Research Article
Journal of Intelligent Systems: Theory and Applications 5(1) 2022: 85-91
DOI: 10.38016/jista.954098

Categorization of Customer Complaints in Food Industry Using Machine Learning Approaches

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Abstract
Customer feedback is one of the most critical parameters that determine the market dynamics of product development. In this direction, analyzing product-related complaints helps sellers to identify the quality characteristics and consumer focus. There have been many studies conducted on the design of Machine Learning (ML) systems to address the causes of customer dissatisfaction. However, most of the research has been particularly performed on English. This paper contributes to developing an accurate categorization of customer complaints about package food products, written in Turkish. Accordingly, various ML algorithms using TF-IDF and word2vec feature representation strategies were performed to determine the category of complaints. Corresponding results of Linear Regression (LR), Naive Bayes (NB), k Nearest Neighbour (kNN), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) classifiers were provided in related sections. Experimental results show that the best-performing method is XGBoost with TF-IDF weighting scheme and it achieves %86 F-measure score. The other considerable point is word2vec based ML classifiers show poor performance in terms of F-measure compared to the TF-IDF term weighting scheme. It is also observed that each experimented TF-IDF based ML algorithm gives a more successful prediction performance on the optimal subsets of features selected by the Chi Square (CH2) method. Performing CH2 on TF-IDF features increases the F-measure score from 86% to 88% in XGBoost.

Keywords: customer complaints, complaint categorization, food industry, machine learning.

1. Introduction

Today's customers are more willing to complain about the products and services they purchase (Mahayudin et al., 2010). Organizations need to know and handle the increasing threat of online public complaints (Tripp and Gregoire, 2011). Academic and sector professionals regard customer satisfaction and complaints as critical input for companies' success in a competitive environment (Pinto and Mansfield, 2012). Besides, some researchers recognized successful complaint solving as a competing benefit (Fox, 2008).

In recent years, companies have collected customer complaints via social media platforms such as websites, Twitter, forums, and blogs, by benefiting from developing technology (Tax et al., 1998). Because social media enables businesses to communicate with their customers and get feedback from them (HaCohen-Kerner et al. 2019). Some organizations combine social media in their complaint handling process (Jin et al., 2013). These companies' customers are encouraged to participate in a survey by a direct message or email from one of the social media platforms after a service experience. One of the most popular social media platforms, Facebook, was mainly preferred by Generation Y (people born between 1981 and 1996) to express their complaints (Rossmann et al., 2017). Even though these surveys enable companies to receive feedback on purchased products and services with star ratings or points (Sohail et al., 2016; Bhole and Hanna, 2017). Customer complaint management has become an essential factor in optimizing the relationship between clients and companies in recent years. However, manual

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Recieved : 18 June 2021
Revision : 31 Aug 2021
Accepted : 04 Oct 2021

analysis of complaints is ineffective and time-consuming, due to the notable rise in complaints in digital platforms. In this direction, more researchers have recently focused on the categorization of customer feedback using Machine Learning (ML) algorithms to handle complaints efficiently. Since many customer complaints are in textual form, techniques collected under Text Mining (TM) become necessary to handle the texts' implicit structure before execution of ML algorithms. TM includes two basic steps, such as pre-processing and creating feature sets for data representation. There are two sorts of research commonly applied for text representation, indexing and term weighting (Harish et al., 2010).

In this study, the customer complaints about package food products were categorized using Logistic Regression (LR) (Wright, 1995), Naive Bayes (NB) (Berrar, 2018), Support Vector Machine (SVM) (Noble, 2006), k Nearest Neighbour (kNN) (Peterson, 2009), Random Forest (RF) (Bioau&Scarnet, 2016), and Extreme Gradient Boosting (XGBoost) (Chen et al., 2015) ML algorithms. To the best of our knowledge, this study is the first attempt to analyze customer complaints for the food industry in Turkish text. It contributes to the literature by experimenting different ML classifiers with different feature vectorization strategies that categorizes the customer complaints written in Turkish. It applies TF-IDF and word2vec text representation methods and then uses the feature reduction technique since the high dimensional training space is produced after pre-processing textual input for ML algorithms. Then, it compares ML classifiers whose parameters are tuned with the use of grid-search algorithm (Kılınç et al., 2016). The remaining parts of the study are organized as follows. Section 2 discusses related works. Section 3 gives dataset, data pre-processing steps, feature engineering and ML methods used in the study. Section 4 presents the details of the experimental study with metrics and results. Finally, Section 5 concludes the study and Section 6 gives information about the threats of validity.

2. Related Works

Intensifying competition and developing technology force businesses to manage customers' complaints. Management of complaints is an effective tool in identifying shortcomings in service quality and creating customer loyalty. More researchers have recently addressed the analysis of customer comments for efficient complaint handling in this respect. For example, Hong and Wang (2021) proposed a framework to summarize customer opinions, including both positive and negative comments, from product reviews using neural networks. The effectiveness of the framework was tested with six datasets from real-world business scenarios. In other study, Chen et al. (2021) identified the affecting factors of customers satisfaction from unstructured online comments by lessening personal communication to collect these reviews. Lee and Choi (2020) studied public environmental complaints to investigate the factors that contribute to reducing ecosystem benefits. They performed statistical and spatial analyses on the complaints received by the Namyangju government. Finally, the citizens' comments were categorized as water, air pollution, electricity problems, etc. In another study, Onan et al. (2020) presented the categorization of service support requests using basic ML algorithms (NB, kNN, RF, C4.5, and SVM) on the dataset, including 17831 bug reports and service support requests. Before experimenting with classifiers, they built a TF-IDF scheme for feature representation. The experimental results showed that the classifiers achieved encouraging results in directing support requests to related services. Krishna et al. (2019) performed sentiment analysis of bank customers using the respective banks' online complaints platforms. They experimented with SVM, NB, LR, Decision Tree (DT), kNN, RF, XGBoost, and Multi-layer Perceptron (MLP) classifiers on data generated of TF-IDF, word2Vec and Linguistic Inquiry and Word Count (LIWC) vectors. Eventually, complaints were labelled as moderate or extreme. Experimental results indicated that the LIWC based RF and NB techniques achieved the best accuracy. The study of Stoica and Özyirmidokuz (2015) aimed to get meaningful data from unstructured customer feedbacks about a telecommunication firm in Turkey. After text processing techniques, k-Medoid was used to cluster documents according to the relevant categories. It was stated that the proposed method is advantageous since similar responses in a cluster could be answered by similar response mails.

Considering the literature, there are very few studies empirically examine the impact of customer complaints in food industry. Lemos et al. (2018) conducted a study to analyze the comments of moldy foods within the expiration date. In another study, Khan et al. (2013) analyzed customer complaints about fast-food products within the service, environmental conditions, price, and taste factors. Comments of four well-known fast-food brands were analyzed using multiple regression and correlation tests to determine which factors have a more critical impact on consumer satisfaction.

3. Materials and Methods

3.1. Dataset

The dataset which was obtained from a packaged food supplier in Turkey, includes 2217 customer complaints obtained through call center, e-mail, web pages, and social media (Facebook, Şikayetvar, etc.). The records were annotated as “unhygienic”, “foreign body”, “texture”, “package/label”, and “taste/smell” (Table 1). The language of the complaints in the dataset is Turkish.

Table 1. Sample complaints in the dataset (TR: Turkish, EN: English)

Complaint ID	Description	Category
1	**TR:** Nutella kavanozunun ağzı kırık çıkmış, içinde cam kırıkları varmış. Ürünü markete iade edecek. **EN:** Nutella jar's mouth was broken. There were glass breaks in it. He will return the product to the market.	Package/Label
2	**TR:** Daha önce de şikayette bulunmuş. xxxxx'nın tadı çok kötü bütün gramajları denedim hepsi aynı çocukluğumun nutellası değil dedi. Değiştirilmesini istiyor. **EN:** He had complained before. He said that he tried all xxxxx sizes, and they did not taste all that great. He wants it replaced.	Taste/Smell
3	**TR:** Ürün içerisinden kırmızı renkte plastik benzeri bir madde çıkmış. Çocuğum onu yutacaktı neredeyse dedi. **EN:** There was a red-colored object like plastic. He said that his child was almost going to swallow it.	Foreign body
4	**TR:** Merhaba, müşteri nutella kavonuzunda ilk aldıklarında kavanoz kapağının altında buhar bulunduğunu ve beyazımsı bir görüntü olduğunu söyledi. **EN:** Hello, the customer said that there was a steam under the jar lid, and it had a whitish appearance.	Texture
5	**TR:** xxxxx'nın dibinden son çatal aldım ekmeğe sürmek üzereyken içinde sinek olduğunu fark ettim. **EN:** I got the last bit of xxxxx from the jar, and when I was about to rub it on the bread, I realized that there was a fly in it.	Unhygenic

3.2. Data pre-processing

Text pre-processing makes raw textual data more useful for subsequent analysis. It forms the raw data by removing non-alphanumeric characters, numbers, punctuation marks, and stop words. In pre-processing, stemming is another important step that provides mapping of connected words into a base form.

In this study, first tokenization was performed to split phrases into tokens (meaningful elements) such as words, numbers, punctuation marks. Then, the customer complaints were evaluated in terms of spelling errors since there were many spelling mistakes in the unprocessed dataset. Therefore, Zemberek normalization module developed by Akın (2007) was employed on the raw data for pre-processing noisy text inputs. The stopwords which refers to commonly used words in a language (e.g., "and", "so", "the" in English) were filtered. Finally, the stemming was performed to reduce unnecessary diversity in the feature vectors. Figure 1 illustrates the pre-processing steps applied in this study.

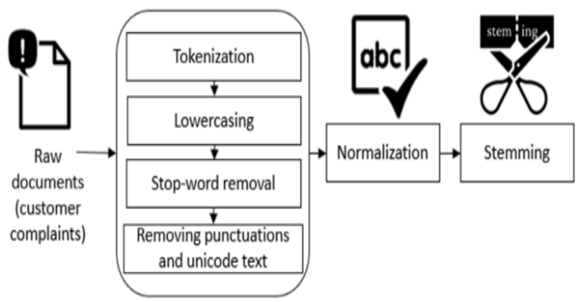

Figure 1. Set of applied pre-processing steps

3.3. Data representation and feature engineering

Unstructured textual data is challenging to process and needs to be described by term sets to represent their contents. The vector space model (Salton and Yang, 1973) is one of the most used text representation models to a host of information retrieval operations. This model also appeals to the underlying metaphor of practicing spatial proximity for semantic proximity (Zhang et al. 2011). There are two sorts of research commonly applied for text representation: indexing and term weighting. Indexing assigns indexing terms for documents, whereas term weighting assigns each term's weight to show its importance. This study uses word2vec method for indexing and the TF-IDF method to calculate each word's weights in the customer complaints.

Word2vec is a method of embedding words in a high-dimensional space. After an external neural network is trained for the word embedding, terms in the document are classified according to their similarities in the word2Vec space. There are two models for representing words in a multidimensional vector space namely skip-gram and Continuous Bag of Words (CBOW) (Onishi&Shina, 2020). In the skip-gram model, the surrounded representations of a context are predicted using the centre word. CBOW model predicts a target word by combining the distributed representations in its context. Due to their simple architecture, skip-gram and CBOW can be trained on a large dataset in a short time. The ability to train on very large datasets allows the model to learn complex word relationships such as vec(Turkish) + vec(food) ≈ vec(kebab).

TF-IDF is obtained by multiplying the term frequency (TF) and inverse document frequency (IDF) for a term in the text. While TF gives the occurrence frequency of a word in the document, the value IDF indicates this term's occurrence frequency in other documents. The main idea in TF-IDF is to classify terms as much as possible into the same category considering their high appearance in one document and high absence in other documents. When a term appears with a high TF frequency in a text document and rarely appears with low IDF frequency in other documents, it is accepted that the term has a good classification accuracy.

Since high dimensionality of textual data imposes high costs on model training and execution, feature set reduction on document representations may be necessary to optimize performance of ML algorithms. In addition to eliminate unnecessary terms, Feature Selection (FS) strategies also provide better model understand-ability, increase generalization capability of the model, and decrease in over-fitting risk (Tunalı&Bilgin, 2012). There are mainly three categories of FS strategies: filter, wrapper, and embedded methods. The most widely used methods in these groups are Information Gain (IG), Chi-Square (CH2), and Correlation Feature filtering (CF) (Özçift et al., 2019). These methods use a metric such as correlation, entropy, and mutual information to obtain the most valuable subset. In particular, CH2 filtering approach covers the relationship between two events (Howell, 2011). The filter tests the occurrence of specific word and occurrence of a complaint class to be independent or not. The rank of selected feature *t* for category c_i, x^2, is calculated using Equation 1.

$$x^{2}(t,c) = \frac{N \times (AD - BC)}{(\mathrm{A} + \mathrm{C})(\mathrm{B} + \mathrm{C})(\mathrm{A} + \mathrm{B})(\mathrm{C} + \mathrm{D})} \quad (1)$$

where A is observed frequency of t when it is included by category *c*, N is the total number of documents, *B* is the observed frequency of *t* when it is not included by category *c*, *C* is the observed frequency of *c* when it occurs without *t*, *D* is the number of documents that do not involve *t* and *c*.

3.4. Baseline machine learning (ML) algorithms

After the pre-processing and feature selection steps were utilized, some baseline ML algorithms, which are commonly used to classify the textual data, were performed.

Logistic Regression (LR): LR is used to analyze a data set within one or more independent features determining output class. It assigns a new sample to one of the determined discrete classes by utilizing a logistic function. Logistic regression is a statistical method used to analyze a data set within one or more independent features determining a result.

Naive Bayes (NB): NB depends on the common principle of Bayes Theorem, i.e., a distinct feature in a class is independent of any other feature’s presence. It describes the probability of an event, based on prior knowledge of conditions using Equation 2.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (2)$$

where P(A) and P(B) are prior probabilities and P(B|A) and P(A|B) are posterior probabilities of event A and B, respectively (Bozyiğit et al., 2019).

k-Nearest Neighbor (kNN): kNN is an instance-based ML algorithm that assigns a new sample’s class according to the majority classes of its most similar *k* neighbours. There are mainly four distance metrics such as Euclidean, Manhattan, Minkowski, and Hamming to determine the k nearest neighbours of an instance to be classified.

Support Vector Machine (SVM): SVM aims to find a hyperplane that can separate the two classes of given samples by a maximal margin. The margin corresponds to the shortest distance between the nearest data points and any point on the hyperplane. The ability to generalize of SVM ensures a high classification accuracy.

Random Forest (RF): RF algorithm builds a multitude of individual decision trees using different training subsets (Bozyiğit et al., 2020). Each tree in the forest gives an output and the final class is determined by the majority vote of them.

Extreme Gradient Boosting (XGBoost): XGBoost is a gradient boosting framework, including an efficient linear model solver and tree learning algorithm. It maintains customized functions so that users are also allowed to define their objectives and evaluation easily. Its most important features are its ability to obtain highly successful predictive results, prevent over-learning, and manage null and noisy records (Kılınç et al., 2015).

4. Experimental Study

In this study, customer complaints about food products delivered to markets in Turkey were categorised under five categories such as Hygiene, Foreign body, Taste/Smell, Texture, and Package/Label. Figure 2 shows the general flow of complaint categorization task by using ML algorithms. First data preparation was utilized to transform the raw data in a useful and efficient format. After pre-processing, two feature representation models (TF-IDF and word2vec) were applied to observe their effects on categorization accuracy. Then, CH2 feature selection strategy was performed on experimented TF-IDF based ML methods to obtain best subset of features. The evaluation results of each ML method were obtained by dividing the data set into 10 pieces by cross-validation.

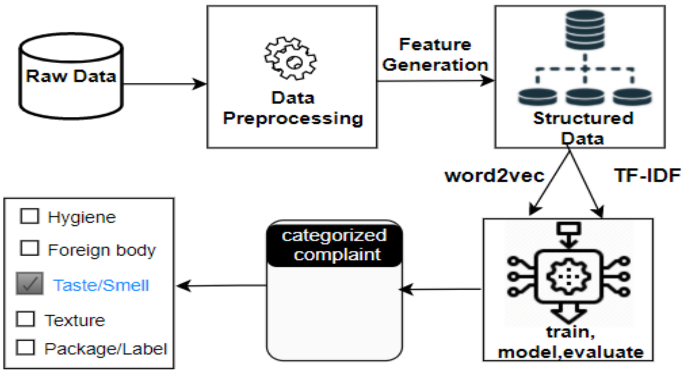

Figure 2. General flow of complaint categorization task by using ML algorithms

4.1. Experimental results

In the experimental studies, the real-world data including customer complaints were used to perform categorization task. Table 2 compares the F-measure scores obtained by performing ML algorithms with TF-IDF and word2vec (CBOW and skip-gram) representations. Considering the experimental results, the highest F-measure values were achieved by XGBoost classifier in all feature representations. On the other hand, NB classifier with both two representations had the lowest F-measure values among all classifiers.

Table 2. Evaluation of different ML algorithms and feature representations

ML algorithm	Feature representations		Precision	Recall	F-measure
LR	TF-IDF		0.80	0.83	0.81
	word2vec	skip-gram	0.66	0.64	0.67
		CBOW	0.54	0.48	0.46
NB	TF-IDF		0.75	0.71	0.73
	word2vec	skip-gram	0.53	0.54	0.53
		CBOW	0.62	0.63	0.62
kNN	TF-IDF		0.80	0.82	0.81
	word2vec	skip-gram	0.56	0.58	0.57
		CBOW	0.57	0.62	0.59
SVM	TF-IDF		0.81	0.81	0.81
	word2vec	skip-gram	0.69	0.74	0.71
		CBOW	0.59	0.66	0.62
RF	TF-IDF		0.82	0.81	0.81
	word2vec	skip-gram	0.53	0.54	0.53
		CBOW	0.62	0.63	0.62
XGBoost	**TF-IDF**		**0.83**	**0.84**	**0.84**
	word2vec	skip-gram	0.62	0.67	0.64
		CBOW	0.76	0.75	0.75

Another point to be noticed is that the ML algorithms with TF-IDF encoding method performed better than ones with the word2vec method (see Figure 3). The poor performance of word2vec representation can probably be based on the limited training data. To increase the accuracy of the word2vec, Pyhton NLP Aug library presenting augmenting for textual data was experimented. However, there was no significant effect on the word2vec performance since NLP Aug library did not perform well on Turkish texts. XGBoost with TF-IDF was evaluated as the most accurate classifier with 84% F-measure value. The closest performance result to XGBoost was achieved by SVM with TF-IDF and RF with TF-IDF with the 81% F-measure value. On the other hand, NB was the worst performing algorithm with 73% F-measure score among classifiers using TF-IDF representation model. There exists adequate evidence to show that the feature selection technique, CH2, improves the categorization accuracy by eliminating extraneous and unnecessary terms from the dataset. Figure 3 shows that the F-measure value increases in all classifiers after CH2 is applied on TF-IDF feature sets. It is obviously seen that TF-IDF feature with dimensionality reduction provides an improvement in prediction accuracy for all experimented classifiers. Performing CH2 on TF-IDF features achieved a statistically significant F-measure scores and increased it from 84% to 88% in XGBoost.

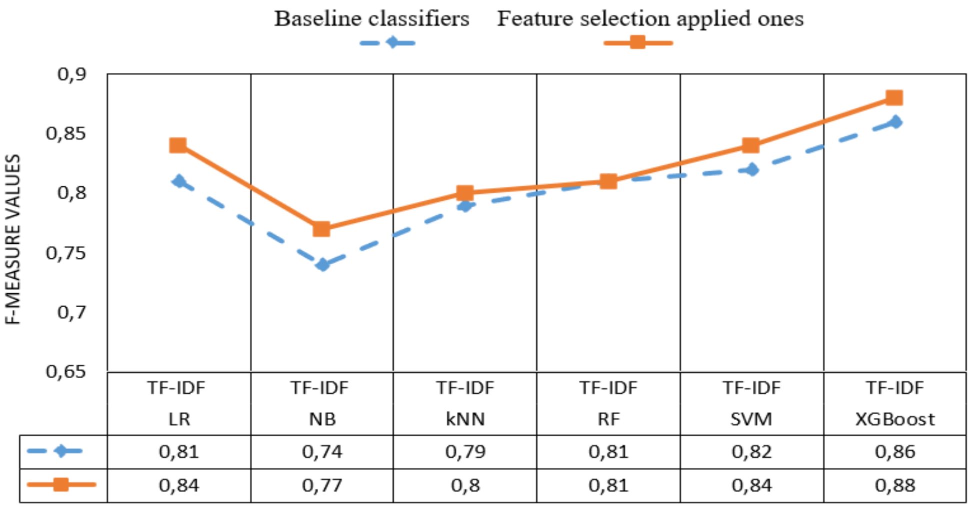

Figure 3. Performance results of the experimented methods after CH2

5. Conclusion

Customer satisfaction is specified as a primary factor for business success according to basic marketing theory. The benefits of the automatic complaint categorization are reducing the initial cost of labeling the complaints with the most appropriate tag, helping maintenance and keeping the efficient process for directing customer complaints to relevant departments, and removing the risk of depending on experts in the management of customer feedback. In this direction, feedback of consumers about the products are analyzed to determine possible problems and effective strategies to handle them. Analysis of customer comments can be challenging task for a human because it may be necessary to analyse high volume data during long time periods. An alternative is to automatically categorize the causes of customer dissatisfaction. In this study, six ML classifiers (LR, NB, kNN, SVM, RF, and XGBoost) with TF-IDF and word2vec feature representations were experimented to categorize customer complaint for food industry in Turkey. Accordingly, the complaints were categorized into “unhygenic”, “foreign body”, “texture”, “package/label”, and “taste/smell” categories. Experimental results showed that the best-performing method is XGBoost with TF-IDF weighting scheme and it achieved %86 F-measure score. The other considerable point is that word2vec based ML classifiers showed poor performance in terms of F-measure comparing to TF-IDF term weighting scheme. Since the performance of word2vec is directly related to training sample size, the data augmentation technique to generate new data was utilized to handle this problem. However, available Python libraries to produce synthetic data did not provide expected increase of F-measure. It was also observed that each experimented TF-IDF based ML algorithms showed more successful prediction performance on the optimal subsets of features selected by CH2 method. Performing CH2 on TF-IDF features increased F-measure score from 86% to 88% in XGBoost. Considering the results, it can be concluded that this study appears promising for future studies on complaint handling systems.

6. Threats to Validity

This section addresses the threats to validity that might have affected the complaint classification using the classification of Wohlin et al. (2000). The main threat to validity is the limited customer complaints analyzed in the experimental study. We examined only 2217 records obtained through call centres, e-mail, web pages, and social media platforms. For the future works, we will create large sized and comprehensive dataset to obtain better classification performances.

References

Akın, A. A., & Akın, M. D. (2007). Zemberek, an open source nlp framework for turkic languages. Structure, 10, 1-5.

Berrar, D. (2018). Bayes’ theorem and naive Bayes classifier. Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics; Elsevier Science Publisher: Amsterdam, The Netherlands, 403-412.

Bhole, B., & Hanna, B. (2017). The effectiveness of online reviews in the presence of self-selection bias. Simulation Modelling Practice and Theory, 77, 108-123.

Biau, G., & Scornet, E. (2016). A random forest guided tour. Test, 25(2), 197-227.

Bozyiğit, A., Utku, S., & Nasiboğlu, E. (2019). Cyberbullying detection by using artificial neural network models. In 2019 4th International Conference on Computer Science and Engineering (UBMK) (pp. 520-524). IEEE.

Bozyiğit, F., Şahin, M., Gündüz, T., Işık, C., & Kilinç, D. (2020) Regression based risk analysis in life insurance industry. International Journal of Engineering and Innovative Research, 2(3), 178-184.

Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., & Cho, H. (2015). Xgboost: extreme gradient boosting. R package version 0.4-2, 1(4), 1-4.

Chen, W. K., Riantama, D., & Chen, L. S. (2021). Using a Text Mining Approach to Hear Voices of Customers from Social Media toward the Fast-Food Restaurant Industry. Sustainability, 13(1), 268.

Fox, G. L. (2008). Getting good complaining without bad complaining. Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior, 21, 23.

HaCohen-Kerner, Y., Dilmon, R., Hone, M., & Ben-Basan, M. A. (2019). Automatic classification of complaint letters according to service provider categories. Information Processing & Management, 56(6), 102102.

Harish, B. S., Guru, D. S., & Manjunath, S. (2010). Representation and classification of text documents: A brief review. IJCA, Special Issue on RTIPPR (2), 110-119.

Haron, S. A., & Fah, B. C. Y. (2010). Unpleasant market experience and consumer complaint behavior. Asian Social Science, 6(5), 63.

Hong, M., & Wang, H. (2021). Research on customer opinion summarization using topic mining and deep neural network. Mathematics and Computers in Simulation, 185, 88-114.

Howell, D. C. (2011). Chi-Square Test: Analysis of Contingency Tables.

Jin, J., Yan, X., Yu, Y., & Li, Y. (2013). Service failure complaints identification in social media: A text classification approach. In: Proceedings of the 34th International Conference on Information Systems.

Kılınç, D., Borandağ, E., Yücalar, F., Özçift, A., & Bozyiğit, F. (2015). Yazılım hata kestiriminde kolektif sınıflandırma modellerinin etkisi. Proceedings of IX. Ulusal Yazılım Mühendisliği Sempozyumu. İzmir, Turkey: Yaşar Üniversitesi.

Kılınç, D., Yücalar, F., Borandağ, E., & Aslan, E. (2016). Multi-level reranking approach for bug localization. Expert Systems, 33(3), 286-294.

Krishna, G. J., Ravi, V., Reddy, B. V., Zaheeruddin, M., Jaiswal, H., Teja, P. S. R., & Gavval, R. (2019). Sentiment Classification of Indian Banks' Customer Complaints. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON) (pp. 429-434). IEEE.

Lee, J. H., & Choi, H. (2020). An analysis of public complaints to evaluate ecosystem services. Land, 9(3), 62.

Lemos, J. G., Garcia, M. V., de Oliveira Mello, R., & Copetti, M. V. (2018). Consumers complaints about moldy foods in a Brazilian website. Food Control, 92, 380-385.

Noble, William S. “What is a support vector machine?” Nature biotechnology 24.12 (2006): 1565-1567.

Onan, A., Atik, E., & Yalçın, A. (2020). Machine learning approach for automatic categorization of service support requests on university information management system. In International Conference on Intelligent and Fuzzy Systems (pp. 1133-1139). Springer, Cham.

Onishi, T., & Shiina, H. (2020). Distributed Representation Computation Using CBOW Model and Skip–gram Model. In 2020 9th International Congress on Advanced Applied Informatics (IIAI-AAI) (pp. 845-846). IEEE.

Özçift, A., Kilinç, D., & Bozyiğit, F. (2019). Application of Grid Search Parameter Optimized Bayesian Logistic Regression Algorithm to Detect Cyberbullying in Turkish Microblog Data. Akademik Platform Mühendislik ve Fen Bilimleri Dergisi, 7(3), 355-361.

Peterson, L. E. (2009). K-nearest neighbor. Scholarpedia, 4(2), 1883.

Pinto, M. B., & Mansfield, P. (2012). Facebook as a complaint mechanism: An investigation of millennials. Journal of Behavioral Studies in Business, 5, 1.

Rossmann, A., Wilke, T., & Stei, G. (2017). Usage of social media systems in customer service strategies. In Proceedings of the 50th Hawaii International Conference on System Sciences.

Salton, G., & Yang, C. S. (1973). On the specification of term values in automatic indexing. Journal of documentation.

Shahzad, K., Majid, H. S., & Fahad, Y. (2013). Determinants of Customer Satisfaction in Fast Food Industry A Study of Fast Food Restaurants Peshawar Pakistan. Studia commercialia Bratislavensia, 6(21), 56-65.

Sohail, S. S., Siddiqui, J., & Ali, R. (2016). Feature extraction and analysis of online reviews for the recommendation of books using opinion mining technique. Perspectives in Science, 8, 754-756.

Stoica, E. A., & Özyirmidokuz, E. K. (2015). Mining customer feedback documents. International Journal of Knowledge Engineering, 1(1), 68-71.

Tax, S. S., Brown, S. W., & Chandrashekaran, M. (1998). Customer evaluations of service complaint experiences: implications for relationship marketing. Journal of marketing, 62(2), 60-76.

Tripp, T. M., & Grégoire, Y. (2011). When unhappy customers strike back on the Internet. MIT Sloan Management Review, 52(3), 37-44.

Tunali, V., & Bilgin, T. T. (2012, June). PRETO: A high-performance text mining tool for preprocessing Turkish texts. In Proceedings of the 13th International Conference on Computer Systems and Technologies (pp. 134-140).

Wohlin, C., Runeson, P., Höst, M., Ohlsson, M. C., Regnell, B., & Wesslén, A. (2012). Experimentation in software engineering. Springer Science & Business Media.

Wright, R. E. (1995). Logistic regression.

Zhang, W., Yoshida, T., & Tang, X. (2011). A comparative study of TF* IDF, LSI and multi-words for text classification. Expert Systems with Applications, 38(3), 2758-2765.