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SURVEY

Sentiment Analysis of Public Social Media as a Tool for Health-Related Topics

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ABSTRACT For decades, researchers have experimented with the possibility that machines can equal human linguistic capabilities. Recently, advances in the field of natural language processing (NLP) as well as a substantial increase in available naturally occurring linguistic data on social media platforms have made more advanced methodologies such as sentiment analysis (SA) gain substantial momentum on contemporary applications. This document compiles what the authors consider to be some of the most important concepts related to SA, as well as techniques and processes necessary for the various stages of its implementation. Furthermore, specific applications related to the extraction and classification of social media data using novel SA techniques are presented and quantified, with an emphasis on those used for the identification of mental health degradation during the COVID-19 pandemic. Finally, the authors present several conclusions highlighting the most prominent benefits and drawbacks of the methods discussed, followed by a brief discussion of possible future applications of certain methods of interest.

INDEX TERMS COVID-19, literature review, public social media, sentiment analysis.

I. INTRODUCTION

Ever since the inception of machine intelligence when Alan Turing devised the Turing Test in 1950 [1], research on how and whether artificial intelligence can equal human linguistic capabilities has been ceaseless and has not suffered from loss of relevance. This effort has of course been redoubled since the advent of the natural language processing (NLP) field, which has posed the question of whether computers can analyze naturally occurring linguistic information to achieve an understanding similar to that of humans [2]. It is worth clarifying that NLP should not be regarded as a single discipline or group of techniques of a static nature but rather a field with an ever-evolving complexity that adapts to contemporary challenges. Over time, a number of techniques spanning from symbolic language representation methods [3] to more recent statistical [4] and machine learning approaches [5] have served the aforementioned purpose with different degrees of success, as is displayed in several surveys and literature reviews [6]–[12]. In some instances, machine learning methods depend on the ability to train a model with large amounts of linguistic information to achieve an adequate level of performance [13], a requirement that has recently been more plausible to fulfill given the vast amount of natural human interaction recorded in social media platforms [14].

The analysis of this continuously increasing amount of information has been useful in many applications related to a variety of fields not necessarily related to computer science, which benefit from the different techniques encompassing NLP. Sentiment analysis (SA) or opinion mining, and

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more specifically its health-related applications, will be the main focus of this paper. SA focuses on studying people's reactions, sentiments, and thoughts regarding events, products, public policies in different fields, and life in general as it is perceived over the internet in written form. SA has made important advances in applications ranging from pin-sharp targeted advertising [15], stock market predictions [16], [17], or even the identification of human emotion in text and its relation to the state of a subject's mental health [18]–[21], or other health-related applications [22]–[25]. Given the context of confinements and social distancing around which society finds itself as a result of the pandemic brought upon by the SARS-CoV-2 virus, this subject has been of special interest to mental health professionals and governments alike, as it can directly impact the well-being of entire populations [25]–[30].

Given the significant increase in the demographic significance of social media participation and the subsequent increased volume of social media data as a result of the COVID-19 pandemic, the main goal of this survey is to provide a systematic review of current advances, applications, and challenges of SA technology for health-related applications, as well as presenting the reader with an introduction to the various methodologies employed in the state-of-the-art SA technology. Thus,the accuracy, applicability, and performance of these methodologies are presented with the intent of informing the development and/or refinement of possible future applications of SA technology. This increase in social media participation is directly related to various mandatory and voluntary quarantine measures executed worldwide and has presented itself both in developed and developing countries despite internet availability being reduced to metropolitan population centers in the latter case. While previous efforts have been conducted on surveying various aspects of the field of SA [31]–[33], these works were conducted before the COVID-19 pandemic and its marked impact on the volume and diversity of social media participation around the globe. Thus, the contributions of the current work span from highlighting key challenges in adapting existing SA techniques with the purpose of informing the impact of public health policies to studying the spread of misinformation [34]–[37] across social media and massive information outlets. Constant monitoring of the information related to the state of mental health of entire populations could even be used as a tool to help craft personalized healthcare for individuals in at-risk mental health situations.

This survey is expected to serve as an introduction to the methods, challenges, and implications of SA technology for disciplines different or adjacent to computer science, especially those related to human development at the governance, health, social, and commercial levels. It is foreseen that these sectors can combine the use of the methods described here, with an emphasis on those that have resulted in positive outcomes or that have presented significant implementation challenges, with information such as opinions and trends obtained from social media sources. From a healthcare professional's perspective, this work describes the most relevant techniques and the steps necessary for implementing SA into their respective specific discipline in an attempt to unite the relevant concepts of social, health, computational, and data sciences in one document.

A postpandemic society is more inclined to do things digitally. While at the beginning of the pandemic this was largely limited to urban centers, the expansion of such a phenomenon will imminently result in a digital transformation on a global social scale. This digitization has increased accessibility for more people in tasks such as the deployment of millions of office jobs to virtual modalities, a change that also results in encouragement for more people to partake in social activities not limited to their work responsibilities in a professional context but also by expressing themselves more in social media or online shopping.

The rest of this document is organized as follows: Section II provides a number of definitions, procedures, and a description of the techniques necessary to perform SA. Applications where SA techniques have been used to attempt to solve or improve different problems pertaining to human health are presented in Section III. Section VIII then draws several conclusions regarding the techniques and their respective applications discussed in the previous sections. Finally, a discussion on the possibility of applying certain techniques to different future scenarios is displayed in Section IX.

II. SENTIMENT ANALYSIS: FUNDAMENTALS

The current section explains the main concepts necessary for understanding the elements and techniques used to perform true SA. We begin with the general definition of a sentiment. A sentiment has been defined by Pang and Lee [38] as "An opinion that a person expresses towards an aspect, entity, person, event, feature, object or a certain target". Therefore, SA can be defined in the field of NLP as a collection of linguistic classification methods that directly focuses on sentiments rather than language structure. Some consider that the purpose of SA is to extract publicly available sentiments, emotions, or opinions in a number of different formats, such as text or audiovisual material [39]. Because of its fundamental nature in contemporary SA, the computational definition of *opinion* expressed by Liu in 2015 [40] is such that *An opinion is a quintuple (entity, entity's feature, sentiment of opinion, opinion holder, and time) where*:

- *An entity e_i may be a service, product, person, or topic that represents the target of the opinions;*
- *The entity's feature a_{ij} is an aspect or feature target of the entity e_j;*
- *The opinion sentiment s_{ijkl} represents the sentiment of the opinion holder h_k on feature a_{ij} of entity e_i at time t_l;*
- *The opinion holder h_k represents the person, user,or author who expresses the opinion;*
- *The time t_l represents when the opinion is expressed.*

In this definition, subindices i, j, k, and l refer to a possible number of elements for each category. The same author also expands on the concept of sentiment of an opinion by

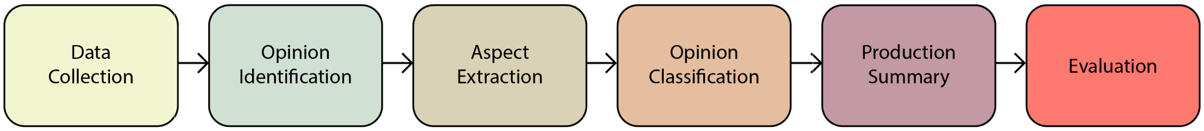

FIGURE 1. General procedure diagram for sentiment analysis applications [13].

expressing that the former can be represented as a triple that contains a sentiment type (which depends on the application of the analysis), a sentiment polarity (positive, negative, or even neutral), and intensity (which indicates the strength of the opinion expressed).

There are four levels of SA mentioned across the surveyed literature, depending on the level of specificity at which the analysis is applied: document level [41], sentence level [42], aspect level [43], and concept level SA [44]. These are all briefly described as follows:

1) **Document Level:** it is the most general level of SA and is applied to whole documents. For this reason, it is not recommended for precise evaluations. The accuracy of this analysis is usually better when focusing on general information about a document's polarity.
2) **Sentence Level:** this analysis evaluates on a sentence level, as its name implies. It can determine a sentence's polarity, topic, or content in general, and its success depends on first determining the objectivity (or lack of) of the sentence before its execution.
3) **Aspect Level:** this fine-grained analysis is performed when a considered comment does not define a single entity or aspect, and it considers the given opinion itself instead of the language structures.
4) **Concept Level:** concept level SA is not always recognized in the literature. This level consists of inferring conceptual information about emotion and sentiment associated with the use of natural language itself.

To execute SA, there is a methodology or modular description commonly made by authors. However, the sequential model with individual obligations that encompasses the entirety of SA was first described by Hemmatian and Sohrabi in [13]. To better understand this method, a simplified block diagram is shown in Fig. 1, and it is defined as follows:

1) **Data Collection:** Consists of using proprietary or third-party APIs to extract large amounts of data from various web resources, such as weblogs, microblogs, social networks, and search engines. Twitter is among the most used platforms for data mining [7], [11], [45], [46] due to its accessibility through an official API and a large amount of retrievable data. Other social media platforms, such as Instagram, Reddit, YouTube, Gab, and Imgur, or even Chinese platforms, such as WeChat, can also be used for multimedia data scraping [47]–[49] or multisource data analysis purposes [50] that do not necessarily require the platform's consent. Some information related to the public's interest in specific topics over time can be obtained from search engines using tools such as Google Trends. [51].
2) **Opinion Identification:** Data are often extracted or conserved according to an arbitrary criterion. Special interest filters, such as the language of the text, the place and time during which it was produced, or the author of the text, can be applied on this stage.
3) **Aspect Extraction:** Depending on the variables of study and according to the type of data collected, this stage applies techniques to adapt the data for the subsequent algorithms.
4) **Opinion Classification:** This stage performs the actual classification of the extracted aspects. This represents the output of one of the many available classification algorithms.
5) **Production Summary:** After the previous stage produces results, this stage summarizes the classified opinions in any desired form of visualization for a clearer understanding. This can be represented in terms of sentiment polarity or a simple sum of requested variables.
6) **Evaluation:** Consists of evaluating the performance of the previous techniques using standardized metrics and the definition of indices of specific variables for more specific studies. In this stage, more abstract conclusions are drawn related to the study's objective.

Based on the previously listed concepts and the bibliographic study of existing literature based around the global scope of this paper, we describe in the following subsections the most relevant aspects pertaining to data collection, aspect extraction, and opinion classification, as well as the most common practices when applying them to the health field.

III. SENTIMENT ANALYSIS TECHNIQUES AND ALGORITHMS FOR HEALTH

Even though SA applications in the health field have gained significant relevance during and after the COVID-19 pandemic, the fundamental concepts have been developed over recent decades. The current section presents a detailed description of the most common techniques and algorithms used in various aspects of health-related SA applications. Based on the contributions described in the literature, we recognize the main elements in the development of a health-related SA application and their respective connections. These elements are presented and contextualized in Fig. 2, which additionally presents some relevant features for each element, according to the surveyed literature. In the current section, we describe the most relevant and practical

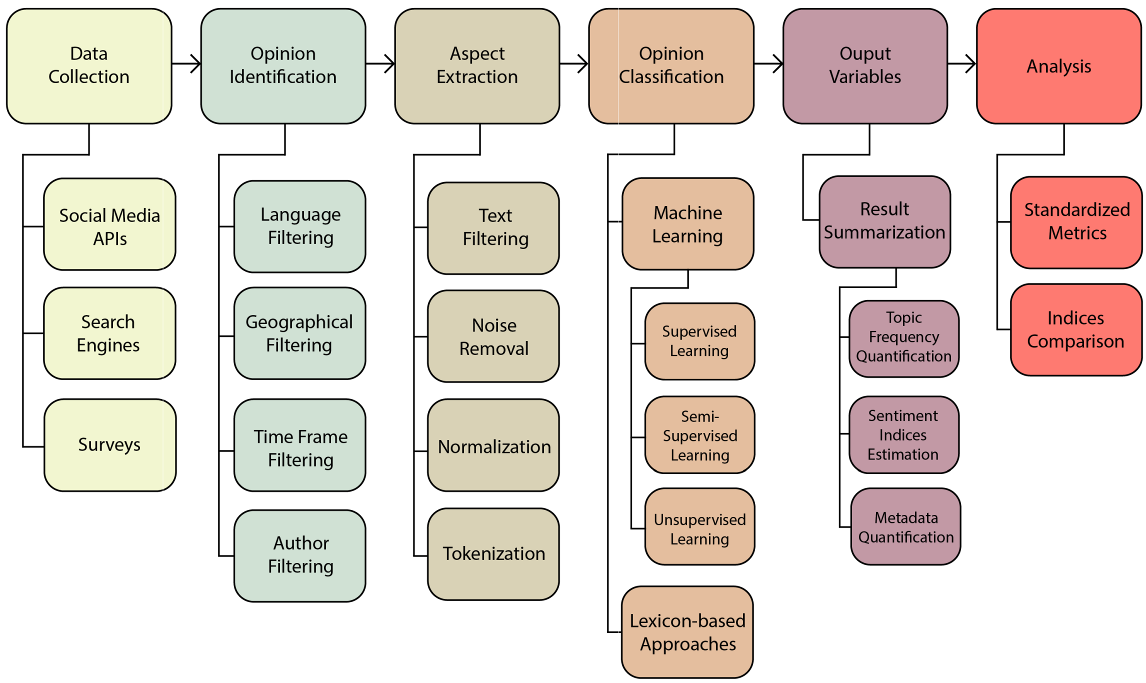

FIGURE 2. Detailed procedure diagram for sentiment analysis applications [13].

aspects regarding the data collection, opinion identification, aspect extraction, and opinion classification activities in an SA health-related application. In addition, we include information relating to final output analysis and result interpretation. For redundancy avoidance, this section omits describing the activities that have been sufficiently elaborated on in the previous section.

To gather information on the techniques used for SA applied to health, a review of state-of-the-art data mining applications was conducted, focusing on the techniques for feature extraction and opinion classification of text-based data.

TABLE 1. Distribution of surveyed literature according to the data sources used.

Data Source	Utilization Count	References
Social Media Services	102	[6], [16]–[18], [23], [24], [27], [29], [34]–[36], [39], [46]–[52], [56], [60]–[62], [62]–[90], [90]–[124], [124]–[140]
Survey Databases	9	[27], [30], [57], [58], [122], [141]–[144]
Review Databases	6	[41], [116], [145]–[149]
Search Engines	4	[28], [56], [107], [150]
Hospital Databases	4	[57], [59], [61], [107]

A. DATA COLLECTION TECHNIQUES

While text data are the most common object of study in SA applications [9], these can also be based on the processing of images, sound, video, or a combination of these data types [52]–[54]. Thus, the specific methodologies and content sources for the data collection step vary depending on the types to be analyzed. Health-related SA applications are most commonly concerned with assessing various sentimental aspects of large populations. For this reason, the surveyed literature shows that text-centered social media services such as Twitter and Reddit are the most commonly used data sources due to the significant percentage of internet users that contribute to these platforms. While there exist additional textual data sources such as search engines [55], [56], medical surveys [57], hospital databases [58], [59], and private data collection services, these have not been thoroughly explored in the literature due to their limited accessibility and demographic scope. Furthermore, textual datasets show significant advantages in terms of dataset sizes, simplicity of data collection procedures, and ease of processing when compared to other data types. For illustrative purposes, Table 1 presents the proportion of surveyed literature according to their data sources.

In the surveyed literature, datasets are commonly not of the structured textual type [21], and as can be observed in Table 1, a significant majority of studies' datasets are extracted from social networks. The most common networks used for SA applications are Twitter, Reddit, and Facebook [18], [21], consisting of approximately 1 million [60] to 1 billion [64] individual data samples per study, which are further processed and reduced to a smaller number in subsequent steps. Additionally, there exist alternate data sources such as ReachOut, a social network for users to provide and receive support regarding mental health-related situations, as well as various mental health forums and personal microblogs [21]. These alternate data sources, while focused on mental health issues, present considerably lower data volumes due to their lower popularity compared to conventional social networks.

Another important data source is structured textual data from psychological surveys, such as the tabular CES-D test [65]. This test consists of a survey originally published in 1977 and contains 20 time-resolved questions from verbal surveys conducted in focus groups for suicide risk detection [63]. In addition, more contemporary surveys are commonly employed, such as DSM-IV, ICD-10, and IPDE-SQ. These tests were conducted with the objective of measuring the state of individuals' mental health and suicide risk [21]. Additionally, more recent efforts have suggested the analysis of images from social media due to increased usage and influenceability of younger generations to these data types [106], [143], [144], as well as increased modern availability of computing power. Finally, research efforts such as the Durkenheim Project have implemented these analyses for assessing predictive suicide risk in individuals [19].

The nature of data acquisition from social networks is commonly referred to as being free of charge [64]; however, there exist paid alternatives to acquire these datasets. For example, MonkeyLearn API (from *MonkeyLearn*) is a machine learning platform that specializes in text mining and includes pretrained text mining models such as a sentiment analyzer. Oracle data mining is a component of Oracle Advanced Analytics that enables data analysts to build and implement predictive models. Additionally, the IBM SPSS Modeler is another data mining solution that allows data scientists to speed up and visualize the data mining process. The SAS Enterprise Miner is also an analytics and data management platform. The goal is to simplify the data mining process to help analytics professionals turn large volumes of data into insights.

B. ASPECT EXTRACTION TECHNIQUES

As global social media use dynamics evolve, various industrial, governmental, and marketing-focused actors develop strategies to make use of the available information towards their respective particular interests [145], [146], [151], [152]. For this reason, collected data from social media sources currently aggregate information from these actors together with the contributions of individual users to personal accounts. With the interest of studying various aspects of individual users' mental health, various studies have focused exclusively on the development of classification methodologies specifically for the purpose of separating institutional data from personal user data [17].

To reduce noise in datasets extracted from social media sources, preprocessing methodologies for textual data often consist of following a common workflow with five main operations:

- **Personal vs Nonpersonal data separation**: This step focused on the segmentation of data according to its source. When conducting a study on a specific population sector, it is imperative to be able to distinguish whether a data point is generated by personal or institutional, automated, or advertisement accounts. These procedures are most often employed in the development of applications related to public health policy management and assessment [23], [92], where only data related to individuals' reactions to health policies are the object of study.
- **Text filtering**: This step consists of removing undesired data from the collected datasets, such as duplicate and corrupted information, hyperlinks, and foreign language text, if required. While the removal of duplicate or corrupted data and hyperlinks in text data can be trivial, language detection is a more complex task to perform at scale [153]. To aid text filtering applications and reduce the requirement of manual language labeling, language filtering of text data can be performed using automated tools such as Google's Compact Language Detector [154], *langid.py* [155] or similar open-source software.
- **Noise removal**: This step consists of the systematic removal of meaningless text such as stopwords (such as pronouns, articles, and prepositions) with no significant contribution to text classification, text noise (such as punctuation and special characters), abusive words, and slang words from the datasets of interest. Noise removal operations are often performed using regular expression matching [156].
- **Normalization**: With the intention of reducing computational complexity by treating similar features as equals, each word in the dataset of interest is converted to its lowercase form, lemmatized (switched to their base dictionary form) [157], and stemmed [158]. Text normalization operations are commonly performed using specialized programming libraries such as NLTK [159].
- **Tokenization**: Also referred to as *vectorization*, is the process where the text elements are tokenized or converted into discrete information elements to treat phrases, symbols, and words as individual features. This step is crucial in NLP applications, as it is in this step that text information is translated and organized into numerical data structures that can be utilized for further automated processing. Algorithms of significant complexity, such as word embeddings, can be used for this task [160], [161].

These methodologies are implemented in most machine learning experiments as a common workflow with slight variations according to the specific machine learning algorithms to be trained. This is performed with the intention of further refining data features for improved machine learning model accuracies. Examples of these variations include the application of geolocation coding (using Google Maps API) [26], [92], [95], [96] or language selection schemes [96], where only English language posts were selected using Google's Compact Language Detector [154].

Complex preprocessing tasks, such as generating word embeddings from text [50], [95], can be achieved using pretrained deep learning models [160]. In addition, other studies have previously achieved their feature engineering operations by stemming words with a text processing algorithm [92] (Lovins Algorithm [158]) or by calculating term frequency–inverse document frequency (TF-IDF), a statistical measure that evaluates how relevant a word is to a document in a collection of documents. In addition, n-gram analysis was applied in [26], [95] to tokenize text into single words (unigrams), sequences of two words (bigrams), three words (trigrams), and so on to maintain the word order and syntactical properties to understand and define relationships between words, which can also be visualized by creating word clouds [26]. Furthermore, syntactical relations can be determined by applying techniques such as parts of speech tagging or dependency parsing to illustrate the syntactic relationship between different tokens. Moreover, a technique known as bag of words can be applied to calculate word frequencies and determine the focal point of the text analysis, ignoring word order and translating texts into one-dimensional arrays depicting word frequencies, including a document term matrix replacing the text corpus and unifying previously calculated arrays [27].

In the case of multimedia data, in [95], a multimodal experiment using deep learning models required the generation of word embeddings. For this purpose, pictures were preprocessed using common resizing and padding techniques, whereas videos were sampled at low framerates to generate images, and each sample was handled with the same image processing procedure.

The process of performing aspect extraction for SA applications can involve the use of various techniques, such as linguistic inquiry and word count (LIWC), latent Dirichlet allocation (LDA), latent semantic analysis (LSA), nonnegative matrix factorization (NMF), word2vec, global vectors for word representation (GloVe), n-gram, principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), keyword filtering (KF), term frequency-inverse document frequency, and machine learning techniques presented in Section III-C2. Following the described procedure, these techniques are summarized in Table 2, which presents the references and the utilization count that were found employing each respective approach.

TABLE 2. Aspect extraction techniques.

Techniques	Tech. References	Utilization Count
LIWC	[47], [69], [71], [74], [81], [111], [112]	7
LDA	[26], [60], [65], [69], [79]	5
KF	[64], [66], [67], [73], [113]	5
Word2Vec	[60], [80], [96], [114]	4
TF-IDF	[60], [82], [92]	3
n-gram	[26], [27], [60]	3
LSA	[78], [79]	2
NMF	[79]	1
GloVe	[115]	1
PCA	[71]	1
t-SNE	[60]	1

Some ML methods were also used for this end.

C. OPINION CLASSIFICATION TECHNIQUES

One of the most important steps when developing an SA application is the selection of an appropriate methodology to classify the desired sentiments. According to works by Wang *et al.* [147] and Petz *et al.* [116], these techniques can be broadly organized into three discrete categories: lexicon-based and automated approaches. While machine learning techniques can be used in this context, it should be noted that several of the techniques reviewed in Section III-B intrinsically use machine learning techniques. Thus, automated approaches used to classify opinions in a dataset of interest can be separated into two subcategories, following the conventions of [21] and [18] as follows: machine learning techniques and techniques involving deep learning (DL).

1) LEXICON-BASED APPROACHES

The methodologies under this category constitute the least computationally complex opinion classification approaches. Lexicon-based approaches operate by extracting phrases containing adjectives or adverbs, estimating the semantic orientation of each phrase, and subsequently classifying the result based on the average semantic phrase orientation [162]. These approaches operate on the assumption that individual words are exclusively used to express absolute positive or negative feelings, which is also referred to as word polarity. Thus, in lexicon-based SA applications, each word is directly associated with the polarity of the word itself regardless of the context and can even contain a certain weight or strength associated with it. Lexicon-based methods are often used to calculate the orientation of documents according to the semantic orientation of words and phrases within documents themselves [163]. Due to the non-contextual nature of their operation, lexicon-based approaches demonstrate considerably reduced robustness in their performance in the presence of sarcasm or nuanced language [164].

The methodologies included under this category operate by extracting phrases containing adjectives or adverbs, estimating the semantic orientation of each phrase, and subsequently classifying the sentiment of the phrase based on the average semantic orientation of the words it contains [162]. Lexicon-based approaches assume that words containing sentiment are used to express positive or negative feelings, which is also referred to as word polarity. Lexicon-based methods are often used to calculate the orientation of documents according to the semantic orientation of words and phrases within documents themselves [163].

2) MACHINE LEARNING TECHNIQUES

These can be categorized into three groups, depending on the level of human input during the training process and the information contained within individual datasets.

- **Supervised Methods:** Supervised methods include computationally inexpensive probabilistic methods such as naive Bayes, which assumes that the existing sentences within the document are subjective in relation to certain semantic orientations of words [148]. In addition, maximum entropy which, unlike naive Bayes, makes no *a priori* assumptions about the relationship between features, which could ultimately result in improved performance when conditional independence assumptions are not met [165].

In addition, this category includes classification methods that are nonprobabilistic in nature, such as support vector machines (SVMs) or artificial neural networks (ANNs), whose training accuracy is highly dependent on the size and quality of the training datasets [166]. Other effective methods, such as K-nearest neighbors (KNN), decision trees, and rule-based methods, are also considered part of this category.

  - **Support Vector Machines:** SVMs are supervised learning models with learning algorithms that analyze data for classification and regression analysis. These methods construct a hyperplane, or set of hyperplanes, which maximizes the separability of individual data points by projecting them onto a higher dimensional space than that of the original dataset. SVMs can be used for classification, regression, or other tasks, such as outlier detection [167].
  - **Regression Analysis:** In broad terms, these probabilistic methodologies estimate the relationships between an output variable and a number of input independent variables. One of the most widely implemented of these methods, linear regression, is frequently used in one or more stages of SA applications [48], [74], [75].
  - **Decision Tree Learning:** Decision trees attempt to create a model that can predict the value of an output variable by taking in several input variables and evaluating them through different consequent rules or decisions. Similar to the aforementioned methods, decision tree learning is often used in SA applications because of its simplicity [168].
  - **K-nearest neighbors:** This nonparametric method assumes that, given a certain attribute and a training data set, a testing data set can be classified by calculating and using the distance between the new data point and its already classified neighbors [148].

- **Semi-Supervised Methods:** Semi-supervised methods employ large amounts of unlabeled data in conjunction with relatively small amounts of labeled data, with the ultimate goal of developing high-performance sentiment classifiers [149]. Some of these methods, such as self-training classifiers, are trained using a small number of manually labeled data points, which are subsequently used for the automated classification of unlabeled samples [89]. In addition, methods such as co-training classifiers operate on the assumption that the sentiment feature of interest in the dataset can be statistically explained by other dataset features with different but complementary information [90]. Further, it is also worth mentioning other methods, such as multiview learning, which operate on the main assumption that the collection of hypotheses is compatible together, and graph-based methods, which assume that tightly correlated sections of text in documents are likely to share their respective belonging classes [169].
- **Unsupervised Methods:** More commonly known as *clustering*, these unsupervised methods consider a set of training samples, and only the input features are specified for them. Due to their unsupervised nature (lack of manually labeled training data) and the fact that they operate solely on statistical properties of individual data points across a given dataset, these methods do not easily produce accurate sentiment outputs. However, they can be a useful tool in exploratory data analysis processes [170] and have been reported to provide adequate performance in SA applications that operate on particularly polarized datasets [117].

  Unsupervised methods can be broadly classified as nonhierarchical or hierarchical. In the former, the individual clusters do not overlap, and any data point will be assigned exclusively to one cluster [171]. Examples of this category include K-means clustering and fuzzy c-means clustering. In the case of the latter, all of the training data are considered to belong to a single cluster, which is subsequently divided in an iterative fashion in relation to the statistical distance between individual point groups within the dataset [172]. Examples of these are divisive methods and agglomerative methods.

The reviewed SA applications are focused on the use of statistical machine learning models to perform SA in different stages, leveraging the advantages of both supervised learning for classification purposes and unsupervised learning for feature engineering. While most of the methodologies presented in this section can be implemented using Python or R specialized libraries, it is worth mentioning that STATA 15 software used in [27] can be integrated with the former programming languages.

Previous work has focused on identifying the most relevant aspects of Twitter discussion relating to the COVID-19 pandemic [26], [118], [119]. For this purpose, n-gram exploratory analysis techniques (unigrams and bigrams) have been implemented using word frequencies as features. This exploratory data analysis process included the generation of word clouds and an unsupervised learning topic modeling algorithm known as latent Dirichlet allocation. This algorithm was employed to find clusters of tweets by mapping them to the set of topics previously determined so that individual words in each tweet were correlated with their assigned topic. Following this, a classification step verifies whether any of the previously identified unigrams or bigrams pertaining to a specific topic were present on a tweet. If this condition was met, then individual tweets were classified into one of the determined topics. Finally, SA was performed by extracting and statistically analyzing metadata (retweets, likes, number of followers, etc.) to calculate an interaction score for each topic (sentiment score varied from -1.0 to 1.0) to gain deeper insight into the relationship between the selected topics of interest and Twitter users.

With the purpose of measuring the degree of concern caused by infectious diseases and informing public health management activities, a methodology was developed to perform SA on Twitter data with real-time geolocation visualization capabilities [92]. In this work, a feature engineering classification methodology was implemented to determine if the type origin of individual tweets was personal or non-personal (such as news articles and advertisements). Furthermore, [92] includes the use of a data augmentation procedure to fix data imbalances, and then a clue-based sentiment classifier was developed. Finally, an SA classification methodology was implemented using naive Bayes, multinomial naive Bayes, and support vector machines (including 10-fold cross-validation) to determine if the emotional state reflected by users in individual tweets was negative or neutral.

Another experiment [27] focused on exploring factors associated with positive and negative sentiments of Twitter users regarding the reopening of economic activities in the United States during the COVID-19 global crisis using SA. After the necessary tokenization and exploratory data analysis procedures, an SA methodology was developed using R to classify individual tweets as positive, negative, and neutral based on matching keywords, word sequences, and pre-written lexicons. Following this, a binary logistic regression model (calibrated and estimated using STATA 15 software) was developed to evaluate the factors that influence people's sentiment towards the lifting of enforced sanitary restrictions using converted categorical dummy variables from the SA ("1" for positive and "0" for negative and neutral). In addition, various socioeconomic and demographic features were incorporated into the model, such as the number of COVID-19 cases, deaths, and other variables integrated from public US Census data [27].

Regarding the processing of heterogeneous data types from multiple sources, a very similar workflow was implemented to measure whether image features could predict a user's engagement and sentiment towards *hashtag activism* and the promotion of anti-vaccination ideologies [99]. In addition, SA was used to study the dynamics of users' reactions to images published by the CDC (Center for Diseases Control and Prevention) in the United States [100]. These contributions consist of a series of feature engineering techniques on image and text datasets using a variety of cloud computing services provided by the Microsoft Azure platform, such as optical character recognition, facial feature recognition, content categorization, and sentiment. Furthermore, low-level image features (pixel-related and visual effects) were processed using Python's library Open CV 2 with the intent of increasing model performance. Finally, these engineered features were used as inputs in machine learning classification models, such as support vector regression [99] or random forests [100], which included 10-fold validation and root mean square error (RMSE) calculations.

With the objective of improving on an existing model developed for predicting the spread of the influenza virus, an autoregressive model was built in [150]. For this application, data were imported from Google Trends in conjunction with the Google Correlate API to determine related posts on 8 different countries in Latin America. The multivariate linear regression model used regularization for hyperparameter tuning and various performance metrics, including Pearson's correlation coefficient, RMSE, and the stationary block bootstrapping method. In addition, it is important to note that [64] developed a model with a correlation score of $R = 0.93$ with the national epidemiological figures of the CDC when analyzing the influenza outbreak figures between 2012 and 2013. Their approach included the use of keyword filtering and SVM for analysis.

As described in Table 2, keyword filtering is among the most commonly used techniques in SA applications. While this technique is not always used specifically for the purposes of SA, it is usually employed as the first step in the data processing pipeline presented in Fig. 2. Thus, the work performed in [64] showed that the developed methodology, which consisted of keyword filtering in conjunction with an SVM model, produced higher performing results than keyword filtering exclusively, which produced 85% and 46% accuracies, respectively. Likewise, in [19], they assert that only using keyword filtering limits the analysis capacity of the model to the words contained in the lexicon used to build the model and ignores any further possible context information found in the semantics of sentences.

The revised general machine learning (ML) techniques include support vector machine (SVM), logistic regression (LR), linear regression (LiR), decision tree (DT), naïve Bayes (NB), K-nearest neighbors (KNN), random forest (RF), gradient boost machines (GBM), rotation forest (RoF), K-means (Km), partitioning around medoids (PAM), hierarchical clustering algorithm (HCA), maximum entropy (ME), association rules (AR) and artificial neural networks (ANN). The usage count of these techniques in the reviewed literature is presented in Table 3, which presents usage counts and references to individual studies where the use of specific techniques was registered.

3) DEEP LEARNING TECHNIQUES

Following the modern increase in the availability of cost-effective computing power and storage capability for large training datasets, deep learning models have undergone extensive development in the context of NLP applications. In particular, the multilayer perceptron (MLP), convolutional neural network (CNN), and recurrent neural network (RNN) deep learning architectures presented in Figs. 3, 4 and 5, respectively, have been considered the most important architectures in this field [175]. Based on these architectures, several methodologies have been developed to assist various aspects of NLP application development:

- **Word embedding:** Constitutes a technique for language modeling, in which words from a certain vocabulary

TABLE 3. Machine learning techniques.

Techniques	Tech. References	Utilization Count
SVM	[48], [64], [65], [70], [71], [82], [83] [72]–[76], [78], [81] [92], [100]	16
LR	[27], [47], [48], [74], [75], [81], [96], [150], [173], [174]	10
DT	[70]–[74], [79], [173]	7
RF	[72]–[74], [81], [99]	5
NB	[70]–[72], [92]	4
Km	[79], [80], [114]	3
AR	[76], [174]	2
PAM	[96], [114]	2
LiR	[69]	1
KNN	[70]	1
GBM	[81]	1
RoF	[71]	1
HCA	[114]	1
ANN	[48]	1
ME	[70]	1

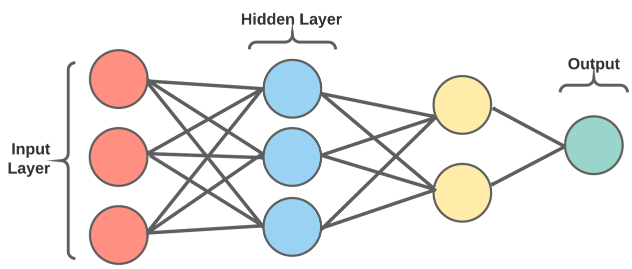

FIGURE 3. Multilayer perceptron architecture diagram.

are converted into a vector of continuous real numbers [176]. Commonly, this process implies embedding from a high-dimensional sparse vector space, such as the case of *one-hot* encoding. The results of word embedding operations can be leveraged to find clusters of similar data according to the numerical distribution of nonzero values across the resulting data structures [50], [92]. The training operation of word embedding algorithms can be achieved using neural networks.

Word embeddings have two main architectures, the continuous bag of words (CBOW) method and the skip-gram method. In the CBOW model, the distributed representations of context (or surrounding words) are combined to predict the word in the middle, while in the skip-gram model, the distributed representation of the input word is used to predict its context within a larger body of text.

- **Autoencoder and denoising autoencoders:** Autoencoders are neural network architectures designed and trained with their target values equal to the input values. The key part of autoencoder networks is a middle layer with fewer trainable parameters than input values, thus creating a computational bottleneck inside the architecture. These networks can be described as consisting of two parts: an encoder section, which encodes the input information into a compressed representation in a smaller vector space, and a decoder section, which reconstructs the input data from its compressed representation produced by the encoding section [177]. Thus, the objective of an autoencoder network is to learn an optimal methodology for compressing the input data into a smaller vector space and to simultaneously decode this representation into an accurate approximation of the input data [175]. Depending on the number of training parameters in the encoder-decoded boundary and thus the degree of constraint on the vector space of possible coded representations, the training operation focuses on incorporating the most relevant aspects of the input data into the encoder output. Denoising autoencoders deliberately constrain the number of trainable parameters for the encoder output, and the training operation is forced to exclude less relevant aspects of the input data, which often coincide with dataset noise. Because of the nature of the nonlinear functions used in autoencoders, it is able to learn nonlinear representations that give it an edge over nondeep learning-based counterparts, such as principal component analysis (PCA) or latent semantic analysis (LSA) [78], [79].

A class of complex deep neural network models named transformers (taking the name from the original transformer [178]) have been significantly developed in recent years. These models were created to overcome typical problems that classical architectures such as RNN and LSTM encounter when dealing with language context. BERT (bidirectional encoder representation from transformers) is a model specialized in context learning, since unlike other architectures, it considers the relations of all the words in a sentence rather than one-by-one in order. Developed by Google [161], it is employed as a pretrained model using transfer learning for various natural language processing tasks. Its applications in SA go from aspect extraction as a word embedding generator for linguistic features [86] and text tokenization [95] or as a sentiment

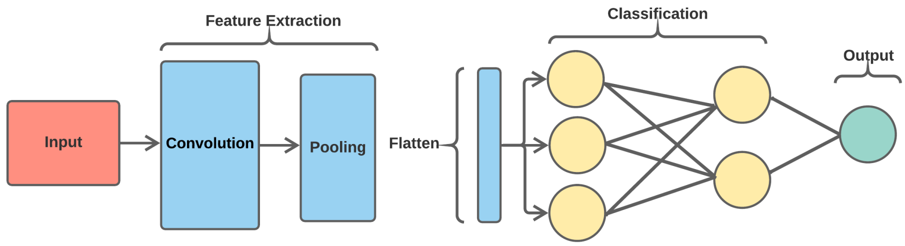

FIGURE 4. Convolutional neural network architecture diagram.

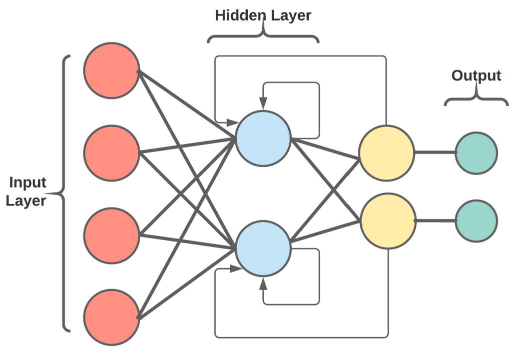

FIGURE 5. Recurrent neural network architecture diagram.

classifier [104]. In this work, researchers used BERT to confirm that emojis and their adjacent words could be used for SA, outperforming traditional models (CNN, BiLSTM, and FastText). Furthermore, BERT can also be used for more specific tasks such as aspect-based SA [142], demonstrating its high versatility and state-of-the-art performance.

- **Convolutional Neural Networks** Following the description of the model in Section III-C3, convolutional neural networks (CNNs), introduced in [179], are a class of biologically inspired neural networks that use a series of convolutional and nonlinear simple filters to learn and process a diversity of features in spatially distributed data. They have shown remarkable results in a wide variety of machine learning problems [180]. Convolutional layers in CNNs play the role of feature extractors. This means that CNNs can spatially incorporate local correlation information by enforcing a local connectivity pattern between neurons of consecutive layers [175]. This is especially useful in the field of NLP, where we expect to find strong local clues regarding class membership, but the clues can appear in different parts of the input. This, of course, assumes that it is desired to learn that certain sequences of words are good indicators of the topic of interest, with little regard to the positions they occupy within a document.
- **Recurrent Neural Networks** By returning the output of deeper layers to layers closer to the input layer, RNNs introduce the concept of internal architectural memory to process a sequence of inputs. This makes RNNs particularly effective for processing sequential information. The presence of this architectural memory means that RNNs can perform the same operations for every element of the input sequence, with each output describing a dependence on all previous connections [181]. Regarding their use in NLP applications, RNNs have presented good results in adequately modeling the importance and influence of individual words (or sequences of words) within the larger context of a document, or documents, within a training dataset. In addition, there exist a number of specialized RNNs, which are popular in the field of NLP, with particular architectural features. These are detailed as follows:
  - **Long Short-Term Memory Networks:** Following the description of the model stated in Section III-C3, LSTMs are a special type of recurrent neural network that are able to recall patterns selectively for a long time. It is an ideal choice for modeling sequential data and is therefore used to learn complex dynamics of human activity [182]. Instead of having a single neural network layer, LSTMs have four mutually interacting layers, as well as two states called the hidden state and cell state. LSTMs are very popular among linguistic applications because of their exceptional performance when compared to more traditional methods [175].
  - **Recursive Neural Networks:** RecNNs learn a directed acyclic graph structure from the given data, which is also seen as a generalization of RNNs [183]. Given the structural presentation of a sentence, RecNNs recursively generate parent representations in a bottom-up fashion. With this information, sentence-level representations can be used to make the final classification for a given sentence within a document [120].
  - **Gated Recurrent Units:** GRUs are a gating mechanism very similar to LSTMs with a forget gate, with the fundamental difference being that they possess fewer parameters, as they lack an output gate [184]. Their performance on certain speech signal modeling and NLP processing tasks has been found to be similar to or better than that of

traditional LSTMs, especially with smaller or less frequent datasets [185].

Deep learning-based NLP experiments for the purposes of SA require the availability of a curated dataset. These approaches are also employed in cases where more complex multimodal analysis procedures are required, such as the case of [95]. Otherwise, it is common practice to evaluate the feasibility of less computationally complex methodologies since the computational requirements of training operations on deep neural networks are significant in comparison to statistical machine learning models.

With the goal of advancing multimodality learning, a publicly available dataset was presented in [95], offering vision and language data within the same context. As a test experiment, a neural network architecture of 5 concurrent encoder-decoder neural networks, in order to account for each type of multimedia data including 3 subtypes of text, was proposed to process multimedia data for the purpose of assessing the attitude of the community towards a particular social media post. This was achieved by modeling a points-ratio statistic, which is calculated using the number of upvotes in a given post divided by the total number of votes.

In [101], an experiment on Instagram multimedia data was carried out with the purpose of modeling the emotional impact caused by the COVID-19 pandemic. Two neural network models (attention-based LSTM and ResNet50 CNN with transfer learning) were trained on caption data together with additional text extracted from images using an optical character recognition Python library (Pytesseract), which incorporates information from subtitles and image samples extracted from video data.

Regarding the training operations for neural networks, the surveyed literature indicates that semisupervised and unsupervised methods provide superior performance due to the reduced introduction of bias in model responses. However, the use of supervised training methods is common [21]. Among the deep learning architectures used, the following were employed in NLP applications: multilayer perceptrons (MLP), convolutional neural networks (CNN), deep convolutional neural networks (D-CNN), recurrent neural networks (RNN), bidirectional encoder representations from transformers (BERT), gated recurrent units (GRU), neural network model synthesis (NewNetS), long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM) and multitask learning (Mt L). Table 4 summarizes the distribution of these architectures across the surveyed literature.

4) NON-AUTOMATED TECHNIQUES

A series of studies have focused their efforts on the use of various methodologies not based on machine learning techniques for the purposes of improving various feature engineering and classification tasks, such as qualitative analysis [47], [97], applied mathematics [50], [96], and external data resources [96].

TABLE 4. Techniques involving deep learning.

Techniques	Tech. References	Utilization Count
CNN	[73], [77], [85], [88], [112], [121]	7
LSTM	[77], [85], [87], [88], [111]	6
GRU	[84], [86]	2
MLP	[122]	1
D-CNN	[187]	1
RNN	[73]	1
BERT	[86]	1
NewNetS	[85]	1
BiLSTM	[115]	1
Mt L	[123]	1

On this topic, the work presented in [47] aims to establish a relationship between acute suicidality and language on Instagram. This was performed using different types of data analysis techniques. The qualitative analysis stage consisted of semistructured interviews with 52 participants through Instagram's chat services, which were subsequently analyzed through ATLAS Ti 7 software. These conversations were later analyzed to calculate their interrater reliability (Kappa coefficient). Subsequent analysis employed interview data paired with LIWC (linguistic inquiry and word count), a computer-based text analysis algorithm that calculates word frequencies based on predefined criteria. This was followed by determining the Flesch-Reading-Ease index for each conversation, which quantifies the ease with which a person could read. Finally, their categorical results were used to build a logistic regression model for the classification of acute and non-acute suicidality tendencies [47].

With the objective of measuring depression levels in voluntary participants from Instagram, a machine learning workflow was developed as an online quantitative analysis tool [102]. In this study, participants were asked to complete a Patient Health Questionnaire (PHQ-8) and grant the researchers access to their Instagram accounts. Following this, lexicon-based SA was conducted on each user's data using two word lexicons (ANEW and LabMT) and emoji analysis using unigrams to train a linear regression model, with elastic regularization to prevent overfitting and tuning the number of posts as model hyperparameters. Validation schemes included 20-fold cross validation for the F1 score, receiver operating characteristic curve (ROC), and area under the curve (AUC) analysis.

Furthermore, previous work [50] focused on detecting patterns on Instagram data to determine the popularity of a given post using different approaches based on topological data analysis. Because extracted data describe a consistent representation in an n-dimensional space, this work employed topological analysis techniques with the objective of clustering images based on their contents using the Mapper algorithm. Following this, a popularity ratio was computed for each cluster to identify the possibility of an image becoming popular. In addition, with the objective of measuring the effectiveness of topological data analysis compared to clustering algorithms, the performance of k-means and hierarchical clustering methods were compared against the Mapper algorithm. The number of clusters was varied between 5 and 15 to observe their effects on popularity. However, only experiments with 5 and 11 clusters were presented.

In addition, extensive research has been conducted with the objective of addressing the diffusion of COVID-19-related information [96]. This was performed using multisource data analysis sourced from Twitter, Instagram, YouTube, Reddit, and Gab social networks. The authors analyzed engagement and interest in the COVID-19 topic to assess the evolution of the discourse on a global scale for each platform and their users in three individual experiments:

- **Interaction Patterns:** This experiment analyzed the engagement level of users with COVID-19 topics on each platform. After generating word embeddings, to assess the topics around which the perception of the COVID-19 debate was concentrated, words were clustered using a partitioning around medoids (PAM) algorithm. In addition,the silhouette index and Jaccard similarity index were calculated to validate clustering. Finally, word clouds were generated to identify the topics in each cluster.
- **Information spreading:** This experiment measured the spreading of information by means of mathematical models applied to epidemic disease spread. According to the gathered data, a monotonic increasing trend in the way new users interact with information related to COVID-19 was observed by fitting two epidemic models to analyze the growth dynamics of user posts on a subject as an ineffective process, where people could start publishing after being exposed to the topic. Afterwards, R0 coefficients, which measure the reproduction rate of a disease in a population, were calculated for each social media platform.
- **Questionable vs Accurate Information:** This experiment compared the diffusion of questionable and reliable news on each social media platform. All posts that contained news hyperlinks were tagged as reliable or questionable according to the data reported by the independent fact-checking organization Media Bias/Fact Check. Then, for each platform, the cumulative number of posts and reactions related to questionable sources were compared to posts, and interactions referring to reliable sources were compared, showing a strong correlation, and facilitating the implementation of a linear regression model to compare growth dynamics on each platform.

A different study addressed the lack of availability of annotated public datasets that could be used to accurately classify and detect fake COVID-19 product sales on social media or so-called "signal" posts [97]. For this, a combination of supervised and unsupervised machine learning techniques was implemented. A topic modeling technique known as biterm topic modeling (BTM) was used as an unsupervised learning tool for grouping and summarizing the contents of filtered social media product data, stratified by product groups of filtered terms and subsequently identifying signal posts to train an LSTM classification model. Afterwards, the output from the trained classification model was used as input for a subsequent content coding stage. The final output calculates interrater reliability with the purpose of associating posts with the illegal marketing and sales of COVID-19 health-related products.

D. QUALITATIVE RESEARCH

A different set of studies, most commonly conducted by researchers in the field of psychology, focus their efforts on employing qualitative analysis techniques for data collection, processing, and extracting various insights.

In [93], [94], a set of qualitative experiments were carried out to thematically analyze ongoing public health issues regarding infectious diseases such as the COVID-19 pandemic and the Zika virus outbreak [94]. In [93], a thematic analysis was conducted to characterize the representation of public health information regarding COVID-19, which required an extensive content coding stage of a dataset consisting of 1612 Instagram posts from 92 accounts. Initially, 1885 key contents corresponding to 160 preliminary codes were found. After reviewing the information (including peer review) and applying Lincoln and Guba's trustworthiness criteria, only 23 themes were deemed representative of public health information.

Similarly, in [94], a thematic analysis was conducted on a dataset consisting of 500 images and their respective captions from Instagram posts to explore how the image sharing platform was used for information dissemination and conversation during the Zika outbreak. An initial sample size of 10 percent was used to identify themes and sub-themes summarized in a codebook, which was subsequently used to code the entire dataset. Finally, the Kappa coefficient was calculated to ensure interrater reliability, a procedure also observed in [97].

Other relevant techniques identified in qualitative studies were axial coding and emoticon inclusion:

- **Axial coding:** Referenced in [62],it is a technique relating the coding method into discrete categories and concepts in qualitative social studies. In the revised work, three categories are used (hence the technique being referred to as tri-axial coding), where this technique is employed as an alternative to a less robust keyword filter. This introduces the advantage of providing the capability to filter and simultaneously quantitatively analyze the frequency of occurrence of topics in the studied data, thus performing the SA with this classified content.
- **Emoticon inclusion:** In the research by C. Chew and G. Eysenbach [62], an interesting combination of SA was used using emoticons. That is, they created a list of these icons with characters and assigned them individual weights within the lexicon used for the SA.

IV. HEALTH-RELATED APPLICATIONS OF SENTIMENT ANALYSIS

The SA-based analysis of social media data for a variety of applications has grown proportionally with its increasing popularity, as described in Section I, with a large proportion of applications being centered around human health or with the objective of improving certain aspects of it. Some of these aspects, such as collective mental health, the progress of epidemics, or even public attitudes towards vaccinations, are of special interest to this work, both individually and as a set of correlated contemporary works. We have explored works centered on these particular topics due to their significantly increased recent research interest and their relevance to current health-related world events and their impact on individual and societal well-being. In addition, social media data present a particular feasibility for SA studies due to the continuously increasing volume and availability of data sets. The current section describes what the authors consider to be important or influential works, befitting of their respective classifications.

A. APPLICATIONS RELATED TO MENTAL HEALTH

Given the large amount of personal information related to individuals' mental state that is shared on social media platforms at any given time [187], social media-centered SA can be a powerful tool to detect certain patterns that could indicate the presence of psychopathologies in a population. The most widely studied of these include mild and severe forms of anxiety and depression, which have been approached by researchers using a wide variety of the techniques mentioned in Section II with the purpose of identifying these conditions from data extracted in different social networks [65], [98], [102], [124], [141], [188]. Regarding data generated by Twitter users, Tsugawa *et al.* [65] devised a workflow consisting of LDA and SVM to extract features that could relate to the presence of active depression from the analysis of their historical Twitter posts. Using a web-based questionnaire as an absolute truth frame, the authors were able to prove that their method could in fact predict depression in the studied subjects with an accuracy of up to 69%. As with many studies related to publicly available microblogging data, a question of ethics is raised. This was addressed in [63] by surveying a number of active Twitter uses with and without a history of mental health who expressed their opinions regarding the use of their tweets for studies on the detection of depression and the ethical implications that this could have. The authors found an overall positive sentiment amongst the polled group in relation to such an application of their publicly available data.

As suicide prevention remains a pressing and complex issue, a large portion of the research throughput in the field focuses on detecting patterns that could be related to it [48], [69], [72], [74], [78], [79], [125], [189]. Using posts from suicide survivors published on Reddit, a method for identifying and classifying mentions of suicide attempts and their underlying methods was proposed [48]. The authors compared the performance of using classifiers based on SVM, LR, an MLP architecture, and linear SVC, eventually finding that the linear SVC classifier outperformed all other methods in all the metrics utilized. Using data collected from tweets containing words or phrases of concern related to suicide, a set of classifiers based on SVM and LR that could categorize given tweets according to the degree of concern they could pose were developed [75]. Their findings showed that the classifiers were able to correctly identify the so-called 'strongly concerning' tweets with at least 80% accuracy but indicated that the system could be improved as the performance did not reach a plateau as the amount of training data increased. Provided that the causes of suicide are as sensitive as they are complex, Du *et al.* devised an approach to detect suicide-related psychiatric stressors based on deep learning methods and transfer learning strategies [73]. Using keyword filtering for feature extraction first, the authors then trained both a CNN and a Bi-LSTM architecture that could consecutively classify and extract the mention of suicide-related tweets and psychological stressors. As the results proved that the deep learning-based methodology could correctly detect suicide-related tweets with an accuracy of up to 78%, the authors proceeded to compare these results with those obtained when using more traditional ML methods such as SVM, ET, and conditional random field (CRF), further asserting the dominance of deep learning methods in this specific problem. On detecting suicidal intentions themselves, Coppersmith *et al.* designed a method for detecting both intentions and attempts based completely on NLP techniques [115]. Using a dataset made up of intentionally donated social media data, including users' tweets and sets of questionnaires, the authors used both word embedding and an LSTM to assess the suicide risk in a user's tweets and reject those that could qualify as false positives. By means of a 10-fold cross validation and the analysis of the ROC curves for the trained models, this methodology proved sufficiently accurate to detect suicidal intention in subjects and validate it with their demographically accurate control population.

It is also noteworthy that given the nature of data found in social networks, some studies also utilize qualitative measures or approximations to perform SA [47], [63], [93], [98], [103]. In [98], for instance, Gupta *et al.* collected Instagram posts related to the treatment of anxiety and depression, specifically their experiences with the use of antidepressants, to analyze them using inferential and descriptive statistical techniques. Using a data sample, a codebook was developed to analyze the remaining data with an overarching code criterion comprising the post's media type (image or video), the user's personal experience, sentiment, and other medical criteria (adverse effects, comorbidities, polypharmacy, etc.), including interrater reliability calculations. Uncommon to most qualitative studies, Fulcher *et al.* developed a web-based application that involved a machine learning scheme to extract data from Instagram to determine how users interact around nonsuicidal self-harm (NSSI)-related hashtags [103]. The web application known as Netlytic performed a query-based data collection stage, preprocessed textual data, and performed SA. Afterwards, a novel approach using deductive and emergent content coding techniques analyzed images using the NSSI behavior screening measure ISAS (Inventory of Statements About Self-Injury) with intraclass coefficients for interrater reliability purposes and the user's Instagram account details (number of posts, followers, likes, etc.).

B. APPLICATIONS RELATED TO EPIDEMICS

Given the increasingly frequent presence of epidemics as a product of urbanization, global travel, changes in the use of land, and other factors [190], epidemic prevention, detection, and tracking have seen an uptick in importance and therefore SA research. Provided that Twitter was formally launched in 2006, by the time of the 2009 H1N1 influenza epidemic, efforts to explore the potential of analyzing social media data for epidemiological public health studies were already underway [62]. In their study, the authors utilized a triaxial coding scheme to evaluate the content of over 2 million tweets that contained a set of words of interest. The results showed that the methodology was able to identify the content of the tweets, roughly discriminating them in categories set by the authors, such as personal opinions, resource sharing, and even misinformation sharing. A few years later, in the context of the 2012-2013 influenza epidemic, a method for Twitter-based epidemiological surveillance using data from users in the United States was developed [64]. The method used a mixture of keyword filtering and SVM to successfully detect infections in users by identifying tweets that could relate to an actual infection while discarding those that mention the disease but do not relate to an infection. By cross-verifying the results with the epidemiological figures provided by the CDC, the model was able to detect the weekly change in influenza prevalence with up to 85% accuracy. In a 2017 study [66], the authors implement a network-based model for predicting influenza-like diseases with data sourced from Twitter in the US. Using a database assembled from keyword-filtered tweets, their findings suggested that the model's predictions aligned with the data on influenza incidence in the US provided by the CDC.

Even more recently, some other viral outbreaks have been proven to produce a significant impact on social media data. For the 2014-2015 Ebola outbreak in Africa, for example, Liang *et al.* studied the spreading pattern of Ebola-related information on Twitter and identified users considered influential to this topic [67], [126]–[128]. Using keyword filtering and diffusion trees, the authors found that, at least in the specific case and time, information was significantly more likely to be spread through broadcasting (retweets) than it was through a user-to-user or *viral* spread. In the context of the 2015-2016 Zika epidemic, Mamidi *et al.* performed a machine learning-based analysis of a number of tweets concerning the disease in an effort to qualitatively determine the nature of the sentiments expressed by the authors of said tweets [60]. For this method, approximately 50,000 tweets were analyzed by a combination of LDA, word embedding, and either an n-gram- or Word2Vec-based classifier model. Given the qualitative attributes of this study, the results demonstrated an overall negative polarity in the sentiments classified.

Similar methodologies focusing on the assessment of social media user responses to other significant outbreaks, such as MERS, dengue, and Zika virus, have also been reported [129]–[135], [191].

V. SENTIMENT ANALYSIS APPLICATIONS RELATED TO THE COVID-19 PANDEMIC

The intersection of all-time high social media usage [136] and the reduced physical interaction in the global population as a product of the sanitary measures instated by governments has resulted in a high level of interest in the use of SA techniques for applications with the objectives of alleviating or studying the effects of the COVID-19 pandemic. The applications explored in this section can be broadly classified into two categories: those focused on exploring, modeling, and/or extracting particular insights of interest from opinions regarding the COVID-19 pandemic and its associated social, political, and/or economic effects and those focused on attempting to evaluate, model, and/or predict the epidemiological progression of COVID-19 across individual populations or greater regional areas.

A. PUBLIC HEALTH ATTITUDES AND OPINIONS ON THE PANDEMIC

Since the beginning of the pandemic, social media has found itself inundated with both information and opinions on all the topics surrounding it. In an effort to characterize the spread of information across five social media platforms during the beginning of the pandemic, Cinelli *et al.* analyzed a large number of interactions by first building vector representations of the words with Word2Vec and subsequently applying a PAM algorithm on the representations [96]. This in conjunction with epidemiological modeling of the information spread and a linear regression analysis allowed the authors to pinpoint activity peaks, the intensity of interactions, and even the level of questionable information on each platform. In another recent study by Abd-Alrazaq *et al.*, approximately 167,000 tweets were analyzed by counting word frequencies of certain n-grams and subsequently identifying topics using LDA to identify those that could cause the most concern and the public's attitudes towards them [26]. The authors found several topics being widely discussed, ranging from the origin of the virus to the measures of containment placed, with economic losses and the impact of the outbreak being the most discussed topic on the sample.

Other public health sentiments, such as vaccine hesitancy or mask acceptance, can also be extracted by means of SA. After extracting a large number of posts from Facebook and Twitter by means of keyword filtering, Hussain *et al.* performed two different NLP techniques to observe vaccine attitudes in the United Kingdom and the United States [192]. By combining a lexicon-based analysis with a pretrained BERT model, the authors were able to point to both temporal and geospatial features in the data analyzed that correlated to marked events related to vaccines or the overall political views of the specific location. Using a combination of sentence-level word embedding and an emotion intensity prediction system based on affective lexicons, n-grams, POS, and word embedding in [105], Garcia and Berton analyze the effectiveness of topic detection and SA on a large database of tweets from Brazil and the USA in the context of the pandemic. The authors successfully detected topics representative of news outlets during the time of the analysis and compared the level of discussion and the relationship with human behavior in Brazil and the USA. Similar studies have reached similar conclusions in other outbreak events, such as the Zika virus [137].

B. EPIDEMIOLOGICAL PROGRESSION OF THE PANDEMIC

At the beginning of 2020 and subsequently at the beginning of the pandemic, policy responses of governments around the world were deployed very differently and at different instances. As a way to provide comprehensive insight into the effectiveness and delay of countries' government responses, Cheng *et al.* assembled a large hand-coded dataset of more than 13,000 policy announcements from more than 195 countries [193]. The authors qualitatively analyzed the policies and their enforcement, as well as quantitatively analyzed them using Bayesian classifiers that reflected the acceleration of policy enforcement at the beginning of the pandemic. With the purpose of predicting COVID-19 outbreak waves in Canada and the US during 2020, Yousefinaghani *et al.* used data extracted from Twitter and Google Trends related to symptoms and preventive measures to predict the probability of a new wave of cases [107]. These predictions were performed using the seasonal-hybrid extreme studentized deviation algorithm, which employs a time series decomposition to determine the seasonal component of a given time series, using both the absolute deviation of the statistical mean and median of the data to detect anomalies. The authors found that the system was able to predict up to 100% of first waves of cases in states that had experienced an initial wave, 2 to 6 days before other data streams, as well as providing proof that in the US, fever and cough are the most important symptoms that provide early warnings of cases.

Given the shortage of testing and difficulty of contact tracing at the beginning of the pandemic, a study developed and evaluated a pipeline for detecting potential COVID-19 cases based on the NLP analysis of Twitter data [138]. In this pipeline, the authors first collected a set of 7 million tweets produced between January and March 2020 that mentioned COVID-19 keywords, were geo-tagged, and/or included user profile location metadata. These tweets were then filtered by manually written regular expressions to eliminate reported speech and obtain expressions that could potentially indicate a user's infection. The remaining tweets were then annotated and split to train two BERT-like classifiers, which were later deployed on more than 85 million unlabeled tweets produced between March and August 2020. Tests on the unlabeled corpus of tweets produced an F1-score of 0.76 for detecting self-reported potential COVID-19 cases, resulting in more than 13,000 geo-tagged potential self-reported COVID-19 cases in US states.

C. MENTAL HEALTH DURING THE PANDEMIC

Loss of life, a deteriorating economy, a lack of human interaction, and conflicting messages from what should be reassuring figures all add up to become major psychological stressors that result in widespread emotional distress or even an increased risk of psychiatric illness [194]. This increased risk and the high level of correlation between a user's social media posts and his or her mental health status [139] are among the motivations for some authors to perform SA on social media data with hopes of detecting or predicting mental illness caused by COVID-19-related stressors. In a mid-2020 study, a random sample of US geo-tagged tweets and a large sample of COVID-19-related tweets were used to estimate a number of mental health indicators and compare them to an equivalent 2019 dataset [113]. By calculating the frequency of specific word and phrase mentions, the authors analyzed the samples with four pretrained machine learning models that obtained overall sentiment, stress, anxiety, and loneliness estimates. Their findings, reflected in Cohen's d scores, indicate a significant deterioration in all four indicators between the 2020 database and its 2019 equivalent.

In a study using a large database of US tweets, Valdez *et al.* performed a longitudinal analysis on said data to characterize the most frequent topics and overall sentiment in 20 major US cities [108]. For this purpose, the evolution of hashtags present in a database of more than 86 million tweets was characterized by means of LDA, which was then used to build a timeline of events. This timeline provided data that were then used to analyze the overall progression of moods with VADER SA scores, which ultimately showed a significant and continuous deterioration in the public's mood. In China, Li *et al.* employed the analysis of Weibo users' data to explore the impact of COVID-19 on said users' mental health [140]. By analyzing the posts of several thousand users using an approach based on online ecological recognition, the authors calculated word frequency and scores of emotional indicators such as anxiety, depression, indignation, and happiness. The results obtained from this study showed that after the state declaration of COVID-19, negative emotions on the network increased, while the quantitative presence of positive emotions and life satisfaction indicators decreased.

VI. CURRENT CHALLENGES AND MOST RELEVANT RESULTS

The field of human healthcare and related policy has been historically cautious when implementing automated models to inform or dictate their activities [195], [196]. This trend stems not from an aversion to technological advancement but from a cautious need to evaluate all conceivable implications of these advancements and their effects on the well-being of both individuals and that of significant demographic sections. To increase the precision and interpretability of advancements in the field, SA presents a series of nontrivial challenges to overcome. Previous works have explored these challenges, which can be broadly grouped into those that are technical in nature and those regarding the interpretation of human language and its various nuances. [31], [32].

The main technical challenges identified in the literature relate directly to the increasing volume of social media data that is being continuously generated at a global scale. An SA model is required to not only be relevant at its time of development and evaluation, but long-term implementations introduce the additional requirement for these models to stay relevant in the face of continuous human cultural shifts. This requires model training methodologies to be able to continuously incorporate the insights from new terms, structures, and trends in human language without the need to process entire, continuously growing data sets to provide accurate results. In addition, the improvement of parallel computing techniques has been identified as a key factor in providing the computational capacity to process these data sets in a timely fashion, as well as providing additional computational robustness through the use of geographically distributed processing architectures. Beyond these computational challenges, the dynamic and nuanced nature of human language introduces nontrivial obstacles to accurate SA methodologies. In most cases, SA models require accurate labeling to produce accurate results. The nonformal nature of the language commonly used in social media results in a significant amount of sarcastic, ironic, and contradicting data points, which must be accurately reviewed by a human reviewer for use in subsequent model training. When reviewing large data sets for labeling, it is a very real possibility that these nuances and biases can be lost to individual human reviewers and therefore would not manifest themselves in the results of models trained with these data. Sarcasm and irony are particularly difficult to model due to their dependency on the emotional context of social media users [197]. Finally, the informal nature of social media language leads to training lexicon issues due to mistyped words, and the dynamic nature of human language can result in individual words having radically different meanings (and thus associated sentiments) over short periods of time depending on particular demographic aspects such as age group, socioeconomic class, and/or geographical location.

Currently, the global conditions of increasing internet access for the developing world have had significant effects on the increase in data availability and cultural diversity of social media participation. Consequently, as presented in Fig. 6, there has been a proportional increase in both interest and research efforts to process and interpret the sentiments and trends that are present in social media data. This substantial increase in research efforts has been identified to have a detrimental effect on the consistency of experimental designs, processing of data sets, and incomparability and/or misinterpretation of results [198]. To this end, the work of Hu *et al.* [198] presents a standardized methodology for the structuring and reporting of future works in the field of SA, which could contribute significantly to the comparability of the results of individual works in this field.

VII. THE SCOPE OF THIS PAPER

The global scope of this paper is on SA techniques and their applications to human health. Because SA can be defined as an integral set of steps each consisting of a number of distinct techniques, it is necessary to clarify that the authors have deliberately chosen to focus on techniques related to the extraction and classification of linguistic information. On the topic of health applications, works related to contagious diseases or mental health have been predominantly chosen, given the context around which SA could be most useful at the current time of this work. It is now generally regarded that both social media and contagious diseases are here to stay, be it a COVID-19 which will remain in medium to low levels of circulation for years to come or any other contagious disease. This presents health authorities on a global scale with a more pressing necessity for improving mental health monitoring or already existing contagious disease tracking techniques, using publicly available data from their respective citizens. The references studied in Section III were obtained by searching in different scientific search engines such as Scopus, Science Direct, IEEE Xplore, and Google Scholar, for the following keywords: *Sentiment Analysis, Text Classification, Social Media, Social Networks, Health, Twitter, Facebook, Instagram, epidemic, pandemic, COVID-19, SARS-Cov-19, Influenza, Virus, Vaccine, Vaccination, Affliction, Mental Health, Mental Illness, Mental Disorder Psychiatric, Suicide, Depression, Public Sentiment, Discourse,* and *Public Health*. These keywords were selected through a search of the most relevant literature on the subject of study of this work, following a literature search methodology based on the one presented in [198]. Upon obtaining a complete reference list, we proceeded to filter the literature based on a series of parameters. First, in terms of the type of article, it is defined that literature reviews, highly cited, or high impact publications should be prioritized given the popularity of the subject in recent months, effectively leaving out those articles that do not meet the criteria. Second, in terms of the topics, we decided to keep articles that describe either SA or health-related applications of SA, with a special interest in those that use data from social media and those that mention mental health or public health policies. Having obtained a filtered reference list, we proceeded to analyze each paper to extract the techniques used and any insight that it could provide in terms of the presented results. Our evaluation considers why the authors focus on certain techniques for the extraction and classification of linguistic information and on how they measure their performance. To assess academic interest in the topic of SA for health applications, Fig. 7 presents the number of individual studies evaluated

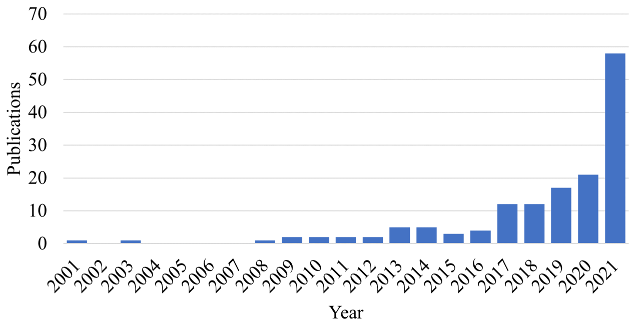

FIGURE 6. Distribution of reviewed scientific literature by year since 2008.

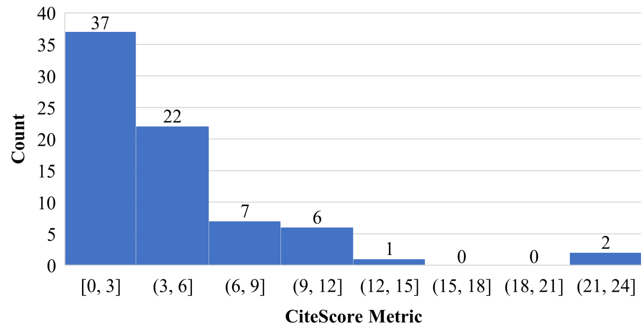

FIGURE 8. Distribution of reviewed scientific literature by CiteScore metric.

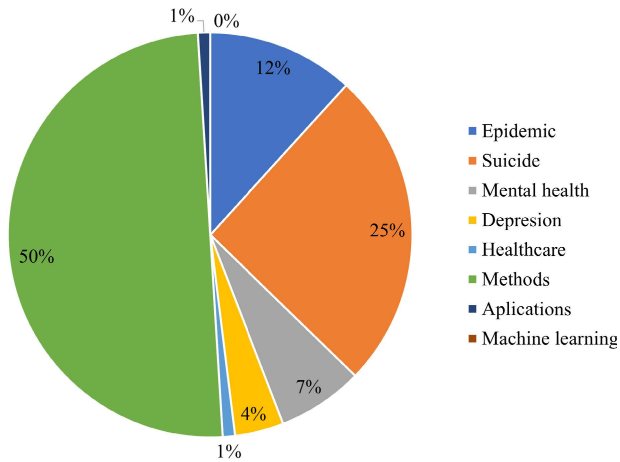

FIGURE 7. Distribution of reviewed scientific literature by topic.

by year. Furthermore, the reviewed literature was organized according to several criteria: affliction types, data processing techniques, data sources, and application objectives. Broadly speaking, we observed a proportionally high number of studies related to mental health, population opinion assessments on public health matters, infectious diseases, and drug use.

Regarding the topics of the references used in this paper, as seen in Fig. 7, the vast majority were about applications on health-related themes. The Methods classification refers to publications used to explain certain techniques and to establish scientific bases to make affirmations.

Finally, the obtained application references were composed of 27% conference proceeding publications and 73% research works published in scientific journals. The CiteScore distribution of the journals where the reviewed literature was published is summarized in Fig. 8.

Currently, different techniques are used in SA to study specific aspects of mental health afflictions, such as suicidal intentions [18]–[21] and depression [63], [65], [173], as the relationship between the information in social networks and the epidemiological figures of contagion of different types of viruses, such as H1N1 [62], Zika [60] and influenza [64], among others, differ. This type of study involves preprocessing the source data coming from social networks, as well as processing one or several layers [20] to extract the relevant information by applying the different models and methods defined below. To determine the best techniques to be used in future studies, the revised techniques were analyzed exclusively with a quantitative approach to understand which techniques were the most used and therefore which techniques had the best reliability at the time of the study.

VIII. CONCLUSION

Relevant conclusions can be drawn from the study to understand the behavior and feelings of citizens in the face of the restriction measures that have emerged from the pandemic in recent years. On the other hand, it is possible to identify past and present articles in the field of sentiment analysis from the perspective of social networks.

From this study, it is possible to understand the need to link interdisciplinary groups of medical specialists and technologists who manage to integrate their specialties to analyze and contribute ideas that clarify lines of action in the face of the COVID-19 pandemic and other pandemics that on a smaller scale have affected the world's population. With this research, important scientific papers have been extracted from various electronic databases that develop various algorithmic techniques of machine and deep learning that study various scenarios of social behavior of the population.

This article shows in its seven sections a wide contextualization, classification, and categorization, providing the reader with a systematized inventory on scientific production in knowledge of AI theories, models, and algorithmic techniques focused on the pandemic study of various viruses such as H1N1, Ebola, ZIKA, influenza, MER, SAR, and COVID-19, and the vast sea of data to be analyzed about these viruses and their contexts. This research provides a timely circulation of information collected and updated. Therefore, a new demand for knowledge has been generated, and comparisons have been made with other knowledge parallel to that found. In addition, we offer in this research different possibilities of understanding the problem treated; we offer more than one study alternative.

After thorough revision of the elaborated sources, it becomes evident that the use of novel forms of ML and

DL is increasingly displacing the use of the more traditional statistical methods used throughout the last few decades. One possible explanation for this phenomenon could be that computationally demanding tasks are less so as a direct result of an increasing availability in cost-effective computing power, as well as the never-ending supply of naturally occurring information on social media. It can also be affirmed that data preprocessing is a fundamental step that can directly alter the results of later classification tasks, even though most of the authors reviewed chose to not elaborate on the details necessary for its execution, as the specifics of these techniques are often derived from well-established methodologies.

The repetition with which a described technique mentioned in this work is used does not necessarily correlate it to an elevated degree of success or effectiveness when compared to other, less utilized methods. This could be attributed to an easier implementation and relatively assured positive results in quantitative analysis, since it is not possible to generalize this assertion without conducting more thorough comparative research on each specific methodology.

IX. FUTURE WORK

While completing this survey, the authors found a number of possible application-specific uses of certain methods or combinations of methods, which could aid in near future applications of SA on health-related issues in specific regions of interest or which could also be used for applications different than those described by their original authors. One of these uses could be to create a real-time georeferenced national mental health degradation indicator that feeds off data from social networks commonly utilized in the country. Such a system could potentially benefit from SA techniques for opinion classification, provided that information posted on these networks is heavily correlated with the user's sentimental state at the moment of expression.

A significant portion of the available research in the field is centered on the analysis of text-based data, most commonly (but not exclusively) sourced from Twitter. In the face of the development and usage increase of social networks based on multimedia content, such as image and video, it is important to develop further research efforts into algorithms that can incorporate sentiment information from these sources in a manner that is fast and scalable enough to provide insights at a comparable rate than current approaches for text-based data.

With regards to the COVID-19 global pandemic event, the applications and algorithms explored in this work present a variety of tools that were employed to evaluate the general public's perception to specific governmental policies regarding public health in the face of outbreak events. These tools could be further employed to measure, in a timely manner, the immediate perceptions of individual populations towards public health policies. In order to further refine the accuracy of these tools, it is necessary to devote additional research efforts towards the development of multilingual models that can monitor public sentiment in linguistically diverse populations with accuracy levels comparable to single-language models. This is of particular importance in populations where a language bias could mask a variety of social, political, or economical aspects of a given population, and thus exclude their opinions from a feedback mechanism for informing public health management activities. When using SA models to inform public policy, it is of utmost important to consider the sources of the data used to measure social response to individual policy. To this end, models could incorporate multivariate analyses of various indicators of social development for a given region in order to ensure the sampled population used for model training are a satisfactory representation of the individual populations to evaluate.

The SA applications explored in this work can similarly be employed towards the monitoring of public sentiment towards environmental issues, such as policies for climate change mitigation, ocean and ecosystem health preservation, and the public aspects of energy transition efforts, for instance. However, it is of utmost importance to consider the ethical aspects of this technology. Training datasets for SA algorithms often include some level of data that can be used to monitor the activities of individuals, as well as their ideologies, convictions and personal preferences. As the amount of publicly available datasets grows, it is important for the community to establish guidelines in order to ensure that SA applications are developed for study and evaluation of societies or demographics as a whole, and do not allow for the monitoring of individuals.

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