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# Turkish Sentiment Analysis on Social Media

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## Abstract

The number of social media users has increased significantly as internet access and internet usage has grown all over the world. As it is the case in any other field, raw data collected from social media platforms are now being transformed into information. Millions of pieces of content are posted every day on platforms such as Twitter, Facebook, and Instagram. Moreover, the ability to extract meaningful information from such content has become an important field of research. This study reports a system for sentiment analysis, based on the data made available on Facebook, Twitter, Instagram, YouTube along with RSS data. Logistic Regression, Random Forest and deep learning algorithm such as Long Short-Term Memory (LSTM) are used to develop the classification model used in the system built as part of this study. Dataset is a new dataset that included data collected from Twitter, used was created and labeled by us. It was found that LSTM model provided the highest accuracy among the models generated using the training dataset. The final version of the model was tested on five different social media platforms and results are communicated.

**Keywords:** Artificial Neural Network, Turkish Natural Language Processing, Social Media Analysis, Sentiment Analysis

## 1. INTRODUCTION

In our modern world, global internet usage has grown rapidly, making it an indispensable part of our daily lives. According to 2018 statistics, 79 of the internet users are also actively using social media [1]. The fact that the number of internet users, and therefore social media users has grown so drastically make it necessary for the academia to conduct sentiment analysis, relationship analysis, etc. on social media. Contents shared on social media platforms, communicating users' ideas and opinions, show distinctive characteristics. Therefore, these contents need to be transformed using natural language processing methods if we want to process them. Literature

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review showed that Twitter is the go-to social media platform for social media analysis. Literature review further showed that natural language processing (NLP) is used for analyses performed in order to identify questions [2], to calculate ratings [3], to track stock exchange trends [4], and to define side effects of pharmaceuticals [5]. The main purpose of sentiment analysis is to explore individuals' moods, behaviors and ideas using textual documents [6]. With the increasing number of social media users today, there is an abundance of texts including ideas which calls for studies on sentiment analysis. In [7], used tweets classified under 4 categories. Authors developed separate Word2Vec models using product sum method. In their study, authors first classified 4 categories (Banking, Football, Retail, Telecom) based on their positive and negative characteristics; then, they reclassified the combined data, again based on their positive and negative characteristics. Authors used Random Forest and SVM classification algorithms. The results of the study showed that the classification based on the cumulative dataset offered more accurate results when compared to the results obtained using separate categories. Moreover, it was found that the Word2Vec model with sum symbol offers better results when compared to the Word2Vec model with product symbol. In [8], analyzed the tweets obtained from Twitter API. Authors defined the features based on BoW (Bag of Words) model and N-gram model at the character level from the tweets collected. The features obtained were then reduced using CfsSubset algorithm and the most useful ones were selected. Boolean, TF and TF-IDF were used to define the weights of the features obtained. Among the classification algorithms, SVM, Naive Bayes, KNN (K Nearest Neighbour) and Multinominal Naive Bayes were used. It was found that, among these algorithms, Multinominal Naive Bayes resulted in the highest success rate with 66.06%. It was further found that, in the feature extraction process, N-gram model gives better results when compared to BoW model. In [9], extracted features from the dataset obtained from Twitter API using n-gram model. Author extracted seven different N-gram features at the word level, namely 1-gram and 2-gram, 1-gram and 3-gram, 2-gram and 3- gram, 1-gram - 2-gram - 3-gram, 1-gram, 2-gram, 3-gram. SVM, Naive Bayes and Logistic Regression classification algorithms were used. Assessment of the study results showed that the highest accuracy was obtained from the dataset which combines 1-gram and 2-gram features using Naive Bayes algorithm with a 77.78% success rate. In [10], collected data from the Twitter API for 9 different categories. Authors used word-based method and N-gram model for the feature extraction from the dataset. Firstly, authors classified the dataset for 9 categories based on positive, negative and neutral characteristics and then reclassified the whole dataset based on positive, negative and neutral characteristics. According to the results of the study, the highest success rate, 89.5%, was obtained using Random Forest Algorithm as part of Word-based methods, while the success rate of the n-gram method for field-specific classification using SVM algorithm was found to be 90%. However, the same level of success couldn't be obtained using field independent methods. In [11], explored supervised and unsupervised term weighting methods for tweets posted in Turkish language. Authors weighted the features obtained using n-gram and word-based method with the help of six different weighting equations –which are commonly used in the literature– and the traditional TF and TF-IDF methods. Naive Bayes, SVM, Decision Tree (J48), Random Forest and 1 k-nearest neighbours algorithm were used in the study. Authors observed that supervised term weighting methods consistently yield more successful results. Nevertheless, it was noted that N-gram model is more successful than the word-based method. In [12], developed a system to automatically tag tweets –posted in Turkish– as positive, negative and neutral. Using both the positive and negative words in tweets based on a dictionary generated as part of the study, and based on 2-grams, 3-grams, and 4-grams, authors tested the tagging success rate of the system. Analyses showed that the system yields the highest success rate using the dictionary-based method. Moreover, it was found that, among the n-gram models used, 3-grams yield more accurate results when compared to the others. In [13], explored the political involvement of Twitter users based on tweets posted in Turkish. Focusing on the tweets posted with regards to 2013 Gezi Park protests, authors first divided the dataset into two, namely objective/nonobjective and neutral; and then divided the objective/non-objective group into pro-protest and anti-protest categories. After creating a tweet-word matrix using the tweet dataset, authors classified the most effective features using chi-square test. According to the results of the study, it was found that SVM had the best performance in the first stage of classification with k=100, while Random Forest algorithm had the best performance in the second stage of classification as k-value did not have a significance in this stage. In [14], collected data from book reviews, movie reviews and shopping reviews posted by Turkish users and analyzed the collected data. Authors developed a multi-classifier system in the classification process. SVM and Naive Bayes algorithms were run with several ensemble methods and it was possible to achieve levels of accuracy up to 86.1 In [15], created a dataset of shopping and film reviews. They studied positive, negative sentiment analysis on this dataset. After preprocessing step, features were extracted from the data set with TF-IDF method and used in Naive Bayes and Logistic Regression Algorithms. In addition to these two machine learning algorithms, a specialized RNN architecture; LSTM, was used. For the LSTM word embedding method used. During the training of the LSTM model, different combinations of learning ratio, loss function, LSTM layer count, LSTM units number, batch size and optimizer parameters were tested. In total, over 10 hours of training, the LSTM model for positive-negative labels achieved success of 83.3% and resulting in a more acceptable result than the LR and NB algorithms. In [16], worked on 6 different datasets. The main aim of the study is to examine the success of different segmentation methods on classification. For this reason, after the data were divided into sentences using Zemberek library, used a total of 13 different segmentation methods on sentences. In the study, it was argued that the areas containing more than one sentence were reduced to a single sentence and that giving one sentence as an introduction to the model was more accurate in terms of emotion analysis. The features, obtained after the applied segmentation process were classified by LSTM. The results show that BPE-5k segmentation method is the most appropriate segmentation method in terms of accuracy and performance. In this study, a model which is able to perform sentiment analysis (positive, negative and neutral) was developed using the data collected from Twitter. This model was then assessed for its performance on Facebook, Twitter, Instagram, YouTube platforms and RSS data. In addition to BagofWords and TF-IDF methods, word indexing method was used in the term weighting process. As an feature extraction method which offered high performance in English [17], but failed to match that performance in Turkish [10,11], word indexing method was used in the system which was developed for Turkish, a language known with its challenging structure. The features extracted using the aforementioned method were then modeled using Logistic Regression, Random Forest and LSTM classification algorithms and the highest success rate was obtained from LSTM model at 84.46%. The data set used in the study; It is a unique data set that contains 3 tags that we label positive, negative and neutral. While using the data collected through Twitter for training the model; The model is used for 5 different social media platforms: Twitter, Instagram, Youtube, RSS and Facebook. Supported with the high success rate obtained in this study, the model was used for sentiment prediction on a large social media analysis interface. Logged into this system, users were able to correct any erroneous tags. After being corrected, these tags were saved on a MySQL database in order to be added to the dataset. The model automatically updated daily with the new data.

## 2. MATERIAL AND METHODS

### 2.1. Dataset

Data was collected from five social media platforms using their APIs in order to be used as an input in the system developed. In the first stage, only the data obtained from Twitter was used for the training of the system as the data tagging is a time-consuming process. A total of 28189 data were tagged by the specialist. Dataset included 5712 positive, 11567 negative, and

11247 neutrals tweets. The data set is divided into 30% test and 70% training data.

### 2.2. Data Pre-Processing

As the data obtained from social media represents an individual idea of a user or a group, such data do not follow a certain pattern or rule. Data obtained from social media include abbreviations (internet slang), emoji's (i.e., pictorial icons that generally display a sentiment) and web links (URL), etc. Thus, a number of data preprocessing steps are used in order to have the social media data ready for processing. In this study, the following data preprocessing steps were taken: – Usernames starting with @ symbol (mention) were removed. – Statements starting with # symbol (hashtag) were removed. – Numerical terms were removed. – Repeated letters were removed. – URLs (https:/, www, etc.) were removed. – Punctuation marks (".", ",", ,"'", etc.) were removed. – All the uppercase letters were turned into lowercase letters. Following the preprocessing, all the remaining words were reduced to their root words using Zemberek Library [19]. Finally, data obtained were subjected to numeric vectorization.

### 2.3. Word Representation

After preprocessing, data need to be transformed into numeric data in order to be processed in the classification stage. Vector representation of words was first used by Bengio et al. [19]. This method allows for integer representation of words and word groups [21]. Literature offers several methods developed for this purpose. Among the methods explored for this study were BagofWords, TF-IDF and Word Indexing.

### 2.4. Bag of Words (BoW)

A text is represented as the words it includes (n-gram) [20]. N-gram modeling is a segment of the character string which includes n characters [21]. In the BoW model, each word available in a text is considered to be a property, while the frequency of such word is the value of this property. Moreover, it is assumed that the order of words in a text has no statistical significance [23]. According to BoW model, words are represented as unigram and bigram n-gram series. Term weights, on the other hand, were used separately with binary methods. In the binary method, an n-gram takes the value of 1 if it exists in the text, and it takes the value of 0 if it doesn't exist in the text.

### 2.5. Term Frequency - Inverse Document Frequency (TF-IDF)

TF-IDF is a weighting method based on the term frequency multiplied by inverse document frequency. This value is obtained following Equation (1), as follows:

$$tf * idf = \frac{f_{(t,d)}}{N} * log\ log\ (\frac{N}{1+n_t}) \tag{1}$$

Here; t represents the relevant n-gram term, d represents the relevant text, $f_{(t,d)}$ represents the term frequency of n-grams in the text, N represents the total number of words in the document, $n_t$ represents how many different documents the term t (n-grams) occurs in [21].

### 2.6. N-Gram Modelling

N-gram modeling is one of the most commonly used methods in document classification. N-gram is a segment of the character string which includes n characters [9]. 1-gram, 2-gram, 3-gram representations at the word level are given below for the sentence, "Bug¨un hava ¸cok g¨uzel" (The weather is very nice today).

– 1-gram model: "Bugün" , "hava", "¸cok" , "güzel".

– 2-gram model: "Bugün hava", "hava ¸cok", "¸cok güzel"

– 3-gram model: "Bugün hava ¸cok", "hava ¸cok güzel"

### 2.7. Creating a Word-Sentence Matrix Using Indexing Method

A corpus was generated using all the data as part of the word indexing method. In this corpus, each unique word was represented with an integer.

Thus, a wordsentence matrix was created for each tweet. Then, a word-sentence matrix is created for each test data based on the sequence of the words available in the corpus. In the feature extraction stage, a total of 5 datasets were created. These datasets are shown in Table 1.

Table 1 Datasets

| Dataset | Method | N-Gram |
|---|---|---|
| Dataset 1 | TF-IDF | Unigram/bigram(1-2–gram) |
| Dataset 2 | BoW | Unigram/bigram(1-2–gram) |
| Dataset 3 | Word Indexing | Unigram (1-gram) |

## 2.8. The Used Libraries

The software for this study was developed using Python programming language. In the development stage, numpy, pandas, keras and scikit-learn libraries were used in addition to Phyton's built-in libraries.

## 2.9. Classification

Several methods were used for different vectors of words for classification as part of this study. Logistic Regression and Random Forest algorithms were used for BoW, TF-IDF and Indexing methods, while LSTM (Long Short Term Memory) deep learning algorithms, were also used for Indexing method.

## 2.10. Multinomial Logistic Regression (MLR)

Multinomial Logistic Regression (MLR) is a machine learning algorithm commonly used for the classification of feature vector belonging to a class among a number of possible classes. A function set is created from the feature vector, and each function stands for the probability of a feature vector to belong to a certain class. Parameters to complete these functions are obtained after the training process using the known class tags and feature vector. When these parameters are compared to a new feature vector similar to those compared in the training, Multinomial Logistic Regression is arrange in a way that the new vector has a high probability of belonging to the same class. Multinomial Logistic Regression converts the binary logistic regression procedure into a multi-class format. Each one of the classes has its own parameter vector which is applied to the feature vector in order to define the probability of feature vector [23]. Multinomial Logistic Regression is explained in Equation (2):

$$P(x_i, w) = \frac{exp\,(w^{(k)}h(x_i))}{\sum_{k=1}^{K} exp\,(w^{(k)}h(x_i))} \qquad (2)$$

Here, h(x) is the vector of constant functions of input, $w^{(k)}$ is logistic regression with K-means clustering (aka. feature vector) and $w = [w^{(1)^T}, \ldots, w^{(K-1)^T}]^T$. It equals zero w(k) = 0, when the density does not depend on w(k) regressors [24].

## 2.11. Random Forest Classifier

Random Forest Classifier is one of the most successful crowd learning techniques used in pattern recognition and machine learning, and it is commonly used for large-scale classification and skewness problems. Random Forest Algorithm is a system consisting of multiple decision trees [19]. Among its disadvantages related to the tree classifier is its inherently high variability. In practice, it is common that training dataset would lead to a whole different tree with the smallest of change. The reason behind this is the fact that tree classifiers have a hierarchical background. If an error occurs at a node closer to the root of the tree, then it disperses up to the farthest parts of the leaves. A decision forest methodology was developed with the purpose of stabilizing the tree classification. This methodology was first suggested by Ho [26], Amit & Geman [27] and later on by Breiman [28] in an integrated manner (as "random forest"). In Random Forest, each decision tree makes its own decision and the class with the majority vote in the decision forest is deemed as the decision class [21]. All the new data added to the classification are classified by each tree in the forest. Thus, each tree offers a classification result. As a rule, decision forest would select the classification with the majority vote of the trees in the forest. Random forest methodology includes Breiman's "bagging" idea and random selection of features, introduced first by Ho. Refers to bootstrap aggregation, bagging is a type of crowd learning which was developed to improve the accuracy of a poor classifier creating a set of classifiers. If the number of samples in a dataset is N, then approx. 2/3 of the original sample size is randomly selected N times using preloading in order to be used in training. Remaining samples, on the other hand, are assessed "out-of-bag." Out-of-bag set consists of observations which are used for testing and those not selected to build the subtrees [29]. A random forest training is performed for each decision tree. Learning system creates a classifier from the sample and it adds all the classifiers obtained from different tests together in order to create the ultimate classifier. In order to classify a sample, each classifier casts a vote for the class that it belongs to and the sample is tagged as the member of the class with majority vote. In case of multiple classes with majority vote, one of them is selected randomly [29].

## 2.12. Recurrent Neural Networks (RNN)

Recurrent Neural Network (RNN) is an artificial neural network model which can utilize long sequences of inputs which is not possible with any other neural network [17]. RNN is especially preferable in Natural Language Processing (NLP) as it offers sequence processing abilities [32]. Basically, RNN learns also taking old data into account. However, such training is not possible due to gradient loss/exploding gradients during the training which is also considered a long-term dependency [17]. The RNN architecture shown in Figure 1 makes use of basic sequential information. In a classic neural network, all the inputs and outputs are assumed to be independent. The term "recurrent" used in RNN as each member of a sequence performs the same task in accordance with the previous outputs [31].

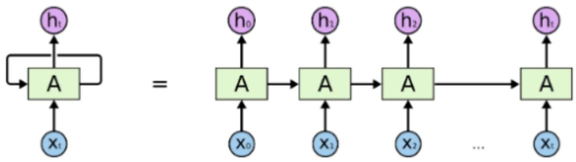

Figure 1 Classic RNN Architecture [22]

## 2.13. Long Short-Term Memory (LSTM)

LSTM models were developed with the aim to eliminate the exploding gradient issue in RNNs. LSTMs include a 'Forget' layer which is not available in recurrent neural network model [32]. The main idea behind LSTM models is to decide whether or not to store the information in the memory. LSTM have a custom architecture as shown in Figure 2.

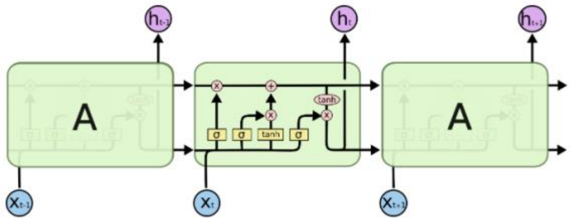

Figure 2 LSTM Model [22]

Memories, aka. cells, available in LSTM decide which information will be stored and which will not be stored. Following this decision, the model combines previous state output, current memory information and current input in a smart way to produce instant state output of the cell [17]. In the developed system, softmax activation function is used in all layers. In the model, "adam" optimization was used and 20 epochs were run.

# 3. EXPERIMENTAL RESULTS

Dataset obtained for this study was first vectorized separately using BoW, TF-IDF and Word Indexing and then tested using five different classifiers. Table 2 shows the classification success rates.

Table 2 Classification Success Rates

| **Dataset/Algorithm** | **Precesion** | **Recall** | **F1-Score** | **Accuracy** |
|---|---|---|---|---|
| Dataset1/ MLR | 0.85 | 0.81 | 0.82 | 83.07 |
| Dataset1/ RF | 0.86 | 0.83 | 0.84 | 84.24 |
| Dataset2/ MLR | 0.82 | 0.79 | 0.80 | 80.91 |
| Dataset2/ RF | 0.85 | 0.83 | 0.84 | 83.93 |
| Dataset3 /LSTM | 0.84 | 0.84 | 0.84 | **84.46** |

According to Table 2, it is seen that Multinominal Logistic Regression algorithm shows less success on Dataset-1 and Dataset-2 than Random Forest algorithm. In addition, it was observed that the highest success on the created data sets was the LSTM model on the set created with the indexing method. The confusion matrices obtained as a result of the data sets created and the algorithms used are given in Figure 3.

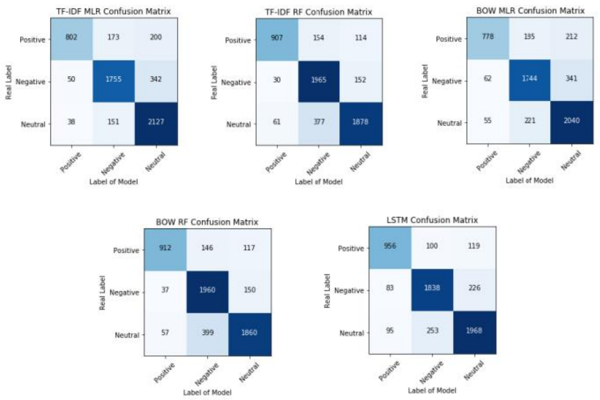


Figure 3 Confusion Matrixes of Models

Analysis results showed that LSTM model which uses indexing method gave the highest accuracy. Following this procedure, the classification model which was trained using Twitter data was tested for Twitter, Instagram, YouTube, Facebook and RSS.

## 4. SYSTEM

LSTM model trained with Twitter data and the corpus generated with these data were used as output in order to be used for 5 different social media platforms. Figure 4 shows how the model was applied to the system.

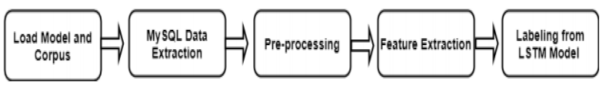


Figure 4 System Model

After the model and the corpus, as output of the previously trained system, were uploaded to the system, data were collected from 5 different tables available in MySQL database. The data were then subjected to the pre-processing steps as defined in Section 2.2. The processed data were digitized using the indexing method as defined in Section 2.3. Finally, digitized data were tested in the model and tags were extracted; then the database was updated using these tags. Figure 5 shows the change in users' moods based on weekly data extracted from YouTube with regards to a selected subject. The graphic shows 6 negative and 1 positive results out of 50 different posts from January 3rd, 2019. Remaining contents were neutral. Neutral contents were not represented in the graphic as they are insignificant for the system. The same applies to Figures 6, 7, 8 and 9.

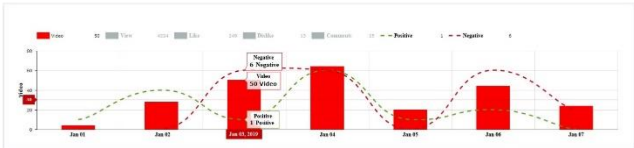

Figure 5 Weekly mood graphic based on a subject selected for YouTube

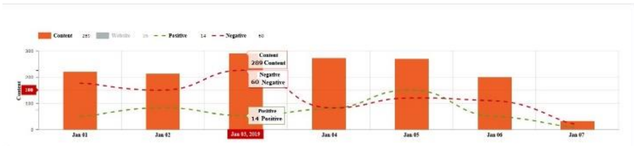

Figure 6 Weekly mood graphic based on a subject selected for RSS

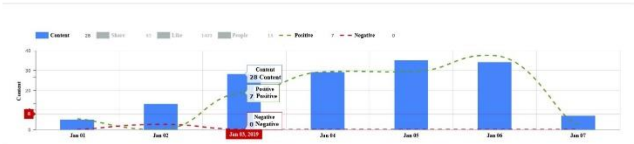

Figure 7 Weekly mood graphic based on a subject selected for Facebook

Figure 8 Weekly mood graphic based on a subject selected for Instagram

Figure 9 Weekly mood graphic based on a subject selected for Twitter

## 5. CONCLUSION

Natural language processing in Turkish is considered a challenge given the complex structure of this language. This challenge doubles when the study focuses on a person's or a group's ideas as in sentiment analysis. Nevertheless, the fact that the use of proper language is no longer the main concern, as reported by studies on social media, brings about a number of problems. Complex nature of social media data, irregularities such as the use of abbreviations, emojis, URLs, and adding emphasis with the use of more than necessary letters require the data to be pre-processed. As a result of the analysis, the highest result was obtained from the LSTM model with a success rate of 84.46%. It is seen that the LSTM model chosen to be used for the developed system has achieved a very high rate compared to the studies in the literature. However, among the other algorithms used, it was observed that the Random Forest algorithm on Dataset 1 and Dataset 2 achieved a higher rate than the Multinominal Logistic Regression algorithm. When confusion matrixes (Fig 3) is examined, it is seen that the data with neutral labels are classified more accurately compared to the other two labels. However, positive data could be labeled with less success than the other two labels. The reason for this is thought to be the low rate of positive labeled data in the total dataset. In the following periods, studies will be continued by expanding the dataset. In addition, the same number of data from each label class will be studied so that inconsistencies between data labels do not negatively affect the model. Due to short data processing times and high success rates, LSTM model was selected to be used in combination with the system developed. Users can edit the wrong tags on the interface and save them, with the developed system. After the saved edits, the model is used in the update step. LSTM model is used by retraining with daily data.

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***The Declaration of Conflict of Interest/ Common Interest***

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

***Authors' Contribution***

The authors contributed equally to the study.

***The Declaration of Ethics Committee Approval***

This study 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.

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