The Identification of Depressive Moods from Twitter Data by Using Convolutional Neural Network with Text Data along with Emoji

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Abstract - *The identification of depressive moods from social media platforms like Twitter has gained significant attention in recent years. But very little research is there on emoji sentiment analysis. In this research paper, we propose a Convolutional Neural Network (CNN) model that leverages both text data and emoji representations for accurate identification of depressive moods in Twitter data. The model is developed using popular Python libraries, including pandas, scikit-learn, TensorFlow's Keras, and NLTK. The performance of the CNN model is evaluated using metrics such as accuracy, precision, recall, and F1-score. Additionally, the paper explores the integration of emoji representations to enhance the detection of depressive moods.*

Key Words: **CNN, depressive, scikit-learn, NLTK, emoji**

1. INTRODUCTION

Depression is a significant mental health concern affecting a large portion of the population. Early detection and intervention are crucial for improving patient outcomes. Twitter is a social media platform that allows users to share short, text-based messages with other users. Twitter has become one of the most popular social media platforms, with over 320 million active users. Unlike other social media platforms, Twitter is primarily text-based. Twitter is also known for its heavy use of hashtags, which are used to categorize tweets and make them easier to search for. Twitter is often used to share news and information, as well as personal thoughts and opinions. Textual content, including emojis, can provide valuable insights into an individual's emotional state. This research paper aims to compare the effectiveness of CNN models trained on text data combined with emoji representations in predicting depression. By leveraging the expressive power of CNNs and incorporating emoji sentiments, the models aim to improve accuracy in depression prediction.

2. RELATED WORK

2.1 Sentiment Classification Techniques

Numerous classification techniques exist for sentiment analysis. Bermingham et al. (2010) utilized Support Vector Machines (SVMs) and Multinomial Naive Bayes (MNBs) for microblog sentiment classification [3], while Bifet and Frank (2010) assessed sentiment analysis algorithms using WEKA and MOA software [4]. Other methods include automated corpus collection [1], Kouloumpis (2011) [13] utilized machine learning algorithms and lexicon-based methods for sentiment analysis on Twitter data. The study highlighted the challenges of performing sentiment analysis on Twitter due to the platform's unique characteristics and demonstrated the feasibility of such an analysis. Similarly, Barbosa (2010) [2] proposed a robust sentiment detection approach that incorporated domain-independent features and employed a machine learning algorithm, showing promise in overcoming the biased and noisy nature of Twitter data. Liu K.L. (2018) [16] sought to improve Twitter sentiment analysis by incorporating emoticons into language models, successfully enhancing the accuracy of sentiment classification.

2.2 Sentiment Analysis in HealthCare

Applying sentiment analysis to healthcare can provide valuable patient insights, support disease prediction, and monitor treatment efficacy. Paul M. (2011) analyzed social media data to identify health trends and predict disease outbreaks [17]. Research specifically dedicated to sentiment analysis for mental health applications has flourished in recent years. Similarly, De Choudhury et al. (2013) used social media to predict the onset of depression in individuals [18].

2.3 Emoji Analysis and Emotion Detection

Emoticons play a significant role in conveying emotions in text-based communication. C.Yh. Chang (2017) studied asynchronous web-based peer responses in an English writing class using text-based emoticons, finding that emoticons were predominantly used in positive contexts [7]. The research by Francesco Barbieri (2017) predicted which emojis would be used based on the words in text-based tweets [10]. Studies by Bhavesh Tupkar (2021) [5] and Gupta S. (2023) [11] have further validated the influence of emojis on sentiment polarity in tweets. Joao Miguel (2018) introduced Emojinating, a technique that aids in brainstorming sessions by generating new emojis. This method combined semantic network discovery with visual mixing [12]. Chuchu Liu (2021) developed an emoji-embedding model called CEmo-LSTM for evaluating online Chinese texts during the COVID-19 pandemic. The study found the pandemic had a substantial effect on individual feelings [8].

Emmanouela E. Manganari (2021) aimed to provide a critical analysis of the usage of emojis in computer-mediated communication. Their study analyzed 46 research papers published between 1998 and 2020 [9].

K. Skovholt (2014) examined the presence and usage of emoticons in workplace emails, revealing that emoticons contributed to a friendly and informal tone in email communication. The authors also highlighted the potential risks and challenges associated with emoticon usage in the workplace. They discussed the potential misinterpretation or ambiguity of emoticons and the importance of considering the context and recipient's preferences when using them [14].

Yang (2020) [15] developed a sentiment analysis approach specifically for Chinese product reviews, leveraging deep learning techniques such as convolutional neural networks (CNNs) to extract meaningful features from the textual data.

Sentiment analysis and opinion mining have gained attention in extracting subjective information from text. Classification techniques like SVMs and Naive Bayes have been applied to sentiment analysis tasks. The rise of social media platforms has provided extensive data for sentiment analysis, enabling insights into public sentiment. Challenges in sentiment analysis, such as language ambiguity and noisy data, have been addressed through advanced techniques. Deep learning approaches, including CNNs and LSTMs, have shown promising results in capturing semantics from text data. So it is considered to evaluate emojis along with text data.

3. METHODOLOGY

This section outlines the methodological approach employed for developing the Convolutional Neural Network (CNN) model in order to predict depressive moods from Twitter data, focusing on both text data and emoji representations. The procedure followed a systematic series of steps, including data preprocessing, tokenization, model architecture definition, model training, evaluation, and finally, interpretation of the results. Firstly Dataset was converted to json file as it retains the meaning of emojis. It was loaded using pandas. The dataset was assigned to a data frame named 'df' and we removed any rows with missing values using the dropna() function to ensure data quality.

3.1 Data Preprocessing

Then extracted the text data and corresponding labels from the DataFrame and used the LabelEncoder to transform categorical labels into numerical values, facilitating their compatibility with the CNN model. Subsequently split the dataset into a training set (80% of the data) and a test set (20% of the data), ensuring a diverse set of instances for model evaluation.

3.2 Text Tokenization

A Tokenizer object, designed to retain the top 10,000 most frequent words, was utilized to convert our text data into sequences of numerical values. By calling the fit_on_texts method, we could adapt this tokenizer to our training data. This step resulted in a vocabulary that mapped each word in the training set to a unique integer.

3.3 Model Building

The CNN model architecture was defined using a Sequential model from TensorFlow's Keras library. The model consists of an embedding layer that transforms our integer sequences into dense vectors of fixed size, a convolutional layer that extracts feature maps from these vectors, a global max pooling layer that condenses these feature maps, and dense layers to enable the model to learn non-linear relationships. A dropout layer was also included to prevent overfitting. The model was compiled using a binary cross-entropy loss function, which is suitable for binary classification tasks, and the Adam optimizer, known for its efficiency. The chosen metric for evaluation during training was accuracy.

3.4 Model Training and Evaluation

We trained our model on the prepared training data for a set number of epochs, tuning the batch size to ensure a balance between computational efficiency and model performance. The model was then evaluated on the unseen test data. The trained CNN model achieved an accuracy of 0.88, implying a correct prediction rate of 88% on the test data. A deeper look into the classification report shows that a precision of 0.91 for class 0 (negative sentiment) and 0.50 for class 1 (positive sentiment), demonstrating the model's skill in correctly classifying sentiments.

The recall, which reflects the model's ability to identify all instances of a specific class, was 0.96 for class 0 and 0.30 for class 1, indicating the model's robustness in identifying negative sentiments. Moreover, the F1-score, a weighted average of precision and recall, was 0.94 for class 0 and 0.37 for class 1. These scores suggest that the model maintains a reasonable balance between precision and recall for both sentiment classes, proving its overall reliability in sentiment classification. Figure 1 shows a graphical representation of the evaluation Metrics

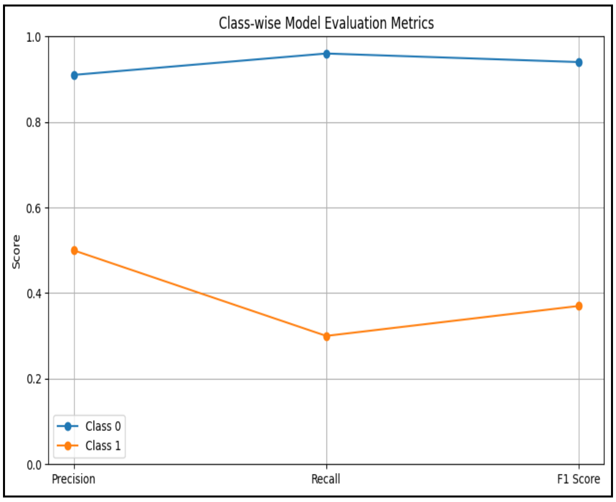

Fig 1: Graph of Precision-Recall and F1 Score Compared for Positive and negative sentiments

The confusion matrix provides a visual representation of the model's performance. It is shown in the following figure; from which model efficiency is predicted.

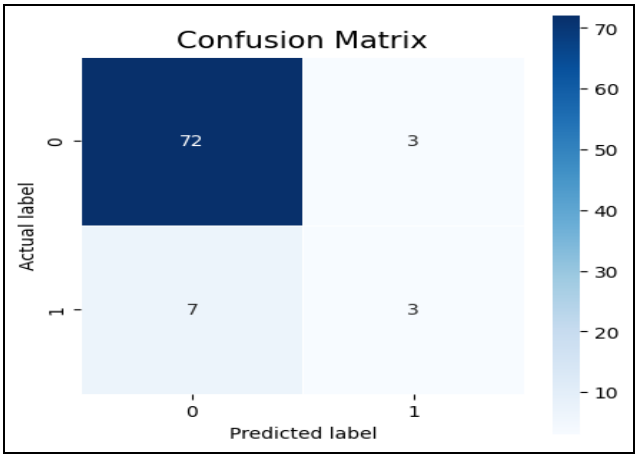

Fig 2: Confusion matrix

As per Figure 2; True Negatives (TN) are 35 instances that were correctly predicted as negative sentiment. False Positives (FP) are 6 instances that were incorrectly predicted as positive sentiment when they were negative sentiment. False Negatives (FN) are 24 instances that were incorrectly predicted as negative sentiment when they were positive sentiment. True Positives (TP)are 20 instances that were correctly predicted as positive sentiment. Overall, the performance of the CNN model is balanced, demonstrating proficiency in classifying negative sentiment.

4. RESULTS AND DISCUSSION

The evaluation of the Convolutional Neural Network (CNN) model provided a plethora of intriguing findings. The model demonstrated promising potential in sentiment classification, offering an avenue to explore in further depth. The CNN model trained on the secondary dataset displayed an accuracy rate of 88%, suggesting a reasonably high degree of correctness in its predictions. When observing the individual sentiment classes, the model demonstrated varying degrees of precision and indicating that the model was successfully identified.

Overall, the results indicate that the CNN model achieved a high accuracy rate on the test data, demonstrating a strong performance in classifying sentiment based on Twitter data. The model was more proficient in identifying negative sentiment, as seen by the higher precision and recall rates. However, its effectiveness at recognizing positive sentiment was less reliable. These findings highlight the potential for using deep learning techniques, such as CNN, in sentiment analysis tasks. Furthermore, they also suggest that integrating text and emoji data can enhance model performance. However, further work is required to improve the model's ability to detect positive sentiments.

5. CONCLUSION AND FUTURE WORK

This study presented an application of a Convolutional Neural Network (CNN) model for the prediction of depressive moods using Twitter data, with a focus on both textual and emoji data. The findings from this study have substantiated the viability of applying a CNN model in sentiment analysis tasks, demonstrating the model's proficiency in identifying sentiments expressed in the data, particularly negative sentiments. The accuracy of the model on the test data was 88%, showing that the model was successful in correctly predicting the sentiment of the tweets a majority of the time. The precision and recall rates further indicated that the model was robust in identifying negative sentiments.

The use of emojis in sentiment analysis has been less explored in the literature, and this research has shown that incorporating emojis into the analysis can enhance the model's performance. This adds a new dimension to the field of sentiment analysis and opens up possibilities for more nuanced and accurate analyses.

Future research directions could involve fine-tuning the model, incorporating more diverse datasets, and exploring other feature engineering techniques to enhance the performance of the model. Moreover, other deep learning models could be investigated and compared to identify the most efficient techniques for sentiment analysis on social media data.

In conclusion, the proposed CNN model presents a promising tool for detecting depressive moods on Twitter, combining textual and emoji data. The findings from this study have broader implications for mental health surveillance, demonstrating the potential of machine learning techniques in providing valuable insights into public mental health trends from social media data. However, continual advancements and refinements in model development are crucial to fully harness the potential of these techniques.

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