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Research Paper

A Comprehensive Review on Conversational Agent-based Sentimental Analysis

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Abstract
AI has been extensively utilized for dispensation data to facilitate decision-making, human interaction, and understanding of emotions. In today's digital age, people communicate their thoughts on daily activities and global events through text messaging platforms enabled by the internet. Consequently, it has become crucial for machinery to discern emotions embedded in opinions, response, and textual exchanges, enabling them to deliver sensitively intelligent responses to users. Text-based emotion detection (TBED) has emerged as a critical area advancing automated solutions across diverse sectors such as business and finance. This field has garnered significant attention recently. This paper conducts a systematic literature review spanning the years 2005 to 2021, analyzing 63 investigate papers sourced from IEEE, Science through, Scopus, and Web of discipline databases. The review addresses four principal examine questions and explores TBED applications in various domains, underscoring its relevance. It provides an overview of emotion models, methodologies, feature extraction techniques, datasets, and examine challenges, along with opportunity research directions.
Keyword :

I. Introduction

The objective of the field of artificial intelligence (AI) within computer knowledge is to develop intelligent systems that emulate individual capabilities such as understanding language, learning, solving problems, and making decisions. A key area of AI, natural language processing (NLP), merges computational and linguistic strategies to enable computers to understand human languages, enhancing human-computer interactions. Current research in NLP focuses on various applications including text summarization, speech recognition, chatbots or conversational agents, machine translation, and sentiment analysis, with sentiment analysis gaining significant traction recently. Additionally, AI has expanded to include Emotional AI and Cognitive AI. The scope of the artificial intelligence field is illustrated in Figure 1.

Thinking AI is designed to handle unstructured data and analyze it to generate new insights or conclusions. Applications of Thinking AI include text mining, audio recognition, and facial detection, which are used to identify patterns in data. This type of AI employs advanced approach such as machine learning and deep learning. Modern decision-support software, including recommender systems, expert systems, and IBM Watson (a question-answering system), exemplifies the capabilities of Thinking AI.

Feeling AI focuses on sympathetic human emotions and facilitates interactive human-machine communication. Recent advancements in Feeling AI include reaction analysis, text-to-speech technologies, chat-bots that emulate individual conversation and robots that can detect emotional signals. Essentially, Feeling AI encompasses AI systems that measure, comprehend, imitate, and respond to human emotions, with sentiment analysis being a prime example.

Emotion detection, a branch of sentiment analysis, focuses on identifying and interpreting complex emotions such as joy, anger, sadness, and other nuanced emotional states. While sentiment analysis evaluates opinions and assigns a polarity (positive, negative, neutral) derived from the understanding of these underlying emotions. Emotions are pivotal in Human-Computer Interaction, enhancing emotionally intelligent technology and improving computers' understanding of human behavior. Consequently, emotion-driven technology is crucial for supervisory across various fields, including management, advertising, user interaction, healthcare, education, finance, public monitoring, and more.

As technology advances and the Internet rapidly expands, a vast amount of digital content—such as text, images, and videos—is now accessible on numerous social media platforms. Textual information is especially prevalent, encompassing product and service discussions, news articles, blogs, and user reviews. These platforms provide a space for individuals to share their opinions and ideas, allowing for the analysis of social trends and sentiments, monitoring of customer feedback to guide corporate strategies, and aiding users in decision-making. Consequently, the study of emotion recognition from text has gained significant importance.

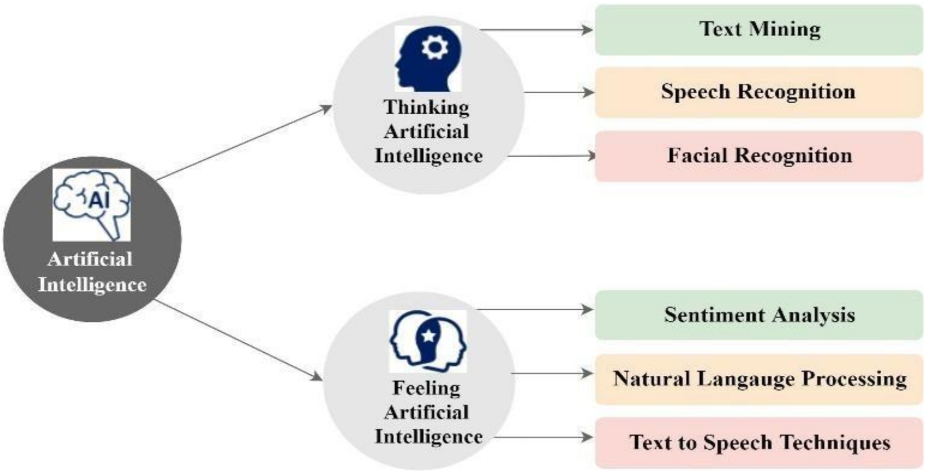

Fig. 1 Artificial Intelligence (AI) Sub domains

Since then, text-based sentiment recognition has found numerous practical applications. A new method for emotion analytics was introduced, utilizing social media data to enhance decision-making, situational awareness, and data collection for administrative purposes. Research was conducted on automated sentiment analysis to assess the sentiment polarity in product or service reviews. The classification of emotions in news articles was explored, leading to the development of a user-reviewed system for e-commerce recommendations. Additionally, a framework was proposed to enable social robots to comprehend emotions.

Investigated the potential of using intelligent conversational bots for diagnosing neuropsychiatric conditions. Explored the use of conversational bots within the healthcare sector, focusing specifically on human-like agents for commercial applications. Developed a picture evaluation structure to assist individuals in production informed choices.

Identifying emotions from vast amounts of digital content on social media is crucial for enhancing human-computer interaction and providing decision support across various domains. Text-based emotion detection (TBED) is an interdisciplinary field that intersects with data mining, human-computer interaction (HCI), psychology, and sociology. This Systematic Literature Review (SLR) provides an overview of recent TBED research, discussing the datasets, methodologies, digital social platforms, and future research opportunities. The aim is to gather insights on how TBED can enhance communication and decision-making in diverse scenarios.

II. Literature Survey

A TBED system utilizes various techniques to analyze and categorize textual data to detect underlying emotions. This process involves several components, as depicted in Figure 5. These components include classifiers, techniques for feature extraction and analysis, datasets, methodologies, application domains, and models for recognizing emotions. Textual data can originate from diverse sources such as discussion forums, social media platforms, product reviews, customer feedback, chatbots, and other text-based interactions where emotion recognition is relevant. Therefore, it is crucial to consider these varied application domains. Moreover, there are online datasets or corpora available that contain pre-labeled or annotated data for training and evaluation purposes.

Enhancing the categorization process would benefit from a deeper understanding of emotions. Emotional modeling encompasses various dynamic methodologies and strategies. Utilizing componential, dimensional, and categorical models is preferred. Prior to feature extraction, data preprocessing is necessary. These extraction processes are crucial for effective classification, as they either streamline data to its core elements or adapt it for categorization algorithms' utilization. Text analysis commonly employs five types of techniques for extracting features: lexical, syntactic, semantic, discourse combination, and sensible examination, particularly when extracting characteristics from text.

Various techniques are utilized for quality extraction, such as Bag of Words (BoW), TF-IDF, POS tagging, among others. Subsequently, these extracted features are processed by a variety of classifiers within the classification system. Both deep learning and traditional machine learning classifiers have gained significant traction in contemporary applications. The following sections offer a comprehensive overview of these methodologies and approaches.

2.1 Text-Based Emotion Detection Model

Figure 6 illustrates the text-based sensation detection model. The process begins with gathering data from diverse text sources, followed by text preprocessing to clean and standardize the data. This step is crucial due to the presence of slang, emoticons, short text, and incomplete words in social media and customer reviews. Text preprocessing involves several tasks such as tokenization, lowercasing, removal of stop words, numerals, punctuation, white places, hashtags (#), URLs, emoticons, and emojis. Additionally, lemmatization and stemming are applied to reduce words to their base form. The subsequent stage involves feature analysis, encompassing feature extraction and selection. During feature extraction, significant features are identified from the data set, ensuring the selection of the most relevant features for subsequent analysis.

The final step involves categorizing the data into potential emotion classes. Emotion recognition utilizes classification algorithms, with deep learning and machine learning being prominent methods. Machine learning techniques commonly referenced in literature include Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), and Naïve Bayes, among others. Unlike deep learning, extensive data preprocessing is not essential. Deep learning learns directly from the data itself, albeit requiring substantial datasets to develop generalization capabilities. Techniques such as data augmentation can artificially increase dataset sizes when they are insufficient.

2.1.1 Emotion Models for Emotion Detection

Emotional psychology traces its origins back to ancient Greek mythology, where a rich tapestry of emotions was depicted in literature. Greek writers categorized emotions into four primary types: libido (desire), metus (fear), aegritudo (sorrow), and Laetitia (joy). Later, in the 19th century, Charles Darwin's theory of emotion extended this exploration to encompass both human and animal emotional expressions. Modern psychology continues to categorize emotions into two main types: basic emotions and complex emotions (such as pride, shame, and regret, which are challenging to articulate). Various models have been proposed to understand emotions, including the detached sensation model and the dimensional model, which are widely recognized in the field. Additionally, the componential model, rooted in appraisal theory, offers another perspective on the complexities of emotional experience.

1) The discrete emotion model, also known as the categorical emotion model, posits that certain emotions can be universally identified rooted in neurological, physiological, behavioral, and communicative characteristics, despite of cultural background. According to this theory, emotions can be categorized into distinct fundamental groups or types, each associated with different neuronal subsystems in the intellect. For instance, Ekman's model classifies emotions into six primary categories: joy, sadness, disgust, anger, surprise, and fear. Similarly, Plutchik's model (Plutchik, 1980) lists eight primary sensation arranged in opposing pairs: anger vs. fear, anticipation vs. surprise, contempt vs. trust, and sadness vs. joy.

2) The Dimensional Emotion Model posits that emotions are interconnected and interdependent. This model suggests that all emotions stem from a unified neurophysiologic system. It categorizes emotions based on a small number of parameters that constitute distinct proportions. Most dimensional emotion models typically utilize two or three proportions, such as "dominance" (indicating the extent of influence over an emotion) and "valence" (representing the positivity or negativity of an emotion). The circumflex model of affect is a widely recognized two-dimensional framework for representing emotions. It features a circular diagram where emotions are plotted based on valence along the erect axis and arousal along the horizontal axis.

3) The Componential sentiment Model extends the dimensional advance, with its basis rooted in the concept of assessment. According to this framework, emotions are perceived by individuals as they evaluate their circumstances. The outcomes of this evaluation are influenced by an individual's objectives, past experiences, and ability to respond.

III. Research Methodology

A systematic literature review (SLR) is a rigorous system used to methodically find, evaluate, and understand existing literature relevant to a specific research topic. In this SLR, adherence was given to the PRISMA standards. PRISMA, representing chosen coverage matter for Systematic Reviews and Meta-Analyses, provides strategy on how to structure and format systematic reviews and meta-analyses. The study design included four key components: selection procedure, criteria for inclusion/exclusion, criteria for collection, and assessment of quality.

3.1 Selection Criteria

The authors primarily utilized databases such as IEEE, Science Direct, Scopus, and Web of Science to locate relevant literature on emotion detection. They started by designing a tailored search query to retrieve pertinent articles across these databases. Subsequently, they employed a filtering process to refine their selection and achieve their research objectives. This process involved removing duplicates, applying insertion and omission criteria, using title and abstract filters, and conducting full-text screening as the final step. Figure 4 presents a detailed flowchart outlining the steps of the literature review process. Table 3 enumerates the search terms and queries incorporating AND and OR Boolean operators, which were utilized to retrieve data from various databases based on primary and secondary keywords.

3.2 Inclusion/Exclusion Criteria

The authors established specific criteria for selecting and rejecting research articles in order to conduct a systematic review. They developed inclusion criteria to identify relevant research articles and exclusion criteria to eliminate those that did not meet the requirements. After identifying all relevant papers, they applied the exclusion criteria to filter out unsuitable ones. Detailed inclusion and exclusion criteria can be found in table 4.

3.3 Significance

With the expansion of digital media and the Internet, detecting emotions in textual data has become increasingly significant. As a result, engineers, corporate strategists, government bodies, and political analysts are keen to leverage this field to enhance companies and their reputations. Various online platforms, including community networking sites like Facebook, media-sharing networks like YouTube and Instagram, and microblogging sites like Reddit and Twitter, are widely accessible on the Internet. The swift increase in the popularity and acceptance of common networks has prompted researchers to explore online pleased and investigate users' social interactions on these platforms.

Customer or product reviews are crucial in shaping consumer behavior and influencing purchasing decisions for businesses Similarly, the integration of chatbots or conversational agents has extended beyond business contexts into healthcare for automating service delivery), enhancing service quality and market competitiveness in business, and facilitating interactive learning in education, particularly in distance or E-learning settings Therefore, there is a growing necessity to explore emotional analysis from textual data across various relevance domains.

3.4 Motivation

Currently, there is a gap in the countryside of text-based sentiment recognition concerning a comprehensive Systematic Literature Review (SLR) that examines methods, datasets, relevance domains, comparative analyses, and potential directions. Existing reviews and surveys lack a thorough investigation into application domains and future trends within this field. Despite the evolution to web 3.0, text-based emotion detection remains crucial due to its predominant role in human-computer interaction through textual input.

The realm of sentiment analysis and emotion detection has witnessed notable growth recently. While this paper concentrates on research articles pertaining to text-based emotion detection, previous studies have predominantly focused on sentiment analysis. Our extensive examination reveals a significant gap in systematic reviews addressing text-based emotion detection, particularly concerning techniques, datasets, application domains, and future research directions.

This efficient review highlights the gaps in the current literature concerning datasets used for emotion detection. While various datasets exist, they are limited both in terms of data volume and the breadth of emotional labels provided. Consequently, training emotion detection systems with these datasets proves unreliable and limits their generalize ability.

Furthermore, the review emphasizes that text-based emotion detection is heavily influenced by the specific domain in which it is applied. Approaches and datasets that perform well in one domain, such as common media, may not be suitable for other domains like review systems Therefore, there is a critical need to investigate these issues further to identify research gaps in the field of text-based emotion detection (TBED).

Overall, this systematic literature review aims to explore existing methodologies, available datasets, applications, challenges, and future directions in the realm of text-based emotion detection.

3.5 Terms and terminologies

3.5.1 In text-based sentiment detection research, the terms commonly utilized are as follows:

3.5.2 Sentiment: According to the Oxford Dictionary, sentiment is described as an emotion or perspective, particularly one based on feelings. It can also refer to overly indulgent expressions of sympathy, sadness, or longing..

3.5.3 Emotion: Emotion encompasses a complex array of interactions involving both objective and subjective variables, influenced by brain and hormonal systems. Emotions can:

3.5.4 Intensify affective experiences such as pleasure and displeasure, and emotional arousal levels ranging from low to high activation or calming to arousing.

3.5.5 Generate cognitive processes relevant to emotions, including appraisals, perceptual affects, and labeling.

3.5.6 Cause significant changes in both the physical and mental responses to various stimuli.

3.5.7 Promote talkative, goal-directed, and adaptive behavior, though this isn't universally the case.

3.5.8 Mood: Moods are more enduring than emotions and encompass both positive and negative attributes.

3.5.9 Feelings: Stances are cognitive perception that are valences, moreover positively or negatively, and are accompanied through physiological adaptations within the body, particularly in how internal organs function to maintain or restore balance within the body and ensuring stability balance.

3.5.10 Affect: Arousal and pleasure are fundamental processes that can be consciously recognized as emotions. Describing emotional experiences is challenging, but they are connected to physical states such as food shortage and dryness, as well as outer stimuli like touch, taste, smell, sound, and visual information.

3.6 Evolution of text-based emotion detection

The concept of "Emotion" was introduced by Charles Darwin, a prominent scientist, in his 1872 essay titled "The Expression of the Emotions in Man and Animals." This groundbreaking work was the first attempt to categorize human emotions and their expressions. Later, in 1980, psychologist R. Plutchik developed the emotion wheel. This model categorized emotions into eight primary categories: surprise, trust, joy, anger, fear, disgust, and sorrow.

He elaborated that every original emotion has its exact reverse. Later, in 1980, Paul and colleagues pioneered the development of the first system to identify emotions through facial expressions.

Known as the Emotion Facial Action Coding System (EFACS), it was developed by Wallace Friesen and Paul Ekman. Ekman's research revealed that across diverse cultures, there are six primary emotions, each corresponding to distinct facial expressions: sadness, fear, anger, disgust, surprise, and happiness. As understanding of emotional cues in speech grew, published the pioneering work on the detection of emotions in speech, marking a significant scientific contribution to the field.

Figure 2 provides a concise summary of the progress in emotion detection research and the evolution of emotions. A significant milestone in this field occurred with the publication of Rosalind Picard's emotional computing theory in 1997. Picard argued that for computers to achieve true intelligence and interact naturally with humans, they must be capable of recognizing, understanding, and expressing emotions .This theory marked a significant shift in emotion detection research, influencing the development of human-computer interaction by advancing computing theory. The year 1997 also saw the creation of ISEAR, the first emotion dataset.

Data from multicultural questionnaire surveys conducted across 37 nations were aggregated to create the International Survey on Emotion Antecedents and Reactions (ISEAR) database. This comprehensive database comprises 7,665 sentences, each annotated with emotions such as guilt, rage, contempt, fear, joy, sadness, and humiliation.

The initial English tongue logical database designed for normal communication Process errands was introduced as Wordnet in 1998 Subsequently, Das and Chen (2001) applied mood and emotion analysis practically for stock market prediction. authored the pioneering paper on annotating emotions and identifying opinions from text.

SenticNet, a freely accessible semantic resource for concept-level reaction analysis, was established in 2009. The term "word embedding" denotes how words are represented in NLP text analysis, with Word2Vec pioneering this technique in 2013. Neural networks were subsequently integrated into NLP tasks in the same year. The concept of transformers was elucidated in a pivotal 2017 paper by Vaswani et al., marking a significant advancement in the field.

Table 1 Comparative analysis of different emotion models

	Discrete Model	Dimensional Model	Componential Model
Description	Emotions can be placed into basic distinct classes or categories. Emotions are independent.	Emotions are not independent, and that there exists a relation between them.	The componential model uses the appraisal theory based on a person's experience.
Advantages	Basic and Universal Model Widely adopted due to its simplicity.	Complex/mixed emotions are addressed well. Highly recommended for projects involving emotional resemblances.	Focus on the variableness of different emotional states.
Disadvantages	Limited to fixed emotions. Difficult to address complex and mixed emotions	Reduction in 3-D space results in loss of information. Not all fundamental emotions are compatible with the dimensional space.	No such standard appraisal criteria. Different variants.
Models	Paul Ekman Model, Robert Plutchik Model, Orthony, Clore, and Collins (OCC) model	Russell circular two-dimensional model, Plutchik 2-D wheel of emotions, Russell and Mehrabian 3-D emotion model, The Hourglass of Emotions	Scherer's Appraisal theory.
References	Ekman Paul et al. 1999, Plutchik 1980, Ortony et al. 1990	Plutchik 1980, Russell et al. 1980, Russell et al. 1977, Cambria et al. 2012	Scherer et al. 2005
Emotions	anger, fear, disgust, joy, surprise, sadness,	acceptance, anger, disgust, surprise, anticipation, fear, joy, sadness	interaction modalities (Pleasantness), interaction contents (Attention), interaction dynamics (Sensitivity), interaction benefits (Aptitude).

IV. Research Goals

The primary goal of this systematic literature review (SLR) is to comprehensively understand the current status of TBED research, while also identifying any remaining questions and challenges. The specific objectives of this study are detailed in Table 1.

Table 1 Research Questions with objectives

RQ Number	Research Question	Objective
RQ1	What are the different Artificial Intelligence (AI) approaches used for TBED?	The aim is to study the different Artificial Intelligence (AI) techniques for TBED, their advantages, and limitations and to show a comparative analysis of different techniques.
RQ2	What application domains have been adopted in text-based emotion detection?	Different application domains have different requirements and, therefore, require different methods, datasets. The aim is to study the different application domains in text-based emotion detection, their requirements, and comparative analysis.
RQ3	What are the different datasets available for research purposes in text-based emotion detection, and which domains have been acquainted in the available data sets?	The goal is to review the available public datasets for text-based emotion detection by analyzing application domains, data sources, data size, emotion labels, and data imbalance.
RQ4	What are the difficulties and open issues concerning TBED?	Text-based emotion detection is a domain-dependent task. Therefore, it is one of the challenges. Therefore, the goal is to identify the challenges and open issues in text-based emotion detection.

3.7 Contribution of the Work

I. This comprehensive journalism review makes several significant contributions:

II. It provides a detailed analysis of existing research on text-based sentiment finding, focusing on methodologies, datasets, application, challenges, and prospect research directions.

III. It discusses and explores various strategies and approaches used to advance the pasture of text-based emotion detection.

IV. It includes a summary of openly existing datasets that sustain further research in this area.

V. The review examines the application domains where text-based emotion recognition plays a crucial role and analyzes its impact.

VI. It outlines key challenges in text-based emotion recognition, including issues with datasets, accuracy of current approaches, and the management of data quality

V. CONCLUSION

Recently, there has been an increasiZg demand for digital web media. This study conducts a comprehensive review of literature related to diarrhea associated with tuberculosis (TBED) using digital web platforms. Artificial intelligence techniques have played a significant role in analyzing digital internet media. The review summarizes findings from an extensive literature review on TBED techniques. The study aims to highlight emotion models used, methods for feature extraction, methodologies employed, validated datasets utilized, application domains covered, and challenges related to TBED. Multiple systematic literature review (SLR) steps were meticulously designed, implemented, and executed for this investigation into TBED.

Research topics were developed based on various factors such as application domains, methodologies employed, datasets utilized, and identification of gaps in the existing literature. Current literature showcases a wide array of artificial intelligence techniques applied in TBED, including rule-based, keyword-based, deep learning-based, and machine learning-based methods. Deep learning and machine learning methodologies are particularly prominent due to their utilization of easily accessible datasets and automated feature mining technique. The authors examined widely offered TBED datasets and explored multiple application domains in their research. Research questions (RQ 3) delve into various challenges in TBED, such as imbalanced datasets and domain-specific dependencies. Furthermore, the paper discusses future prospects for TBED leveraging artificial intelligence technologies.

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