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 (KNN), 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, Rasgele 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 are evaluated through machine learning algorithms namely, random forest, support vector machine (SVM), multilayer perceptron (MLP), k-nearest neighbors (KNN), 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 used for this reason to evaluate customer satisfaction. Sentiment analysis is used in social media posts, tweets, and online product reviews. In terms of customer service and experience, sentiment analysis's significance cannot be ignored. Because it is great a way as market research, brand or product reviews and customer experience analysis.

There are many studies other than the Turkish language for sentiment analysis. The number of Turkish language studies is still limited today. Recently, there has been an increase in the studies carried out in this direction. In particular, there has been an increase in studies using deep language techniques machine learning and sub-science and natural language processing together.

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 was asked to be expressed and classified as machine learning algorithms, which is widely used in sentiment analysis. Machine Learning methods used are Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), 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. in this paper [1] classified movie reviews for sentiment analysis using popular tool WEKA. Their work is done in sentiment categorization which analyzes opinions that express the either positive or negative sentiment. In [1], 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 [2, 3], unsupervised learning using sentiment lexicons [4, 5] and a hybrid approach, which combines the two techniques [5, 6].

Reviews of some studies on sentiment analysis with machine learning technologies have been in this section about telecom companies. A. M. Qamar, A. Alsuhibany and S. S. Ahmed [7] made alike work on Saudi Telecom Companies in Saudi Arabia. This work [7] 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 [8], it used methods were K-NN and NB machine learning. In [8], it was able to get an accuracy of 80.1% with an asymmetric variant of K-NN while using cosine similarity. The other work [9] will be shown that machine learning for NB and SVM methods can be used to applied given from Saudi Telecom Companies tweets. In [9], they will complete this content in August 2022 (since 2015).

Akshay Amolik et. al. in [10] generated the datasets using twitter shared comment of movie reviews and related tweets about those movies. In [10], by used different classifiers like NB, SVM, Ensemble classifier, K-NN, and Artificial Neural Networks, tweets were classified into positive, negative and finally neutral classes. Their results have shown that 75 % accuracy with SVM.

In addition, one important problem in sentiment analysis is the categorization of sentiment polarity if used to Turkish words. Because Turkish words are complex by construct. The a of many problems is to categorize given a piece of written Turkish text into positive and negative. M. Kaya, G. Fidan, I. H. Toroslu, in [11], sentiment classification techniques are used in the domain of political news from columns in different Turkish news sources from sites. Their methods were Naive Bayes, SVM, and Maximum Entropy Classification. These methods developed with different features; all their approaches reached an accuracy of 65% to 77%.

Result of literature research, 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 models for the telecom sector satisfaction.

# Proposed Model

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

## Data Collection

In this study, in order to estimate the satisfaction of the Turkish Telecommunication Corporates, comments in Twitter are examined between 1 December 2019 and 1 September 2019. For this purpose, we estimate the satisfaction of the operators of Turkcell, Turk Telekom (TT) and Vodafone by analyzing customer comments from Twitter.

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 use 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 generally used for text categorization. SVM has been chosen for the classification in the experiments. SVM are supervised learning algorithms that can be utilized to solve classification and regression problems. In [12], applied 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 Neighbors (K-NN)*

In this study, K-Nearest Neighbor Classifier is selected to use a classifier. Sentiment analysis is a binary classification and many huge datasets which can be executed. A manually generated training set or ready datasets are utilized for the classifier at K-NN. basically of score to obtain is defined by the targeted datasets words with positive, negative or neutral. [13]

* *Naive Bayes (NB)*

Naive Bayes [14] method represents a parallel learning method or a statistical method for classification. Naïve Bayes is a probabilistic model. In addition, the algorithm is permitted us to capture doubt about in a way determining probabilities. Naive Bayes helps to solve predictions. The Naive Bayes [15] method can also help in classifying a class to results that are used in parallel in increasing the scale of the dataset, especially in large-scale data case studies.

* *Multilayer Perceptron (MLP)*

Artificial Neural Networks (ANNs) are models in machine learning. The Multilayer Perceptron model is for machine and supervised learning. [16] Multilayer Perceptron is a feed-forward model that maps data onto a set of related outputs. As the number of hidden layers’ increases can be lead to performance issues.

* *Decision Tree (DT)*

In [17], decision tree has been considered as one of the most practical and simple to classification. Decision tree can be easily reduced into rules and comprehensible. When used properly, the decision tree has been shown to provide robust performance.

* *Random Forest (RF)*

In [18], Random Forest is an algorithm for machine learning. Random Forest, as can perform both regression and classification tasks. It's a kind of learning method that assembles a few weak learning models to form a strong model. In Random Forest, in contrast to a single tree decision, more from creates multiple trees.

## Proposed Framework

In this study, user comments from Twitter are collected 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 attract user comments from Twitter. First, the collected raw data set was 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” [19] methods are applied. Zemberek is the main 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 was shown.

Fig 1. Preprocessing flow diagram of text in documents

TexBlob is utilized, to label the preprocessed datasets. However, because of the lack of Turkish pre-trained datasets in the TextBlob, used pre-trained datasets.

In this study, we used the Turkish pre-trained dataset by employing Turkcell customer reviews from the website of Yıldız University Kemik Labs (<http://www.kemik.yildiz.edu.tr/>). The labeled dataset is acquired, the dataset is split into training and test sets, 80% and 20%, separately.

In “Fig 2”, after we feed the fetched tweets (customer satisfaction reviews tweets) into the machine learning classifier mentioned, machine learning algorithms evaluate each tweet and label them with 1 and 0. Tweets that are positive will get labeled as 1 and negative tweets will get labeled as 0. In this study, we took each word of a document into consideration, and depending on the features extracted, the algorithms tried to find the positivity and negativity score of each word and hence predict the polarity of the tweets. These labelled datasets are total of size 14.725 by positive 9205 and negative 5520.

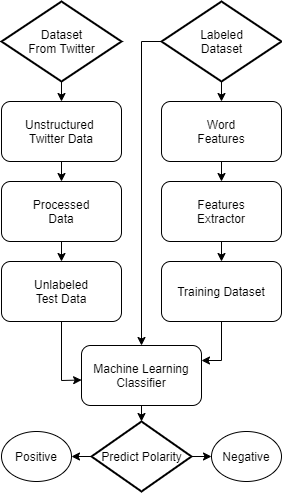


Fig 2. Methodology Model - Flowchart

In this study, we took each word of a document into consideration, and depending on the features extracted, the algorithms tried to find the positivity and negativity score of each word and hence predict the polarity of the tweets.

# 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 was presented in the form of at 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 divided into two sentiments, positive and negative so there will be two classes for Turk Telekom (TT).

Table V 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 performance than other machine learning algorithms.

RF reached the 0.926 accuracy number. Table I represents the evaluation between 6 machine learning classifier algorithms for classification process of reviews of Turk Telekom (TT).

1. Algorıtms Comparıson For Classıfıatıon Of Turk Telekom

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Precision** | **Recall** | **F1-score** | **Accuracy** |
| ***SVM*** | 0.87 | 0.89 | 0.87 | 89.29 |
| ***K-NN*** | 0.86 | 0.88 | 0.84 | 88.44 |
| ***RF*** | 0.89 | 0.89 | 0.86 | **89.33** |
| ***MLP*** | 0.86 | 0.87 | 0.87 | 86.76 |
| ***DT*** | 0.86 | 0.87 | 0.87 | 86.76 |
| ***NB*** | 0.86 | 0.89 | 0.86 | 88.59 |

In “Fig 3”. shows the result of sentiment analysis for customer reviews of Turk Telekom (TT). There are negative reviews than positive ones. “Fig 3” shown on a total of 96K customer reviews. 11627 of customer reviews are positive and 84434 are negative.

Fig 3. Sentiment Analysis of Customer Reviews of Turk Telekom (TT)

Line interruptions were 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 were observed to be satisfied because the invoices were affordable. It was observed that the problems like other operators 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 divided into two sentiments, positive and negative so there will be two classes 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 86.69% accuracy number.

Table II represents the evaluation between 6 machine learning classifier algorithms for classification process of reviews of Vodafone.

1. Algorıtms Comparıson For Classıfıatıon Of 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” shown on a total of 32K customer reviews. 7090 of customer reviews are positive and 25077 are negative.

Fig 4. Sentiment Analysis of Customer Reviews of Vodafone

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

## Customer Satisfaction Reviews of Turkcell Operator

For Turkcell, reviews are classified into each review divided into two sentiments, positive and negative so there will be two classes 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 84% accuracy number.

Table III represents the evaluation between 6 machine learning classifier algorithms for classification process of reviews of Turkcell.

1. Algorıtms Comparıson For Classıfıatıon Of 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 was seen that Turkcell was at a point between two other operators in a similar date range.

These are also reflected in the number of positive and negative reviews. “Fig 5” shown on a total of 53K customer reviews. 13159 of customer reviews are positive and 40023 are negative.

Fig 5. Sentiment Analysis of Customer Reviews of Turkcell

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

## Customer Satisfaction Reviews of All Operators

In this study, operators had problems due to the earthquake between the date of the study. The earthquake special day was also evaluated in terms of customer satisfaction. Table IV this date is also included in the summary of the results table. Table IV represents the evaluation between SVM, K-NN, DT, MLP, RF, and NB classifier algorithm for the classification process of reviews of all operator.

1. Data Training Result of Machine Learnıng

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Operator** | **SVM** | **K-NN** | **RF** | **MLP** | **DT** | **NB** |
| ***TT*** | 89.29 | 88.44 | **89.38** | 86.76 | 88.59 | 75.89 |
| ***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. The accuracy of the RF method is better than other methods. In addition, NB compared to the other machine learning methods is which have an accuracy rate the lowest accuracy.

# Discussıon and Conclusıons

Sentiment of users were evaluated with machine learning algorithms such as RF, SVM, MLP, K-NN, NB and DT. The experimental results are aimed to compare the classification performance of machine learning algorithms for all telecom operators. The experiment result best classification performance with accuracy of RF for Turk Telekom in Turkey. The result of a comparison of the value of accuracy made on the Random Forest method, DT and NB which can be seen in Table IV, where the accuracy of the Random Forest method is better with the results of 89.39% ≈ 89.4%, compared to the MLP which has an accuracy rate of 86.76% and with the lowest accuracy value of 75.89% using NB for Turk Telecom. Meanwhile, in Table IV we can see the comparison of the accuracy of the RF, MLP, DT, NB, KNN and SVM methods. The accuracy of the predictions made indicates that the accuracy of the RF is better than both methods that is 89.4%. While, the level of accuracy by SVM is only 89.29% and the lowest accuracy level is NB with 75.89%. For Turk Telekom, it was observed that almost all the accuracy results were close to each other except RF. The worst result was found to be NB. The TT subset, ***TT a***, shows special accuracy values for the earthquake date. The results here have similarities. As a result, RF> SVM>K-NN>DT> MLP> NB was evaluated.

The experiment result best classification performance with accuracy of RF for Vodafone in Turkey. The result of a comparison of the value of accuracy made on the Random Forest method, DT, MLP, NB, SVM and KNN which can be seen in Table IV, where the accuracy of the Random Forest method is better with the results of 80.66%, compared to the KNN which has an accuracy rate of 78.22%, the SVM which has an accuracy rate of 80.44%, the MLP which has an accuracy rate of 77.92%, the DT which has an accuracy rate of 78.90%, and with the lowest accuracy value of 67.96% using NB for Vodafone. For Vodafone, it was observed that almost all the accuracy results were close to each other except RF. The worst result was shown to be NB. The Vodafone subset, ***Vodafonea***, shows special accuracy values for the earthquake date. The results here have similarities. As a result, RF> SVM>DT>K-NN>MLP>NB was evaluated.

The experiment result best classification performance with accuracy of RF for Turkcell in Turkey. The result of a comparison of the value of accuracy made on the Random Forest method, DT, MLP, NB, SVM and KNN which can be seen in Table IV, where the accuracy of the Random Forest method is better with the results of 79.03%, compared to the KNN which has an accuracy rate of 76.65%, the SVM which has an accuracy rate of 78.74%, the MLP which has an accuracy rate of 76.20%, the DT and K-NN which has a same accuracy rate of 76.65%, and with the lowest accuracy value of 70.38% using NB for Turkcell. For Turkcell, it was observed that almost all the accuracy results were close to each other except RF. The worst result was shown to be NB. The Turkcell subset, ***Turkcell a***, shows special accuracy values for the earthquake date. The results here have similarities. As a result, RF> SVM>DT=K-NN>MLP>NB was evaluated.

Customer satisfaction is an important 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 operators customer reviews using six machine learning algorithms. Decision Tree, Multilayer Support Machine, Random Forest, K-Nearest Neighbors, Support vector machine and Naïve Bayes classifier are implemented to classify sentiment analysis for three big operators customer review. It is observed that RF algorithm outperforms than other five machine learning methods in classifying the sentiment of review. As part of sentiment analysis, sentiment tables are produced showing the percentage of positive and negative reviews of services. Overall, Vodafone has 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 operator needs to prioritize improvement to the aspects with majority of negative reviews. Future study, may use classifying review with deep learning methods for better accuracy number between 1 September 2019 and 1 December 2019.

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