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Depression Predicting Model For Social Media User's Emotions Using Deep Learning Methods

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Abstract

There is a growing interest in leveraging social media platforms for the early identification of depression among the youth due to a rising occurrence. The study investigates the feasibility of utilizing Twitter data specifically emojis are included along with text content to predict degrees of depression among its users. The study examined Twitter data and used machine learning and deep learning to predict depression. Previous research on emotion detection mainly focused on text alone, but the contemporary landscape of communication integrates both text and emojis. The significant rise in usage of emojis in underlines their crucial role in emotional expression, necessitating their inclusion in analytical processes. The study shown the impact of combining text with emojis to determine the polarity of expressed sentiments. The study employed Convolutional Neural Networks (CNN) for sentiment analysis, with promising findings in reliably recognizing negative feelings and the potential for high performance to sentiment categorization. The study created a model capable of not only recognizing depression levels within a dataset but also identifying people who have higher-than-average levels of depression. This model acts as an early warning sign for mental health support, enabling mental health practitioners and social media platforms to offer timely assistance and interventions.

Keywords: Depression, Sentiment Analysis, Deep Learning, Machine Learning, NLP

I. Introduction

It's crucial to recognize that depression is associated with an elevated risk of suicide. Consequently, pinpointing the underlying causes of depression is of paramount importance. The inspiration for embarking on this research is closely tied to the widespread adoption of online communication through smartphones and electronic

devices. Social media has occurred as a vital means of interaction for young people. However, it's worth noting that platforms like Twitter and SMS pose constraints due to character limits, often necessitating the use of emojis to convey sentiments.
This transition to visual expression provides individuals with a unique avenue to articulate their thoughts and emotions on social networking sites. It not only facilitates the sharing of one's perspectives but also fosters an environment for self-reflection and the effective expression of personal frustrations through digital tools. In this study, the primary focus will be on examining comments and shares across social media platforms to identify negative comments. This aims to assist in determining whether an individual may be dealing with depression. Also, previous work is only on English sentences. Inclusion of emojis can influence the sentiment analysis outcomes, potentially leading to positive sentiments being identified when positive emojis are present and negative sentiments associated with negative emojis.
This research will focus to work on emojis to classify positive and negative posts as younger generations write comments by use of emojis to express themselves. Early prediction of the depression level of users can decrease the death rate.
The inspiration for doing this research comes from the widespread adoption of specialized online techniques facilitated by electronic devices and mobile phones. Social media has developed as a prevalent communication channel, especially among the younger generation. However, platforms like Twitter and SMS are restricted by word limitations when it comes to expressing viewpoints, leading to the prevalent use of emoticons and emojis as alternatives for textual expression.
The study included social media Twitter; containing English phrases and expressions. The focus on examining comments and shares on social media, specifically to identify negative comments, is a response to the need for early forecasting of depression. The choice to explore the use of emojis, rather than solely relying on English sentences, acknowledges the evolving nature of communication, especially among younger generations. This is essential, as early prediction of depression levels has the potential to contribute to reducing the overall death rate associated with mental health challenges. While the research itself is not explicitly linked to any specific case like that of Sushant Singh Rajput, it aligns with a broader trend of increasing awareness about mental health issues, especially in the context of high-profile cases that have garnered public attention. The goal is to leverage technological advancements and evolving communication patterns to understand mental health indicators and contribute to early intervention and support.
The research is driven by a global understanding of the incidence of depression, the need for early forecasting, and the changing dynamics of online communication, particularly the use of emojis. While it may not be directly linked to any specific individual's case, it aligns with the broader societal shift towards recognizing and addressing mental health challenges.

II. Related Work

Previous research on emotion detection mainly focused on text alone, but the contemporary landscape of communication integrates both text and emojis. The significant rise in the use of emojis in modern conversations underlines their crucial role in emotional expression, necessitating their inclusion in analytical processes. The study endeavors to unveil the impact of combining text with emojis to determine the polarity of expressed sentiments.
Recent research has shown that social media text can be analyzed to predict depression in users. Machine learning models, such as Support Vector Machines (SVM), Logistic Regression, Naïve Bayes, Regression and deep learning have been found to be effective in predicting depression in social media users with practical implementation in real-world scenarios [1]. While SVM and Logistic Regression have both been used, Logistic Regression has been found to be more efficient in terms of execution time [1]. To make sense of the sentences, models need to adapt to slang used in social media posts [1]. Text mining techniques and data mining algorithms, such as term-based mining (TBM) and phrase-based mining (PBM), can be utilized to detect the rate of depression found in posts made by individuals on social media [1]. Using single words to identify depression would not work as the same word could mean different things depending on how it is used and crucial clues regarding the context in which a word is used would be overlooked if a single word were to be identified as a trigger for depression [1]. In fact, community-generated social media content contains information indicative of a social media user's depression, and a model trained on the combination of user-generated and community-generated social media data outperforms models using either data source alone [2]. Data pre-processing techniques such as data cleaning, tokenization, stop words removal, stemming, lemmatization, bigram creation, sentiment classification, duplicate removal, and URL and number removal can improve tweet content for depression prediction, and machine learning classifiers such as XGB Classifier,

Random Forest, Logistic Regression, and support vector machine can be used to build depression sentiment models [3][1]. This automatic analysis of texts can be used to create predictive models that can detect individuals at risk of a mental disorder and provide them with help as early as possible, which can provide new insights into the next generation of population-level mental illness risk assessment and intervention delivery [2][3][2]. Emojis and emoticons are increasingly being recognized as having sentimental value and are used in sentiment analysis of social media reviews [3]. They can help in the study of various sentiments, including depression [3]. Emoticons carry more weight than ordinary words as they have a greater impact on tweets [3]. WeChat emoticons have proven useful in sentiment classification for perinatal depression analysis [3]. However, the use of emojis and emoticons can pose challenges as they contain unique symbols that cannot be pre-processed using NLP tools [3].

Despite this, negative Twitter emoticons, also known as emotion icons, were found to be significantly associated with the occurrence of depression symptoms in a study analyzing sentiments from Twitter [4]. In a related study, emojis played a role in the prediction of depression through social media as they were used as features to identify depression [4]. Barhan and Shakhomirov used emoticons and sentiments based on N-gram to classify feelings from Twitter data, achieving 81% accuracy and 74% recall in depression detection [4]. Emoticons were also used in Hutto and Gilbert's sentiment analysis algorithms for analyzing social network messages [4]. Vateekul and Koomsubha used a deep learning technique to classify sentiments of Thai Twitter data, achieving higher accuracy than traditional techniques including Naïve Bayes and Support Vector Machine [4]. However, Note that existing research focused on using emoticons as majorly analytical features of Twitter users, but it is not the only information used for depression detection [4].

The use of social media data for predicting mental health conditions has gained significant attention in recent years. However, deploying such methods to predict mental health conditions using social media data raises ethical concerns. The study mentioned in the previous paragraph does not discuss any ethical considerations related to the use of social media data for predicting mental health conditions [5]. literature review explored different approaches, various text categorization approaches, such as perceptron learning and SVM, have been utilized in sentiment analysis tasks. Feature selection methods are critical in text classification systems because they ensure the selection of relevant features.

The research references included providing a broad overview of the advancements in artificial intelligence, from feature selection methods to sentiment analysis and opinion mining techniques. Also observed the importance of understanding various factors like cultural nuances and language variations in sentiment analysis. Several tools like open-source tools like NLTK (Natural Language Toolkit), TextBlob had developed. Each tool offers different functionalities and can be more or less suited to a particular task or data type [5, 6, 7]. Pre-trained models that can handle a variety of NLP tasks, including sentiment analysis. These tools are typically more robust and scalable, but they also require payment and may not provide the flexibility required for specific or complex tasks.

III. Problem Statement

Create a prediction model that will forecast depression based on their past emotional expressions in form of emojis and text on social media. This involves analyzing user-generated content to classify their emotional states and make predictions regarding their mental well-being. This provides a chance to examine personal and social online information for clients' emotions and feelings. It is possible to analyze their dispositions and perspectives when they use these internet tools to express themselves.

Objectives:

- To Design a model by using different techniques of deep learning which identify depression
- To identify the most depressed people from prediction.
- To reduce the time to detect depression from emojis.
- To minimize suicidal rate by early prediction of depression.

IV. Methodology

To create a prediction model, applied machine learning and deep learning techniques, specifically the Naïve Bayes, Decision Tree, Random Forest Algorithms, RNN, and CNN. Using these algorithms, the model was trained to produce precise predictions based on the supplied data. Python code, sentiment analysis tools, and machine learning and deep learning models, especially CNNs, were utilized to understand the relationship between textual content, emojis, and sentiment expression.

a. Data Collection:

The dataset comprises sentiments expressed on Twitter, with labels indicating the sentiment classes (positive, negative, neutral). Primary data was collected directly from the microblogging site Twitter. This data-gathering process was performed utilizing the Twitter API and the web scraping tool, Octoparse version 8.6.2. The Twitter API allows for the extraction of a variety of data points associated with a tweet, including its **content, the timestamp of when it was posted, the date of the tweet, the user profile that posted the tweet, and the URL of** the tweet. A total of 11216 tweets were collected.

In sentiment analysis on social media data, it's essential to recognize that emotions are often conveyed not only through textual content but also via emojis. Textual data, as seen in the sentence "This is a great day, and I am happy," provides valuable context, but the inclusion of emojis, such as enhances the accuracy and depth of sentiment analysis. Emojis are expressive visual elements that can convey nuanced emotions that text alone may not capture adequately.

For instance, the sentence "I love this place!" with 😁 😔 a positive emoji clearly signifies a positive sentiment, while "The weather is terrible today" with a negative emoji conveys a negative sentiment. Emojis, therefore, play a crucial role in understanding the emotional landscape of social media content, and their consideration can significantly improve the effectiveness of sentiment analysis techniques. When faced with the choice of selecting a dataset, there were two file formats available: JSON and CSV, both containing data sourced from social media platforms. During the comparison of these datasets, several factors were considered. The data was found to be intricate, filled with noise, and included a plethora of emojis. JSON emerged as a preferred format due to its ability to handle complex data structures. It excels in managing data hierarchies and nested elements, making it highly adaptable to a wide array of data formats. Furthermore, JSON proved to be an ideal choice for storing metadata alongside text and emojis. This feature allowed for the inclusion of supplementary information like user profiles, timestamps, or associated data.

The flexibility of the JSON structure became particularly advantageous when dealing with text data that exhibited complications, such as varying formatting, unusual characters, or non-standard encodings. JSON's versatility and robustness in managing both intricate data structures and textual intricacies made it the optimal choice for this dataset with its noisy and emoji-rich content.

b. Data Preprocessing:

The raw data is usually not suitable for direct input into a model and needs to be pre-processed. This involves tasks such as data cleaning, handling missing data, normalization, and dealing with outliers. In this case, converted emojis into textual descriptions using the emoji library in Python to retain their sentiment information. Additionally, the text was cleaned to remove URLs, non-alphanumeric characters, and stop words (commonly used words like 'is', 'the', which are usually filtered out as they do not provide valuable information for the analysis).

Cleaning and preprocessing data 1is a pivotal step in the domain of natural language processing, especially in the context of sentiment analysis. The task involves transforming raw, unstructured data into a refined, well-organized dataset, essential for training robust machine learning models. This process of refining raw data significantly impacts the accuracy, reliability, and overall efficiency of the subsequent analysis or modeling. Texts and labels were extracted from the datasets. Labels were converted into NumPy arrays. Texts were vectorized using the CountVectorizer from the sklearn library.

The subsequent step involves text standardization through lowercasing and tokenization. Lowercasing all text ensures uniformity in the dataset, avoiding multiple forms of the same word from being treated differently. Tokenization breaks down the text into meaningful units or tokens, facilitating better processing and analysis. Another crucial step is the removal of stop words—common words like 'the', 'is', or 'and' that do not carry significant meaning for sentiment analysis. By discarding these words, the dataset becomes more efficient, reducing noise and improving the effectiveness of sentiment analysis. Normalization and lemmatization are then applied, aiming to reduce words to their base form and standardize text. This helps in making different forms of the same word identical, such as 'running', 'ran', and 'runs' being reduced to 'run', promoting consistency in the dataset.The final and essential step is labeling sentiments. This step involves assigning sentiment labels (positive, negative) to each tweet based on their content. Whether through human annotation or automated methods, this labeling is critical for training sentiment analysis models.

c. Feature Extraction:

Feature extraction is an important step in machine learning and text analysis because it helps turn raw data into a type that can be understood by machine learning models. Let's review some of the main ideas used for text

and measure emoji:
Bag of Words (BoW): This is a simple system where we represent text from many frequencies of each word, regardless of the order in which they occur. This can be done at the language level or at the character or n-gram level.
TF-IDF (Time Frequency - Inverse Document Frequency): This is an improvement on the BoW standard. It determines not only the frequency (time frequency) of the word from a document, but also the importance of that word in the entire corpus (reverse document frequency). This will help cut down on words that are often used but have minor meanings such as "yes", "and".
Word Embeddings (Word2Vec, GloVe, FastText): Word embeddings are dense vectors that capture multiple words to represent semantic information based on the context in which words appear. Similar expressions include vectors closely to each in the vector space. These are the more common methods and have been found to provide good results for many paper review projects.

d. Statistical Analysis:
The dataset was divided into two primary groups based on the polarity of the tweets. Tweets with a polarity greater than 0 were classified as positive, while those with a polarity less than 0 were categorized as negative. The sentiment scores were then isolated for each group to facilitate a comparative analysis. To ascertain whether there exists a statistically significant difference in sentiment scores between positive and negative tweets, an independent samples t-test was employed. This test is particularly suitable for comparing the means of two independent groups. The t-test produced a T-statistic of 177.81 with a corresponding p-value of 0.0, indicating a highly significant difference in sentiment scores between positive and negative tweets. This statistical evidence supports the hypothesis that there is a substantial divergence in the emotional tone expressed within these two categories of tweets. The number of data points (tweets or observations) used for each sentiment group analysis.
In the Positive group, there are 5483 samples, and in the Negative group, there are 2140 samples. The sample size provides context for the reliability of the mean and standard deviation values – larger sample sizes generally result in more reliable estimates.

Table 1: Comparison of Sentiment Scores

Group	Mean Score	Median Score	Standard Deviation	Sample Size
Positive	0.594455	0.6114	0.236873	5483
Negative	-0.482186	-0.4767	0.237821	2140

The Chi-Square Test produced a Chi-Square value and a p-value. The Chi-Square value quantifies the extent of deviation for sentiment and time of day. The p-value indicates the probability of observing such an association by random chance.
Finally, it interprets the results by comparing the p-value to a predefined significance level (alpha), typically set at 0.05. It suggests significant association between sentiment and time of day. Conversely, if it is greater than or equal to alpha, it implies no significant association. The interpretation is printed as an output message, summarizing whether a statistically significant relationship exists between sentiment and the time of day in the analyzed dataset. Resulting in a Chi-Square Value of 24.702 and a p-value of 0.0003876. These results indicate a significant association between sentiment and time of day. The low p-value suggests that the observed distribution of sentiments across different times of the day is unlikely to have occurred by chance alone. Therefore, it indicated that there is a relationship between sentiment and the time of day in the dataset.

e. Model Training and Evaluation:
Various machine learning models were employed, including Naïve Bayes, Decision Tree, Random Forest, the training,
CNN demonstrated superior precision, recall, and F1-Score values across all datasets, making it the preferred choice among the models evaluated. Therefore, CNN stands as the most effective model in terms of accuracy and overall performance, making it well-suited for the classification task at hand. Convolutional neural networks (CNNs), which are extensively employed in the processing of images and videos, are constructed using convolutional layers. These layers apply a set of learnable filters (also known as kernels) to input data, typically images.
The filters slide or convolve across the input, performing element-wise multiplication and summing up the results to produce feature maps. This technique captures various features such as edges, textures, and patterns in the input data. Given an input image or feature map I and a filter/kernel K, the convolution operation

produces a feature map C:

$$C[i][j] = \sum_m \sum_n I[i+m][j+n]*K[m][n] \quad \ldots (1)$$

Convolution Formula:
C[i][j] is the value at position (i, j) in the output feature map.
I[i+m][j+n] are the input values at position (i+m, j+n).
K[m][n] are the filter values.
Evaluation process involved data splitting, model training, accuracy evaluation, label prediction, confusion matrix generation, and classification report generation.

V. Results and Discussion:

Research Findings recorded performance metrics, including accuracy, precision, recall, and for each model across the three datasets. Table 2 shows the performance metrics of various machine learning models, including Naïve Bayes, Decision Tree, Random Forest, RNN (Recurrent Neural Network), and CNN (Convolutional Neural Network), across different datasets:

Table 2: Comparison chart between all methods used in study

Method	Dataset	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	Primary Data	0.520	0.52	0.48	0.47
Decision tree	Primary Data	0.80	0.77	0.78	0.77
Random Forest	Primary Data	0.81	0.80	0.77	0.78
RNN	Primary Data	0.93	0.81	0.74	0.77
CNN	Primary Data	0.96	0.91	0.81	0.85

In the research findings, model's highest accuracy of 0.96 on Primary Data is noted. As well as its effectiveness in handling diverse and complex datasets is measured. CNN demonstrated superior precision, recall, and F1-Score values across all datasets, making it the preferred choice among the models evaluated.
Therefore, CNN stands as most effective model in terms of accuracy and overall performance, making it well-suited for the classification task at hand. Its ability to capture intricate patterns and relationships within the data, especially evident in Primary Data, positions it as the best-performing model among those considered in this analysis.

The CNN model, initially designed for image processing tasks, demonstrated remarkable potential in sentiment analysis. It exhibited high accuracy and excelled in precision, recall, and F1 score for sentiment classification. This versatile nature of CNN implies its adaptability across various data domains, including text-based sentiment analysis. The research findings indicate that the selected models, namely the Naive Bayes classifier, Decision Tree classifier, RNN, and CNN, hold potential for effective sentiment analysis and prediction tasks. While traditional machine learning methods presented certain limitations, the deep learning models demonstrated superior performance, particularly the RNN and CNN models.

The model predicted depression levels for each person in the dataset and identifies the person with the highest average depression level. This can provide additional perceptions into emotion analysis results and help identify individuals who might require support or further attention. Model further filters the DataFrame to select text with a predicted depression level equal to or greater than a specified threshold. The selected text is printed, providing examples of more negative text based on the predictions.

Table 3. Count of Depressed and Non-Depressed Texts

Depressed Texts	986
Non-Depressed Texts	10231

This comprehensive analysis not only quantifies the prevalence of depressed and non-depressed texts but also unearths a poignant text encapsulating the depths of negative sentiment within the dataset. The results serve as a testament to the efficacy of sentiment analysis in deciphering emotional nuances within textual data. The combination of quantitative and qualitative analyses provided by these functions serves as a valuable tool for understanding and interpreting emotional trends within text datasets, particularly in the context of depression analysis.

VI. Conclusion

Emojis emerged as a crucial dimension, influencing sentiment interpretation and adding complexity to the prediction task. This model acts as an early warning sign for mental health support, enabling mental health practitioners and social media platforms to offer timely assistance and interventions. CNN demonstrated remarkable adaptability to sentiment analysis tasks, positioning it as the preferred choice among the models. Deep learning technique such as CNN was found to enhance precision in sentiment prediction, especially in the context of identifying depression on social media. Room for improvement highlighted, particularly in addressing misclassifications and refining model classification abilities, as seen in the Random Forest classifier's performance.

VII. Limitations of Research Work

- Identifying stress solely based on social media content has its limitations. Not all individuals openly express their feelings of stress in their public posts. Sometimes, stress can be inferred from the way users interact with others and how their friends respond to their posts. Depending solely on a user's content of social platforms may not provide a complete and accurate picture of their stress levels. Moreover, individuals experiencing significant psychological pressure might be less active on online platforms, leading to lower performance in emotion classification.
- The wrong use of few emojis can change the intended meaning, demonstrating how even minor images can have a big impact on how a message is received. A single phrase, too, can convey diverse meanings depending on how it is written, ranging from expressing positivity and excellence to conveying negativity.

VIII. Future Scope

The ongoing research on predicting depression through text data that includes emojis suggests an opportunity for enhancement by incorporating diverse multimedia elements such as images and videos. By expanding the features beyond textual content, researchers can capture a more comprehensive understanding of users' expressions and emotions, potentially leading to more accurate depression predictions. This method provides a deeper framework for analysis by acknowledging that people can express their sentiments not just through words but also via visual and audio cues. Moreover, broadening the scope of the research to encompass various social media platforms, such as Instagram, Facebook, YouTube, and Reddit, can contribute to a more holistic perspective of users' online behaviors.

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