A Comprehensive Review of Twitter-Based Sentiment Analysis During the COVID-19 Pandemic

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ABSTRACT

The COVID-19 pandemic is the catalyst that led to the greatest activity on social media, making Twitter an important source of information about the opinion of the masses, emotional reactions and the trends in behavior under the influence of the global crisis. With over 500 million tweets being posted every day, during the most critical stages of the pandemic, researchers had access to new corpuses of real-world sentiment information never before. Lexicon-based, machine learning, deep learning, and transformer-based methods have been applied in the past to analyze COVID- 19-related tweets in locations and languages. The paper provides a systematic review that synthesizes the data collection processes, pre-processing pipelines, sentiment classification processes, nation-specific sentiment trends, emotion and topic modelling insights, model performance comparisons, research limitations, and research gaps in Twitter-based COVID-19 sentiment analysis. Our review of over 30 peer-reviewed papers shows that transformer models, and more so BERT variants are never worse than traditional methods, and it has still much to offer in terms of multi-lingual analysis, real-time tracking, and epidemiological integration. The article is a well-structured information reservoir of the researchers and practitioners who intend to work on the domain of crisis-based social media analytics.

Keywords: Sentiment Analysis, Twitter, COVID-19, NLP, Machine Learning, Deep Learning, Transformers, BERT, Emotion Detection, Topic Modeling, Social Media Analytics

I. INTRODUCTION

The World Health Organization (WHO) has officially declared the COVID-19 pandemic a global health crisis in March 2020 and essentially altered the human pattern of communication and created a wave of social media usage never seen before.

Sentiment analysis, the computational identification of subjective opinions, attitudes and emotions in the text, sentiment analysis, has a long history in Natural Language Processing (NLP). However, the COVID-19 crisis has put everyone into a high-stakes game where there is a need to adopt new methodological strategies human-Nonetheless, the situation created by the COVID-19 crisis presented the pace, volume, and emotional depth of the general conversation at a high level that demanded new methodological approaches. The deficiency of traditional opinion mining through surveys like delays, geographic and sampling bias were put to the test when a crisis which required real time decision support arose.

The reaction of scientists worldwide was to create and apply diverse computational techniques to the COVID-19 Twitter data. These included rule-based lexicon systems like VADER and TextBlob.

The number of separate studies notwithstanding, the synthesis of all studies is needed to discover convergent results, the best practices in methods and the unsolved problems. The rationale behind the development of this review is the need to bring evidence on the topic together in a systematic fashion, the study including over 30 studies across continents, languages, and paradigms of analysis. The remainder of this paper is organized in the following way: Section 1.3 Data, describes data collection and methodology to process the data; Section 1.4 Techniques, reviews classification techniques; Section 1.5 Trends, analyzes sentiment country-level trends; Section 1.6 Emotion, analyzes emotion; Section 1.7 Topics, analyzes topic modeling; Section 1.8 Comparison, compares model performance.

II. DATA COLLECTION AND PREPROCESSING

A. *Data Collection Platforms and Tools*

COVID-19 sentiment Twitter data were gathered mainly through the Twitter Streaming API, Twitter Academic Research API (v2), Tweepy (Python wrapper), RTweet (R package) and third-party tools like RapidMiner [2]. Data collection tool was of great importance in determining the scope of the dataset and reproducibility. In 2021, Twitter Aca- demic API was freely available to researchers and made the entire archive of tweets openly accessible to researchers, allowing them to create longitudinal datasets covering the entire pandemic [16].

The most common collection strategy as keyword-based filtering, and queries were constituted based on the keywords such as #COVID19, #coronavirus, #lockdown, and #vaccine and other similar phrases in several

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languages [18]. Other studies added geolocation limits to keyword filters and limited data to countries or cities to allow analysis of a particular region[12], [17]. The sizes of datasets differed significantly, a few thousand tweets used in narrow, single-country analyses [5], and tens of millions in broad, cross-country corpus [4].

B. Dataset Characteristics

Table I is a summary of the notable datasets used in studies reviewed. The temporal coverage, language scope, and annotation methodology is a heterogeneous field, as the research landscape is diverse.

TABLE I
SUMMARY OF THE NOTABLE DATASETS USED IN STUDIES REVIEWED

Study	Dataset Size	Language
Naseem et al. [4]	90,000+	English
Manguri et al. [2]	10,500	English
Gupta et al. [17]	24,000+	English
Kruspe et al. [18]	1.6M+	Multilingual
Boon-Itt et al. [6]	1,200	English
Lyu et al. [16]	300,000+	English
Samaras et al. [15]	500,000+	Greek/Eng.

C. Preprocessing Pipeline

Raw Twitter data preprocessing is a very crucial and labor-intensive step that directly affects model performance. General preprocessing measures used in studies are:

Noise elimination: Removal of URLs, HTML tags, user mentions +handles and prefix retweet (RT).

Normalization: Reduction, the use of contraction, and Unicode characters and emojis.

Tokenization: Division of text into word or subword level tokens suitable to the model.

Stopword removal: Removal of high-frequency and low- information words based on language-specific stop lists.

Morphological normalization: Lemmatization (preferred with semantic tasks) or stemming.

Language detection and filtering: Keeping only target-language tweets with the help of such tools as langdetect or the lang field of Twitter.

Removal of duplicates and near-duplicates: This will remove retweets and near-similar posts to prevent data leakage.

More sophisticated preprocessing measures were also reported in a part of the studies like bot detection with Botometer [13], spam filtering, n- gram and Part of Speech (POS) tag extraction to perform feature engineering [11] and geolocation inference based on user profile and twit metadata [17]. Interestingly, the processing of emojis and emoticons turned out to be a nontrivial task due to the large rates of their use in tweets during the pandemic time to convey the emotional subtleties[7]

III. SENTIMENT CLASSIFICATION TECHNIQUES

Sentiment analysis methods applied to COVID-19 Twitter data can be broadly organized into four paradigms: lexicon-based, classical machine learning, deep learning, and transformer-based models. Each paradigm carries distinct trade-offs in accuracy, computational cost, interpretability, and suitability for real-time deployment.

A. Lexicon-Based Approaches

Lexicon-based approaches use matches between tokens and a set of sentiment dictionaries to assign sentiment polarity. They do not need any labeled training data and can be deployed immediately, which is appealing to real-time monitoring [9]. Key tools applied in Covid-19 research include:

VADER (Valence Aware Dictionary and sEntiment Reasoner): Particularly social media text aware; slang, capitalization, emphasis on punctuation, and. Emoticons [9]

TextBlob: A simple API to the polarity and subjectivity scoring on a pattern-based lexicon; commonly used as a baseline [2].

NRC Emotion Lexicon: Categorizes words based on eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust) along with binary polarity, making it possible to perform fine-grained emotion analysis [13].

SentiStrength: Predicts the intensity of positive and negative sentiment, useful for capturing mixed emotional states[7]

Although they are computationally efficient, the lexicon-based approaches are still inferior to supervised methods with respect to COVID-19 datasets. Their principal weaknesses include in- ability to detect sarcasm and irony, poor handling of domain- specific vocabulary (e.g., “virus spreading” being incorrectly scored positively), and limited multilingual support [18].

B. Classical Machine Learning Models

Supervised machine learning classifiers trained on manually labeled COVID-19 tweets demonstrated substantially higher performance than lexicon tools. Standard feature representations included Bag-of-Words (BoW), Term Frequency–Inverse Document Frequency (TF-IDF), and Word2Vec embeddings [20].

Support Vector Machines (SVM) consistently achieved the highest accuracy among classical models, with Machuca et al. [20] reporting 97.67% accuracy on a Twitter COVID- 19 dataset using a linear SVM kernel with TF-IDF features. SVM’s strong performance on high-dimensional sparse text data is well-documented in the NLP literature and was con- firmed across multiple

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COVID-19 studies [14], [22].

Naive Bayes classifiers, despite their simplifying independence assumption, achieved competitive accuracy (typically 75–85%) and remained popular due to their low training cost and interpretability [14].

Logistic Regression and **Random Forest** were also widely applied, often as ensemble baselines against which deeper models were benchmarked [21].

LinearSVC achieved 84.4% accuracy on balanced COVID-19 datasets [10].

C. Deep Learning Models

Deep learning architectures introduced the capacity to capture sequential and contextual semantic patterns in tweet text without manual feature engineering. The following architectures were prominent in reviewed studies:

Convolutional Neural Networks (CNN): Applied to text classification via 1-D convolutions over word embeddings, CNNs captured local n-gram features effectively and served as strong baselines [8].

Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM): These recurrent architectures explicitly model sequential dependencies in text. Bi-LSTM, which processes sequences in both forward and backward directions, captured richer contextual information than unidirectional LSTM and was applied by Sunitha et al. [19] in an ensemble configuration achieving over 95% accuracy on Indian and European COVID-19 datasets.

Gated Recurrent Units (GRU): GRU networks offer a computationally lighter alternative to LSTM with comparable performance. Hybrid GRU–CapsNet (Capsule Network) architectures, which combine sequential modeling with dynamic routing for relational feature capture, achieved the highest deep learning performance in the surveyed literature, reporting 95–97% accuracy [19].

Attention Mechanisms: Self-attention layers were incorporated into several architectures to allow models to weight the importance of individual tokens relative to the classification task, improving performance on longer tweets [24].

D. Transformer-Based Models

Transformer architecture, introduced by Vaswani et al (2017) and operationalized through large pre-trained models, represent the current state of the art for NLP tasks including sentiment analysis. Their ability to capture bidirectional long- range context via self-attention makes them particularly suited to the ambiguous, informal, and context-dependent language of Twitter[4].

BERT (Bidirectional Encoder Representations from Transformers): The most widely applied transformer in re- viewed studies. BERT fine-tuned on COVID-19 tweet corpora substantially outperformed all classical and deep learning baselines, particularly on nuanced multi-class sentiment tasks [4], [15].

RoBERTa and BERTweet: RoBERTa, a robustly optimized BERT variant, and BERTweet, pre-trained specifically on 850 million English tweets, demonstrated superior performance on informal social media text relative to standard BERT [23].

DistilBERT: A distilled, lighter version of BERT retaining approximately 97% of BERT's accuracy at 60% of its size, which enables faster inference suitable for near-real-time applications [15].

XLNet and ELECTRA(ElecBERT): XLNet (permutation based) autoregressive training represented richer contextual dependencies, and ELECTRA (discriminative pre-training) on replaced token detection generated efficient representations. ElecBERT had an accuracy of 92-94% on COVID-19 sentiment benchmarks[4].

Domain-Adapted Models: COVID-Twitter-BERT (CT-BERT), which was pre-trained on 160 million tweets related to COVID-19, found that domain-adaptive pre-training leads to significant improvements in downstream sentiment and intent classification performance over generic BERT[4].

IV. SENTIMENT TRENDS ACROSS COUNTRIES

A. Global Trends

In all the considered studies, the neutral sentiment was the most prevalent in the COVID-19 Twitter corpora, with 4060% of the tweets in most datasets being neutral [6]. This observation is indicative of the high number of informational tweets with pure information giving news updates, statistics and health care advice with no detectable emotional coloring. The most noticeable positive sentiment was in the initial period of the pandemic (January-March 2020), when most people shared the sentiment of community solidarity, appreciation of healthcare workers, and hope that the measures to contain the disease will work [1], [5]. The negativity shot to the heavens whenever lockdowns were announced, infections waves were high, and political scandals of high profile involving the pandemic management [17].

B. Country-Specific Findings

Table II summarizes country-specific sentiment findings from reviewed studies, illustrating the considerable

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variation driven by local political, cultural, and epidemiological con- texts.

TABLE II
COUNTRY-SPECIFIC SENTIMENT FINDINGS IN COVID-19 TWITTER STUDIES

Country	Dominant Sentiment	Key Finding
India	Negative/Mixed	Negative spikes during lockdown; fear dominant [17]
Nepal	Positive/Neutral	Solidarity and awareness tweets dominated early phase [5]
Iran	Negative	Strong vaccine hesitancy; distrust of government [3]
Philippines	Mixed	Vaccine acceptance sentiments tracked policy shifts [14]
Canada	Negative	Social distancing resistance correlated with non-compliance [12]
Europe (Multi)	Mixed	Cross-language analysis revealed shared fear but divergent trust [18]

India: Gupta et al. [17] examined more than 24, 000 tweets in the national lockdown of India, and discovered a significant rise in negative sentiment, which is linked to economic anxiety and mobility constraints. Government relief measures and appreciation of healthcare workers were positively correlated with the positive sentiment. The study of India-Europe ensemble by Sunitha et al. [19] was yet another confirmation of the fact that Indian Twitter discourse surrounding COVID-19 was more emotional volatile than European.

Iran: Nezhad and Deihimi [3] specifically studied the tweets on vaccines in Iran, and the majority of the posts were negative due to lack of trust in the safety of the vaccines and governmental communication. This research paper has pointed out the interplay between political environment and civil health feeling.

Multilingual Europe: Kruspe et al. [18] conducted cross- language sentiment analysis on 13 European nations, and found out that there was a consistent elevation of fear, but the level of trust on governments and health authorities had significant differences, with the northern European countries having higher trust than. southern and eastern European counterparts.

V. EMOTION ANALYSIS

In addition to binary or ternary classification of polarity, a growing body of COVID-19 Twitter studies embraced multi- dimensional emotion detection models. The NRC Emotion Lexicon, a wheel of emotions by Plutchik, and custom annotated corpora helped the researchers to discover a broader range of affective states [13].

Table III summarizes the dominant emotions identified across reviewed studies.

TABLE III
DOMINANT EMOTIONS IDENTIFIED IN COVID-19 TWITTER STUDIES

Emotion	Prevalence	Primary Cause
Fear	Very High	Rising cases, uncertainty, mortality
Trust	Moderate	Government and healthcare updates
Anticipation	Moderate	Vaccine development, policy changes
Sadness	High	Deaths, unemployment, isolation
Anger	Moderate	Political disputes, misinformation
Joy	Low–Moderate	Support for healthcare workers
Disgust	Low	Perceived policy failures, negligence
Surprise	Low	Sudden lockdowns, variant emergence

The most prevalent negative emotion was consistently fear, which was the highest at the time of initial outbreak announcements and new variants waves [17]. Bhat et al. [13] discovered that fear-related tweets greatly anticipated spikes in the number of local cases in certain areas, which indicated the possibility of using emotion-based social media monitoring as an early-warning system. Trust had time-dependent dynamics associated with policy events: trust rose after the government announced the availability of vaccines and fell after adverse events or inconsistencies in policies were reported [3]. Lyu et al. [16] determined that Twitter discussion around vaccines went through highs and lows based on clinical trial outcomes and regulatory clearances being announced. The focus of anger was on political stories, and peaks are seen during election campaigns, leadership scandals, and perceived governmental failures in testing and resource distribution to the healthcare sector [15], [17].

VI. TOPIC MODELING INSIGHTS

A. Latent Dirichlet Allocation (LDA)

Unsupervised topic modeling, primarily through Latent Dirichlet Allocation (LDA), was employed in several studies to identify latent thematic structures in COVID-19 tweet corpora without relying on predefined categories [6], [16]. LDA models the corpus as a mixture of topics, each characterized by a probability distribution over vocabulary terms. The optimal number of topics was determined using coherence scores or perplexity measures across studies.

Table IV presents the major topics identified across re- viewed LDA-based studies.

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TABLE IV
MAJOR TOPICS IDENTIFIED USING LDA IN COVID-19 TWITTER CORPORA

Topic	Description and Representative Terms
Outbreak Severity	Case counts, deaths, hospitalization, spread, variants
Government Policies	Lockdowns, curfews, travel bans, stimulus packages
Public Awareness	Masks, hand hygiene, social distancing, guidelines
Vaccine Discussion	Safety, efficacy, side effects, rollout, hesitancy
Political Narrative	Elections, leadership criticism, partisan debate
Global Coordination	WHO, international aid, cross-border collaboration
Mental Health	Anxiety, depression, isolation, wellbeing resources
Economic Impact	Job loss, business closure, financial support

B. Vaccine Discourse Analysis

Lyu et al. [16] conducted a dedicated topic modeling and sentiment analysis of COVID-19 vaccine-related Twitter discussions, identifying six primary sub-topics: vaccine development, clinical trials, regulatory approval, distribution logistics, public trust, and misinformation. Their analysis revealed that sentiment within vaccine discourse was strongly polarized, with positive clusters centered on efficacy and scientific achievement and negative clusters focused on side effects and governmental coercion. A temporal shift toward more positive vaccine sentiment was observed as vaccine deployment scaled globally.

C. Misinformation and Political Topics

Several works found politically charged and misinformation related issues to be prominent aspects of Twitter COVID-19 discussions [13], [24]. Conspiracy theories, alternative medicine, and election-associated posts and stories always yielded more engagement (retweets, likes) than factual posts on the subject of public health, which underscores the difficulty of organic quality of information on social media.

VII. Comparative Analysis of Models

Figure 1 shows a comprehensive performance comparison of sentiment analysis models across reviewed studies, organized by methodological category.

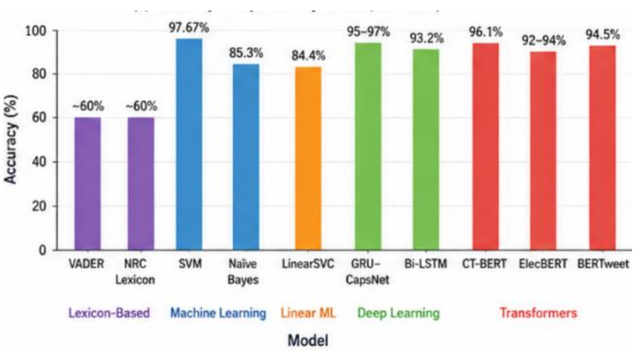

Fig. 1. Accuracy comparison of different models

There are some notable things which come out through this comparison. To begin with, there is a significant difference in task framing: binary (positive/negative) classification demonstrates greater accuracy rates as compared to three-class (positive/neutral/negative) or multi-class emotion classification. The 97.67% SVM outcome of Machuca et al. [20] was obtained on a binary task, but transformer models generally deal with more complicated multi-class models. Second, domain-adapted transformers (CT-BERT, BERTweet) are always more effective than generic BERT on COVID- 19 Twitter data, which highlights the significance of pre-training domain alignment. Third, GRU-based deep learning models are competitive with smaller transformers at a fraction of the computational cost and are applicable to resource-constrained deployment conditions.

VII. RESEARCH GAPS

The literature review synthesis helps us to determine the following critical research gaps that further inquiry should follow:

a. **Multilingual and Low-Resource Sentiment Analysis:** There is an urgent necessity to have models that can analyze the sentiment of COVID-19 in languages with limited annotated data, such as Arabic, Hindi, Swahili, and Bengali [18].
b. **Sarcasm and Figurative Language Detection:** Dedicated modules for sarcasm, irony, and metaphor detection integrated into sentiment pipelines remain underdeveloped for pandemic discourse [24].
c. **Real-Time Monitoring Infrastructure:** Production-scale, low-latency sentiment monitoring systems which may be used as decision-supports to the public health authorities are not extensively discussed in the literature[7].
d. **Epidemiological Data Integration:** The literature on which Twitter sentiment time series are connected with epidemiological indicators (case counts, hospitalizations, vaccination rates) is limited and methodologically immature [13].
e. **Cross-Domain Transformer Adaptation:** Investigating transfer learning from COVID-19 models to other crisis contexts (natural disasters, conflict, disease outbreaks) is an underexplored area [4].
f. **Longitudinal and Causal Analysis:** Establishing causal relationships between social media sentiment and behavioral outcomes (compliance, vaccination uptake) re- quires longitudinal study designs that most reviewed work does not employ [12].
g. **Multi-Platform Analysis:** Restricting analysis to Twit- ter ignores the substantial COVID-19 discourse occur- ring on Reddit, Facebook, WhatsApp, and YouTube, each with distinct demographic and linguistic profiles [21].

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VIII. Future Directions

Based on identified gaps, we propose the following future research directions:

Cross-Lingual Transformer Models: Deploying multi-lingual pre-trained models such as mBERT, XLM-R, and mDeBERTa for zero-shot and few-shot COVID-19 sentiment analysis across low-resource languages represents a high- priority direction. Domain-adaptive pre-training on multilingual COVID-19 corpora would further enhance performance [18].

Hybrid Architectures: Combining the sequential modeling strength of recurrent networks with the contextual represen- tation power of transformers through architectures such as BERT-BiLSTM or transformer-GRU hybrids may yield further accuracy improvements over pure transformer baselines [19].

Explainable AI (XAI) Integration: Adding explanatory models, including LIME, SHAP, or attention visualization, to sentiment models will enhance interpretability and establish confidence among the health practitioners in the society [4].

Real-Time Sentiment Dashboards: Near-real-time monitoring of the public sentiment during health emergencies could be supported through the construction of streaming pipelines using Apache Kafka and Spark streaming alongside fine-tuned lightweight transformers (DistilBERT, MobileBERT) [15].

Misinformation-Aware Sentiment Analysis: Training models that are jointly sensitive to sentiment and veracity-Jointly training sentiment and misinformation-flagging models may provide more practical information about how to govern the platform and communicate health information to the public [13].

Integration with Epidemiological Models: Time-series combination of Twitter sentiment signals and compartmental epi- demiological models (SIR, SEIR) can enhance the predictive power of both behavioral and disease transmission predictions [17].

IX. Conclusion

The review has reviewed systematically more than 30 studies on twitter-based COVID-19 sentiment analysis, including lexicon-based tools, classical machine learning, deep learning architecture, and transformer models at the state-of-the-art in various countries and languages. A number of strong conclusions can be drawn out of this synthesis.

First, transformer-based models, especially domain-adapted models like CT-BERT and BERTweet, are both at the top of the scoreboard on COVID-19 Twitter sentiment benchmarks, and outperform both traditional machine learning and standard deep learning models. Second, the sentiment analysis of the COVID-19 Twitter revealed a preponderance of the neutral and fear-based content, and temporal trends followed the pandemic-related milestones, including lockdowns, waves of infections, and vaccinations. Third, there is considerable cross-national difference in sentiment by showing the influence of political context, cultural norms and trust in healthcare systems on the formation of public discourse. Although significant methodological advances have been made, multilingual coverage, sarcasm management, real-time implementation, and integration with epidemiological information have critical gaps. It will be necessary to fill these gaps by adopting the opportunities of the future, as proposed in this review, to make the full potential of Twitter-based sentiment analysis as a tool of public health decision-support become a reality. As outbreaks of infectious diseases are increasingly becoming a more common aspect of the global health policy, scalable, multilingual, and robust social media sentiment analysis will continue to be an irreplaceable part of crisis monitoring and prevention systems.

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