Sentiment Analysis on Predicting Presidential Election: Twitter Used Case

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Abstract. Twitter is a popular tool for social interaction over the Internet. It allows users to share/post opinions, social media events, and interact with other political and ordinary people. According to Statista web site 2019 statistical report, it estimated that the number of users on Twitter had grown dramatically over the past couple of years to research 300 million users. Twitter has become the largest source of news and postings for key presidents and political figures. Referring to the Trackalytics 2019 report, the recent president of the USA had posted 4,000 tweets per year, which indicates an average of 11–12 tweets per day. Our research proposes a technique that extracts and analyzes tweets from blogs and predicts election results based on tweets analysis. It assessed the people's opinion and studied the impact that might predict the final results for the Turkey 2018 presidential election candidates. The final results were compared with the actual election results and had a high accuracy prediction percentage based on the collected 22,000 tweets.

Keywords: Twitter API · Virtualization · Data mining · Sentiment analysis · Tweets · Election · Positive polarity · Negative polarity

1 Introduction

At present, social media provides a massive amount of data about users and their social interaction. This data plays a useful role in policy, health, finance, and many other sectors as well as predicting future events and actions. In a relatively short period, social media has gained popularity as a tool for mass communications and public participation when it comes to political purposes and governance. Obtaining a successful data forecast helps to understand the limitations of predictability in social media and avoid false expectations, misinformation, or unintended consequences. Rapid dissemination of information through social networking platforms, such as Twitter, enables politicians and activists to broadcast their messages to broad audiences immediately and directly outside traditional media channels.

During the 2008 US election, Twitter had used as an essential tool to influence the results of Barack Obama's campaign [1]. Obama's campaign succeeded in using Twitter as a campaign and gaining more followers. Accordingly, more voters had elected during

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the 17 months of the election period. The campaign published 262 tweets and gained about 120,000 new followers. As a result of the Twitter campaign, all major candidates and political parties nowadays use social media as an essential tool to convey their messages [1]. This paper aims to study the expected patterns of political activity and Twitter campaigns in this context. The Turkish presidential election is used as a case scenario to extract and analyze the final campaign results. The second section of the paper highlights the related work on election prediction around the Asia region.

Furthermore, the third section addresses the work approach and methods adopted. The results section was organized in Sect. 4 of the paper. A final discussion and conclusion section was listed in Sect. 5.

2 Related Work on Election Prediction Based on Twitter

The Twitter tool is used as a vital component to assess the needs of social media among users [2]. It has many benefits, such as social and political sentiments, measuring the popularity of political and social policies, marketing products, extracting positive and negative opinions, discovering recent trends, and detecting product popularity. Besides all, sarcastic and non-sarcastic tweets are also crucial for detecting sentiments. There have been many studies examining the characteristics and features of the political discourse of Twitter during the US 2016 election. The objective of these studies is to develop a robust approach that can be applied to extract data from Twitter to predict the results of the upcoming elections. According to [1, 3, 4] Twitter is a popular application on social media. During the US presidential election of 2016, people used social media to express their admiration or dissatisfaction for a particular presidential candidate. The authors measure how these tweets expressed and compared to the poll data. The authors used an Opinion Finder Lexicon dictionary and the Naive Bayes Machine Learning Algorithm to measure the sense of tweets related to politics. In another research paper [3], there were 3,068,000 tweets contains 'Donald Trump' text, and 4,603,000 contains 'Hillary Clinton' text collected within 100 days before the election period (see Fig. 1). Also, [1] has collected 3 million tweets within the same period. In both types of research, authors have manually labeled the collected tweets. Also, another technique was used to automate label based on the hashtag content/address. The authors concluded that Twitter had become a more reliable environment. By observing the tweets during 43 days before

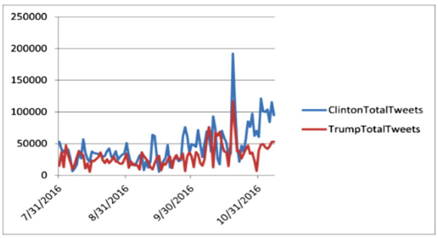


Fig. 1. Tween volume chart

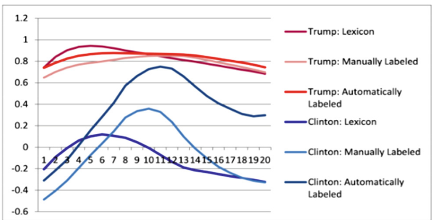


Fig. 2. Correlation Coefficient for Trum and Clinton Tweets 43 days before election using a Moving Average of k days

the election period, when using "moving average technique," it was noticed that 94% correlation was recorded with poll data used as illustrated (see Fig. 2).

The lexicon dictionary [3] contains 1600 positive and 1200 negative words. The result of applying this analysis was shown in Figs. 3 and 4.

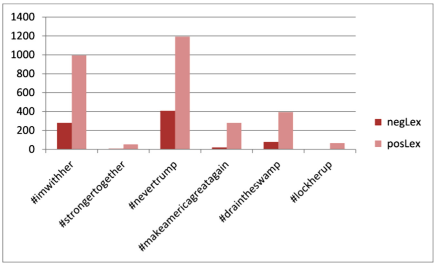


Fig. 3. Lexicon sentiment for Trump hashtags

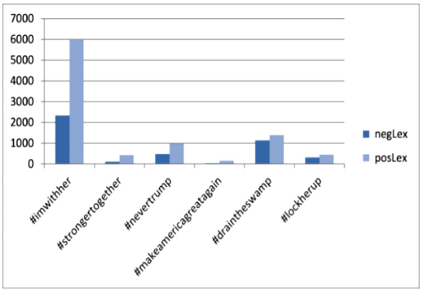


Fig. 4. Lexicon sentiment for Clinton hashtags

National Language Toolkit (NLTK) was used in the Naïve Bayes algorithm. There were five hundred negative and five hundred positive tweets labeled in this algorithm. Two key search words ('Hillary Clinton') and ('Donald Trump') were used. The criteria of this algorithm and the analysis results are shown in Figs. 5 and 6. Authors in [1] have used a machine learning approach for automatic tweet labeling. Convolution Neural Network (CNN) was performed using Python and Tensorflow. The collected tweets are trained by 140 sentiment data set. After that, tweets were labeled as a positive or negative sentiment. The election dataset is used for evaluation and predicting the votes by using two algorithms and sentiment analysis. The predicted votes were compared with the polling statistics collected during the election period, and it shows that the expected result was matched with the actual voting result [5].

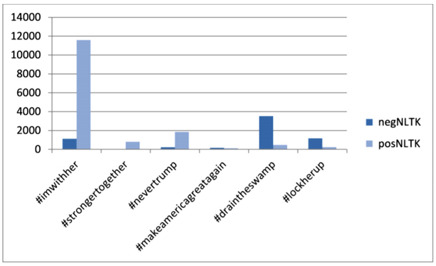


Fig. 5. NLTK sentiment for Clinton hashtags

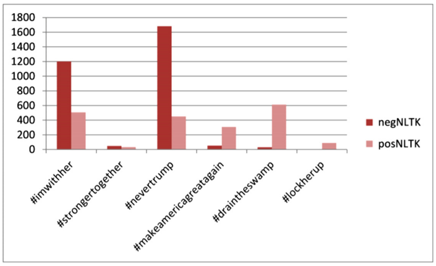


Fig. 6. NLTK sentiment for Trump hashtags

Moreover, [6] produced an analytical text on the American Elections in 2016. In this research, three million tweets were collected within 21 days before and after Election Day. Emotion analysis was used to examine the user's sentiment behavior regarding his Twitter profile and its associated features. Both research papers have studied the topic of

Twitter and discuss its relevance to news and events. More often the SentiStrength is used for sentiment score calculation. The collected tweets were cleaned based on messages referring to the keyword search terms ‘election 2016’, ‘Hillary Clinton’ or ‘Donald Trump.’ Furthermore, [6] has conducted several hypotheses to study and discuss the characteristics of Twitter’s political user behavior, views, and other discussions. The result of the analysis showed that the majority of feelings of the collected tweets were negative for both candidates.

There is a sign of unpleasant sensations of the latest elections. Also, it was discovered from the analytic results that few numbers of tweets posted during debate sessions and were mostly re-tweeted. Authors in [7] provided a novel method to facilitate data mining related to the participant’s opinion with the support of linguistic analysis and sentiment ratings. It was used to identify the sentiment score level of political involvers in Pakistan. According to the literature, this original paper was recognized as the first one that studied the sentiment analysis on social media. The authors have introduced a new technique for mining opinion in a political context. Two classifications analyses were applied among the collected data using the Bayes Naïve probability distribution and Support Vector Machine (SVM) algorithms. The result of applying this approach was shown in Fig. 8. The sentiment analysis was performed on the Sentiment viz web-interface that provides a graphical analysis of the different levels of sentiments categories, as shown below (see Fig. 7). Figure 8 also shows that SVM performed better than Naïve Bayes algorithm and gave higher accuracy.

Fig. 7. Sentiment classification defined over the keyword “PTI”

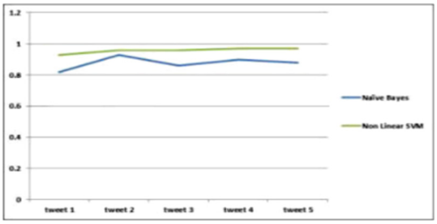


Fig. 8. Comparisons of SVM and Naive Bayes

Figure 9 shows an output display of the invented model. This model has an option to display the data in a visual environment. Authors of [7] have used this model to represent the negative opinion for Pakistan People’s Party (PPP) among different places and cities. From the display of Fig. 9, it was noticed that Lahore city has the highest negative opinion level about PPP. The highlighted information leads to many facts.

Furthermore, other parties can see this fact from a different angle. This leads to an easy comparison and clarity concerning PPP. The proposed model was tested on the Pakistan Election. Sentiment analysis was performed and shows that Lahore has the highest negativity percentage among the country, as it is listed in Fig. 9. SVM was also used for determining the polarity of the sentiment. SVM is based on features of the data, and label polarity of the tweet’s sentiment, whether it is positive or negative, otherwise,

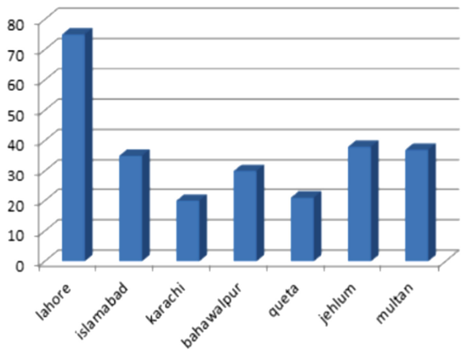


Fig. 9. The magnitude of negativity about PPP in different cities

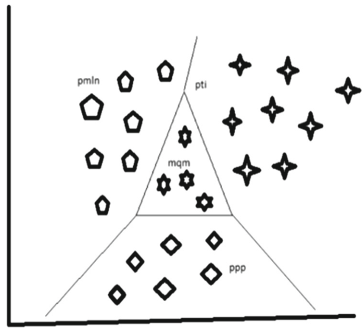


Fig. 10. Working of SVM Model

it will be labeled as neutral, along with the political party name for the posted tweets [9] (see Fig. 10).

The author in [8] has improved the political sentiment analysis on Twitter using a dynamic keyword method. This paper presents a new method for collecting data to predict election results and a way for subject models to extract topics [10]. The RSS aggregator uses news articles and dynamic keywords shared on Twitter at the same time, creating an intelligent prediction method that mainly depends on the size of Twitter. It also attempts to enhance electoral predictions on social media using a dynamic word-based methodology for Delhi Assembly Election 2015. There were two channels for data collected using RSS (see Fig. 11) and Twitter API. Two types of analysis were applied to the collected data (volume and sentiment-based analysis). This analysis is useful to detect the voting activity from the tweets by using keywording searches related to 'election' using the LDA-based approach, as shown in (see Fig. 12). This analysis is based on simple opinion and comparison-based opinion. It is evident from the graph (see Fig. 10) that SVM techniques give good results.

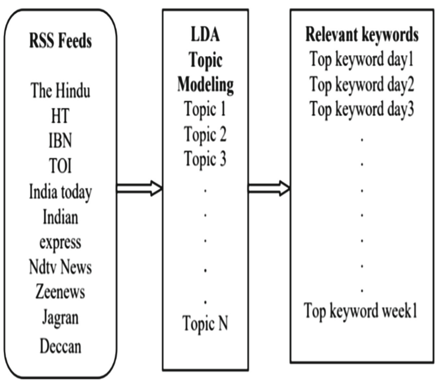


Fig. 11. Selection procedure for topics and keywords from RSS feeds

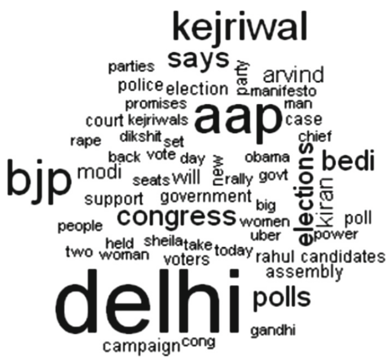


Fig. 12. Tag cloud showing the most relevant keywords in RSS

3 Methodology

Two datasets were generated using the Twitter application for data collection. Each dataset has 22000 tweets. The collected tweets were extracted before the Turkish Presidential Election period. The election took place during the period of 22nd and 24th June 2018. Spyder Python development environment was used for the data mining and sentiment analysis process (see Table 1). Multiple stages were performed on this dataset during the analysis processes. Step 1 of the process involves translating the text portion in the datasets to the English Language text format. We selected the python spyder programming script and the translator parser.

Table 1. Tools and Software packages used in the Tweet Analysis

Tools used	Software package used
Twitter API	Tweepy package
Spyder Python Development Environment	Json and CSV packages
Anaconda Navigator Environment	Textblob package
SentiStrength Classifier Toolbox	Naive Bayes Analyzer package
Twitter API	Wordcloud package

Furthermore, step 2 investigates the dataset's text conversion into a lower case text format. A filtering process was applied to eliminate the unwanted text. This filter was used to remove redundant data for better extraction. A custom stopwords lexicon dictionary that contained English and Turkish words were used to filter the dataset's text. The output text from this filter was extracted from any punctuations symbols, URLs, and hashtags. Besides, all the re-tweeted texts were excluded from the filtered text. After that, word and sentence tokenize process was completed. Then, each tweet was divided into two parts; discrete words and sentences. The output of the text was further extracted for better sentiment analysis performed on the output text using a Naïve Bayes Classifier. It classifies the sentiment polarity level using three levels of polarity, positive, negative, and neutral.

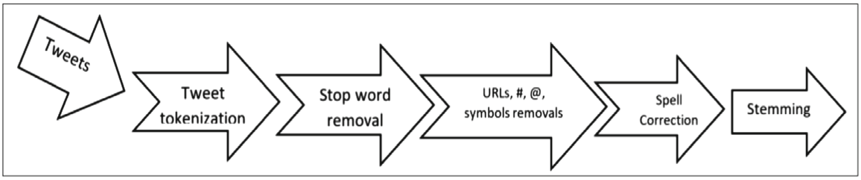


Fig. 13. Typical scenarios of pre-processing on standards text and Tweets

Finally, several data processes were implemented on the dataset text using the word cloud and word frequency algorithms. Multiple visual presentation and measurements were generated and displayed. Finally, the actual election results were compared with the Twitter sentiment analysis results and evaluated the precision percentage of the overall effect. Figures 13 and 14 show the processes performed on the data sets.

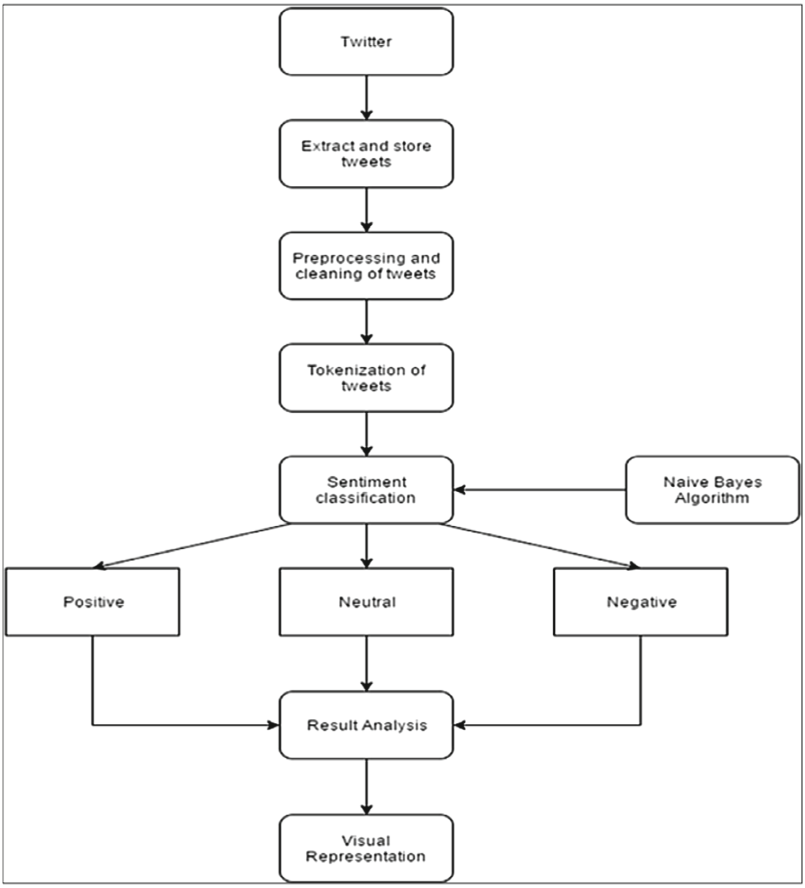


Fig. 14. Flowchart sentiment analysis algorithm

4 Sentiment Analysis Process

a. **Tokenize each text into words**
   Each tweet will be tokenized and split into separated words as showed in Fig. 15.

```
#tokenize words
        blobwords=[lstlst for sublist in blobs for lstlst in sublist]
```

Fig. 15. Tokenize each text into words

b. **Converting text to lower case and spell check process**
Each tokenized word is converted into a lower case. After that it will be validated by comparing it with an English word list dictionary. If there is a typo mistake, it will be corrected and returned back to its dataset as shown in Fig. 16.

```
#load dictionary from disk into memory converting to lower case
        def openDictionary(lang):
            if (lang == 'en'):
                with open("wordsEn.txt") as words:
                    DictCache = set(word.strip().lower() for word in words)
                    return DictCache

#to check the content of the tweet and compare it with the dictionariy and adjust its meanings
#compare the validity of the tokenized words if it is correct, if not it will adjust the correct
#word
        def wordsCheck(words, Dict):
            validWords=[]
            for word in words:
                if (word.lower() in Dict):
                    validWords.append(word.lower())
            return removeStopwords(validWords)

# get list of valid words
         words=wordsCheck(blobwords, openDictionary('en'))
```

Fig. 16. Converting text to lower case and spell check process

c. **Create a custom stop words and remove the unwanted text from the main data set**
Two custom stopwords dictionaries were created using *utf-8* encoding. Stopwords list for English and another one for Turkish. These stopwords lists have most frequent words that people usually use. It should be removed from the dataset before and after the data processing as shown in Fig. 17.

```
#TO DO add custom stopwords
        def removeStopwords(wordlist):
            stopw= list()
            foo = open("mystopWords.txt",encoding='utf-8')
            for word in foo:
                stopw.append(word.rstrip())

#print(stopw)
            qwords=[w for w in wordlist if not w in stopw]
            return qwords
```

Fig. 17. Create a custom stop words and remove the unwanted text from the main dataset

d. **Sentiment Polarity Analysis Process**
TextBlob and NaiveBayesAnalyzer packages were installed and imported. Naïve Bayes Sentiment classifier is used to word sentiment classification. This function returns a score between [1-1 and 1]. *If sentiment score* > 1, this means that the tweet has a positive sentiment. *Else if sentiment score* < 1, this means that the tweet has a negative sentiment. Else if sentiment score is equal to zero, it is considered that this tweet has a neutral sentiment as shown in Fig. 18.

```
from textblob import TextBlob
from textblob.sentiments import NaiveBayesAnalyzer
k=0
for tweet in f:
    try:
        pos=0
        neg=0
        neu=0
        blobs=[]
        for tweet in f:
            try:
                k=k+1
                blob=TextBlob(tweet)
                analyzer=NaiveBayesAnalyzer()
                blobs.append(blob.words)

                if(blob.sentiment.polarity > 0.0):
                     pos = pos + 1
                     print('\n end of postive tweet')
                     print(blob.sentiment)

                elif(blob.sentiment.polarity < 0.0):
                     neg = neg + 1
                     print(blob.sentiment)
                     print('\n end of negative tweet')
                else:
                     neu = neu + 1
                     print(blob.sentiment)
                     print('\n end of neutral tweet')
            except Exception:
                pass
```

Fig. 18. Sentiment polarity analysis process

e. **Measure the overall polarity sentiment level for each elector**
The overall polarity level percentage (positive, neutral and negative) is calculated for each elector (see Fig. 19).

```
 # We construct lists with classified tweets:
 # Now that we have the lists, we just print the percentages:
 # We print percentages:
pos_percentage=pos/k*100
neg_percentage=neg/k*100
neu_percentage=neu/k*100
print("\n\tthe positive sentiment percentage is:{}%".format(str(pos_percentage)))
print("\n\tthe negative sentiment percentage is:{}%".format(str(neg_percentage)))
print("\n\tthe neutral sentiment percentage is:{}%".format(str(neu_percentage)))
```

Fig. 19. Measure the overall polarity sentiment level for each elector

5 Observation

The datasets were examined using the above-mentioned approach. Exciting results were generated. The testing was introduced using two election candidates. Those are *Mr. Regep Tayyip Erdogan* (*RT Erdogan* - candidate #1) and his competitor *Mr. Muharrem Inci (Inci* - candidate #2*)*. Similar experimental procedures were applied to these two candidates' datasets. Table 2 shows samples of positive, negative and neutral opinions for candidate #1 using the Naïve Bayes Classifier.

The results showed that candidate #1 has more positive sentiment votes. A "48%" positives sentiments reflect that more people are pleased to elect him. The competitor has

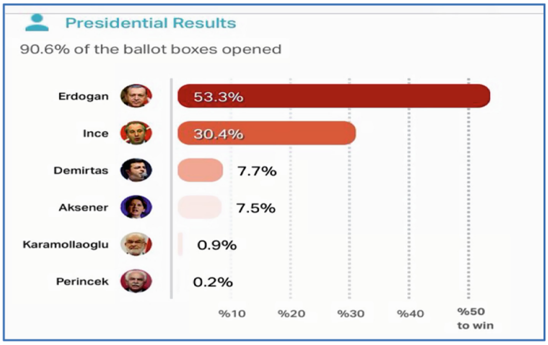
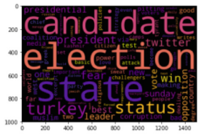
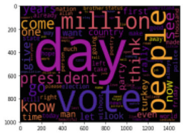
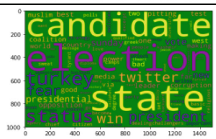
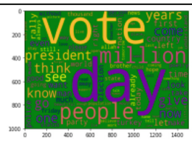


Fig. 20. Actual Turkey presidential elections 2018 results [11]

Table 2. Comparison between actual Turkey presidential final result vs. Twitter predicted result

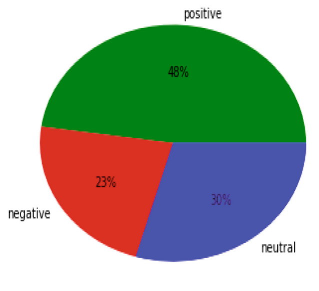
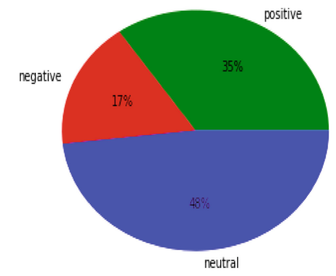
Turkey presidential elections 2018	Candidate 1	Candidate 2
Actual final election results on June 25, 018	53.3%	30.4%
Predicted election results through the proposed Twitter sentiment analysis on June 20–24, 2018	48.0%	35.0%
Accuracy error percentage	**9.94%**	**11.84%**

Table 3. The word cloud results from the collected dataset during June 22nd–24th, 2018, for both electors. It shows the top 100 words that are frequently repeated and the most 100 positive words about both electors

Related Tweets to:	Relevant tweets words - Candidate 1	Related tweeted words - Candidate 2
Top 100 frequent words on Twitter related to each elector		
Top 100 positive words related to elector		

"35%" positive sentiment votes. Moreover, 23% of tweets have negative feelings votes for candidate one whereas 30% recorded tweets were neutral votes. As for candidate 2, 35% of the tweets were identified as positive sentiments; on the other hand, only 17% of the tweets listed as negative feelings. For this candidate, the neutral votes were recorded as 48% of the overall tweets. These results are comparable to the official election results listed, as shown in Fig. 20 and Tables 2, 3 and 4.

Table 4. Positive, negative and neutral sentiment

Sample	Candidate 1		Candidate 2	
Positive	**Sentiment :** polarity= 0.42023809523809524, subjectivity= 0.559077380952381	Zeeshan Haider, iamshanichadhar, 2018-06-22 03: 55,0,0," ""I do not know what he say in this video but every word is important for every Muslim he is real Hero as a leader	**Sentiment:** polarity=0.4, subjectivity=0.625	Now look, where are the citizens of **a great country** when the president is in the palaces? how is this country represented from this profession? just open your mind and look at the state of the country. how does it look?
Negative	**Sentiment** polarity=-0.6999999999999998, subjectivity=0.6666666666666666	Vicki Andrada, BlindNewsGirl, 2018-06-22 03: 27,0,1," ""I fear if # Erdogan realizes by doing it the democratic way is not working," he will go really violent on the Turkish people, worse than he I have already had it .. Perhaps then he'd go too far for Turks," but it's a very scary situation	**Sentiment**: polarity=-0.46875, subjectivity=0.8	No trolls! It is no? Peace, theft, contradiction with Allah
Neutral	Sentiment (polarity=0.0, subjectivity=0.0)	Helmi Deris, helmi_deris, 2018-06-22 03: 37,0,0," ""In Turkey's pious heartland"," faith in Erdogan trumps economy worries - World | The Star Online	**Sentiment:** polarity=0.0, subjectivity=0.0	The AKP lie beneath the party feet that it enlists.
Sentimental Polarity Percentage				

6 Analysis and Discussion

The actual Turkey Presidential results are shown in Fig. 14. It indicates that candidate 1 received 53.3% from the overall election votes. In contrast, candidate 2 received 30.4% of the total electoral votes. As shown in Table 3, the proposed sentiment analysis model was successful in predicting the final results of the presidential election votes. This model predicted that candidate 1 has positive support from the community with 48% of the predicted twitter votes. When the actual voting result was received during the election period, it shows that there is 9.94% accuracy. Nowadays, social media plays an essential role in sentiment analysis, mainly if it is used in predicted votes before running the actual election results [12, 13]. This proposed model can also be useful for politicians, especially if they need to understand their followers and supporters. As shown in Table 4, the word cloud has a critical impact, in collecting the negative sentiments from the community and visualize them. By doing so, the voters can have a useful resource from these data to improve their proposed strategy seeking more supporters. On another hand, this model can be used in several cases, such as to study the activities of the elector's followers on social media to understand their thought, opinion, and subjectivity.

7 Conclusion and Future Work

In this research, a systematic sentimental analysis of collected tweets towards predicting presidential election results was introduced. The data was collected from tweets blogs using Twitter API aggregator. A polarity sentimental analysis and word cloud counts were applied to the collected tweets. Text files were created to compare the tweets. In this context the classification (i.e. Naïve Bayes Classifier) of the tweets was based on three levels; positive, negative and neutral. When the experiment was executed we were able to generate a word cloud for the most repetitive words found in the tweets retriever. The classified data was visualized by the pie chart and word cloud based on the sentiment scores. As future work, the authors would like to develop an in-depth analysis of the emotional behavior for election candidates. Besides we would like to enhance our prediction approach by adapting multiple classifiers and compare the outcome with the real results.

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