Twitter'da Müşteri Görüşlerini Analiz Ederek Türkiye'deki Telekom Operatörlerine İlişkin Müşteri Memnuniyetinin Değerlendirilmesi

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**Özet**

Duygu analizi, bir yazının olumlu, olumsuz veya nötr olup olmadığını belirleme sürecidir. Metin analizine dayalı duygu analizi, bir cümle veya cümle içindeki varlıklara, konulara, temalara ve kategorilere yönelik duygu puanlarını belirlemek için doğal dil işleme modellerini ve makine öğrenme tekniklerini birleştirir. Ayrıca, müşteri memnuniyeti, bir şirket tarafından sağlanan ürün ve hizmetlerin müşteri beklentilerini nasıl karşıladığını veya aştığını değerlendirir. Bu çalışmada, Türkiye'deki Turkcell, Türk Telekom ve Vodafone olmak üzere üç büyük telekomünikasyon operatörünün müşteri memnuniyetini, müşterilerinin duygu analizini kullanarak analiz etmeyi öneriyoruz. Bu amaçla, Twitter sosyal medya platformu, operatörlerin müşterileri tarafından hashtag'lerle belirtilen ilgili tweetleri toplamak amacıyla kullanılmaktadır. Sistem performansını iyileştirmek için noktalama işaretlerini kaldırma, dur sözcükleri ortadan kaldırma, etiketleri kaldırma, URL filtresi, stemming gibi çeşitli ön işleme modelleri kullanılır. Son olarak, kullanıcıların duyguları rastgele öğrenme, destek vektör makinesi (SVM), çok katmanlı algılayıcı (MLP), k-en yakın komşular (k-NN), saf Bayes (NB) ve karar ağacı gibi makine öğrenme algoritmaları ile değerlendirilir. Deney sonuçları, tüm telekom operatörleri için yüzde 80'in üzerinde doğrulukla dikkat çekici bir sınıflandırma performansı sunmaktadır. Böylece, bu çalışma telekomünikasyon şirketlerine sosyal medya platformu aracılığıyla müşteri memnuniyetini analiz etmeleri için ilham verebilir.

**Anahtar Kelimeler:** Duygu Analizi, Müşteri Memnuniyeti, Rastgele Orman, Destek Vektör Makineleri, Çok Katmanlı Algılayıcı, Telekom Operatörleri

Evaluation of Customer Satisfaction about Telecom Operators in Turkey by Analyzing Sentiments of Customers through Twitter

**Abstract**

Sentiment analysis is the process of determining whether a piece of writing is positive, negative or neutral. Text analysis based sentiment analysis consolidates natural language processing models and machine learning techniques to determine sentiment scores to the entities, topics, themes and categories within a phrase or, sentence. Furthermore, customer satisfaction is an evaluation of how products and services supplied by a company satisfy or exceed customer expectation. In this work, we propose to analyze customer satisfaction of three big telecommunication operators which are Turkcell, Turk Telekom, and Vodafone in Turkey by utilizing sentiment analysis of customers of them. For this purpose, Twitter social media platform is used for the purpose of gathering the related tweets that are mentioned with hashtags by the customers of operators. In order to improve the system performance, various pre-processing models are used such as removing punctuation marks, stop-words elimination, removing tags, URLs filter, stemming. Finally, sentiment of users is evaluated through machine learning algorithms namely, random forest, support vector machine (SVM), multilayer perceptron (MLP), k-nearest neighbors (k-NN), naive Bayes (NB), and decision tree. The experiment results present remarkable classification performance with accuracy of over 80 percent for all telecom operators. Thus, this study can inspire telecommunications companies to analyze customer satisfaction through the social media platform.

**Keywords:** Sentiment Analysis, Customer Satisfaction, Random Forest, Support Vector Machines, Multilayer Perceptron, Telecom Operators

# Introduction

Sentiment analysis aims to define text data is positive, negative or neutral. Sentiment analysis is generally employed for this reason to evaluate customer satisfaction. Sentiment analysis is utilized in social media posts, tweets, and online product reviews. In terms of customer service and experience, the significance of sentiment analysis cannot be ignored. Because it is a great way as market research, brand or product reviews and customer experience analysis. Accordingly, the accuracy of sentiment analysis and predictions can be obtained by behavioral analysis based on social media. In this study, we focus to reveal the views of the customer of three big telecommunication operators in Turkey, datasets are collected from the user accounts of Twitter, and according to this on the measurement of customer satisfaction with sentiment analysis.

Machine learning is a subfield of artificial intelligence and big data science [[1](#ref1)]. The main applications of machine learning include various fields such as computer vision, natural language processing, image processing, speech recognition, etc. In machine learning, learning methodology is divided into four main branches namely, supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbors (k-NN), Naive Bayes classifier (NB), Decision Tree are commonly employed in the literature as machine learning techniques. In this study, we concentrate on supervised learning technique by evaluating SVM, DT, RF, NB, MLP and k-NN.

In this paper, we present the sentiment analysis of tweets belonging to different Turkey telecommunication companies that are Turk Telekom (TT), Turkcell, and Vodafone Turkey. In particular, tweets in Turkish have been selected, also, 1 October 2019 and 1 December 2019. We have not missed a single tweet in Turkish belonging to the aforementioned companies. Our idea in this research is to detect the sentiment, which could be either customer experience. It covers the classification of three different vectors containing Turkish tweets from three major telecom operators for sentiment analysis and interpretation of customer satisfaction. Accordingly, this study examines social network site mining techniques for the purpose of capturing user satisfaction towards Telecom companies (Turkcell, Turk Telekom (TT), Vodafone Turkey) in Turkey, and how we can use that data to provide recommendations to these companies. For this purpose, Turkish texts are gathered from Twitter by employing web-scraper. After getting textual data, various pre-processing techniques are implemented to remove the influence of dirty data and remove stop-words for the Turkish language. The study is asked to be expressed and classified as machine learning algorithms, which is widely used in sentiment analysis. Machine Learning methods used in this work are Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbors (k-NN), Naive Bayes (NB), Decision Tree.

# The rest of the article is organized as follows: Section 2 of previous studies have been focused. Section 3 of datasets, methods, tools, sentiment analysis system components and classification. Section 4 of the tests is described. Experimental results and conclusions are given in Section 5.

# Related Work

In this section, a brief summary of the literature review of the studies' effort on customer reviews.

Humera Shaziya et al. [[2](#ref2)] classified movie reviews for sentiment analysis using popular tool WEKA. This work is done in sentiment categorization which analyzes opinions that express the either positive or negative sentiment. They report that accuracy has been of 85.1% for NB.

Other research has reviewed and classified the state of the art, based on the different methods used for Arabic subjectivity and sentiment analysis which are: supervised learning using machine learning methods [[3](#ahmed), [4](#mountassir)], unsupervised learning using sentiment lexicons [[5](#Abdulla), [6](#Ohana)] and a hybrid approach, which combines the two techniques [[6](#Ohana), [7](#ref7)].

Reviews of some studies on sentiment analysis with machine learning technologies have been in this section about telecom companies. Qamar et. al [[8](#ref8)] focus on Saudi Telecom Companies in Saudi Arabia. This work is shown that machine learning methods can be used to give direction to brand and product management by giving information about customer experience. Their study made to tweets written in English, belonging to the various telecommunication companies. In [[9](#Zimbra)], The performances of k-NN and NB as machine learning models are evaluated. In [[9](#Zimbra)], the proposed model is able to get an accuracy of 80.1% with an asymmetric variant of k-NN while using cosine similarity. The other work [[10](#Latifah)] compares NB and SVM methods can be used to applied given from Saudi Telecom Companies tweets. In [[10](#Latifah)], they present this content in August 2022 (since 2015).

Amolik et. al. in [[11](#Akshay)] generate the datasets using Twitter shared comment of movie reviews and related tweets about those movies. They use different classifiers such as NB, SVM, ensemble classifier, k-NN, and Artificial Neural Networks, for the purpose of classifying tweets as positive, negative, and neutral classes. Experiment results have shown that 75% of accuracy with SVM classifier is obtained. Kaya et. al [[12](#Mesut)] present sentiment classification techniques that are used in the domain of political news from columns in different Turkish news sources from sites. They evaluate the results of Naive Bayes, SVM, and Maximum Entropy classification by developing with different features of each classifier. They report the classification accuracy boosts from 65% to 77%.

Result of literature researches, there have not found to use machine learning at Turkish in the telecom sector customer satisfaction. As a result, in this study, we propose to provide a valuable resource using machine learning methods for the customer satisfaction in telecom sector by analyzing sentiment of their customers.

# Proposed Model

In this section, a summary of the methods, materials and proposed framework are presented.

## Data Collection

In this study, in order to estimate the satisfaction of the Turkish Telecommunication Corporates, comments in Twitter are collected between 1 December 2019 and 1 September 2019. Thus, we propose to estimate the satisfaction of customers in their praetors of Turkcell, Turk Telekom (TT) and Vodafone by analyzing customer comments in Twitter between aforementioned date interval.

Turkish customer comments from Twitter are collected with the label of each operator of names. These are mentions of #vodafone, #turktelekom and #turkcell. Selenium browser is used to collect as many tweets as we like without worrying about the limit by the Twitter APIs. In addition, there are using many filters to Twitter with Selenium browser. For example, basically only text tweets between two dates are used as a source in our study.

## Machine Learning Algorithms

In this study, we utilize commonly used machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbors (k-NN), Naive Bayes (NB), Decision Tree.

### Support Vector Machine (SVM)

Support Vector Machine (SVM) is also used in text categorization field in addition to image classification, voice classification, etc. SVM has been chosen for the classification in the experiments. SVM is a supervised learning algorithm that can be utilized to solve classification and regression problems. In [[13](#Onan)], it is utilized to classify both linear and non-linear data. Support vector machines create a hyperplane in a higher dimensional area to solve the classification or regression problem. The hyperplane aims to make a best-solution separation by getting the largest distance to the closest training data points (known as functional margin) of classes.

### K-Nearest Neighbords (k-NN)

k-NN is a kind of lazy learning technique that is employed for both classification and regression problems. K nearest neighbors is a simple algorithm that can be implemented easily with the help of distance functions. This technique stores all available cases and classifies new cases based on a similarity measure such as Euclidean, Manhattan, and Minkowski [[14](#Tsigkritis), [15](#Valdivia)]. In both classification and regression problems, the input depends on the k closest training examples in the feature space while the output consists of whether k-NN is utilized for classification or regression.

In this work, k-NN method is used for the classification task by implementing Euclidean model as a distance function and adjusting k as 3.

### Naïve Bayes (NB)

Naïve Bayes is a member of probabilistic classifiers depended on performing Bayes' theorem that assumes independence among features [[16](#Cheung)]. Naïve Bayes classifier particularly is taken into consideration when the dimensionality of the input features is high. In [[17](#Horn)], Naïve Bayes classifier is considered to be a good algorithm in terms of speed performance, and accuracy success. The short computational time for training is one of the major advantage of the naive Bayes classifier.

### Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) is a popular supervised learning technique among other models of artificial neural networks that is implemented for estimation problems in the literature. The multilayer perceptron consists of basically three layers; the input layer, hidden layer, and the output layer. In additional, the hidden layer may have one or more than of more activation defined. Multilayer perceptron is a feed-forward model that maps data onto a set of related outputs [[18](#Mamgai)]. As the number of hidden layers’ increases can be lead to performance issues. The multilayer perceptron has robust computing competency due to that enable the solution of non-linear sectional problems.

### Decision Tree (DT)

Decision tree is one of the most commonly employed predictive model especially used in statistics, data mining and machine learning. The main purpose of a decision tree is to go from observations about an item which is demonstrated in the branches) to conclusions about the item's target value (demonstrated in the leaves). The Decision Tree or classification tree uses a tree representation to learn that forebodes the value of the variable dedicated to the values of parameter input. The Decision Tree use into divided sub-trees the smaller datasets ensure the questions it. In [[19](#Friedman)], decision tree has been considered as one of the most practical and simple to classification method.

### Random Forest (RF)

Random Forest is performed both regression and classification tasks. It is a kind of learning method that assembles a few weak learning models to form a strong model [[20](#Kam)]. Random Forest is one of the most reliable model in the classification tasks because of consisting of decision consensus of each models. Its sensibility and sensitivity depend a lot on overfitting.

## Proposed Framework

In this study, user comments from Twitter are gathered using with the mentions: #vodafone: a total of 32167 tweets, #turktelekom: a total of 96061 tweets, #turkcell: a total of 52.182 tweets. A total of 180,410 Turkish tweets are collected with the three different labels using the Selenium crawler to collect user comments from Twitter. First, the collected raw data set is cleaned with different pre-processing techniques. In this study, removing punctuation marks, stop-word elimination, removing Twitter hashtags, removing special characters, removing URLs with Twitter search filters are applied. Then, all characters in all words are transformed to lower-case. Stemmer words using a Turkish stemmer named “Zemberek Library” [[21](#ref21)] methods are applied. Zemberek is the known and applied NLP tool in Turkish that is used for morphological analysis. Zemberek has functions that can be used for stemming. In “Fig. 1”, text pre-processing flow diagram is demonstrated.

Remove punctuation

marks

Stop-words elimination

Removing tags

URLs filter

Stemming

Fig 1. Pre-processing flow diagram of text in documents

TextBlob is a Python library for processing textual data. TexBlob [[22](#Oscar)] is utilized, to label the preprocessed datasets. However, because of the lack of Turkish pre-trained datasets in the TextBlob, we use Turkish pre-trained dataset by employing Turkcell customer reviews from the website of Yıldız University Kemik Labs (<http://www.kemik.yildiz.edu.tr/>). With the usage of pre-trained dataset, each tweet that are released from customers of telecom operators are labelled through TextBlob. Machine learning algorithms used in this work evaluate model and each comment/tweet is labelled as 1 and 0. Tweets that are positive are labeled as 1 and negative tweets are tagged as 0. These labelled datasets are total of size 14,725 by positive 9,205 and negative 5,520.

After acquiring labelled dataset, it is splitted into training and test sets, 80% and 20%, separately. After arranging training set percentage of the dataset, we feed the fetched tweets (customer satisfaction reviews tweets) into the machine learning classifier aforementioned. These machine learning techniques are support vector machine, k-nearest neighbors, naive Bayes, decision tree, random forest as an ensemble learning method, and multilayer perceptron as an artificial neural network. Thus, we also measure the impact of traditional machine learning methods, ensemble learning methodology, and artificial neural networks by comparing the classification performance of them in datasets of telecom operators. In “Fig. 2”, The flowchart of proposed model is presented. In order demonstrate the classification performance of the system, precision, recall, f1-measure, and accuracy are employed as evaluation metrics.

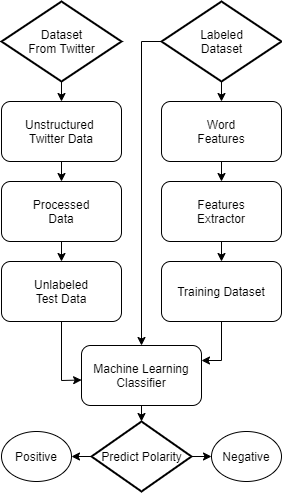


Fig 2. The Flowchart of Proposed Model

# Experiment Result

This section discusses the result of a classification of aspects and sentiments for customer reviews of Turk Telekom (TT), Turkcell, and Vodafone telecom operator. The confusion matrix represents the comparison between SVM, k-NN, DT, RF, MLP, and NB performance for the text classification process. The result of sentiment analysis is presented in the form of table total accuracy which for all telecommunication operators.

## Customer Satisfaction Reviews of Turk Telekom Operator

For Turk Telekom (TT), reviews are classified into each review by dividing into two sentiments as positive and negative which means there are two classes to be assigned for Turk Telekom (TT) dataset.

Table I represents the evaluation between SVM, k-NN, DT, MLP, RF, and NB classifier algorithm for the classification process of reviews of Turk Telekom (TT). From the accuracy of the text classification, it is shown that RF has better classification performance than other machine learning algorithms. RF exhibits the best classification performance with 89.33% of accuracy. Table I represents the results of each evaluation metric by analyzing six machine learning classifier algorithms for classification process of reviews of Turk Telekom (TT).

1. Classıfıcatıon Performance of Ecah Algorıtm In Terms Of Dıfferent Evaluation Metrıcs In Turk Telekom

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Precision** | **Recall** | **F1-score** | **Accuracy** |
| ***SVM*** | 0.87 | 0.89 | 0.87 | 89.29 |
| ***k-NN*** | 0.82 | 0.81 | 0.81 | 81.15 |
| ***RF*** | 0.89 | 0.89 | 0.86 | **89.33** |
| ***MLP*** | 0.86 | 0.87 | 0.87 | 86.76 |
| ***DT*** | 0.86 | 0.88 | 0.84 | 88.44 |
| ***NB*** | 0.81 | 0.80 | 0.80 | 79.92 |

In “Fig 3.” shows the result of sentiment analysis for customer reviews of Turk Telekom (TT). There are negative reviews than positive ones. The number of positive and negative sentiments of customer reviews in Turk Telekom (TT) dataset. There are totally 96k customer reviews that of 11,627 customer reviews are positive and 84,434 are negative.

Fig 3. The Number of Positive and Negative Sentiments of Customer Reviews in Turk Telekom (TT).

Line interruptions are observed to be the most problematic issues based on customers' comments. Complaints are therefore increasing, as it has a wider audience in terms of the range of customers. In addition, customers are observed to be satisfied because the invoices are affordable. It is observed that the problems like other operators are experienced during the earthquake that occurred in Istanbul during our research period, and the longer problems continued in for comparison to other operators negatively affected customer satisfaction.

## Customer Satisfaction Reviews of Vodafone Operator

For Vodafone, reviews are classified into each review by dividing into two sentiments as positive and negative which means there are two classes to be assigned for Vodafone. Table II represents the evaluation between SVM, k-NN, DT, MLP, RF, and NB classifier algorithm for the classification process of reviews of Vodafone. From the accuracy of the text classification, it is shown that RF has better performance than other algorithms. RF reached the 80.66% accuracy number. Table II exhibits the evaluation performance of each evaluation metrics in terms of six machine learning classifier algorithms for classification process of reviews of Vodafone.

1. Classıfıcatıon Performance of Ecah Algorıtm In Terms Of Dıfferent Evaluation Metrıcs In Vodafone

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Precision** | **Recall** | **F1-score** | **Accuracy** |
| ***SVM*** | 0.78 | 0.80 | 0.77 | 80.44 |
| ***k-NN*** | 0.76 | 0.78 | 0.76 | 78.22 |
| ***RF*** | 0.80 | 0.81 | 0.76 | **80.66** |
| ***MLP*** | 0.77 | 0.78 | 0.78 | 77.92 |
| ***DT*** | 0.76 | 0.79 | 0.72 | 78.90 |
| ***NB*** | 0.73 | 0.68 | 0.70 | 67.96 |

In “Fig 4”. shows the result of sentiment analysis for customer reviews of Vodafone. There are negative reviews than positive ones. The number of positive and negative comments of Vodafone is as follows: “Fig 4.” shows the result of sentiment analysis for customer reviews of Vodafone. There are totally 32k customer reviews that of 7,090 customer reviews are positive and 25,077 are negative.

Fig 4. The Number of Positive and Negative Sentiments of Customer Reviews in Vodafone

The operator is complained of short-term disruptions in line cuts. Similarly, problems are observed when an earthquake is occurred. However, it is observed that users’ express satisfaction because they provide faster solutions compared to Turk Telekom (TT). For Vodafone, the most negative review is that they were not less campaign and financially customer-centric. In addition, the customer is dissatisfied with the expensive phone invoice based on performance.

## Customer Satisfaction Reviews of Turkcell Operator

For Turkcell, reviews are classified into each review by dividing into two sentiments as positive and negative which means there are two classes to be assigned for Turkcell. Table III represents the evaluation between SVM, k-NN, DT, MLP, RF, and NB classifier algorithm for the classification process of reviews of Turkcell. From the accuracy of the text classification, it is shown that RF has better performance than other algorithms. RF reached the average 79% accuracy number. Table III shows the evaluation performance of each evaluation metrics in terms of six machine learning classifier algorithms for classification process of reviews of Turkcell.

1. Classıfıcatıon Performance of Ecah Algorıtm In Terms Of Dıfferent Evaluation Metrıcs In Turkcell

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Precision** | **Recall** | **F1-score** | **Accuracy** |
| ***SVM*** | 0.77 | 0.79 | 0.76 | 78.74 |
| ***k-NN*** | 0.74 | 0.77 | 0.70 | 76.65 |
| ***RF*** | 0.78 | 0.80 | 0.75 | **79.03** |
| ***MLP*** | 0.75 | 0.76 | 0.76 | 76.20 |
| ***DT*** | 0.74 | 0.77 | 0.70 | 76.65 |
| ***NB*** | 0.71 | 0.70 | 0.70 | 70.38 |

In “Fig 5.” shows the result of sentiment analysis for customer reviews of Turkcell. There are negative reviews than positive ones. It is seen that Turkcell is at a point between two other operators in a similar date range. These are also reflected in the number of positive and negative reviews. There are totally 53k customer reviews that of 13,159 customer reviews are positive and 40,023 are negative.

Similarly, in operator line interrupts, most of customers complain about the long waiting time needed for communication. For operator Turkcell based on a high-speed packet access aspect, the most negative review is being exceed the connection problems of an operator, especially on special days. However, it is observed that these complaints do not take too long. The success of Turkcell in providing quick solutions can be derived from this. Customer satisfaction oriented studies have been observed. In addition, moreover, the customer is not satisfied with the expensive phone invoice by performance. It is similar to Vodafone in this regard.

Fig 5. The Number of Positive and Negative Sentiments of Customer Reviews in Turkcell

## Customer Satisfaction Reviews of All Operators

In this study, operators have problems due to the earthquake occurred in time interval aforementioned before. The earthquake special day is also evaluated in terms of customer satisfaction number between 1 September 2019 and 1 December 2019. In Table IV, this date is also included in the summary of the results table. Table IV also demonstrates the evaluation between SVM, k-NN, DT, MLP, RF, and NB classifier algorithm for the classification process of reviews of all operator.

1. Classıfıcatıon Accuracıes of Sıx Datasets In Terms Of Ecah Algorıtm At Traınıng Set 80%

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Operator** | **SVM** | **k-NN** | **RF** | **MLP** | **DT** | **NB** |
| ***TT*** | 89.29 | 81.15 | **89.33** | 86.76 | 88.44 | 79.92 |
| ***Vodafone*** | 80.44 | 78.22 | **80.66** | 77.92 | 78.90 | 67.96 |
| ***Turkcell*** | 78.74 | 76.65 | **79.03** | 76.20 | 76.65 | 70.38 |
| ***TT a*** | 90.40 | 89.91 | **90.68** | 88.74 | 89.98 | 76.18 |
| ***Vodafone a*** | 82.36 | 78.97 | **82.72** | 81.76 | 82.24 | 69.22 |
| ***Turkcell a*** | 74.57 | 72.06 | **75.23** | 71.74 | 72.56 | 66.87 |

1. Special Date of Earthquake

The following is the result of a comparison of the value of accuracy made on the RF method, other machine learning algorithms which can be seen in Table IV, RF outperforms other methods in all datasets in terms of accuracy results. In addition, NB compared to the other machine learning methods is which have an accuracy rate the lowest accuracy.

# Discussıon and Conclusions

Customer satisfaction is a significant factor that determines business success of an operator. Therefore, evaluation of high-speed services and not interrupt service based on customer reviews are critical as it provides constructive comments, so the telecommunication operator can measure and improve quality of services in order to achieve customer satisfaction. This study demonstrates text mining techniques of sentiment analysis to extract information from customer reviews of operators using six machine learning algorithms namely, decision tree, multilayer perceptron, support vector machine, random forest, k-nearest neighbors, and Naïve Bayes classifier to classify sentiment of customer reviews for three big operators.

In this way, we propose a customer satisfaction model for three big telecommunication operators which are Turkcell, Turk Telekom, and Vodafone in Turkey by analyzing sentiment analysis of customers of them. For this purpose, Twitter as a social media platform is employed for gathering the related comments that are mentioned with hashtags by the customers of operators. To enhance the system performance, pre-processing models are utilized such as removing punctuation marks, stop-words elimination, removing tags, URLs filter, and stemming. Eventually, sentiment of users is appraised through machine learning algorithms namely, random forest, support vector machine (SVM), multilayer perceptron (MLP), k-nearest neighbors (k-NN), Naive Bayes (NB), and decision tree. The experiment results demonstrate considerable classification success with accuracy of over 80 percent for all telecom operators. Thus, this study can inspire telecommunications companies to analyze customer satisfaction through the social media platform. In details, the best classification performance is observed with the usage of random forest model for all telecom operator datasets while Naive Bayes techniques exhibits the poorest performance among others. Meanwhile, in Table IV it is seen that the classification accuracy of RF outperforms all methods with 89.38% of accuracy. It is followed by SVM, DT, MLP, k-NN, and NB with 89.29%, 88.44%, 86.76%, 81.15%, and 79.92% of accuracies, respectively in Turk Telekom dataset. The classification accuracies of all machine learning algorithms exhibit similar attitude in remaining datasets. Thus, the classification success of the system can be generalized as following performance order: RF > SVM > DT > k-NN > MLP > NB.

In conclusion, it is found that the Vodafone telecom operator dataset exhibits better quality of services and facilities than the other two terminals based on the predominance negative reviews on some aspects. The finding of this study shows that telecommunication operators need to prioritize improvement to the aspects with majority of negative reviews. In future, we plan to evaluate the impact of deep learning methodologies on these telecom operator for the purpose of enhancing classification performance of system.

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