



BERT-deep CNN: state of the art for sentiment analysis of COVID-19 tweets

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Abstract

The COVID-19 pandemic has led to the emergence of social media platforms as crucial channels for the dissemination of information and public opinion. Comprehending the sentiment conveyed in tweets on COVID-19 is of paramount importance for individuals involved in policymaking, crisis management, and public health administration. This study seeks to conduct a comprehensive review of the current BERT and deep CNN models utilized in sentiment analysis of COVID-19 tweets. Additionally, the study aims to propose potential future research directions for the development of a BERT model that is both lightweight and high quality. The BERT model acquires contextual representations of words and effectively captures the intricate semantics of tweets related to COVID-19, whereas the deep CNN captures the hierarchical organization of the tweet embeddings. The performance of the model is exceptional, exceeding the current sentiment analysis methods for tweets related to COVID-19. Our study involves a comprehensive analysis of vast COVID-19 tweet datasets, wherein we establish the efficacy of the BERT-deep CNN models in precisely categorizing the sentiment of COVID-19 tweets in real time. The outcomes of the research offer significant perspectives on the public's attitudes, supporting decision-makers in comprehending the general viewpoint, detecting disinformation, and guiding emergency response tactics. Additionally, this study serves to enhance the progress of sentiment analysis methodologies within the realm of public health emergencies and establishes a standard for forthcoming investigations in the sentiment analysis of social media data pertaining to COVID-19.

Keywords COVID-19 · BERT · Deep learning · Sentiment analysis · Natural language processing · Tweets

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1 Introduction

The coronavirus disease 2019 (COVID-19) has been a catastrophic occurrence that has had a primary influence on many aspects of life, including the economy, people's mental health, and society (Chandra and Krishna 2021). Researchers from all around the world were encouraged to gather insights into many facets of the COVID-19 pandemic as a result of the sudden changes in socioeconomic conditions. During this period, the potential of machine learning has been given a lot of attention (Shawe-Taylor and Cristianini 2000). In addition to this, deep learning models have been quite helpful in estimating the total number of fatalities and active cases (Ling 2020).

To further extract and identify the authors' emotions from their tweets or messages, sentiment analysis employs text analytics and natural language processing (NLP) technologies (Nair et al. 2021). These emotions might range from being neutral to being unpleasant. Twitter in particular has served as a platform for people to share their reactions to the outbreak. When combined with sentiment analysis (Hutto and Gilbert 2014), social media postings and tweets revealed new levels of insight. Anxiety and fear were the most common reactions to the epidemic at first. Sentiment analysis using Twitter made use of topic modeling. Sentiment research in Nepal (Sadia et al. 2020) and Australia (Zhou et al. 2021) showed generally favorable attitudes tinged with apprehension. The influence of the digital platform on COVID-19 in Spain was evaluated by sentiment analysis in a separate research (Las Heras-Pedrosa et al. 2020). A further investigation indicated that the mood dropped after hearing about the lockdown but quickly rebounded (Kruspe et al. 2008).

Social media platforms such as Twitter, Instagram, Reddit, and Facebook have been immensely indulged in examining and fast-checking to combat misinformation due to the emergence of bizarre conspiracy theories (Naseem et al. 2021). The analytics tools to sojourn such misinformation were the need of the hour in pandemic scenarios. The temperament and the prevailing mood of the general human population could be revealed by analyzing social media space. In the NLP domain, pretrained language models such as BERT (Bidirectional Encoder Representations from Transformers) showcase their efficacy (Biswas et al. 2020). These language models are pretrained on a considerable amount of unannotated text and yield superior performance with a mitigated requirement of labeled data, and provide faster training than conventional training. BERT has recorded state-of-the-art performance in NLP tasks, including sentiment analysis, by substantial margins (Jiang et al. 2019).

Procedures for overall pre-training and fine-tuning BERT are shown in Fig. 1 (Devlin et al. 2018). The same architectures are utilized for pre-training and fine-tuning, except for output layers (Sun et al. 2019; Munikar et al. 2019; Song et al. 2002). Models are initialized for various downstream tasks using the same pretrained model parameters. All parameters are adjusted during fine-tuning. Every input example now has a special symbol (CLS) before it, and (SEP) is a unique token that separates questions and answers (Devlin et al. 2018).

People with COVID-19 symptoms must get examined and isolate themselves to mitigate the spread (Jalil 2022; Mehmood et al. 2021). Social media is a way to express their feelings during the isolation period. Data from social media may be misleading at times, although it contains valuable and real-time information as well (Sadia et al. 2021a). Misleading information may lead to a new height

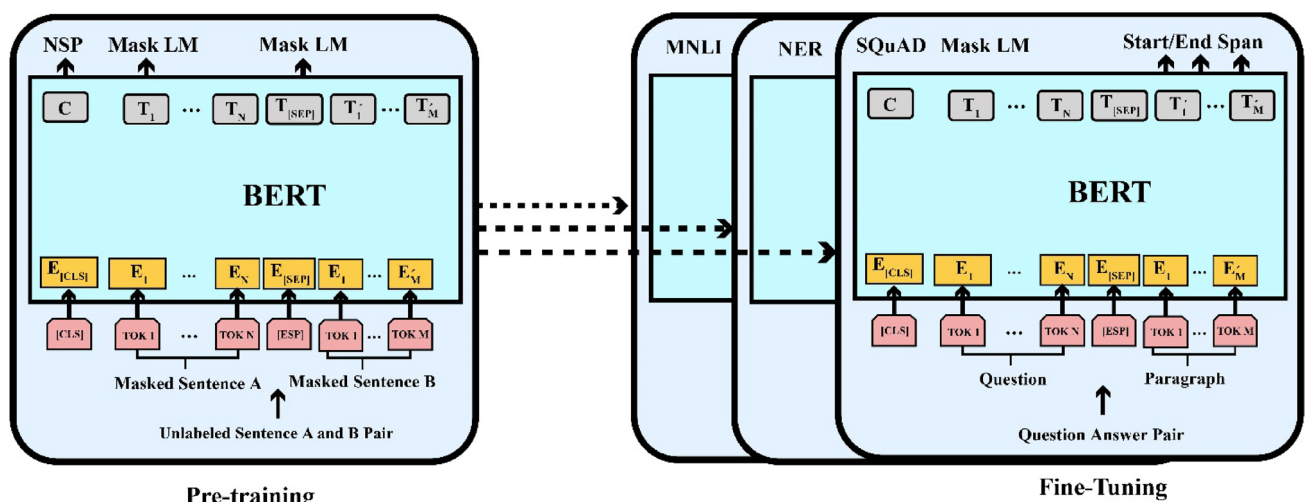


Fig. 1 Procedures for overall pre-training and fine-tuning BERT

in sufferings for such patients. A COVID-19 patient passed through several mental and physical traumas.

Social media platforms are susceptible to the spread of misinformation and rumors during crises such as the COVID-19 pandemic. Sentiment analysis can help identify and flag tweets containing misleading or false information, supporting efforts to combat misinformation. Analyzing sentiment in COVID-19 tweets can foster public engagement by providing a platform for individuals to express their opinions and concerns. Additionally, researching sentiment analysis of COVID-19 tweets using advanced techniques like BERT-deep CNN can provide valuable insights into public sentiment, support decision-making, and contribute to the broader understanding of sentiment analysis in the context of public health crises. This motivates us to review the state-of-the-art BERT and deep CNN-based models for sentiment analysis of COVID-19-based tweets realizing the significance of such research.

The main contribution of the study is as follows:

1. We reviewed the state-of-the-art BERT and deep CNN models for sentiment analysis of COVID-19 tweets.
2. The article includes a complete and in-depth comparison of CNN and BERT-based models for semantic analysis of tweets linked to COVID-19.
3. In addition to the models described above, complete and exhaustive lists of state-of-the-art transformer-based models have been introduced and reviewed.
4. The articles reviewed in this paper are highly extensive and inclusive aspects of COVID-19 tweets such as vaccinations, lockdown, public thoughts, and attitudes about the COVID-19 pandemic, as well as fake news about it and its world cloud.
5. Future research directions for devising a lightweight, high-quality BERT model are proposed.

The remainder of the paper is structured as follows. In Sect. 2, we discussed transformer-based sentiment analysis models. Section 3 describes the social media analytics process, and Sect. 4 is devoted to the discussion. Section 5 concludes with the results and future research directions.

2 Transformer-based models for the sentiment analysis

This section includes the interpretation of transformer models and the latest achievements in the field of analysis of covid tweets. NLP covers various language processing applications such as sentiment analysis, chatbots, question-answering systems, machine translation, etc. The primary component of NLP approaches transformer models, which are used to predict the next character or word in a sequence.

Examples of well-known transformer models are Google's BERT, Transformer-XL, XLNet, BiGRU, OpenAI's GPT-2, Fine-tuned Transformer LM, RoBERTa, ALBERT, ULMFiT, and BERTweet.

2.1 Transformer models

- (1) ULMFiT (Universal Language Model Fine-Tuning), released in 2018, delivers good performance using NLP techniques. After training on the Wikitext 103 dataset, the model is fine-tuned for a new dataset. Based on ULMFiT, Anand et al. (1904) proposed a suggestion-mining approach for forums and online reviews. They also presented a system description for the SubTask of SemEval 2019 Task 9. The objective is to determine whether a sentence contains a suggestion or not. For training the classification model, various preprocessing techniques are used. The trained model achieved an F1-score of 0.7011.
- (2) Fine-tuned Transformer LM: this approach has a significant role in recent developments of NLP. In the past, recurrent neural networks (RNNs) were used to implement machine translation and answering systems. The transformer approach outperforms RNNs and CNNs (Pota et al. 2018) thanks to a considerable reduction in training resource requirements. To model the relationship between words in a sentence regardless of their positions, a self-attention mechanism is used. Radford et al. (2018) generated pretrained models on different structured unlabeled texts. The models were then fine-tuned for specific tasks. Their approach was tested on 12 benchmark tasks. In the Stories Cloze Test for commonsense reasoning, RACE for question answering, and MultiNLI for text entailment, the performance was improved by 8.9%, 5.7%, and 1.5%, respectively.
- (3) OpenAI's GPT-2: utilizing transformer models, the GPT-2 approach can predict the next word in a large volume of internet text (about 40 GB). GPT-2 can generate high-quality conditional synthetic text samples outperforming rival methods on Wikipedia, news, or books. This approach has also performed well on tasks such as question answering, reading comprehension, summarizing, and translation from raw text. Without any direct supervision, Radford et al. (2019) presented language models on WebText, which consists of millions of web pages. GPT-2 achieved an F1-score of 55% on the CoQA dataset in question answering. The performance was further improved in a log-linear fashion.
- (4) BiGRU: the RNNs are incapable of memorizing long sequences. This issue is addressed by bidirectional gated recurrent unit (BiGRU), which can predict a

text paragraph with ease. This stems from the fact that BiGRU regularizes information flow using internal called gate mechanisms. BiGRU has already been used in various applications, such as speech recognition and synthesis. The fine-grained attention model (Feng and Liu 2019) is based on a lengthy review in which the attention layer focuses on word-level, sentence-level, and paragraph-level features. This method has been validated on JD review and IMDB datasets.

- (5) Google's BERT: bidirectional encoder representations (BERTs) consider both the left and right sides of a word to determine its context. BERT is capable of multitask learning and performing different NLP tasks simultaneously. BERT is the first bidirectional and deep system for unsupervised learning of NLP tasks. Biomedical text mining is considered very valuable among researchers. Lee et al. (2020) investigated the possibility of adapting BERT for biomedical corpora, which resulted in the BioBERT (bidirectional encoder representations from Transformers for biomedical text mining) method. BioBERT outperformed BERT and other existing methods with 0.62% and 2.8% improvement on the F1-score for biomedical entity recognition and relation relaxation, respectively. BioBERT also achieved a 12.24% MRR improvement in biomedical question answering.
- (6) Transformer-XL: this method uses a new architecture for NLP without any fixed-length limitations (Houlsby, et al. 2019). Transformer-XL is significantly faster than Transformer. Using relative positional encoding is one of the critical ideas of Transformer-XL. In addition to single embedding, this method computes an embedding for each pair of tokens to capture the relation between them. While transformers can capture dependencies in longer sequences, they are limited to static-length scenarios. Dai Zihang et al. (1901) proposed a method based on static length and fixed/constant temporal coherence. Their approach addressed the fragmentation problem and captured dependency for longer sequences.
- (7) XLNet: this method is a generalized auto-regressive model (Yang et al. 2019) capable of learning bidirectional contexts. XLNet can outperform BERT and other methods on several tasks by borrowing some of the techniques from BERT and Transformer-XL. The crux of XLNet is a novel objective function used during the pre-training phase. Integrating a two-stream attention mechanism and Transformer-XL, XLNet can achieve better performance in various tasks in machine vision and reinforcement learning. This method outperformed BERT in terms of error reduction on several datasets.
- (8) RoBERTa (robustly optimized BERT approach), (Liu et al. 1907) was born by modifying the pre-training steps of BERT. Contrary to BERT, RoBERTa is trained on longer sequences, and NSP loss is not used. Moreover, during training, for feeding each series to the model, the generation of the masking pattern is done dynamically.
- (9) ALBERT (Lan et al. 1909) has been proposed as a lightweight version of BERT to deal with GPU/TPU memory limitations and the long training times of BERT. To this end, the number of parameters is reduced using cross-layer parameter sharing and factorized embedding parameterization without significant performance degradation. Despite having a lower number of parameters, ALBERT has more extensive architecture compared to BERT leading to computational complexity higher than BERTLARGE. However, ALBERT has outperformed BERTLARGE on GLUE, RACE, and Squad benchmarks.
- (10) BERTweet (Nguyen et al. 2005), which was pretrained on 850 million English tweets using the RoBERTa pre-training methodology.

2.2 The state-of-the-art BERT models on Sentiment Analysis of Tweets

In this section, we review the studies that have been conducted on sentiment analysis of COVID tweets, specifically, the BERT-based models to exploit COVID-19-related tweets.

The study (Sadia et al. 2022) examines various techniques for identifying offensive language in 13 languages with mixed Indic scripts. First, Transformer-based architecture is compared to baseline classical machine learning models. The second section of the research compares four cutting-edge transformer-based models, including XLM-RoBERTa, indic-BERT, MurilBert, and mBERT, through experimental analysis. XLM Roberta with BiGRU performs best among these models. Thirdly, emoji embeddings are fed into the experimental setup of the most effective model, XLM-RoBERTa, which further improves the performance of the used model. To compare the model's performance to that of individual language models, the combined dataset of 13 Indic languages is used to train it. F1-score and accuracy results showed that the combined model performed better than the individual models, probably as a result of the code-mixed nature of the combined model. With a training loss of 0.28, a validation loss of 0.31, and an AUC score of 0.94 for both training and validation, this model gets an F1 score on test data of 0.88.

In Gupta et al. (2021a), the authors proposed a novel emotion care strategy to analyze multimodal textual data from real-time tweets about COVID-19. Additionally, this study

examined eight emotions on an 8-point scale (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) across a variety of domains, including nature, lockdown, health, education, the market, and politics. The study is among the first linguistic analysis of this kind on a variety of pandemic-related modes. Using India as a case study, it was deduced from this textual analysis that "joy" has decreased toward everything (9–15%) except nature (17%) due to the apparent fact that pollution has decreased. Due to the dedication of the teachers' fraternity, there was a higher level of trust (29%) in the educational system. As human lives were on the line, the health sector saw that fear (18%) and grief (16%) were the two most common emotions among the populace. Furthermore, a state- and emotion-based representation is given. For the same, an interactive web application has also been created.

The integrated system produces opinionated aspect-based graphical and extracting summaries from a sizable number of mobile reviews as described in Gupta et al. (2019). The system concentrates on three tasks: (a) aspect identification in a given area; (b) sentiment polarity computation for each aspect; and (c) generation of opinionated aspect-based graphical and textual summaries. The method outperformed the baseline technique in terms of precision and recall after being tested on three mobile-review datasets. Without instruction, the system created summaries from reviews.

The research study (Gupta et al. 2022) investigated political echo chambers using a Twitter dataset that included more than a million tweets about the Bharatiya Janata Party (BJP) and the Aam Aadmi Party (AAP), the two main political parties competing in the Delhi Election 2020. By implementing forth a fundamental model of information exchange in online social networks, the authors looked into the factors that contribute to the development of echo chambers in these networks. Additionally, they looked into how "opposition" party users, who consume information with a variety of leanings but produce partisan content (with a single-sided lean), contribute to the growth of echo chambers.

To analyze the sentiment found in Hindi language text taken from Twitter, the study (Gupta et al. 2021b) first investigated the machine learning-based algorithms Naive Bayes, Support Vector Machine, Decision Tree, and Logistic Regression. The article also discussed lexicon-based techniques for sentiment analysis in Hindi (Hindi Senti WordNet, NRC Emotion Lexicon), while also suggesting a domain-specific sentiment dictionary. To analyze sentiment from 23,767 tweets in the Hindi language that were divided into positive, negative, and neutral tweets, an integrated convolutional neural network (CNN)—recurrent neural network and long short-term memory—was developed. The accuracy of the suggested CNN method was 85%.

Using India as a case study, the authors of Dhingra et al. (2021) examined emotional well-being throughout the

lockdown phases. Eight emotions—anger, anticipation, disgust, fear, joy, sadness, surprise, and trust—were used to underpin the study's empirical findings. The authors also discussed how each lockdown affected how people felt about COVID-19 instances in the worst-affected Indian states by examining how a particular lockdown comes to be associated with both relief and distress. The research study proposed a social media-based emotion analysis method as well as suggestions for impending emergencies.

A study was conducted by Basiri et al. (2021) to understand the general opinion of people in eight countries about the COVID-19 pandemic from their tweets. A hybrid fusion framework was proposed employing five deep-learning classification techniques. The prime findings were (i) every country had a unique sentiment pattern, (ii) the first reported infected case was correlated with a rise in information about the disease, and (iii) when there was a rise in active cases or deaths, negative sentiment was also at the peak.

Hayawi et al. (2022) devised a new COVID-19 vaccine misinformation identification approach based on machine learning. They annotated and gathered COVID-19 vaccine-related tweets and utilized them to classify vaccine misinformation by training machine learning algorithms. They exploited the BERT model, LSTM, and XGBoost using 15,000 annotated tweets. BERT recoded an F1-score of 0.98 and hence proved its efficacy.

Another study by Vishwamitra et al. (2020) analyzed hate speeches on Twitter against older adults and the Asian community triggered by the coronavirus pandemic. Their framework was trained to identify hate speech using the BERT strategy and applied the multiheaded attention mechanism of BERT to detect new keywords (100 keywords targeting older people and 186 keywords against the Asian community). Their study confirmed that BERT focused on particular word associations to identify hate speech in the Boomer-hate dataset, whereas BERT focused on varied attention between numerous words in the case of the Asian-hate dataset.

It is interesting to note that in Luxembourg, the discussion of policy and everyday living continued before the announcement of the first case and quickly escalated afterward. Figure 4 depicts a word cloud of the subjects from 22 January to 1 March (the date of the first case) in Luxembourg, which demonstrates that the themes are primarily related to travel (Chen et al. 2021). This may be attributed to the region's 47.4% immigrant population, and the fact that locals are more concerned with travel-related laws in Luxembourg and other nations.

Two machine learning approaches were presented by Kabir et al. (2021) for phrase extraction, and multi-label binary classification on an emotion dataset comprised of COVID-19 tweets applied for ten emotion labels classification and to choose a phrase that signified each emotion the best. They used a pretrained technique, RoBERTa, with a

custom Q&A head that tried to detect a word best suited for a particular feeling by taking the emotion label as a question. Their study showcased the adaptation of the pandemic over time and staying more optimistic by people.

Valdes et al. (2021) designed an automatic classification model for COVID-19-related Twitter posts. Their model was based on BERT. Their objective was to determine whether a model pretrained on a corpus in the domain of interest could perform better than the one trained on a larger general domain corpus. They achieved encouraging F1-scores. They confirmed that a model trained with quality domain-specific data could achieve superior results compared to a model trained with a vast amount of general domain data.

A study by Tzifas et al. (2104) proposed an ensemble system for misinformation identification in the context of the COVID-19 pandemic and called it the TOKOFOU system. It was based on six different pretrained transformer-based encoders and fine-tuned each model on specific questions. The prediction scores were aggregated by applying the majority voting technique. The model achieved an F1-score of 89.7%.

Sadia et al. (2021b) explored Twitter opinions about the COVID-19 pandemic and devised a sentiment analysis model. They converted the Twitter data related to the pandemic into tokens. They utilized BERT and fine-tuned it with an extra classifier layer to categorize sentiments into three classes such as neutral, negative, and positive. Their model exhibited high scores in evaluation metrics.

The COVID-19 disinformation model was proposed by Song et al. (2021) to classify pandemic-related misinformation that confused health-related issues among people. They presented a manually annotated COVID-19 misinformation corpus and a model for topic discovery and COVID-19 misinformation classification. They extensively examined misinformation classification concerning origin source, media type, wrong type, volume, and time.

The disinformation identification on Twitter can be categorized into two subtasks: (i) stance identification to detect whether the posts disagree, agree, or express no stance toward the wrong conceptions and (ii) extraction of disinformation being checked for integrity. Hossain et al. (Hossain et al. 2020) gathered 6761 annotated tweets dataset called COVIDLIES1, for the COVID-19-related disinformation detection system. They evaluated their dataset on the prevailing NLP models and delivered the initial benchmarks to improve upon.

BERT Model was utilized by Chintalapudi et al. (2021) to explore the tweets by netizens from India during the COVID-19 lockdown. They labeled the text as joy, anger, sadness, and fear. Their model was compared with long-short term memory (LSTM) (Baziotis et al. 2017), support vector machines (SVM), and logistic regression (LR) models. They computed the accuracy of every sentiment



Fig. 2 Word cloud of Luxembourg Tweets from 22 January 2020 to 1 March 2020

separately. The BERT model outperformed the other models in terms of accuracy. A high prevalence of associated phrases and keywords among the tweets is recorded, some of them mentioned in Fig. 2 (Rustam et al. 2021).

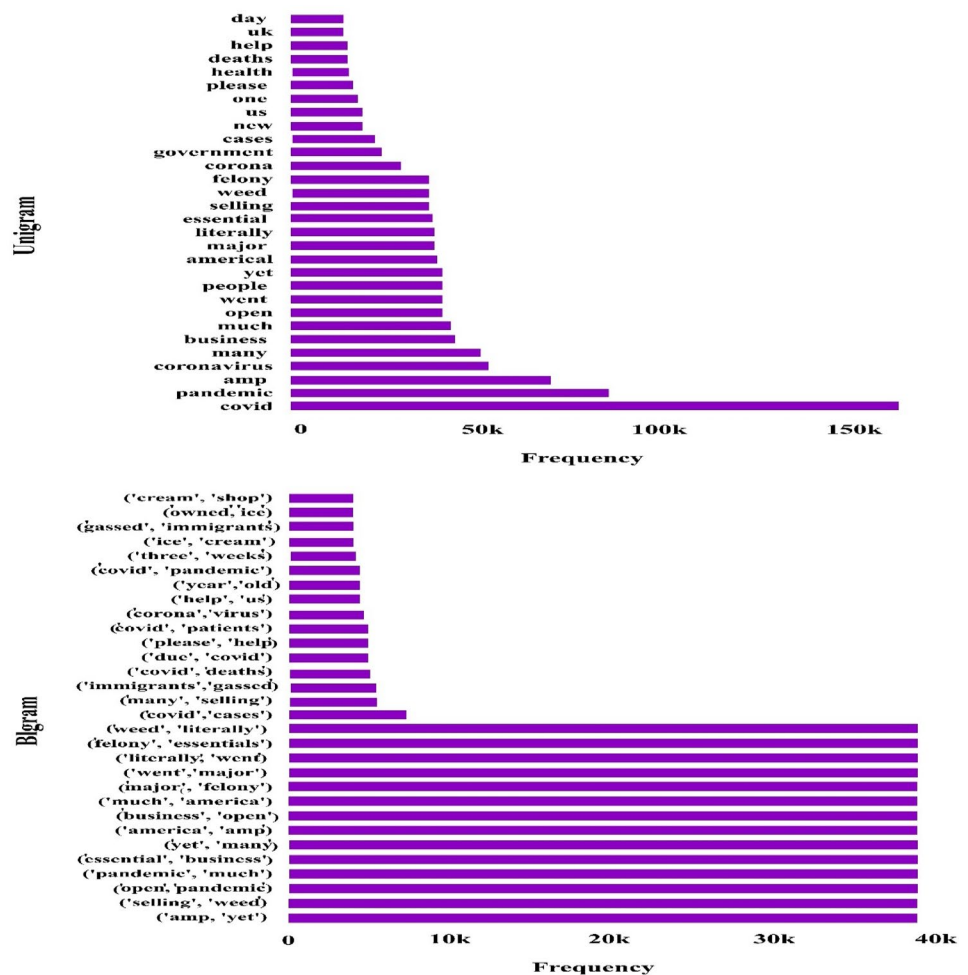
Müller et al. (2005) proposed a transfer-oriented method dubbed COVID-Twitter-BERT (CT-BERT), pretrained on the topic of COVID-19 with a large Twitter message corpus. The precise way to examine the performance of the domain-specific model was to utilize it on downstream tasks. 10–30% marginal enhancement was achieved by their model compared to the base model, BERT-LARGE. Their approach could be applied in different natural language processing tasks, including chatbots, question-answering, and classification.

COVID-19 fake news identification framework was presented by Glazkova et al. (2021) based on ensembling learning and CT-BERT. They used additional data as a pre-processing step to achieve the weighted F1-score of 98.69. They empirically confirmed that BERT-based models achieved better binary classification outcomes.

In Rustam et al. (2021), a supervised machine learning technique was introduced to execute sentiment analysis of COVID-19 tweets. Tweepy library was exploited to extract tweets by a crawler. The pre-processing methods included cleaning the dataset, and the TextBlob library was employed to extract sentiments. Tweets were categorized as negative, positive, and neutral. LSTM architecture was also applied, but it yielded low accuracy as compared to other machine-learning classification techniques. Extra Trees Classifiers demonstrated superior performance than other models with 93% accuracy.

These terms suggest that people discuss COVID-19-related government policies, lockdowns, and deaths. Anti-vaccination tweet detection could provide vital information in devising strategies to mitigate such sentiments among

Fig. 3 The counts of the most common unigram and bigram phrases as provided by the IEEE data port



different groups. The study (To et al. 2021) explored the anti-vaccination tweets during the COVID-19 pandemic using natural language processing techniques. They employed BERT and Bi-LSTM with pretrained GLoVe embeddings with Naïve Bayes (NB) and SVM. The BERT model showcased significant performance compared to other models.

Gencoglu et al. (2020) utilized 26 million COVID-19-related tweets to devise a language-agnostic model based on BERT. For crisis management like the COVID-19 pandemic, quantifying the characteristics of public opinion is critical. Their study confirmed that lightweight classification techniques made comprehensive surveillance of public dialogue feasible by out-of-the-box exploitation of those demonstrations.

Chandra et al. (2021) introduced a deep learning language model using LSTM for sentiment analysis of Indian people during the peak and rise of COVID-19 cases in India. Their architecture contained a state-of-art BERT language model and LSTM language model with a global vector embedding. Multilabel sentiment classification was applied with more than one sentiment expressed at once. They observed

mostly optimistic tweets during the period, but a portion of the population expressed annoyance toward the authorities.

Pretrained language models were applied by Babu et al. (2009) to gather information from tweets during the COVID-19 pandemic. They designed their framework as a binary text classification problem. Their CT-BERT model yielded an 88.7% F1-score, while their ensemble model containing SVM, RoBERTa, and CT-BERT showed an 88.52% F1-score.

Limiting negative emotions and irrelevant information are critical during catastrophic events like a pandemic. Malla et al. (2021) presented a Majority Voting technique-based Ensemble Deep Learning (MVEDL) model to extract informative information from tweets. For training and testing, they used the “COVID-19 English labeled tweets” dataset. For the best performance with their model, they utilized state-of-the-art language models such as CT-BERT, BERTweet, and RoBERTa. The MVEDL model showed its efficacy by yielding high accuracy and F1-score compared to other deep learning counterparts (Fig. 3).

Figure 3 (<https://github.com/thunlp/PLMpapers>) depicts the transformer family and clearly shows the relationship

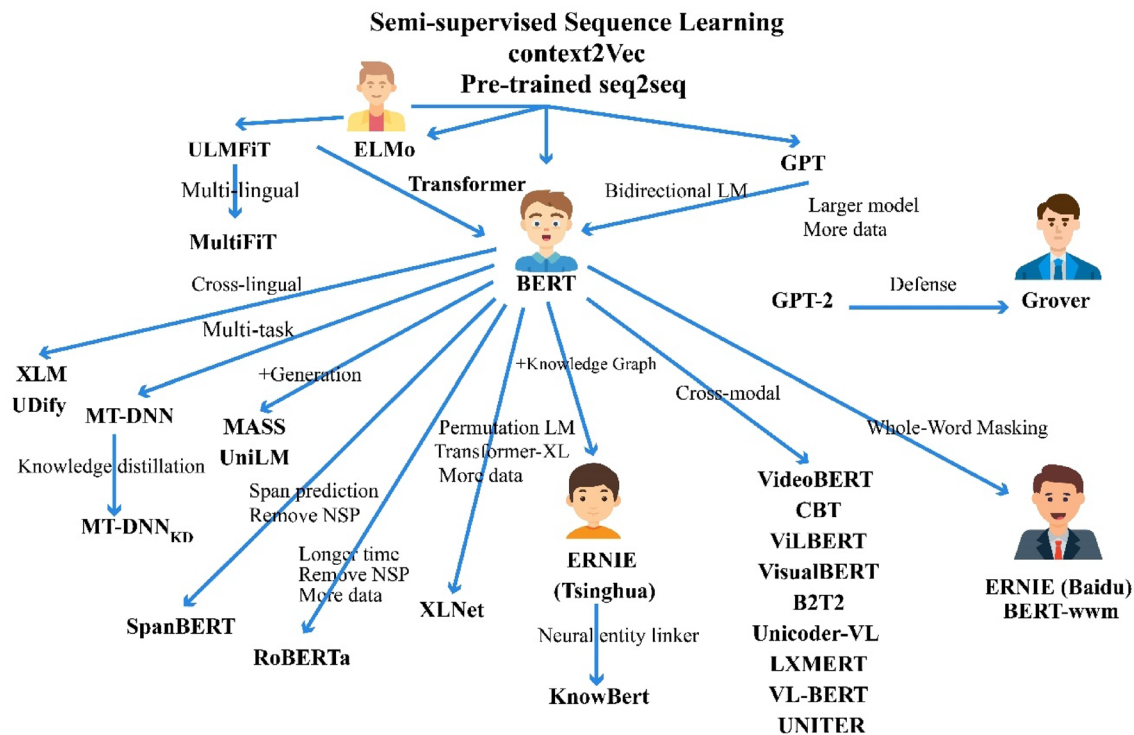


Fig. 4 The transformer family

between the various transformers discussed in this paper, including BERT and RoBERTa.

According to Fig. 3, in transfer learning, the common practice is using a big generic model that has been pretrained on a large-scale (text) dataset. The pretrained model is later fine-tuned on a new possibly smaller dataset so that it will fit a particular task (Fig. 4).

The advantages and limitations of the previous studies for sentiment analysis of COVID-19 Tweets are described in Table 1.

3 Process of social media analytics

According to the studies, the Internet and mobile technologies are the crux of social media, which lay the foundation for information dissemination, interactive communication, and content generation. Social media has claimed a pivotal role in the information ecosystem. In recent years, research on social media has attracted much attention from different domains. Social media analytics revolves around the development and evaluation of informatics tools and frameworks for the collection, monitoring, analyzing, summarizing, and visualization of social media data. As shown in Fig. 5, social media analytics consists of three stages, namely “capture,” “understand,” and “present” (Ling 2020).

Based on Fig. 5, we describe the steps in detail.

Capture By gathering vast amounts of pertinent data from numerous social media sources, the capture stage helps find information on social media platforms connected to its activities and interests. These data are available and archived to be used to complete tasks. The preprocessed data are provided to the understanding stage through several preprocessing steps, such as data modeling, information and recorded linkage from diverse sources, stemming, part-of-speech tagging, feature extraction, and other syntactic and semantic procedures that enable the analysis.

Understand The data acquired from various uses and sources during the capture stage typically include a significant percentage of noisy data that must be eliminated before helpful analysis. Then, various methods, from data mining, network analysis, machine translation, text, and natural language processing, can be used to retrieve insight from the purified data.

At this point, it is possible to generate a wide range of valuable data and trends about users, encompassing their histories, interests, problems, and social networks. The comprehension phase, it should be noted, is at the center of the whole social media evaluation. The information and analytics at this time will be significantly

Table 1 Papers related to COVID-19-based sentiment analysis

References	Year	Topic of discussion	Advantages/Limitations	Performance
D'Andrea et al. (2019)	2019	Sensing the public opinion on vaccination automatically from tweets	Bag-of-words and SVM for classification were utilized	Accuracy: 65.4%
Zhang et al. (2007)	2020	The exploitation of the largest Twitter English depression dataset	Their models could be readily applied to the monitoring of stress and depression trends in targeted groups. XLNet, RoBERTa, and BERT were used	Accuracy 76.5% (BERT)
Chatsiou (2020)	2020	Auto-assign sentences for the corpus of the COVID-19 press briefing	CNN classifiers integrated with transformers like BERT outperformed models with other embeddings (Word2Vec, Glove, ELMo)	Accuracy 68.65% (CNN + BERT)
Jelodar et al. (2020)	2020	Based on COVID-19 comments, deep sentiment classification was performed	LSTM achieved superior classification compared to its machine-learning counterparts	Accuracy 81.15%
Chakraborty et al. (2020)	2020	Sentiment analysis based on 226,668 tweets related to COVID-19	Employing a fuzzy rule base for Gaussian membership	Accuracy 81%
Kairon et al. (2021)	2021	Comparison of continuous-variable quantum neural networks and quantum backpropagation multilayer perceptron (QBMPLP)	Significant results were demonstrated on complex and sporadic data	P-value 0.9849 for QBMPLP Model on Indian confirmed case prediction
Abdelminaam et al. (2021)	2021	Fake news on the COVID-19 identification system	Modified GRU and Modified-LSTM were utilized to enhance the accuracy	Accuracy 98.6% (LSTM two layers)
Garcia et al. (2021)	2021	Positive and negative emotions of COVID-19 were explored	They integrated recent embedding models (SBERT, mUSE, Fast-Text) for feature extraction	Accuracy 83%
Naseem et al. (2021)	2021	They developed a novel massive sentiment data set, COVIDSENTI, which consisted of 90,000 COVID-19-related tweets	BiLSTM, CNN, distilBERT, BERT, XLNET and ALBERT were applied	Accuracy 94.8% (BERT)
Sitaula et al. (2021)	2021	The first work of sentiment analysis on Nepali COVID-19 tweets with three classes. They prepared a public Nepali COVID-19 tweets dataset, called NepCOV19Tweets, for COVID-19-related sentiment analysis in the Nepali language	Three different feature extraction methods—fastText-based feature extraction (ft), domain-specific probability-based (ds), and domain-agnostic probability-based (da) feature extraction. Three different CNN models for the sentiment classification of tweets using three different feature extraction methods based on ft, ds, and da, respectively. In addition, for the results, an ensemble CNN model that captured the three different pieces of information was also designed	Accuracy 68.7% (Ensemble CNN)
Shahi et al. (2022)	2022	They used three different feature extraction methods—TF-IDF, FastText-based, and TF-IDF-weighted FastText-based (hybrid) features—for the representation of COVID-19-related tweets written in the Nepali language. Here, the hybrid feature extraction in the Nepali language is a novel work in the study	They evaluated the performance of each feature extraction method on nine widely used machine learning classifiers	Accuracy 72.1% (SVM + RBF with hybrid feature extraction method)
Sitaula et al. (2023)	2022	They designed a novel multi-channel convolutional neural network (MCNN), which ensembled the multiple CNNs, to capture multi-scale information for better classification	Their proposed feature extraction method and the MCNN model were utilized for classifying tweets into three sentiment classes (positive, neutral, and negative) on the NepCOV19Tweets dataset	Accuracy 71.3% (MCNN)
Saadah et al. (2022)	2022	Indonesian public opinion about COVID-19 vaccination tweets	BERT, IndoBERT, and CNN-LSTM were utilized for classifying COVID-19-related vaccination tweets	Accuracy 80% (IndoBERT)

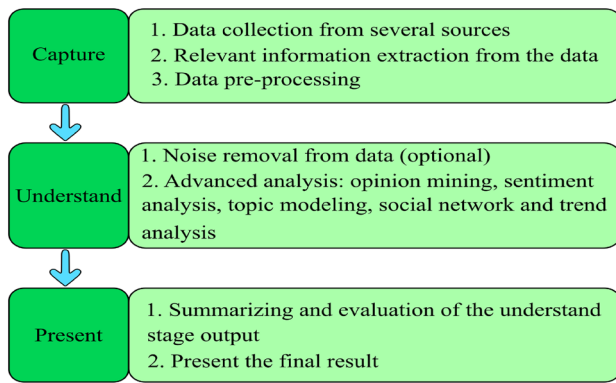


Fig. 5 Flow diagram of social media analytics

impacted by its results, which will greatly assist businesses in making decisions.

Present The findings of various analytics are analyzed, compiled, and presented understandably as the final step. Helpful information can be explained using a variety of visualization methods.

4 Discussion

Social media are an integral part of today's life, and they have too many users all over the world. For example, Facebook, Instagram, and Twitter have 2910, 1487, and 436 million users as of January 2022, respectively (<https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/>). Hence, these platforms provide a vast inexhaustible resource of data, to exploit in different research topics.

On the other hand, such a large amount of information has made it impossible for humans to analyze and review this data, and after that, the broad demand for data analysis in recent years has led to a growth in the quest for automatic systems that can categorize the sentiment analysis, which is the sentiment assigned to a sentence.

Among the topics that have been discussed and trended ubiquitous in social media over the last two years was the COVID-19 pandemic. Coronavirus disease 2019, or in brief, COVID-19, is a contagious disease caused by the SARS-CoV-2 virus. The first recognized case was detected in Wuhan, China, in December 2019 (<https://www.tweetbinder.com/blog/covid-19-coronavirus-twitter/>). The disease spread worldwide so fast, resulting in the COVID-19 pandemic that affected the lives of people worldwide in many aspects. Consequently, as of March 2020, over 628 million tweets were sent or retweeted (<https://www.wsj.com/articles/in-hunt-for-covid-19-origin-patient-zero-points-to-second-wuhan-market-11614335404>). These

facts clearly show the importance and complexity of analyzing tweets related to COVID-19.

In this research study, we reviewed the state-of-the-art BERT and deep CNN models for sentiment analysis of COVID-19 tweets. It is worth noting that recently, CNN and also, recurrent neural network (RNN)-based models are ubiquitous algorithms for sentiment analysis and have been widely implemented in this field of study. However, relying merely on the CNN-based model in sentiment analysis may lead to an extremely low accuracy, which is a result of disregarding semantic associations that exist within the context of the review texts. Therefore, a suitable and efficient alternative for CNN-based models is to use BERT models. BERT implements masked language methods to empower pretrained deep bidirectional language model representations, which decrease the requirement for a wide range of massively engineered context-specific frameworks. Moreover, it is the first finetuning-based representation method that obtains state-of-the-art implementation on many token and sentence-level tasks, which dominates and overcomes various task-specific frameworks.

In the conclusion of this section, the performance of several literature studies on sentiment analysis of COVID-19 tweets using BERT or CNN-based models is shown in Table 2.

The research projects we employed for our study have the limitation of ignoring the effects of worldwide COVID-19 news and data on the general sentiment of some other countries. Also, there are two types of sentiment classification. Positive and negative sentiment is categorized as binary. However, text sentiment can be separated into more than two classifications as multi-class sentiment. As an example, consider three classes whose sentiment is categorized as positive, negative, or neutral. Some of the research projects here include a classification of news headlines into either positive or negative classes as their primary objective (binary). However, there is unquestionably a chance that multi-class sentiment classification may lead to more effective outcomes.

The computational resources required to train, fine-tune, and derive conclusions are the fundamental limitations of employing BERT and other large neural language models. However, more recent studies have suggested many solutions to deal with this problem (Rogers et al. 2020).

Finally, one of the significant limitations in sentiment analysis of messages sent about a specific phenomenon in a social network with many users from all over the world is that moods, opinions, and attitudes toward that topic may be influenced by culture. Different communities' views and beliefs are not well reflected in the messages, resulting in errors in the analysis performance. Furthermore, in a phenomenon such as the COVID-19

Table 2 The performance of several literature studies on sentiment analysis of COVID-19 tweets

Research study	Method	Dataset	Number of samples	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Babu et al. (2009)	Ensemble of CT-BERT, RoBERTa, and SVM	WNUT-2020 Task 2	10,000	n/a	89.24	87.82	88.52
Gencoglu (2020)	SVM + LaBSE embedding	Publicly available COVID-19 tweets between 4 January and 5 Apr (2020)	26,759,164	86.92	n/a	n/a	88.10
Rustam et al. (al. 2021)	Extra Tree Classifier using concatenated features	IEEE data port (on May 31, 2020)	7528	93	90	89	89
Basiri et al. (2021)	Ensemble deep Learning using five base Learners	Stanford Sentiment140	1,600,000	85.8	n/a	n/a	85.8
To et al. (2021)	BERT	Anti-vaccination tweets between 1 January and 23 August (2020)	1,651,687	91.6	93.4	97.6	95.5
Malla and Alphonse (2021)	Majority Voting-based Ensemble Deep Learning(MVEDL)	WNUT-2020 Task 2	10,000	91.75	89.94	93.58	91.14
Glazkova et al. (2021)	g2tmn	COVID-19 Fake News Dataset	10,700	n/a	n/a	n/a	98.69
Hayawi et al. (2022)	BERT	ANTi-Vax	15,073	98	97	98	98

pandemic, fake news or incorrect scientific results can lead to the sending of mass messages on social networks that do not reflect reality, and such challenges are aimed at sentiment analysis.

5 Conclusions and future research directions

Since tweets are written in informal language, they use misspelled words and employ careless grammar. Sentiment analysis involves various natural language processing (NLP) (Martínez-Cámara et al. 2014; Carvalho and Plastino 2021) tasks, including sarcasm detection, aspect extraction, and subjectivity detection. Accordingly, deep convolutional neural network architectures are capable of recognizing binary sentiment in Twitter data, but in comparison with other sentiment classification tasks, they fail to perform nearly as well (Shah et al. 2021; Chaturvedi et al. 2018). With pandemic diseases like COVID-19, which require many resources and equipment types, deep learning models perform better with a more extensive and comprehensive dataset (Hernández-García and König 1806; Pham et al. 2021). Therefore, it is necessary to conduct further research to generate and share a complete

dataset for research purposes. This paper determined ways to improve future research. Most of the research is limited to English-language text, which was considered a selection criterion. Therefore, the results do not reflect comments made in other languages, such as Persian language or another one. In addition, much of the research was limited to the remarks retrieved in short timelines. Consequently, the period between the completion of the research and the subsequent studies may have affected the timeliness of the results. So, the other directory should be related to different languages' text as a selection criterion. A new sentiment analysis model using BERT and deep CNN can be developed by researchers. Based on a sentiment dictionary inserted into the word vector of some models, recurrent neural networks can extract forward and reverse contextual information (Sachin et al. 2020). Therefore, BiLSTM might be able to emphasize different words in a text more or less by adding an attention mechanism to its output. There is also the possibility of using a high-quality and lightweight BERT model to perform downstream tasks.

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limitations and contributions of the study. The final version of the paper has been edited by JHJ, SH, MAN, RB, RA, and AT. RB supervised the project, and RL co-supervised the study. All authors have read and approved the final manuscript.

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Declarations

Conflict of interest The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

References

- Abdelminaam DS, Ismail FH, Taha M, Taha A, Houssein EH, Nabil A (2021) Coaid-deep: an optimized intelligent framework for automated detecting covid-19 misleading information on twitter. *IEEE Access* 9:27840–27867
- Anand S et al. (2019) Suggestion mining from online reviews using ulmfit, *arXiv preprint arXiv:1904.09076*
- Babu YP, Eswari R (2020) CIA_NITT at WNUT-2020 task 2: classification of COVID-19 tweets using pre-trained language models, *arXiv preprint arXiv:2009.05782*
- Bansal V, Tyagi M, Sharma R, Gupta V, Xin Q (2022) A transformer based approach for abuse detection in code mixed indic languages. In: *ACM transactions on Asian and low-resource language information processing*
- Basiri ME, Nemati S, Abdar M, Asadi S, Acharrya UR (2021) A novel fusion-based deep learning model for sentiment analysis of COVID-19 tweets. *Knowl-Based Syst* 228:107242
- Baziotis C, Pelekis N, Doukeridis C (2017) Datastories at semeval-2017 task 4: Deep lstm with attention for message-level and topic-based sentiment analysis. In: *Proceedings of the 11th international workshop on semantic evaluation (SemEval-2017)*, pp 747–754
- Biswas E, Karabulut ME, Pollock L, Vijay-Shanker K (2020) Achieving reliable sentiment analysis in the software engineering domain using bert. In: *2020 IEEE international conference on software maintenance and evolution (ICSME)*, IEEE, pp 162–173
- Carvalho J, Plastino A (2021) On the evaluation and combination of state-of-the-art features in Twitter sentiment analysis. *Artif Intell Rev* 54(3):1887–1936
- Chakraborty K, Bhatia S, Bhattacharyya S, Platos J, Bag R, Hassanien AE (2020) Sentiment analysis of COVID-19 tweets by deep learning classifiers—a study to show how popularity is affecting accuracy in social media. *Appl Soft Comput* 97:106754
- Chandra R, Krishna A (2021) COVID-19 sentiment analysis via deep learning during the rise of novel cases. *PLoS ONE* 16(8):e0255615
- Chatsiou K (2020) Text classification of COVID-19 press briefings using BERT and convolutional neural networks
- Chaturvedi I, Cambria E, Welsch RE, Herrera F (2018) Distinguishing between facts and opinions for sentiment analysis: Survey and challenges. *Inf Fusion* 44:65–77
- Chen N, Zhong Z, Pang J (2021) An exploratory study of COVID-19 information on twitter in the greater region. *Big Data Cogn Comput* 5(1):5
- Chintalapudi N, Battineni G, Amenta F (2021) Sentimental analysis of COVID-19 tweets using deep learning models. *Infect Dis Rep* 13(2):329–339
- D’Andrea E, Ducange P, Bechini A, Renda A, Marcelloni F (2019) Monitoring the public opinion about the vaccination topic from tweets analysis. *Expert Syst Appl* 116:209–226
- Dai Z, Yang Z, Yang Y, Carbonell J, Le QV, Salakhutdinov R (2019) Transformer-xl: Attentive language models beyond a fixed-length context, *arXiv preprint arXiv:1901.02860*
- de Heras-Pedrose CL, Sánchez-Núñez P, Peláez JI (2020) Sentiment analysis and emotion understanding during the COVID-19 pandemic in Spain and its impact on digital ecosystems. *Int J Environ* 17(15):5542
- Devlin J, Chang M-W, Lee K, Toutanova K (2018) Bert: pre-training of deep bidirectional transformers for language understanding, *arXiv preprint arXiv:1810.04805*
- Dhingra S, Arora R, Katariya P, Kumar A, Gupta V, Jain N (2021) Understanding emotional health sustainability amidst COVID-19 imposed lockdown. In: *Sustainability measures for COVID-19 Pandemic*, pp 211–235
- Feng X, Liu X (2019) Sentiment classification of reviews based on BiGRU neural network and fine-grained attention. In: *Journal of Physics: Conference Series*, vol 1229, no 1: IOP Publishing, p 012064
- Garcia K, Berton L (2021) Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA. *Appl Soft Comput* 101:107057
- Gencoglu O (2020) Large-scale, language-agnostic discourse classification of tweets during COVID-19. *Mach Learn Knowl Extr* 2(4):603–616
- Glazkova A, Glazkov M, Trifonov T (2021) g2tmm at constraint@aaai2021: exploiting CT-BERT and ensembling learning for COVID-19 fake news detection. *International Workshop on Combating On line Ho st ile Posts in Regional Languages during Emerg ncy Si tuation*. Springer, Berlin, pp 116–127
- Gupta V et al (2021a) An emotion care model using multimodal textual analysis on COVID-19. *Chaos Solitons Fractals* 144:110708
- Gupta V, Dass P, Arora R (2022) Pendulating or resonating? a case of echo-chambers in twitter. *J Discrete Math Sci Cryptogr* 25(1):231–240
- Gupta V, Jain N, Shubham S, Madan A, Chaudhary A, Xin Q (2021b) Toward integrated cnn-based sentiment analysis of tweets for scarce-resource language—Hindi. *Trans Asian Low-Resource Lang Inf Process* 20(5):1–23
- Gupta V, Singh VK, Mukhija P, Ghose U (2019) Aspect-based sentiment analysis of mobile reviews. *J Intell Fuzzy Syst* 36(5):4721–4730
- Hayawi K, Shahriar S, Serhani MA, Taleb I, Mathew SS (2022) ANTi-Vax: a novel Twitter dataset for COVID-19 vaccine misinformation detection. *Public Health* 203:23–30
- Hernández-García A, König P (2018) Data augmentation instead of explicit regularization, *arXiv preprint arXiv:1806.03852*
- Hossain T, Logan IV RL, Ugarte A, Matsubara Y, Young S, Singh S (2020) COVIDLies: detecting COVID-19 misinformation on social media
- Houlsby N et al. (2019) Parameter-efficient transfer learning for NLP. In: *International conference on machine learning: PMLR*, pp 2790–2799
- Hutto C, Gilbert E (2014) Vader: a parsimonious rule-based model for sentiment analysis of social media text. *Proc Int AAAI Conf Web Soc Media* 8(1):216–225
- Jalil Z et al (2020) A novel benchmark dataset for COVID-19 detection during third wave in Pakistan. *Comput Intell Neurosci* 2022:25741
- Jalil Z et al (2021) Covid-19 related sentiment analysis using state-of-the-art machine learning and deep learning techniques. *Public Health Front* 9:4158
- Jelodar H, Wang Y, Orji R, Huang S (2020) Deep sentiment classification and topic discovery on novel coronavirus or COVID-19

- online discussions: NLP using LSTM recurrent neural network approach. *IEEE J Biomed Health Inform* 24(10):2733–2742
- Jiang H, He P, Chen W, Liu X, Gao J, Zhao T (2019) Smart: Robust and efficient fine-tuning for pre-trained natural language models through principled regularized optimization. *arXiv preprint arXiv:1911.03437*
- Kabir MY, Madria S (2021) EMOCOV: machine learning for emotion detection, analysis and visualization using COVID-19 tweets. *Online Soc Netw Media* 23:100135
- Kairon P, Bhattacharyya S (2021) COVID-19 outbreak prediction using quantum neural networks. In: *Intelligence enabled research*: Springer, pp 113–123
- Kruspe A, Häberle M, Kuhn I, Zhu XX (2020) Cross-language sentiment analysis of european twitter messages during the covid-19 pandemic. *arXiv preprint arXiv:2008.12172*
- Lan Z, Chen M, Goodman S, Gimpel K, Sharma P, Soricut R (2019) Albert: a lite bert for self-supervised learning of language representations. *arXiv preprint arXiv:1909.11942*
- Lee J et al (2020) BioBERT: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics* 36(4):1234–1240
- Ling J (2020) Coronavirus public sentiment analysis with BERT deep learning. Springer, Berlin
- Liu Y et al. (2019) Roberta: a robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*
- Malla S, Alphonse P (2021) COVID-19 outbreak: an ensemble pre-trained deep learning model for detecting informative tweets. *Appl Soft Comput* 107:107495
- Martínez-Cámara E, Martín-Valdivia MT, Urena-López LA, Montejoráez AR (2014) Sentiment analysis in Twitter. *Nat Lang Eng* 20(1):1–28
- Mehmood M, Rizwan M, Abbas S (2021) Machine learning assisted cervical cancer detection. *Public Health Front* 2:2024
- Munikaar M, Shakya S, Shrestha A (2019) Fine-grained sentiment classification using BERT. In: *2019 artificial intelligence for transforming business and society (AITB)*, vol 1: IEEE, pp 1–5
- Müller M, Salathé M, Kummervold PE (2020) Covid-twitter-bert: A natural language processing model to analyse covid-19 content on twitter. *arXiv preprint arXiv:2005.07503*
- Nair AJ, Veena G, Vinayak A (2021) Comparative study of twitter sentiment on covid-19 tweets. In: *2021 5th international conference on computing methodologies and communication (ICCMC)*, IEEE, pp 1773–1778
- Naseem U, Razzak I, Khushi M, Eklund PW, Kim J (2021) COVID-Senti: a large-scale benchmark Twitter data set for COVID-19 sentiment analysis. *IEEE Trans Comput Soc Syst* 8(4):1003–1015
- Nguyen DQ, Vu T, Nguyen AT (2020) BERTweet: a pre-trained language model for English Tweets. *arXiv preprint arXiv:2005.10200*
- Pham HT, Rafieizonooz M, Han S, Lee D-E (2021) Current status and future directions of deep learning applications for safety management in construction. *Sustainability* 13(24):13579
- Pokharel BP (2020) Twitter sentiment analysis during covid-19 outbreak in nepal. Available at SSRN 3624719
- Pota M, Esposito M, Palomino MA, Masala GL (2018) A subword-based deep learning approach for sentiment analysis of political tweets. In: *2018 32nd international conference on advanced information networking and applications workshops (WAINA)*, IEEE, pp 651–656
- Radford A, Narasimhan K, Salimans T, Sutskever I (2018) Improving language understanding by generative pre-training. Springer, Berlin
- Radford A, Wu J, Child R, Luan D, Amodei D, Sutskever I (2019) Language models are unsupervised multitask learners. *OpenAI Blog* 1(8):9
- Rogers A, Kovaleva O, Rumshisky A (2020) A primer in bertology: What we know about how bert works. *Trans Assoc Comput Linguist* 8:842–866
- Rustam F, Khalid M, Aslam W, Rupapara V, Mehmood A, Choi GS (2021) A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis. *PLoS ONE* 16(2):e0245909
- Saadah S, Auditama KM, Fattahila AA, Amorokhman FI, Aditsania A, Rohmawati AA (2022) Implementation of BERT, IndoBERT, and CNN-LSTM in Classifying Public Opinion about COVID-19 Vaccine in Indonesia. *Jurnal RESTI (rekayasa Sistem Dan Teknologi Informasi)* 6(4):648–655
- Sachin S, Tripathi A, Mahajan N, Aggarwal S, Nagrath P (2020) Sentiment analysis using gated recurrent neural networks. *SN Comput Sci* 1(2):1–13
- Sadia K, Basak S (2021b) Sentiment analysis of COVID-19 tweets: how does BERT perform? In: *Proceedings of international joint conference on advances in computational intelligence*, Springer, pp 407–416
- Shah AM, Yan X, Tariq S, Khan S (2021) Listening to the patient voice: using a sentic computing model to evaluate physicians' healthcare service quality for strategic planning in hospitals. *Qual Quant* 55(1):173–201
- Shahi T, Sitaula C, Paudel N (2022) A hybrid feature extraction method for Nepali COVID-19-related tweets classification. *Comput Intell Neurosci* 2022:552
- Shawe-Taylor J, Cristianini N (2000) An introduction to support vector machines and other kernel-based learning methods
- Sitaula C, Basnet A, Mainali A, Shahi TB (2021) Deep learning-based methods for sentiment analysis on Nepali covid-19-related tweets. *Comput Intell Neurosci* 2021:85
- Sitaula C, Shahi TB (2022) Multi-channel CNN to classify nepali covid-19 related tweets using hybrid features. *arXiv preprint arXiv:2203.10286*
- Song X, Petrak J, Jiang Y, Singh I, Maynard D, Bontcheva K (2021) Classification aware neural topic model for COVID-19 disinformation categorisation. *PLoS ONE* 16(2):e0247086
- Song Y, Wang J, Liang Z, Liu Z, Jiang T (2020) Utilizing BERT intermediate layers for aspect based sentiment analysis and natural language inference. *arXiv preprint arXiv:2002.04815*
- Sun C, Qiu X, Xu Y, Huang X (2019) How to fine-tune bert for text classification? *China national conference on Chinese computational linguistics*. Springer, Berlin, pp 194–206
- To QG et al (2021) Applying machine learning to identify anti-vaccination tweets during the COVID-19 pandemic. *Int J Environ Res Public Health* 18(8):4069
- Tziafas G, Kogkalidis K, Caselli T (2021) Fighting the COVID-19 infodemic with a holistic BERT ensemble. *arXiv preprint arXiv:2104.05745*
- Valdes A, Lopez J, Montes M (2021) UACH-INAOE at SMM4H: a BERT based approach for classification of COVID-19 Twitter posts. In: *Proceedings of the sixth social media mining for health (#SMM4H) Workshop and Shared Task*, pp 65–68
- Vishwamitra N, Hu RR, Luo F, Cheng L, Costello M, Yang Y (2020) On analyzing covid-19-related hate speech using bert attention. In: *2020 19th IEEE international conference on machine learning and applications (ICMLA)*, IEEE, pp 669–676
- Yang Z, Dai Z, Yang Y, Carbonell J, Salakhutdinov RR, Le QV (2019) Xlnet: generalized autoregressive pretraining for language understanding. In: *Advances in neural information processing systems*, vol 32
- Zhang Y, Lyu H, Liu Y, Zhang X, Wang Y, Luo J (2020) Monitoring depression trend on Twitter during the COVID-19 pandemic. *arXiv preprint arXiv:2007.00228*

Zhou J, Yang S, Xiao C, Chen F (2021) Examination of community sentiment dynamics due to COVID-19 pandemic: a case study from a state in Australia. *SN Comput Sci* 2:1–11

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