# Sentiment Analysis of Arabic Tweets on the Great March of Return using Machine Learning

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**ABSTRACT**

Social media platforms such as Twitter and Facebook are becoming powerful sources of people's perception of major events. Most people use social media to express their views on various issues and events and develop their information on a diverse economic, political, technical, social and occurrences related to their life. The overarching aim of this paper is to apply machine learning techniques to extract Arab users' opinions from 500 Arabic tweets on the Great March of Return rallies in the Gaza strip (Gaza border protests) collected over a two years span from 2018 to 2019. The majority of Sentiment Analysis (SA) studies concentrate on the English language, while other popular languages, such as Arabic, are seldom covered. In addition, on the Internet, publicly accessible Arabic datasets are hardly found. Three Arabic sentiment analysis datasets were used to train and evaluate four machine learning algorithms, namely, Support Vector Machine, Logistic Regression, Decision Tree, and Neural Network. In term of accuracy, logistic regression outperformed the other three algorithms with a percentage of 83%. Application of logistic regression on the sample tweets revealed that 85.8% of the tweets opposed the Great March of Return, whereas 14.2% of the tweets supported it.

**Keywords**: Opinion mining, sentiment analysis, Arabic language, machine learning.

## I INTRODUCTION

The Great March of Return (GMR) rallies (Arabic: مسيرة العودة الكبري) started on the 30th of March, 2018 with a series of demonstrations held on every Friday in the Gaza Strip. This event marked peaceful protests of 40,000-50,000 Palestinian men, women and children at the border fence separating the Gaza Strip from Israel. The purpose of the Great March of Return rallies was to demanded the right of Palestinian refugees to return to cities and villages of origin from which they had been displaced by what is now called Israel (Khoury et al., 2018). They also protested in rejection to the tight blockade imposed on the Gaza Strip by the Israeli occupation. The weekly protests lasted for a year and attracting broad and diverse audiences, including men, women, teenagers, the elderly, civil society leaders, political activists and public figures. However, the GMR activities evolved during the past twelve months to include night-time disruptions along the fence in addition to demonstrations along the Gaza coastline (MSF, 2019). At least 110 Palestinians were shot dead between 30 March to 15 May, 2018 (Sanchez, 2018).

Nowadays, sentiment analysis is gaining special emphasis due to the widespread use of social networks. Sentiment analysis is a natural language processing (NLP) field that attempt to classify and extract opinions within a document. In this respect, the phrases 'study of sentiments; and 'mining of opinions' are quite the same. Whereas the word "opinion" is broader in use than the word "sentiment," yet the two words have been used interchangeably by prior researchers. When evaluating opinions and sentiments, an audience's views and beliefs are tracked on the web to assess whether the audience perceives certain ideas or events positively or negatively. The purpose of this evaluation is intended to help companies and other concerned entities to define the various methods to enhance the quality of their goods.

With more users sharing more information across various platforms, the popularity of social media has expanded exponentially. This vast wealth of data offers unique opportunities for data mining professionals. Currently, there are over 2.50 billion active Facebook users worldwide and more than 300 million active twitter users (Clement, 2020). Fig. 1 shows the social networks users in April 2020 (in millions). Furthermore, Figure 2 shows a timeline with the number of monetizable daily active Twitter users worldwide as of the second quarter of 2020.

The political sphere and the identification of people's views and attitudes towards ongoing political activities are one of the most important areas of opinion mining. In this regard, one of the advantages of analysing political opinions is that it does not require much time and effort, and it returns acceptable results. Therefore, an experiment was designed to evaluate Arabs' opinions on the Great March of Return rallies using simple models. It is worth remembering that Arabic is one of the world's most significant languages and is used by more than 290 million people every day (UNESCO, 2012). In

this paper, four supervised learning algorithms were trained using three sentiment analysis Arabic tweet datasets. Then, the four algorithms were evaluated in terms of accuracy. Finally, the algorithm with the highest accuracy was used to predict opinion mining of Arab people on the Great March of Return rallies in the Gaza strip. The Arabic tweets were collected using social media APIs and were then preprocessed and prepared to train the most accurate algorithm.

The rest of this paper is organized as follows: Section 2 reviews some opinion mining techniques. Section 3 explains the methodology, section 4 demonstrates the experiments and results, and the conclusion is presented in Section 5.

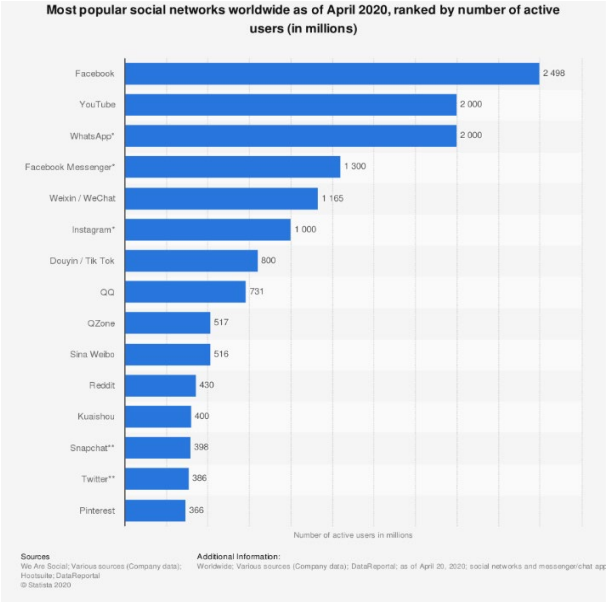


**Figure 1. Social Networks as of April 2020 (in millions) (Clement, 2020)**

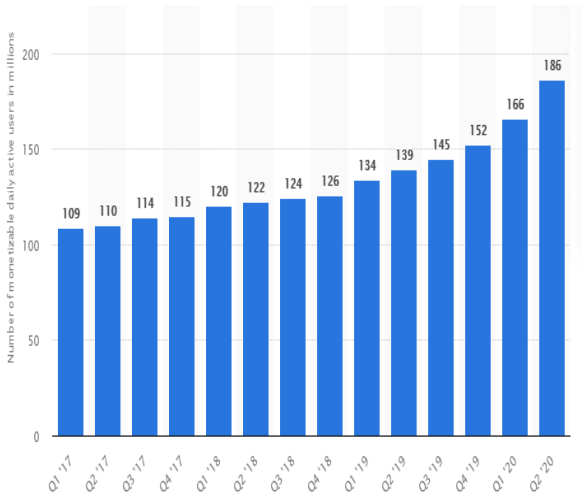


**Figure 2. Number of Daily Active Twitter Users 2017-2020 (in millions) (Clement, 2020)**

## II RELATED WORKS

The related works are divided into three categories which are, sentiment analysis on Arabic tweets, sentiment analysis on English tweets and analyze reactions on social media about Palestinian and Israel conflict. The works achieved by classifying opinions about Arabic tweets were based on opinion mining approaches such as machine learning, semantic orientation and deep learning. A classification model was proposed by Pak & Paroubek (2010) to identify tweets as objective, positive and negative. They created an Arabic Twitter corpus by gathering tweets using the Twitter API and by automatically annotating those tweets. Using that corpus, they created a sentiment classifier that uses features like n-gram and POS-tags, based on the multinomial Naive Bayes (NB). Rushdi Saleh et al. (2011) used Support Vector Machines (SVM) method to train systems for testing different domains of data sets with numerous features. Also, the SVM-based framework was designed for subjectivity and emotion analysis for Arabic social media genres (Abdul-Mageed et al., 2012) for both Modern Standard Arabic and dialectal Arabic. The results indicated that solutions for each domain and task should be created. In addition, Omar et al. (2013) used an ensemble of machine learning classifiers; NB, SVM, and Rocchio classifiers to deal with the sentiment analysis of Arabic customer reviews. They found that NB algorithm outperformed the other algorithms on the basis of comparing the efficiency of the algorithms. The work of Duwairi et al. (2014) utilized three machine learning classifiers, namely, SVM, NB, and k-nearest classifier (KNN). The corpus encompassed data in Modern Standard Arabic. The best performance of NB was achieved when no filtering of stop words and no stemming were used. Moreover, an Arabic lexicon stored on the device was given by Badaro et al. (2015). The text is stemmed at first, and then the words are compared to their own existing ArSenL. In this respect, ArSenL is the first large-scale Standard Arabic sentiment lexicon available to the public (ArSenL). On a published collection of Arabic tweets, the method was tested, and an average accuracy of 67 percent was achieved. Recently, in order to predict the feeling of Arabic tweets, Heikal et al. (2018) implemented an ensemble model by integrating Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models. More recently, Al Omari et al. (2019) suggested a logistic regression method combined with the term frequency and inverse document frequency

(TF*IDF) for the Arabic evaluation arrangement in the Lebanon nation for administrative reviews. Their model was biased in predicting adverse sentiment reviews. In addition to that, we discuss the sentimental analysis related works on English language based on opinion mining approaches. As an example, Alrehili & Albalawi (2019) used a sentiment classification model to classify customer reviews using ensemble voting method which combined NB, SVM, random forest (RF), Bagging and Boosting. Moreover, there are subject related works that aims to analyze reactions on social media about a specific issue. As for Palestinians, social media is used as a tool to allow them to express their voice and opinion (Siapera, 2014). Since Palestinians people don't have their cultural and sociality equality. And the work of Siapera et al. (2015) explore the "proliferation of Palestine content in online spaces," which they claim has kept Palestine's "memory and current issues alive" in the global arena since the Gaza War of 2014. Both studies illustrate the extensive role of digital media in the Israel-Gaza conflict, which can be incorporated into a larger theoretical context on the 'mediatisation' process. Deegan et al. (2018) discussed in his paper how to use twitter as a tool to represent the conflict between Palestine and Israel and how much the Palestinian side suffers.

As far as the Palestinian-Israeli problem is concerned, very few studies have exploited the content of social media to catch trends or patterns relevant to the ongoing conflict (Siapera 2014, Siapera et al. 2015, Deegan et al. 2018). However, these studies focused on systematic statistical reviews, rather than on data mining or sentiment analysis. In our work, we use text mining techniques including some machine learning classifiers to predict the opinions of Arab people on the Great March of Return rallies in the Gaza strip during their trending on Twitter.

## III METHODOLOGY

This section discusses people's opinions on "The Great March of Return" using "#مسيرة_العودة_الكبرى" twitter hashtag. Our framework consists of three main steps: data collection, preprocessing of the collected data and classifying the analyzed data into either positive or negative data. Fig. 3 demonstrates the basic overview of sentiment analysis framework.

### A. Dataset for Training

To conduct our experiments, three sentiment analysis Arabic datasets (predefined data), as shown in Table 1 were used to train four machine learning algorithms. The first dataset is AJGT, which is Arabic Jordanian General Tweets Corpus consisted of 1,800 tweets annotated as positive and negative (Dahou et al., 2019). The second dataset is ASTD, which is Arabic Sentiment Tweets Dataset from (Dahou et al., 2019). The third dataset is Twitter, using a tweet crawler, 2000 classified tweets were used on various topics such as politics and arts (1000 positive tweets and 1000 negative ones). These tweets contained opinions written in both Modern Standard Arabic (MSA) and the dialect of Jordan (Abdulla et al., 2013).

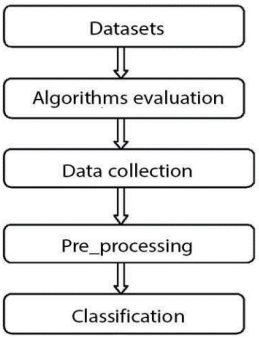


**Figure 3. The Proposed Sentiment Analysis Framework**

**Table 1. Sentiment Analysis Arabic Datasets**

| Name | Positive | Negative | Total |
|---|---|---|---|
| **AJGT** | 900 | 900 | 1800 |
| **ASTD** | 799 | 1684 | 2483 |
| **Twitter** | 1000 | 1000 | 2000 |

### B. Machine Learning Classifiers

Machine Learning (ML) systems are categorized into three different types: supervised, unsupervised, and semi-supervised learning which combines supervised and unsupervised methods (Almunirawi & Maghari, 2016). Text classification is often performed using supervised machine learning algorithms due to the large number of labeled text datasets. The four used supervised classifiers are described as follows:

*Artificial Neural Networks (ANN).* ANN are a representation of a network of interconnected "neurons" that can use an objective function to calculate a set of values as inputs to generate the desired output (Irsoy & Cardie, 2014).

*Decision Tree (DT).* DT begins by selecting a feature as a root node, and then generates a leaf for each possible level of that feature (Trstenjak et al., 2014), (Zoroub & Maghari, 2017).

*Logistic Regression* (LR). LR is one of linear binary classification methods. It depends on the probability that the object belongs to a particular class (Firyulina & Kashirina, 2020). LR performs a statistical analysis to test for associations, or relationships, between variables. LR is a predictive analysis where the model

is tested to find out whether the value of one or multiple variables, can predict the value of another variable (Frey, 2018).

*Support Vector Machine (SVM).* SVM is a supervised algorithm for machine learning. It builds a hyper plan in the training process of opinion mining in which it divides positive emotions with a maximum margin from negative feelings. It classifies reviews according to their position in the built hyper plan during the test process (Andrew, 2001).

### C. Classifiers Evaluation

Three Arabic opinion datasets were used to train the four machine learning algorithms (classifiers) which are SVM, LR, DT, and ANN. The algorithms were evaluated in terms of accuracy. Then, the classifier with the highest accuracy score was used to predict opinion mining of Arab people on the Great March of Return rallies in the Gaza strip.

### D. Data Collection

For data collection, a python code was used to collect data for the hashtag "#مسيرة_العودة_الكبرى" (#The Great March of Return). We collected approximately 500 tweets which were stored individually in a text file. Then, these files were assembled in one folder to be used later in classification. Table 2 shows a sample of the collected tweets. It is worth noting that these 500 tweets constituted all the possible tweets that were available for us to collect.

**Table 1. Sample for the Collected Tweets and their English Translations**

| |
|---|
| هذه المحتلة، وهؤلاء هم أبنائها من ملح الأرض هم، من وجع السنين انتفضوا، لسان حالهم الله معنا وقسما بالله إنا لعائدو |
| This is the occupied (land) and these are its children emerging from the salt of Earth, uprising from the agony of the years, feeling the solidarity of God, and swearing by God: We will return. |
| وات لمسيرات مليونية زاحفة نحو الحدود الشرقية على طول قطاع غزة يوم مايو ضمن مسيرات العودة وكسر الحصار |
| Calls for rallies towards the Eastern borders along the Gaza Strip on May 15 within the Great March of Return rallies and breaking the siege. |
| لوحة فنية في مخيم العودة شرق جباليا شمال قطاع غزة اليوم |
| An artistic portrait painting at the Return Camp east of Jabalia in the northern Gaza Strip today. |

### E. Data Preprocessing

Appropriate preprocessing steps helps to improve the opinion mining process and get logical and satisfactory results (Maghari & Zendah, 2019). It can enhance the data quality and improve the classification accuracy (Alhaj & Maghari, 2017). The pre-processing steps used in our experiments are as follows:

*Filtering*. Repeated letters in phrases such as "أيااا" have also been used to illustrate the depth of speech. In the dictionary, however, these words are missing, so the extra letters in the word have been omitted. Figure 4 below shows an instance of such words.

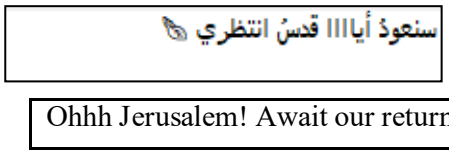


**Figure 4. Example of Filtering from Tweets**

*Question words.* Words like "كيف" ,"ماذا" do not contribute to polarity and, thus, they were removed. Figure 5 shows an example of question words.

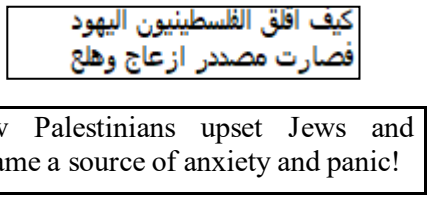


**Figure 5. Example of Questions from Tweets**

*Removing special characters.* Special characters like '[] {} 0/' were also removed. Figure 6 shows an example of tweet containing "/".

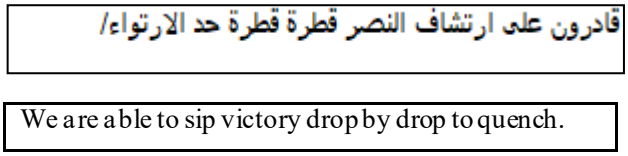


**Figure 6. Example of Special Characters from Tweets**

*Removing Stop words and emoticon*. In order to continue with the SA system, stop words should be omitted. These include determiners and prepositions (في, الى, من) and thus were filtered. Examples of Arabic stop words and tweets with emotions are shown in Figures 7 and 8 respectively.

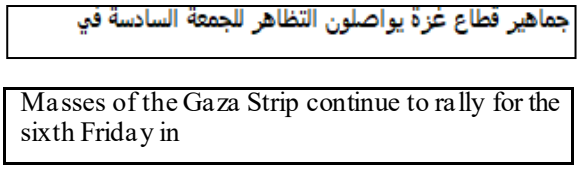


**Figure 7. Example of Stop Word from Tweets**

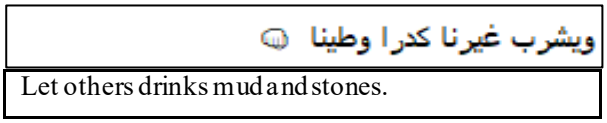


**Figure 8. Example of Emotion from Tweets**

*Stemming.* Stemming tends to reduce a word to a popular base form in inflectional and related types, such as (أحبُ,يحب,يحبون,أحبو,تحب).

*Tokenization.* Tokenization refers to the division of the sentence into its desired component elements. In all NLP activities, it is an essential step.

*Feature extraction.* Bag Of Word (BOW) is used for text representation. It presents the word in fixed-length, but it ignores the order of words and the grammatical structure. We also considered the TF-IDF (Term Frequency - Inverse Document Frequency), which is a popular term weighting method for feature selection (Saad & Ashour, 2010).

### F. Classification

In this phase, the algorithm (classifier) with the highest accuracy score was used to predict opinion mining of Arab people on the Great March of Return rallies in the Gaza strip. The classifier was applied on the preprocessed tweets to see the opinion.

## IV RESULTS & DISCUSSION

We used four different algorithms to train three different datasets and to build a model. All the training data stored in the folders (AJGT, ASTD, Twitter) were gathered in a new folder. Then, the four algorithms were simultaneously applied on the three sentiment analysis datasets. Table 3 to Table 6 show the accuracy, recall, precision, and F1-Measure values for the four classifiers.

### A. Classifiers Evaluation Results

Table 3 represents the results of applying machine learning classifiers on sentiment analysis Arabic datasets. It shows that the Neural Network classifier gave an F1-Measure values of 0.82% and 74% for negative and positive tweets respectively with an average value of 78.0%. The classification accuracy was 79.0% which is considered a good value.

**Table 2. Classification Report Neural Network [MLP]**

| | Precision | Recall | F1-Measure | Accuracy |
|---|---|---|---|---|
| **Negative** | 0.77 | 0.89 | 0.82 | |
| **Positive** | 0.84 | 0.66 | 0.74 | |
| **Avgerage** | 0.80 | 0.78 | 0.78 | |
| **Accuracy** | 0.79 | | | |

Table 4 represents the results of applying Decision Tree classifier on the Arabic datasets. It shows that Decision Tree classifier gave accuracy value of (73.0%) and an average F1-Measure of (71.0%).

**Table 3. Classification Report Decision Tree**

| | Precision | Recall | F1- Measure |
|---|---|---|---|
| **Negative** | 0.76 | 0.75 | 0.75 |
| **Positive** | 0.70 | 0.71 | 0.70 |
| **Avgerage** | 0.71 | 0.71 | 0.71 |
| **Accuracy** | 0.73 | | |

Table 5 represents the results of applying Logistic Regression classifier on the Arabic datasets. As shown, Logistic Regression Classifier achieved the best accuracy and average F1-Measure values of (83.0%) and (82.0%) respectively. Logistic Regression also returned the best average recall (82.0%).

**Table 4. Classification Report Logistic Regression**

| | Precision | Recall | F1- Measure |
|---|---|---|---|
| **Negative** | 0.79 | 0.94 | 0.86 |
| **Positive** | 0.90 | 0.70 | 0.79 |
| **Avgerage** | 0.85 | 0.82 | 0.82 |
| **Accuracy** | 0.83 | | |

Table 6 represents the results of applying Support Vector Machine classifier on the Arabic datasets. It shows that SVM gave an accuracy value of (82.0%) and an average F1-Measure values of 81.0%, which are considered very good results and came second in rank compared to the other three classifiers.

**Table 5. Classification Report Support Vector Machine (SVM)**

| | Precision | Recall | F1- Measure |
|---|---|---|---|
| **Negative** | 0.79 | 0.93 | 0.86 |
| **Positive** | 0.88 | 0.68 | 0.77 |
| **Avgerage** | 0.84 | 0.80 | 0.81 |
| **Accuracy** | 0.82 | | |

Based on the previous results, Logistic Regression achieved the best score to the predefined data. Therefore, logistic regression was applied on the collected tweets of the hashtag (#The Great March of Return) for opinion mining on GMR rallies. Dreiseitl and Ohno-Machado urged that logistic regression has lower generalization error than decision tree classifier. It also easier to build than SVM (Dreiseitl & Ohno-Machado, 2002). Bolbol & Maghari (2020) also applied some ML classifiers on Arabic tweet datasets and found that LR outperformed other classifiers as DT.

### B. Opinion Mining Results on GMR

Logistic Regression classifier was applied on the 500 tweets collected from twitter using the "#مسيرة_العودة_الكبرى" (#The Great March of Return) hashtag. A large difference was found in the results of sentiment analysis of twitter data. The classification results showed that only 71 tweets out of the 500 tweets were positive (with 14.2%), and 429 tweets were negative (with 85.8%). Overall, the number of the negative tweets was greater than that of the positive tweets.

## V CONCLUSION AND FUTURE WORK

This paper aimed to introduce a simple approach for Sentiment Analysis through extracting opinions from Arabic tweets using machine learning. We used three sentiment analysis Arabic datasets to train and

evaluate four machine learning algorithms. The best accuracy achieved was 83% by using Logistic Regression. Application of logistic regression on the sample tweets revealed that 85.8% of the tweets opposed the Great March of Return, whereas 14.2% of the tweets supported it. In future, we will use CNN architecture in order to improve the results and enhance the classification performance. We can check the model over other datasets that are larger than ASTD, AJGT and Twitter, which were used primarily to equate our findings with the Arabic-language deep learning model.

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