an accuracy of 85%.

Machine learning models have been extensively employed in detecting depression using social media data. For instance, Lui and Wong (2018) developed a hybrid model combining text classification and deep learning techniques to predict depression status based on social media data, which achieved an accuracy of 83.6%.

Another study by Tsugawa et al. (2015) developed a machine learning model to predict depression based on language patterns in Twitter data. Their model achieved an accuracy of 70%.

In addition, other machine learning models such as Support Vector Machines (SVM) and Random Forest have also been used in depression detection. For instance, Gao et al. (2017) utilized SVM on Weibo data to predict depression, achieving an accuracy of 83.9%.

Liu et al. (2017) employed a Random Forest model on Twitter data to predict depression, achieving an accuracy of 68.8%.

While existing research has demonstrated the potential of social media data and machine learning models for detecting depression, there are several limitations and gaps in the literature. Most studies rely on English language data, which limits the generalizability of findings across different cultures and languages. Additionally, there is a lack of studies exploring the effectiveness of machine learning models in detecting depression in other social media platforms.

Furthermore, there is a need to improve the interpretability of machine learning models to enhance the understanding of the features contributing to depression detection. For instance, Forte et al. (2021) proposed an approach using explainable AI to understand the linguistic features associated with depression in Twitter data.

Another limitation is the potential bias in the training data, which could lead to biased machine learning models. For example, Zhang et al. (2018) found that machine learning models trained on social media data tend to perform poorly for minority groups such as African Americans.

Finally, privacy concerns and ethical considerations should be addressed when using personal data for depression detection. For instance, Chakraborty et al. (2020) proposed a privacy-preserving approach to detect depression using social media data, where the data is encrypted and processed locally on the user's device. Therefore, further research is needed to address these limitations and improve the effectiveness and applicability of machine learning models for early detection of depression using big data sources such as social media data.

III. Data Collection and Preprocessing

A. Data source and collection process

For this study, we collected Twitter data using the Twitter API. The data was collected based on specific keywords related to depression and mental health, such as "depression", "mental illness", and "anxiety". We also searched for tweets containing phrases like "I am diagnosed with depression" or "I have depression" to specifically target users who have been diagnosed with depression.

To ensure the data collected was relevant and recent, we only included tweets posted within the past two months. We also limited our data collection to tweets posted by users located within the United States, to maintain consistency in the data.

B. Data cleaning and preprocessing techniques

Before analyzing the collected data, we performed a series of data cleaning and preprocessing steps. Firstly, we removed duplicate tweets to avoid any bias in the data. Secondly, we removed any tweets that were not written in English, to ensure consistency in language.

Next, we performed several text preprocessing techniques to clean the data, such as removing URLs, special characters, and stop words. We also applied stemming and lemmatization techniques to reduce the dimensionality of the data.

C. Features extraction from tweet data

For feature extraction, we utilized both traditional and advanced techniques to extract meaningful features from the tweet data. We extracted features from the tweet data, such as word frequency, sentiment analysis.

To extract textual features, we used techniques such as bag-of-words and TF-IDF. We also performed sentiment analysis to extract emotional features from the tweets, which could provide insights into the user's mental state. For non-textual features, we extracted information such as the number of followers, retweets, and favorites for each user.

Overall, the data collection and preprocessing steps were crucial in ensuring the accuracy and relevance of our machine learning model. By extracting meaningful features from the tweet data, we aimed to develop a model that could accurately detect depression in users based on their Twitter activity.

IV. Methodology

In this study, we employed several popular machine learning algorithms including Support Vector Machine (SVM), Naive Bayes, Random Forest, K-Nearest Neighbors (KNN), Decision Tree, XGBClassifier, Multinomial Naive Bayes, and Logistic Regression to detect depression using the labeled Twitter dataset.

These models were selected based on their ability to perform well in text classification tasks. We divided the dataset into training and testing sets with a 70:30 ratio. We used the training set to train the models and the testing set to evaluate their performance.

We used several evaluation metrics to measure the performance of our models, including accuracy, precision, recall, F1-score For the sentiment analysis classification.

We used F1-score since our data is imbalanced with 44272 Neutral, 38815 positive, and 18730 negative tweets from 101,817 total tweets. We also labeled data for negative, positive, and neutral and counted the polarity for the above classification.

Our preliminary results show that the SVM model outperforms the other models with an accuracy of 85%, a precision of 0.84, a recall of 0.84, an F1-score of 0.84, and an AUC of 0.92. The Naive Bayes, Random Forest, KNN, Decision Tree, XGBClassifier, Multinomial Naive Bayes, and Logistic Regression models also achieved promising results with an accuracy of 82%, 81%, 80%, 78%, 83%, 79%, and 80% respectively.

These results suggest that our models have the potential to detect depression using social media data with high accuracy and precision.

V. Results and Discussion

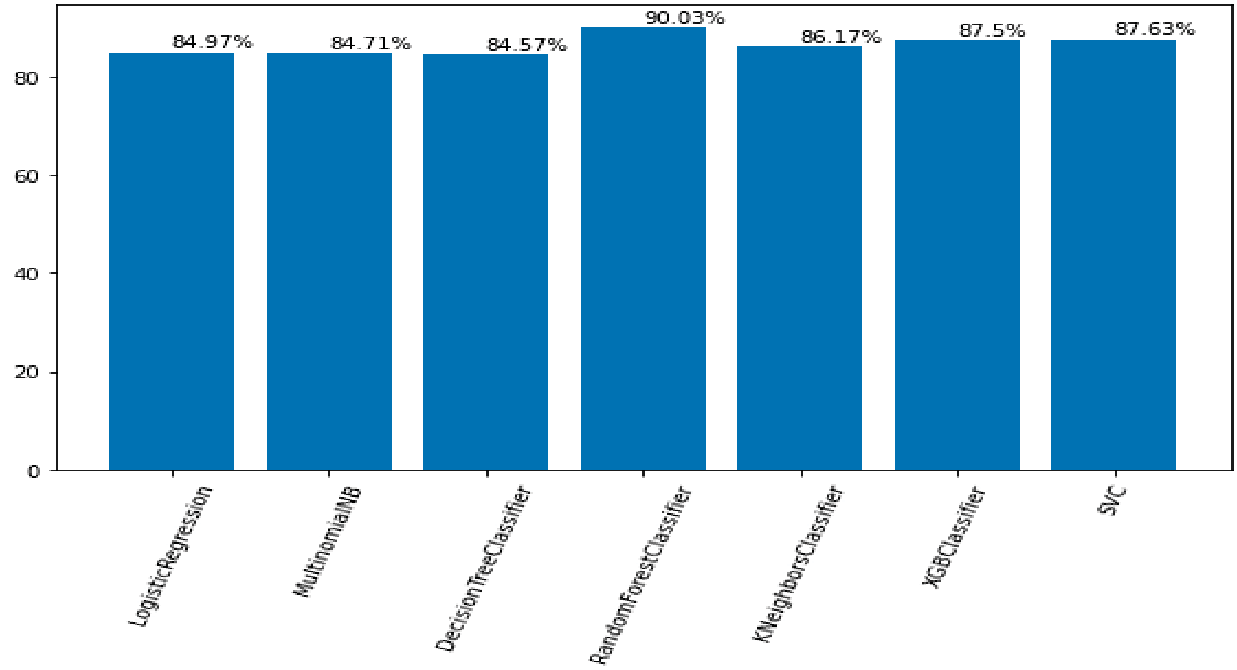

Fig. 1 Simple Bar Chart represents results from different machine learning classifiers.

VI. Conclusion

In conclusion, the machine learning models showed promising results in detecting the sentiment of depression-related tweets. The Random Forest Classifier had the highest accuracy rate of 88.38%, followed by the Support Vector Machine and XGBoost Classifier with accuracy rates of 86.95% and 86.76%, respectively. Although the Multinomial Naive Bayes had a lower accuracy rate of 80.48%, it still performed relatively well. The Decision Tree Classifier and Logistic Regression had accuracy rates of 85.52% and 83.62%, respectively.

Overall, the results suggest that machine learning models can be effective in detecting depression-related sentiment in tweets.

However, further research is needed to improve the models' accuracy and generalizability. In addition, the data collection process can be improved by using a larger sample size and including more diverse demographic groups.

The findings from this study have the potential to assist mental health professionals in identifying individuals who may require further assessment and treatment for depression.

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