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EMOTIONALLY WRAPPED SOCIAL MEDIA TEXT: APPROACHES, OPPORTUNITIES, AND CHALLENGES

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Abstract. With the evolution of several online platforms for information sharing such as social media, blogs, product review sites, and discussion forums, people have become more proactive in sharing their expectations, views, feelings, and experiences. This large amount of emotionally wrapped data motivates many researchers to perform data mining and present the crux of hidden emotions or mental states in a more presentable and comprehensible manner. It has several applications in different domains such as business, education, psychology, politics, and many more. This paper presents a detailed literature review projected to rigorously analyze the existing approaches to identify the mental or emotional state of a person from unstructured textual data. We include the most relevant papers which were published during 2001-2022. The selected papers are classified into three categories: granularity level, contextual level, and cognition level. Each category is carefully analyzed followed by a detailed and critical discussion. Finally, open challenges, opportunities, applications, and future directives are presented in-depth to facilitate the researchers working in the domain of emotion mining.

Key words: Emotion Mining; Opinion Mining; Sentiment Analysis; Social Media; Affective Computing; Emotion; Mental-state

1. Introduction. The evolution of the web has given users the opportunities to participate, share, and contribute to various platforms like social media, blogs, product review websites, online forums, and discussion platforms. Now, it has been very common that as a kind of relief, people suffering from mental health issues frequently either directly or indirectly reveal their emotions, feelings and everyday battles with mental health concerns on social media ([6]. As a result, a large amount of multi-modal data is generated.

With the advancement of data, affective computing (AC) and emotion mining (EM) have emerged as new areas of research. Affective Computing (AC) is a field that relates to, arises from or deliberately influences emotion or other affective phenomena [97]. It plays a vital role in effective communication. It is broadly classified as emotion recognition, modeling, and expression (as shown in Fig. 1.1). Emotion recognition means extracting the emotional state from different modalities such as image, video, text, and audio-visual. Emotion modeling refers to the study of the effects of emotions on different cognitive processes and generating synthetic emotions. Emotion expression means expressing emotions using different modalities. It is important to mention that the researchers have used different vocabulary like sentiment, emotion, opinion, etc in the literature. According to Gordon [39], sentiments can be defined as a collectively formed set of neuronal responses, emotional attitudes, and common definitions normally coordinated around another individual. Emotion [124] has four interrelated components: sensory stimuli, physiological shifts, verbal movements, and an emotion tag which indicates the local correlation of the components.

In consideration of the similarities of how emotions and sentiments have been described, we will use these words interchangeably in this study to refer to perceptions that arise from the cumulative forces of the mental, behavioral, and personal [121] Many researchers have worked towards identifying the polarity of emotions in terms of negative, positive, or neutral emotions and called it as emotion mining [2],[83]. However, some researchers identified emotions in terms of discrete emotions such as happiness, sadness, fear, anger, and so [151]. Predominantly, both kind of work is called emotion mining. Emotion mining is one of the most challenging tasks to extract the emotions of people from the web, inferring from the text, and predicting the underlying intent. The eruption of research in emotion mining took place during 2001-2022, as shown in (Fig. 1.2). We

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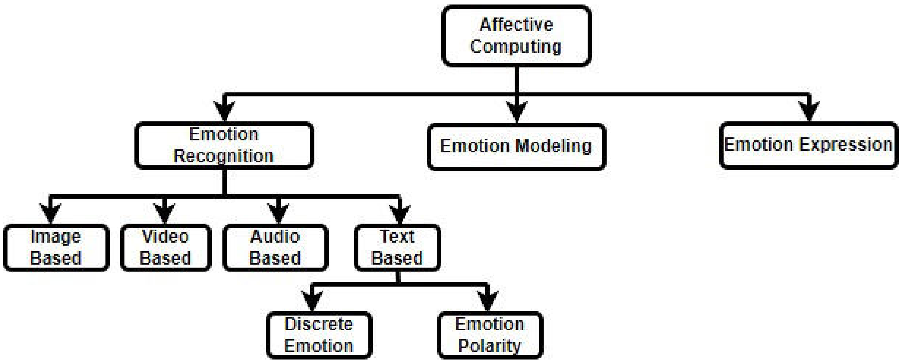

Fig. 1.1: Affective Computing Classification

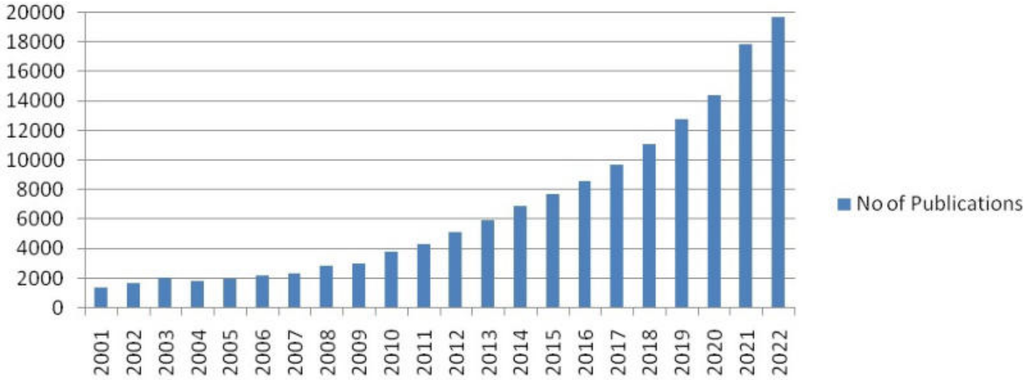

Fig. 1.2: Graph showing the research in “Emotion Mining from Text” in Google Scholar Database

sought to ensure the reliability and relevance of our dataset by implementing specific inclusion and exclusion criteria. The inclusion criteria are as follows:

1. Publications were included if they directly addressed the research topic of ”Emotion Mining from Text” on the Google Scholar Database.
2. Only peer-reviewed journal articles and conference proceedings were considered to maintain the quality and reliability of the sources.
3. Publications within the time frame of 2001 to 2022 were included to focus on recent research trends.
4. Inclusion was limited to publications in English to facilitate data extraction and analysis.

The Exclusion Criteria:

1. Publications lacking titles, abstracts, or keywords directly related to the phrase “Emotion Mining from Text” research topic were excluded.
2. Non-peer-reviewed sources, such as books and theses, were excluded to ensure data quality.
3. Publications outside the specified date range 2001-2022 were excluded to maintain a focus on recent research.
4. Publications in languages other than English were excluded due to language proficiency constraints.

Since then, emotion mining has explored various domains such as E-therapy, psychological health services, counseling online, terrorist attacks [16], prediction of the financial market [56], medicine, and the healthcare domain [29], [110]. Recently, researchers [5], [45], [35] used a combination of cognitive and affective information with human language to tackle acute issues such as irony and sarcasm detection [80] The authors used crowd-sourcing [20] to build a common sense knowledge base, which is used to link the semantic gaps between word-level and concept-level analysis. Furthermore, for context-aware and cognition-based emotion mining, strenuous attempts are advancing from polarity detection to more complex nuances of users' social behavior on online platforms [41], [60].

This paper presents a critical analysis of the work done by experts in the field of emotion mining while extracting emotional and mental states from textual data available on the web. The key features of the paper are:

1. An extensive literature survey of the most relevant papers published in the last two decades is presented to demonstrate the incremental approaches and improvements.
2. Categorical analysis (Fig. 2.1) and critical discussion of each category is presented.
3. Tabular summary of important papers is illustrated to provide a quick overview.
4. Generalized framework of emotion mining extracted from papers is presented to guide beginners in this field.
5. Over the year evolution of different techniques for emotion mining is presented pictorially to give a comprehensive view.
6. Various challenges encountered over the year are discussed in detail and presented pictorially.
7. Applications of emotion mining are discussed.
8. Overall discussion on EM with future directives is presented at the end of the paper.

The paper follows the incremental approach on the timeline of the last two decades. To the best of the authors' knowledge, no survey paper covers belief-based and semantic-based emotion mining which is the future of the field.

The rest of the paper is organized as follows: Section 2 reviews the advances in emotion mining and Sections 3,4 and Section 5 discusses various levels of text-based emotion mining. Section 6 summarizes the discussed approaches. Existing challenges, opportunities, and their applications are discussed in Sections 7,8, and Section 9 respectively. Finally, Section 10 concludes the paper and provides future directives.

2. Advances in Emotion Mining from Text. Textual emotion mining consists of collecting facts about beliefs, thoughts, and emotions that persons express about topics of interest. The field of emotion mining in computational linguistics focuses primarily on classifying different emotional contents within a word, phrase, or document. This field typically includes tasks such as defining emotions, classifying subjectivity, and understanding polarity [87] Analyzing the sentiment of textual data can, therefore, involve investigating the emotion/mental behind that text. In certain cases, emotion motivates an individual to evaluate an event and to create opinions about it. The field depicts a large problem space. There are a few terms that have mutual meaning such as sentiment analysis, opinion mining, emotion mining, and subjectivity analysis, affect analysis, review assessment, opinion extraction. However, all these terms come under emotion mining. Although the terminology sentiment analysis is most widely used in industry, in academia, both emotion mining and sentiment mining are often employed [67] Hence, this paper explores all aspects of emotion mining (such as emotion analysis, emotion mining, opinion mining, etc.) termed differently in literature. These terms are used interchangeably throughout the paper to retain the original terminology used in different articles that are discussed here.

A range of focused and advanced fields are already being explored. However, text-based emotion mining still has a long way to go. Studying emotions in different fields provides us with useful information on what kind of emotions people experience while dealing with different situations.

This paper broadly investigates the literature under three categories: granularity level, cognition level, and contextual level. The same has been shown in (Fig. 2.1) and discussed in detail in subsequent sections.

3. Granularity-based ttextual Emotion Mining. In this section, we include a discussion on the related research for emotion mining based on granularity such as word level, sentence level, and document level.

3.1. Word-level Processing. Words may be demonstrative, expressive, and sensitive. Identifying the describing words (adjectives, adverbs, some nouns, and verbs) out of the whole text is the main focus at word-level emotion mining where each word is assigned a value on a scale from 0 (negative) to 10 (positive) based upon its polarity. SentiWordNet [31] is designed to annotate WordNet. It is used for calculating the score of a particular word in a sentence using machine learning approaches. For example, “This place is beautiful”, this

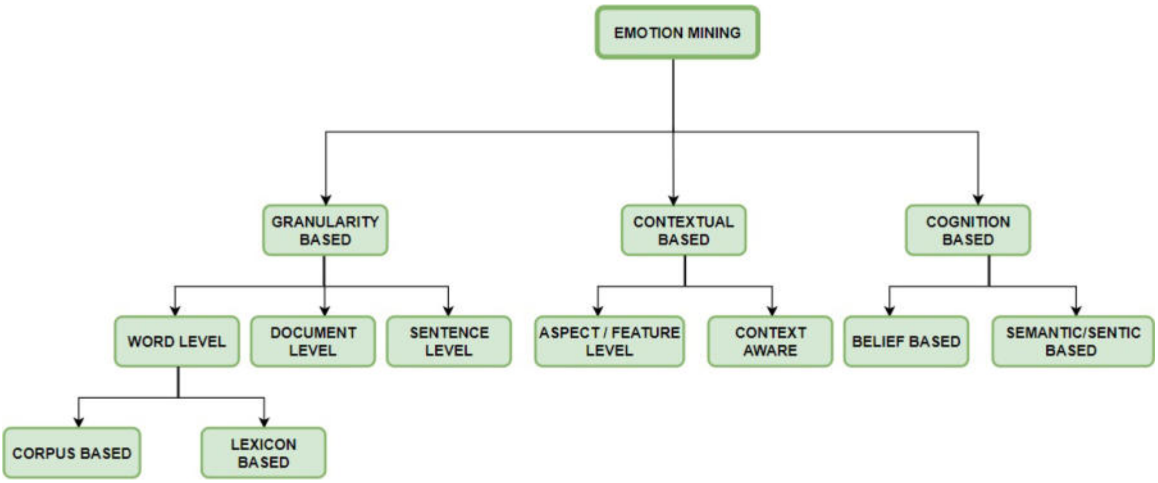

Fig. 2.1: Classification criteria of Text-Based Emotion Mining

sentence has the word 'beautiful' that has some score as defined in lexicons, which leads to a positive polarity. Each word has some probability score for each emotion. The highest score is chosen as the emotion of that word. It has been observed that in natural language, opinionated content or the word, which expresses the emotion, is most commonly conveyed by certain parts of speech (POS). For instance, adjectives such as disastrous or lovely convey emotions more effectively than the verb running or eating. Hence, POS is used to mark words and search for polarity terms (adverbs and adjectives, [76]. Broadly, word-level EM can be done in three steps:

1. Detecting the subjectivity of different words. For example, love and hate, both are subjective words.
2. Calculating the polarity of words i.e. positive, negative, or neutral by using polarity scores. For instance, love is positive and hate is negative
3. Calculating the intensity of the word i.e. depth of positive, negative by analyzing the polarity words.

Opinion orientation can be determined by two approaches [3] a) Corpus-based b) Lexicon-based. The corpus-based approach detects opinion words with context-specific orientation [137] and lexicon-based approaches detect the seed words and search them with the associated lexicons such as WordNet along with their synonyms and antonyms [135]. Recently, domain-specific areas are explored rigorously by researchers. They have been working to increase the classifier's reliability by augmenting word-level emotive information, i.e., constructing and utilizing various forms of custom dictionaries [64].

3.2. Document-level Processing. At the document level, the aim is to analyze and classify the whole document as positive or negative. Several studies have been explored at the document level, especially, in cross-domain, cross-language, and opinion categorization [125], [27], [139]. Bellstam et al. [7], used the finance-related corpora, generated by financial analysts. They explored the emotions/sentiments in textual descriptions of business operations to quantify corporate innovation in finance.

Duyu et al. [123] proposed Convolution Neural Networks (CNN) and Recursive Neural Network (RNN) based document-level analysis [34], [133] called User Product Neural Network (UPNN). This model assimilates user and object-level information for sentiment classification for document-level analysis. They experimented with improved accuracy using vector-based and matrix-based user and object representation. Liu et al. [71] compared the sentiment classification approaches, using Recursive Neural Network and Recurrent Neural Network, and found that the sentiment topics or target entities cannot be identified by document or sentence level, hence need to analyze at a more granular level.

3.3. Sentence-level Processing. The goal of sentence-level emotion mining is to separate emotional information from facts to improve the prediction accuracy of the document's overall polarity [143]. At this level, the concern is basically on two steps:

1. The subjectivity of the sentence
2. Polarity (+ve or -ve) of the sentence

The following section will discuss the major input for both tasks.

3.3.1. Classifying Subjective Sentence. There are many approaches to classify a given sentence as subjective or objective. An objective sentence provides some factual information about the environment, while a subjective sentence communicates some personal emotions, perceptions, or opinions. Emotions are considered subjective feelings and thoughts [70], [144]. Some researchers feel that objective sentences do not imply emotions. However, they can also express emotions, and ignoring them may result in the wrong prediction. In this context, Liu [68] has discussed that subjectivity and opinion should not be compared. He also discussed that a subjective sentence may not convey any emotion such as "I am using the latest version of Android OS" is a subjective sentence, even then it doesn't express any emotion. Similarly, an objective sentence may imply emotion such as "After updating the latest android OS, my phone kept hanging". While this sentence is stating a fact, it shows an implicit emotion about the topic (the phone hanging).

Classification of subjective sentences is one of the most important and foundation schemes. The existence of subjective words determines the subjectivity of a sentence [42], [154], [47]. Moreover, these studies have been able to differentiate between subjective and objective sentences which subsequently improved sentence-level emotion mining. Several machine-learning approaches with language-specific features for Urdu languages are used [86] to identify the subjectivity of sentences. Therefore, different sentences may be dealt with differently at sentence-level analysis.

3.3.2. Polarity identification. The purpose of polarity identification is to determine text as positive, negative, or neutral according to its emotional significance. Some authors [1] the WordNetAffect Affective database [99] to distinguish between positive, negative, and neutral emotions. However, these emotional categories may help predict polarity, but not quite enough to predict the polarity intensity. Therefore, the authors use a few emotional categories such as love, happiness, joy, fear, sadness, anger, and so on. One approach is to use parts-of-speech (POS) tags syntactic patterns to express opinions/sentiments/emotions. The researchers [58] used the approach of multiplying all the scores of emotional words in the sentence as +1 and -1. They also used classification techniques to identify a particular type of emotional orientation. The hierarchical sequence learning model identifies polarity in both sentences as well as document-level and also improved the accuracy at both levels.

In 2010, Hassan et al. [4] proposed a method to identify online users' behavior using the Markov Model. Then, they identified the polarity orientation of the attitudes. Some researchers worked on target-dependent sentiment classification, where the target is classified into some category [51]. Researchers admitted that there are a variety of sentences and each sentence expresses emotions differently. Therefore, one technique cannot be applied to all kinds of sentences. Handling sarcastic sentences is still a big challenge as positive sentences may have negative meanings and vice versa. These types of sentences are more used in online discussions and political forums. Tsur et al. [127] proposed a semi-supervised learning approach to identify sarcastic and non-sarcastic sentences. Initially, they used the labeled set and expanded it automatically through a web search. Many researchers [66], [157] experimented with Convolution Neural Networks (CNN) for sentence-level classification. They built the model on top of the unsupervised pre-trained word vector, tuned hyper-parameters, and performed well with remarkably improved results.

3.4. Critical Analysis of Granularity-based Emotion Mining. Though a lot of research is conducted at a granular level, it has several limitations when used in real-life applications, such as which features or aspects of the entities are liked or disliked. Several sentences are not easily classified as emotion orientation varies on different targets or entities, e.g., "Trying out Airtel sim because Jio voice calls being cut after every 10 mins." and "Vodafone is doing well in this awful environment". In the latter sentence, sentence-level classification is insufficient. We need to go to the aspect-level analysis. It is assumed that a sentence has an overall positive or negative orientation but some of its parts may convey the opposite emotion. E.g., "India's labor-intensive agriculture has achieved steady increases in food grain production despite the often unfavorable weather conditions". Here, the overall message is positive but it also contains a negative emotion "unfavorable" which cannot be ignored and only aspect-level analysis can solve this problem. Moreover, comparative sentences cannot be dealt with at the sentence level. For instance, the sentence "Amul butter tastes better than Mother Dairy butter" can't be simply classified as positive, negative, or neutral. Therefore, further, fine-grained analysis is required to handle them.

4. Context-based Textual Emotion Mining. Features are the attributes of an entity. Feature-based emotion mining extracts the emotions towards some features of the entity [115]. It also analyzes the emotion while considering the surrounding context of the feature. This section discusses the two types of feature-based emotion mining: aspect-level and context-aware.

4.1. Aspect-level Emotion Mining. The aspect-level analysis mainly focuses on entities and their components, where entities may be a product, an organization, a service, or a topic. The components can be referred to as features or attributes of the entity. Aspect-based emotion mining, also known as feature-based emotion mining, identifies different aspects of the target entity in a long sentence and its polarity [93]. Earlier, this kind of analysis required a set of features which are manually designed. Nowadays, the focus has shifted to other approaches such as graphs of dependency relationships [152], and lexicon-based supervised learning approach [55]. It is observed that identifying entities, their components, and knowing their polarity is not sufficient to know the sentiment of a sentence. For instance, a negative emotion about an entity does not mean that all the aspects of that entity will have a negative orientation [120].

The aspect-based emotion mining is carried out at two levels: aspect extraction and aspect-based classification. Several methods of aspect extraction such as nouns and noun phrases identification followed by PMI [47], balances category feature (BCF) and the other is the categorical proportional difference (MCPD, [21], sequential learning method [69] such as Hidden Markov Models (HMM, [101], [54] and Conditional Random Fields (RF, [61], frequency-based approach for emotional noun phrases [11], C-value measure-based method to retrieve multi-word aspects [158], dependency parser [159] and double propagation method [100] are discussed in the literature.

Recently, researchers have started using various evolutionary algorithms [84], semi-supervised [38], [85], [21], supervised approaches such as SVM [155], RNN [116], CNN [150], [95], [74], deep RNN [49], pre-trained word embeddings [149], LSTM [122], SLSTM [134], Memory network [136], deep recurrent belief network [22], multi-task learning network (IMN, [44], and unsupervised approaches [14] such as pLSA (Probabilistic Latent Semantic Analysis, [46], LDA (Latent Dirichlet allocation, [92], LSA based aspect-sentiment mixture model [79], joint topic sentiment model [65] for aspect extraction.

In supervised learning, attention networks are gaining popularity in the field of emotion mining, Several attention networks Attention Encoder Network (AEN, [117], relative position attention network (RPAEN, [146], Multi-grained attention network (MGAN, [32], Bi-GRU-based Position-aware Bidirectional Attention Network (PBAN, [40], recurrent attention mechanism [24], attention mechanism with GRU [43] are being used in the literature. Machine learning methods were commonly used in emotion mining but require a substantial amount of training data to achieve improved accuracy [18]. In view of the lack of large amounts of annotated data, researchers started working on ontology [98] based methods. They used a combination of hierarchical learning (HL) process and sentiment ontology tree (SOT, [140], knowledge-based along with linear SVM, or a review-based and a sentence aggregation algorithm [28], to categorize the data on the basis of emotions.

4.2. Context-Aware Emotion Mining. The digital world is becoming more informal. People use new words or phrases to express themselves. The emotional lexicons (such as NRC, WordNet, SenticNet, etc.) are not acquainted with such new words/phrases. Though, humans can interpret the meaning of such new words/phrases with the help of the surrounding context. However, in any computational model, these unseen words/phrases are simply ignored, and hence the expression of emotion may get lost. To make the computational model more robust, the need arises to make use of semantics to extract the contextual meaning.

Researchers spent lots of time exploring and selecting regular features. Several emotion-mining tools rely on emotion lexicons to support linguistic resources. These lexicons contain polarity values and some weight to emotional words. But, it is observed that emotion mining requires more evolutionary approaches that may lead to semantic-level analysis [19]. A word may change its polarity based on its context. With this idea, Gangemi et al. [37] gave importance to emotion contextualization and consider it as a major challenge in the field of emotion mining. Some of the common context-aware approaches used by researchers are Rule-based approaches

[111], Sentence and discourse-based context shifters, Linguistic patterns [147], and Vector space modeling [153].

A process to segregate contextualized emotion lexicons i.e. a way to isolate sentiment terms from stable polarity terms. This process allows changing the ambiguous word's polarity as the context changes in some other textual information. With the evolution of contextual knowledge, traditional emotion lexicons are reinforced with context knowledge [73]. An iterative regression and a random walk method are used to label ConceptNet [119] with emotion values [126]. Several studies have been done to develop contextualized, cross-domain lexicons with sentiment mining and various decision-support applications [141]. It was assumed that disambiguation and contextualization can give better performance on cross-domain emotion mining using ontological lexicons. These lexicons can be used at three levels. The first level detects an ambiguous word with the help of existing labeled corpora. The second level determines the emotion score of co-occurring contextual terms and finally at the last level determines the combined polarity values for ambiguous and unambiguous terms. Experimentation and evaluation were performed on various datasets such as product reviews, hotel reviews, and movie reviews and successfully achieved better performance on each dataset. They extended the process by using the group concept from SenticNet, ConceptNet [119], Freebase [13], and DBpedia [10]. Recently, deep learning-based methods are becoming more popular as they have greatly improved the performance of emotion mining. Deep learning approaches use the structure and context of the sentence, instead of just emotion-bearing words in isolation.

Often context-based emotion mining is domain-specific and is based on the assumption that words always have the same association in that domain. For example, the use of the word unexpected: may signify positive emotion when describing the plot of an action film ("the film had an unexpected ending"), while it is not a good sign in the sense of the battery life of a laptop. Though, this may not always be valid. Consider a "leaves" description that says "The children love to play in the leaves but they do not like it when their father leaves for work." One can easily see that within the same domain, in the first case the word "leaves" communicates positive emotion, and in the second case a negative emotion. It is, therefore, reasonable to conclude that domain considerations alone are not enough to conduct context-based emotion mining.

Word embedding is becoming more popular, which is a low dimensional continuously-valued vector representation of words and is explored extensively by researchers [142], [81] The most commonly used word embeddings are CBOW, SkipGram, and GloVe [132]. Nguyen [88] proposed a semi-supervised approach to utilize an immense amount of available unlabeled data. He represented the semantic similarity of textual and user context using deep learning and latent low-dimensional space representation. He used networked characteristics also besides textual content i.e. the way users are connected via social relationships because this conveys the emotional behavior of connected users. A semantic model [138] is proposed to monitor the fluctuating emotional phases or emotions of learners while participating in MOOC's online courses. The authors used machine learning and semantic network approach in real-time to know learners' emotions about courses. Observing the change in the emotional states of a learner during the course can improve the graduation probability.

4.3. Critical analysis of Contextual Based Emotion Mining. Though lots of work has been carried out in the field of context-aware emotion mining, still it is far from the human touch. Streaming data is still a challenge, as contextual information is difficult to deal with. Nowadays, most organizations need aspect-level emotion analysis for feature details. It is observed that machine learning and deep learning with word embeddings are widely used by researchers for aspect-based emotion mining. However, accuracy and precision are still an open challenge as the existing methods/algorithms are still not able to deal with complex problems. Most of the cases are handled by emotional words. However, words or information are highly diverse, countless, and exceptional. It becomes very difficult to learn patterns via statistical methods only because there are several ways to express emotions. Lots of research, so far, mainly focus on products, movies, and restaurant reviews as well as Twitter data. In these domains, fairly good accuracy can be achieved. This is because the reviews are short and rich in emotions. However, for the other domains such as health, politics, forum discussions, commentaries, etc., the situation becomes very difficult as the emotions are either objective or factual statements in these domains.

Sometimes, the sentences are very complex due to a mixture of objective and subjective statements or sarcastic sentences. Besides this, all the social platform data is very noisy, and consists of various errors, whereas, all the analysis tools require clean data for analysis purposes. Therefore, a lot of focus is required for pre-processing tasks and methods. Some researchers incorporated the ontology method due to the non-availability of training data, but ontology features are not robust. The ontology method also needs training data to interpret them. It is very difficult and time-consuming to manually build ontology; therefore, there is a need to automate the process to create the ontology for multiple domains. However, due to the multidisciplinary area, emotion mining takes advantage of psychology also. As per psychology, the successful evolution of online platforms is the ability to bring people together and serves very different needs of people.

Chen et al.[23] explored how opinion about any object gets affected by the user's connection with their friends, family, or relatives. They have developed a content-based sequential opinion influence framework to monitor users' behavior on social media. This framework uses an RNN to seize the opinion expressed in the sequence. The user's opinion is checked with the past information that the user acquired from his/her relation with others and his/her personal opinions. Based on the learned influence, the user's future influence prediction is determined. This valuable information can be used by companies for their future business planning.

5. Cognition-based Textual Emotion Mining. With the evolution in the field, researchers have started using cognitive features for emotion mining. As per Izard et al. [50], cognition alludes to the mental process that is impacted by emotions (desires and feelings). Human emotions (such as feelings, moods, and motivations) can impact both the way they think and the choices/decisions they make. Cognition is one of the most important events that operate and control emotions. Cognition-based emotion mining can provide us with more insights into the emotion behind words. Broadly, cognition-based emotion mining is classified into two categories: Belief based and semantic-based. They are discussed in brief in the following sections.

5.1. Belief Based Emotion Mining. Understanding mental states such as the beliefs and goals of a person enables an individual to explain behavioral patterns. According to psychologists, beliefs impact the arousal of emotions and emotions in turn influence beliefs [36], [30], Ortony et al. [91], concentrate on the cognitive elicitors of emotions [53], [51] in their hypothesis. They proposed that emotions are positive or negative reactions to their beliefs or perceptions of reality [52]. Thus, one may be glad or dissatisfied with the outcomes of an event; one can support or oppose a person's activities, and one can like or dislike the characteristics of an item. The human emotional process, according to Lazarus [62], is made up of two distinct processes: evaluation (which describes a person's connection with their environment) and coping (which suggests strategies for altering or maintaining this relationship). Both of these processes are aided by cognition. Cognition aids evaluation by constructing mental representations of how experiences relate to inherent nature or temperament such as beliefs and goals. Coping deals with the situation through suggestions and exploration of methods for changing or sustaining the individual social relationship.

In a recent study, Masland et al. [78] examined the impact of emotional reasoning on reliability assessments in people with a moderate personality disorder. The findings show that in comparison to the control group, participants with suspected moderate disorder produced more emotionally fragile evaluations and were more affected by negative experiences or beliefs. As a result, persons with moderate characteristics may be impacted differently and more precisely by unfavorable afflictions. The mental state, if it is subjected to mental illness, then the diagnosis is sometimes difficult since it necessitates detailed and in-depth psych evaluations by trained psychiatrists at an early stage [108], as well as interview sessions, lengthy questionnaires, self-reports, or evidence from friends and family. In such cases, it becomes very important to understand the underlying emotion, feelings and behavior shown by patients. Furthermore, it is highly usual for patients suffering from mental illness often avoid going to health centers to seek medical care in the early phases of their illness [161]

Hamad et al. [160] proposed the automatic depression method, which extracts depressive content using various strategies such as key phrase matching and document summarization, named entity recognition (NER), etc. on the user tweets, resulting in more granular and relevant content, which is then directed to a deep learning framework consisting of convolutional neural networks associated with attention-enhanced gated recurrent units. Vetriselvi et al. [131] provided a review of cognitive-based emotions and insights on the importance of cognitive theories especially cognitive and intuitive theory to improve emotion classification. Long et al. [72] proposed an attention-based neural network model for sentence-level sentiment classification. They trained this model with cognition-grounded eye-tracking data and built a cognition-based attention (CBA) layer for emotion mining. Further research with formal models is needed so that future systems can usefully detect emotions and accurately predict behavior.

In light of the present COVID-19 epidemic, where religion, religiosity, and emotions play crucial roles in coping, it follows that a connection between religiosity—which encompasses a variety of religious activities and beliefs—and people's emotional states and assessments of their general well-being should be obvious. Regardless of their allegiance with a particular religion, people in a wide range of geographical areas show a wide range of emotions through their religious behavior, which is inextricably linked to a formal or informal belief in God or the Divine.

5.2. Semantic / Sentic Based Emotion Mining. Emotion mining at the conceptual level while considering the common sense or semantics of the text is called sentic/semantic-based emotion mining. In 2013, Raina [[102] proposed the sentiment analyzer where emotions can be associated with a common-sense knowledge base. The author analyzed sentiments in news articles. In 2018, Ferru et al. [33] used machine learning approaches to classify a message as positive or negative towards a particular topic and on a five-point scale. They used a cognitive computing tool (i.e. IBM Watson) to extract the semantic features. Their experimental results showed that semantic features play a very important role in classification. However, the authors would like to further research semantic features extracted from other cognitive computing systems.

Irony detection is one of the challenging tasks in the field of emotion mining as it has an ambiguous interpretation. Vijay D. et al. [12] addressed the problem of irony detection. From a cognitive perspective, it is a test to think about how humans utilize irony as a specialized instrument to communicate. To detect irony, the authors constructed a Hindi-English code-mixed corpus using tweets. They used various feature vectors such as character N-gram, word N-gram, laugh words, and emoticons. In 2018, Corriga et al. [25] proposed a tool that accepted an image as information and did the classification based on the person's gender and afterward recognized their emotions.

As per Cacioppo et al. [17], it is related to a person's tendency to engage in and enjoy thinking. Das et al. [26] mentioned in the paper that it has a moderating effect on variables such as human behavior, intent to purchase, and also web surfing. Li [64] used cognitive theories for emotion mining on the linguistic feature, where sentiments are classified as target-dependent and target-independent. Zou et al. [162] proposed a strategy utilizing indirect relations in specific user structure likeness to analyze opinion. The authors experimented and verified that similar users connected via common friends have similar opinions. The authors used the sociological phenomenon of homophily to understand the connection between similar people. Their experimental results showed that indirect relation (through some common friend) has a better performance than user-direct relations to improve the accuracy of sentiment classification.

Social media has recently attracted medical natural language processing researchers to detect various medical abnormalities such as depression, anxiety, etc. Recently, many researchers explored the application of emotion mining in the medical field. Emotion mining can be used in providing healthcare assistance. Nowadays depression is one of the most prevailing issues which is often talked about on social media. Zucco et al.[163] proposed affective computing and emotion-mining methodologies to monitor depression conditions. The authors used mobile technologies to collect input data. Many researchers are working towards detecting loneliness [129], [118], depression [106], [9], [104], [105], or suicidal thoughts [75] However, the results obtained are highly data-dependent and far from cognitive theories of emotions.

5.3. Critical Analysis of Cognition-Based Emotion Mining. Very few researchers have addressed cognition-based emotion mining in recent years. Cognitive approaches talk about the human mind and behavior. Such approaches talk about how emotions are produced and what their effects are. One's belief [112] plays an important role in emotion modeling. Someone can have many emotions at the same moment, each with varying degrees of intensity. The construction of a computationally efficient model of emotion is an extremely complicated reality. For instance, "it is raining outside" may convey positive or negative emotions depending upon the person's belief. If someone believes that rain is good in pursuit of his goal, then this sentence expresses positive emotion else negative.

By reviewing and incorporating significant information, it is studied how intelligence analysis better explains challenging circumstances and boosts useful insights for effective decision-making. Intelligence analysis may assist in determining patterns and social behavior. For this kind of analysis, a high-level cognitive theory of emotions [89] can be used. Unfortunately, this area of research is still untouched. Moreover, cognition-based emotion mining can do wonders in the healthcare domain. These studies can impact a patient's life quality

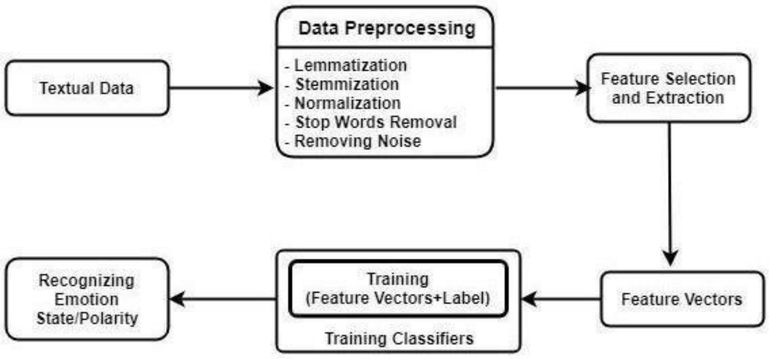

Fig. 6.1: Generalized Framework of Emotion Mining from Textual Data

and health status. This study helps in knowing how emotions influence social relationships, reasoning, memory, and their function in psychological illness/disorder.

6. Summarization and Discussion. In the literature survey, researchers have applied different techniques to identify emotions from unstructured text. It is observed that all the models follow a common process flow (as shown in Fig. 6.1). At first, the unstructured data is preprocessed and cleaned to make it ready for processing. This preprocessing may involve many steps such as stop word removal, stemming, normalization, removal/replacement of slang and abbreviations, etc. Next, features are extracted and feature vectors are generated by various means such as using word embeddings, POS tagging, PMI, TFIDF, etc. Once, a feature vector is ready, it is fed to a learning model to get the output. Emotion mining is the most widely studied topic. However, emotion mining at the granularity level has been the subject of a lot of research studies. The limited number of studies on context-aware, semantic-based, and cognitive perspective is carried out because it requires knowledge of cross-domain and criticality of human nature/human perspective. There are several approaches to performing emotion mining; the machine learning approaches outperformed the traditional approaches. It is also seen that some supervised classifiers such as Support Vector Machine, Neural net, and Naïve Bayes have repeatedly been applied. The effectiveness of these classifiers is probably the reason behind this.

The same thing can be said about the used features; word stem and n-grams are frequently chosen as features. Regarding datasets, most of the researchers have used Twitter data and the IMDB dataset while some researchers built and used a new dataset. Thus, no common dataset was used for benchmarking results and evaluating experiments. In the early days, researchers analyzed texts collected from the web and focused on the word, sentence, or document level. By contrast, researchers have recently treated principally social media texts and dealt with deep learning. Very few attempts have, however, been concerned with Affective Cognitive Emotion Mining. These tasks still need much deeper investigation and research.

Although research on emotion mining started around the year 2000, studies on this issue have shown an active rise in the last few years. This is mainly due to the exponential growth of social media, online reviews, and social networking sites. The literature survey carried out in the previous sections has revealed that researchers have dealt with different emotion mining tasks: subjectivity classification, opinion classification, aspect-based emotion mining, building lexicons/resources, extracting opinion holders, belief-based emotion mining, context-aware and cognition-based emotion mining (as shown in Fig. 6.2). The excerpt of some important papers is summarized in Table 6.1. The table contains information about the dataset and methodology used. Moreover, the pros and cons of each paper are also discussed.

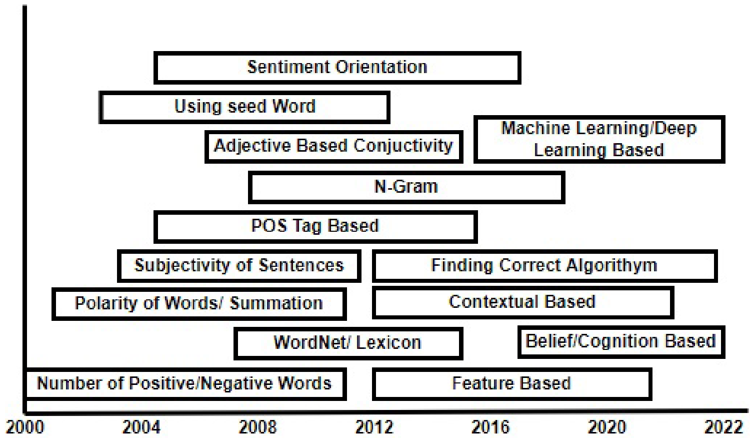

Fig. 6.2: Different Approaches for Emotion Mining over the Years

Table 6.1: Different Approaches for Emotion Mining over the Years

Ref	Approach	Level	Dataset	Algorithms	Advantage	Disadvantage
[44]	Supervised	Aspect-level	Restaurant reviews, twitter reviews, and Laptop reviews	Interactive multitask learning network.	Attentional encoder network prevents recurrence and uses attention-based encoders for context-to-target modeling. Raised the label unreliability issue. Demonstrate the effectiveness and light-weight of the proposed model.	The approach lack in calculating the hidden states.
[77]	Supervised	Character level, Word level	Hotel, Restaurant reviews	Aspect orientation rules	1.Annotated corpus will be freely available. 2.The corpus can be annotated with part-of-speech tags at the word- level which could yield better results.	1. Not generalized to many languages.
[115]	Semi-supervised	Context-aware	Amazon.com and IMDb.com	SVM and Naïve Bayes approach	1.Provides valuable background information for advanced emotion mining. 2. Provides a platform to identify ambiguous sentiment terms, and extract context information for disambiguating	1. Lack of emphasis on scalability and throughput.
[48]	Unsupervise	Document-Level	Stanford Twitter, Sentiment (STS) and ObamaMcCain Debate (OMD).	Semisupervised deep learning, a bilinear embedding model (CaTER method)	1. Provides the effectiveness of exploiting user context information for leveraging social media emotion mining using social relation graph. 2. Best accuracy among all the other methods like SVM, Distant Supervision (DS), Label Propagation (LPROP) and Logistic Regression with word embedding.	1.Unavailability of unlabelled data for word representations.
[150]	Pretraining and multi-task learning	Document-level	SemEval 2014, 2015, and 2016	CNN with gating mechanisms	Improved word representation in aspect-level sentiment classification.	Unable to handle sarcastic and irony in sentences

[107]	Supervised learning	Document-level	Twitter data set, political forum	Linguistic based approaches, SVM	1. Bigram and trigram feature significantly outperformed unigram features for the forum data. 2. Emotion mining improved. 3.Sarcasm detection.	1.Domain-specific Latent Sentiments.
[72]	Cognition based	Document level/sentence -level	IMDB, Yelp 13, Yelp 14 and IMDB2	Cognition based attention model, LSTM	1. It works well both at a sentence and at a document level. 2. Gives higher weights to the sentiment-linked words.	1.Domain dependent.
[2]	Supervised	Sentence-level	Online textual corpus	Emotional ontology approaches	Emotional ontology improves the result. Provides a platform to translate emotional dimensions into emotional categories.	1. Limited scope for speech output
[37]	Unsupervised	Sentence-level	MPQA opinion corpus	Heuristic graph, ML, Knowledge representation	1. The approach deals with a factual sentiment. 2. Assists in identifying relational features. 3. Provides improved performance. 4. Domain-independent	1. Does not perform well for noise data and sarcasm.
[8]	Semi-supervised	Sentence-level	Yahoo! Finance, Raging Bull.	Multi-View classification	1.Can mine a large corpus of domain-specific sentiment expressions	1. Does not support cross-domain.
[69]	Supervised	Sentence-level	Twitter dataset	Support Vector Machine (SVM)	1. Using related tweets along with the current tweets outperformed the results. 2. Utilized graph-based optimization techniques to improve performance.	Relations between a target and any of its extended targets are not explored.
[58]	Supervised/ unsupervised	Sentence-level	Moview & customer reviews, TREC question Dataset, Google News	Convolutional Neural Network	1. Use of pre-trained vectors 2. One layer of convolution has improved the performance.	1.Hyperparameter tuning is required.
[33]	Supervised cognition-based	Topic-based	Twitter and annotated using Crowd-Flower	Decision Trees, Linear Regression and Naive Bayes	1. Successfully classified the message on a two-point scale.	1. Dataset is unbalanced. 2.The scarcity of training data
[41]	Supervised	Word-level	Pattern from pages www.alltheweb.com	Point-wise mutual information measure	1. Lexical patterns that are precise enough for finding emotion-bearing, affect words. 2. Re-use of the SOPM\I formula	1. Only a few emotive patterns for adjectives are used

[146]	Unsupervised	Aspect-level	Emotion Dictionary	Attention-based LSTM	Explored the complex multiangle analysis of transitions in public emotions under the pandemic scenario. Helpful in recognizing public behavior and the prevention and regulation of pandemic situations. The issue of identifying polarity in the dictionary is strengthened effectively.	1. The size of the specific dictionaries chosen is too small.
[148]	Supervised	Character Level	Microblogs	CNN	1. Using the word vectors yield higher accuracy than those using words as feature elements. 2. Effectively improve the overall accuracy	Proposed model performs better on Chinese text but not generalized on other languages
[82]	Supervised	Word-level	EmoInt	SVM, CNN, LSTM and BiLSTM	1. Automated robust feature representation rather than manually engineered features. 2. Emotion dimensionality score provides a reliable and fine- grained analysis of text instead of just assigning the discrete emotion class. 3. All the data is made freely available	1. Manually identified the intensity score of basic emotions, therefore need to automate the process.
[59]	Supervised	Document-level	Tweets	RNN	1.Use of word embeddings improved the performance by reducing the high dimensional vectors.	1.Dataset size is too small to exploit deep learning Techniques. 2.Comparability and generalization is lacking
[113]	Rule Based	Document-level	ISEAR	Semantics rules	1.Paid special attention to Phrasal verbs.	Contextual meaning is missing. Not enough terms in the vocabulary.
[128]	Supervised	Document-level	Tweets with NRC emotion lexicon	SVM	1. Identify actionable emotion patterns in Tweets, with results of 84.92 percent and 88.01 percent accuracy.	1. Due to the limited number of emotional class, generalisation is not possible.
[94]	Supervised	Document-level	Tweets and ROC story Data	CNN (DL)	1. An embedding emotion model is created with the best accuracy of 73.3% for a positive emotion such as a pleasure and lowest for sadness around 36.7 %	1. Negative sentences did not perform well. 2. Negation handling could improve the accuracy.

[114]	Supervised	Aspect level	Publically available data	LRA-DNN	1. Compared to the current ANN, DNN, and CNN approaches, LRA-DNN gets the highest performance with accuracy, sensitivity, and specificity at rates of 94.77%, 92.23%, and 95.91%, respectively 2. It effectively lowers categorization and misprediction errors.	1. Execution time may get high while assigning rank to the given feature.
[130]	Unsupervised Approach	Aspect Level	Product reviews	LDA Model	1. Proposed a filtered and strong semantic approach, successfully extracted relevant aspects from product reviews.	1. The use of regular expression makes the approach little complex.
[63]	Supervised	Sentence Level	Food Comments	Bidirectional long-term and short-term memory network (BiLSTM)	1. This sort of approach examines, interprets, infers, and analyses the emotional remark content before coming to the appropriate conclusion.	The approach is not compared and generalized.

7. Challenges in Text-based Emotion Mining. Text is a challenging medium for analyzing hidden emotions. Due to the high complexity and the raw data available online, the area is still lacking. This section summarizes the challenges which still need the attention of researchers. The same has been depicted pictorially (Fig. 7.1). The open challenges are:

1. Domain dependence: Existing approaches mainly focus on the opinionated text, where the sentiments and emotions are explicitly expressed. Syntactical approaches have been used as the text is domain-dependent. Therefore, many language patterns are missed. Therefore, there is a need to focus on the deep analysis of the semantics of the sentences containing implicit emotions. At the same time, the emotion mining model should be domain-independent.
2. Dynamic effective model: To adjust the system to the social platform's user affectivity, the system should identify the user's emotions. The system needs to know when the user is negative about their service/ topic/ product/policy etc. The services or products must be customized as per the user's opinion regarding the product/ services. The affective history of the author should be maintained in the affective user model. It helps to respond appropriately to the user's emotions. Therefore, we need a dynamic affective model. The model should consider the changes in the emotional states of the user, to improve the accuracy significantly. Developing a dynamic affective model is very challenging because of the complex human cognitive states.
3. Feature engineering: People convey their emotions in complex ways like sarcasm, irony, etc. Such sentences do not specifically communicate their meaning but implicit meaning can mislead emotion mining. The only way to understand this issue is through context. Though a lot of research has been conducted in context-based emotion mining, there is a need to focus more on feature engineering as little attention has been paid to it so far. Feature engineering creates new features in a model. These features help to better understand the context and emotions of the users. Engineered features can help to boost accuracy and get an overall sense of what the social platform's user is trying to convey.
4. Context extraction: Truthful words and expressions inferring emotions have scarcely been considered, but they are exceptionally useful for numerous domains. The contextual information of emotional words stays to be highly challenging indeed with so much research.
5. Unknown/unseen words: The large vocabulary of words is available widely. However, it is a very tedious task to manually annotate these huge numbers of features. Moreover, unseen words in the text also cause problems. Therefore, it is very important and challenging to establish domain-independent affective words that can be used in language transfer.
6. Labeled data: Accessing the labeled data to train the model is very difficult. For the best long-term results, it is suggested to train our models. Therefore, need to find out ways to access data quickly.

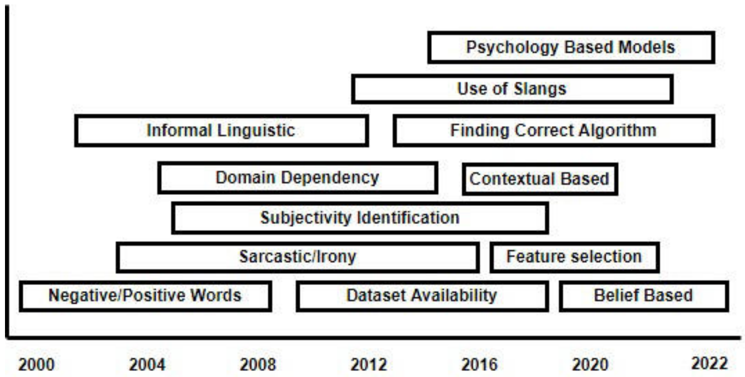

Fig. 7.1: Challenges in Textual Emotion Mining

7. Different sentences: Nevertheless, the question type of sentences, which do not depict any opinion about any particular entity such as “Are you serious?” “Have you gone mad?” also conveys significant emotions and should be handled.
8. Belief incorporation: For the same event or product, two people can express different emotions or the same person can express different emotions at different instances of time. This is due to the difference in beliefs and expectations. To date, no textual emotion mining model considers these parameters

8. Opportunities. As discussed, the practice of collecting and understanding human emotions from diverse data sources, such as text, audio, and video, is known as ”emotion mining”. However, we have limited our study to text data. While the field of emotion mining has advanced significantly in recent years, there are still a lot of untapped or understudied areas. Here are a few innovative prospective research areas:

1. Emotional State Prediction: Construct predictive models capable of anticipating fluctuations in emotional states by leveraging historical data. These models have versatile applications spanning mental health monitoring, customer service optimization, and educational contexts.
2. Emotion Mining for Mental Health: Use emotion mining methods to aid in diagnosing and keeping track of mental health problems. This might mean looking at what people write or how they talk (speech data) on social media to find signs of depression, anxiety, or other mental health concerns.
3. Human-Robot Emotion Interaction: Delve into the application of emotion mining within human-robot interaction scenarios, empowering robots to gain a deeper understanding of human emotions and respond more effectively. This can significantly enhance their performance in tasks like detecting an early risk of emotion disorders, caregiving, and customer service.
4. Emotion Mining’s Biases and Ethical Considerations: Study the moral questions raised by emotion mining, like how it affects people’s privacy, whether they’ve given permission, and whether the algorithms that recognize emotions are treating everyone fairly. Create rules and guidelines for doing emotion mining that are ethical and fair.
5. Understanding Emotions in Legal and Forensic Contexts: Explore how emotion mining can be applied in legal situations and forensic investigations. This involves examining voice recordings or written statements to identify signs of deception or emotional distress.

9. Applications. Emotion mining has made it easier to estimate others’ emotions, feelings, and psychology. Based on the result generated through emotion mining, one can always adjust/control the present situation and manage customer needs in a better way. It allows for staying dynamic throughout. Due to its various advantages, it has been connected to numerous application zones. It has been used in various fields such as the medical healthcare domain, sports, education, the financial sector, online social media, politics, hospitality, tourism, and many more. Some of the emerging application areas are briefed below:

1. Medical health-care domain: Using textual emotion mining, it is possible to assess the psychological health of a person with the help of his online posts [145] and avoid suicide to some extent. Moreover, it can be used to analyze the reaction of people to some disease outbreaks [57] and come up with some feasible solutions.

2. Sports domain: Emotion mining can be used for the spatial relationship between crime events and Twitter activity in the context of any popular game [109] Also, it can be used to assess the passionate reactions of fans [156].
3. Education domain: It can be used by the instructor to monitor the student's overall interest over time in the course [90] which can further help to improve the teaching and learning system [103]
4. Politics: Emotion mining can be used to predict the election results [107] and the reaction of citizens to any new policy.
5. Hospitality and Tourism: To improve the hospitality sector, customer reviews play an important role. Emotion mining can be used to predict customers' orientation based on reviews they posted on social media [77], [96].

10. Conclusion and Future Directions. The process of identifying an individual's mental state/ emotions/ opinions/ sentiments is an ongoing field of research. Most organizations are availing of it and incorporating it into their processes. A plethora of surveys can be found in the relevant literature either focusing on conventional approaches or machine learning approaches. Online social networking platforms have expanded exponentially over the past few years and consequently generated an enormous amount of data. Now, the attention is rapidly escalating to the problem of how to analyze the available data. This paper provides a systematic survey of the state-of-the-art approaches for emotion mining for textual data. Besides polarity identification, emotion mining also about knows the interpersonal relationships in the context of social networks, which affect information flows such as identifying behavioral features that may contain a strong emotional signal [15]. Accordingly, emotion mining needs to do deeper semantic analysis as social online platforms are very noisy.

In the future, research can be conducted in the direction of analyzing or recognizing the emotions hidden in the text understandably to recognize various aspects of human nature and behavior. This research can provide very predictive influences on the public attitude towards various issues and can also explain the state of human mental well-being. Further, information repositories of texts such as online chats, blogs, forums, etc., which are the source of opinioned or emotional content, are expected to give more emphasis on sincerity, spontaneity, and effectuality by combining the models of human cognitive capabilities that may include emotion mining.

Moreover, a human's mental state approach, more specifically the belief-desire-intention (BDI) model, can be used to know the human's intentions or behavior, which may be helpful to predict the human action pattern more accurately and improve emotion prediction. The main goal of using this approach is to capture emotions from the cognition viewpoint. Moreover, in today's scenario, only domain-dependent keywords are not sufficient, we need to explore a commonsense knowledge base that extends the cognitive and affective information associated with the social platform's information. Future emotion mining strategies need broader common-sense approaches which should be driven by the process of human cognition so that the effects are more realistic, reliable, and related to human psychology. We hope that this survey serves as a starting point for much more to come.

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