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Classification of Tweets about Violence against Women

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***Abstract* - Many studies have been done to draw attention to violence against women around the world. The aim of the studies is to awaken the society in general and to encourage women. For this purpose, this paper is aimed to draw attention to the violence against women by using data mining classification algorithms. The purpose of this study is to analyze the data on Twitter, which is one of the most widely used social media platform, and how much of the words such as violence, women and harassment are related to violence against women as cybercrime. For this, tweets from Twitter should be taken with certain words. Tweets were obtained according to some attributes using the Python language and the streaming API. The Tweepy library also used for this streaming API. Tweets were taken and analyzed in WEKA tool using various data mining classification algorithms. According to the experimental results, the best classifier was J48 algorithm with 82.9% accuracy and 0.902 F-Measure value.**

***Keywords* – Classification, Cybercrime, Data mining, Tweepy, Violence against women.**

I. INTRODUCTION

VIOLENCE against women (VAW) dates back to the history of mankind. Several forms of abuse have been described in our ancient epics, like Mahabharat and Ramayana. There have been efforts at global level to eliminate VAW. The United Nations (UN) Declaration on the Elimination of VAW (1993) states that "VAW is a manifestation of historically unequal power relations between men and women, which have led to domination over and discrimination against women by men and to the prevention of the full advancement of women, and that VAW is one of the crucial social mechanisms by which women are forced into a subordinate position compared with men."[1].

The term "VAW" encompasses a multitude of abuses directed at women and girls over the life span. The UN Declaration on the Elimination of VAW defines it as: "….any act of gender-based violence that results in, or is likely to result in physical, sexual or psychological harm or suffering to women, including threats of such acts, coercion or arbitrary deprivation of liberty, whether occurring in public or in private life." [2]. This statement defines violence as acts that cause, or have the potential to cause harm, and by introducing the term "gender based" emphasizes that it is rooted in inequality between women and men.

The term gender based violence (GVB) has been defined as "acts or threats of acts intended to hurt or make women suffer physically, sexually or psychologically, and which affect women because they are women or affect women dis-proportionally."[3]. Therefore, GVB is often used interchangeably with VAW. Both these definitions point at violence against women as a result of gender inequality. This inequality can be described as discrimination in opportunities and responsibilities and in access to and control of resources that is rooted in the social culturally ascribed notion of masculinity as superior to femininity.

II. RELATED WORKS

There are many studies on violence against women. In a study named as #NotOkay [4], an author launched a conversation on Twitter that encouraged women to share their first attack experience. Too much tweet has been achieved to do this. The results show that social media is an important aid for people to discuss GBV problems.

In another study [5], it was aimed to fill the gap in the literature about gender based violence. In this study, it was described how violence against women in Turkey, has been viewed and how it is perceived that both civil society as well as what kind of control methods developed at the state level. In the qualitative part of the study, the authors interviewed almost 150 women from approximately 50 women organizations from 27 provinces, and evaluated the strengths and weaknesses of these experiences by examining the problems of women's organizations and the state in order to problematize violence against women and the development of their struggles over time. In the quantitative part of the research selected by a representative samples throughout Turkey in 1800 married woman of 56 with scattered settlements (cities, towns and villages) conducted the field research, they live their women peers about violence experiences and opinions were identified.

A. *Social Movements*

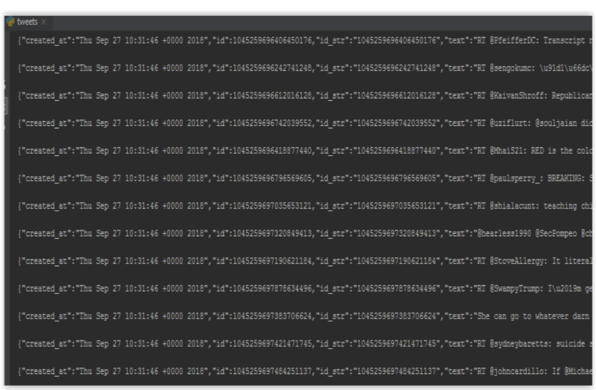
Nowadays, the place of social media is very big. Especially with the computer, the internet is changing not only the ontological transformation of the communication adventure but also all the horizontal and vertical transitions by touching all elements of the social structure. In this respect, despite its very existence in the history of mankind, the internet has provided a new environment that cannot be limited by any field and subject, but crosses the borders of the whole world. This new environment, which created a unique cultural world, became the driving force of new social and individual forms of relationship, the emergence of new identities and the formation of a new cultural environment. In this direction [3], thanks to the interaction of the internet, the individuals and the computers they have. This freedom environment provides for the participation of individuals not only in daily news, information or communication, but also in political, ideological, economic and cultural fields. It is clear that this new media arrangement now has a sounding and fast-spreading structure. This new network and journalism; all the rules that the order establishes have a dynamic structure that is prepared for drilling and knitting. It is a field in which the news is not a different editor than himself and the news is not subject to auto-censorship [6].

The social media's overriding structure of all socially existing dynamics is manifested by its accessibility and the shaping of the reaching channels. A look at social media content influences and transforms identities. This conversion is proportional to the content used and shared. Participants, social media has "become a preferred media in the prevention of violence for women because of their characteristics such as openness, speech, society, connection, accessibility, accessibility, usability, innovation and durability.

III. Social Media Data

In this study; tweets were obtained from specific words and user information of Twitter. The tweets taken were classified according to whether they contain violence against women or not. The data was extracted from Twitter using Python programming language. While the data was taken, Twitter streaming API and Tweepy library were used.

While tweets are taken, a lot of information can be obtained, such as the date of the tweet was taken as shown in Figure 1, the person who tweeted, the place where it was taken, and the time taken. This data includes 1000 tweets and was first recorded as csv as shown in Figure 2, then it was transformed to the .arff format for data analysis with Weka.



{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259696406450176,"id_str":"1045259696406450176","text":"RT @PfeifferDC: Transcript
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259696242741248,"id_str":"1045259696242741248","text":"RT @sengokumc: \u91d1\u66dc
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259696612016128,"id_str":"1045259696612016128","text":"RT @KaivanShroff: Republica
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259696742039552,"id_str":"1045259696742039552","text":"RT @uziflurt: @souljaian di
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259696418877440,"id_str":"1045259696418877440","text":"RT @MhaiS21: RED is the col
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259696796569605,"id_str":"1045259696796569605","text":"RT @paulsperry_: BREAKING:
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697035653121,"id_str":"1045259697035653121","text":"RT @shialacunt: teaching ch
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697320849413,"id_str":"1045259697320849413","text":"@hearless1990 @SecPompeo @c
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697190621184,"id_str":"1045259697190621184","text":"RT @StoveAllergy: It litera
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697878634496,"id_str":"1045259697878634496","text":"RT @SwampyTrump: I\u2019m g
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697383706624,"id_str":"1045259697383706624","text":"She can go to whatever darn
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697421471745,"id_str":"1045259697421471745","text":"RT @sydneybaretts: suicide
{"created_at":"Thu Sep 27 10:31:46 +0000 2018","id":1045259697484251137,"id_str":"1045259697484251137","text":"RT @johncardillo: If @Micha

Figure 1: Getting tweets as json.

1	RT	gender	location	followers_	friends_co	listed_cou	favourites	date	frequency	frequency	frequency	frequency	frequency	frequency	frequency	Violence
2	yes	m	Medfordil	2770	3029	42	7563	9	0	1	0	0	0	0	0	0
3	yes	f	San Anton	1091	961	2	19785	12	0	0	1	0	0	0	0	1
4	yes	m	Singapore	403	356	6	2280	11	0	0	1	0	0	0	0	1
5	yes	f	null	2066	334	45	30611	13	0	1	0	1	0	0	0	0
6	yes	f	null	1028	667	7	80818	15	0	0	0	0	0	1	0	0
7	yes	u	null	376	1078	9	62976	13	0	0	0	0	1	0	0	0
8	yes	f	A pool	376	406	30	16716	11	0	0	1	0	0	0	0	1
9	yes	f	Westervil	1787	1625	15	18964	11	0	1	0	0	0	1	0	1
10	yes	f	null	193	221	2	4484	14	0	0	0	0	1	0	0	0
11	yes	u	Abuja,Nig	2199	2082	5	16	11	0	0	0	0	1	0	0	0
12	yes	f	null	386	889	6	3493	10	0	1	0	0	0	0	0	0
13	yes	f	London,Er	9	22	0	39	10	0	0	1	0	0	1	0	1
14	yes	u	London,Er	587	531	6	909	15	0	0	0	1	0	0	0	0
15	yes	u	null	355	81	3	6959	12	0	1	0	0	0	0	0	0
16	yes	f	null	1969	2075	38	65018	9	0	1	0	0	0	0	0	0
17	yes	f	Houston,T	3867	1726	52	5116	12	0	0	1	0	0	0	0	0
18	yes	f	Philippine	689	448	3	4322	12	0	0	1	0	0	0	0	0
19	yes	f	EGNEVER	3391	1139	24	69014	11	0	1	0	0	0	0	0	0
20	yes	f	In my don	1563	1072	4	9449	11	0	0	1	0	0	0	0	0
21	yes	m	null	23	62	0	8	16	0	0	0	0	0	0	1	0

Figure 2: Information of tweets.

The tweets that contain specific words and the frequencies of these words are also obtained. Some of these words are violence, abuse, assault, rape, woman, etc. It is determined that the class of the tweet is not violent or violent according to their presence or frequency.

A. *Weka*

The Waikato Environment for Knowledge Analysis (WEKA) [7] came about through the perceived need for a unified workbench that would allow researchers easy access to state-of-the-art techniques in machine learning. WEKA would not only provide a tool for learning algorithms, but also a framework inside which researchers could implement new algorithms for data manipulation and scheme evaluation. Recently, WEKA is recognized as a landmark system in data mining and machine learning [7]. It has achieved common acceptance within academia and business circles, and has become a widely used tool for data mining. The book [8] is a popular textbook for data mining and is frequently cited in machine learning publications. This tool is free access for users and open-source to develop many projects.

In this study, 15 attributes which are RT,gender,followers_count,friends_count, listed_count, favourites_count, date, frequency_violence, frequency_woman, frequency_women, frequency_abuse, frequency_assault, frequency_rape, frequency_harrasment, class were used as shown in Figure 3.

```
@attribute RT { yes,no }
@attribute gender { m,f,? }
@attribute followers_count real
@attribute friends_count real
@attribute listed_count real
@attribute favourites_count real
@attribute date { 9,12,11,13,15,14,10,16,8,17,18,7}
@attribute frequency_violence { 0,1,2 }
@attribute frequency_woman { 1,0,2,3 }
@attribute frequency_women { 0,1,2,3 }
@attribute frequency_abuse { 0,1,2 }
@attribute frequency_assault { 0,1,2 }
@attribute frequency_rape { 0,1,2 }
@attribute frequency_harrasment { 0,1 }
@attribute class { 0,1 }
```

Figure 3: The attributes used in the dataset.

IV. EXPERIMENTS

From the simplest to the most complicated, experiments were run with the classifiers in Weka. The data analysis will be done by applying various classification algorithms with Weka tool. Weka offers 4 options to measure the success of classifiers. The cross validation option is mostly used in the study. The "cross-validation" option splits the data set into the set number of clusters. Firstly, the system is trained by accepting one of the subclasses as the training cluster. This training result is then tested on another subset (which is given the name validating set or test set). It tries to improve the system by repeating this process for the specified number of clusters. As shown in Table 1, the used classification algorithms in this study were explained. Also, cross validation method was used in this study with these classifiers.

Table 1: Classification methods.

Method	Description
ZeroR	ZeroR algorithm can be considered as the simplest algorithm. If the data set has more than one class, it accepts everything from that class.
OneR	OneR can be said to be the advanced form of the ZeroR algorithm. This algorithm yields better results than ZeroR algorithm. One of the results has chosen that can give user the best possible result from the classes in the train given at the moment.
Naive Bayes	In the Naive Bayes classification, data is presented to the system on a specific basis (e.g. 100). There must be a class / category of the data presented for teaching. With the probability operations on the taught data, the new test data presented to the system is operated according to the previously obtained probability values and it is tried to determine which category of test data is given. The greater the number of data that is taught, the more accurate it is to determine the true category of test data.
BayesNet	BayesNet algorithm is a Bayes type algorithm. It is similar to Naive Bayes algorithm.
Logistic	The logistic classification predicts the likelihood of a result that can only have two values (ie, it can be divided into two). The estimate is based on the use of one or more predictors (numerical and categorical).
KNN	According to KNN algorithm used in classification, feature extraction is used to look at the closeness of k to the k of the previous individual who is wanted to classify. In default, K is generally taken as 3.
J48	Using C4.5 decision tree algorithm, the bottom lines will be the child of the top lines. It is one of the fastest and the most accurate working algorithms.
HoeffdingTree	A Hoeffding tree is an incremental decision tree induction algorithm that is capable of learning from massive data streams. The distribution generating examples does not change over time.
RandomTree	RandomTree algorithm is a tree-based classification algorithm.
RepTree	RepTree algorithm is a tree-based classification algorithm.

V. CONCLUSION

Today, the importance of Twitter can not be denied. It is one of the environments where people can get the most accurate information about other people in this social environment where every kind of people share their views. There are a lot of activist tweets shared every day against the violence of women. In general, people appear to be doing tweets RT. This shows how important interaction is.

In tweets, people can access most things, such as where people are tweeted, who is tweeted, who is the number of followers. When these tweets were classified with various classification algorithms, whether they included violence or not, and then observed that according to the Table 2 the best performance with 82.9% accuracy and 0.902 F-Measure value was J48 algorithm, which is a tree-based data mining algorithm and a type of C4.5 decision tree algorithm. The worst performance was observed with K-Nearest Neighbor (KNN) algorithm, which is a lazy type data mining algorithm.

Table 2: Classification results.

Algorithm	Correctly Classified Instances (%)	F-Measure
ZeroR	79.4%	0.885
OneR	78%	0.874
Naive Bayes	76.6%	0.857
BayesNet	81.1%	0.892
Logistic	81.8%	0.894
KNN	75.3%	0.855
J48	**82.9%**	**0.902**
HoeffdingTree	79.4%	0.885
RandomTree	71.3%	0.819
RepTree	80.4%	0.889
DecisionTable	79.7	0.884

VI. FUTURE WORK

In the study, each word in all documents was not taken as frequency. In the next study, each word in the documents will be taken as attributes and their frequencies will be calculated. As a future work, more accurate results can be obtained by using more tweets.

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