DETECTION OF TYPES CYBER-BULLYING USING FUZZY C-MEANS CLUSTERING AND XGBOOST ENSEMBLE ALGORITHM

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Abstract

In this study a neural network model (XGB_CTD) that will prediction which type of bullying the users may expose to, through dataset gained by the cyberbullying scale applied to the young internet users is formulated. Extreme Gradient Boosting (XGboost) algorithm, one of the ensemble learning methods is used in this method. There while this model contains 13 input parameters taken from the scale, there exist one output parameter classified one of the 9 outputs. The reliability of the data set obtained through survey is confirmed by statistical methods. Data set has been fragmented with Fuzzy C-Means (FCM) which is one of fuzzy clustering algorithms. Hyper-parameters for the maximum efficiency of the model training have been defined as model, learning and boosting method. Independent variables in data set have been scaled through standard normalization. As a result, the model has yielded % 91,75 accuracy rate in prediction of the classification as 9 different cyberbullying types. The same data set has been trained by different machine learning algorithms. It is seen that the proposed model has reached the highest accuracy when compared to the conventional machine learning algorithms.

This study aims at prediction cyberbullying through the proposed model including different questions without claim by the young users as they were bullied. Similarly, type of the cyberbullying will also be able to be estimated by the help of internet using habits of the young users. Therefore, it is thought that the young can be prevented from experiencing psychological pressure or digital life fear.

Keywords: *Classification, Cyberbullying, Ensemble Learning, XGBoost, FCM, Machine Learning*

1. Introduction

Communication is one of the essential phenomena for the human. People convey their messages including their feelings and thoughts to others or to various targets whether in one or two-way direction (Lowry et al. 2016). Internet has become the most notable media as a result of technological development. Social media is one of communication methods on Internet [2]. The ever increasing and developing technology commonly affects each level of the society as does the young people [3]. Use of new tech products such as computer, tablet pc and mobile phone shows an increase among the young people [4]. It is seen that technology, apart from its positive effects, causes side and devastating effects like cyberbullying [5]. Cyberbullying in general terms, is defined as threatening or humiliating others via information and communication technologies [6]. Increase in the number of the internet users and emerge of different applications creates new cyberbullying areas. [7] Accordingly, ever increasing cyberbullying incidents necessitates cyberbullying detection applications much more than before. [8-9]. Use of Machine learning is of vital importance in developing applications in this sense.

Machine learning is neural network model which deducts from the data through mathematical and statistical techniques [10]. There are many methodologies and algorithms for machine learning models. [11]. In some applications there exists only one algorithm used whereas others contain hybrid algorithms [12]. Learning algorithms when used singularly may yield negative results stemming from the limitations of the algorithm used [13]. In this context, it has become a new approach that more than one machine learning algorithms are used together in the recent studies. One among the new approaches is ensemble learning [14].

Ensemble learning is a method which gathers more than one inductives so as to give a decision in the process of controlled machine learning [15]. Main approach in ensemble learning is to produce many classifiers and regulate the results so as to improve the performance of the classifiers one by one. Feature selection and parameter optimization steps in ensemble learning requires expertise.

When these steps are accompanied by planned learning algorithms, classification performance and parameter optimization in ensemble learning model can be maximized [16]. Studies in the literature show that ensemble learning prove successful results in neural network models such as classification [17], estimation [18], speaker recognition [19], sentiment analysis [20].

Generally, cyberbullying is attempted to be detected in social media activities of the user. The detections include interpretation of comments by the person or made by others on his or her page, shares or emoticons. Unlike other studies in the literature, this study presents an approach which can estimate which type of cyberbullying the internet user did and may expose to through their activities on internet. This approach does not focus only on the social media as does the other studies. Therefore, both type of the cyberbullying could be detected and necessary precautions could be taken

Essential contributions and innovations by this study are as follows:
• It may detect the type of the cyberbullying the user did or may expose to.
• Data set of the model has been formulated as the result of survey for the young people, and are original to this study.
• FCM fuzzy clustering method has been used in fragmentation of the data set.
• XGBoost ensemble learning algorithm which provides high classification performance in training of the model has been used.

In the second part of the study, cyberbullying studies in the study are examined and compared to our study. Motivation in the study is evaluated with a comparison to the other studies. In the method section of the study, the way that data set is gathered through survey, is explained and the reliability test of the data is applied. In the section of formulating estimation model, data to be used in the training and test of the model as well as fragmentation of FCM algorithms thereof and improvement of model through XGBoost algorithms are dealt with. In the ending section, performance data acquired from the model is assessed and compared to machine learning algorithms.

2. Related Work

In the literature, there are two main research branches related to the subject of the study. These are cyberbullying detection and automated word discovery. Automated word discovery efforts provide pre-processing, feature extraction and classification tasks. [21]

In many studies content-based [21,24], sentiment-based [25], user-based [26] and network-based [27] methods are applied to cyberbullying detection. In this methods, full control learning models such as Naïve Bayes, Support Vector Machines (SVM) and Decision Trees (J48) are preferred. It is seen that due to language differences they apply to only one language or country in content-based estimation [24,22-29].

Labeled word in social made shares are focused in literature studies on cyberbullying detection. Shares or tweets extracted from social media accounts (Twitter, Instagram, YouTube and Facebook) constitute the data sets [30]. Applying learning algorithms to these data sets allows cyber-bullying detection. In several cases, age and gender estimation as well as cyber-bullying is made [31 -32].

Raisi and Huang [33] tried to detect cyber-bullying in labelled words by machine learning method. The study detects the level of cyber-bullying through the labelled words in the comment and shares on Twitter. Garcia et.al, [34] offers a word-based detection model applying K-Nearest Neighbour (KNN) and Sequential Minimal Optimization (SMO) algorithms to data set. This model has been trained with Waikato Environment for Knowledge Analysis (WEKA) and 92% accuracy has been achieved. Balakrishmana et. Al [35] have formulated automatic cyberbullying perception mechanism. Perception mechanism is based on physiological features of Twitter users such as character, sentiment and emoticons. Random Forest, Naïve Bayes and J48 algorithms and WEKA have been used and approximately 91% accuracy has been achieved. Sahay et.al. [36] has applied machine learning and natural language processing (NLP) to data set acquired from UCI Machine Learning Repository for detection of cyberbullying. At the end of training and test of the model an accuracy rate between 75% - 90 % has achieved.

This study is motivated by other studies regarding detection of cyberbullying in the literature. Other studies take social media correspondence as a focus for detection of cyberbullying. Conclusively, for the past incidents cyber-bullying is defined "as it exists" or "does not exist". Moreover, they do not concentrate on the type of the cyberbullying. The study hereby aims at detection of type of cyber-bullying threats to which young internet users did or may expose to. A survey, regarding internet use of the young people has been prepared and data set has been formed. Which type of cyberbullying young internet users did or may expose to and who do not or cannot express of that may also be detected at the end of this study.

3. Principles of Detection Methods

3.1. Data Collection

In order to get data set, Cyberbullying Scale which was developed by Stewart et.al was used [37]. The scale aims at measuring cyberbullying behaviors. As a data collection tool, a Google Form which consists of 15 items analyzing the views of young people about cyberbullying was designed. Then, data was collected online by using this form. During data collection process, no questions about their identity was asked. The created form includes Turkish and English language options.

The first question is multiple choice which ask if he/she is disturbed vie e-mail, video, text message, social communication webs on online platform. The rest 14 questions are measuring individual's exposure to cyberbullying. These 14 questions are composed by using 5 category Likert type scale. On the scale, the levels of exposure to the cyberbullying are designed as; Never (0), Almost never (1), Sometimes (2), Often (3), Always (4) (Appendix 1).

A total of 542 students aged between 18-27 were recruited as a convenience sample. 313 of the participants were aged 18-22, 229 of them are aged 23-27. 291 of the participants were female and 251 of them were male.

The first multiple choice item scaled 0-9 analyzed what kind of bullying the participants were exposed to. The question with no answers was scaled as "0". When the category of "never" and the questions with no answers were considered as "0", the reliability of the scale was calculated as (Cronbach Alpha) 0,919. The calculation was made to test internal consistency [39] and the results in data set were found as reliable.

3.2. Model Development

Extreme Gradient Boosting (XGBoost) is a popular machine learning algorithm which was introduced by Chen in 2014 [40]. XGBoost is a scalable, fragile tree boosting system which used tree-based model serving as weak students and Gradient boosting model [41].

Data set must be classified before the training of the model. The divisions of the internet using behavior of the young people are different here. Dividing data set randomly reduces the consistency of the test and model training. To divide data set, FCM clustering algorithm was used for c=2 according to the scale of the answers of the questions. The membership degree of each answer and which cluster they belong to was calculated via FCM membership degrees and cluster matching are minimized according to Equation 1 and Equation 2 [42].

$$v_i = \frac{\sum_{k=1}^{n} u^m{}_{ik} x_k}{\sum_{k=1}^{n} u^m{}_{ik}} ; 1 \le i \le c \qquad (1)$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}{}^{2}A}{d_{jk}{}^{2}A}\right)^{\frac{2}{m-1}}} \qquad (2)$$

For FCM algorithm, data set was described as “SZO”. The aim of this classification is to make the loss function shown in Equation3 reach the minimum value.

$$J(U,V) = \sum_{j=1}^{N}\sum_{i=1}^{c}(u_{ij})^2(d_{ij})^2 \qquad (3)$$

Here, u_{ij} denotes the degree of membership of j. SZO belonging to the i. cyberbullying scale problem, and the degree of membership denotes that j. SZO belongs to the i. question. All classification where FCM was used was shown in Algorithm 1. Before starting algorithm, the number of cluster (c), stop criterion (ε), blur parameter (p) must be described and cluster prototypes ($\boldsymbol{V}(\boldsymbol{0})$) and initial membership matrix ($\boldsymbol{U}(\boldsymbol{0})$) must be created.

Algorithm 1 - Pseudo code of FCM clustering algorithm.

Input: Data Set:

$$D_{SZO} = \{SZO_1, SZO_2, SZO_3, ..., SZO_N\}$$

Output: Optimum and answer Level:

$$D_{level} = \{Level_i\},\ i = 1,\ 2,3,4,5\}$$

Step 1: Clustering number c=2, iteration t=0 and fuzzy value p=2
Step 2: for c <cmax
Step 3: Rise c (c =c+1)

Step 4: Start core for subtractive clustering in D_{SZO}:

$$V^{(0)} = \{v_1, v_2, v_3, ..., v_c\}$$

Step 5: for $|U^{(t+1)} - U^{(t)}| > \varepsilon$

Step 6: Rise t (t =t+1)
Step 7: Calculate (u_{ij})

Step 8: $U^{(t+1)} == \{u_{ij}\};\ u_{ij} = \dfrac{1}{\sum_{k=1}^{c}(\frac{SZO_i - v_j}{SZO_i - v_k})^2}$

Step 9: Calculate (v_j)

Step 10: $V^{(t+1)} == \{v_j\};\ v_j = \dfrac{\sum_{i=1}^{N}(u_{ij})^2 xSZO_i}{\sum_{i=1}^{N}(u_{ij})^2}$

Step 11: Calculate Indicator (GD) and Calculate Exit (CD) and c

Step 12: If (GD < CB)

Step 13: assign ($c^* = c,\ U^* = U,\ V^* = V$)

Step 14: back c^* and D_{SZO}

To assess the hitting of the clusters obtained from data set, one of the validity indexes Partition Coefficient (PC) was used (Equation 4) [43].

$$V_{PC}(U) = \frac{1}{n}\left(\sum_{i=1}^{c}\sum_{k=i}^{n}u_{ik}{}^{2}\right) \qquad (4)$$

Developed classification prediction model was described as XGB_CTD. XGB_CTD is an operation of determining which cyberbullying class it belongs to according to the answers to the questions on the scale (Figure 1). The XGB_CTD model maps the answers to individuals ' questions involving internet activities according to the types of cyberbullying given in Table 1.

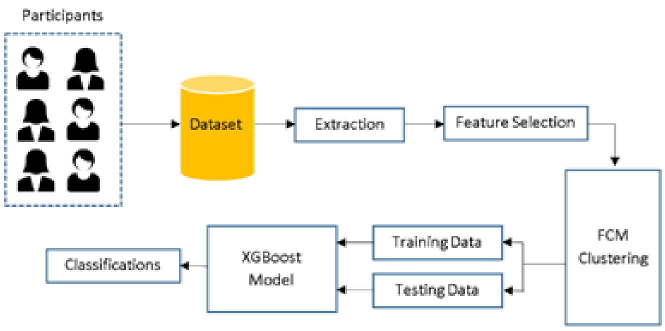

Figure 1- The architecture of the proposed model.

Table 1- Classification output types.	
Explanation	Output Code
E-mail	0
Text message	1
Picture message	2
Instant message	3

Personal Videos	4
Social Communication Webs	5
Chat Rooms	6
Games on virtual platform	7
An insulting website or forum related to the individual	8

In order to create a better classification effect in XGB_CTD, more than one decision trees were integrated. For each decision tree adding iteration, the value of loss function will decrease. Thus, those decision trees which were added are used for powerful classification.

Data set on XGB_CTD is $\{(X_i, Y_i)\}, (i = 0,1,2,...,N)$. $X_i = \{0,1,2,3,4\}$ indicates questions and answers, $Y_i = \{1,2,3,...,9\}$ indicates exit prediction. In XGB_CTD, each tree is optimized by using gradient Boosting. The output of each tree is like this; $f(x) = w_q(x_i)$. Here X, the input vector, and wq is the score of the q. digit in a tree. The output of K tree community is calculated as $y_i = \sum_{k=1}^{K} w_q(x_i)$.

On the t step of XGB_CTD, Equation 5 is used to minimize the j loss function. Here, L is the loss function of training between real y and $\hat{y}$ exit in n number of sampling.

$$j(t) = \sum_{i=1}^{n} L(y_i, \hat{y}_i^{t-1} + f_t(x_i)) + \sum_{i=i}^{t} \Omega(f_i) \qquad (5)$$

The start parameters of the model which were obtained for optimum performance in education and their values are given in Table 2.

Table 2- Optimum parameters of XGB_CTD.

Parameter	Value
learning rate	0.05
Gamma	0
Eta	0.3
Alpha	0
n_estimators	500
max_depth	5
Lambda_l1	0.2

4. Performance Evaluation

All figures should be numbered with Arabic numerals (1,2,3,....). Every figure should have a caption. All photographs, schemas, graphs and diagrams are to be referred to as figures. Figures must be embedded into the text and not supplied separately. Figures should be placed at the top or bottom of a page wherever possible, as close as possible to the first reference to them in the paper.

4.1. Environment Setup

In the process of developing XGB_CTD model suggested in the study, Python was used as a programming language. Python language has several libraries for preparing data, preprocessing and developing a model. XGB_CTD, In Spyder software, Scikit-learn, Keras, FCM and XGBoost libraries were used. As hardware, Intel I7-8500H 3.60 GHz CPU and a laptop with a 12GB RAM were used.

4.2. Evaluation Indicator

In order to assess the result in XGB_CTD algorithm, Accuracy (Equation 6) which represents the accuracy rate between the estimated value and the real value [44]. Furthermore, in order to be able to see the error value, Mean Square Error (MSE) was used as it is seen in Equation [45].

$$Accuracy = \frac{FP + TN}{TP + FP + TN + FN} \qquad (6)$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} | y_i - p_i |^2 \qquad (7)$$

4.3. Detection Results and Analysis

Initially, the accuracy of clustering was evaluated using FC validity index. Clustering results are shown in figure 2 when clustering number is considered as 2. The validity concept of clustering is open to interpretation. In the clustering study, the number of clustering couldn't be increased as it will be used for model training and test. Moreover, the big size of data set was also blocked this increase. When evaluated over original data set, the result was nearly same as the original structure for c=2.

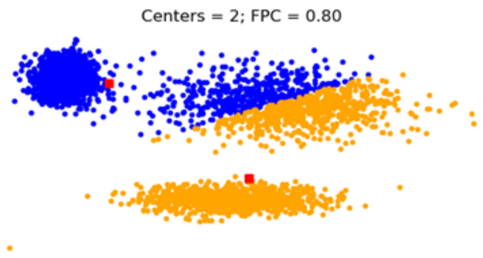

Figure 2- In data set, the results of fuzzy clustering according to the number of clustering for c= 2

It performed in the classification of multiple types of cyberbullying with XGB_CTD in the confusion matrix shown in Figure 3. The answers of the questions in data set shows that there is a relationship between they type of cyberbullying which young people were exposed to and the reason why they use the internet. When the confusion matrix of the model is analyzed, the prediction classification average 91.75% accuracy was obtained. So, it is seen that the incorrect classification of the model is similar to the reasons why young people use the internet. As a result, misclassification shifts are thought to occur mostly in young people who have more internet use purposes.

Additionally, to evaluate the performance of XGB_CTD model, it was compared with other machine learning methods (Gradient Boosting Decision Tree (GBDT), Random Forest and SVM). In this comparison, the model has gotten the best estimate accuracy as accuracy mean. The accuracy performance mean obtained from XGB_CTD and other machine learning and MSE error values are given in Table 3.

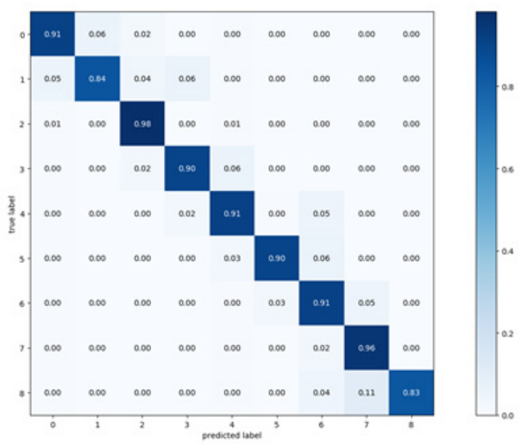

Figure 3- Confusion Matrix which belongs to XGB_CTD classification.

Table 3- The comparison of XGB_CTD and machine learning algorithm

Algorithm	Accuracy(%)	MSE	Training Epoch
XGB_CTD	91.75	0.1250	500
GBDT	89.20	0.1720	500
Random Forest	88.50	0.1805	500
SVM	75,75	0.2475	500

5. Conclusions

In this study, a neural net which provides us to estimate the type of cyberbullying which young people were exposed to and which they can possibly do by looking at their aim of using the internet was developed. It is an XGBoost based method which is one of the model community learning algorithms called XGB_CTD. Cyber security scale which was taken as a sample to create data set was turned into a survey. Data set was created by using the results of the survey which was applied to young internet users. Data set was clustered with FCM by making it normalize. XGB_CTD was trained by determining optimum hyper parameters in order to ensure high accuracy. The average accuracy rate of XGB_CTD is %91,75 when looking at the performance of classification according to nine different types of cyberbullying. In order to see the superiority of XGB_CTD, it was compared with other traditional machine learning methods. As a result, it has been seen that the model has the highest accuracy rate in estimate classification.

In future studies of the XGB_STM model, the dataset will be expanded by including social media shares of young people who are exposed to cyberbullying. As a result of this, it has been expected that the accuracy performance will increase more. The model will be put into practice in the last step of XGB_CTD. Thus, it will be estimated what kind of cyberbullying young people who are exposed to cyberbullying and can't utter this are exposed to by looking at their internet usage habits. At the same time, it will be able to envisage what kind of cyberbullying young people will possibly be exposed to by looking at their internet usage habits.

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