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AI BASED TEXTUAL BIG DATA FOR EMOTION DETECTION

B.Rajesh Kuma
Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, INDIA

Nupur Soni
Babu Banarasi Das University, Lucknow (U.P.) India

Abstract: Online Social Media (OSM) like Facebook and Twitter has emerged as a powerful tool to express via text people's opinions and feelings about the current surrounding events. Understanding the emotions at the fine-grained level of these expressed thoughts is important for system improvement. Such crucial insights cannot be completely obtained by doing AI-based big data sentiment analysis; hence, text-based emotion detection using AI in social media big data has become an upcoming area of Natural Language Processing research. It can be used in various fields such as understanding expressed emotions, human–computer interaction, data mining, online education, recommendation systems, and psychology. Even though the research work is ongoing in this domain, it still lacks a formal study that can give a qualitative (techniques used) and quantitative (contributions) literature overview. This study has considered 827 Scopus and 83 Web of Science research papers from the years 2005–2020 for the analysis. The qualitative review represents different emotion models, datasets, algorithms, and application domains of text-based emotion detection. The quantitative bibliometric review of contributions presents research details such as publications, volume, co-authorship networks, citation analysis, and demographic research distribution. In the end, challenges and probable solutions are showcased, which can provide future research directions in this area.
Keywords: artificial intelligence; machine learning; natural language processing, (NLP); text-based emotion detection (TBED); online social media

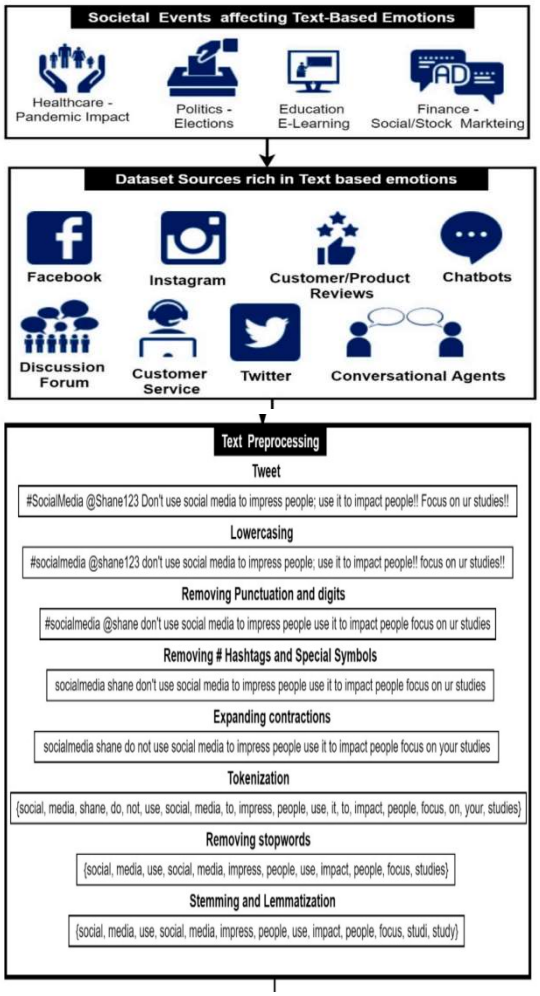
Introduction

Out of 7.8 billion people worldwide, 50.64% of the population uses social networks, irrespective of their age [1]. Presently popular social networking sites like Facebook, Instagram, YouTube, WhatsApp, FB messenger, Twitter, and Reddit are used by this population. In addition, Twitter, Instagram, and Reddit are very widely used microblogging sites where people make short, frequent posts from these social networks. Online Social Media (OSM) platforms provide the opportunity to express, communicate, and share people's opinions, thoughts, views, and perspectives—on local and international issues, matters, and topics—through text, image, audio, and video posts. Posts on social media are public and abundant in emotions. Analyzing and studying these posts from social media may indicate emotional states and the reasons behind those emotions. However, the massive volume of this data makes this analysis very difficult. Artificial Intelligence can help to find emotions, feelings, personal traits, views, and their effects on social trends in an automated manner. Societal events such as pandemics andelections cause emotional variations in masses which are expressed via

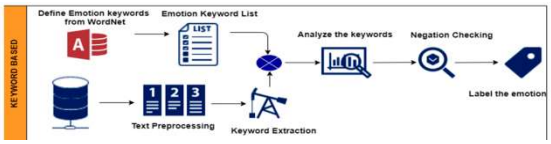
online social media.

Even though various modes of communication are available, the text remains one of the most prevalent forms of communication in a social network. So, text-based emotion detection becomes a vital part of the research. Text-based emotion detection using artificial intelligence employs Natural Language Processing (NLP) [2], which combines techniques in linguistics and computations to help computers comprehend and produce texts and speech/voice in the form of human languages. Wider applications in NLP consist of machine translation, speech recognition systems, sentiment analysis, text classification, questions and answering, chatbots, text summarization, and so on. Emotion detection is an extended derivative of sentiment analysis. Emotion detection is taking out finer-grained emotions like anger, happiness, sadness, anxiety, depression, etc., and applying this feedback to future decision making. This study of text-based emotion detection using artificial intelligence methods will be useful in many fields, including human–computer interaction, education, data mining, psychology, E-learning, software engineering, website customization, information filtering systems, gaming, etc. The focus of sentiment analysis is to derive information from human language for interpreting views and feelings to assign polarities like positive, negative, or neutral. However, emotion detection aims at finding out more specific sentiment tones such as happiness, sadness, depression, anxiety, etc. Emotion detection can be applied to three classes, i.e., text, speech, and facial expressions. Emotion detection [3] from text is a process of determining the emotions of the written text using a set of predetermined emotionlabeled datasets and data analysis algorithms. Such kind of text emotion analysis helps in understanding the feedbacks given through online social media, customer reviews, product reviews, discussion forums, online recommendation systems, conversational agents, emails, web blogs, and many more. Emotion detection from text is addressed by two approaches: (1) Explicit detection and (2) Implicit detection. Explicit means clearly stated words or emotion-bearing words like “happy” are used in the written text to express the emotions. Explicit detection is identifying and classifying written text into emotion classes with the help of emotion-bearing words. Explicit detection is used where more specified key phrases are used to express emotions, such as the keyword-based approach of emotion detection. In contrast, identifying and categorizing text into emotion classes without emotion-bearing words is referred to as implicit emotion detection. The issues in accurately detecting emotions from the text are short/incomplete text, emojis, grammatical mistakes, use of special characters, etc. Emotion detection can be done at different levels in texts such as word level, sentence level, paragraph level, and document level. Text-Based Emotion Detection: Overview Figure 1 shows the process flow of text-based emotion detection using artificial intelligence. In any text-based emotion detection system, initially, datasets are created by downloading the data from online social media using APIs like Twitter data can be downloaded by using Tweepy on Python. After data generation, text pre-processing steps involve making the text suitable for any machine or deep learning algorithm to process it. Text preprocessing involves tokenization, text cleaning, normalization, and creating feature vectors/embedding. Particularly, the text from social media, product/customer reviews, etc., consists of slang words, emojis, hashtags, HTML tags, short text, incomplete words, etc., which requires preprocessing. Next, machine or deep learning is applied to generated feature vectors. These feature vectors are fed into any machine learning algorithm or deep learning neural network where feature vectors with emotion

labels are trained. Then the trained system is used to classify and predict the labels of unseen text. Here we take a brief look at the applications of text-based emotion detection. Table 1 shows the prominent application domains where text-based emotion detection with artificial intelligence is utilized



2.2. Text-Based Emotion Detection Approaches The general approaches used for detecting emotions from the text are the keywordbased approach, rule-based approach, classical learning–based approach, and deep learning– based approach. Figure 3 shows the approaches used for text-based emotion detection.



(1) Keyword-based approach—A keyword-based approach is built on locating the occurrences of a keyword in a given text and matching with the labels stored in the Big Data Cogn. Comput.2021, 5, 43 9 of 45 dataset. In this approach, the emotion keyword list is initially defined from standard lexical databases such as WordNet-Affect [20] or WordNet [21]. Next, preprocessing is carried out on the

dataset. After that, keyword spotting is done between emotion keywords from the text and predefined keyword lists. Then keyword intensity of emotion is analyzed. Afterward, negation checking is performed to identify negation cues and the scope of the cue, and finally, the emotion label is determined. In our analysis, we surveyed [22–25], which are centered on a keyword-based approach. To have a better understanding of how this approach works, we examined [22]. In [22], J. Tao explained the keyword-based emotion recognition approach. Each sentence is considered as a combination of content words or Emotion Function Word (EFW). EFWs can take three forms: emotion keyword, modifier word, and metaphor word. Emotion keywords can take six emotion labels from Ekman's emotion model and assigned specific weights. Modifier words consist of words that emphasize strong or weak emotions. Metaphor words show spontaneous expressions or personal characteristics. This approach first applies POS tagger to each sentence and check EFW then assign emotional ratings to EFW. The next step is to give weights to emotion keywords and constructs a link to EFW. Then, scores across all sentences are summed. To determine an overall score, it goes through a fuzzy logic process. In the last step, sentences are assigned suitable emotion labels according to the overall score. Figure 3 outlines the keyword-based approach.

(2) Rule-based approach—The rule-based approach defines logical and grammatical rules to detect emotions from the text. Initially, text preprocessing is done on the emotion dataset. Then, rules for emotion recognition are mined from text using linguistic and statistic theories. In this, probabilistic affinity or lexical affinity is attached to each word. Then, the best of the rules are selected. Lastly, the selected rules are used for emotion detection to detect emotion labels. Refs.[26–29] surveyed in the rule-based approach. Lee et al. [26] suggested a rule-based approach for identifying emotion cause events. Lee et al. used the Chinese microblogging website—SinaWeibo—as a data corpus. The expressly communicated thoughts or experiences that generate a related emotion are referred to as cause events. Initially, a labeled corpus is constructed based on emotional causes. Then, the grouping of cause events and the place of cause events pertaining to emotional experiences are determined. Then, keywords are defined for every emotion category. Following that, seven groups of linguistic clues are found, along with two groups of linguistic rules to detect emotion causes are developed. The authors constructed 15 linguistic rules to detect emotions. Finally, a system that identifies the causes of emotions is constructed based on linguistic criteria. a general overview of the rule-based approach.

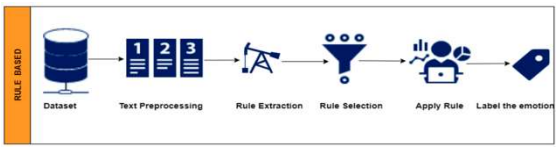
(3) Machine Learning/Classical Learning–based Approach

Outlines the machine/classical learning–based approach.The machine learning–based approach enables systems to learn and develop as a result of their experiences automatically. Machine learning algorithms classify the text into different emotion classes. There are two categories of machine learning algorithms—supervised or unsupervised. In most of the reviewed papers, supervised machine learning algorithms are widely used. This approach generally starts with the text preprocessing step. Then the useful features are extracted from the text, and only features are selected with the most information gain. After that, with the given feature set and emotion labels, the system is trained. Lastly, the trained system is used to classify the emotion from the unseen text, termed prediction. The authors surveyed Refs. [30–35], which used the machine learning–based approach. To better understand how this approach works, we examined [32], where Bruyne et al. presented an

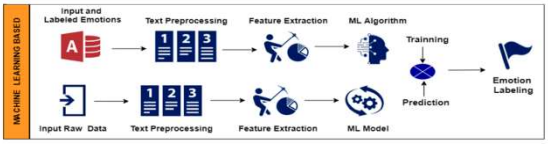
emotion classification system for English tweets. Initially, text preprocessing has performed using word and sentence tokenization, stemming, lowercasing, and POS-tagging. Next, feature extraction is accomplished using n-gram features, lexicon features, and various semantic and syntactic features. Then to solve a multi-class multi-label problem, an ensemble of eleven binary classifiers was created for each possible emotion class, anger, anticipation, disgust, trust, fear, love, joy, pessimism, optimism, surprise, and sadness where each model Big Data Cogn. Comput. 2021, 5, 43 10 of 45 gets the previous models' predictions as supplementary features. To create a multi-label representation of the predictions, the predicted labels are concatenated.

(4) Deep Learning–based approach—deep learning is a variant of machine learning in artificial intelligence with networks capable of unsupervised learning from unstructured or unlabeled data. Figure 3 outlines the deep learning–based approach. This approach enables neural networks to learn complex concepts by constructing them from simpler ones. Initial preprocessing is carried out on the dataset. After that, the embedding layer is built, where tokens are represented in the form of numbers. Then, depending on the number of emotion labels, these feature vectors are input into one or more Deep Neural Network layers. Patterns are learned from data and used to predict the labels by using classification. References [8,19,36–43] surveyed the deep learning–based approach. To have a better understanding of how this approach works, we examined Ref. [41]. A deep learning system for multi-label emotion identification problems for micro-blogs was proposed by Rathnayaka et al. [41]. For preprocessing, they used the Ekphrasis tool. Word normalization, tokenization, spell correction, and segmentation are all performed by Ekphrasis. GloVe, a pre-trained word embedding algorithm, was used. The features from the embedding layer are provided to two Bidirectional–Gated recurrent unit layers. After that, the output of the first Bi-GRU layer is given to the first attention layer. The output combined from the first and second Bi-GRU and embedding layer is given to the second attention layer. Then, combined, two attention layers are provided to a DNN with a sigmoid activation function for classification. The authors used 11 emotion categories to classify emotions: anger, anticipation, disgust, trust, fear, love, joy, pessimism, optimism, surprise, and sadness. In Table 2, a qualitative analysis of the relevant literature is shown. This table highlights the datasets, algorithm/technique/methods, objectives, advantages, disadvantages, application domain, evaluation performance, and emotions detected, that have been surveyed in different emotion-detection approaches. The table is arranged according to the application domain. In our qualitative analysis, it has been discovered that social media is the application area [43] where prominent research has been done in text-based emotion detection, with little research on conversational systems (chatbots) public monitoring. It has also been discovered that the categorical emotion model is the most used by researchers in text-based emotion detection, while the componential emotion model has been less preferred. The major emotions detected in all the application domains are happiness, anger, fear, surprise, disgust, sadness. Machine learning and deep learning–based approaches performed well on the different evaluation measures like accuracy and precision. 2.3. Dataset/Corpora Following the selection of a model to classify the emotions, appropriate data acquisition is the next important step in text-based emotion detection. In emotion detection from text, researchers either create their datasets according to study or use available datasets. Datasets available for text-based emotion detection research are labeled or annotated customized datasets. These annotated datasets are created

with the help of expert human annotators from respective fields. Researchers have preferred existing datasets or created their datasets according to experiments' requirements to specific application domains. Most of the datasets are easily available and can be downloaded freely. P



Most datasets are multi-labeled datasets that are suitable for emotion detection from text. There are few structured datasets with annotations designed for text-based emotion detection, publicly available for research purposes. Information for many datasets is collected from online social media platforms such as Facebook, Twitter, Reddit, etc. Data collected from online social media has been in the form of tweets, posts, comments, while some datasets are built from Google news, newspapers, essays, letters, travel guides, conversations, story tales, etc.



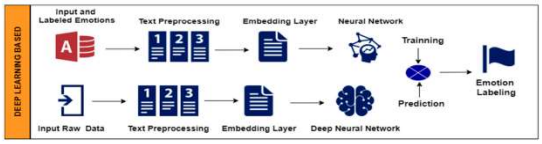
3. Quantitative Analysis—Bibliometric Contributions Analysis Bibliometric analysis is referred to as a statistical examination of published scientific journals, books, or papers. This analysis provides insights into the contribution of various countries, institutes, authors, and journals in the research area. A detailed study of existing literature in this field will help to evaluate the quality of research work with its merits and demerits and provides support to researchers in shaping and enhancing further research actions. The applicability of bibliometric analysis differs with the factors that are being analyzed and methods being used in various subject areas like those that we surveyed in the manufacturing field [53] and in the medical field [54]. The aim is to provide new ideas and ongoing development in the area by visually reflecting and mapping the literature on text-based emotion detection using artificial intelligence over the past 16 years in terms of augmentation, potency, social, and abstract structure. First, this survey depicts research using artificial intelligence with citation data and publication data between 2005 and 2021 (augmentation). Second, this study finds the research areas and the popular journals impacting the field's growth, along with the important authors and prominent countries in text-based emotion detection using artificial intelligence (potency). Third, the study indicates the collaborative connection between the authors and the countries (social structure). Fourth, the study exposes the current focus (abstract structure) of the research on text-based emotion detection using artificial intelligence over the past years.

3.1. Search Strategy For this analysis, two parallel searches were performed on Elsevier's Scopus and Clarivate Analytics' Web of Science databases. All the searches and document retrieval were performed on the last week of March 2021. The first search targeted text-based and consists of only one search keyword in focus: ["text-based"]. The subsequent search was aimed to get research focusing on artificial intelligence. Following keywords included in search in the topic field ["artificial intelligence," "deep learning," "machine learning," "natural language processing"]. In the next search, emotion detection keywords related to text-based were inputted. The following keywords included in the title field: ["emotion detection," "sentiment analysis," "emotion analysis,"

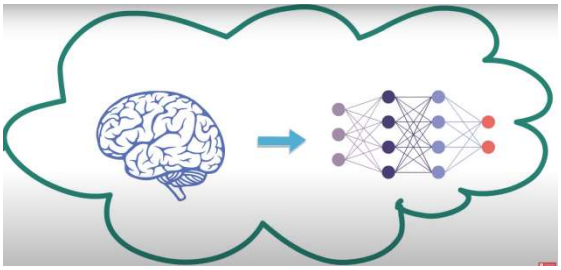
"emotion recognition," "chatbots," "conversational agents," "social media," "Twitter," "Facebook," Reddit," "Instagram," "reviews"].

The OR Boolean operator is used between keywords while searching to obtain a greater number of appropriate documents. Additionally, in Web of Science searches, asterisks are used as wildcards. Web of Science permits you to use asterisks as a wildcard in all the searches that accept words and groups of words. All of the searches were restricted to journal articles and reviews that were written between 2005 and 2021. The English language was implemented in the search. This search approach retrieved a total of 910 documents: 827 documents from Scopus and 83 from Web of Science. After extracting the duplicates, a total of 902 research papers were chosen and included in the paper. Each document's publication title, publication year, Journal/Source title, the number of citations are considered for analysis. Thus, the abstract, the title, the keywords, and cited references were retrieved. Figure 4 shows the methodological outline of the search strategy and data analysis approach used to retrieve the Scopus and Web of Science documents.

3.2. Data Analysis Procedure The documents retrieved in the earlier search were examined using illustrative and bibliometric methods to provide a general outline of the progress going in text-based emotion detection using artificial intelligence. To describe the development curve in the research on text-based emotion detection using artificial intelligence, publication count and citations per year were obtained. The tables were created to describe the summary of the research in terms of subject areas, journals/source titles, publication types, countries, funding agencies contributing to the growth of the research field. Bibliometric analysis is performed in VOS viewer and Gephi software to study and visually illustrate the social Big Data Cogn. Comput.2021, 5, 43 18 of 45 and abstract formation of the field. VOS viewer is a free software for visualizing and exploring bibliometric maps [55]. In VOS viewer, the types of analysis are co-occurrence, co-authorship, citations, co-citations, bibliographic coupling, and units of analysis are authors, organizations, keywords, documents sources, countries, or references depending on the attention of the analysis. Big Data Cogn.Comput. 2021, 5, x FOR PEER REVIEW 18 of 46 "conversational agents," "social media," "Twitter," "Facebook," Reddit," "Instagram," "reviews"]. The OR Boolean operator is used between keywords while searching to obtain a greater number of appropriate documents. Additionally, in Web of Science searches, asterisks are used as wildcards. Web of Science permits you to use asterisks as a wildcard in all the searches that accept words and groups of words. All of the searches were restricted to journal articles and reviews that were written between 2005 and 2021. The English language was implemented in the search. This search approach retrieved a total of 910 documents: 827 documents from Scopus and 83 from Web of Science. After extracting the duplicates, a total of 902 research papers were chosen and included in the paper. Each document's publication title, publication year, Journal/Source title, the number of citations are considered for analysis. Thus, the abstract, the title, the keywords, and cited references were retrieved. Figure 4 shows the methodological outline of the search strategy and data analysis approach used to retrieve the Scop

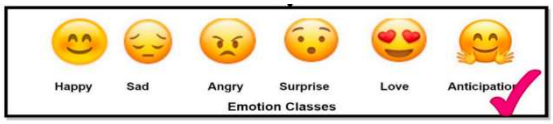


The software approximates the differences between the nodes in the first stage. Then it creates a two-dimensional map in the second step, with the distance between nodes reflecting their similarity. The VOS viewer groups closely related nodes into clusters in the third stage [56].



Data Analysis Procedure The documents retrieved in the earlier search were examined using illustrative and bibliometric methods to provide a general outline of the progress going in text-based emotion detection using artificial intelligence. To describe the development curve in the research on text-based emotion detection using artificial intelligence, publication count and citations per year were obtained. The tables were created to describe the summary of the Figure 4. Methodological Outline. The units of analysis are often depicted in the graphs as circular nodes or rectangular frames. The node/frame size represents the number of publications, authors, or keywords, etc. A link, which is a connection or a relation between the two nodes, is called an Edge. An Edge may represent bibliographic coupling links between publications, co-authorship links between authors, and co-occurrence links between keyword nodes, and each edge is a strength of that relationship. A cluster is a set of nodes included in a map relating to each other, and the color of each node denotes to which cluster a node belongs. The software constructs the bibliometric maps in three steps using a distance-based method [56]. Co-authorship and bibliographic coupling analyses were done to survey the social structure of research on text-based emotion detection using artificial intelligence. The units of analysis considered authors, organizations, countries/territories, documents, and sources. Each node in the map represents one of the units of analysis, and the nodes' Big Data Cogn. Comput. 2021, 5, 43 19 of 45 relationships are shown by the edges linking them. The clusters correspond to collaboration networks that exist between groups of authors or countries. Finally, the field's abstract structure was discovered via a keyword co-occurrence analysis. The unit of analysis considered the keywords of the authors. If two keywords appear in the publication, their co-occurrence link is stronger. Clusters of co-occurring keywords correspond to the current focus of the research on text-based emotion detection using artificial intelligence over the past 15 years. The second bibliometric software Gephi is a free and open-source software for analyzing and visualizing large network graphs. A network in Gephi comprises two parts: a list of the vertices/nodes that make up the network and a list of the edges (interactions between nodes). Two attributes are attached to the nodes: a label and a numeric attribute. The color of the nodes is determined by attribute. In addition, the size of a node is determined by its "Degree Centrality" value (its number of connections). Centrality is an essential metric to analyze the position of a node in a network. 3.3. Data Collection This bibliometric analysis utilized Elsevier's Scopus and Clarivate Analytics' Web of Science (WoS) databases for document retrieval. First, the search started with the "text-based" keyword introduced in the WoS

and Scopus. Afterward, the results were narrowed down by the specific selection criteria and years. Table 4 shows the list of keywords used for document retrieval from Scopus and Web of Science. We initially retrieved search query results from Scopus, which were 1011, and that from Web of Science were 234. After applying some selection criteria—we considered papers written only in English; considered only conference papers, articles, reviews as document type; limited our search from 2005 to 2021; and restricted research areas to computer science, engineering, psychology, social sciences, and decision sciences—we obtained 827 publications from Scopus and 83 publications from Web of Science as a result, after applying the selection criteria. Then, removing duplicates (08) from both databases, we had 902 publications for analysis



Conclusion

Deep learning is the best approach for detecting the emotions.For more difficult emotion detection tasks, new datasets are required. Domain adaptation techniques are required to address technical requirements, such as the need for a large amount of labelled data.

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