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A REVIEW ON MACHINE LEARNING AND DEEP LEARNING TECHNIQUES FOR TEXTUAL EMOTION ANALYSIS ON SOCIAL NETWORKS

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ABSTRACT

In recent times, emotion detection has achieved significant attention in the field of Natural Language Processing (NLP) due to the abundance of text data available on different social network platforms like Twitter, LinkedIn, and Reddit. This article presents a thorough review of existing emotion detection techniques on text analysis. The methodology involves a comparative analysis of different machine learning and deep learning models, approaches and datasets utilised for emotion detection. The article discusses the limitations and challenges of traditional methods and delves into the theoretical foundations of machine learning and deep learning techniques such as SVM, CNN, and BERT. By exploring the current state-of-the-art in emotion detection from social networks, this review aims to provide insight for researchers to advance the field of emotion detection.

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Introduction

In recent times, text has become the main source of communication due to the rise of social network platforms which fuelled interest in the field of natural language processing and sentiment analysis. Emotions on social network convey the feelings, opinions, and reactions. These emotions can be expressed in the form of text, images, and videos. On social networks, textual emotions can be expressed in the form of posts, comments, and messages. In this digital age, social media is an integral part of daily communication. Social networks provide real-time data, allowing researchers to analyse the sentiments and it also attracts the users from the diverse backgrounds, so, the formulation of the datasets on social networks are quite unique. This large volume of diverse data on social networks provides an excellent opportunity to train and evaluate emotion detection models more effectively. Focusing on social networking service (SNS), data allows the research to have a direct impact on these real-world scenarios. The growing interest in analysing SNS data within the research community highlights its relevance and importance. Moreover, focusing on SNS data allows the research to leverage the rich, diverse, and dynamic nature of the data to advance the field of emotion detection and develop practical solutions for real-world applications. Detecting emotions in text is difficult to perform as the nature of the word is not directly related to an emotion [1]. The lack of facial expressions and vocal modulations makes recognising emotions from text a very difficult task [2]. In comparison to other sources, emotion detection from text is still growing and not used widely in real-time applications.

An individual's emotional state reflects a person's feelings such as happiness, sadness, fear, anger, and surprise, as influenced by their surroundings. Early research indicates that most work has been focused on categorising emotions as positive, negative, or neutral, often overlooking the nuances of different emotional experiences. Most of the techniques under review are deep learning techniques [3]. Now in the era of machine and deep learning, text emotion detection methods have changed. This study focuses on the articles which include classifiers from these two techniques as well as hybrid approaches that contains classifiers from both machine learning and deep learning algorithms.

This article is designed to support novice researchers in the field of in-text emotion detection. A survey was conducted on deep learning (DL) methods used in the research of natural language processing [3]. The study discusses only DL methods used in emotion classification methods and applications for emotion analysis. This research article also compares the different machine learning techniques used in sentiment analysis for market prediction. A survey was done only on machine learning techniques for sentiment analysis [4]. This survey also conducted a detailed research review on state-of-the-art techniques, methods, and data sources related to emotion detection to determine the direction of future research. Through this a detailed literature review of articles from between 2018 and 2023, two essential contributions on the direction of research, namely opportunities in improving the detection of emotions from text and discussion about what is achieved so far were discussed. The article also considered the results and the limitations of the previous work done.

By reviewing recent studies, this article aims to give insights into where the research is heading and identify areas where there is room for improvement. This can help inspire more research in the field and encourage people to explore new ideas for better detecting emotions from text.

Section 2 highlights different emotional detection approaches used in text-based emotion detection. Section 3 discusses evaluation metrics for machine learning and deep learning approaches. Section 4 summarises the existing approaches in terms of datasets, limitations, while Section 5 provides the conclusion and the direction of future work.

Process of Emotion Detection

Emotion detection process consists of different steps which are collection of datasets, preprocessing of data, feature extraction, model construction, and evaluation as illustrated in Figure 1.

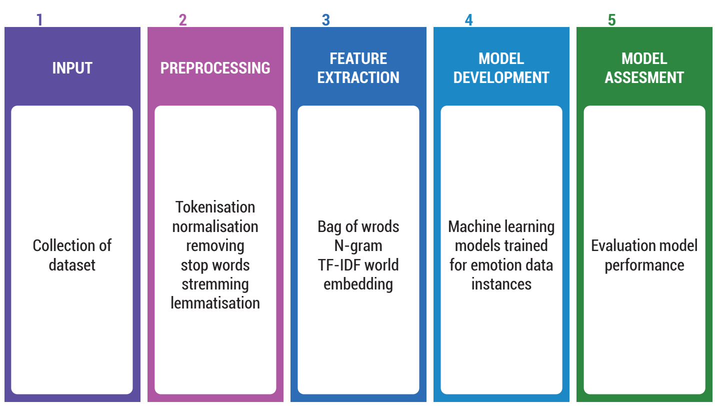

Figure 1: Steps involved in emotion detection process

Figure 1 outlines the different steps involved in the emotion detection process through text data: Dataset collection, preprocessing, feature extraction, model development, and model assessment. The details of each step will be discussed in the following sections.

Datasets for Emotion Detection

The most common datasets used in the literature are International Survey on Emotional Antecedents and Reactions (ISEAR) [5], EmoBank [6], and SemEval [7]. These datasets consist of different tweets, Facebook posts, and news articles. This section contains the details about widely use datasets in the literature under review.

ISEAR Dataset

The International Survey on Emotion Antecedents and Reactions (ISEAR) database was constructed via an extensive collaboration between psychologists [5]. The ISEAR database encompasses seven distinct emotional categories, namely joy, anger, sadness, guilt, disgust, shame, and fear. The database was compiled through surveys conducted in various countries around the world. One of the strengths of the ISEAR database is its inclusion of data from diverse cultural and geographical contexts. This enables researchers to investigate how emotional experiences may vary across different cultures and societies.

EmoBank

EmoBank provides a rich source of annotated text samples with detailed emotion labels categorised according to Ekman's basic dual representational design. The EmoBank dataset consists of a large collection of text snippets extracted from various sources, which includes different news articles, social network posts, literature, and online forums [6].

SemEval

SemEval is a publicly available dataset that categorises emotions as happy, angry, sad, and others. SemEval datasets are typically available for research purposes. The data in the SemEval database contains emotional content for emotion extraction and is categorised into six emotional categories, which are joy, anger, sadness, surprise, fear, and disgust, based on Ekman's model [8].

AIT-2018 Twitter Dataset

Affect in Tweets (AIT) dataset is a collection of tweets dataset focused on emotion detection in Twitter data. The AIT-2018 dataset consists of a large collection of tweets sampled from the Twitter platform. The Twitter dataset is publicly available for research purposes. With each tweet, there is an emotion and the corresponding intensity of that tweet [9].

Preprocessing of Text

The data is in its raw form and requires preprocessing to remove duplicate texts and symbols. Preprocessing is an essential data mining method [10]. The steps involved in text preprocessing includes tokenisation, stop word removal, and POS tagging. For data analysis, purpose cleaning the text in preprocessing step is essential part to remove data noise from the text. In some of the techniques described above, there are chances for some data loss, which needs to be addressed.

The tokenisation technique breaks a big chunk of text into small block of text, these small parts of the text are tokens which are derived from the text [11]. This step is crucial for text analysis as it enables the computer to understand and process at the word level. For example, the sentence is "Food is delicious" and post-tokenisation it will become "food", "is", "delicious". It is important to convert the text into standard form to achieve uniformity in the data [12]. Some prepositions and words which are not necessary in the text need to be removed. These types of words are considered "stop words". Stop words are like "is", "to", "in", which have nothing to do with emotions, so these words should be removed in preprocessing.

Feature Extraction

Machine learning algorithms cannot understand the raw data. Most machines understand texts in the form of numbers. So far, this purpose, there is a need to perform "feature extraction" from the original text to pass different numerical features to the machine learning algorithm. To map text to a number, we could count the occurrence of each word. In feature extraction technique a sentence is broken into different words and a feature matrix is built according to the frequency of the words. The feature matrix consists of rows and columns, where rows represent a sentence, or documents and column represent the word in dictionary. All types of data features related to text and images; videos are extracted through feature extraction. There are different feature extraction methods applied to text including the "bag of words" (BOW), N-gram, term-frequency, and counter vectorisation methods.

Emotion Detection Approaches

The general approaches used for emotion detection from text are keyword method, rule-based method, machine learning, deep learning, and hybrid method. Figure 2 illustrates the approaches used for text-based emotion detection.

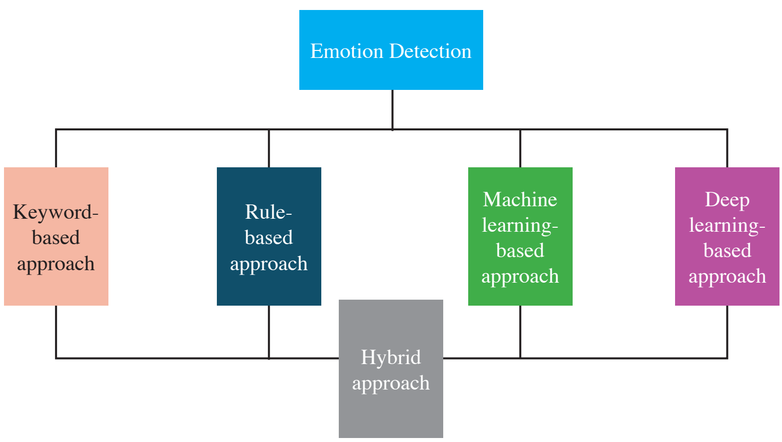

Figure 2: Text based emotion detection approaches

Keyword-based Approach

A keyword-based approach relies on finding specific words, which appear in each text and comparing them with labels stored in the dataset [13]. The keyword spotting technique involves identifying instances of specific words (in this case, emotion words) within a given text document. Employing emotion-related keywords offers a direct process for identifying corresponding emotions. However, in many instances of words, these keywords may vary and be ambiguous, as many words can change meaning depending on how they are used and the context in which they appear [13].

The keyword-based approach depends on the word in the database. "I won the match today" and "Hooray! I won the match today", in the latter sentence, "Hooray" denotes joy. In other sentence, this keyword is not mentioned, it is difficult to predict the emotion. Asghar *et al*. [15] introduced a method for detecting emotions at the sentence level and established 25 emotional categories. This approach includes different tasks such as keyword analysis, negation of keywords, short words, and emoticons, which achieved an accuracy rate of 80% [14].

Rule-based Approach

The rule-based technique is used to establish logical and grammatical rules for extracting emotions from text. Rules for emotion detection are derived from the statistics, linguistics, and computational theories. The best rules are selected and applied to the emotion dataset to determine the emotion labels. It is easy to create rules for a few documents but dealing with a large volume of documents, may increase the complexity.

Asghar *et al*. [15] proposed method enhances emotion-based sentiment analysis in online communities using rule-based technique. A mixed-mode classifier for emotion detection was developed. Evaluation metrics include precision, recall, F-measure, and accuracy at sentence level. The lexicon-enhanced sentiment analysis framework proposed by Ab. Nasir *et al*. [16] improves sentiment classification in user reviews. The proposed model enhances sentiment classification by considering emoticons, modifiers, and negations. The emoticon handling features contribute to a 74% improvement in accuracy.

Machine Learning-based Approach

The machine learning-based technique allows systems to learn and improve on their own through experiences automatically. These systems use algorithms to categorise text into different emotions. There are two types of machine learning algorithms; (i) supervised and (ii) unsupervised. In most cases, supervised algorithms are preferred. The process usually begins with text preprocessing, followed by feature extraction to identify the most important aspects of the text. The dataset is split into two sections: A training and a testing set. The training set is used to teach the model about the various attributes of different instances. Later, the testing set is employed to assess how well the model learned on the training set. Naïve Bayes (NB), Support Vector Machine (SVM), conditional random field, and Random Forest are the most common traditional supervised machine learning algorithms with different pros and cons of each algorithm.

Suhasini and Srinivasu [13] proposed machine learning approaches for emotion detection from Twitter messages, using dataset obtained from sentiment [14]. They compared Naïve Bayes and K-Nearest Neighbour (KNN), finding that Naïve Bayes achieved a higher accuracy than K-Nearest Neighbour.

Similarly, A. Chatterjee *et al*. [17] worked on detecting emotions using a Twitter dataset. They proposed a classification system for detecting emotions from tweets, where the text is preprocessed into words and sentences, reduced to their base form, converted to lowercase, and assigned part-of-speech tags. Features are then extracted from the text using N-grams and lexicon features. An ensemble of 11 binary classifiers is created to handle the problem of multiple emotions assigned to the text, with each model receiving the predictions made by the previous models as additional information.

Likewise, R. Rahman *et al*. [14] implemented Naïve Bayes and KNN in developing a text-based system for emotion prediction using machine learning algorithms. They evaluated four text classifiers: SVM, Naïve Bayes, KNN, and Decision Tree. The Multinomial Naïve Bayes classifier showed the best performance, achieving an average accuracy of 64.08%. This classifier performed particularly well on emotion classes such as "fear", "joy", and "sadness". The ISEAR dataset was used for evaluating the different machine learning algorithms.

Previous studies also used semantic-based methods and achieved good results, as demonstrated by M. Z. Asghar *et al*. [15]. They proposed the Semantic-Emotional Neural Network model (SENN) for emotion recognition from text, using Bidirectional Long Short-Term Memory (Bi-LSTM), and Convolutional Neural Networks (CNN). The model's performance was evaluated against various state-of-the-art approaches.

De Bruyne *et al*. [16] proposed a classification system for detecting emotions from tweets, text is preprocessed into words and sentences, reducing words to their base form, converting all text to lowercase, and assigning part-of-speech tags. Then, features are extracted from the text using N-grams and lexicon features, an ensemble of 11 binary classifiers is created to handle the problem of multiple emotions assigned to the text. Each model receives the predictions made by the previous models as additional information.

Deep Learning-based Approach

Deep learning is a subset of machine learning that involves understanding concepts arranged in a hierarchy, where each concept is connected to simpler ones. In various research papers, deep learning models are described in many forms such as Long Short-Term Memory (LSTM). LSTM is a special type of Recurrent Neural Network (RNN) that can handle long-term dependencies and solves the problem of disappearing gradients often found in traditional RNNs.

M. Hasan *et al*. [19] proposed cross-lingual transfer learning for emotion detection in Hindi, demonstrating that cross-lingual word embeddings can enhance emotion detection. This approach improves emotion classification performance, achieving a better F1-score of 0.53 with transfer learning techniques.

Similarly, Akhtar *et al*. [20] developed deep learning and classical models for emotion and sentiment analysis. They combined these models to enhance performance, creating an ensemble model that integrates LSTM, CNN, GRU, and SVR for sentiment prediction. Their evaluation on the EmoInt-2017 and SemEval-2017 datasets showed improved performance over existing state-of-the-art systems.

In contrast, Ishiwatari *et al*. [21] proposed a different approach, using relational position encodings to enhance emotion recognition in conversations (ERC). Their model employs relational graph attention networks, which contribute to a state-of-the-art average F1-score. The proposed model outperforms baselines and other state-of-the-art methods, suggesting that RNN-based models may be more suitable for certain labelled utterances.

Li *et al*. [22] introduced the IDS-ECM model for the dialogue emotion prediction task. This model accurately simulates emotional changes in dialogue and found that positive emotions like "happiness" are more contagious in communication. The IDS-ECM model outperforms the baseline in emotion prediction tasks, although it does not adequately address data imbalance issues. Chatterjee *et al*. [17] develops emotion detection technique in text dialogues using contextual information. Analyse neural architectures for emotion classification in textual dialogues. Bi-directional and LSTM two neural architecture used. Emoticons are frequently used in textual dialogues. Revealed top systems' performance, with Bi-directional LSTM as common choice. Limited performance for the happy emotional class compared to the sad emotional class.

Hybrid Techniques

Emotion classification, achieving an accuracy of 90% in correctly classifying text messages. Similarly, E. Batbaatar *et al*. [21]. The combination of machine learning and deep learning approaches has significantly improved classification performance compared to using either machine learning or deep learning alone. This hybrid approach leverages the strengths of both methodologies to enhance the overall accuracy and robustness of the model. Many researchers have combined different machine learning and deep learning approaches to develop more effective and efficient hybrid tools [18].

Hasan *et al*. [19] proposed a hybrid classification approach for emotion detection. They developed Emotex Stream for real-time emotion tracking in text streams. Hashtags were used to collect different emotion-labelled messages for training classifiers. Naïve Bayes, SVM, and Decision Tree classifiers were employed to a proposed hybrid model for text-based emotion recognition by combining deep learning and machine learning techniques. This model integrates CNN, Bi-GRU, and SVM to enhance accuracy. The hybrid model achieved an accuracy of 80.11% using CNN and Bi-GRU while the SVM alone achieved 78.97% accuracy and Bi-GRU achieved 79.46%. However, some challenges in extracting contextual information from sentences were observed.

In another study, D. Haryadi [22] proposed a hybrid approach using both deep learning and rule-based techniques for aspect extraction and sentiment scoring. A deep Convolutional Neural Network (CNN) was used to tag aspects in opinion sentences. The proposed method was compared with state-of-the-art techniques, achieving an accuracy of 87%, whereas a modified rule-based approach achieved 75% accuracy. These studies demonstrate the effectiveness of hybrid approaches in improving emotion detection and sentiment analysis by combining the strengths of machine learning and deep learning techniques.

Research Methodology

This study focuses on different machine learning and deep learning algorithms used in Emotion Detection (ED) from text. In this way, researchers categorised the approaches used in the classification of emotions. Different articles were reviewed from a pool of over 100 research articles sourced from Google Scholar, focusing on various approaches used in emotion detection. Articles from recent years were specifically included to ensure the research is up-to-date and reflective of the latest advancements and trends in machine learning and deep learning. The articles were compared based on the approaches used in the research. The keywords used in this research were chosen more precisely and were narrower in scope compared to previous works. Keywords such as "embedding", "emotions", and "pretraining" were used and the survey covered the years 2015 to 2020. This targeted approach ensured that a more focused and relevant set of studies was included in the research.

The inclusion and exclusion criteria for selecting papers were based on the usage of the most applied classifiers in both machine learning and deep learning algorithms. Figure 3 shows a summary of the article selection process. Different articles were reviewed from a pool of over 100 research articles on various approaches used in emotion detection. The articles were compared based on the approaches used in the research, with an analysis of both machine learning and deep learning approaches.

Machine learning algorithms used in the literature review worked on Support Vector Machine (SVM) used in emotion detection from text [20] used SVM for text-based emotion detection to classify sentences or phrases into different emotional categories [16] used Support Vector Machine along with Logistic Regression to detect emotions and achieved a high accuracy. Most of the techniques used were Support Vector Machine (SVM), Naïve Bayes, Random Forest, and K-Nearest Neighbour (KNN). K-Nearest Neighbour mostly used for emotion detection from image and text dataset. Random Forest (RF) due to its robustness and accuracy used for both text and speech emotion detection.

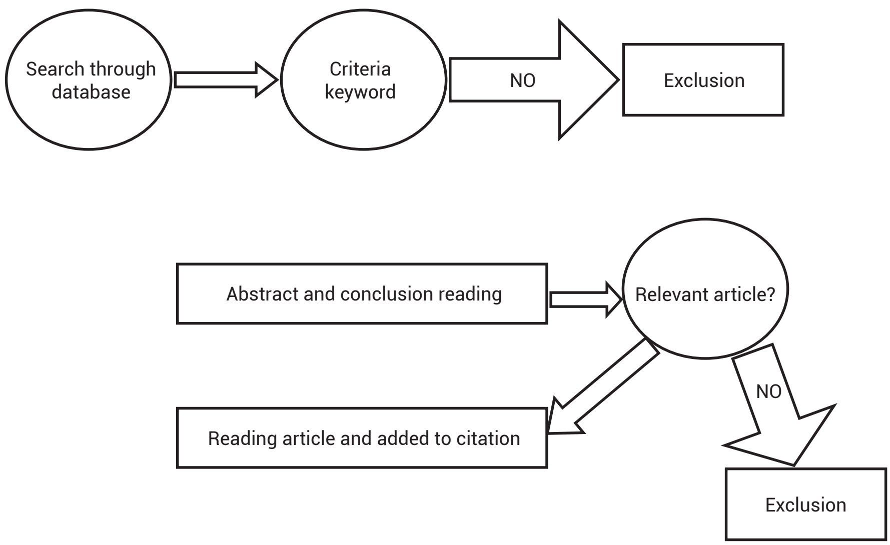

Figure 3: Summary of article selection process

Results

Table 1 discusses the summary of article selection process, which includes existing approaches, datasets used in experiments, contributions of the author, and the limitations of the existing body of literature.

Table 1: Summary of the recent existing approaches in text-based emotion detection

Author	Dataset	Model/ Algorithm	Contribution	Limitation
Ab. Nasir *et al*. [20]	ISEAR NLKT corpus	Machine learning-based emotion prediction model	Classified seven emotions using Nested LSTM and LSTM with high accuracy. Compared results with Support Vector Machine (SVM) for emotion detection	SVM and KNN classifiers showed low performance
E. Batbaatar [21]	EmoInt, ISEAR, Tweets	SENN model for emotion recognition	Evaluated model performance against various state-of-the-art approaches. Combined CNN and Bi-LSTM for semantic and emotional information	Over-reliance on handcrafted features needing manual design and adjustment
Haryadi *et al*. [28]	Twitter	Nested LSTM and LSTM	Classified seven emotions using Nested LSTM and LSTM with high accuracy. Compared results with Support Vector Machine (SVM) for emotion detection	No specific limitation found
Ragheb *et al*. [24]	SemEval-2019	Hybrid of learning-based and deep learning method	Identified best-performing hybrid and learning-based approaches with key features. Compared rule-based, classical learning-based, deep learning, and hybrid approaches	Implicit emotion recognition is challenging due to hidden emotions in text
Bruyne *et al*. [18]	Tweets	SVM, logistic regression	Used classifier chain with 11 binary classifiers for emotion detection	Limited predictive features for optimism and surprise emotions
Ahmad *et al*. [19]	Emo-SemEval, Sem-Eval 2018	CNN, Bi-LSTM	Proposed cross-lingual transfer learning. A new dataset created for disaster domain	Limited research done of a specific language
Akhtar *et al*. [20]	EmoInt-2017, SemEval-2017	LSTM,CNN,GRU	Develops deep learning and classical models for emotion and a stacked ensemble method for predicting emotion and sentiment intensity	Implicit sentiment and numeric entities cause misprediction
Ishiwatari *et al*. [21]	MELD, EmoryNLP	Dialogue RNN, dialogue GCN	Proposed relational position encodings for conversational emotion recognition	Model did not perform on certain labels
Chattarjee *et al*. [2]	SemEval-2019	BERT, LSTM	Revealed top systems' performance with Bi-directional LSTM. Analysed system used in Emo-context task	Limited performance for happy emotion class compared to sad

Bharti *et al.* [26]	ISEAR, WASSA	CNN, Bi-GRU	Proposed hybrid model for emotion detection using deep learning techniques. Achieved accuracy of 80%	Existing limitation include insufficient emotion keywords and semantics
Ray *et al*. [27]	Twitter, SemEval Task4	CNN	Improved aspect extraction and sentiment scoring methods for sentiment analysis	Rule-based method fails to extract implicit aspects accurately

Table 1 shows the five different methods used for emotion detection. The first method which is keyword method works with the help of Natural Language Processing and detecting the emotion based on word matching and the intensity of the emotion. The main issue with this method is the size of the dataset as the dataset increases it becomes difficult for word matching to mark the emotions. The second method is the rule-base method, which cannot extract the implicit aspects from the sentence by defining the rules and extracting the emotions from the text based on those rules. Machine learning and deep learning methods works on already trained data. Hybrid method is much more useful as it combines the previous two mentioned methods for much more accurate and reliable results.

Challenges in Emotion Detection

In this modern digital world, people use a lot of text on social media. Due to this huge volume of content, it is very difficult to understand the context. This content consists of slang words, incorrect grammar, and typing errors. This makes it a challenge for machines to understand the feelings behind the words. Most of the time, people do not even express their emotions clearly.

One major problem on platforms like Twitter, Facebook, and Instagram is the use of slang abbreviations. People often express their anger in a sarcastic manner, which is very hard to understand. Therefore, detecting emotional cues from sarcastic sentences are a big task. Multiple emotion extraction from a sentence is another significant challenge, as the wording of the sentence can be so complex that it is difficult to determine whether the sentence conveys positive or negative emotions due to its comparative nature.

It has been observed that preprocessing text and extracting features through different methods has a massive impact on extracting emotions from text using the approaches described above.

Conclusions

In this article, a detail review between various computational approaches use for emotion detection from textual data has been done. Approaches used for extracting individual's emotional state include keyword-based approach, rule-based approach, machine learning-based approach, deep learning-based approach, and hybrid approach was discussed. Furthermore it explores the critical evaluation of the existing state-of-the-art applied approaches with focus on the dataset and the technique used, as well as the existing limitations in the work. Most of the work done through machine learning and deep learning algorithms are highly accurate depending upon the text preprocessing method and size of the data. In most cases, deep learning algorithms outperform machine learning algorithms, mostly the implicit aspects of text, where machine learning algorithms do not perform accurately and where the data set size is large.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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