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Research Article

Comparison of Various Machine Learning Methods for Detecting Cyberbullying in Twitter Messages

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Abstract

With the development of the social network, the number of cyberbullying started to increase in the world. Cyberbullying detection is receiving increasing attention, especially in Machine Learning communities. The reason for the increase in cyberbullying is that the bullying on the Internet cannot be detected or even if they are detected, they think that legal sanctions will not be applied. These types of cyberbullying crimes leave mental scars in their lives in the future by putting psychological pressure on people. It is very difficult to identify and counter cyberbullying in a timely manner.

Cyberbullying will be a growing problem in Turkey as in the rest of the world. By the findings so far, 20% are already becoming cyberbullies in Turkey. In this regard, there are few studies in the literature on the detection of cyberbullying in Turkish texts. Machine learning is also being used in ongoing research to detect and eliminate cyberbullying. Although there is a lot of cyberbullying detection in English, there is little research in Turkish.

Moreover, only a limited number of algorithms and methods have been used in Turkish studies. Moreover, the aim of this study is to use different machine learning algorithms to detect Turkish cyberbullying messages. In this study, those who made their quartet drawings on a dataset consisting of 3000 Turkish social networks using cyber techniques. Precision, accuracy, cross-validation, recall and F1 scores were used to appraise the performance of the classifiers. In the study, Linear SVC performed best Train Models for CountVectorizer, with cross-validation score of 89.92% and F1 score of 99.96%, and Linear SVC performed best Train Models for TfidfVectorizer, with cross-validation score of 89.79% and F1 score of 99.96%.

Keywords: Cyberbullying Detection, Machine Learning, Linear SVC, TF-IDF, Twitter Messages

1. Introduction

Large numbers of children around the world are subjected to sexual discrimination and gender-based violence, corporal punishment, war, and other forms of violence. Many also experience gang violence, shootings, rape, molestation, sexual and gender-based violence by their peers in the schoolyard. In addition, as a new form of violence, events such as cyberbullying, especially through cell phones, computers, websites, and social networking sites, negatively impact children's lives [1].

The development of information technology and the rapid introduction of communication tools into the lives of users have paved the way for the development and diversity of social media platforms, websites and sharing networks [2].

The fact that cases of cyberbullying, which can be dangerous to children and adolescents, have become a growing social problem worldwide has prompted educators, academia, and lawmakers to examine the risks, prevalence, and causes. the consequences of cyberbullying and find solutions in this regard. Particularly in recent years, it has been observed that more and more countries are creating educational policies on this issue, supporting research and projects on this topic, and partnering with non-governmental organizations, academics, educators, and families working on this issue [3].

The early habituation of young people to technological tools and the widespread use of the Internet with digital tools facilitate communication. While this is seen as an advantage, it also carries many risks. Young people can commit violence through the virtual environment and attack, threaten, hurt and shame each other. These attacks and violent incidents that take place in a virtual environment are referred to as "cyberbullying". Cyberbullying is a new phenomenon that has spread and developed rapidly in society and has become a serious problem [4].

Governments, institutions, or individuals collect a lot of data in order to draw meaningful conclusions from its content and use it when needed. In every field, data created using materials such as numbers, texts, expressions, drawings, graphs have been transferred to electronic media using computers. As the computer, internet and related technologies are increasingly used in all walks of life, the data obtained through these technologies are also stored. The increasing spread of information technology has changed people's living, working and environmental conditions; places, occupations, employees have become "mobile", and the devices used have become "mobile" and "smart" [5].

In addition to these conveniences brought by information and communication technologies, it is clear that excessive and uncontrolled use causes various problems. These include pornography, online contact, excessive use of information and communication technologies, interfering with students' academic performance, preferring real social relationships, sharing personal information with everyone in the virtual environment, and using the virtual environment to buy drugs such as medication. For example, on Facebook, a social network where many people are members, there are many virtual groups where addicts meet and socialize, where they sell bonsai, which is called synthetic drugs and is often on the agenda in Turkey [6].

The study found no significant difference between helpless coping behaviors and gender. Another study found that students of grade 9 and 10 were significantly better at helpless coping than students of grade 11. The study found that aggressive coping behavior was significantly higher in students of grade 11 than students of grade 9. It was found that there was no significant difference in the aspects of care seeking, control, prevention and technical adjustment depending on the level of education [7].

Academic research in various countries has focused on the perceptions and awareness of cyberbullying children, the effects of cyberbullying on them, and how they try to cope with the problem. While the nature of cyberbullying, the behaviors of cyberbullying, and the consequences of this phenomenon vary from country to country, it is clear that there are many commonalities that depend on the culture created by new media [8].

As a result of many studies on cyberbullying, it has been shown that cyberbullying and victimization have an extremely bad impact on people's social, academic, and emotional lives [9].

In this study, conducted using a relational screening model, data on socio-demographic variables believed to influence cyberbullying and victimization of adolescents, as well as variables related to Internet use, expression styles of anger and rage, stress management, and subordinate behavior variables, were collected and systematically statistically evaluated, analyzed, and the data obtained were explained through a descriptive method [10].

In this study, the aim was to determine the relationship between cyberbullying behaviors, problematic Internet use, and risky online behaviors among secondary school students and to determine the effects of these variables on age, gender, school type, daily Internet use, and preferred Internet sites. , parents use of the Internet. It will be explored in relation to demographic characteristics such as provision of time and content control [11].

The data collection method used in the study was a survey method in addition to a literature review, and the participants were asked two questionnaires with a total of 48 questions. In this study, the Cyberbullying Scale (SCI) and Cyber Victimization Scale (CSS) were used according to the objectives of the study (scale in the appendix) [12].

The aim of this study is to contribute to the existing research in the literature by building different artificial neural network models for cyberbullying detection in Turkish textual content [13].

This study, which aims to determine the relationship between elementary teacher candidates' level of digital citizenship and their cyberbullying tendencies, and prospective teachers' level of digital citizenship and their cyberbullying tendencies, uses a survey method, one of the quantitative research methods was used [14].

A study presented by Kontostathis et al attempted to automatically detect cyberbullying content through many types of queries created by combining undesirable terms commonly used in virtual environments and achieved 90% success [15].

Another early study in this area was conducted by Reynolds et al In the study, the survey dataset was created from the content of Formspring.me, a question-and-answer site where bullying occurs at a much higher level. The process of tagging the large amount of data obtained in this study was performed using the web service Amazon Mechanical Turk. Applying the C4.5 decision tree method of machine learning to the generated dataset revealed that texts containing cyberbullying were detected with an accuracy of 78.5% [16].

Ignacio Arroyo-Fernandez et al, tested a number of vector space modeling techniques along with several well-known training machines (classifiers) to predict each of the aggression levels individually. The vector space modeling techniques included TF-IDF vectors, hidden semantic analysis of TF-IDF vectors (LSA of different sizes). Both TF - IDF and LSA were computed for n-gram features of characters and words. Moreover, a word embedding based message presentation was used [17].

Rekha Sugandhi et al, tested different classifiers on our bullying dataset to see which classifier gave us the best accuracy. To do this, they split our labeled data into 80-20 sections, using 80% of the data for training and 20% for testing the classifier. The labeled data consisted of 393 bullying messages and 2886 non-bullying messages. They compared the LinearSVC kernel, Multinomial Naive Bayes and SVM classifiers with the KNN algorithm [18].

N Novalita et al, upon completion of the final project, it was revealed how to identify both cyberbullying and non-cyberbullying tweets. Looking at the results of the random forest classification test, it was found that the system successfully identified cyberbullying tweets with the best F1 score of 0.90 [19].

Sani Muhammad Isa et al. Investigated the most appropriate SVM kernel for cyberbullying classification and found that it was a poly kernel with an average accuracy of 97.11%, as the data used in this study was not linearly separable. Therefore, the most appropriate function for separating an instance into different classes is the poly-kernel SVM [20].

2. Study Offered

This study aims to compare the effectiveness of detecting Turkish cyberbullying messages using different machine learning algorithms. The proposed study consists of machine learning methods such as preprocessing and feature extraction. The steps performed in our study and the flow between them are visualized with Figure 1.

In our study, the dataset used was that of Bozyiğit et al [21]. First, various preprocessing steps were applied to the corresponding dataset. After the preprocessing steps, stop word, n-gram and TF-IDF approaches were applied to find the texts in the dataset as features. The different developed machine learning algorithms were then tested on a dataset prepared to detect Twitter messages containing cyberbullying. Finally, the results of the developed models were compared in terms of prediction success.

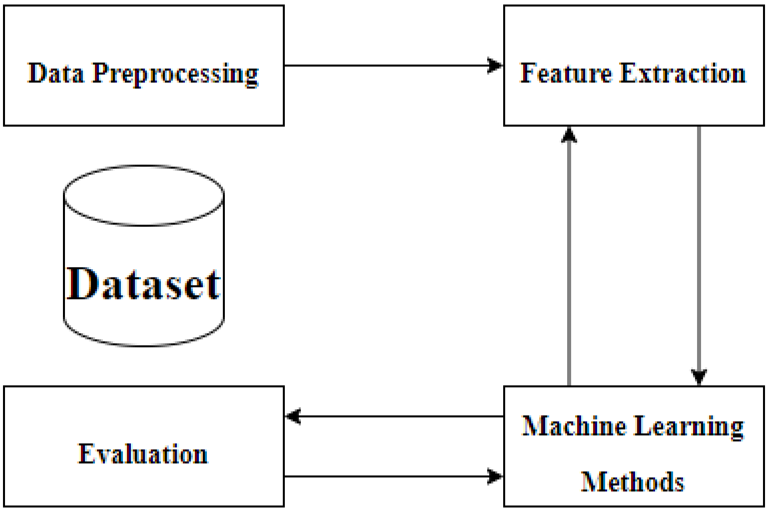

Figure 1: Flow of Proposed Work

2.1. Dataset

The dataset used in the proposed study consists of 3,000 Twitter shares. Half of the messages in this cluster were manually marked as positive (containing cyberbullying) and the other half as negative (not containing cyberbullying). In order to obtain better results for the dataset used in the study, some preprocessing steps were performed. In the first step, numeric characters, punctuation marks and web links were removed from the shared folders in the dataset and converted to lowercase. It is noticeable that the dataset used in this direction has a very balanced distribution. Some common resources and their tags in the dataset are shown in Table 1 as an example.

Sharing#	Sharing	Tag
1	rabbim kalan ömrünü geçen ömründen hayırlı eylesin	Negative
2	bende biliyorum benden bı bok olmicak	Positive
3	dogruyu soyleyince kadro verince adalet yerini bulacak	Negative
4	hava gavur şeyi gibi yanıyor diyorlar ama o konuda hiç tecrübem yok bilemiyorum	Positive
5	eğlenceli geceye devam	Negative

Table 1: Some Shares in the Dataset

The dataset contains 3,000 Twitter posts, of which 1,500 are related to cyberbullying (cyberbullying = 1) and 1,500 are not related to cyberbullying (cyberbullying = 0). Classification with machine learning is used because it is important to have a balanced distribution and an equal number of labels.

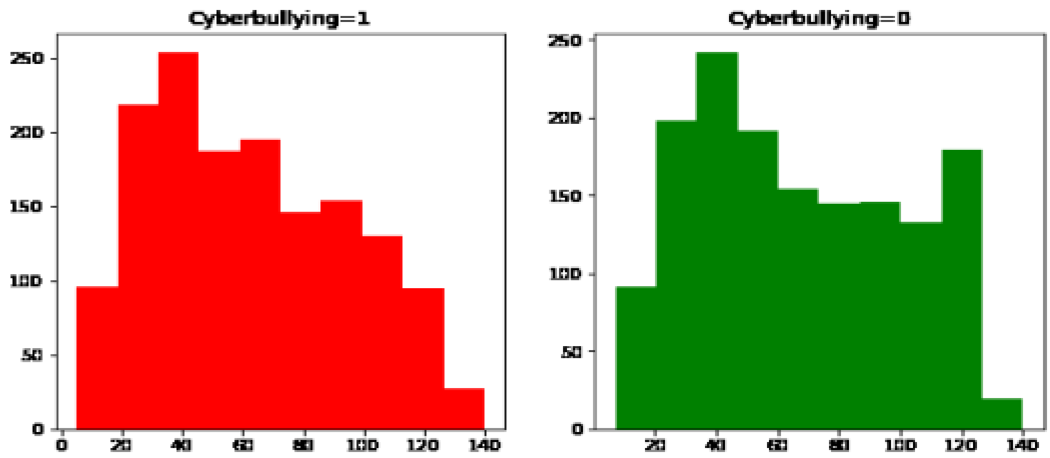

Figure 2: Characters in Tweets

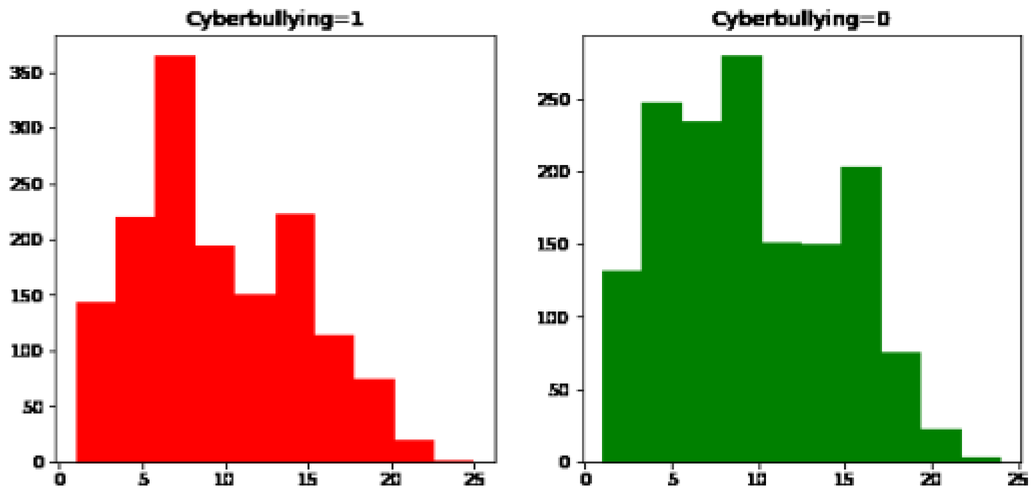

Figure 3: Words in a Tweet

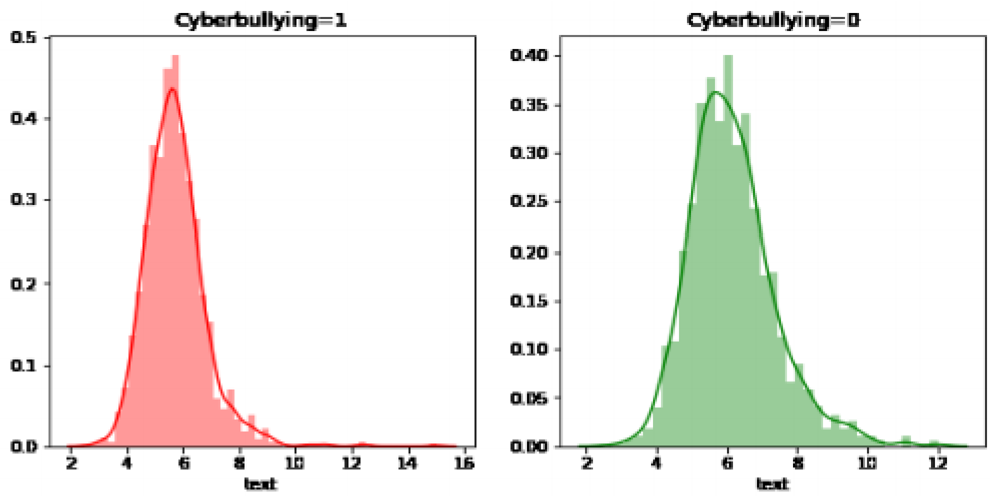

Figure 4: Average Word Length of Each Tweet

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In addition, an exploratory analysis of the word, character, and average word length of each tweet from tweets with and without cyberbullying was performed, and the results are shown in Figures 2 and 3, Figure 4. The experiment found formal similarities between Turkish messages with and without cyberbullying.

2.2. Feature Extraction

At this stage, the texts for posting on social networks were converted into a vector format of features on which machine learning could operate, and weighting calculations were performed.

Unlike other Turkish language studies on cyberbullying detection, the fractions in the dataset are expressed numerically in the document term matrix using the n-gram string killing method (for n = 1,2,3). Thus, the aim is to evaluate the slang word sequences as a whole in the classification process. As an example, the following terms are taken from the message " çok gerizekalı birisin".

- gram terms: {"çok", "gerizekalı", "birisin"},
- gram terms: {"çok gerizekalı", "gerizekalı birisin"},
- gram terms: {"çok gerizekalı birisin"}

The TF-IDF weights were used to calculate how important the stock-derived terms are to the corresponding stock. The weight of a TF-IDF term is obtained by multiplying the term frequency (the number of times the term is contained in a document) by the inverse term frequency (the log ratio of the number of documents in the dataset to the number of documents containing the corresponding term) [21].

More formally, the TF-IDF score for word t in document d is computed from the document set D as follows:

$$\mathrm{tf\,idf}(\mathrm{t,d,D}) = \mathrm{tf}(\mathrm{t,d}) * \mathrm{idf}(\mathrm{t,D})$$

Where,

$$\mathrm{tf}(\mathrm{t,d}) = \log\big(1 + \mathrm{freq}(\mathrm{t,d})\big)$$

$$\mathrm{idf}(\mathrm{t,D}) = \log\Big(\frac{\mathrm{N}}{\mathrm{count}(\mathrm{d} \in \mathrm{D}: \mathrm{t} \in \mathrm{d}}$$

2.3. Machine Learning

Machine learning is an independent computer solution based on data and experience [22]. The decisions to be made in machine learning are usually aimed at prediction or classification [23]. Machine learning was used in the study to test whether Twitter posts were used for cyberbullying. The resulting data is referred to here as training data. Training algorithms are used to train computer models and classify test data. There are some training methods that are for labeling training data. By labeling here I mean that the data is first classified by humans and then used for machine learning. And also if a model is supervised learning then it depends on labeled data. Unsupervised learning is when the learning data is unlabeled. In unsupervised learning, the machine learns to classify itself based on the similarities and differences between the data. Semi-supervised learning is learning applied to a combination of labeled and unlabeled data [25]. In this study, it is commonly used in supervised learning.

Depending on the labeling of the training data with different training methods, the algorithms used in the present study are presented below.

- **Multinomial Naive Bayes (MNB):** In our current study, a naive Bayesian classifier uses statistical methods to compute the probability that a requirement is related to a particular topic. The probability that requirement R is related to a topic is calculated using Bayes' rule as follows:

$$P(top_R|W) = \frac{P(W|top_R) * P(top_R)}{P(W)}$$

- **Decision Tress:** The main idea is based on multiple partitioning of the input data into groups using a clustering algorithm. Clustering continues until all members of the group have the same class label. Many algorithms have been proposed in two categories, namely Entropy Classification Trees (ID3, C4.5) and Regression Trees (CART). We will first look at entropy decision trees. To understand these algorithms well, you need to have a good knowledge of entropy. Entropy, known as a measure of the indeterminacy of a random variable, is the expected value of the information contained in all samples for a process. Information is a measure of knowledge about the occurrence of a random event. Situations with equal probability represent high uncertainty. According to Shannon, when the state of the system changes, the change in entropy determines the information obtained. Accordingly, it is likely that the change of state with maximum uncertainty provides the maximum information. The following maxims are used in the calculation of decision trees:

$$I(x) = log\frac{1}{P(x)} = -logP(x)$$

$$H(X) = E\big(I(X)\big) = \sum_{1\le i\le n} P(x_i) * I(x_i) = \sum_{i=1}^{n} P(x_i)log_2\frac{1}{P(x_i)} = -\sum\nolimits_{i=1}^{n} P_i log_2 P_i$$

• **Random Forest:** The Random Forest machine apprentice is a meta-apprentice; that is, it consists of many individual students (trees). The random forest uses multiple classifications of random trees to vote for the general classification for a given set of inputs. Usually, different votes have equal weight in voting with machine learning. The forest selects the individual classification with the most votes. Figure 5. Below is a visual representation of the unweighted random forest algorithm.

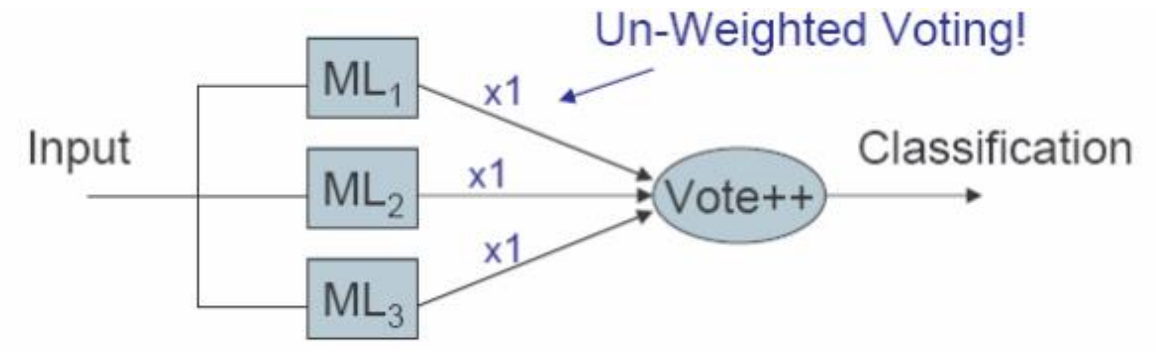

Figure 5: Meta Learners

• **Linear SVC:** Linear Support Vector Classifier (LSVC) is one of the popular representatives of machine learning, which is a supervised learning model that analyses data for classification. LSVC is the fastest growing part of classification and regression methods in data mining and machine learning. The working logic of the linear SVM algorithm is shown in flow.

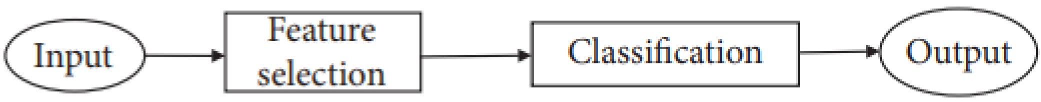

Figure 6: Logic Diagram of Linear SVC

2.4. Evaluation Measurements

Since cyberbullying detection is a classification task, the accuracy score is also considered as the first rating scale. Thus, it is intuitively clear that only the linear part is included in the classification. When approach and precision are measured, a maximum precision of 80% is achieved here. Also the precision value is used in case of unbalanced class distributions. gives different results.

Since this seems to be a problem, it is addressed with the metrics accuracy and recall. The best result is obtained with a mixed mean of accuracy and recall with an F1 score.

Predicted Value (predicted by the test)	Actual Value (as confirmed by experiment)	
	positives	negatives
positives	**TP** True Positive	**FP** False Positive
negatives	**FN** False Negative	**TN** True Negative

Table 2: Confusion Matrix

In Table 2, the learning performance was calculated using the confusion matrix. The F1 score, accuracy, precision and recall were obtained in the following equations.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \qquad Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN} \qquad F\ Score = \frac{2*Precision*Recall}{Precision+Recall}$$

3. Cross-Validation

Cross Validation is one of the methods for dividing the dataset into parts for evaluating classification models and training the model.

For example, suppose we have a dataset with one thousand records. We want to train our model with part of this dataset and evaluate the success of our model with part of it. A simple approach is to provide 75% for training and 25% for testing. However, since the data is fragmented, there may be some biases and errors in training and testing the model, depending on the distribution of the data. Here, cross-validation divides the data into equal parts according to a certain k-number and ensures that each part is used for both training and testing, minimizing deviations and errors caused by scatter and fragmentation.

4. Result and Discussion

As shown in Table 3 and Table 4, the cross-validity of the machine learning models was low for unsuccessful predictions. The accuracy and F1 score values of the first 14 of the 4 models ranged from 85% to 90%.

Models	F1-score	Cross-validation score	Precision	Recall	Accuracy
Linear SVC	99.96	89.92	100	99.92	88.35
Multinomial Naive Bayes	99.88	87.38	99.83	99.92	87.02
Decision Tree	99.96	87.21	100	99.92	87.19
Random Forest	99.21	88.08	99.66	98.75	86.36

Table 3: Evaluation Results of Machine Learning Models in Train Models for CountVectorizer

For detecting cyberbullying in Turkish tweets, the best result of the TfidfVectorizer training model is the Linear SVC algorithm with 99.96% F1-score and 89.79% cross-validation, and the best result of the CountVectorizer training model is 99.96% F1-score and 89.92% cross- validation. rate was obtained using the Linear SVC algorithm.

The F1 score of the CountVectorizer training model was 99.21% and the cross validation rate was 88.08%, the F1 score of the TfidfVectorizer training model was 99.16% and the cross validation rate was 85.58%. In the context of the developed classification for detecting cyberbullying in Turkish texts;

• The F1 score of 99.96% obtained with the algorithm Linear Svc is the most successful result known in Turkish literature using classical machine learning models.

• Comparing the results of the research conducted in different languages in the research section with the current results, meaningful results can be obtained in Turkish as well.

Models	F1-score	Cross-validation score	Precision	Recall	Accuracy
Linear SVC	99.96	89.79	100	99.92	88.69
Multinomial Naive Bayes	99.92	87.96	99.92	99.92	87.35
Decision Tree	99.16	85.58	99.16	98.42	85.69
Random Forest	99.16	87.12	99.66	98.67	86.86

Table 4: Evaluation Results of Machine Learning Models in Train Models for TfidfVectorizer

5. Conclusion and Future Works

The highest F1 score values obtained as a result of the study were compared with the results of Bozyiğit et al., and it was seen that they were higher than the highest 91% F1 score [13].

Recently, our social life has helped people to tell about themselves on many topics.

But unfortunately, some of the users do not use social media in good faith with cyberbullying-like actions, and they use some abusive, cursing and threatening words against users they know or do not know. For this, machine learning models were used in my work to love such malicious actions. For cyberbullying detection, many studies have been presented in the international field by using machine learning algorithms, which I also use, even only in Turkish language. In this study, cyberbullying was detected by using 4 different machine learning algorithms considering Turkish social media messages such as Twitter.

The best results of TfidfVectorizer training model using linear SVC algorithm are 99.96% F1 score and 89.79% cross validation, while the best results of CountVectorizer training model are 99.96% F1 score and 89.92% cross validation.

In this context, according to future studies, it is aimed to increase the performance of the recognition model for bad words used in Azerbaijani language by including posts in Azerbaijani language from Youtube as well as Twitter. At the same time, various machine learning methods are being considered.

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