SAKARYA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ DERGİSİ

Sakarya University Journal of Science
SAUJS

e-ISSN 2147-835X | Period Bimonthly | Founded: 1997 | Publisher Sakarya University |
http://www.saujs.sakarya.edu.tr/en/

Title: A Sentiment Analysis Model for Terrorist Attacks Reviews on Twitter

Authors: Ibrahim A. FADEL, Cemil ÖZ
Recieved: 2020-03-31 05:27:09

Accepted: 2020-09-22 13:00:33

Article Type: Research Article

Volume: 24
Issue: 6
Month: December
Year: 2020
Pages: 1294-1302

How to cite
Ibrahim A. FADEL, Cemil ÖZ; (2020), A Sentiment Analysis Model for Terrorist Attacks Reviews on Twitter . Sakarya University Journal of Science, 24(6), 1294-1302, DOI: https://doi.org/10.16984/saufenbilder.711612
Access link
http://www.saujs.sakarya.edu.tr/en/pub/issue/57766/711612

Sakarya University Journal of Science 24(6), 1294-1302, 2020

A Sentiment Analysis Model for Terrorist Attacks Reviews on Twitter

Ibrahim A. FADEL*[1], Cemil ÖZ[2]

Abstract

Twitter is considered as one of the famous microblogs that attract politicians and individuals to express their views on political, economic and social issues. The phenomenon of terrorist operations is one of the largest security and economic problem facing the world in recent years. Twitter users' comments on terrorism issues are important to understand users' sentiment about terrorist events. Sentiment analysis is a field of research for understanding and extracting users' views. In this paper, we propose a model for automatically classifying users' reviews on Twitter after occurrence of a terrorist attack, the model is built using lexicon and machine learning approaches. Lexicon approach is used to create labelled training dataset while machine learning approach was used to build the model. Scores of some domain related words were neutralized to avoid their negative effect. Features were selected based on PoS. Majority voting between NB, SVM and LR machine learning classification algorithms was applied. The performance of classification algorithms was measured using accuracy and F1 scores. The results obtained are compared to identify the best classification algorithm for features selection. Result show that our model achieved 94.8% accuracy with 95.9% F1 score.

Keywords: Sentiment Analysis, Machine Learning, lexicon-based approach, Terrorist mining.

1. INTRODUCTION

The phenomenon of terrorism has become a distinctive feature of this century. Terrorist groups have changed from their traditional ways of communicating and have increasingly adapted the use of internet and social media platforms [1] for propaganda, financing, training, planning, executing cyberattacks, and recruiting new members and followers [2].

In order to prevent future terrorist attacks, law enforcement and intelligence agencies have

* Corresponding Author: ibrahim.fadel@ogr.sakarya.edu.tr
[1] Sakarya University, ORCID: https://orcid.org/0000-0003-4726-7805
[2] Sakarya University, E-Mail: coz@sakarya.edu.tr ORCID: https://orcid.org/0000-0001-9742-6021

adopted the use of computer technologies to develop effective deterrent strategies. Group detection, link prediction and Key-Player Identification are among the mostly used strategies [3]. However, growing use of sentiment analysis and opinion mining affirms the adoption of these techniques in detecting terrorist groups and their activities on social media platforms [4]–[6].

Sentiment Analysis (SA), also known as opinion mining, is a challenging Text Mining and Natural Language Processing (NLP) problem. It deals with deriving sentiments and opinions from people's attitudes and emotions about events, topics and their attributes [7] to detect user's feelings, reactions and beliefs [8]. Most of the research work in this area focus on classifying texts according to their sentiment polarity, which can be positive, negative or neutral.

Sentiment classification techniques can be traditionally done in two ways: Machine learning (ML) approach and lexicon-based approach. However, a hybrid of both approaches has also been used. The ML approaches apply the famous ML algorithms and uses linguistic features. Lexicon-based approach is dependent on the collection of known and precompiled sentiments and terms [9],[10].

In this study we combine ML and lexicon approaches to build a model for automatically detecting terrorist sympathizers on twitter from their comments that are posted immediately after occurrence of a terrorist attack to express their feelings and opinions after their success in carrying out a terrorist attack. About one hundred thousand tweets after nine terrorist attacks in different countries across the globe was collected. Verb, adjective, and a combination of verb and adjective Part-of-Speech (PoS) types was used on selection features. Classification in the model employs majority voting (MV) between 3 different ML algorithms to determine tweet polarity.

The rest of the paper is outlined as follows. Section 2 presents related works that have been done in the area. Section 3 covers details of the proposed work including the pre-processing, labelling and classifying. Section 4 presents experiments and the results obtained. The conclusion and future works are presented in Section 5.

2. RELATED WORK

The increasing use of internet and social media by terrorist groups to disseminate their ideologies and attracting individuals has prompted researchers to analyze text using sentiment analysis approaches to detect terrorists. Text containing terrorism content on social media and internet exist in different forms. To detect this content lots of data is collected to build a dataset using different search terms. For example (Ashcrof et al.) [11] used terrorist groups' tweets to detect new terrorist supporters. They used AdaBoost, Naive Bayes (NB), and Support Vector Machines (SVM) machine learning algorithms to automatically classify tweets that were released by jihadist groups on Twitter as radical or non-radical. Three different datasets were used such as: TW-PRO consist of tweets of known Jihadist sympathizers, TW-CON containing tweets from accounts that were talking or against Islamic State of Iraq and Syria (ISIS) and TW-RAND contain random tweets discussed in various topics not related to ISIS. TW-RAND and TW-CON labelled as negative while TW-PRO is positive. Then, stylometry-based, time-based and sentiment-base features was selected. information gain was performed to select features. TW-CON and TW-RAND datasets were used as test dataset while TW-PRO used as training dataset. Classification results show that AdaBoost performs very well with 100% accuracy than both NB and SVM.

(Magdy et al.) [12] collected a huge number of Arabic tweets depending on how the terrorist group name was used in the tweets and divided them into two classes. pro-ISIS when the user used the full name of ISIS and the description as "state" is associated to refer to the organization and anti-ISIS when the abbreviated version was used. By analyzing pro-ISIS's historic timelines, they found the support for ISIS stems from frustration with the missteps of the Arab Spring. Also, they gained 87% accuracy by building an

SVM classifier to predict future support or opposition of the ISIS. authors also showed some of the interesting geographical and temporal trends for both pro- and anti-ISIS tweets.

Frequency of using nouns in the terrorist blogs was used also by (Park et al) [13] to analyze 6 Islamic forum posts on the dark web to find people who have radical tendencies. Radical users were extracted by using PoS tagger to select the top 100 most frequent nouns in each post. Then SentiStrength keyword analysis was used to determine polarity and score of each post. Sentiment scores for posts were divided into monthly radical scores to map each user's opinion change over time. Comparison was done to determine possible relationship or connection between users.

(Gatti et al.) [14] used extremist and benign contents on terrorist groups web sites. The approach uses ML methods to build and evaluate a text classifier that can distinguish Sunni extremist propaganda on the internet, Darknet and social media. Data collected from anonymous postings on "paste" sites frequently visited by terrorists is manually classified and labelled as to whether there is presence of Sunni extremism to form a training set. This training dataset was used to train a predictive classifier to perform binary classification of documents which were represented as a doc2vec vector. Class "1" was assigned to "extremist document" and class "0" was assigned to "benign document". The classifier is capable of taking in text in any language and classifies it as being related to Sunni extremist propaganda or not.

Hashtags associated with ISIS can be analyzed and capture the sentiment of the tweets. (Mirani and Sasi) [15] used hashtags referring to ISIS such as #DAESH, #ISIS, #ISIL, #IS, #ISLAMICSTATE to collect dataset from Twitter. Initially, a lexical dictionary was used to define the polarity of dataset. Then, five different algorithms were trained on this dataset. The results showed that Maximum Entropy achieved the best result with 99%, while the other algorithms performed with an average accuracy of more than 90%.

(Ali) [16] employed data mining tools to analyze ISIS-related tweets both in English and in Arabic. KNN clustering algorithm was used to find out the frequently appearing words in the tweets. Network graph was used also to verify three ISIS-sympathizing accounts that contain ISIS supporting tweets.

User behavior on social media has also been used for sentiment analysis to detecting a sentiment that leads to terrorism on Twitter. (Azizan and Aziz)[6] conducted a study for the detection of extremist affiliations using machine learning techniques. They used historical tweets of particular users based on specific keywords related to the terrorism issue. Previous tweets sentiment scores of these particular users compared with the sentiment score of the latest statement detected. They found that the machine learning approach is more accurate as compared to the lexicon-based approach.

3. PROPOSED TECHNIQUE:

The proposed model system consists of three main steps as follow: pre-processing, lexicon-based approach and ML-based approach. To extract sentiment from new tweet, we only used pre-processing and ML-based approach as illustrated in Figure 1.

Pre-processing is an essential step before analyzing the data. Any data collected from primary sources including Twitter, contains significant amounts of noise. For example, twitter data contains symbols, URLs, emoticons, etc. There is need to transform these phrases into normal text. We automatically removed Retweets (RT), hashtags (#), URL's and emoticons. duplicate tweets also removed in order to reduce tweets that may be produced by bot accounts.

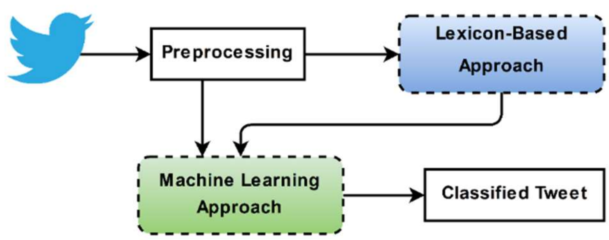

Figure 1 Main steps of the proposed Model

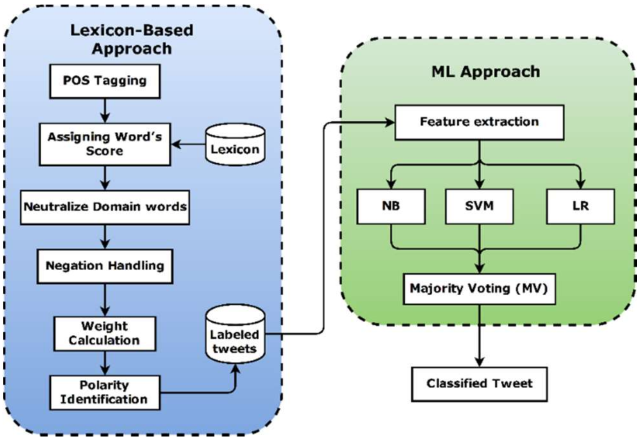

Figure 2 Lexicon and ML approaches processes in details

Second step is lexicon-based approach. In this step we build a training dataset using the following process as seen in Figure 2. Firstly, we employed python Natural Language Toolkit (NLTK) tokenize package to tokenize tweets into PoS which covers nouns, verbs, adjectives and adverbs. Then, SentiWords lexicon was used to determine polarity of the words. SentiWords contains approximately 155,000 English words that categorize words into nouns (N), verbs (V), adjectives (A) and adverbs (R) in alignment with WordNet lists. SentiWords assigns each word a sentiment score between -1 and 1 by learning from SentiWordNet [17],[18].

In the reviews of terrorist attacks domain, some words such as bomb, attack, kill, injured, explosion, etc. occur frequently and automatically reveal negative feelings.

According to SentiWords, these words have high negative scores. These high negative scores affect the final polarity of tweets making the sentiment of the tweet appear to be negative. To avoid this effect, we selected these words that automatically reveal negative feelings related to our domain and assigned them a score of zero, i.e. we neutralized them. These neutralized words are shown in the Table 1.

Example the review tweet of Wera Hobhouse (Figure 3); Member of Parliament for Bath in UK, after the Finsbury mosque attack in London.

Figure 3 Wera Hobhouse tweet

Table 1
Neutralized domain lemmas

Lemma	PoS	Score	Lemma	PoS	Score
Arrest	V	-0.668	Gun	N	-0.335
Attack	V	-0.750	Gun	V	-0.335
Attack	N	-0.75	Gunman	N	-0.500
Attacker	N	-0.694	Incident	N	-0.200
Attacking	A	0.158	Incident	A	-0.2
Blood	N	-0.380	Injured	A	-0.389
Blood	V	-0.380	Kill	N	-0.798
Bloody	R	-0.535	Kill	V	-0.798
Bloody	A	-0.535	Killer	N	-0.815
Bloody	V	-0.535	Killing	A	-0.763
Bomb	N	-0.633	Killing	N	-0.763
Bomb	V	-0.633	Murder	N	-0.880
Bomber	N	-0.540	Murder	V	-0.880
Bombing	N	-0.725	Murderer	N	-0.770
Broken	A	-0.563	Murderous	A	-0.738
Casualty	N	-0.418	Shoot	V	-0.375
Dead	A	-0.745	Shoot	N	-0.375
Dead	R	-0.745	Shooter	N	-0.325
Dead	N	-0.745	Suicidal	A	-0.713
Deadliest	A	-0.745	Suicide	N	-0.855
Deadly	A	-0.775	Terror	N	-0.563
Deadly	R	-0.775	Terrorism	N	-0.850
Deadly	R	-0.775	Terrorist	N	-0.663
Death	N	-0.778	Terrorize	V	-0.625
Die	N	-0.833	Victim	N	-0.738
Die	V	-0.833	Weapon	N	-0.263
Died	V	-0.833	Weaponry	N	-0.323
Explosion	N	-0.458	Wound	V	-0.440
Explosive	N	-0.215	Wounded	A	-0.420
Explosive	A	-0.215			

On the lookout, this tweet gives positive sentiment. When we flat this tweet using PoS tagger to give scores from SentiWords to each word Table 2. Before neutralizing the domain words (victims, terror, and attack) the total score is negative implying negative sentiment. After neutralizing the domain words, the sentiment of the tweet changes from the negative to positive.

Negation Handling is a major issue while analyzing a given sentiment, which can be attributed to the fact that sentences contain a negation word such as not, don't, shouldn't etc.

These words shift the polarity of the sentence. For example, “I don’t like the movie”. The word “Like” carries a positive meaning, but “don’t” reverse the sentence meaning. We applied the window sizes approach to invert the polarity of the word following the negation word [19]. We used size =1 because we think the influence of the negation word mostly affects the meaning of the word that precedes it.

To deal with this problem we multiply the score of the word that precedes the negation word by (-1).

Then, we calculate tweet score by summing up all the scores of words in the tweet. We finally assign each tweet a polarity as follows:

$$polarity = \begin{cases} pos\ if\ Score >= \ \ 1 \\ neg\ if\ Score =< -1 \\ nat\ \ else \end{cases} \qquad (1)$$

Each tweet in the dataset passes through this processing to produce labelled tweets.

Table 2
Wera Hobhouse tweet’s neutralization

Token	Tag	Description	Before	After
my	PRP$	Pronoun	NA	NA
heart	NN	Noun	0.488	0.488
goes	VBZ	Verb	0.330	0.330
out	RP	Particle	NA	NA
to	TO	To	NA	NA
The	DT	Determiner	NA	NA
Victims	NNS	Noun	-0.738	0
of	IN	Preposition	NA	NA
the	DT	Determiner	NA	NA
vicious	JJ	Adjective	-0.593	-0.593
terror	NN	Noun	-0.563	0
attack	NN	Noun	-0.75	0
an	DT	Determiner	NA	NA
attack	NN	Noun	-0.75	0
on	IN	Preposition	NA	NA
all	DT	Determiner	NA	NA
of	IN	Preposition	NA	NA
us	PRP	Pronoun	NA	NA
and	CC	Conjunction	NA	NA
our	PRP$	Pronoun	NA	NA
shared	VBN	Verb	0.305	0.305
Values	NNS	Noun	0.545	0.545
Total:			-1.725	1.075
Sentiment:			**Negative**	**Positive**

Last step is ML approach, in this step the collection of assigned positive and negative polarities (labelled tweets) is used as training dataset to build the model. The major task during this step is feature extraction. There are different types of features extraction techniques that been applied in state-of-art such as Bag-of-Words models, n-grams models, lexicons-based models, and PoS based models.

In this work we used PoS models. PoS is a group of words or phrases that have similar grammatical properties, adjectives, adverbs, nouns, and verbs.

These phrases are extracted and used for classification of sentiments [20].

To obtain the final sentiment polarity, we used Logistic regression (LR), NB, and SVM.

We use NB, which is one of simplest and commonly used classifier in text categorization problem and sentiment analysis. It basically uses ‘Bayes theorem’ to describe the probability P for an event (class) to occur that is based on the conditions (features) that are thought be related to the event occurring. Given a class c and a dependent feature vector f_1 through f_n Bayes’ theorem states the following relationship:

$$P(c|f_1, \ldots, f_n) = \frac{P(c)P(f_1, \ldots, f_n|c)}{P(f_1, \ldots, f_n)} \qquad (2)$$

SVM is widely regarded as one of the best text classification algorithms and it is robust when the problem is separate linearly. In SVM a few samples of data are used in classification, that make it very useful for the large data sets [21]. The main concept of SVM is to determine linear separators between a set of objects having different class memberships.

LR also known as Maximum Entropy is a probabilistic statistical method for classifying data into discrete outcomes. It is named as ‘Logistic Regression’, because it’s underlying technique is quite the same as Linear Regression. But the biggest difference lies in what they are used for. This model is not only used for regression but also the classification task [22]. It is one of the machine learning algorithms that provide low variance and great efficiency.

Then, voting between classification algorithm was used to determine the final decision of polarity. Our model determines the final decision depending on majority voting (MV) between the three classifiers (LR, NB and SVM). We define this MV as follows:

$$MV(x) = mode\,\{LR(x), NB(x), SVM(x)\} \quad (3)$$

That means, we predict the class of the voting classifier (MV(x)) via majority voting of each classifier (LR(x), NB(x), SVM(x)). Assuming that the prediction of the classifiers LR, NB and SVM are positive, negative and positive respectively, then.

$$MV(x) = mode\,\{pos, neg, pos\} = pos \quad (4)$$

4. EXPERIMENT & RESULTS

In this Section we present an experiment performed in order to evaluate the sentiment analysis process described in the proposed technique section. The proposed model is implemented using Python and R Language. R used for collection and cleaning the dataset while python used in the others process. The running environment for our experiment used was R studio and Python 3.6 running on PC (Intel Core i5 2.5 GHz / 8 GB DDR3). with Windows 10 operating system.

The dataset we used in this experiment contains 96,679 user review tweets after terrorist incidents that took place in different countries between 22 May 2017 to 31 October 2017.All these tweets were in English. Table 3 shows the places of these attacks, data collection date and number of tweets collected and the hashtags used. The data was collected based on the hashtags used.

The collected tweets were pre-processed followed by lexicon-based stage. At this stage as we explained above in the section 2; the result of this stage is labelling the dataset in 3 sentiment polarities: Positive if the total score of the tweet is equal or more than one, negative is the total score was equal or less than -1, otherwise is neutral.

From the total 96,679 tweets, result show that 21,140 tweets were positive sentiment, 9,838 tweets were negative, while the majority 65,701 of the tweets was neutral Figure 4.

Table 3
Collected tweets for each terrorist incident

Attack Date	Target place	Data collection dates	#Hashtags	Number of Tweets
22/05/2017	Manchester Arena, UK	22-30/05/2017	#manchesterattack, #manchesterbombing, #manchesterarena	12,472
03/06/2017	London Bridge, UK	03-06/06/2017	#Londonattacks, #Londonbridge	9,527
07/06/2017	Parliament building, Tehran, Iran	07-15/06/2017	#Tehranattacks, #Iranattacks, #Tehranunderattack, #Iranparliamentattack	7,898
19/06/2017	Finsbury Park mosque, London, UK	19-21/06/2017	#finsburyparkmosque, #Finsburymosque #finsburyparkterrorattack, #finsburypark	10,554
17/08/2017	La Rambla, Barcelona, Spain	17-22/08/2017	#Barcelonaattack, #barcelonaterrorattack, #Barcelona, #Prayforbarcelona	13,767
14/10/2017	center of Mogadishu, Somalia	15-18/10/2017	#Prayformogadishu, #Mogadishu, #Somalia, #Somaliaattack, #Mogadishutruckbomb	9,693
19/10/2017	Kandahar, Afghanistan	19-20/10/2017	#Taliban, #Kandahar, #Afghanistan	7,408
28/10/2017	Hotel- Mogadishu, Somalia	28-29/10/2017	#Prayformogadishu, #mogadishu, #somaliaattack, #mogadishutruckbomb	8,216
31/10/2017	Manhattan - New York, USA	31/10-01/11/2017	#NYTerrorAttack, #NYCStrong, #PrayForNYC, #Manhattan	17,144
TOTAL				**96,679**

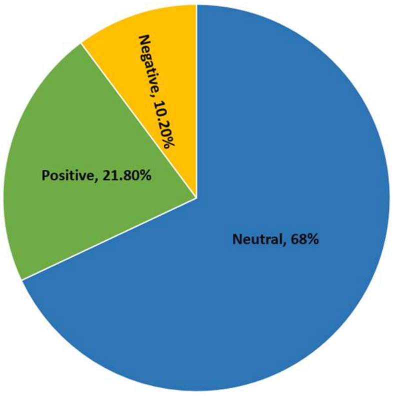

Figure 3 Lexicon-based labeled tweets

In the ML stage; only positive and negative labelled tweets were run. The labelled dataset was split into 3/4 training and 1/4 test. In this experiment, we examine three features types such as verb (VER), adjective (ADJ), and a combination of verb and adjective (VER+ADJ). Each feature type is classified using LR, NB, SVM, and MV classification algorithms

We applied the confusion matrix (Table 4) to evaluate the classification performance in terms of accuracy and F1-score for the both sentiment classes (Positive pos and Negative neg).

Accuracy *Ac* is used to calculate the proportion of the total number of predictions that were correct. While F1-scorei *F1* is used to calculate the weighted average of Recall *R* (proportion of actual pos/neg cases which are correctly identified) and Precision *P* (proportion of *pos*/*neg* cases that were correctly identified).

Table 4
Confusion matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Positive (FP)
Actual Negative	True Negative (TN)	False Negative (FN)

These measures are calculated as follows.

$$\mathrm{Ac} = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \tag{5}$$

$$\mathrm{P_{pos}} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \ , \ \mathrm{P_{neg}} = \frac{\mathrm{TN}}{\mathrm{TN+FN}} \tag{6}$$

$$\mathrm{R_{pos}} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \ , \ \mathrm{R_{neg}} = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \tag{7}$$

$$F1_{pos} = \frac{2.P_{pos}.R_{pos}}{P_{pos}+R_{pos}} \ , \mathrm{F1_{neg}} = \frac{2.\mathrm{P_{neg}}.\mathrm{R_{neg}}}{\mathrm{P_{neg}}+\mathrm{R_{neg}}} \tag{8}$$

We extract the result of these performance measure and compare it based on the classifier algorithm and the feature type to find out which roads are better.

The result show that MV classifier achieve best result with high *Ac,* and *F1* performance on all features in both *neg* and *pos* documents.

LR classifier achieved the second-best results in the most performance measures, but the result of $F1_{neg}$ of ADJ comes slightly lower than SVM result. SVM was third-best in performance results, while the worst performing approach in the all measure is NB. See Table 5.

According to the features the combination of the two features VER+ADJ achieve the high performance followed by VER while ADJ achieve the worst performance. That means the combination of features produces best results than a single type feature.

In General, all the classifications algorithms achieve pretty good accuracy with lowest being 90% achieved by NB with ADJ feature and highest 94.8% achieved by MV with VER+ADJ features. *F1* for *pos* documents achieves better performance than the *neg* documents. *pos* documents achieve score between 92.8% - 96.2% while the *neg* document was 83.8% - 91.6%.

Table 5
Classification measures result

Classifier	**ADJ**			**VER**			**VER+ADJ**		
	Ac	$F1_{pos}$	$F1_{neg}$	Ac	$F1_{pos}$	$F1_{neg}$	Ac	$F1_{pos}$	$F1_{neg}$
NB	90%	92.8%	83.8%	91.3%	93.7%	85.9%	90.8%	93.3%	85.6%
SVM	90.7%	93.2%	85.4%	92.4%	94.4%	87.9%	92.5%	94.5%	88.1%
LR	90.8%	93.4%	85.2%*	92.5%	94.6%	87.9%	93%	94.9%	88.6%
MV	93.1%	95%	88.7%	94.3%	95.9%	90.8%	94.8%	96.2%	91.6%

5. CONCLUSION

In this study we combine ML and lexicon approaches to build a model that automatically detects terrorist supporters on twitter from their comments using tweets after 9 terrorist attacks in different countries across the globe. The lexicon-based approach stage involved building a training dataset of labelled tweets as being positive, negative or neutral. In the ML stage, only positive and negative labelled tweets were used to build a classification model for feature extraction. Negative polarity tweets are regarded as terrorist supporters while positive polarity was regarded as non-supporters. PoS types such as VER, ADJ, and a combination of both VER+ADJ were used on selection features. Our model achieved high performance up to 94.8% accuracy and 95.9% F1 score. Accordingly, the combination of features produces better results than a single type feature. This study will be helpful for Law enforcement and intelligence agencies in their quest to develop effective deterrent strategies to prevent future terrorist attacks. In the future work, features will be extracted based on N-gram, and the obtained results will compare with PoS based features.

Funding

The authors received no financial support for the research, authorship or publication of this study.

The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

Authors' Contribution

İ.F: Constructing the idea of the article, planning the methodology to reach the conclusion, collecting the dataset, data management, execution of the experiments and reporting. logical interpretation and presentation of the results, writing of the body of the article, reviewing the article before submission.

C.Ö: Supervising the course of the article, Reviewing the article before submission.

The Declaration of Ethics Committee Approval

This work does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

REFERENCES

[1] J. Klausen, "Tweeting the Jihad: Social media networks of Western foreign fighters in Syria and Iraq," Stud. Confl. Terror., vol. 38, no. 1, pp. 1–22, 2015.

[2] Council of Europe, "Cyberterrorism: The Use of the Internet for Terrorist Purposes," United Nations Off. Drugs Crime, vol. 12, no. 1, p. 497, 2007.

[3] P. Choudhary and U. Singh, "A Survey on Social Network Analysis for Counter-Terrorism," Int. J. Comput. Appl., vol. 112, no. 9, pp. 24-29, 2015.

[4] P. Burnap et al., "Tweeting the terror: modelling the social media reaction to the Woolwich terrorist attack," Soc. Netw. Anal. Min., vol. 4, no. 1, pp. 1–14, 2014.

[5] T. Chalothorn and J. Ellman, "Using SentiWordNet and Sentiment Analysis for Detecting Radical Content on Web Forums," Nrl.Northumbria. Ac. Uk, no. 1.

[6] A. Azizan, Sofea, Aziz, "Terrorism Detection Based on Sentiment Analysis

Using Machine Learning.pdf," J. Eng. Appl. Sci., vol. 12, no. 3, pp. 691–698, 2017.

[7] B. Liu, "Sentiment Analysis and Opinion Mining," Synth. Lect. Hum. Lang. Technol., vol. 5, no. 1, pp. 1–167, 2012.

[8] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up?: sentiment classification using machine learning techniques," in The Conference on Empirical Methods in Natural Language Processing (EMNLP), 2002, vol. 10, pp. 79–86.

[9] N. A. S. Abdullah, N. I. Shaari, and A. R. A. Rahman, "Review on sentiment analysis approaches for social media data," Journal of Engineering and Applied Sciences, vol. 12, no. 3. pp. 462–467, 2017.

[10] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," Ain Shams Eng. J., vol. 5, no. 4, pp. 1093–1113, 2014.

[11] M. Ashcroft, A. Fisher, L. Kaati, E. Omer, and N. Prucha, "Detecting Jihadist Messages on Twitter," Eur. Intell. Secur. Informatics Conf. EISIC 2015, pp. 161–164, 2016.

[12] W. Magdy, K. Darwish, and I. Weber, "#FailedRevolutions: Using Twitter to study the antecedents of ISIS support," First Monday, vol. 21, no. 2, 2016.

[13] A. J. Park, B. Beck, D. Fletche, P. Lam, and H. H. Tsang, "Temporal analysis of radical dark web forum users," Proc. 2016 IEEE/ACM Int. Conf. Adv. Soc. Networks Anal. Mining, ASONAM 2016, pp. 880–883, 2016.

[14] A. H. Johnston and G. M. Weiss, "Identifying sunni extremist propaganda with deep learning," 2017 IEEE Symp. Ser. Comput. Intell., no. December 2015, pp. 1–6, 2017.

[15] T. B. Mirani and S. Sasi, "Sentiment analysis of ISIS related Tweets using Absolute location," in International Conference on Computational Science and Computational Intelligence Sentiment, pp. 1140–1145, 2016.

[16] G. A. Ali, "Identifying Terrorist Affiliations through Social Network Analysis Using Data Mining Techniques," Valparaiso University, 2016.

[17] L. Gatti, M. Guerini, and M. Turchi, "SentiWords: Deriving a High Precision and High Coverage Lexicon for Sentiment Analysis," IEEE Trans. Affect. Comput., vol. 7, no. 4, pp. 409–421, 2016.

[18] Natural Language Processing, "SentiWords | HLT-NLP." [Online]. Available: https://hlt-nlp.fbk.eu/technologies/sentiwords. [Accessed: 19-Mar-2018].

[19] A. Hogenboom, P. Van Iterson, B. Heerschop, F. Frasincar, and U. Kaymak, "Determining negation scope and strength in sentiment analysis," in Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics, pp. 2589–2594, 2011.

[20] C. Bhadane, H. Dalal, and H. Doshi, "Sentiment analysis: Measuring opinions," Procedia Comput. Sci., vol. 45, no. C, pp. 808–814, 2015.

[21] J. M. Moguerza and A. Muñoz, "Support Vector Machines with Applications," Stat. Sci., vol. 21, no. 3, pp. 322–336, 2006.

[22] J. Feng, H. Xu, S. Mannor, and S. Yan, "Robust Logistic Regression and Classification," Neural Inf. Process. Syst., pp. 1–9, 2014.