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Review:

Beyond Sentiment Analysis: A Review of Recent Trends in Text Based Sentiment Analysis and Emotion Detection

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Sentiment Analysis is probably one of the best-known area in text mining. However, in recent years, as big data rose in popularity more areas of text classification are being explored. Perhaps the next task to catch on is emotion detection, the task of identifying emotions. This is because emotions are the finer grained information which could be extracted from opinions. So besides writer sentiments, writer emotion is also a valuable data. Emotion detection can be done using text, facial expressions, verbal communications and brain waves; however, the focus of this review is on text-based sentiment analysis and emotion detection. The internet has provided an avenue for the public to express their opinions easily. These expressions not only contain positive or negative sentiments, it contains emotions as well. These emotions can help in social behaviour analysis, decision and policy makings for companies and the country. Emotion detection can further support other tasks such as opinion mining and early depression detection. This review provides a comprehensive analysis of the shift in recent trends from text sentiment analysis to emotion detection and the challenges in these tasks. We summarize some of the recent works in the last five years and look at the methods they used. We also look at the models of emotion classes that are generally referenced. The trend of text-based emotion detection has shifted from the early keyword-based comparisons to machine learning and deep learning algorithms that provide more flexibility to the task and better performance.

Keywords: sentiment analysis, emotion detection, text, machine learning, deep learning

1. Introduction

Sentiment analysis is the task of categorizing a text as having positive or negative meanings. This task can be considered as a classification task with binary (positive, negative) or multi (positive, negative, neutral) classes. Opinion mining includes the task of sentiment analysis and aims to summarize the opinions of a dataset. Opinion mining are normally synonymous with sentiment analysis as sentiment analysis are performed on opinionated text. Opinions of public or customer group are helpful for businesses to gauge product or service acceptance or ideas for their improvements. As the Fourth Industrial Revolution occurs, big data is a phrase commonly heard of. The potential of using public opinions in various decision making and even prediction of events occurrence has an encouraging effect on the application of sentiment analysis in big data researches [1]. The emotions of the public and customers are also a form of their opinions. Emotions also have polarities. Happy, surprised, and love are considered positive emotions, whereas sadness, anger, and disgust are considered negative emotions. Classifying the emotion of a text can add to the accuracy of sentiment analysis and produce a better opinion summary. Instead of just knowing the polarity of opinions, emotions can add to the weight of sentiment polarity or rather they can go hand in hand in discovering the interest of the person or group [2].

Text based emotion detection is the task of identifying the underlying emotion of text authors based on their language expressions and text features. In this era where technology has opened up different ways of communication, the expression of feelings and ideas are not just limited through verbal communication. The modern generation uses technology and social media as a channel of expression. Social media and the internet are now platforms for various opinion and emotion expressions whether its someone's opinion regarding a certain topic or just daily description of their feeling and thoughts. Since the internet connects everyone to the world, the abundant emotion expressions available can be harnessed for psychological and behavioral analysis or gauging public sentiment of a product or topic. The potential application of text-based emotion detection can be extended to the areas of marketing, advertising, social behavioral analysis, public sentiment analysis and human computer interaction.

Sentiment analysis as one of the earliest method of harnessing public opinions through text and emotion detection is the natural extension to explore more. Through this review we seek to look at the recent trends involved in text sentiment analysis and emotion detection. As sentiment analysis have been heavily explored in the past, methods are well sharpened to produce very accurate results. On the other hand, text-based emotion detection poses much more of a challenge as there are more emotional categories to be classified depending on the variation in emotions. So, what are the differences in trends of techniques being used between sentiment analysis and emotion detection and what are the variation in methods explored to perform effective emotion detection given the larger number of classes?

Emotion detection is a task which have been approached through different angles. As there are several ways which human can express their emotions, there also various types of data for emotion detection. Emotions can be detected through written text, spoken language, facial expression or even brain wave activity. The reason emotion detection is an interesting research area might be motivated by the idea that a persons' feelings will affect the decisions that they make. Because of this, knowing the emotion of a person or crowd can help us know how to approach the person or crowd and give us the edge when communicating with them.

2. Challenges in Text Classification

One of the challenges for any text-based classification task is to figure out which features or marker can help us accurately identify the different classes. For sentiment analysis that would be positive or negative classes whereas for emotion detection it would be the different emotion classes. The general approach used in any text processing and mining related task is to assume each word in the piece of text as a feature or a single datum. This scheme is known as the Bag-of-Words model where each word is considered an individual element [3, 4]. This approach although simple and direct has its flaws and limitation. A single word on its own does not reflect the content of an entire piece of text, when used in different context, they could have totally different meaning [5]. Therefore, it is always better to include other text features which could reflect the context of the text in order to increase information expressed and accuracy of classification [6].

Other challenges that present itself when dealing with text related classification are the text context, ambiguity, sarcasm and implied semantics. Context as mentioned before affects how a word is interpreted in a given text [7]. Therefore, to gather the general information of the text, single words are not enough, there needs to be attached markers or pairing of words that provides a context to the word. The next challenge is word ambiguity which can be related to context. Certain words can have several meanings depending on the word pairing or context of the word usage. For example, "break a glass," "take a break," and "break a leg," the use of the single word "break" in the three different phrases brought about three entirely different meanings and sentiment. "Break a glass" implies negative sentiment or emotion whereas "take a break" and "break a leg" are phrases with more positive sentiment and emotions. These emotions cannot be fully reflected when looking at just the single word "break."

Sarcasm is a challenging issue for speech and text-based task. Sarcasm generally carries the opposite meaning of the words used and audience are expected to catch the intended meaning based on speech tones and topic context. However, since it's not easy to catch the tone of the author in texts, we have to rely on other markers. This task is complex enough to be another classification task on its own. The real emotion and sentiment of the author are implied rather than explicitly expressed. This brings us to the next challenge, implied meanings rather than explicitly expressed meanings.

Everyone has different ways to express their opinions and emotions. Some prefer to be direct and say what's on their minds, whereas some prefer to keep it to themselves, however, their speech and attitude could reflect the state of emotion they are in. Direct expressions of emotion are easier to detect through the use of certain keywords and punctuations. Implicit sentiment or emotion detection is more challenging because there might not be clear use of sentiment or emotion keywords. They have to be interpreted with consideration of context, usage of metaphors, and even cultural and social backgrounds as the usage of words and speech pattern differs [8].

The different challenges stems from the diversity and dynamics of language. As there are different speech patterns of different people, it is not a simple task to come out with general rules to categorize ideas expressed in text. So, there are many text features that can be combined and to provide a better indication of the ideas, meaning, emotions, and sentiments of the author. Single word is the basic feature, however there are other supporting features such as phrases, punctuations, and emoticons which are more commonly used in informal texts such as in social media. These different features help to give a better understanding of the meaning of the text.

Another issue in text classification related to language usage is the difference between formal written text and social media text. Formal text adheres to the grammar rules which each language has defined, thus having a certain recognizable pattern. Articles, newsletters, reports, and scientific reading materials are mostly written in formal language. Social media text on the other hand do not necessarily follow the standard language patterns and are considered informal text. However, they are sought after because they are available in abundance and mostly contain opinions and expressions of the public which are helpful for tasks such as sentiment analysis, emotion detection, depression, and suicide detection. Available through social media sites such as Twitter, Facebook, Instagram, and Reddit, these sites give people the channel to openly express their feelings and opinions and harnessing those text can help to detect, analyze and discover social behaviors. Most natural language processing tools such as lexicons and annotators have been created according to the rules and grammar patterns of formal language. Thus, they might not be sufficient to handle tasks related to informal text. But since informal text seems to be more widely analyzed due to its abundance, this is a challenge in itself.

Baldwin et al. [9] concluded some characteristics of social media text which makes it different from formal text. First, social media texts contain many non-standard word forms such as short forms or acronyms, redundant repetition of letters and misspelled words. For example, “LOL,” “loooooooove,” “ur,” “wht” [10]. These happens for a couple of reasons. Postings on social media often do not require proofreading and because they are musings of one’s own mind, there are no rule to conform them to formal language. Some platforms have imposed word counts thus indirectly encouraging use of short forms and also for the convenience of typing. Repetition of letters sometimes acts as a way of expressing exaggeration and intense emotion [11]. Secondly, fragment of sentences. Formal text has full sentences with proper start and ending but social media text could be phrases, half constructed sentences or rhetorical questions. Thirdly, appearance of site related markups such as hashtags, labels, mention, and URL. Hashtags such as “#depressed” and “#love” are helpful to extract text since they are a form of label about what the posted text is about, but in the actual classification task these labels are removed or at least the “#” sign is removed because it does not contribute much information [10]. Mentions or tagging of another user using the “@” symbol is also another feature of social media text that do not contribute knowledge to tasks and are mostly removed.

In the following sections, the recent works in sentiment analysis and emotion detection are reviewed and through them the contributions of this review are presented. First, a look at the transition of works from sentiment analysis to works which combine sentiment analysis and emotion detection for opinion analysis to show the growing use of emotion detection. Second, reviewing and showing recent trends in the methods used to perform effective emotion detection.

In this review, recent work in sentiment analysis and emotion detection from the recent five years are taken. The papers reviewed were from the indexed sources. The review is organized in three parts, it starts off with sentiment analysis and the recent trends in sentiment analysis. Then, we see works of combined sentiment analysis and emotion detection showing that emotion detection is gaining importance. Then the third part describes techniques in emotion detection and trends in research of emotion detection. The works in both sentiment analysis and emotion detection is summarized in tables showing the techniques used. In review of emotion detection there are more details such as emotion models, features, methods, and performance discussed. Through the summarized table, the trends in classifying techniques for sentiment analysis and emotion detection are observed and studied.

3. Sentiment Analysis and its Trend

3.1. Sentiment Analysis and Opinion Mining

Sentiment analysis is no longer a foreign topic after the hype of big data and its related tasks. The abundance of public opinions and reviews available through various social media platforms enables easier summarization of public sentiments with the help of sentiment analysis. But the fact is sentiment analysis is not a new task and the methods of sentiment analysis have evolved through the years.

Big data describes data that have volume, variety, and velocity. These characteristics of big data is brought about with the digital age where usage of the internet transactions and social media is undetachable from everyday life. Social media texts classification presents new application avenues and also new challenges. Social media continuously produces streams of analyzable data every second. Thus, sentiment analysis is not only performed on static data but could also be done in real time as new texts are being posted. The challenge now lies on the processing time. The amount of time it takes to retrieved analyzable text and classify them needs to be significantly short in order to produce almost instant analysis results [12, 13]. The most common task of sentiment analysis on big data is classifying and summarizing reviews for product evaluation and ratings for finance and marketing purposes. Reviews of previous customers influences purchasing decisions of other customers, even more so as shopping habits move towards e-commerce websites that makes rating and reviews abundantly available. Sentiment analysis is directly applied most of the time in summarizing huge amounts of reviews. But more than that now is the need of detection of fake reviews which could very much sway the decisions of potential customer. Sentiment analysis and similarity scores are used to detect reviews that might have been mass generated by duplicating the same review multiple times to show more reviews of the same category [14]. Characteristics of the review text and pattern of posting may also hint at fake reviews as discovered in [15]. They found that besides high similarity, text that are short with too many positive or negative words and large amounts of these reviews being posted in a short duration of time, points to fake reviews [15]. Sentiment analysis is also used in stock market and also market behavior prediction by classifying public sentiment on mentions of company names or business news articles [16, 17]. Sohangir et al. [18] applied sentiment analysis on big data mined from a financial social network site to try to predict the future stock prices based on the exchanges between financial experts and general public. Besides financials, there is also application of sentiment analysis on big data related to social and country well-being [19] performed sentiment analysis on mass public sentiments while negotiations were happening regarding the Brexit issue as a measure for government decision making [20] applied sentiment analysis on public social media posts that were generated in the event of natural disasters as a way of im-

Table 1. Recent works in text based sentiment analysis.

Authors	Features	Methods
Appel et al. [24]	Words	Hybrid of lexicon, semantic rule, and fuzzy set approach
Khan et al. [25]	Words with part-of-speech and SentiWordNet tags	Support vector machines (SVM)
Tang et al. [26]	Words with sentiment embeddings	Neural network with context prediction and sentiment prediction model
Tripathy et al. [27]	N-gram (unigram, bigram, trigram)	Naïve Bayes, maximum entropy, SVM, stochastic gradient descent
Poria et al. [28]	Word embeddings, part-of-speech	Convolutional neural network (CNN)
Onan et al. [29]	Word	Ensemble machine learning (Naïve Bayes algorithm, SVM, logistic regression, Bayesian logistic regression, and linear discriminant analysis)
Al-Sharuee et al. [30]	Words (part of speech)	Ensemble k-means clustering
Xiong et al. [31]	Word embeddings	Neural network
Ankit [32]	Words	Ensemble machine learning (Naïve Bayes, random forest, SVM, logistic regression)
Akilandeswari and Jothi [33]	Words, emoticons and short forms	Lexicon scoring
Sailunaz and Alhajj [2]	Words (noun, adjective, verb, adverb)	Naïve Bayes

proving the relief response. Generating a list of keywords related to needs of victims such as food or shelter, sentiment analysis helps to summarize the related posts to understand which of the needs are having positive or negative response. Then this in turn helps the response team to provide accordingly.

The earliest approach on sentiment analysis was based on linguistic features in identifying parts of sentence which contained sentiments [21]. This led to the lexicon method [22] and later the machine learning method [23]. **Table 1** summarizes the recent works in sentiment analysis to give an overview of the trend in sentiment analysis in recent years.

Lexicon and rule-based methods are considered the start of works in sentiment analysis. Although machine learners are more popular in later works, Appel et al. [24] shows why this method is still applicable by creating a hybrid model consisting of lexicon labeling, semantic rule and fuzzy set approach. The performance of the hybrid model is compared against machine learners in analyzing datasets consisting of review sentences and the results showed that the hybrid model could perform much better than machine learners. The model continuously refines classification rules through three layers of algorithms that determine final sentiment based on polarity intensity, influence of neighboring words and the frequency of sentiment words. Other than that, the lexicon used is also continuously enriched with new words. This shows that rule-based methods could perform very well through refinement of rules and also a rich lexicon of words.

Al-Sharuee et al. [30] performed another unsupervised method of sentiment analysis by using the clustering technique instead. They also applied the ensemble concept which is normally applied in machine learning. The ensemble concept is applied to create multiple vector space model representation of data for clustering. After clustering is done individually for each vector space model applied, the final decision is achieved through majority voting. The authors results shows that their algorithm could produce good and stable results across different datasets.

Other than that, machine learning techniques are still widely favoured. Generally, Naïve Bayes, SVM, and neural network are the commonly known machine learners that perform well. With the popularity of deep learning surging, various forms of neural network are applied for sentiment analysis. The advantage of neural networks can be seen in the feature representation phase where neural network mostly rely on just words and not the common feature representation. Instead, neural networks have their own word embedding schemes as feature representation. But for unsupervised techniques and traditional machine learners such as Naïve Bayes, SVM, and decision trees, they rely and various feature representations to enrich information content. Various length of N-grams and part-of-speech labeled words are still the most popular features. Higher level N-grams such as bigram and trigram preserve more contextual information compared to words but will increase the number of features greatly and hence the need for feature selection to filter the influential features. Whereas for part-of-speech, words that carry opinion generally belongs to the group of adverbs and adjectives, thus choosing words that belong to these groups is helpful to obtain the sentiment of the document [25].

3.2. Sentiment Analysis and Emotion Detection

Sentiment analysis classifies text as having positive or negative connotations. It may be sufficient in certain cases where we only want to know the general sentiment of crowds, but for social topics, diving into the emotions of the writer of texts maybe more appropriate. Sentiment analysis maybe the basis of opinion mining whereas emotion detection is the next level in the process. In recent years too, the works in sentiment analysis are often extended to include emotion detection.

Poria et al. [28] performed an extensive work on multimodal sentiment analysis and emotion detection where it involves multiple media. The data used were videos from which they extracted text, audio, and visual data to perform both sentiment analysis and emotion detection. Different models were trained for different data, the focus of this paper is on the text data. A combination of recurrent neural network and CNN was applied for the task and the features used were word embeddings and six groups of part-of-speech words (noun, verb, adjective, adverb, preposition, conjunction). The challenges that the authors faced is in the emotion detection phase where, emotions belonging to same sentiment groups are more difficult to distinguish. For example, angry and sad are both negative sentiments and are tougher to distinguish by their classifier models.

Sailunaz and Alhajj [2] presented a work with both sentiment analysis and emotion detection as a basis for their future work of a recommender system. In their model, the machine learning algorithms, Naïve Bayes, SVM, and random forest were applied upon a twitter dataset that the authors extracted. From the dataset, word features were extracted to form two feature sets, one consisting of all words from the cleaned or preprocessed dataset and another where only noun, adjectives, verbs, and adverbs groups of words were filtered. The classification results were not very satisfactory and the authors highlighted some findings and challenges they faced. First off, the feature set with full cleaned text words performed better than the part-of-speech filtered feature set. Secondly, the characteristics of social media text which are informal without structure also affected their classification accuracies as they compared their model performance on another dataset which has proper sentences and performed better. Lastly, their dataset was not balanced in terms of distribution of emotion classes thus the accuracy of emotion classification was affected.

Imran et al. [34] recently created a model to analyse the reaction of the public in twitter towards the COVID-19 pandemic. The model included sentiment analysis and emotion detection. Deep learning and neural networks were used with various word embeddings to first perform sentiment analysis upon tweets. After the tweets have been classified into positive and negative then emotion detection is performed on the tweets. From positive tweets, they were further classified into joy or surprise emotion classes, whereas for negative tweets, they were classified into sad, fear, and anger emotions. So, there were three classification models and the results were satisfactory where the sentiment classification and positive emotion classification have accuracies of 80% and above but the negative emotion classification did not perform as well with 69.9% highest accuracy. This might be because the previous classifiers were binary classifiers (positive vs. negative and joy vs. surprise), whereas the negative emotion classification involved three classes.

Ohman et al. [35] is another work which performed both sentiment analysis and emotion detection. However, their work focused more on creating a dataset of English and Finnish text for both tasks. In their dataset, the texts were annotated into classes of positive emotions (anger, disgust, fear, and sadness), negative emotions (anticipation, joy, and trust) and neutral text. In order to evaluate the dataset, BERT and SVM classifier were applied. There were several findings, firstly, positive emotions were more accurately classified. Next, "disgust" is a challenging class as it is often confused with "angry." Thirdly, "anger" and "disgust" along with "joy" and "trust" are highly correlated to each other.

The transition for sentiment analysis task to emotion detection is logical when more detail analysis is needed of opinion analysis. Referring to **Fig. 1**, a search of trending research work for combined text sentiment analysis and emotion detection through the website lens.org shows an increase of interest in recent years. This indicates that the work of combined sentiment analysis and emotion detection is showing more potential of application. After looking at increasing interest of extending sentiment analysis to emotion detection, the next section will start the discussion of work in text-based emotion detection.

4. Emotion Models

In order to perform emotion detection, the intended classes of emotion that are to be classified must be established first. Emotions are "strong feelings" as defined by Cambridge Dictionary. Human emotions are complex and varies, however to perform the task of emotion detection, we need to narrow down to some basic classes of emotion that commonly appear. Classifying multiple classes can be challenging for text-based classification, therefore emotion classes are also limited to a smaller set. There are several emotion models that can be used in the task of emotion detection and they are often taken from psychology studies. **Table 2** summarizes some of the common emotion models.

Emotion models are generally categorized into two groups, discrete/categorical and dimensional. Discrete or categorical models assume that the emotion classes are separate and unrelated and that there is only a limited set of emotions [6]. Dimensional models projects emotions onto a plane or multidimensional space and each emotion is a point on this plane that can be influenced by variables. Emotions are considered interconnected as they can be explained based on single or multiple dimensions [42].

The most common emotion model is established by

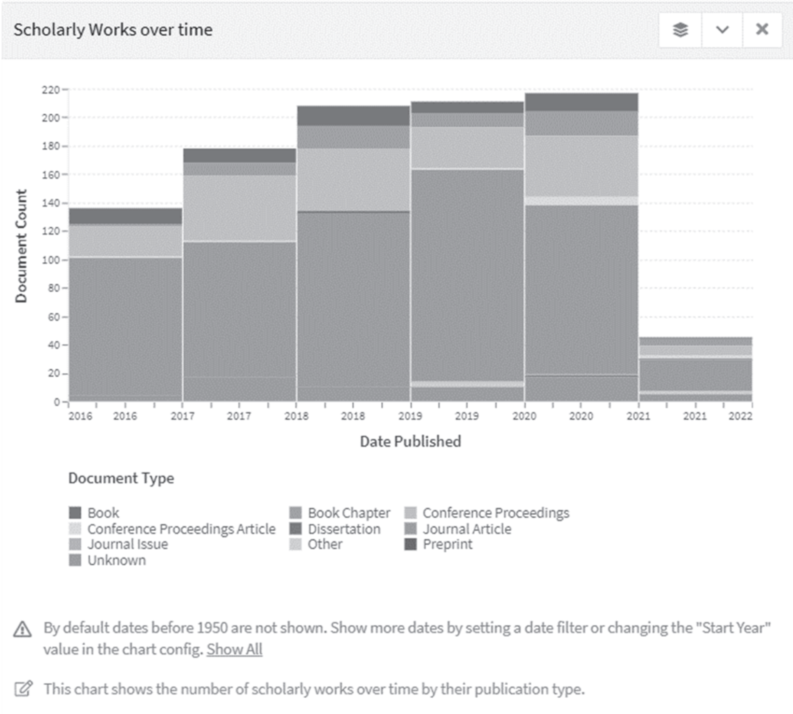

Fig. 1. Trends in sentiment analysis and emotion detection research [36].

Table 2. Emotion models.

Model	Ekman [37]	Plutchik [38]	Parrott [39], Shaver [40]	Ortony–Clore–Collins [41]
Positive emotions	happiness	joy, trust	joy, love	happy-for, liking, appreciation, gratitude, gratification, hope, relief, pride, admiration
Negative emotions	sadness, anger, fear, disgust	sadness, anger, fear, disgust	sadness, anger, fear	anger, fear, sorry-for, resentment, fears-confirmed, disappointment, self-reproach, reproach, remorse, disliking, shame, pity
Neutral emotions	surprise	surprise, anticipation	surprise	gloating

Ekman [37] and it is a well-known discrete emotion model. There are six basic emotion classes in this model, which are sadness, happiness, anger, fear, disgust, and surprise. This model is still commonly used in recent works of emotion detection [43–46]. Another discrete emotion model is the Ortony–Clore–Collins (OCC) model [41]. This model defines 22 emotions that humans react based on different situation. It gives some knowledge to which situation the emotion will appear, so that the classification of emotions will not be influenced by different language and culture. The 22 emotions are happy-for, sorry-for, resentment, gloating, hope, fear, fears-confirmed, relief, disappointment, pride, self-reproach, appreciation, reproach, gratitude, anger, gratification, remorse, liking, disliking, shame, admiration, and pity [47]. Parrott model [39] and Shaver model [40] both defines emotions as a tree like structure where both starts off with six basic emotions which are anger, fear, joy, love, sadness, and surprise. From the basic emotions, other finer emotions can be expanded and added to the tree in layers.

For dimensional models, Plutchik's model of emotion is the most popular model. Plutchik's model defines eight basic emotions which are paired in opposite polar of each other. The pairings are joy–sadness, anger–fear, surprise–anticipation, trust–disgust [38]. These basic emotions are expanded based on different dimension where pairings with other emotions can produce another emotion. Other dimensional model includes Russell's model [48] which defines emotions based on a polarity dimension and emotion activation dimension.

5. Techniques

The techniques or emotion detection through text are somewhat similar to text mining tasks. In this section some of the techniques will be described along with the recent works and techniques that they use. There are generally two ways of conducting emotion detection through text. They are keyword comparison and learning based methods.

5.1. Keyword Based Methods

Keyword based method is the earliest method used for emotion detection. This method involves creating a collection of keywords for each emotion class and detecting the presence of these keywords in the text that is to be classified. This method is straightforward and easy to use. The key to accurate emotion detection for this method is the effective extraction of keywords from text and how extensive is the keyword dictionary created [49].

The steps involve simple text processing methods. First, a piece of text is broken down into word token. From the tokens, emotion keywords are extracted and matched to the emotion keyword dictionary. However, before defining the emotion class, negation words are searched because negation words such as "not" and "no" will inverse the sentiment and emotion of a word. Thus, negation words are taken into account before deciding on the final emotion contained in the piece of text [50].

However, its downfall lies on the rigidness. The ability to detect emotions rely heavily on the presence of the emotion keywords in the dictionary and also in the text that is supplied. Without a match on both sides, the emotion classes cannot be found. Besides that, the lack of context when sentences have been broken down into individual word tokens, lead to the problems of word ambiguity and failure to detect emotion without the keywords [51].

Keyword based method are mostly seen in earlier works of emotion detection [52–54] probably due to the rigidness of the method.

5.2. Learning Based Methods

Learning based methods are widely used classification methods which are not only limited to text classification task. There are two kinds of learning based methods, unsupervised learning and supervised learning. Unsupervised learning classifies the emotions based on mathematical calculations. Some well-known formulas are pointwise mutual information (PMI), latent semantic analysis (LSA) and its variants. These formulas normally calculate the similarity or affinity of a document to other class specific documents and determine the classes based on the nearest similarity. In the early work of Strapparava and Mihalcea [55], they applied LSA on news headlines from major news portals to detect the emotions contained. Agrawal and An [56] applied PMI to classify emotions based on extracted part-of-speech words that are adjectives, verbs, adverbs and nouns.

Unsupervised learning methods do not rely on training documents to help them classify data, supervised learning on the other hand does. Supervised learning uses machine learning algorithms to detect underlying pattern of data occurrence. Machine learners can perform a variety of classification tasks however it does this by relying on the supply of a good training set which is already classified or annotated to the intended classes. Preparation of an informative and extensive training set is vital and may make or break the performance of the machine learner. The data required by machine learners are called features and although general text processing just uses words as single data, the features for machine learner varies. There are word features, phrase features, labeled features, and with social media text, even punctuations and emoticons can be features to machine learners [5]. The goal of the different features is to increase the knowledge of the learning algorithm about the data it is classifying, in this case, the emotion indicators contained in the text. The more informative the feature set, the better the performance of machine learners. Therefore, the challenge of supervised learning methods is to find or create an informative feature set that can include all necessary indicators for the multiple classes of emotion. This is because machine learners generally perform better when classes are less. As classes increase the tasks becomes more challenging [49]. Nonetheless, machine learning methods are still generally favored for classification task due to its versatility and ability to produce good results [46].

The task of machine learning classification can be split into three steps, feature extraction, feature selection, and classification. Prior to classification, the data needs to be extracted via feature extraction methods, then features that can help discriminate between classes are selected as final feature set [5]. The feature set is then supplied for classification. In the classification task, the classifier needs to be trained with a set of data with known classes before it can predict classes of unlabeled data. Among the earliest work for emotion detection using machine learning method is done by Alm et al. [57] who used a network of Winnow classifiers to classify emotion in fairy tales. Other early works of emotion detection using machine learners include Teng et al. [58] who used SVM to classify emotions and Yang et al. [59] who used conditional random fields as classifier.

5.3. Recent Works

Generally, there are two methods for emotion detection highlighted in the prior sections. However, there are also hybrids of the two methods such as the work done by Wu et al. [51] that uses the dictionary method to extract features to train a machine learner that classifies the emotions. Emotion keywords still remains the most important feature for emotion detection. Therefore, it is valuable for other methods too. For this section we plan to look at the more recent works in text-based emotion detection to see the evolution of methods for this task. Listed in **Table 3** are the recent works on text-based emotion detection.

From **Table 3**, it can be seen that most researchers still use the Ekman model of emotions to define the emotion classes of their work. There are many others that choose to reduce the classes of emotion to four critical emotions (joy, sad, anger, and fear). As mentioned before, multiple class classification gets more challenging as the number

Table 3. Recent works in text based emotion detection.

Authors	Emotions	Features	Method	Results
Wang and Pal [60]	anger, fear, joy, sad	N-grams, smiles, #exclamation mark, question mark, curse words, greeting words, sentiment polarity	Keyword/Lexicon with rule based	Avg. recall: 0.6–0.7 Avg. precision: 0.6–0.7 Avg. F_1: 0.6–0.7
Shivhare et al. [61]	love, joy sadness, anger, fear, surprised	words	Keyword based with ontology	Avg. accuracy: 0.8
Douiji et al. [62]	sadness, happiness, anger, fear, disgust, surprise	words	Unsupervised learning – normalized PMI	Avg. accuracy: 0.68 Avg. recall: 0.72 Avg. precision: 0.92
Perikos and Hatzilygeroudis [44]	sadness, happiness, anger, fear, disgust, surprise	words	Supervised learning ensemble – Naïve Bayes, maximum entropy	Avg. accuracy: 0.7–0.8 Avg. precision: 0.8 Avg. sensitivity: 0.7–0.8 Avg. specificity: 0.7–0.8
Herzig et al. [63]	happiness, sadness, anger, surprise, fear, disgust, confusion, frustration, hopefulness, disappointment, gratitude, politeness, neutral	unigrams, bigrams, NRC lexicon features, presence of exclamation marks, question marks, usernames, links, happy emoticons, sad emoticons, weighted features	Supervised learning ensemble with SVM	Avg. F_1: 0.5–0.6
Mohammad and Bravo-Marques [64]	anger, fear, joy, sadness – intensities	word, character	Supervised learning – SVM	
Mashal and Asnani [65]	joy, sadness, fear, anger	words	Supervised learning	Avg. accuracy: 0.8–0.9 Avg. recall: 0.8–0.9 Avg. precision: 0.9 Avg. F_1: 0.8–0.9
Kumar et al. [66]	joy, sadness, anger, neutral	word, character, NLP features	Supervised learning – Logistic regression, Naïve Bayes, CNN	Avg. accuracy: 0.8–0.9 Avg. recall: 0.8–0.9 Avg. precision: 0.8–0.9 Avg. F_1: 0.7–0.9
Gaind et al. [43]	happiness, sadness, anger, surprise, fear, disgust	word, emoticons	Hybrid, supervised learning (SMO, J48), word scoring	Avg. accuracy: 0.8–0.9
Witon et al. [67]	anger, disgust, fear, joy, sadness, surprise	word	Deep learning – ensemble of CNN	Avg. accuracy: 0.6 Avg. F_1: 0.5
Kratzwald et al. [68]	anger, fear, joy, sadness	word, word embeddings	Machine learning – random forest, support vector machine deep learning – deep neural network	Avg. F_1: 0.3–0.6 Avg. sensitivity: 0.3–0.6 Avg. specificity: 0.7–0.9
Sailunaz and Alhajj [2]	anger, disgust, fear, joy, sadness, surprise	words (noun, adjective, verb, adverb)	Supervised learning – Naïve Bayes	Avg. accuracy: 0.1–0.6
Ibraheim et al. [69]	anger, fear, joy, sadness	word, emotion lexicon score	Deep learning – CNN	Avg. recall: 0.08–0.7 Avg. precision: 0.6–0.8 Avg. F_1: 0.1–0.7
Batbaatar et al. [70]	anger, disgust, fear, joy, sadness, surprise	word	Deep learning – CNN with bidirectional long-short term memory (biLSTM)	Best accuracies: 0.5–0.9
Baali and Ghneim [71]	anger, fear, joy, sadness	word, character	Machine learning – Naïve Bayes, support vector machines, multilayer perceptron deep learning – CNN	Avg. accuracy: 0.9 Avg. recall: 0.9 Avg. precision: 1.0 Avg. F_1: 0.9
Tan et al. [72]	happy, sadness, love, fear, anger, surprise.	N-gram	Semi supervised learning with SVM	Avg. accuracy: 0.8
Erenel et al. [73]	anger, disgust, fear, guilt, joy, shame, sadness	word	SVM	Avg. accuracy: 0.8–0.9
Zad and Finlayson [74]	joy, anger, fear, sadness, or neutral	word	Unsupervised labelling	Avg. accuracy: 0.5-0.8 Avg. F_1: 0.5–0.8
Abdul Razak et al. [75]	anger, afraid, happy, excited, sadness, bored, relax	word	CNN	Avg. accuracy: 0.9 Avg. recall: 0.9 Avg. precision: 0.9 Avg. F_1: 0.9
Chowanda et al. [76]	anger, sadness, fear, joy	word	Supervised machine learning	Avg. accuracy: 0.6–0.9 Avg. recall: 0.6–0.9 Avg. precision: 0.7–0.9

of classes increase. The dataset and training sets need to contain information that can differentiate all classes equally.

Majority of the works used basic word features and some inclusion of emoticon and emotion lexicon scoring. Quality features have been shown to contribute to the accuracy in text classification tasks [77, 78]. Text mining tasks are not only confined to formal text but includes informal text from social media text. Informal text offers more features in the form of emoticons, hashtags, and punctuation usage. These diverse features can be used to provide more information to aid the classifier. For the work of Mohammad and Bravo-Marquez [64], their model makes use of hashtags containing emotion words to measure the intensity of the emotion, showing that when the author includes a hashtag with emotion label in their tweet, the emotions they exhibit are stronger. Features such as emoticon, exclamation marks, and slangs are commonly used in other social media text related tasks. These features could help address some of the challenges in text classification. Hashtags, Emojis and emoticon in particular, could shed light on presence of sarcasm. In particular, there are positive and negative emojis, if the emoji sentiment is opposite to the text sentiment, it indicates a sarcastic text [79]. Besides that, they are also great indicators towards the classes of emotions. The inclusion of non-textual indicators could enrich the information for classification features and thus aid to relieve some of the challenges in text classification such as sarcasm and lack of context.

Table 3 also shows the methods used by related works to perform text-based emotion detection. It can be seen that keyword-based methods are less common in recent years. Direct keyword comparison may not be sufficient to categorize large datasets of emotions, therefore in previous works there are added models to expand the dictionary used for comparison and establishing extra rules to guide classification. Such as the work of Wang and Pal [60], rules are added to not only expand the dictionary used but also to handle situations whether there are multiple emotion markers present in a single document and classify according to dominant emotion. For keyword-based methods, there is the need to keep updating the dictionary and rules applied either when dealing with changing language usage such as with social media or different cultural usage of language.

The trend shows that supervised learning is commonly used with variations. Machine learner are favored over keyword-based methods as they are more efficient in handling large datasets. The algorithms already exists and there is no need to create rules for handling different situations. Besides that, machine learners are able to produce good results with majority of the works shown in **Table 1** scoring 80%–90% accuracy. Some popular machine learners used are Naïve Bayes and SVM, which are well known to be good learners in text classification task. Ensemble is the concept of using multiple machine learning algorithms [44] or different models of the same algorithm [63] to produce a combined output that is better than a single classifier.

Perikos and Hatzilygeroudis [44] used an ensemble classifier of Naïve Bayes and maximum entropy combined with a knowledge based tool to vote on the classification of emotion. The accuracy obtained from the ensemble was better that individual performance of each machine learning algorithm. However, their individual results show that machine learning algorithms perform better than the knowledge-based tool.

Classification methods for text-based emotion detection have evolved from keyword-based methods to supervised learning to the most recent deep learning method. Deep learning methods are in actual fact a subset of the machine learning. The advantage of deep learning methods lies in its ability to process unstructured data thus saving the work done on feature engineering. Deep learning is widely used to perform tasks related to big data. This could be because it is able to effectively model relationships between data and thus increasing knowledge content. The work of text-based emotion recognition in recent years is also mostly skewed towards deep learning methods, with CNN being the most common algorithm used. Generally, most works show deep learning performs better that machine learning. Ibraheim et al. [69] trained a network of CNN classifiers and compared the results with machine learning methods such as Naïve Bayes and SVM, their results shown that the network of CNN classifiers performed better. However, [66] performed emotion analysis using single machine learners and deep learning algorithm, their results show that machine learning algorithm manage to outperform deep learning algorithm, CNN. The reason to this can be explained by Kratzwald et al. [68], who presented a detailed work of using deep neural network for emotion detection and they conclude that simply applying the method is not enough, the algorithm needs to be modified according to the needs of the task in order to perform well in the intended task. From the works involving deep learning, the superiority of the method can be clearly seen where there is less focus on feature engineering but the performance still good. This is the opposite for the case of machine learners that depends quite a lot on features supplied.

Though direct comparisons cannot be made on performances of the different work as they used different datasets, but looking at the results, we see the reason for the popularity of supervised methods both machine learning and deep learning. In general, the unsupervised method could produce accuracies between 70%–80%. Supervised methods instead could achieve higher accuracies of 80%–90%. The performance between machine learning and deep learning are quite similar, thus it can be seen that both methods are still used in recent years.

6. Conclusion

In the above section, some recent works of sentiment analysis has been summarized to show the methods which are more common in recent years. Other than that, there is increase in works which combine sentiment analysis and emotion detection in a single model. This is to extract deeper information from opinionated text especially when dealing with social behavior analysis. Emotions are expressions of feelings that can influence the decision that human make. Because of this, they are valuable input to support decision making for larger entities such as businesses, companies, and countries. Technology and the internet have made expressing and harvesting text-based emotion an easy task. The critical task here is how to analyze and accurately detect the emotions contained in huge amounts of text so that it can be used for further decision-making tasks. In this review, we looked at the recent application and trends of sentiment analysis which shows that machine learning and deep learning are the dominant techniques applied in recent years. Next, we see some works which combined sentiment analysis and emotion detection to provide in depth analysis of public opinion for the purposes of recommending products and also understanding social effects. Lastly, a look at the trends of emotion detection. There are a few emotion models that provide different levels of emotional depth, the most commonly applied is the Ekman model with six classes, namely, sadness, happiness, anger, fear, disgust, and surprise. Besides that, what are some of the techniques used and what are the recent methods that are chosen? We see the shifting of emotion detection from the earliest keyword comparisons to the modern deep learning algorithms that are favored in recent works. Through the comparison of performance, we see the reason for this, being that machine learning and deep learning are comparable in performance and outperforms unsupervised methods.

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