SAKARYA UNIVERSITY JOURNAL OF COMPUTER AND INFORMATION SCIENCES
VOL. 5, NO. 3, DECEMBER 2022
DOI: 10.35377/saucis.05.03.1121830

*Research Article*

# Using Multi-Label Classification Methods to Analyze Complaints Against Cargo Services During the COVID-19 Outbreak: Comparing Survey-Based and Word-Based Labeling*

Tolga Kuyucuk[1], Levent Çallı[2]
[1]Department of Information Systems Engineering, Sakarya University, tolga.kuyucuk1@ogr.sakarya.edu.tr
[2]Corresponding Author; Department of Information Systems Engineering, Sakarya University, lcalli@sakarya.edu.tr

Received 26 May 2022; Revised 18 November 2022; Accepted 21 November 2022; Published online 31 December 2022

## Abstract

This study investigates how cargo companies managed their last-mile activities during the Covid-19 outbreak and suggest a solution to the adverse outcomes. The data used in the study included complaints made about cargo companies from sikayetvar.com between February 2020 and September 2021 and was collected using Python language and the Scrapy module web scraping methods. Multi-label classification algorithms were used to categorize complaints based on assessments of training data obtained according to the topics. Results showed that parcel delivery-related themes were the most often complained about, and a considerable portion were delay issues.

**Keywords:** Covid-19, web scraping, cargo companies, customer complaints, multi-label classification, text mining

## 1. Introduction

A series of pneumonia cases of unknown origin emerged in Wuhan, China, in the late days of December 2019, triggering an investigation that the source of this infection is thought to be linked to the Wuhan South China Seafood Market. In January, the Chinese government reported this situation to the World Health Organization (WHO), and the pathogen causing this epidemic was defined as a new type of coronavirus on January 7, 2020, and named Covid-19 [1]. The virus expanded to other nations and had a huge global impact when the number of cases increased rapidly till January 23, 2020 [2]. The first Covid-19 case in Türkiye was seen on March 11. WHO declared that this newly emerged virus was a pandemic on the same date [3]. Due to the coronavirus, nearly 527 million cases have been reported globally as of May 24, 2022, and as a result of this outbreak, it permanently influenced all aspects of consumers' needs and daily habits with a new lifestyle [4]–[7].

During the pandemic, e-commerce has increased globally, especially in countries where e-commerce was previously less developed have been more remarkable. The growth of the digital economy will undoubtedly continue to be influenced by the changing shopping and payment behaviors of customers brought about by the pandemic conditions [8]. In 2020, Türkiye's e-commerce volume increased 66% compared to 2019 and reached 226.2 billion TL from 136 billion TL [9]. In 2021, Türkiye's e-commerce volume climbed by 69% from the previous year and reached 381.5 billion TL, while the orders increased by 46%, from 2 billion 297 million to 3 billion 347 million [10]. The asymmetrical growth that resulted inevitably affected the delivery step, the most crucial part of e-commerce. According to Güven [11], customers' main complaints during the Covid-19 outbreak were discovered to be customer service / live assistance and the delivery process, considering complaints received on e-commerce sites.

Additionally, Parlakkılıç et al. [12] found a significant negative relationship between trust and cargo tracking during the Covid-19 period. A similar problem has also been mentioned from the industry side; for example, Etid's [13] report states that the high instantaneous increase in demand during the pandemic led to problems in the logistic organization, warehouse, and order preparation operations resulting in

---

* This study was produced from the master's thesis prepared by Tolga KUYUCUK with the supervisor Levent ÇALLI at Sakarya University, Institute of Natural Sciences.

customer dissatisfaction. In this regard, it is strategically vital for cargo companies to identify the reasons that trigger consumer complaints during the delivery phase of e-commerce to take the necessary precautions.

In this sense, it is thought that this research will make an academic and practical contribution to the literature from a different perspective. First of all, this research fills the gap in the literature with sample size and puts forward an alternative method considering studies carried out by a relatively small number of complaints in the local literature. Hence, in this study, much more complaints were classified by machine learning approaches, and a method will be proposed for the literature. In addition, in extraordinary situations such as Covid-19, practical contributions to cargo firms will be provided according to research findings.

## 2. Literature Review

When a consumer has an issue with a product or service they purchase, they have three options under the complaint behavior. The first of these options is to cease buying the relevant brand and promote negative word of mouth among the social circle. The second is the direct contact of the consumers with the company, and the last way is to initiate the legal process [14]. Today, with social media applications, it has become easier for the consumer to use these different methods of complaint behavior simultaneously, and it has provided convenience for consumers in terms of solutions for complaints [15][16]. For example, sikayetvar.com [17] has emerged as an online platform that acts as a bridge between customers and brands by allowing companies to resolve complaints and increase customer satisfaction. Users who visit the system can easily see the brands that received the most complaints or those with the most resolved complaints. In this sense, the platform, which creates pressure on brands, has gained much popularity in Türkiye and has resolved approximately 2 million complaints. This platform is also a resource used in academic studies. For instance, Çallı and Çallı [16], who conducted research into the complaints mentioned by airline passengers during the Covid-19 pandemic on the sikayetvar.com platform, highlighted the service quality issues and proposed potential solutions for both low-cost carriers and full-service airlines. In another study that analyzed complaints regarding private hospitals, topics and sub-topics were revealed using data from sikayetvar.com [18]. In a qualitative study, Güler [19] found that half of the complaints against banks during the pandemic period were related to credit cards via sikayetvar.com.

A limited number of studies in the academic literature focus on the topic of customer complaints made against cargo services at sikayetvar.com. All of these studies use a qualitative method, which means they can only deal with a small number of complaints. In this regard, this study is expected to fill a gap in the relevant literature in terms of the methodology applied and the number of complaints obtained. In the study conducted by Burucuoğlu and Yazar [20], which was prepared by considering 300 complaints, the main complaint topics for cargo services operating in Türkiye before the pandemic are; business processes, product-related problems, courier-related issues while receiving the parcel, delivery/distribution-related issues, pricing, communication, and personnel. According to Gürce and Tosun's [21] findings, the most common complaint themes for the cargo services were providing the promised service, timely delivery, fulfilling good service, willingness to assist, and sincere problem-solving. The study considered 300 complaints made to various online shopping sites and found that one of the most frequently mentioned complaint topics in the Covid-19 period is mainly related to cargo services and was revealed as unfair shipping charges, sending to the wrong address, not receiving the orders, and not delivering the product on time [11]. In another study considering 690 complaints against online shopping sites during the Covid-19 outbreak [22], it is stated that similar complaints about the delivery process that Güven [11] mentioned are the second most frequently mentioned issues.

Considering local research about complaints other than sikayetvar.com against cargo services, Deniz and Gödekmerdan [23] found that delay is the most common problem while determining the factors that cause dissatisfaction in cargo transportation in Türkiye with the survey method. According to Akkan [24], the first two most common service issues are delivery times, such as the delivery of the parcel late or delivery later than promised, and communication difficulties, like not answering calls or leaving a note even though the customer is at home for Turkish customers. Duran et al. [25] evaluated the opinions of consumers about cargo services within the framework of five factors. The first is logistics values, including parcel delivery time and a widespread transportation network. Reliability, which includes the concepts of timely delivery of the product and easy communication with the customer, is another concept evaluated within the model's scope. Delivery speed is evaluated under the time factor, which includes the delivery at the promised time, the return process, and the provision of information to the customer. The factor that includes price-quality consistency, compensation for faulty situations, and promotional elements is the economic expense. Finally, the concept of personnel and service consists of dimensions that include fulfilling expectations, assurance, being kind to the customer, product follow-up, and solving complaints in a short time. A study examining 300 complaints about the three largest cargo companies operating in Türkiye stated that the customers mostly expressed problems related to not being found at the address, issues with the delivery, not delivering to the address, and the attitudes and behaviors of the service personnel [20].

The practical solution to customer complaints is a critical factor in customer satisfaction and loyalty. For example, in their study, Cho et al. [26], considering the complaints of e-commerce customers, determined that customer service, product, price, delivery problems, misleading information, security & trust issues, tracking and tracing, and promotion are general complaints topics. They state that online customers should be provided with the best service, customer demands and complaints should be responded to more quickly than offline customers, and strategies should be developed in line with the product category, such as giving more detailed information with different multimedia tools for cosmetic products.

If businesses manage complaints effectively, they can develop their products/services to meet the expectations of their customers. A dissatisfied customer decides whether to leave or stay based on the complaint's solution. If the business handles this process successfully, it will offer an excellent opportunity for the firm, considering that acquiring new customers is five or six times more expensive than retaining existing customers [27].

### 2.1 Machine Learning for Complaint Classification

Many online customers experiencing issues with delivery service companies due to the pandemic have been looking for answers by posting their complaints on online complaint sites. Examining each complaint in a sector with a high volume of complaints can be costly for firms' budgets since it requires more human resources and intelligence. Instead, reviewing only a few complaints with machine learning algorithms allows future complaints to be categorized more quickly and at a lower cost.

The concept of machine learning is an area of Artificial Intelligence that attracts excellent attention in the digital world and is a crucial component of digitization solutions. Depending on the types and categories of training data, methods such as supervised, unsupervised, semi-supervised, and reinforcement learning are used [28]. Basically, machine learning (ML) can define as a continually changing computing program that, in some ways, mimics human intelligence by learning from its surroundings [29]. Regression, classification, clustering, dimensionality reduction, ensemble methods, neural nets, deep learning, transfer learning, reinforcement learning, natural language processing, and word embeddings are commonly used machine learning approaches applied to any data scenario [30].

Text mining, one of the fundamental techniques in data mining, is described as discovering knowledge by the computers automatically extracting information from various unstructured or structured textual sources [31], [32]. Natural Language Processing (NLP) is a branch of artificial intelligence in which computers efficiently analyze and understand human language with machine learning. While sentiment and grammatical structure can be extracted with NLP from language, frequency, correlation, and word patterns may be revealed with text mining as statistical indicators with a multidiscipline approach [33]–[35].

A more complex situation is encountered in complaint cases in text mining practices. While the analysis process assumes that each item belongs to a single class in classification problems, this is not possible in complaints due to their nature. For example, a consumer complaining about undelivered cargo may also say he could not reach customer service in the same complaint message. Multi-label classification is known as a solution for this type of challenge, which may categorize each complaint such that it may be allocated to more than one topic using machine learning techniques [36].

In this study, Python language, which has become one of the leading technologies in creating models for the industry and developing new methods for researchers, together with machine learning libraries, was used to perform multi-label classification using the Scikit-multilearn [37].

## 3. Methodology

### 3.1 Text Mining Process

The data for the study were collected using Python scripts and the Scrapy module from the sikayetvar.com website, an online complaint management platform, between February 2020 and September 2021. The database consists of 16332 customers who received service from cargo companies in Türkiye and expressed their dissatisfaction on the sikayetvar.com website. Complaints against cargo companies in Türkiye during the Covid-19 outbreak were classified using machine learning and multi-label classification algorithms.

The qualitative approach was used to discover the most common complaints of cargo customers during the pandemic period by reviewing a random sample of the complaints in the database considering the literature findings. The frequent complaints were formed under six topics as follows; *delayed or not delivered parcel*, *the note was written "customer was not at home" was left at the door or parcel not brought to the door*, *customer service has not answered the call*, *returning processes*, *parcel not received or delivered*, and *hygiene rules related issues*.

The dataset's first 3000 rows were used as training data and were refined using natural language processing (NLP) techniques. Labels were assigned to the training data using two approaches. The first method used a written python script to label complaints, while the second method included the survey method to label complaints based on participant responses. The text mining process used in the study is presented in Figure 1.

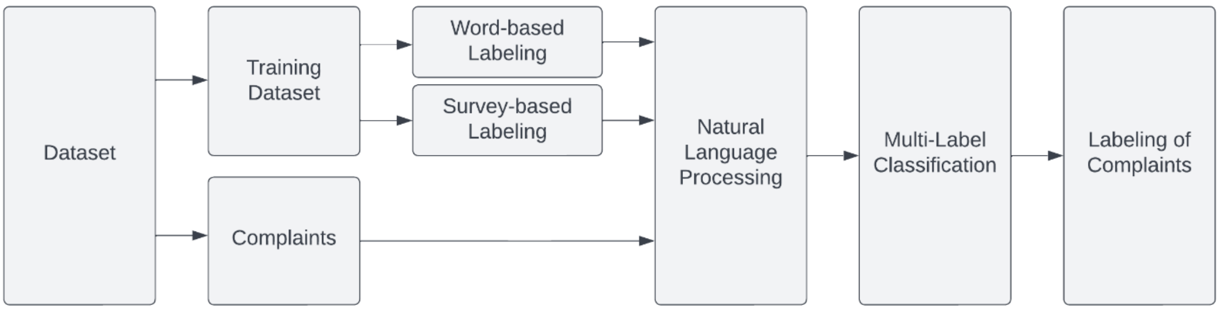


Figure 1 Text Mining Process

Logistic Regression, OneVsRest Classifier, and vectorization methods were used for multi-label classification.

#### 3.1.1 Multi-Label Classification

This section explains the results of word-based and survey-based labeling methods for selecting the appropriate topics for each complaint in the training dataset.

### 3.1.1.1 Word-Based Labeling

After tokenizing each complaint in the training dataset, a script written in Python programming language checked whether the determined words related to the relevant topic for labeling the complaint to the appropriate topics. This process is illustrated in figure 2.

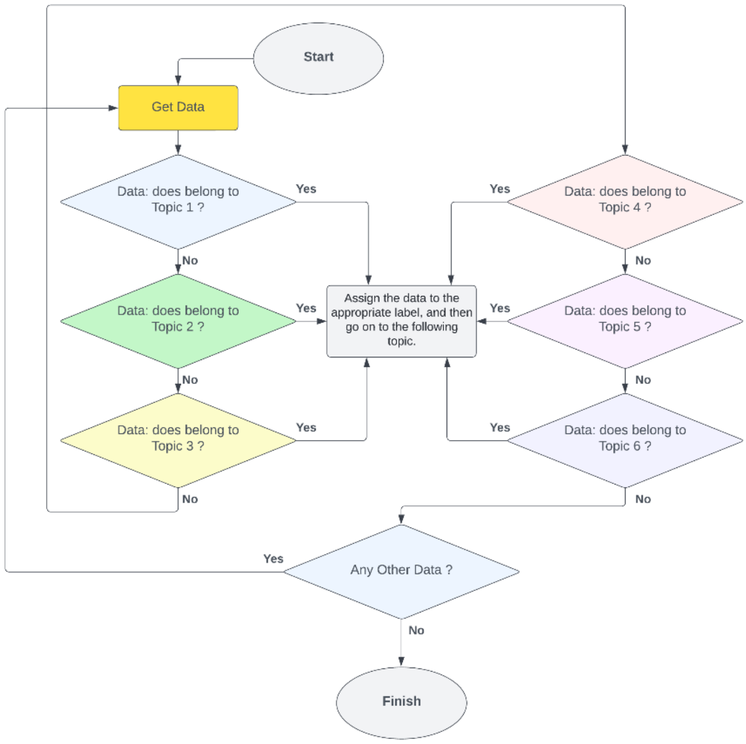


Figure 2 Word-based Labeling Flowchart

### 3.1.2.2 Survey-Based Labeling

Survey-based labeling aims to get more accurate labeling with human intelligence by having different participants assign labels to each complaint in the training dataset. Three thousand complaints from the training dataset were primarily uploaded to the Google Sheets platform in Turkish and English for Turkish and foreign participants to access the survey. The numbers generated between 3000 and 1 were assigned to the complaints as temporary random IDs, and a dynamic structure was obtained with the page renewed every 4 minutes.

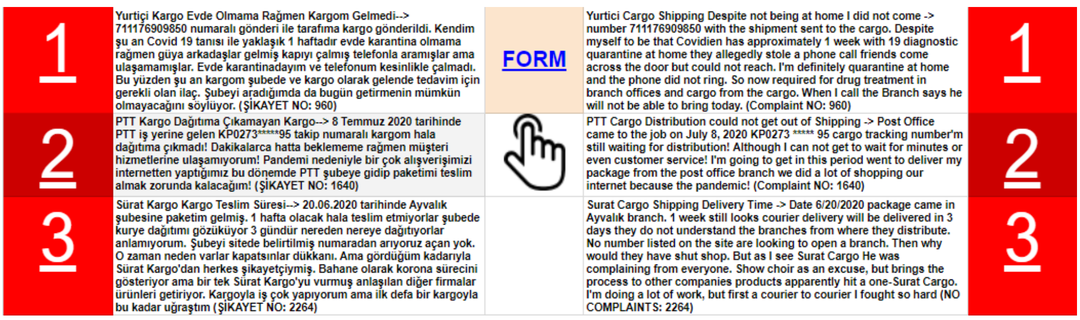


Figure 3 Google Form Survey

Complaints with IDs between 1 and 10 were shown to the participants to show different complaints to the different participants at different times. The participant who accesses the web page is directed to the survey page created on Google Form by clicking the "Form" button, as seen in Figure 3. The participant is asked to determine which of the ten different complaints belong to the pre-determined categories on the survey page.

### 3.1.2 Text Vectorization Algorithms

Vectorization is a crucial stage in NLP for machine interpretation of data by transforming textual materials into meaningful numerical representations [38]. This study used Tf-Idf Vectorizer, Hashing Vectorizer, and Count Vectorizer methods.

One of the most widely used text vectorization algorithms in today's information retrieval systems is the Term frequency-Inverse Document Frequency (TF–IDF) [39]. TF-IDF method weights word counts by measuring how often they appear in documents. The equation is as follows.

$$w_{i.j} = tf_{i.j} \times \log\left(\frac{N}{df_i}\right) 100 \qquad (1)$$

The description of terms used in equation 1 is as follows [40];

$\mathbf{w_{i,j}}$ : The weight for Term i in document j.
**N** : The number of documents in the collection.
$\mathbf{tf_{i,j}}$ : The term frequency of Term i in document j.
$\mathbf{d_{fi}}$: The document frequency of Term i in the collection.

The second method used for text vectorization is hashing. Tokens are stored as strings in the hashing-vectorizer, and the hashing trick is used to encode features as numerical indexes [41]. The hashing trick creates a unique association between the input and the hash value and replaces the authenticity of a large quantity of information with a much smaller hash value [42]. The Count Vectorizer is used as the third method for text vectorizing in this study as a simple technique based on the count of word occurrences in the document [41].

#### 3.1.3 Classification

One-vs-rest (OvR) method was used for the multi-label classification with Python coding, as seen in figure 4. OvR applies binary classification methods for multi-class classification by splitting the multi-class dataset into multiple binary classification models. Then, each binary classification problem is used to train a binary classifier, and the most confident model is used to make predictions [43].

```python
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)


from sklearn.feature_extraction.text import HashingVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier
from sklearn.pipeline import Pipeline


train = pd.read_excel('input/train.xls')
sikayetsayisi=len(train)
yontem=HashingVectorizer

print(train.info())
print(train.describe())
print(train.icerik.head())

#creating x and y
x=train.loc[:,'icerik']

z=[0,1,2,3,4,5]
z[0]=train.loc[:,'Gecikti veya Dağıtıma Çıkmadı']
z[1]=train.loc[:,'Evde yok notu düşüldü veya Kapıya Getirilmedi']
z[2]=train.loc[:,'Telefonlara Cevap Verilmedi']
z[3]=train.loc[:,'İade Süreci']
z[4]=train.loc[:,'Teslim Alınmadı veya Teslim Edilmedi']
z[5]=train.loc[:,'Hijyen Kurallarına Uyulmadı']

y = train.drop(['id','icerik'],axis=1)

tks = '[A-Za-z0-9]+(?=\\s+)'


pl = Pipeline([
        ('vec', yontem(token_pattern = tks)),
        ('clf', OneVsRestClassifier(LogisticRegression()))
    ])

# Fit to the training data
pl.fit(x,y)
```

Figure 4 Example of Python Coding

Logistic regression was used as the prediction method. The first five rows of the database are shown in Table 1 as an example of the coding procedure. The mean score of each category in the training dataset was used to determine categories for each complaint, and scores above the mean score were coded as 1, as seen in Table 2.

Table 1 Category Prediction Scores of Complaints

| ID | Delayed or Not Delivered Parcel | The Note Was Written "Customer Was Not at Home" Was Left at The Door or Parcel Not Brought to The Door | Customer Service Has Not Answered the Call | Returning Processes | Parcel Not Received or Delivered | Hygiene Rules Related Issues |
|---|---|---|---|---|---|---|
| **1** | 0,2612 | 0,4362 | 0,44955 | 0,1009 | 0,0873 | 0,0633 |
| **2** | 0,3179 | 0,2796 | 0,4277 | 0,2112 | 0,2756 | 0,094 |
| **3** | 0,6167 | 0,3059 | 0,26176 | 0,1664 | 0,1481 | 0,5855 |
| **4** | 0,3715 | 0,1817 | 0,64245 | 0,0859 | 0,1601 | 0,0408 |
| **5** | 0,6186 | 0,2144 | 0,16975 | 0,0903 | 0,0893 | 0,0556 |

Table 2 Binary Coding of Each Complaint

| ID | Delayed or Not Delivered Parcel | The Note Was Written "Customer Was Not at Home" Was Left at The Door or Parcel Not Brought to The Door | Customer Service Has Not Answered the Call | Returning Processes | Parcel Not Received or Delivered | Hygiene Rules Related Issues |
|---|---|---|---|---|---|---|
| **1** | 0 | 1 | 1 | 0 | 0 | 0 |
| **2** | 0 | 0 | 1 | 1 | 1 | 1 |
| **3** | 1 | 0 | 0 | 0 | 0 | 1 |
| **4** | 0 | 0 | 1 | 0 | 0 | 0 |
| **5** | 1 | 0 | 0 | 0 | 0 | 0 |

Analysis processes were carried out with each text vectorization algorithm to discover the general complaint topics. The topics that lead to the most significant number of customer complaints were identified, and the rates of complaints topics according to the cargo firms were calculated.

## 4. Results

### 4.1 Density Map

All complaints containing the words corona, covid, and pandemic listed on the sikayetvar.com website were acquired within the specified period with Python code using the Scrapy module, data including company name, number of reads, and created date. Complaints regarding cargo companies were isolated, and a density map was generated based on March 2020 to September 2020 data, as seen in Figure 5.

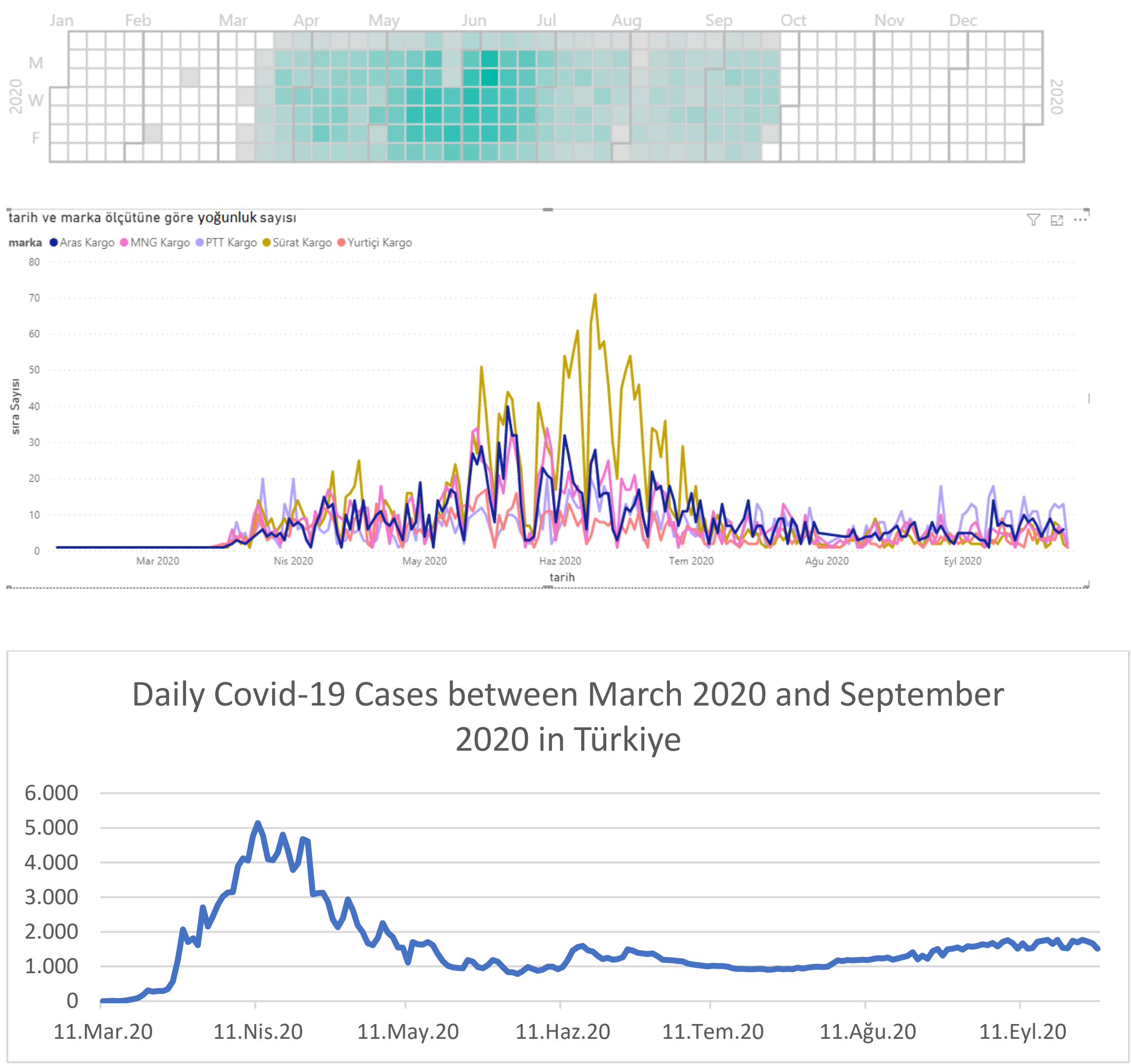


Figure 5 Density Map

Accordingly, it is observed that the most intense complaints are made between the end of May 2020 and the beginning of July 2020, which shows a pattern with the Covid-19 cases in Türkiye that are most intense between April 2020 to May 2020 [44]. Following the peak of Covid-19 cases in April and May 2020, it was observed that complaints increased between May and July 2020.

### 4.2 Prediction Results

A computer program was created to generate the training data by determining the words and word groups that are assumed to be related to each category, as illustrated in Figure 6. The first 3000 complaints are used for creating the training dataset in this method.

```
if 'dağıtım' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'çıkmadı' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'çıkış şube' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'gelmedi' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'beklet' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'süredir' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'gecik' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'bekli' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'hala çıkış' in icerik:
    dagitimdegisken=dagitimdegisken+1
if 'geç ' in icerik:
    dagitimdegisken=dagitimdegisken+1
if(dagitimdegisken*100)/len(splitWords)>oran:
    print("Gecikti veya Dağıtıma Çıkmadı")
    print(dagitimdegisken)
```

```
if 'telefonu' in icerik:
    telefondegisken=telefondegisken+1
if 'telefona' in icerik:
    telefondegisken=telefondegisken+1
if 'telefonlar' in icerik:
    telefondegisken=telefondegisken+1
if 'açmadı' in icerik:
    telefondegisken=telefondegisken+1
if 'cevap' in icerik:
    telefondegisken=telefondegisken+1
if 'açmıyor' in icerik:
    telefondegisken=telefondegisken+1
if 'ulaşılamıyor' in icerik:
    telefondegisken=telefondegisken+1
if 'ulaşamı' in icerik:
    telefondegisken=telefondegisken+1
if 'açan yok' in icerik:
    telefondegisken=telefondegisken+1
if(telefondegisken*100)/len(splitWords)>oran:
    print("Telefonlara Cevap Verilmedi")
    print(telefondegisken)
```

Figure 6 Example of Word-Based Labeling Code

Table 3 shows the confusion matrix based on 53.982 predictions using word-based labeling. The method's accuracy rate was calculated to be 92%.

Table 3 Confusion Matrix Based on Word-Based Labeling

| % 92 | Prediction: No | Prediction: Yes | Total |
|---|---|---|---|
| Actual: No | 33528 | 1406 | 34934 |
| Actual: Yes | 2874 | 16174 | 19048 |
| Total | 36402 | 17580 | |

Two hundred forty-nine participants filled out the online survey, which was used to generate training data using human intelligence. A total of 1887 questionnaires were found to be suitable for the research after the filtering process. Table 4 shows the confusion matrix prepared according to 33.966 predictions, according to the model trained with survey-based labeling. The accuracy rate of this method was calculated as 87%.

Table 4 Confusion Matrix Based on Survey-Based Labeling

| % 86 | Prediction: No | Prediction: Yes | Total |
|---|---|---|---|
| Actual: No | 21631 | 805 | 22436 |
| Actual: Yes | 3620 | 7910 | 11530 |
| Total | 25251 | 8715 | |

According to the results, the distribution of the complaint topics is shown in table 5. While considering the means values, It is seen that the most common complaint topics are as follows respectively: delayed or not delivered parcel, customer service has not answered the call, parcel not received or delivered, returning processes, and hygiene rules-related issues.

Table 5 Distribution of Predicted Complaint Topics by Methods

| Method | Text Vectorization | Delayed or Not Delivered Parcel | The Note Was Written "Customer Was Not at Home" Was Left at The Door or Parcel Not Brought to The Door | Customer Service Has Not Answered the Call | Returning Processes | Parcel Not Received or Delivered | Hygiene Rules Related Issues |
|---|---|---|---|---|---|---|---|
| Word-Based | TF-IDF Vectorizer | 8156 | 6176 | 6902 | 4189 | 5696 | 3104 |
| | Count Vectorizer | 8614 | 6336 | 7610 | 3431 | 5100 | 1078 |
| | Hashing Vectorizer | 8075 | 5770 | 7001 | 3894 | 5375 | 4017 |
| Survey-Based | TF-IDF Vectorizer | 7019 | 5991 | 6514 | 4751 | 7706 | 5196 |
| | Count Vectorizer | 5941 | 6265 | 5418 | 2542 | 6568 | 2958 |
| | Hashing Vectorizer | 7198 | 5961 | 6590 | 4617 | 7473 | 5605 |
| | *Mean* | *7501* | *6083* | *6673* | *3904* | *6320* | *3660* |

Another goal of this research is to identify the most common complaints about each cargo operator during the pandemic. Table 6 shows the five cargo firms' complaint topics based on the prediction results.

Table 6 Distribution of Predicted Complaint Topics According to Cargo Firms

| | Delayed or Not Delivered Parcel | The Note Was Written "Customer Was Not at Home" Was Left at The Door or Parcel Not Brought to The Door | Customer Service Has Not Answered the Call | Returning Processes | Parcel Not Received or Delivered | Hygiene Rules Related Issues |
|---|---|---|---|---|---|---|
| **Firm A** | 1549 | 1074 | 1337 | 961 | 1494 | 984 |
| **Firm B** | 1725 | 1413 | 1550 | 1127 | 1853 | 1183 |
| **Firm C** | 730 | 672 | 715 | 499 | 855 | 612 |
| **Firm D** | 1660 | 1383 | 1548 | 1102 | 1823 | 1218 |
| **Firm E** | 1354 | 1447 | 1364 | 1059 | 1678 | 1195 |

Complaints involving non-delivery and delays are more common, while those about return processes and hygiene rules are relatively less frequent, as seen in Table 6.

## 5. Conclusion

As a result, our study shows that customers primarily complained about the delay or lack of delivery of their cargo. The least common complaint was that cargo staff did not follow the hygiene rules during the pandemic. According to the research results, the number of complaints about each topic and the total number of complaints reveals the best and worst parts of the leading cargo companies in Türkiye. While some companies have difficulties in specific areas, some have had a relatively successful period. In this context, adopting the decision support method used in the study to companies is critical for reviewing real-time complaints and discovering missing or unsatisfactory situations. The findings of this study reveal how the leading cargo companies in Türkiye manage the pandemic within the scope of the sample data. If cargo companies want to achieve customer satisfaction, receiving fewer complaints is the best method to be accomplished. They should focus on removing their shortcomings to be more successful and observe their competitors' activities by reviewing complaints.

When the research findings are compared with the relevant literature, Burucuoglu and Yazar's [20] findings show high similarities in consideration of the topic called delivery/distribution, which includes; the issues of "you were not at the address" note, the return of the cargo without the knowledge of the customer, delivery to the wrong address, no delivery to the address, no delivery, late delivery, and delivery to the wrong person is considered as one of the most intense complaints of the customers that revealed. Güven [11], Kocabaş [22], and Tosun & Gürce's [21] studies partially show similarities with our findings, such as delayed or not delivered parcels, parcels not received or delivered, and returns processes. The issues related to hygiene rules revealed the complaint topic different from the relevant literature considering cargo services in our study.

Within the scope of the research, it was seen that the word-based labeling method estimated a total of 100,524 complaints, while the survey-based method estimated a total of 104,313 complaints. When we examined it for accuracy, the word-based label assignment method was found to be 92%, whereas the survey-based method was 87%. Although the survey-based labeling method predicts many more complaints, the prediction accuracy rate is decreased. The accuracy rates of each method are shown in Table 7.

Table 7 Accuracy Rates of Methods

| Word-Based | | | | | Survey-Based | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **TfidfVectorizer** | | | | | **TfidfVectorizer** | | | | |
| | | Prediction | | | | | Prediction | | |
| | | **No** | **Yes** | Total | | | **No** | **Yes** | Total |
| **Actual** | **No** | 11059 | 519 | 11578 | **Actual** | No | 6950 | 252 | 7202 |
| | **Yes** | 1075 | 5341 | 6416 | | Yes | 1467 | 2653 | 4120 |
| | Total | 12134 | 5860 | 17994 | | Total | 8417 | 2905 | 11322 |
| | *Accuracy* | *91%* | | | | *Accuracy* | *84%* | | |
| **HashingVectorizer** | | | | | **HashingVectorizer** | | | | |
| | | Prediction | | | | | Prediction | | |
| | | **No** | **Yes** | Total | | | **No** | **Yes** | Total |
| **Actual** | **No** | 10356 | 879 | 11235 | **Actual** | No | 6339 | 553 | 6892 |
| | **Yes** | 1778 | 4981 | 6759 | | Yes | 2078 | 2352 | 4430 |
| | Total | 12134 | 5860 | 17994 | | Total | 8417 | 2905 | 11322 |
| | *Accuracy* | *85%* | | | | *Accuracy* | *76%* | | |
| **CountVectorizer** | | | | | **CountVectorizer** | | | | |
| | | Prediction | | | | | Prediction | | |
| | | **No** | **Yes** | Total | | | **No** | **Yes** | Total |
| **Actual** | **No** | 12113 | 8 | 12121 | **Actual** | No | 8342 | 0 | 8342 |
| | **Yes** | 21 | 5852 | 5873 | | Yes | 75 | 2905 | 2980 |
| | Total | 12134 | 5860 | 17994 | | Total | 8417 | 2905 | 11322 |
| | *Accuracy* | *99%* | | | | *Accuracy* | *99%* | | |

The CountVectorizer vectoring method has the highest accuracy rate of 99% in both labeling approaches. This result is believed to be related to the method's operating basis. The CountVectorizer vectoring approach makes vectorization by counting the words in the document. Since the training and test data were comprised of the same samples throughout the testing of the training data, it is likely that the approach discovered identical word counts on the same samples and, as a result, made highly accurate predictions. It should be noted that this result may be misleading.

The period with the highest number of complaints followed a period in which the number of Covid-19 cases increased in Türkiye dramatically for the first time. During this period, the Turkish Ministry of Health requested that citizens stay home. The main reason for the increase in complaints is the growing number of customers who prefer to order via the internet rather than traditional methods and that most cargo companies were caught unprepared for this demand. As a result, cargo companies should need to anticipate future demand and create a variety of operational approaches in the case of similar scenarios in the future.

In general, it is seen that most complaints are experienced during the delivery of the parcels, which is the number of delayed cases is relatively high. In order to reduce the number of complaints about this theme, cargo businesses must increase the number of branches in proportion to the increase in business volume and employees.

Another finding based on the research findings is that branch staff, and customer service professionals experience a lack of control in the face of increased business volume, just like field personnel. Customers have complained about the carelessness of customer service and the lack of consideration for their requests (for example, delivery in the branch, although customers were requesting delivery at the door). Undoubtedly, this research field should be handled with an interdisciplinary approach, as in this study, and the underlying causes of the complaints should be dealt with in more detail. For example, from the perspective of the management or human resources discipline, it can be said that the perception of burnout in the employees who were recruited with insufficient training due to the workload may be an important reason for these complaints. In this scenario, the cargo companies devoting emphasis to the in-company training and considering the aspects that motivate their personnel may significantly minimize the number of complaints. According to recent studies [11], [12] done during the pandemic, the number of orders on e-commerce sites has steadily grown, and logistics problems have become more challenging. In this sense, our study findings are similar to the literature studies.

## 6. Limitation and Future Studies

Several limitations must be considered in evaluating the findings of this study. The first limitation is that the data used in this study was obtained only from a single web page. Using data from various platforms may reveal different outcomes. The second limitation of the study is that the complainants' demographic characteristics are unknown, and it cannot be determined whether they have written more than one complaint about the same problems or whether the complaints written are genuine. The third limitation is about methods. In the survey-based labeling method, the accuracy of the participants' answers could not be checked.

Furthermore, the study solely used the logistic regression method to make the prediction. In this context, using different methods will be beneficial for the relevant literature, as it will provide the chance to make a comparison in future studies. Future studies in this field may improve predicted consistency by increasing the amount of learning data and employing various methods for estimating word weights or implementing different classification algorithms.

## References

[1] V. Surveillances, "The epidemiological characteristics of an outbreak of 2019 novel coronavirus diseases (COVID-19) in China," *Zhonghua Liu Xing Bing Xue Za Zhi*, vol. 41, no. 2, pp. 145–151, 2020, doi: 10.3760/cma.j.issn.0254-6450.2020.02.003.

[2] Z. Y. Zu *et al.*, "Coronavirus Disease 2019 (COVID-19): A Perspective from China," *Radiology*, vol. 296, no. 2. pp. E15–E25, 2020, doi: 10.1148/radiol.2020200490.

[3] F. Budak and Ş. Korkmaz, "Covid-19 Pandemi Sürecine Yönelik Genel Bir Değerlendirme: Türkiye Örneği," *Sos. Araştırmalar ve Yönetim Derg.*, no. 1, pp. 62–79, May 2020, doi: 10.35375/sayod.738657.

[4] GoogleNews, "Koronavirüs (COVID-19)," 2022. https://news.google.com/covid19/map?hl=tr&mid=%2Fm%2F02j71&gl=TR&ceid=TR%3Atr.

[5] M. Bulut, "Analysis of The Covid-19 Impact on Electricity Consumption and Production," *Sak. Univ. J. Comput. Inf. Sci.*, vol. 3, no. 3, 2020, doi: 10.35377/saucis.03.03.817595.

[6] B. Kaya and A. Günay, "Twitter Sentiment Analysis Based on Daily Covid-19 Table in Turkey," *Sak. Univ. J. Comput. Inf. Sci.*, vol. 4, no. 3, 2021, doi: 10.35377/saucis...932620.

[7] L. Çallı and B. A. Çallı, "Covid-19 Aşı Tereddütüne Sahip Hekimlerin Gizli Dirichlet Ayrımı (GDA) Algoritmasıyla Twitter Paylaşımlarının Konu Modellemesi," in *8th International Management Information Systems Conference*, 2021, no. October, pp. 91–103.

[8] V. Alfonso, C. Boar, J. Frost, L. Gambacorta, and J. Liu, "E-Commerce in the Pandemic and Beyond," *BIS Bull.*, vol. 220, no. 44, 2021, [Online]. Available: https://ideas.repec.org/p/bis/bisblt/36.html.

[9] E-TicaretBilgiPlatformu, "2020 Yılı İstatistikleri (Ocak - Aralık)," 2021. https://www.eticaret.gov.tr/istatistikler.

[10] ETBİS, "Elektronik Ticaret Bilgi Sistemi (Etbis) 2021 Yılı Verileri," 2022. https://www.eticaret.gov.tr/dnnqthgzvawtdxraybsaacxtymawm/content/FileManager/Dosyalar/2021 Yılı E-Ticaret Bülteni.pdfpdf.

[11] H. Güven, "Covid-19 Sürecinde E-Ticaret Sitelerine Yöneltilen Müşteri Şikâyetlerinin İncelenmesi," *J. Turkish Stud.*, vol. Volume 15, no. Volume 15 Issue 4, pp. 511–530, 2020, doi: 10.7827/turkishstudies.44354.

[12] A. Parlakkılıç, M. Üzmez, and S. Mertoğlu, "How Does Covid-19 Pandemic Effect Online Shopping in E-Commerce?," *J. Bus. Digit. Age*, vol. 3, no. 2, pp. 117–122, 2020, doi: 10.46238/jobda.823955.

[13] Etid, “EY Parthenon & ETİD COVID 19 Yönetici ve KOBİ Anketleri,” 2020. [Online]. Available: https://assets.ey.com/content/dam/ey-sites/ey-com/tr_tr/pdf/2020/07/ey-turkiye-parthenon--etid--covid-19-anketleri.pdf.

[14] L. Jean Harrison-Walker, “E-complaining: A content analysis of an Internet complaint forum,” 2001.

[15] D. Istanbulluoglu, S. Leek, and I. T. Szmigin, “Beyond exit and voice: developing an integrated taxonomy of consumer complaining behaviour,” *Eur. J. Mark.*, vol. 51, no. 5–6, pp. 1109–1128, 2017, doi: 10.1108/EJM-04-2016-0204.

[16] L. Çallı and F. Çallı, “Understanding Airline Passengers during Covid-19 Outbreak to Improve Service Quality: Topic Modeling Approach to Complaints with Latent Dirichlet Allocation Algorithm,” *Transp. Res. Rec. J. Transp. Res. Board*, p. 036119812211120, 2022, doi: 10.1177/03611981221112096.

[17] sikayetvar.com, “About Us,” 2021. https://www.sikayetvar.com/hakkimizda.

[18] D. Gündüz Hoşgör and H. Hoşgör, “Sağlık Hizmeti Tüketicileri Perspektifinden Özel Hastane Şikâyetlerinin İncelenmesi (Sikayetvar.Com Örneği),” *Hacettepe Sağlık İdaresi Derg.*, vol. 22, no. 4, pp. 823–842, 2019, [Online]. Available: https://orcid.org/0000-0002-1377-4617.

[19] H. N. Güler, “Koronavirüsü (COVID-19) Günlerinde Bankalara İletilen Müşteri İtiraz ve Şikayetlerinin İncelenmesi,” *Avrasya Sos. ve Ekon. Araştırmaları Derg.*, vol. 7, no. 4, pp. 85–99, 2020.

[20] M. Burucuoğlu and E. E. Yazar, “Üçüncü Parti Platformda Kargo Firmalarına Yapılan Müşteri Şikayetlerinin İçerik Analizi,” *Ekon. ve Sos. Araştırmalar Derg.*, vol. 16, no. 1, pp. 99–114, 2020.

[21] M. Y. Gürce and P. Tosun, “Kargo Hizmetlerine İlişkin Müşteri Şikayetleri: Bir İçerik Analizi,” *J. Bus. Res. - Turk*, vol. 3, no. 9, pp. 177–196, 2017, doi: 10.20491/isarder.2017.294.

[22] İ. Kocabaş, “Covid- 19 Döneminde E - Şikâyet Yönetimi Perspektifinden Müşterilerin Çevrimiçi Alışverişte Karşılaştıkları Sorunlar,” *Selçuk İletişim Derg.*, vol. 15, no. 1, pp. 323–359, 2022.

[23] A. Deniz and L. Gödekmerdan, “Müşterilerin Kargo Firmalarının Sunduğu Hizmetlere Yönelik Tutum ve Düşünceleri Üzerine Bir Araştırma,” *Atatürk Üniversitesi Sos. Bilim. Enstitüsü Derg.*, vol. 15, no. 2, pp. 379–396, 2011.

[24] S. Kapıkıran, F. Öztürk, and E. Akkan, “Kargo Hizmetlerine Yönelik Hizmet Hatası Seviyesi , Hizmet Telafisi ve Tatminin Müşteri Sadakati Üzerindeki Etkisi Belirlemeye Yönelik Pilot,” pp. 0–2, 2021.

[25] A. H. Özaydın, S. Çelikkaya, and G. Duran, “Kargo Hizmetlerinin Tüketici Davranışlarına Etkisi Üzerine Bir Çalışma: Süleyman Demirel Üniversitesi Örneği,” *Enderun Derg.*, vol. 3, no. 2, pp. 86–97, 2019.

[26] Y. Cho, I. IM, R. Hiltz, and J. Fjermestad, “An analysis of online customer complaints: Implications for Web complaint management,” *Proc. Annu. Hawaii Int. Conf. Syst. Sci.*, vol. 2002-Janua, no. c, pp. 2308–2317, 2002, doi: 10.1109/HICSS.2002.994162.

[27] M. N. Alabay, “Müşteri Şikâyetleri Yönetimi,” *Uluslararası Yönetim İktisat ve İşletme Derg.*, vol. 8, no. 16, 2012.

[28] S. Ray, “A Quick Review of Machine Learning Algorithms,” in *Proceedings of the International Conference on Machine Learning, Big Data, Cloud and Parallel Computing: Trends, Prespectives and Prospects, COMITCon 2019*, 2019, pp. 35–39, doi: 10.1109/COMITCon.2019.8862451.

[29] I. El Naqa, R. Li, and M. J. Murphy, *Machine Learning in Radiation Oncology*. Cham: Springer International Publishing, 2015.

[30] J. Castañón, "10 Machine Learning Methods that Every Data Scientist Should Know," 2019. https://towardsdatascience.com/10-machine-learning-methods-that-every-data-scientist-should-know-3cc96e0eeee9.

[31] T. Kwartler, "What is Text Mining?," in *Text Mining in Practice with R*, 2017, pp. 1–15.

[32] L. Çallı, F. Çallı, and B. Alma Çallı, "Yönetim Bilişim Sistemleri Disiplininde Hazırlanan Lisansüstü Tezlerin Gizli Dirichlet Ayrımı Algoritmasıyla Konu Modellemesi," *MANAS Sos. Araştırmalar Derg.*, pp. 2355–2372, 2021, doi: 10.33206/mjss.894809.

[33] M. Roukalova, "Text Mining vs. Natural Language Processing," *Scion Analytics*, 2021. https://scionanalytics.com/text-mining-vs-natural-language-processing.

[34] A.-H. Tan, "Text Mining: The state of the art and the challenges," *Proc. PAKDD 1999 Work. Knowl. Disocovery from Adv. Databases*, vol. 8, pp. 65–70, 1999, doi: 10.1.1.38.7672.

[35] S. Kazan and H. Karakoca, "Product Category Classification with Machine Learning," *Sak. Univ. J. Comput. Inf. Sci.*, vol. 2, no. 1, pp. 18–27, 2019, doi: 10.35377/saucis.02.01.523139.

[36] A. C. P. L. F. de Carvalho and A. A. Freitas, "A Tutorial on Multi-label Classification Techniques," 2009, pp. 177–195.

[37] P. Szymanski and T. Kajdanowicz, "Scikit-multilearn: A python library for multi-label classification," *J. Mach. Learn. Res.*, vol. 20, no. 6, pp. 1–22, 2019.

[38] A. K. Singh and M. Shashi, "Vectorization of text documents for identifying unifiable news articles," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 7, pp. 305–310, 2019, doi: 10.14569/ijacsa.2019.0100742.

[39] A. Aizawa, "An information-theoretic perspective of tf-idf measures," *Inf. Process. Manag.*, vol. 39, no. 1, pp. 45–65, Jan. 2003, doi: 10.1016/S0306-4573(02)00021-3.

[40] W. Zhang, T. Yoshida, and X. Tang, "A comparative study of TF*IDF, LSI and multi-words for text classification," *Expert Syst. Appl.*, vol. 38, no. 3, pp. 2758–2765, 2011, doi: 10.1016/j.eswa.2010.08.066.

[41] S. Kaur, P. Kumar, and P. Kumaraguru, "Automating fake news detection system using multi-level voting model," *Soft Comput.*, vol. 24, no. 12, pp. 9049–9069, 2020, doi: 10.1007/s00500-019-04436-y.

[42] J. Deepakumara, H. M. Heys, and R. Venkatesan, "FPGA implementation of MD5 hash algorithm," *Can. Conf. Electr. Comput. Eng.*, vol. 2, pp. 919–924, 2001, doi: 10.1109/ccece.2001.933564.

[43] J. Brownlee, "One-vs-Rest and One-vs-One for Multi-Class Classification," *Machine Learning Mastery*, 2020. https://machinelearningmastery.com/one-vs-rest-and-one-vs-one-for-multi-class-classification/.

[44] TurkishMinistryofHealth, "COVID-19 Bilgilendirme Platformu," 2022. https://covid19.saglik.gov.tr/.