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CENG 407
Sentiment Analysis of the Feedback from Airplane Passengers

LITERATURE REVIEW REPORT

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Contents

Abstract

The enlargement of the internet environment in recent years has provided us researchers with a great data opportunity. Nowadays, many people can share their opinions on many issues such as a service, a product, or an event through social media accounts such as Twitter, Facebook, Instagram, etc. In some cases, it is difficult for people to read and interpret all of these comments because they are too many. For this reason, we will make a sentiment analysis on Twitter data, which is one of the most frequently commented social media accounts. We will perform this analysis based on the comments made by the passengers on Twitter as a result of the services provided by American airports to their passengers. A lot of research has been done in this area before. During this researches, various methods and algorithms have been tried. In this report, we will share the research we made to use more accurate methods and algorithms in our project process. You can examine the details of our research in the following sections.

1. Introduction

Work on sentiment analysis continues today and is used in many areas. Today, there is a lot of data on social media as social media is used by many people. People share their thoughts on many issues through their social media accounts. Sentiment analysis is needed because the comments in some posts are too many to read and decide on all of them. These data are generally classified as positive, negative, and neutral, making it easier for institutions and people doing research. Institutions can make improvements in their products or services based on these analyzes. People can also make a more accurate decision based on these analyzes at the product purchase stage. We will determine the level of satisfaction by analyzing the comments made by the American airport passengers on Twitter about the service they receive. Actually, online reviews don't need sensitivity classification as most reviews are user-assigned star ratings. In practice, forum discussions and blogs need sentiment classification to identify people's opinions about different entities and topics such as products and services. [1] During these analyzes, Machine Learning algorithms such as Support Vector Machine, Neural Network, Naive Bayes, Bayesian Network, Maximum Entropy are generally used. You can examine the work done with these algorithms, their usage, and efficiency in the following sections.

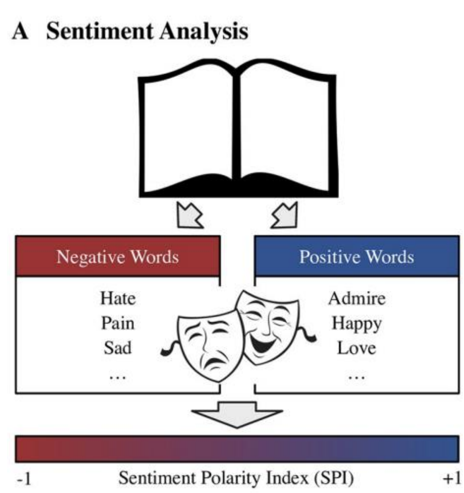


Figure 1. A Sentiment Analysis[15]

2. Sentiment Analysis

Sentiment analysis is a field of study that analyses the ideas, feelings, evaluations, attitudes and feelings of entities such as products, services, organizations, individuals, problems, events, issues and their characteristics. [1] Sentiment analysis mainly focuses on ideas that express or imply positive or negative emotions. Research in sentiment analysis has a significant impact only on NLP (Natural Language Processing). It can also have a profound influence on management sciences, political science, economics and social sciences because they are all influenced by people's opinions. With the rapid growth of social media today, individuals and organizations are increasingly using the content on this media to make decisions. Automatic sentiment analysis systems are needed because long blogs and forum posts always contain a large volume of opinion text that cannot be easily deciphered.

3. Problem Definition of Sentiment Analysis

In this chapter, we focus on the problem definition of Sentiment Analysis or opinion mining. Problem definition is important to understand it's solutions.

3.1. Opinion Definition

The most important feature of our opinions and thoughts is that they are subjective. The reason is that they contain only the commenter's thoughts. Therefore, researchers or product sellers collect much more person's opinions and try to understand what society generally thinks.

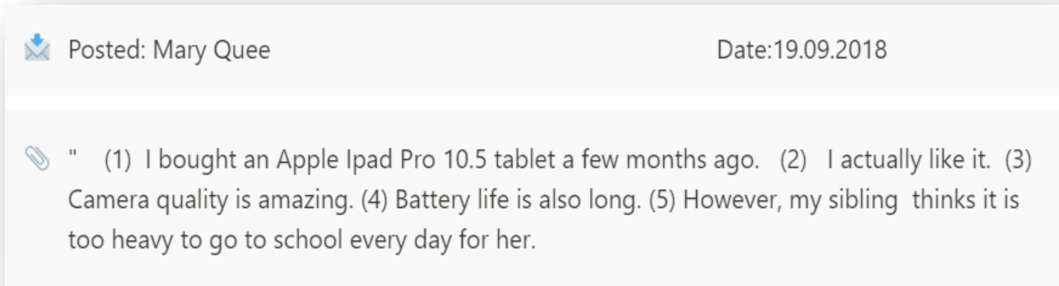
It is also reliable in terms of assessment and evaluation, and since many people from many platforms with Twitter, Facebook, and forum applications express their opinions and thoughts that they share every day, we have a lot of opinion data on that topic.

Twitter posts have short sentences compared to other forum comments and include some internet slangs in these sentences. But It is also easy to review this data because it is short. Because these comments are short, it means that they do not contain too much unnecessary information rather than forum applications.

Tweets have been useful for users with these features. We will also use Twitter comments for sentiment analysis in our project.

3.1.1. Sentiment Analysis Tasks

An example is given to explain this analysis.



Posted: Mary Quee Date:19.09.2018

" (1) I bought an Apple Ipad Pro 10.5 tablet a few months ago. (2) I actually like it. (3) Camera quality is amazing. (4) Battery life is also long. (5) However, my sibling thinks it is too heavy to go to school every day for her.

Figure 2. An example of sentiment analysis

This tweet contains several positive, negative comments for the Apple Ipad Pro 10.5. Sentence (2) contains a generally positive opinion. Sentence (3) makes a positive comment about the camera quality of the Apple Ipad Pro. Sentence (4) makes a negative comment on battery life. Sentence (5) contains a negative opinion about the weight of the tablet. However, this negative opinion in the sentence (5) belongs to the commenter's sibling.

This sample tweet actually gives us pretty good information about the structure of the comments. The Apple Ipad Pro 10.5 actually has many features such as camera quality, size, battery life, and individual comments that can be made for all of them. Also, as it appears in the sentence (5), it is important to whom the opinion belongs. Because the opinion in this sentence belongs to the commenter's sibling and does not belong to him/her. So we must know who the opinion belongs to. A complex definition makes it difficult to solve the problem. We use the opinion **"quintuple"** structure to symbolize it. [1]

$$(ei, aij, sijkl, hk, tl) ;$$

- where *ei* is the name of an **entity**,
- *aij* is an **aspect** of *ei*,
- *sijkl* is t**he sentiment** on aspect *aij* of entity *ei,*
- *hk* is the opinion **holder** and

- *tl* is **the time** when the opinion is expressed by *hk*.
- d is given an opinion **document**

We intentionally use subscripts here. In this definition, we purposely use subscripts to emphasize that the five pieces of information in the quintuple must correspond to one another. That is, the opinion sijkl must be given by opinion holder hk about aspect aij of entity ei at time tl. Any mismatch is an error. [1]

The sentiment sijkl is positive, negative, or Sentiment Analysis and Opinion Mining neutral, or expressed with different strength/intensity levels. Here, ei and aij together represent the opinion target.

In this example,

- Apple Ipad Pro represents entity e.
- Camera quality(a11) and battery life(a12) represents entity e of aspects.
- s111 of the sentiment on aspect a11(Camera quality) of entity e1 and it is possitive and s112 of the sentiment on aspect a12(battery life) of entity e1 and it is also possitive .
- The opinion holder is double. First one is Mary Quee(h1) who share its opinion on web and the second is her sibling(h2).

With the definition, we can now present the objective and the key tasks of sentiment analysis. [2][3]

Given an opinion document d, discover all opinion quintuples (ei, aij, sijkl, hk, tl) in d. [2][3][4]

The key tasks are derived from the 5 components of the quintuple. The first component is the entity. That is, we need to extract entities. The task is similar to named entity recognition (NER) in information extraction [5]. Thus, the extraction itself is a problem.

After extraction, we also need to categorize the extracted entities. In natural language text, people often write the same entity in different ways. For example, Motorola may be written as Mot, Moto, and Motorola. We need to recognize that they all refer to the same entity.

3.1.2. Model of opinion document:

While An opinion document d contains opinions on
a set of entities {e1, e2, ..., er} and a subset of their aspects from a set of
opinion holders {h1, h2, ..., hp} at some particular time point.

To summarize, given a set of opinion documents d, sentiment analysis consists of the following 6 main tasks.[1]

1. Entity extraction and categorization
2. Aspect extraction and categorization
3. Opinion holder extraction and categorization
4. Time extraction and standardization
5. Aspect sentiment classification
6. Opinion quintuple generation

Sometimes more than one word can represent an entity. We should define both of them as the same entity and analyse it truly. But this rich feature of language poses a problem in sentiment analysis. The same problem applies to aspects. For instance, picture, image, and photo represent the same aspect. This is a problem of sentiment analysis.

4. Sentiment Classification

Before 2000, there was little research in NLP or linguistics as there was very little opinion text in digital forms. This field has grown rapidly after 2000 and has become one of the most active research areas in NLP (Nature Language Process).

Sentiment analysis is mainly studied at three levels:

1. **Document level:** It is to classify whether an entire opinion document expresses a positive or negative emotion. This level of analysis assumes that each document expresses opinions about a single entity.
2. **Sentence level:** The task at this level goes to sentences and determines whether each sentence is positive, negative, or neutral. We should know that subjectivity is not equivalent to sensitivity, as many objective sentences can imply ideas. However, the substance level is still not sufficient.
3. **Entity and Aspect level:** Both document level and sentence level analyzes do not find out exactly what people like and dislike. For example, although the sentence "I still love this restaurant even though the service is not that good" has a positive tone, we cannot say it is positive. As a result, there are two types of opinions, regular opinions, and comparative opinions.

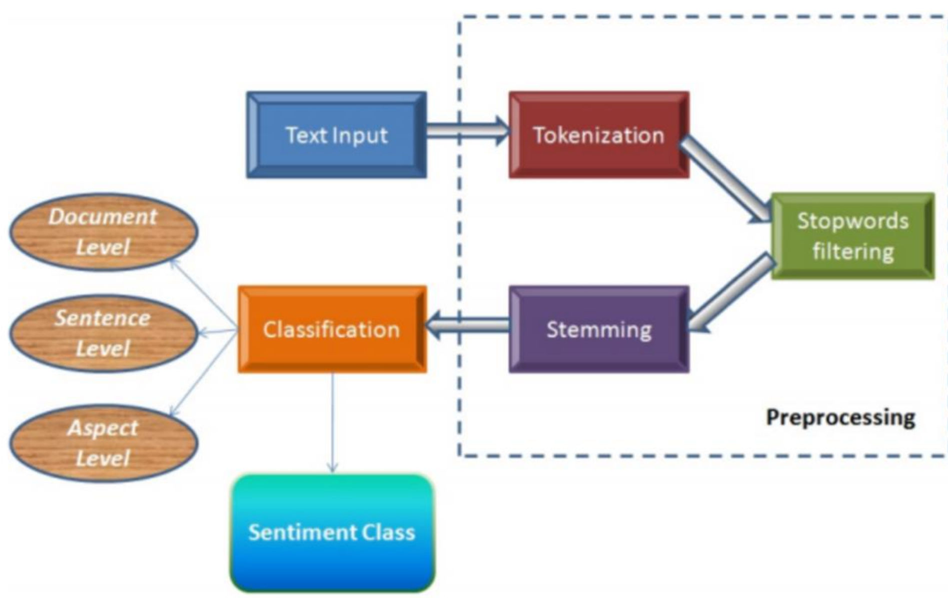


Figure 3. Steps of Sentiment Analysis [11]

A vocabulary of emotions is necessary but not sufficient for emotion analysis. Below you can see some of the reasons for this.

1. Emotion words can be in opposite directions in different application areas.
2. A sentence may not express any emotion.
3. Sarcastic phrases are hard to handle.
4. Many sentences that do not contain sensitive words can also imply people's opinions.
5. Idea spam has become a major problem. There are people who give fake opinions in reviews and forum discussions. There are also some companies that write fake reviews and fake blogs for their customers. This is an important problem for analysis.

4.1. Document Sentiment Classification

Problem definition: When an opinion document evaluating an entity is given, determine the overall sentiment s of the opinion holder about the entity should be determined.

Assumption: When an opinion document evaluates more than one entity, opinions about institutions may differ. Also, it does not make much sense for multiple viewers to express their views in a single document, because their views may also differ.

4.2. Sentiment Classification Using Supervised Learning

The emotion classification is usually formulated as a classification problem in two categories, positive and negative. The neutral class can be used, but most research does not use a neutral class. Not using the neutral class significantly eases the classification problem, but it is possible to use the neutral class. We will use the neutral class in our project. In traditional text classification, related words are key features. However, words of emotion or opinion that express positive or negative opinions are more important. This is a text classification problem. For this reason, one of the controlled learning methods such as Naive Bayes classification, and support vector machines (SVM) can be used. For example, this approach has been used by some researchers to categorize film criticism into two categories, positive and negative. [7] Terms and their frequency, part of speech in Figure 1, rules of opinions, sentiment shifters, syntactic dependency are some of these sample features. [1][6]

Tag	Description	Tag	Description
CC	Coordinating conjunction	PRP$	Possessive pronoun
CD	Cardinal number	RB	Adverb
DT	Determiner	RBR	Adverb, comparative
EX	Existential *there*	RBS	Adverb, superlative
FW	Foreign word	RP	Particle
IN	Preposition or subordinating conjunction	SYM	Symbol
JJ	Adjective	TO	*to*
JJR	Adjective, comparative	UH	Interjection
JJS	Adjective, superlative	VB	Verb, base form
LS	List item marker	VBD	Verb, past tense
MD	Modal	VBG	Verb, gerund or present participle
NN	Noun, singular or mass	VBN	Verb, past participle
NNS	Noun, plural	VBP	Verb, non-3rd person singular present
NNP	Proper noun, singular	VBZ	Verb, 3rd person singular present
NNPS	Proper noun, plural	WDT	Wh-determiner
PDT	Predeterminer	WP	Wh-pronoun
POS	Possessive ending	WP$	Possessive wh-pronoun
PRP	Personal pronoun	WRB	Wh-adverb

Figure 4. Penn Treebank Part Of Speech (POS) tags [1]

Categorizes according to some fixed syntactic patterns used to express ideas. Syntactic patterns are created according to part-of-speech (POS) tags.

4.3. Sentiment Rating Prediction

Not all researchers solve this problem using regression techniques. However, since the ranking scores are listed, the problem can be formulated as a regression problem. The graphical method improves the ratings by solving and revising the optimization problem to ensure that they are uniform throughout the graph in terms of both ratings and link weights. There have been researchers who presented a different view from the traditional bag representation word. [8] This view provided a bag view representation of the documents to capture the power of n-grams with ideas. Each of the views has been classified as a triple, sentiment word, modifier and negator. As an example, in "not very good", sentiment word is "good", modifier is "very" and negator is "not". Knowing these addictions is useful for accuracy. Two models have been proposed, namely the aspect model (working on individual aspects) and the agreement model (modeling the rating agreement across directions). Both models are combined in learning.

4.4. Cross-Domain Sentiment Classification

To make matters worse, the same word in one field could mean positive and negative in another. The authors suggested transferring emotion classifiers to new domains in the absence of large amounts of tagged data in those domains. [13]

They tried four strategies:

1. Training and testing in the target area on a mix of tagged reviews from other areas where such data are available.
2. Training a classifier as above, but limiting the feature set to only those observed in the target area.
3. Using classifier assemblies from areas with existing labeled data and testing them in the target area.
4. Combining small amounts of labeled data with large amounts of unlabeled data in the target area (this is the traditional semi-supervised learning environment)

SVM was used for the first three strategies and EM for semi-supervised learning for the fourth strategy [12]. As a result of their experiments, they observed that the 4th strategy showed the best performance. This is because it showed that it can use both tagged and untagged data in the target area.

4.5. Cross-Language Sentiment Classification

Cross language sensitivity classification means making the sensitivity classification of opinion documents in more than one language, but we will make our classifications on a common language, English.

5. Approaches For Sentiment Analysis

Sentiment analysis uses Lexicon Based (LB) or Machine Learning (ML) methods. The words are ranked by grouping according to their polarity using the LB method. After the scores obtained from the relevant document are added, a conclusion is reached. In another method, ML methods, the texts are classified and sentiment estimation is made.[9] We will use machine learning methods while continuing our project.

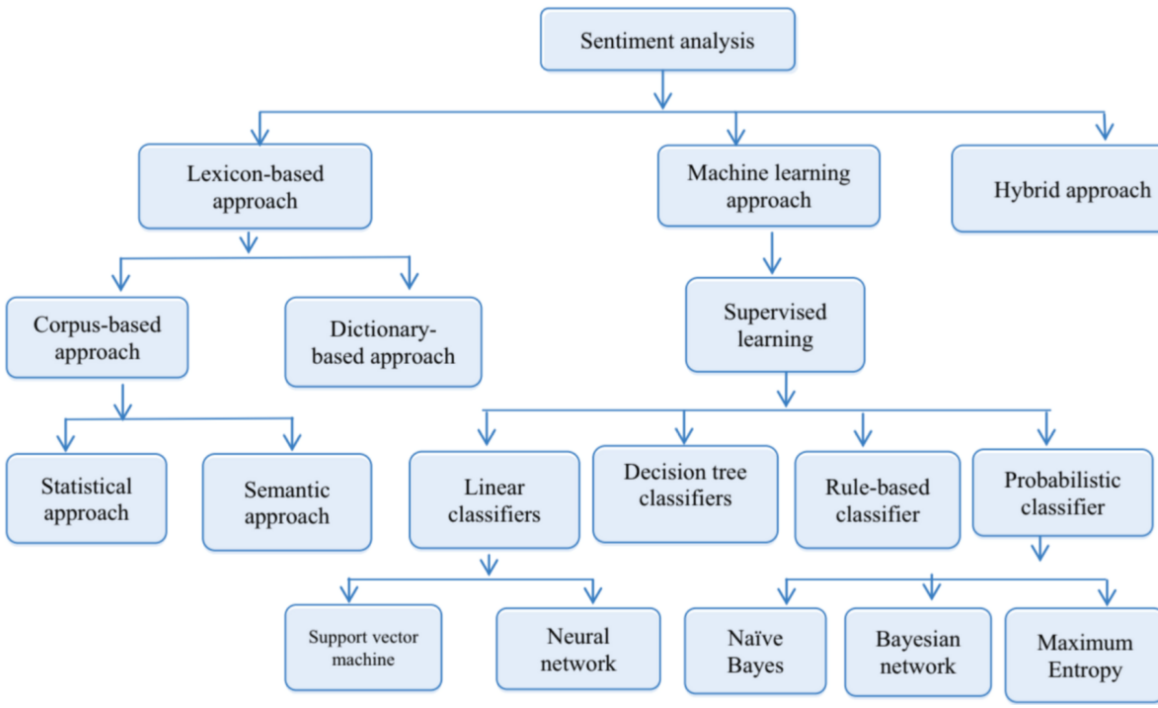


Figure 5. Classification techniques of sentiment analysis [10]

The corpus-based approach also makes sense of the analysed words according to the general structure of the sentence, for example, classifies them as a whole according to conjunctions such as OR, BUT, AND in the sentence. Also, researchers clustered on the graph to determine whether they are positive or negative from the results obtained from the analysis of these sentences. [14] According to the Dictionary based approach, synonyms and antonyms are summed up and classified as positive and negative. [1]

Also, we test these approaches with their accuracy.

$$Accuracy = \frac{T}{N}$$

T: the correct samples number
N:the total samples number

5.1. Lexicon-based Approach

Figure 6. Classification techniques of sentiment analysis [11]

6. Comparison of Commonly Used Machine Learning Approaches for Sentiment Analysis

	Approaches				
	Rule-based system	**SVM**	**NB**	**ME**	**n-gram**
Advantages	Writing and implementing rules is easy.	1. High dimensional input space. 2. Document vectors are sparse.	1. Simple and intuitive technique. 2. It combines efficiency with reasonable accuracy.	This technique does not assume the independent features like NB technique.	Usage of 2-gram and more improve accuracy of SA instead of single word SA.
Disadvantages	It loses track when the data and scenario change faster than updates in rules.	1. More datasets are required in training phase. 2. Data collection is not easy.	1. Machine can be trained with less datasets. 2. It works with conditional independence between the linguistic features.	It is tedious.	1. n-gram dependencies can not be handled if n value is large. 2. Corpus data required to train machine.

SVM: Support vector machine; NB: Naïve Bayes; ME: Maximum entropy; SA: Sentiment analysis.

Table 1-Pros and cons of commonly used machine learning approaches for sentiment analysis

We compared the applications used in the sentiment analysis with previous articles. We examined and worked on peer-reviewed publications between 2010-2020.

In our first study, we examined the sentiment analysis studies that were made only in the Turkish language.

The studies are shown in Table 2. [31]

Authors	Methodology	Data	Indicators	Performance result
Erdogan et al. [16]	n-gram (1, 2, 3) method, logistic regression	2018	Five most used cryptocurrencies in English text tweets	94.60
Ciftci et al. [17]	RNN-based algorithm	2018	Turkish Wikipedia articles	83.30
Coban et al. [18]	BoW vs W2VC model	2013	Turkish Twitter messages in the telecom sector	59.17
Ecemiş et al. [19]	Support vector machine	2018	Turkey-based geographical user data	0.954
Isik et al. [20]	Novel stacked ensemble method for sentiment analysis	2018	IMDB dataset including 1000 positive and 1000 negative; 2000 movie comments have been used	0.791
Karcioglu et al. [21]	Linear SVM and logistics regression	2019	Random English and Turkish texts have been collected by Twitter	65.62
Uslu et al. [22]	Logistics regression	2019	User reviews have been collected from Turkey's most preferred movie site	77.35
Kanmaz et al. [23]	Decision trees, support vector machine, and Naive Bayes methods	1996–2018	News text-related stock exchange	0.64–0.80
Doğan et al. [24]	LSTM recurrent neural networks	2019	In the study, a single mixed data pool with two categories is created with data collected from multiple social networks	0.9194–0.9266
Salur et al. [25]	Random forest classification method	2019	Tweets collected about special tourism centers	88.974
Santur [26]	Gated recurrent unit method	2019	Turkish e-commerce platform user reviews	0.955
Kamis et al. [27]	Multiple CNN's and LSTM network	2017	A corpus of different datasets is utilized based on three datasets used in SemEval (semantic assessment)	0.59
Ogul et al. [28]	Logistic regression classifier	2017	Public SemEval (semantic assessment) in three different sentiment analysis datasets containing both Turkish and English texts	79.56
Rumelli et al. [29]	k-nearest neighbor classifier	2019	The dataset is built by using e-commerce website (http://www.hepsiburada.com); the user review, rating, and URL of the product have been analyzed	73.8
Hayran et al. [30]	Support vector machine (SVM) classifier	2017	A Turkish text dataset classified (16000 positive and 16000 negative emotion) by emoji icon	80.05

Table 2-Sentiment analysis studies in Turkish Language

As can be seen in these tables, the study [16] performed with logistic regression methods with n-gram showed the highest performance result. The second higher performance result is the study [25] performed with the random forest classification method. The study which belongs third higher performance result is performed with Recurrent Neural Networks (RNN) -based algorithm. [17]

In our second study, we examined the sentiment analysis studies that were made in the English language. While doing our literature review, we learned that sentiment analysis not only examines product evaluation and people's emotional comments on social media but also doctors use this sentiment analysis to use it for the best treatments.

We made this Table-3 by considering the 2020 study of Sharma C, who has worked in the field of pharmacotherapy. These studies were carried out using the Lexicon-based approach and Machine Learning-Support Vector Machine Approach. [35]

Authors	Title, Journal and year	Data source and quality assessment (QA)	Type of SA and data pre-processing	Outcome of interest	Result	Significance
Cobb et [32]	*Sentiment Analysis to Determine the Impact of Online Messages on Smokers' Choices to Use Varenicline*, Journal of the National Cancer Institute Monographs. 2013	QuitNet QA not stated	LB (Salience Engine 4.1) Data pre-processing - No	Whether exposure to positive messages re: varenicline resulted in more people switching to it and sticking with it	Registrants who started or continued with varenicline were exposed to a statistically significantly greater number of positive-sentiment varenicline messages than negative-sentiment messages	While they cannot draw conclusions about causality, emotional content of online communications about health behavior intervention is associated with decision making around pharmaceutical choices
Korkontzelos et [33]	*Analysis of the effect of sentiment analysis on extracting adverse drug reactions from tweets and forum posts*, Journal of Biomedical informatics. 2016	DailyStrength forum and Twitter	LB, 5 lexica used - the Hu&Liu Lexicon of Opinion Words (H&L), the Subjectivity Lexicon (SL), the NRC WordEmotion Association Lexicon (NRC), the NRC Hashtag Sentiment Lexicon (NRC#), and the Sentiment 140 Lexicon (S140)	Whether the addition of sentiment analysis feature to ADRMine (a software already designed to pick up ADR mentions) would increase accuracy of picking up ADRs	There was an increase in pick up rate of ADRs for posts taken from twitter but not for posts from daily strength	Thus, there is potential for sentiment analysis to be used to pick up ADRs
		QA not stated	Data pre-processing - Yes		Of all the lexica used, Sentiment140 performed the best (lexica generated from twitter)	
Ebrahimi et [34]	*Recognition of side effects as implicit-opinion words in drug reviews* Emerald Insight. 2016	www.drugratingz.com QA Not stated	ML using SVM and a Rule based version of lexicon based Data pre-processing - Yes	To evaluate if implicit sentiment can be used to identify drug side effects from disease symptom. These were tested against the manual annotation of the same drug reviews by a pharmacist	Experimental results show that ML outperforms the rule-based algorithm significantly for both disease symptom and especially side effect detection where it was almost two-fold better	The main finding was that drug review side effect recognition can be handled by using the ML algorithm, which significantly outperforms the regular expression-based algorithm

You can see the multi-linguistic sentiment analysis studies of the 2017 year in our third table. In these studies, the highest accuracy level was provided by the work with the Support Vector Machine (SVM), Naive Bayes, and K-Nearest Neighbors tools. [46]

Year	Ref. no.	Method	Target Language(s)	Dataset/ Domain	Major Contributions	Tools Used	Accuracy
2017	[36]	Deep learning model with parameter sharing and word embedding	Chinese, Japanese	Twitter data	Unifies parameter sharing and heterogenous word embedding methods in a deep learning model for a multilingual environment	CNN, FastText, Mecab, NLPIR, TweetTokenizer	57.3
	[37]	Deep learning with optimized convolution and character embedding	German, Portugese, Spanish	Twitter data	Uses character based embedding in deep learning models and eliminates the need of machine translation.	CNN, LSTM	66.0 – 69.7
	[38]	Convolutional n-gram Bi-LSTM word embedding	Italian	YouTube comments	Enhances word embedding by multiple convolutions, encodes long distance contextual dependencies.	LSTM	55.03 – 65.6
	[39]	Convolutional nets using n-gram	French, Greek	Restaurant reviews	Uses n-gram level information and works in a language independent manner, excludes code-switching and language translation	CNN	Precision : 0.84 – 0.93
	[40]	Deep CNN with character-level embedding	German, Portugese, Spanish	Twitter data	Language agnostic and translation free analysis depending on fewer parameters, reduces memory usage	CNN	69.7 – 77.0
	[41]	Bi-View CNN (BiVCNN)	Chinese	Book, movie, music reviews	Captures document-level cross-lingual relations in a parallel sentiment space, works on shared polarity between parallel texts	CNN, ICTCLAS, Word2Vec, Google Translate	80.16
	[42]	(a) Bi-LSTM Random Field classifier (b) aspect- based LSTM	Arabic	Hotel reviews	Employs (a) to extract aspect opinion target expression based on n-gram, finds polarity of extracted aspects using (b) using word and aspect embeddings	LSTM, Word2Vec, FastText, AdaGrad	(a) F1 score : 69.98 (b) Accuracy : 82.7
	[43]	Multi-layer CNN for weakly supervised sentiment classification	French, German, Italian	Twitter data	Uses three variants of multilayer CNN on sequences of word embeddings of weakly supervised data and doesn't require translation	CNN	F-measure: 0.63- 0.67
	[44]	Aspect Target Sequence Model (ATSM)	Chinese	Product reviews	Performs multi-grained aspect level sentiment analysis, learns intra-sentence context using word embeddings	LSTM, CNN	75.59 – 5.95
	[45]	Multilingual Sentiment Analysis via Text Summarization (MSATS)	Over 50 global languages	Product reviews	Performs text summarization to extract meaningful information, which is then utilized for polarity detection	SentiWordNet, kNN, SVM, NB, Bing translator	Precision : 0.86
	[46]	Multilingual emotion classification	Portugese, Spanish, French	News items	Evaluated effect of translation and language combination on emotion classification, applies stacking of monolingual classifiers	SVM, NB, Radial Basis Function (RBF), Google Translate	F- measure: 0.91-0.95

Table 3-Summary of work done on multi-lingual and cross -lingual researches

6.Conclusion

As a result of this researches, we learned what sentiment analysis is, how sentiment classification is done, and what are various sentiment analysis approaches. We have examined the advantages and disadvantages of sentiment analysis approaches. Each has at least one pros and cons. We also compared the accuracy of sentiment analysis approaches against each other. When we look at the studies, the accuracy of the SVM tool is higher than machine learning in general. In addition, the accuracy of the studies using NB, K-NN, and CNN tools were found to be high. When we look at these results, we can consider using these methods in our project.

References

[1] Bing Liu. Sentiment Analysis and Opinion Mining, Morgan & Claypool Publishers, May 2012.

[2] Zhai, Zhongwu, Bing Liu, Hua Xu, and Peifa Jia. Clustering Product Features for Opinion Mining. in Proceedings of ACM International Conference on Web Search and Data Mining (WSDM-2011). 2011. 385. Zhai, Zhongwu, Bing Liu, Hua Xu, and Peifa Jia. Constrained LDA for Grouping Product Features in Opinion Mining. in Proceedings of PAKDD-2011. 2011.

[3] Zhang, Lei and Bing Liu. Extracting Resource Terms for Sentiment Analysis. in Proceedings of IJCNLP-2011. 2011a.

[4] Liu, Bing. Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data, 2006 and 2011: Springer.

[5] 296. Sarawagi, Sunita. Information extraction. Foundations and Trends in Databases, 2008. 1(3): p. 261-377.

[6] Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up?: sentiment classification using machine learning techniques. in Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP-2002). 2002.

[7] Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up?: sentiment classification using machine learning techniques. in Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP-2002). 2002.

[8] Qu, Lizhen, Georgiana Ifrim, and Gerhard Weikum. The Bag-of-Opinions Method for Review Rating Prediction from Sparse Text Patterns. in Proceedings of the International Conference on Computational Linguistics (COLING-2010). 2010.

[9] Sharma C, Whittle S, Haghighi PD, Burstein F, Keen H. Sentiment analysis of social media posts on pharmacotherapy: A scoping review. Pharmacol Res Perspect. 2020;e00640.

[10] Medhat W, Hassan A, Korashy H. Sentiment analysis algorithms and applications: a survey. Ain Shams Eng J. 2014;5:1093-113.

[11] A Review on Multi-Lingual Sentiment Analysis by Machine Learning Methods Santwana Sagnika, Anshuman Pattanaik, Bhabani Shankar Prasad Mishra and Saroj K. Meher/ Journal of Engineering Science and Technology Review 13 (2) (2020) 154 - 166

[12] Nigam, Kamal, Andrew K. McCallum, Sebastian Thrun, and Tom Mitchell. Text classification from labeled and unlabeled documents using EM. Machine Learning, 2000. 39(2): p. 103-134.

[13] Gamon, Michael, Anthony Aue, Simon Corston-Oliver, and Eric Ringger. Pulse: Mining customer opinions from free text. Advances in Intelligent Data Analysis VI, 2005: p. 121-132.

[14] Hatzivassiloglou, Vasileios and Kathleen R. McKeown. Predicting the semantic orientation of adjectives. in Proceedings of Annual Meeting of the Association for Computational Linguistics (ACL-1997). 1997.

[15] Min S, Park J (2019) Modeling narrative structure and dynamics with networks, sentiment analysis, and topic modeling. PLoS ONE 14(12): e0226025

[16] M. C. Erdogan and M. Canayaz, "Crypto-currency sentiment˘analyse on social media," in Proceedings of the 2018 Inter- national Conference on Artificial Intelligence and Data Pro- cessing (IDAP), pp. 1–5, Malatya, Turkey, September 2018.

[17] B. Ciftci and M. S. Apaydin, "A deep learning approach to sentiment analysis in Turkish," in Proceedings of the 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), pp. 1–5, Malatya, Turkey, Sepetember 2018.

[18] O. Çoban and G. T.¨Ozyer, "Word2vec and clustering based¨twitter sentiment analysis," in Proceedings of the 2018 Inter- national Conference on Artificial Intelligence and Data Pro- cessing (IDAP), pp. 1–5, Malatya, Turkey, Sepetember 2018.

[19] A. Ecemis¸, A. S¸. Dokuz, and M. Çelik, "Sentiment analysis of posts of social media users in their socially important loca- tions," in Proceedings of the 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), pp. 1–6, Malatya, Turkey, September 2018.

[20] Y. Emre Isik, Y. G¨ormez, O. Kaynar, and Z. Aydin, "NSEM: novel stacked ensemble method for sentiment analysis," in Proceedings of the 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), pp. 1–4, Malatya, Turkey, September 2018.

[21] A. A. Karcioglu and T. Aydin, "Sentiment analysis of Turkish˘and english twitter feeds using Word2Vec model," in Pro- ceedings of the 2019 27th Signal Processing and Communi- cations Applications Conference (SIU), pp. 1–4, Sivas, Turkey, April 2019.

[22] A. Uslu, S. Tekin, and T. Aytekin, "Sentiment analysis in Turkish film comments," in Proceedings of the 2019 27th Signal Processing and Communications Applications Conference (SIU), pp. 1–4, Sivas, Turkey, April 2019.

[23] M. Kanmaz and E. Surer, "Positive or negative? a semantic orientation of financial news," in Proceedings of the 2019 27th Signal Processing and Communications Applications Confer-ence (SIU), pp. 1–4, Sivas, Turkey, April 2019.

[24] E. Doğan and B. Kaya, "Deep learning based sentiment analysis and text summarization in social networks," in Proceedings of the 2019 International Artificial Intelligence and Data Processing Symposium (IDAP), pp. 1–6, Malatya, Turkey, September 2019.

[25] M. U. Salur, ̇I. Aydin, and S. A. Alghrsi, "SmartSenti: a twitter-based sentiment analysis system for the smart tourism in Turkey," in Proceedings of the 2019 International Artificial Intelligence and Data Processing Symposium (IDAP), pp. 1–5, Malatya, Turkey, September 2019.

[26] Y. Santur, "Sentiment analysis based on gated recurrent unit," in Proceedings of the 2019 International Artificial Intelligence and Data Processing Symposium (IDAP), pp. 1–5, Malatya, Turkey, September 2019.

[27] D. Goularas and S. Kamis, "Evaluation of deep learning techniques in sentiment analysis from twitter data," in Pro- ceedings of the 2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML), pp. 12–17, Istanbul, Turkey, August 2019.

[28] H. A. O˘gul and A. G¨uran, "Imbalanced dataset problem in sentiment analysis," in Proceedings of the 2019 4th Interna- tional Conference on Computer Science and Engineering (UBMK), pp. 313–317, Samsun, Turkey, September 2019.

[29] M. Rumelli, D. Akkus¸, O. Kart, and Z. Isik, "Sentiment¨analysis in Turkish text with machine learning algorithms," in Proceedings of the 2019 Innovations in Intelligent Systems and Applications Conference (ASYU), pp. 1–5, Izmir, Turkey, November 2019.

[30] A. Hayran and M. Sert, "Sentiment analysis on microblog data based on word embedding and fusion techniques," in Pro- ceedings of the 2017 25th Signal Processing and Communi- cations Applications Conference (SIU), Antalya, Turkey

[31]Sentiment Analysis of Shared Tweets on Global Warming on Twitter with Data Mining Methods: A Case Study on Turkish Language Yasin Kirelli and Seher Arslankaya Hindawi Computational Intelligence and Neuroscience Volume 2020, Article ID 1904172, 9 pages

[32] Cobb NK, Mays D, Graham AL. Sentiment analysis to determine the impact of online messages on smokers' choices to use varenicline. *J Natl Cancer Inst Monogr*. 2013;2013:224-230.

[33] Korkontzelos I, Nikfarjam A, Shardlow M, Sarker A, Ananiadou S, Gonzalez GH. Analysis of the effect of sentiment analysis on ex- tracting adverse drug reactions from tweets and forum posts. *J Biomed Inform*. 2016;62:148-158.

[34] Ebrahimi M, Yazdavar AH, Salim N, Eltyeb S. Recognition of side effects as implicit-opinion words in drug reviews. *Online Inform Rev*. 2016;4:1018-1032

[35] Sharma C, Whittle S, Haghighi PD, Burstein F, Keen H. Sentiment analysis of social media posts on pharmacotherapy: A scoping review. Pharmacol Res Perspect. 2020;e00640.

[36] Lu, Y., & Mori, T. (2017). Deep Learning Paradigm with Transformed Monolingual Word Embeddings for Multilingual Sentiment Analysis. arXiv preprint arXiv:1710.03203.

[37] Becker, W., Wehrmann, J., Cagnini, H. E., & Barros, R. C. (2017). An Efficient Deep Neural Architecture for Multilingual Sentiment Analysis in Twitter. FLAIRS.

[38] Nguyen, H. T., & Le Nguyen, M. (2018). Multilingual opinion mining on YouTube–A convolutional N-gram BiLSTM word embedding. Information Processing & Management, 54(3), 451-

[39] Medrouk, L., & Pappa, A. (2017, November). Deep Learning Model for Sentiment Analysis in Multi-lingual Corpus. In International Conference on Neural Information Processing(pp. 205-212). Springer, Cham.

[40] Wehrmann, J., Becker, W., Cagnini, H. E., & Barros, R. C. (2017, May). A character-based convolutional neural network for language- agnostic Twitter sentiment analysis. In Neural Networks (IJCNN),2017 International Joint Conference on(pp. 2384-2391). IEEE.

[41] Chen, Q., Li, W., Lei, Y., Liu, X., Luo, C., & He, Y. (2017, April). Cross-Lingual Sentiment Relation Capturing for Cross-Lingual Sentiment Analysis. In European Conference on Information Retrieval (pp. 54-67). Springer, Cham.

[42] Al-Smadi, M., Talafha, B., Al-Ayyoub, M., & Jararweh, Y. (2018). Using long short-term memory deep neural networks for aspect- based sentiment analysis of Arabic reviews. International Journal of Machine Learning and Cybernetics, 1-13.

[43] Deriu, J., Lucchi, A., De Luca, V., Severyn, A., Müller, S., Cieliebak, M., & Jaggi, M. (2017, April). Leveraging large amounts of weakly supervised data for multi-language sentiment classification. In Proceedings of the 26th international conference on world wide web (pp. 1045-1052). International World Wide Web Conferences Steering Committee.

[44] Peng, H., Ma, Y., Li, Y., & Cambria, E. (2018). Learning multi- grained aspect target sequence for Chinese sentiment analysis. Knowledge-Based Systems, 148, 167-176.

[45] Bhargava, R., & Sharma, Y. (2017, January). MSATS: Multilingual sentiment analysis via text summarization. In Cloud Computing, Data Science & Engineering-Confluence, 2017 7th International Conference on (pp. 71-76). IEEE.

[46] Becker, K., Moreira, V. P., & dos Santos, A. G. (2017). Multilingual emotion classification using supervised learning: Comparative experiments. Information Processing & Management, 53(3), 684-