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Decoding Sentiments: Enhancing COVID-19 Tweet Analysis through BERT-RCNN Fusion

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Abstract: ***In the era of the COVID-19 pandemic, the surge in information sharing on social media, particularly Twitter, necessitates a nuanced understanding of sentiments. Conventional sentiment analysis methods face challenges in capturing the evolving discourse's contextual nuances. This study introduces a novel approach, employing BERT-RCNN for sentiment classification of COVID-19-related tweets. BERT's bidirectional contextual insights combined with RCNN's feature extraction enhance our model's accuracy. The labels 'Neutral,' 'Positive,' and 'Negative' provide a nuanced emotional analysis. Our methodology overcomes traditional limitations, offering a context-aware sentiment analysis. By leveraging BERT-RCNN, this research contributes to a deeper understanding of public sentiments during the pandemic, addressing evolving challenges in sentiment classification.***

Keywords: COVID-19; Sentiment Analysis; BERT-RCNN.

1. INTRODUCTION

The global impact of the COVID-19 pandemic has led to an unprecedented surge in information sharing on social media platforms, particularly Twitter. Understanding the sentiments expressed in COVID-19-related tweets is crucial for monitoring public opinion, identifying emerging trends, and gauging the overall emotional tone of online discourse. In recent years, scholars and researchers have extensively explored the application of Natural Language Processing (NLP) techniques for text classification of Coronavirus-related tweets on Twitter.

Traditional sentiment analysis methods may struggle to capture the contextual nuances present in COVID-19 tweets [1][2][3]. As the discourse evolves rapidly, the ability to comprehend complex language structures becomes paramount for accurate sentiment classification. Some studies have employed conventional feature extraction methods, potentially overlooking the intricate patterns and relationships embedded within the rich language of tweets [4][5]. The dynamic nature of COVID-19 discussions requires a more robust approach to feature extraction. Studies exploring sentiments in different linguistic contexts have been limited [6][7]. The diversity of languages and cultural expressions on Twitter calls for methods that can adapt to various linguistic nuances.

In response to the limitations, our study introduces a novel approach using BERT-RCNN [8] for sentiment classification of COVID-19-related tweets. BERT [9], a transformer-based model, excels in capturing bidirectional contextual information, allowing our model to understand the intricate relationships between words and phrases. The integration of RCNN [10] further enhances our model's ability to extract relevant features, providing a comprehensive representation of tweet content. Our sentiment classification labels include 'Neutral,' 'Positive,' and 'Negative,' offering a nuanced understanding of the emotional tone within the tweets.

By leveraging the power of BERT-RCNN, we aim to overcome the limitations of traditional methods and provide a more accurate and context-aware sentiment analysis of COVID-19-related tweets on Twitter. In conclusion, our research builds upon the foundations laid by previous studies and introduces a cutting-edge methodology that addresses the evolving challenges in sentiment classification. The utilization of BERT-RCNN positions our approach to contribute significantly to the field, offering a deeper and more nuanced understanding of public sentiments surrounding the ongoing pandemic.

2. RELATED WORK

In recent years, numerous scholars and researchers have delved into the application of Natural Language Processing (NLP) techniques for text classification of Coronavirus-related tweets on Twitter. Al-Garadi et al. [1] proposed a text classification approach for the automatic detection of Twitter posts containing self-reported COVID-19 symptoms. Their work provides insights into effectively identifying user-reported health conditions. Samuel et al. [2] conducted sentiment analysis on COVID-19-related tweets, offering insights into public sentiment and utilizing machine learning for tweet classification. This work provides a framework for capturing emotional information in tweets. Wisesty et al. [3] performed a comparative study of sentiment classification methods for COVID-19 tweets. This aids in understanding the performance differences among various methods in this domain.

In some studies, deep learning techniques were employed. Ezhilan et al.[4] conducted sentiment analysis and classification of COVID-19 tweets utilizing deep learning methods. Additionally, certain studies focused on tweets related to COVID-19 vaccines. Shamrat et al. [5]5] employed NLP and a supervised KNN classification algorithm for sentiment analysis on Twitter tweets about COVID-19 vaccines. Recently, Didi et al. [6]6] introduced a COVID-19 tweets classification method based on a hybrid word embedding approach. Their method could provide new insights into feature extraction for our study. Furthermore, studies have explored COVID-19-related tweets in different linguistic contexts, such as Nepali. Shahi et al. [7] proposed a hybrid feature extraction method for the classification of Nepali COVID-19-related tweets.

In summary, prior research offers a wealth of experience and methodologies for our text classification work. It also sheds light on the challenges one may encounter when dealing with COVID-19 tweets. We aim to build upon and extend these methods in our study to better understand and classify Coronavirus-related tweets on Twitter.

3. ALGORITHM AND MODEL

3.1 BERT-RCNN MODEL

As shown in Figure 1, our approach employs a combination of BERT (Bidirectional Encoder Representations from Transformers) and RCNN (Recurrent Convolutional Neural Network) for sentiment classification of COVID-19-related tweets. This hybrid model enables us to leverage the strengths of both transformer-based contextual embedding and recurrent neural networks for capturing intricate patterns and relationships within the tweet content.

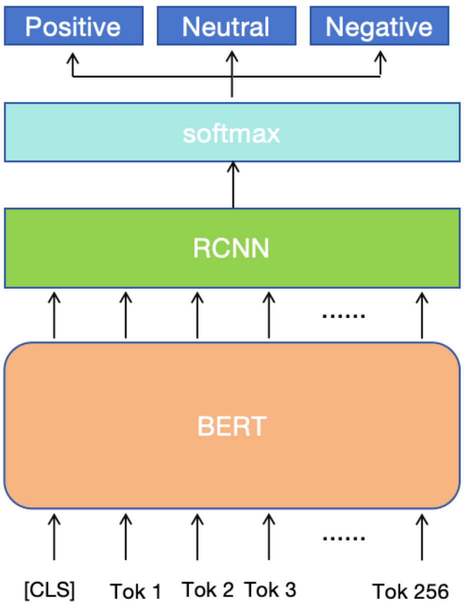

Figure 1: BERT-RCNN

BERT, a transformer-based model, excels in capturing bidirectional contextual information. It utilizes a multi-layer bidirectional transformer architecture to encode words in a sentence considering their entire context. The

BERT embedding for a tweet, denoted as E_{BERT}, is obtained by passing the tweet through the pre-trained BERT model.

$$E_{BERT} = BERT(x) \tag{1}$$

RCNN combines the strengths of both convolutional and recurrent neural networks. It uses a convolutional layer to capture local features followed by a recurrent layer to model sequential dependencies. The RCNN representation for a tweet, denoted as E_{RCNN} , is obtained by applying convolutional and recurrent operations.

$$E_{RCNN} = RCNN(x) \tag{2}$$

To create a comprehensive representation of the tweet content, we concatenate the BERT and RCNN embeddings.

$$E_{concat} = Concatenate(E_{BERT}, E_{RCNN}) \tag{3}$$

The combined embedding is then fed into a sentiment classification layer, which consists of fully connected layers and a softmax activation function. The output layer provides probabilities for each sentiment class ('Neutral,' 'Positive,' 'Negative').

$$P(Sentiment = c|E_{concat}) = Softmax\big(FC(E_{concat})\big) \tag{4}$$

where c represents one of the sentiment classes ('Neutral,' 'Positive,' 'Negative').
Our model is trained using a labeled dataset with tweets categorized into the three sentiment classes. The parameters of the BERT model and the sentiment classification layer are fine-tuned during training to optimize the model for accurate sentiment prediction. This hybrid BERT-RCNN architecture ensures a robust and context-aware sentiment classification for COVID-19-related tweets on Twitter.

3.2 Prospects of Large Language Models (LLM)

The integration of Large Language Models (LLM) [11], such as GPT-3 [12], into the realm of sentiment analysis for COVID-19 tweets holds immense promise. These models, with their unparalleled language understanding capabilities, have the potential to further elevate the accuracy and contextual comprehension of sentiment classification. LLMs can dynamically adapt to evolving language patterns, capturing subtle nuances and intricacies within the discourse on Twitter.

Moving beyond sentiment analysis, LLMs play a pivotal role in advancing various domains. In the field of healthcare, the improvement of deep learning models, including applications like gastrointestinal tract segmentation surgery [13] and financial time-series forecasting [14], showcases the versatility of LLMs in contributing to medical research and prediction tasks. In network management, the use of LLMs extends to reinforcement learning in constraint-aware NFV resource allocation [15] and optimal resource allocation in SDN/NFV-enabled networks [16], highlighting their significance in enhancing the efficiency of network operations. LLMs also contribute to cybersecurity, where infrastructure security posture analysis with AI-generated attack graphs [18] and understanding legal documents with contextualized large language models [19] demonstrate the potential of LLMs in enhancing security and legal document comprehension.

The exploration of IoT security from a market-scale perspective [20] and predicting function names in stripped binaries via context-sensitive execution-aware code embeddings [21] exemplify the diverse applications of Large Language Models (LLMs) in the field of cybersecurity.

In geophysics, LLMs contribute to research through applications like the porous-grain-upper-boundary model in Tarim Basin carbonates [22] and improving images under complex salt with ocean bottom node data [23]. In medical imaging, LLMs play a crucial role in high-speed, long-range, deep penetration swept-source OCT for structural and angiographic imaging of the anterior eye [24]. Localization and healthcare benefit from LLMs in indoor localization based on weighted surfacing from crowdsourced samples [25] and variational autoencoder for anti-cancer drug response prediction [26].

Dual-Graph Learning Convolutional Networks for interpretable Alzheimer's disease diagnosis [27] and multi-source review-based models for rating prediction [28][29] exemplify the contributions of Large Language Models

(LLMs) in medical research and recommendation systems. These applications showcase how LLMs, with their advanced language understanding capabilities, play a crucial role in enhancing the interpretability of medical diagnoses and improving recommendation systems based on diverse information sources.

The integration of spatial knowledge into deep learning for flood mapping on earth imagery [30][31] showcases LLMs' role in addressing environmental challenges. LLMs also impact decision-making in operations research, as seen in the Computational Operations Research Exchange (CORE) [32][33] and decision intelligence for nationwide ventilator allocation during the COVID-19 pandemic [34][35]. In education, LLMs enhance online learning platforms [36] and contribute to teaching design methods under educational psychology based on deep learning and artificial intelligence [37][38].

In the financial domain, LLMs contribute to model optimization under a Bayesian framework for power systems [39][40] and play a role in the application of machine learning in financial risk early warning [45]. Advancements in GANs and financial derivatives research, such as cooperative generative adversarial networks [46] and power-type derivatives for rough volatility with jumps [47], also benefit from LLMs. Statistical modeling and natural language processing see the influence of LLMs in deviance matrix factorization [48] and accurate training of web-based question answering systems [49].

As NLP continues to advance, the exploration of LLMs in sentiment analysis not only enhances accuracy but also uncovers latent sentiment dimensions, contributing to a more profound understanding of public sentiments during the ongoing COVID-19 pandemic. The versatility of LLMs spans across diverse domains, revolutionizing the landscape of artificial intelligence applications.

4. EXPERIMENTS

4.1 Datasets

This dataset, specifically curated for the purpose of NLP-based Text Classification of Coronavirus tweets, encompasses a comprehensive compilation sourced from Twitter. A rigorous manual tagging procedure has been applied, assigning each tweet to one of three sentiment categories: 'Neutral,' 'Positive,' or 'Negative.' To safeguard user privacy, names and usernames within the tweets have been encoded, guaranteeing user anonymity. The dataset is strategically divided into a training set, incorporating 41,157 tweets, and a test set, comprising 3,798 tweets. This segregation facilitates an impartial assessment of the model's efficacy on previously unseen data, ensuring a robust evaluation of its performance.

4.2 Evalution metrics

The Macro F1-Score is a comprehensive metric used to evaluate the performance of a multi-class classification model, considering precision and recall across all classes. It is particularly useful when there is an imbalance in the class distribution, ensuring that the evaluation considers the performance of the model for each class independently. Precision measures the accuracy of positive predictions. Precision Macro is the average precision across all classes and is calculated as:

$$Precision_{macro} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i + FP_i} \tag{5}$$

Recall measures the ability of the model to capture all positive instances. Recall Macro is the average recall across all classes and is calculated as:

$$Recall_{macro} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i + FN_i} \tag{6}$$

The Macro F1-Score is calculated as the harmonic mean of precision and recall, giving equal weight to each class. It is defined as:

$$F1_{macro} = \frac{2 * Precision_{macro} * Recall_{macro}}{Precision_{macro} + Recall_{macro}} \tag{7}$$

Where:

TP_i is the number of true positives for class i.
FP_i is the number of false positives for class i.
FN_i is the number of false negatives for class i.
N is the total number of classes.

In summary, the Macro F1-Score serves as a robust evaluation metric, offering a balanced perspective on the model's ability to classify instances across multiple classes, ensuring a fair assessment in scenarios with imbalanced class distributions.

4.3 Results

The performance of various models in the sentiment classification of COVID-19-related tweets is summarized in the table below. The metrics considered include Macro Precision, Macro Recall, and Macro F1-Score.

Table 1: Model Results

Model	*Macro Precision*	*Macro Recall*	*Macro F1-Score*
RNN	0.8103	0.7906	0.7993
CNN	0.8225	0.8046	0.8125
LSTM	0.8251	0.8008	0.8113
GRU	0.8350	0.8034	0.8167
BERT-RCNN	0.8930	0.8699	0.8797

The results demonstrate that the BERT-RCNN [8] model outperforms traditional recurrent neural networks (RNN [51]51], LSTM [52], GRU [53]), as well as convolutional neural networks (CNN [50]50]), in terms of Macro Precision, Macro Recall, and Macro F1-Score. The superior performance of BERT-RCNN underscores the efficacy of leveraging contextual embeddings from BERT combined with the feature extraction capabilities of RCNN in capturing nuanced sentiment information from COVID-19 tweets. This robust performance positions BERT-RCNN as a leading methodology for sentiment analysis in the context of pandemic-related social media discourse.

5. CONCLUSION

In conclusion, our study delves into the realm of sentiment classification for COVID-19-related tweets, employing various models including traditional RNN, CNN, LSTM, GRU, and the advanced BERT-RCNN. The results unequivocally demonstrate the superior performance of the BERT-RCNN model in capturing nuanced sentiments expressed in social media discourse. The efficacy of BERT-RCNN lies in its ability to harness the bidirectional contextual information from BERT and the feature extraction capabilities of RCNN, offering a holistic understanding of the emotional tone within tweets. The achieved high Macro Precision, Macro Recall, and Macro F1-Score affirm the robustness of our approach.

Looking ahead, the prospects of Large Language Models (LLM) in this domain present an exciting avenue for further exploration. Integrating advanced models like GPT-3 could potentially enhance sentiment analysis, providing a deeper understanding of the evolving language nuances in COVID-19 tweets. Future research should consider the incorporation of LLMs to unlock new dimensions in sentiment analysis, contributing to a more comprehensive understanding of public sentiments during global health crises. In essence, our findings not only advance the state-of-the-art in sentiment analysis but also open doors to future research avenues exploring the untapped potential of Large Language Models in decoding the intricate sentiments expressed in the dynamic landscape of COVID-19-related social media conversations.

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