A Survey of Textual Emotion Detection

Samar Al-Saqqa
Department of Computer Science
Princess Sumaya University for Technology
Amman, Jordan

King Abdullah II School for IT
The University of Jordan
s.alsaqqa@ju.edu.jo

Heba Abdel-Nabi
Department of Computer Science
Princess Sumaya University for Technology
Amman, Jordan
heb20179004@std.psut.edu.jo

Arafat Awajan
Department of Computer Science
Princess Sumaya University for Technology
Amman, Jordan
awajan@psut.edu.jo

Abstract—**Emotion detection in text is a research field that gained an extensive interest recently. The advancement in communication networks and the spread usage of social web is the reason of massive amount of emotions that can be extracted frequently. The extraction and analysis of such emotions provides a powerful tool in detecting and recognizing the feelings, and this provides many advantages in diverse areas. In this survey, we focused on the textual emotion detection as a task of sentiment analysis. This survey explored the latest state of art approaches for emotion detection in text, and discussed their classification according to the used techniques, the used emotional model and the different used datasets. The outcome of this paper tends to highlight the limitation and gaps of these recent works and direct the possible future research to fulfill these gaps in this increasingly developed field.**

Keywords— Emotion Detection, Lexical Based, Supervised Learning, Unsupervised Learning.

I. INTRODUCTION

Sentiment Analysis is the study of the attitudes, opinions, and emotions of human beings. It a natural-language-processing (NLP) task that classify these opinions and emotions into either positive, negative or neural [1]. The field of sentiment analysis is composed of primary two subfields; rational sentiment words, and concepts, the opinion mining is related to the rational field and it can be further decomposed into subjectivity detection, opinion polarity classification, opinion spam detection …etc. On the other hand, emotional sentiments or emotional mining is the conceptual level of the sentiment analysis and consists of: emotion detection, emotion polarity classification, emotion classification and emotion cause detection. [2]

An emotion is a complex conscious experience that characterize a mental state [3], such as joy, anger, love, fear and so on, they are important because they are part of human nature. Emotions can be detected from different information sources like speech intonation, body posture and gestures, facial expressions physiological data, such as skin temperature and by written text. Emotion Detection in text can be considered as a classification problem that classify a given text input into several emotions based on both natural language processing concepts and Machine Learning [4].

The field of Emotion Detection in text gains a lot of growing interest in the scientific community lately because of the advances of the Web 2.0 and the spread of the Internet scope [5]. Thus, in a world dominated by technology, where words are powerful tools, this consequently leads to the popularity of many online social media sources that allows people to express their opinions, feelings, and thoughts, and also lead to the existence of the reviews websites, in which people express their opinions by writing reviews about persons, products, hotels, songs, politics...etc. Moreover, emotion detection importance came from its capability of being deployed in many applications, it has countless applications in areas such as education, political forecasting, brand marketing, and human-robot interaction.

Text can capture only a portion of emotions expressed by a human [6]. There are only two modes for the expression of emotion as follows

- **Emotive vocabulary**: words directly referring to emotional states such as love, hate, good etc.
- **Affective items:** Sometimes the expression of emotion does not include words from the emotive vocabulary, i.e., words dependent on the context that do not have a direct reference such as interjections like shh,ow,uh-huh.

In this survey, we discuss and classify the recent and most relevant emotion detection works based on the used emotional model and the used detection techniques, the examined papers range from the years 2014 to 2017. Figure 1, represents the distribution of the summarized articles in this survey over this interval. Furthermore, to achieve more in-depth understanding, we explain and state the emotional models that are most popular in the literature, the emotion detection approaches in text, the famous datasets and the performance metrics that are used to evaluate the proposed works. To the best to our knowledge, although there exist numerous numbers of surveys, there are no surveys that cover the emotion detection research works in this time interval (2014- 2017), even the ones that are published in 2017 such as [2] which only took the works that are proposed up to the year 2015.

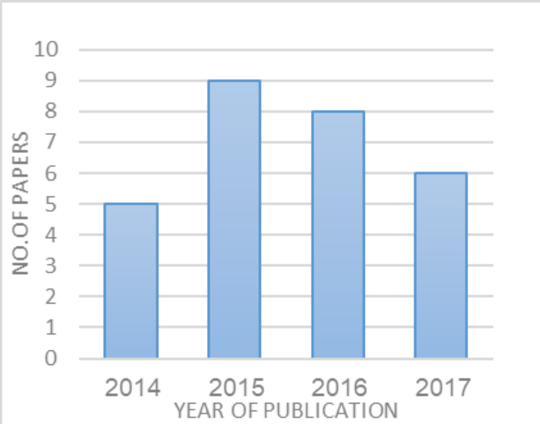

Fig. 1. Number of research papers included in this survey according to the year of publication

This survey is organized as follows: In Section 2, the different emotional model theories are discussed. In Section 3, a set of The textual emotion detection approaches are presented. The required preprocessing of text is explained in section 4. In section 5, the performance metrics and the famous datasets are listed. The conclusion and future work are outlined in section 6.

II. Emotion Theories

Researchers have proposed A number of theories of emotions, each theory contains a set of basic emotions, and there are two models of emotions: categorical and dimensional. The categorical model assumes that there are discrete emotions which are believed to be distinguishable by an individual's facial expression and biological processes [7]. Each emotion category is characterized by a set of emotion patterns or structures that sets it apart from other categories. An emotion label is used to represent each category. Ekman's emotion [8] is one of widely used categorical model used by researchers. Ekman concluded that the six basic emotions are Anger, Disgust, Fear, joy, Sadness, Surprise. Plutchik added trust and anticipation to Ekman's set, Plutchik's eight emotions are organized into four bipolar sets: trust vs. disgust, joy vs. sadness, anger vs. fear, and surprise vs. anticipation [9]. Izard defined ten categories as basic emotions which are: anger, contempt, disgust, distress, fear, guilt, interest, joy, shame and surprise [10], [11]. The dimensional model describes emotions according to one or more of dimensions, circumflex model [12], [13] of affect is one of particular dimensional approach, identifies two main dimensions, containing arousal and valence dimensions, valence referred to as polarity measures whether an emotion is pleasant or unpleasant. Arousal measures the degree of activation, which can range from calm to excited. Table 1 represents some of the references that used these two models.

Table 1. The emotional models and the papers that used them

Emotion Theory	Examples	Basic Emotion	Ref no.
Categorical / Discrete	Ekman model	Six emotions: (anger, disgust, fear, happiness, sadness, supervise)	[15],[18],[19], [25],[30],[32], [34], [38],[39],[40]
	Plutchick model	Eight emotions forms four bipolar sets: (joy vs. sadness, anger vs. fear, trust vs. disgust, super vs. anticipation)	[35]
Dimensional	Circumplex model of affect	2 dimensions: valence, and arousal dimensions	[20],[21],[26]

III. Textual Emotion Detection Approaches

The approaches for emotion detection from text can be divides into four approaches: keyword lexical based approach, Lexical /Corpus Based Approach, learning based approach and hybrid approach

A. Keyword Based Approach

It is the simplest and naïve approach for detecting emotions in the text, it depends on the existence and the frequency of the words that indicate emotions directly in the sentence. In this approach, a text document containing one or more sentences are taken as input, then it is portioned into tokens, then the emotional words are detected and extracted from each one of these tokens, afterwards the frequency of the emotion words are found by simply counting the words. Finally, a certain emotion class will be outputted for this given input. Sometimes a lexicon of words to assist classifying the emotions is constructed. This lexicon will include a list of words and the emotions that best describe them. Emotions of this approach is expressed in a single word, however, it fails when the emotions are expressed by interrelated words.

B. Lexical /Corpus Based Approach

This approach can be considered as an extended version of the keyword based approach which assigns a probability or weight for an arbitrary word for a certain emotion, this approach can be divided into lexicon based with weights and -emotion ontology based; where primary Emotion are placed at the top of emotion ontology with high weight, and tertiary emotion classes are placed at the bottom of ontology with low weights. Table 2 list an examples of research articles that uses this approach.

C. Learning Based Approaches

To overcome the limitations of the keyword based approach and the lexical approach, this approach learns from the data itself and tries to find the relation between a given input text and the corresponding output emotion by building a prediction model, instead of requiring an explicit connection to the emotion in the input text. This approach can be divided into two categories:

- Supervised learning approaches, which are based on a labelled or annotated dataset, and take part of this data for the training process using an emotion classifier. This trained data is then analyzed and a model is built. the remaining data in the dataset is classified based on this previously trained classifier into emotion category that it belongs to. The research articles that uses this approach are summarized in the Table 3.
- Unsupervised learning approach, which is based on non labelled dataset. This approach inherent the drawbacks of the machine learning algorithm, it requires a large dataset for the training process to be accurate.

D. Hybrid Approaches

Since no standalone approach gives a satisfactory result, a hybrid approach that uses a combination of the previously mentioned approaches is used to improve the performance of emotion detection, an examples of articles that adopts this approach is listed in Table 4.

IV. Text Preprocessing

Preprocessing the data is very important step in text classification. it involves the process of cleaning the text of noise data and uninformative parts from original text such as hashtags, which should help improve the performance of classification process [42]. There are many researches of emotion detection in text have applied text preprocessing in their work, as shown in Table 5, the following are the general text preprocessing steps that have been used:

1- Tokenization: In this phase, the text is divided into multiple tokens based on separator characters such as white space, comma, tab, etc.

2- Noise removal: this step encompasses cleaning the text from some irrelevant information which may decreases the performance of the classifier such as numbers, punctuation marks, special characters and non-Arabic text.

3- Stop words removal: stop words is commonly usage words and which have little information content such as conjunctions, prepositions.

4- Stemming: stemming is reducing words to their stems and removing the suffix of the word, according to some grammatical rules.

V. The Evaluation Process

A. Performance metrics

The evaluation process of emotion detection is complicated and considered a complex process due to many things, the emotions are subjective and differ among people, the varying and unbalanced available datasets, and the true validity of data annotation in these datasets, if exists, how much does it reflects the true emotion behind the tested statement. All these reasons make it hard to develop golden standards to compare the performance with. However, below are some of the metrics that are used in assisting the performance of the works proposed in the emotion detection research field, while Table 6 list a list of article examples that used these metrics:

1.Inter-annotator agreement, or known as, inter-judge agreement: is an indicator of the way how two or more annotators or human judges reach the same annotation conclusion, it has a theoretical value between 0 and 1 and is measured using the kappa coefficient. A score of 0 indicates no agreement between judges, while, a score of 1 indicate a 100% agreement between human judgments. the higher the coefficient, the stronger the agreement.

2. Precision and recall: Precision measures the percentage of successful positive emotion detection made by the classifier, while, Recall is the percentage of the emotion detected.

3. The F-Score, or, F1 score, or F value, or F measure: it is the weighted average of Precision and Recall. The higher the F score, the better the performance. The F score, the precision and recall are considered a coarse evaluation metrics.

4. Accuracy: measures of the effectiveness of the machine learning model. In emotion detection research field, the accuracy indicates the correctness while precision indicate the reproducibility.

5. 10-fold cross validation: it divides the dataset into 10 partitions, and use one for testing and the others for training. After testing is conducted, the overall performance will be measured using a resulted average score.

6.Pearson Correlation coefficient: measures the correlation between the predicted and the true emotion probabilities. This coefficient is considered a fine grained evaluation metric.

B. Datasets

As mentioned earlier, one of the challenges in emotion detection is finding a dataset, especially a good labeled one. However, there are a few standard famous datasets that are used by some works. In this section, we discuss some of these datasets.

- ISEAR (International Survey on Emotion Antecedents and Reactions): it is introduced by [43] and considered one of the oldest reliable labeled emotion datasets. This survey consists of 7,666 sentences annotated by participants from different cultural background. They were asked to report experiences regarding seven emotions: joy, fear, anger, sadness, disgust, shame, and guilt. The annotation is done on document level. Examples on research works that used this dataset are [16], [33], [34], [36], and [41].
- Fairy Tales: it is developed by [44]. It contains a total of 15,000 sentences from 185 different children's stories written by Beatrix Potter, Brothers Grimm, and Hans Christian Andersen with each sentence is given a manual label using one of the following emotions: anger, disgust, fear, happiness, sadness, positively surprised, negatively surprised, or neutral. Examples on research works that used this dataset are [34], and [41].
- SemEval 2007: it is developed by [45] for the SemEval 2007 workshop on the shared task of affective computing. It consists of the headlines of extracted news from famous newspapers such as The New York Times, CNN, and BBC News, in addition to the Google News search engine.

TABLE 2. SUMMARY OF THE ARTICLES THAT USES THE LEXICAL BASED APPROACH.

Ref no.	Year	language	Detection Technique	Evaluation metric	Dataset
[14]	2014	English	Lexicon based: NRC hash-tag emotion lexicon	Pearson Chi Squared test	dataset from the myPersonality project
[15]	2015	English	keyword based approach and ontology of emotions	Human judges	135 blogs
[16]	2015	English	Lexicon based	10-fold cross , precision, recall, and F-score.	SemEval , ISEAR, Twitter Dataset (1800 tweets)
[17]	2015	English	Lexicon based: J48 decision	-	
[18]	2017	English	Build emotion lexicon	F score	Blogs, news, twitter,

TABLE 3. SUMMARY OF THE ARTICLES THAT USES THE MACHINE LEARNING BASED APPROACH.

Ref no.	Year	language	Detection Technique	Evaluation metric	Dataset
[19]	2014	Arabic	Support Vector Machine and Naive Bayes	F measure, Precision, recall	twitter
[20]	2014	English	supervised machine learning	Kappa coefficient	-
[21]	2014	English	Classifiers	F1 score, precision and recall	-
[22]	2014	Chinese	Machine learning	averaged Pearson's correlation coefficient.	Dataset from ictclas.org news site
[23]	2015	English	Machine learning : support vector machine and naïve Bayes multilayer label classifier	precision , accuracy, F1 score	Tweets
[24]	2015	English and Chinese	Machine learning: maximum entropy classifier	F1 score	Dataset from weibo.com
[25]	2015	English	Weighting and classification using naive Bayes algorithm (supervised learning)	10-fold cross validation for accuracy	105 tweets
[26]	2015	English	Machine learning: transfer learning method	Precision, recall, F1 score, accuracy human judges	3600 samples of 10 participants
[27]	2015	Chinese	logistic regression model : LDM and eLDM,	Precision, recall, 10-fold cross validation	Two news datasets: sina news, Tencent news
[28]	2016	English	topic-level maximum entropy (TME) model	accuracy, average precision (MAP), and averaged Pearson's correlation (AP).	BBC, Digg, Myspace, Runners, World, Twitter, YouTube
[29]	2016	Arabic	Support Vector Machine and Multinomial Naive Bayes	F score, Precision, recall	twitter
[30]	2016	English	unsupervised machine learning algorithm	accuracy, Precision, recall	YouTube comments
[31]	2016	English	Deep convolutional neural networks	accuracy	MOUD dataset
[32]	2016	Portuguese	Support Vector Machine, Naïve Bayes, Random Forest and CART Decision Tree.	10-fold cross-validation accuracy	newspaper headlines
[33]	2016	English	maximum entropy model and the L-BFGS algorithm	F1 score, accuracy	Semeval, SSTweet, ISEAR
[34]	2016	English	support vector machine classifier	precision, recall, F1 score, accuracy	Affective Text, Fairy Tales, ISEAR, Facebook,
[35]	2016	Chinese	KNN, SVM, Bayes	Euclidean, Squared X2, KL divergence, Intersection and Fidelity	RenCECps corpus
[36]	2017	English	Machine learning: Dominant Meaning classifier and Appraisal Method	Kappa coefficient. Average precision, recall, F1 score	ISEAR
[37]	2017	English	Machine learning / classification: decision tree	-	-

TABLE 4. SUMMARY OF THE ARTICLES THAT USES THE HYBRID APPROACH.

Ref no.	Year	language	Detection Technique	Evaluation metric	Dataset
[38]	2015	English	Hybrid: keyword based and machine learning based, it combine contextual and historical information with the present data	-	comments from YouTube videos
[39]	2017	Multilanguage	Hybrid: emotion lexicons, and Naive Bayes algorithm and Support Vector Machine	precision, recall, accuracy, and F-measure	Election, healthcare, sports
[40]	2017	Different languages, i.e., English and Greek	machine learning and lexicon- based approaches, Probabilistic classifiers, Tree-based classifiers, Statistical-based classifiers	precision, recall, F1-measure	News, agencies, Twitter, and Facebook
[41]	2017	English	ensemble approach that combines both a linear model based on BOW, and a non-linear model based on the pre trained word vectors	Average f score	ISEAR, SemEval, Fairy tales, Twitter Dialogs, Blog Posts

TABLE 5. OVERVIEW OF PREPROCESSING STEPS

Ref no.	language	Pre -Processing
[19]	Arabic	Removal of non-Arabic letters, punctuations and multiple spaces) in addition to the removal of stop words, stemming
[22]	Chinese	Chinese words segmentation
[23]	English	stemming, stop word cleaning and tokenization
[25]	English	cleansing, stop words removal, emoticons conversion, negation conversion and tokenization
[15]	English	data cleaning and data transformation
[27]	Chinese	Removal of stop words, words appearing in less than 30 documents are discarded to reduce feature dimensions.
[29]	Arabic	Removing --non Arabic characters, diacritics. , definite articles, special characters, numbers, stop words, hashtag.
[32]	Portuguese	cleaning (tokenization), stop words removal, stemming
[40]	Different languages, (English and Greek)	Cleaning noises, tokenization, stemming
[36]	English	Removal of stop words
[37]	English	Tokenization, filtering, Lemmatization, Stemming
[41]	English	Lemmatization.

TABLE 6. EXAMPLES OF ARTICLES USED THE PERFORMANCE METRICS.

Papers	Performance metric
9,11	Human judges
2,	Kappa coefficient
1,3,6,11,12,13,16,17,21,24,25,26	Precision and recall
1,3,6,7,11,13,16,20,21,23,24,25,26,28	F-score
4,5,15	Pearson correlation coefficient
8,12,13,19	10–fold cross validation

The annotation was done manually according to six emotions: anger, disgust, fear, joy, sadness, and surprise. Unlike the previous two datasets, a headline is allowed to have multiple emotions, each with a different degree. Examples on research works that used this dataset are [16], [33] and [41].

VI. CONCLUSION AND FUTURE WORK

Emotion Detection is an important field in human-computer interaction research. However, the emotion detection uptake has been slow, mainly due to the challenges involved in modelling fine-grained subjectivity and the subtlety of emotive expressions in text [46].

There are some limitation and gaps in the emotion detection approaches discussed in section 3. For example, the advantages of the word based approach such as its simplicity and ease of implementation, do not cover its major drawbacks that includes the ambiguity of the word selection found on double meaning words, or the words that change their meaning according to the context, the existed subjectivity of determining the emotion lexicon contents, the existence of a sentences with no direct emotional keywords, and finally its inability to be applicable in a wide range of application.

The disadvantage of the lexical based approaches and especially the ones that are based on ontology design [15], is that the creation process of an ontological view of emotion require an extensive amount of knowledge and also considered a time consuming process. Also, the biased assignment of the weight of the word based on the context, make it hard to generate a domain-independent model.

As can be noted from Tables 3 and 4, that most of the used approaches for detecting emotion from text are based on machine learning techniques, since it provides better results and do not require a direct mentioning of the emotions in the text.

Therefore, a future research including the use of deep learning is promising, especially if provided with a large good annotated dataset. Also, a future research on constructing and finding a global dataset that is labelled correctly will aid and increase the advancements in textual emotion detection, because it will provide a standard dataset that can be used to compare different proposed researches.

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