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*Research Article*

## Machine Learning Based a Comparative Analysis for Detecting Tweets of Earthquake Victims Asking for Help in the 2023 Turkey-Syria Earthquake


***Anıl Utku*[1], *Umit Can*[2]**

[1,2] *Computer Engineering Department, Munzur University, 62000 Tunceli, Türkiye*



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ABSTRACT

Two major earthquakes in Kahramanmaraş on February 6, 2023, 9 hours apart, affected many countries, especially Turkey and Syria. It caused the death and injury of thousands of people. Earthquake survivors shared their help on social media after the earthquake. While people under the rubble shared some posts, some were for living materials. There were also posts unrelated to the earthquake. It is essential to analyze social media shares to manage the process effectively, save time, and reach the victims as soon as possible. In this study, about 500 tweets about the 2023 Turkey-Syria earthquake were analyzed. The tweets were classified according to their content as user tweets under debris and user tweets requesting life material. Popular machine learning methods such as DT, kNN, LR, NB, RF, SVM, and XGBoost were compared in detail. Experimental results showed that RF has over 99% classification accuracy.


## 1. Introduction

People have expressed their thoughts and experiences using different tools throughout their lives. Today, depending on the development of internet technologies, the use of social media is increasing, and sharing is done through social media [1]. Therefore, social media has become a powerful tool that directs events rather than just a communication tool. Sharing on social networks, an effective way of sharing thoughts is increasing daily and creates information stacks [2]. However, various methods are needed to process this information and make the data meaningful. Sentiment analysis comes to the fore to analyze and classify shared feelings, thoughts, and opinions. Sentiment analysis is a classification problem in which each share in the dataset is represented in different categories according to its content. Sentiment analysis is a text processing process that aims to determine the emotion expressed in the text [3].

Social media is a powerful communication tool. Especially when communication networks such as earthquakes are damaged, the use of social networks becomes more prominent [4]. Earthquake victims share their help needs on social media. In addition to the tweets posted by earthquake victims who need help, there are also tweets posted by malicious people. In addition, it is necessary to separate the tweets of the people under the rubble and the tweets that demand life materials. For this reason, analyzing tweets using artificial intelligence methods will be effective in terms of time and process management [5-6].

2023 Turkey-Syria earthquakes occurred on February 6, 2023, in the Pazarcık and Ekinözü districts of Kahramanmaraş, nine hours apart. The size of the earthquakes was announced as 7.8 MW and 7.5 MW [7]. As a result of earthquakes, approximately 50,000 people in Turkey and about 10,000 people in Syria were killed, and more than 129 thousand people were injured. After the


1 * Corresponding author
e-mail: ucan@munzur.edu.tr


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earthquakes, nearly 17 thousand aftershocks reached up to 6.7 MW. The first earthquake was felt in a large area, including Turkey and Syria, as well as Cyprus, Egypt, Iran, Iraq, Israel, Jordan and Lebanon. The two major earthquakes have caused damage to approximately 350,000 km2 and affected 14 million people, which comprised 16% of Turkey's population.

Studies on analyzing posts shared through online social networks about various disasters, especially earthquakes, are remarkable in the literature. For example, sentiment analysis was used to predict the perspective of the society by analyzing the tweets, or many studies were conducted to understand whether the tweets were a call for help.

Mendon et al. [8] used various data pre-processing techniques. They proposed a hybrid model to analyze the sentiment of 243,746 posts shared on Twitter after the Kerelas natural disaster in India in 2018. Their study used TF-IDF, K-means, LDA, and Doc2Vec techniques.

Behl et al. [9] categorized earthquake-related datasets in Italy, Nepal, and the Covid-19 pandemic with supervised learning techniques. In these studies, a Multilayer Perceptron (MLP) model was proposed for classifying Twitter posts. It is compared with popular machine learning and deep learning methods. They tried categorizing tweets as 'resource availability,' 'resource needs, and 'others.'

Another study tried to understand whether the tweets about any emergency were analyzed and whether they were available or needed. This study proposed a hybrid deep learning model consisting of LSTM and CNN models. This model also aims to categorize non-English posts [10].

They proposed a deep learning-based model that analyzes the images obtained from smart infrastructures to support the solution to the problem of healthy disaster management and directing the available resources to the disaster areas in need at the right time. Deep learning models have shown higher accuracy than machine learning models [11].

Wang et al. [12] proposed a model for detecting rumors about disasters in social networks. In this study, 3793 content collected from Sina Weibo, a social networking platform, was analyzed. Various natural language processing techniques were used for sentiment analysis, and Support Vector Machines (SVM), Logistic Regression (LR), Random Forest (RF) and Extreme Gradient Boosting (XGBoost) models were used for rumor detection. As a result of the study, a robust model for rumor detection is proposed.

Ruz et al. [13] conducted sentiment analysis using two Twitter datasets related to the Chilean earthquake in 2010 and the 2017 Catalan independence referendum in 2017. They proposed a Bayesian network classifier and compared it with SVM and RF models. Their proposed model achieved successful results.

It is crucial to utilize instant information flow to strengthen the management processes of various disasters. Kryvasheyeu et al. [14] proposed a sensor method to analyze the sentiment of 50 million tweets sent before, during, and after Hurricane Sandy.

Huang et al. [15] proposed a text dynamic clustering-based method for early detection of events such as natural disasters, health, and social security emergencies using social media posts. They obtained very successful results with the BERT-Att-BiLSTM model.

Kumar et al. [16] proposed a multi-channel convolutional neural network (MCNN) model to classify tweets about disasters into eyewitness, non-eyewitness, and do not know classes. In doing so, they used a separate word embedding vector with this model. Their model gave the best results compared to popular deep learning and machine learning methods.

As seen in the literature, after disasters such as floods, hurricanes, and earthquakes that affect large regions and cause significant damage, early and correct intervention in the affected regions is crucial in crisis management. Many studies have been conducted in this domain, and different models have been proposed. Unlike traditional methods, advanced models are created thanks to the data obtained from social networks. In this study, tweets from the Turkey-Syria earthquake, which affected a large region and caused great destruction, were analyzed, and aid requests were classified. Here, it is aimed to reach users who need help quickly by utilizing the power of social networks.

In this study, machine learning methods such as Decision Tree (DT), LR, k-Nearest Neighbor (kNN), Naive Bayes (NB), RF, XGBoost and SVM are used to classify tweets posted after the earthquake in Kahramanmaraş, Turkey in February 2023. The used machine learning methods are used to classify tweets to identify users asking for help and relief supplies. Various metrics are used in the literature to compare machine learning methods [17-18]. In this study, F-score, precision, accuracy, and recall metrics were used. Experimental results showed that machine learning models successfully detected people seeking help and relief materials during the earthquake.

## 2. Material and Method

In this study, it was aimed to develop a model for earthquake combat, rescue, and aid efforts. It is classifying user tweets according to their content aimed at developing a model that could support search and rescue efforts and reach needy areas. For this purpose, a comparative analysis based on popular machine learning methods such as DT, kNN, LR, NB, RF, SVM, and XGBoost is presented.

### *2.1. Dataset*

This study used a dataset consisting of 499 tweets about the 2023 Turkey-Syria earthquake. The tweets in the dataset consist of two classes. Class 1 consists of 299 tweets sent by earthquake victims seeking help. Out of 200 tweets, Class 0 has 150 tweets with keywords like "earthquake," "meal," and "blanket," and 50 tweets with no reference to the earthquake. The dataset used is publicly available on Kaggle via [19]. A sample representation of the dataset is shown in Table 1.

**Table 1** A sample from the dataset

| Text | Label |
|---|---|
| Kahramanmaraş türkoğlu ilçesi şekeroba köyü ça... | 1 |
| Teyitli, ses var, köpekler tepki veriyor. Her... | 1 |
| 0539 693 27 99 bu arkadaş Kahramanmaraş'ta çad... | 1 |
| Babamın yaşadığı yere henüz yardım ulaşmamış ş... | 1 |
| Samsun Atakum'da 18 adet yeni eşyalı daire var | 1 |

The top 50 words in tweets belonging to class 0 are shown in Figure 1.


**Figure 1** The top 50 words in tweets belonging to class 0

Figure 2 shows the 50 most frequently mentioned words in tweets of class 1 sent by earthquake victims asking for help.


**Figure 2** The top 50 words in tweets belonging to class 1

### *2.2. Data Pre-Processing*

This study aimed to determine the tweets of the earthquake victims asking for help by analyzing the tweets shared about the 2023 Turkey-Syria earthquake. For this purpose, a comparative analysis based on popular machine learning methods such as DT, kNN, LR, NB, RF, SVM, and XGBoost is presented.

In natural language processing projects, text pre-processing is critical to ensure data can be processed correctly. Data pre-processing steps include cleaning, standardizing, and normalizing the data. In the data pre-processing phase, tokenization was performed first. Tokenization is the practice of breaking the raw text into small pieces. In the text normalization phase, spaces and accents were removed, uppercase letters were converted to lowercase, special characters and emoji were removed, numbers expressed in the text were converted to numbers, abbreviations were converted to their explicit form, and misspellings were corrected. Stemming and lemmatization followed. Stemming is the removal of affixes from each word in a text. Lemmatization is the morphological analysis of words to get to the word's root. Then, stop words that have no significance in the text were removed. Bag of words was used for feature extraction from the text. Bag of words is one of the methods for converting text into vectors. After preparing the matrix, the TF-IDF method was applied to statistically express the importance of a term in the document to weigh the terms in the text. Parameter analysis ensured that all machine learning algorithms applied in this study gave the most successful results. The parameters with the highest accuracy value were selected for each model. The parameters used for DT are criterion: gini and max_depth: 8. The k value determined for kNN is 15. For LR, C: 1.0 and penalty: l1. For RF, max_depth: 20 and n_estimators: 100. For SVM, gamma: 0.0001, C: 0.1 and kernel: rbf. For XGB, min_child_weight: 5 and max_depth: 5. Cross-validation was used to solve the overfitting problem. Cross-validation was done by choosing the k value as 10.

### *2.3. Baseline Models*

Machine learning methods used in this study are briefly explained in this section.

DT: There are several methods in the literature that use tree structure [20]. DT is among the most preferred methods because the rule structure created is simple and understandable. This method aims to create a systematic tree structure to classify available data [21]. DT is carried out by first training the model with known examples and classifying different examples using the trained model [22].

kNN: This method is one of the most well-known, easy, and fast to implement among machine learning algorithms. This method makes classification using the closeness between a selected feature and the closest feature. The k samples in the closest distance from the data set to the new sample to be classified are looked at. Whichever class the k samples are in more often; the new sample is included in that class [23].

LR: LR is a statistical model that models the relationship of a dependent variable with one or more independent variables [24]. LR uses the sigmoid function to model the probability distribution of the dependent variable. The sigmoid function produces an output of either 0 or 1. The output produced expresses the probability of an event occurring [25].

NB: Naive Bayes algorithm, which is preferred for text classification because it is fast and easy to apply, is one of the machine learning methods that perform classification with a probabilistic approach. Assuming that each attribute in the dataset is independent of the other, it calculates the probability of indicating which class each belongs to and is based on Bayes' theorem [26-27].

RF: RF is an ensemble learning method based on decision trees [28]. Decision trees analyze the classes of training data and determine which class the test data belongs to base on rules extracted from the training data. These rules consist of a large number of if-then conditions [29].

SVM: One of the statistical learning techniques is called SVM, which is essentially a linear classifier for differentiating between two classes. The main purpose of SVM is to define the optimal decision function that separates the two classes. The optimal decision function is created by maximizing the distance between the support vectors and the points closest to them. SVM was later generalized for multi-class and non-linear data using a kernel function [30].

XGBoost: It is an ensemble tree algorithm developed by Chen and Guestrin [31]. XGBoost uses the gradient boosting algorithm. XGBoost is a model that combines decision trees to create a unified model with successful predictive performance. The inclusion of normalization in the objective function is used to reduce model complexity, reduce overfitting, and speed up the learning process. It minimizes cost, reduces overfitting, and improves the performance of model generalization. XGBoost is fast to interpret and can handle large datasets well [32].

### *2.4. Evaluation Metrics*

Classification algorithms use labeled training datasets to make predictions. Precision, accuracy, recall, and F-score metrics are used to evaluate the performance of classification algorithms. These metrics are calculated using the Confusion Matrix (CM) seen in Table 2.

**Table 2** The CM

| | | Real | |
|---|---|---|---|
| Predicted | | Label 0 | Label 1 |
| | Label 0 | TP | FP |
| | Label 1 | FN | TN |

As seen in Table 2, the CM consists of False Positive (FP), True Positive (TP), False Negative (FN), and True Negative (TN) values. TN refers to the number of samples classified as positive that are actually positive. FN refers to the number of samples whose actual label is positive but is classified as negative. FN refers to the number of samples whose actual label is negative but is classified as positive. TN refers to the number of samples classified as negative that are actually negative. Accuracy is defined as the count of correctly classified samples and is calculated using Eq. 1.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

Precision expresses how many of the samples predicted as positive are actually positive and is calculated using Eq. 2.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall, calculated by Eq. 3, calculates the proportion of correctly predicted positive examples among all positive examples.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

The F score, calculated by Eq. 4, represents a measure of test accuracy and is calculated as the harmonic mean of precision and recall.

$$F - score = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

## 3. The Experimental Results

In this study, a comparative analysis of kNN, DT, LR, NB, RF, SVM, and XGBoost algorithms were presented. Experimental results were obtained for each algorithm according to precision, accuracy, recall, and F-score metrics.

The CM of DT is shown in Table 3.

**Table 3** DT's CM

| | | Real | |
|---|---|---|---|
| | | Label 0 | Label 1 |
| Predicted | Label 0 | 56 | 5 |
| | Label 1 | 1 | 88 |

As seen in Table 3, DT correctly classified 134 tweets and incorrectly classified 16 tweets. For DT, TP is 56, FP is 5, FN is 1, and TN is 88.

The CM of kNN is shown in Table 4.

**Table 4** kNN's CM

| | | Real | |
|---|---|---|---|
| | | Label 0 | Label 1 |
| Predicted | Label 0 | 48 | 6 |
| | Label 1 | 9 | 87 |

As seen in Table 4, kNN correctly classified 134 tweets and incorrectly classified 16 tweets. For kNN, TP is 48, FP is 6, FN is 9, and TN is 87.

The CM of LR is shown in Table 5.

**Table 5** LR's CM

| | | Real | |
|---|---|---|---|
| | | Label 0 | Label 1 |
| Predicted | Label 0 | 55 | 2 |
| | Label 1 | 2 | 91 |

As depicted in Table 5, LR correctly classified 134 tweets and incorrectly classified 16 tweets. For LR, TP is 55, FP is 2, FN is 2, and TN is 91.

The CM of NB is shown in Table 6.

**Table 6** NB's CM

| | | Real | |
|---|---|---|---|
| | | Label 0 | Label 1 |
| Predicted | Label 0 | 54 | 1 |
| | Label 1 | 3 | 92 |

As shown in Table 6, NB correctly classified 134 tweets and incorrectly classified 16 tweets. For NB, TP is 54, FP is 1, FN is 3, and TN is 92.

The CM of RF is shown in Table 7.

**Table 7** RF's CM

| | | Real | |
|---|---|---|---|
| | | Label 0 | Label 1 |
| Predicted | Label 0 | 57 | 1 |
| | Label 1 | 0 | 92 |

As shown in Table 7, RF correctly classified 149 tweets and incorrectly classified 1 tweets. For RF, TP is 57, FP is 1, FN is 0 and TN is 92.

The CM of SVM is shown in Table 8.

**Table 8** SVM's CM

| | | Real | |
|---|---|---|---|
| | | Label 0 | Label 1 |
| Predicted | Label 0 | 56 | 2 |
| | Label 1 | 1 | 91 |

As seen in Table 8, SVM correctly classified 147 tweets and incorrectly classified 3 tweets. For SVM, TP is 56, FP is 2, FN is, 1 and TN is 91. The CM of XGBoost is shown in Table 9. As seen in Table 9, XGBoost correctly classified 148 tweets and incorrectly classified 2 tweets. For XGBoost, TP is 57, FP is 2, FN is 0 and TN is 91. Comparative experimental results for all algorithms are shown in Table 10 and Fig.3.

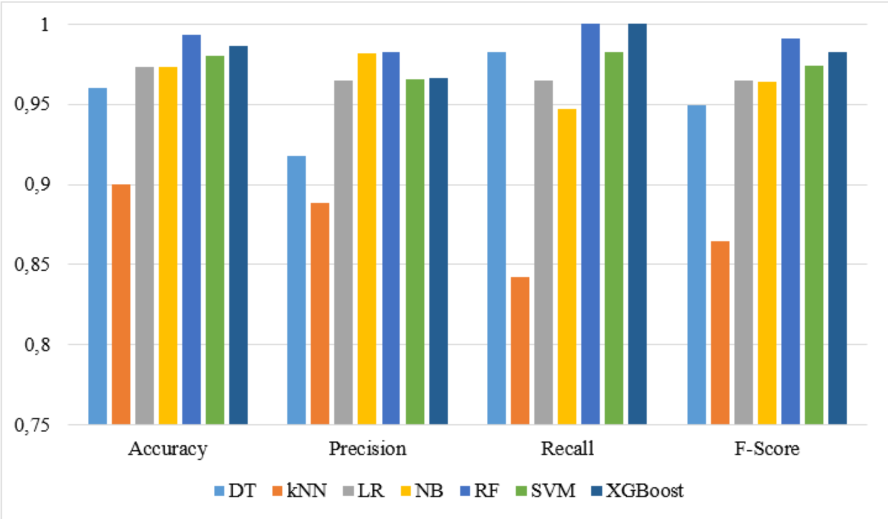


**Figure 3** Comparative experimental results

**Table 10** Comparative experimental results

| Algorithm | Accuracy | Precision | Recall | F-Score |
|---|---|---|---|---|
| DT | 0.9600 | 0.9180 | 0.9824 | 0.9491 |
| kNN | 0.9000 | 0.8888 | 0.8421 | 0.8648 |
| LR | 0.9733 | 0.9649 | 0.9649 | 0.9649 |
| NB | 0.9733 | 0.9818 | 0.9473 | 0.9642 |
| RF | **0.9933** | **0.9827** | **1.0000** | **0.9912** |
| SVM | 0.9800 | 0.9655 | 0.9824 | 0.9738 |
| XGBoost | 0.9866 | 0.9661 | 1.0000 | 0.9827 |

As seen in Table 10 and Figure 3, RF was more successful than all other compared algorithms. After RF, XGBoost, SVM, LR, NB, DT, and kNN were successful, respectively.

In the conducted experiments, RF proved to be more effective than DT as it considers the results of multiple decision trees and selects the outcome with the highest number of votes. The superior performance of RF in comparison to XGBoost can be attributed to the dataset's noisy nature. XGBoost builds individual decision trees sequentially, with each subsequent tree aiming to rectify the mistakes of the previously trained tree. RF trains each tree independently using random data samples. For this reason, RF has been more successful than linear classifiers such as LR and NB. The dataset's low noise level may provide an explanation for LR's superior performance in comparison to kNN. kNN is robust to noisy training data and is effective when the number of training samples is large.

SVM outperforms LR, NB, DT, and kNN, but SVM has a worse classification performance than RF. RF works with a combination of numeric and categorical features. When the features are at different scales, RF has the advantage that it can process the data as they are. SVM is based on maximizing the margin between different data points. Due to the structure of the data set, RF was more successful than SVM.

## 4. Conclusion

Natural disasters such as hurricanes, floods, and earthquakes occur in various parts of the world. It is challenging for people in the affected areas to cope with these disasters by their means. These disasters cause widespread loss of life, property, economic and environmental losses. One of the prominent features of the crisis and chaotic environment after disasters is communication problems. Social media is the most accessible communication tool that disaster victims can use in disasters. Primarily through Twitter, many aid messages are shared quickly. Social media was widely used in the severe earthquakes in Kahramanmaraş in Turkey. Unlike traditional media, social media plays a different role in disaster management. From this point of view, analyzing the posts on social media platforms during an earthquake and identifying the posts containing aid can provide rapid intervention to the places in need after the disaster.

This study analyzed the tweets sent after the Karamanmaraş earthquake to determine whether these tweets asked for aid or relief supplies. For this purpose, popular DT, kNN, LR, NB, RF, SVM, and XGBoost machine learning methods were used. These models were compared using success metrics, and the RF method had the highest success. Thus, a model was developed to classify the tweets posted during a disaster with high success. This model can make significant contributions to adequate and accurate disaster management. The developed model can be improved to make crisis management more effective after earthquakes and other disasters. For example, hybrid methods can be developed with deep learning models, and more significant results can be produced with larger datasets.

## References


[1] S. Kwayu, M. Abubakre, and B. Lal, "The influence of informal social media practices on knowledge sharing and work processes within organizations," *International Journal of Information Management*, vol. 58, 102280, 2021.

[2] H. Shirado, G. Iosifidis, L. Tassiulas, and N. A. "Christakis, Resource sharing in technologically defined social networks," *Nature Communications*, vol. 10, no. 1, pp. 1079. 2019.

[3] K. Ravi and V. Ravi, "A survey on opinion mining and sentiment analysis: tasks, approaches and applications," *Knowledge-based systems*, vol. 89, pp. 14-46, 2015.

[4] J. Y. Jung and M. Moro, "Multi-level functionality of social media in the aftermath of the Great East Japan Earthquake," *Disasters*, vol. 38, pp. 123-s143, 2014.

[5] J. B. Houston, J. Hawthorne, M. F. Perreault, E. H. Park, M. Goldstein Hode, M. R. Halliwell, and S. A. "Griffith, Social media and disasters: a functional framework for social media use in disaster planning, response, and research," *Disasters*, vol. 39, no. 1, pp. 1-22, 2015.

[6] D. Yates, and S. Paquette, "Emergency knowledge management and social media technologies: A case study of the 2010 Haitian earthquake," *International Journal of Information Management*, vol. 31, no. 1, pp. 6-13, 2011.

[7] S. Ni, H. Sun, P. Somerville, D. A. Yuen, C. Milliner, H. Wang, and Y. Cui, "Complexities of the Turkey-Syria doublet earthquake sequence," *The Innovation*, vol. 4, no. 3, 100431, 2023.

[8] S. Mendon, P. Dutta, A. Behl, and S. Lessmann, "A hybrid approach of machine learning and lexicons to sentiment analysis: Enhanced insights from twitter data of natural disasters," *Information Systems Frontiers*, vol. 23, pp. 1145-1168, 2021.

[9] S. Behl, A. Rao, S. Aggarwal, S. Chadha, and H. S. Pannu, "Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises," *International Journal of Disaster Risk Reduction*, vol. 55, 102101, 2021.

[10] A. Bhoi, S. P. Pujari and R. C. Balabantaray, "A deep learning-based social media text analysis framework for disaster resource management," *Social Network Analysis and Mining*, 10, 1-14. (2020).

[11] N. Chaudhuri, and I. Bose, "Exploring the role of deep neural networks for post-disaster decision support," *Decision Support Systems*, vol. 130, 113234, 2020.

[12] S. Wang, Z. Li, Y. Wang, and Q. Zhang, "Machine learning methods to predict socia media disaster rumor refuters," *International Journal of Environmental Research and Public Health*, vol. 16, no. 8, pp. 1452, 2019.

[13] G. A. Ruz, P. A. Henríquez, and A. Mascareño, "Sentiment analysis of Twitter data during critical events through Bayesian networks classifiers," *Future Generation Computer Systems*, vol. 106, pp. 92-104, 2020.

[14] Y. Kryvasheyeu, H. Chen, E. Moro, P. Van Hentenryck, and M. Cebrian, "Performance of social network sensors during Hurricane Sandy." *PLoS one*, 10(2), e0117288, 2015.

[15] L. Huang, P. Shi, H. Zhu, and T. Chen, "Early detection of emergency events from social media: A new text clustering approach." *Natural Hazards*, 111(1), 851-875, 2022.

[16] A. Kumar, J. P. Singh, N. P. Rana, and Y. K. Dwivedi, "Multi-Channel Convolutional Neural Network for the Identification of Eyewitness Tweets of Disaster." *Information Systems Frontiers*, 25(4), 1589-1604, 2023.

[17] M. Kaya, and B. Hasan Şakir, "Classification of

Parkinson speech data by metric learning." In 2017 International Artificial Intelligence and Data Processing Symposium (IDAP), pp. 1-5. IEEE, 2017.

[18] Ž. Vujović, (2021). Classification model evaluation metrics. International Journal of Advanced Computer Science and Applications, 12(6), 599-606.

[19] Turkey Earthquake Relief Tweets Dataset, Available:https://www.kaggle.com/datasets/ulkutuncerkucuktas/turkey-earthquake-relief-tweets-dataset. [Accessed: April. 20, 2023].

[20] A. Şenol, M. Kaya, and Y. Canbay, “A comparison of tree data structures in the streaming data clustering issue.” Journal of the Faculty of Engineering and Architecture of Gazi University, 39(1), 217-231, 2024.

[21] S. B. Kotsiantis, “Decision trees: a recent overview,” *Artificial Intelligence Review*, vol. 39, pp. 261-283, 2013.

[22] H. Bhavsar and A. Ganatra, “A comparative study of training algorithms for supervised machine learning,” *International Journal of Soft Computing and Engineering (IJSCE)*, vol. 2, no. 4, pp. 2231-2307, 2012.

[23] S. Zhang, X. Li, M. Zong, X. Zhu, and D. Cheng, “Learning k for knn classification,” *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 8, no. 3, pp. 1-19, 2017.

[24] X. Su, X. Yan, and C. L. Tsai, “Linear regression,” *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 4, no. 3, pp. 275-294, 2012.

[25] D. Maulud, and A. M. Abdulazeez, “A review on linear regression comprehensive in machine learning,” *Journal of Applied Science and Technology Trends*, vol. 1, no. 4, pp. 140-147, 2020.

[26] L. Jiang, S. Wang, C. Li, and L. Zhang, “Structure extended multinomial naive Bayes. Information Sciences,” vol. 329, pp. 346-356, 2016.

[27] S. Wang, L. Jiang and C. Li, “Adapting naive Bayes tree for text classification,” *Knowledge and Information Systems*, vol. 44, pp. 77-89, 2015.

[28] M. M. Ghiasi and *S. Zendehboudi, “Application of decision tree-based ensemble learning in the classification of breast* cancer,” *Computers in biology and medicine*, vol. 128, 104089, 2021.

[29] T. Amraee, and S. Ranjbar, “Transient instability prediction using decision tree technique,” *IEEE Transactions on power systems*, vol. 28, no. 3, pp. 3028-3037, 2013.

[30] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua, and A. Lopez, “A comprehensive survey on support vector machine classification: Applications, challenges and trends,” *Neurocomputing*, vol. 408, pp. 189-215, 2020.

[31] T. Chen, and C. Guestrin, Xgboost: A scalable tree boosting system. Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining. San Francisco, California, USA, 785-794. 26, 2016.

[32] I. H. Sarker, Machine Learning: Algorithms, RealWorld Applications and Research Directions. SN Computer Science, vol. 2, no. 160, pp. 1-21, 2021.