Online Detection of Child Grooming Conversation

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ABSTRACT

Abstract- The extensive spread proliferation of social media has unlocked up possibilities for criminals to direct the crime of online child grooming. Because of the pervasiveness of the problem scale, it can only be nominated effectively and efficiently using an automatically negotiated conversation recognition system. Previously, Gunawan, Soivito and Pranotto, [1] developed a logistic model for this purpose and the model was able to achieve 95% detection accuracy. The present study intends to solve the problem using the support vector machine and the k-nearest neighbor classifier. In addition, the study also proposes a low computational cost classification method based on the number of negotiation characteristics of the current grooming. All proposed methods are evaluated using 130 conversational texts, out of which 95 texts are prepared and 45 texts are not prepared. We recognize that there are 15 features in grooming interactions. The results suggest that SVM and K-NN are able to identify interactions at 97.6% and 96.8% of the level of accuracy. Meanwhile, the proposed simplex method has 96.8% accuracy. Empirical studies also show that between two seventeen features are unimportant for classification.

Keyword: - *Child grooming online, SVM, Grooming Classifier, k-nearest Neighbor.*

1. INTRODUCTION

Online child grooming is defined as the process to approach, persuade, and engage a child in activity using the Internet as a medium. The criminal goes to the victim build not only here but emotional connection as well [2]. The widespread proliferation of social media has opened up possibilities for criminals to conduct online child grooming crime in a large scale [3], [4]. According to the Child Exploration and Online Protection Agency, online child grooming is the highest crime in the UK in 2009–2010 [3]. It affects the victim life psychologically, physically, emotionally, behaviorally and socially [5]. To disclose these sorts of crimes, the investigator typically trusts on formal or informal conversational texts, where the grooming pattern is cautiously examined [6]. With the vast amount of conversational text data, the process becomes extremely difficult and requires significant amounts of time. The manual approach of examining the grooming pattern is also error-prone [6]; In addition, the grooming process takes an average of one month [7]. For the reason described above, it is important to develop an automated system to analyze a conversation text and explore the possibility of grooming online. During the last five years, many research work has been done addressing the issue using different pattern detection schemes, including the k-means clustering by Kontostathis, Edwards, and Letherman [6], a regime-based approach by McGhee et al. Support vector machine (SVM), of Pandey, Khapfti, and Manandhar [4]. Recently the Gunawan, Pranotto and Sauvit developed [1] a grooming detection system by using the logistic regression models. The SVM (Support Vector Machine) method works best for text-based classification according to Ref. [10]. However, SVM has also been demonstrated for illustration-based classification such as corona artery disease [11] and cancer [12]. Reference [13] used SVM to develop an intrusion detection system. This study seeks to propose a simple method to explore the interaction of grooming an online child. In doing so, the study first identifies the main features of the type of interaction. The proposed methodology is developed based on the number of existing features which are also here used and are actual good in terms of result. Different number of theories used which show as below with detail explanation and are effective against the online grooming attacks which helps broadly in cybercrime on social media.

2. ASSISTING THEORIES

2.1 Online Child Grooming Characteristics

Conversation texts promoting online hair are complex because it depends on characteristics and behavior, varying in duration, type, and intensity. However, in general, Fergyanto [13] have identified specific steps in the online hair grooming process. The first is the state of friendship. The criminal tries to introduce the child and then establishes the possibility of exchanging names, places, ages, and etc.

In addition, the offender checks other online information related to the child, so that the photo can be requested to confirm the child is actually a child.

The second is the state of relationship building. The criminal and the child talk about family, school, interest and the child's hobby so that he can cheat and exploit them, the child believes that they are in a relationship. The third is the risk assessment phase. The offender tries to reduce the level of danger and danger by talking to the child. He makes sure that the child is alone and no one else is reading their conversation. The fourth specialty is the platform. The criminal tries to gain complete trust of the child. Often, the concept of love and care is initiated by the offender at this stage.

The fifth is the stage. The criminal and the child talk about activities and developing fantasy. Finally, the sixth conclusion is the phase. In this case, the culprit

Contact the child to meet in person. These steps of grooming online may or may not be in order. The frequency, order and extent of occurrence of these steps can vary from chat to chat.

Based on previous work [1], and Refs. [3], [13], we have identified 1 Grooming characteristics, see Table 1, and their relationship to Grooming stages are presented in Table 2. These features will be used to classify online conversation texts.

Table -1: The Well Identified Grooming Characteristics

No	Characteristics, Description and Source
1.	Profile asking. Criminals and victims exchange information about personal information, For example, name, age and place [13].
2.	Contact in other ways. Criminals and victims talk about another way of communicating Kate, such as, phone, email, and social media [13].
3.	Asking photos. The criminal asks the victim to send his picture Verse [13].
4.	Congratulations. Praises the offender for making the perpetrator a victim Suffering happy and flattering [13].
5.	Activity, favorite hobbies and talking about school. Conversation of offender and victim Regarding daily activities, favorite hobbies and school activities of the victims [13].
6.	Talking about friends and relationships. Criminals and victim friends talk about ships or relationships, such as, asking about a relationship with another son per se [13]. It is easy if the victim is not in a relationship with another person To get closer to the culprit.
7.	Asking questions to find out the risks of the conversation. Criminal tries figure At the risk of their conversation, is it known from their conversation The victim's parents [1] Typically, the perpetrator will ask about someone who uses the victim The computer, the location of the computer and whether the victim's parents know Chat application password.
8.	Wrongdoing. The offender will inform the potential victim whether They are doing wrong, and there are legal risks for the perpetrator [1]. By telling this For the victim, the offender has a purpose, which the offender will be free from legal Cases that will put him in jail in the future.
9.	Asking if the child is alone or under the supervision of an adult or friend. Criminal It seeks to ensure that the victim is alone or under surveillance [3].
10.	Trying to build mutual trust. Trying to build mutual trust with a criminal Victims, next level relationships will be easier for the perpetrator if the perpetrator Gain trust from the victim [1].

11.	Fall in love-filled words. In the conversation between the perpetrator and the victim, They use words to express that they are in love [3], [13].
12.	Using the word to express emotion. In a conversation between the criminal and Suffering, they use words to express their feelings [1].
13.	Using the word about biology, body, intimate parts, and abusive category. In Conversations between the perpetrator and the victim, they use words that include reference [1].
14.	Hot picture asking. Criminal theme photo or asks the victim for it Versa [1], [13]. These images can be used as imagery or threatening tools.
15.	Convictor introduction to steps, the conversation started with talking about the context, like ask about experiences of sex [1], [13].

Table -2: The 15 Grooming Characteristics and Grooming Stages Relation

No	Stage of Grooming	Characteristic Name
1.	Make friendship	Asking profile
2.		Contact in another way
3.		Asking photo
4.		Praising
5.	Building relationships	Talking about activity, favorites, hobbies, school
6.		Speaking of friend and relationship
7.	Risk Assessment	Asking questions to find the risk of negotiation
8.		Recognizing Doing wrong
9.		Asking if the child is single or alone or an teen
10.	Exclusiveness	Trying to build mutual trust
11.		Using words like fall in love
12.		Using words to express emotion
13.	Sexual	Using words about biology, body, intimate parts and erotic category
14.		Hot picture asking
15.		Introducing sexual phase

2.2 k-nearest neighbor

K-Near Neighbor (K-NN) is a rapid-based learning algorithm for classifying data based on data from a training dataset that is similar to the data. In the k-NN method, the method will retrieve the k data from the most similar data from the training dataset along with the data. The similarity between the data and the distance to the data from the training dataset is measured by calculating the distance. Before calculating the distance, data and data from the training dataset are represented in the VSM. Usually Euclidean distance which is commonly used in calculating the distance between vectors [8].

The training phase only involves storing the feature vectors and class labels of the training set. In the classification phase, the training is transformed into a vector using the data so that the distance along the vectors from the training dataset can be calculated and the closest distance is selected. The annotated range of test data is predicted based on the closest point that is assigned to a particular category, and then, the test data is assigned to the class that contains most of the neighbors.

2.3 SVM (Support Vector Machine)

In the present study, we only use the SVM (support vector machine) for linearly separable data. SVM is a numerical method to compute a hyperplane to separate a two-tier dataset. This can easily be extended to multiplecase problems. SVM establishes a governed hyperplane by (w, b), using support vectors, which are the data points closest to the hyperplane. The following SVM formulation is taken from Refs. [13]; Two sources are recommended to readers for detail.

We consider the points of sets as $x_i \in \Re^d$, as support vectors, with ranges $y_i \in [-1, +1]$. The hyperplane that separates $y_i = -1$ satisfy from $y_i = +1$ must be satisfied

$$\langle w, x \rangle + b = 0, \qquad . (1)$$

Where $w \in \Re^d$, $\langle w, x \rangle$ denote the inner dot product of w and x, and b is a scalar constant. The hyperplane is obtained by solving:

$$\min_{w,b} L_p = \frac{1}{2}\langle w, w \rangle - \sum_i \alpha_i [y_i(\langle w, x_i \rangle + b) - 1], \qquad . (2)$$

Where, $\alpha_i \geq 0$. For the case where the data are not linearly different, the feature vector xi will be replaced with a kernel function. Two types of kernel functions will be evaluated: polynomial type where, $\mathrm{K}(x, y) = (1 + \langle x, y \rangle)^d$, and radial basis function (RBF) type where $\mathrm{K}(x, y) = \exp(- < (x - y), (x - y) > / 2\sigma^2))$. The parameter d is an integer, and will be evaluated for d = 1, 2, and, 3, and will have a positive value of σ.

2.4 Accurateness Indicator

Classification accuracy is calculated by:

$$Accuracy = \frac{TP + TN}{TP + TN + Fp + FN}, \qquad . (3)$$

Where TP means True Positive, TN for True Negative, FN for false negatives and FP for false positives.

3. Research Methods

The research process is schematically shown in fig. 1 and also some important steps are summarized in the following diagrammatical representation.

3.1 Preparation of Dataset

This research requires two types of conversation texts: the first type is the actual online child grooming conversation and the second type is the conversation of non-grooming conversations, but the grooming features. The first type of interaction is chosen randomly from www.perverted-justice.com, a website that has more than 500 texts related to conversations involving criminals and children, juvenile victims, or undercover law enforcers. Only 105 texts have been selected. The source has also been used by previous researchers [1], [6], [8], [9]. The second type of interaction is selected from www.literotika.com. The web has a dialogue script for people that legally expresses their passion. There are eighty-four none grooming conversation texts randomly selected from the site. Then the next method is preprocessing.

3.2 Preprocessing

The text of an online conversation contains many noises from the point of view of document classification. Those noises must be minimized or eliminated before analysis to determine grooming characteristics. All texts of this research are subject to the following procedures. Token: Non-letter characters will be removed in the document and each document is divided into word changes: words will be changed in the document

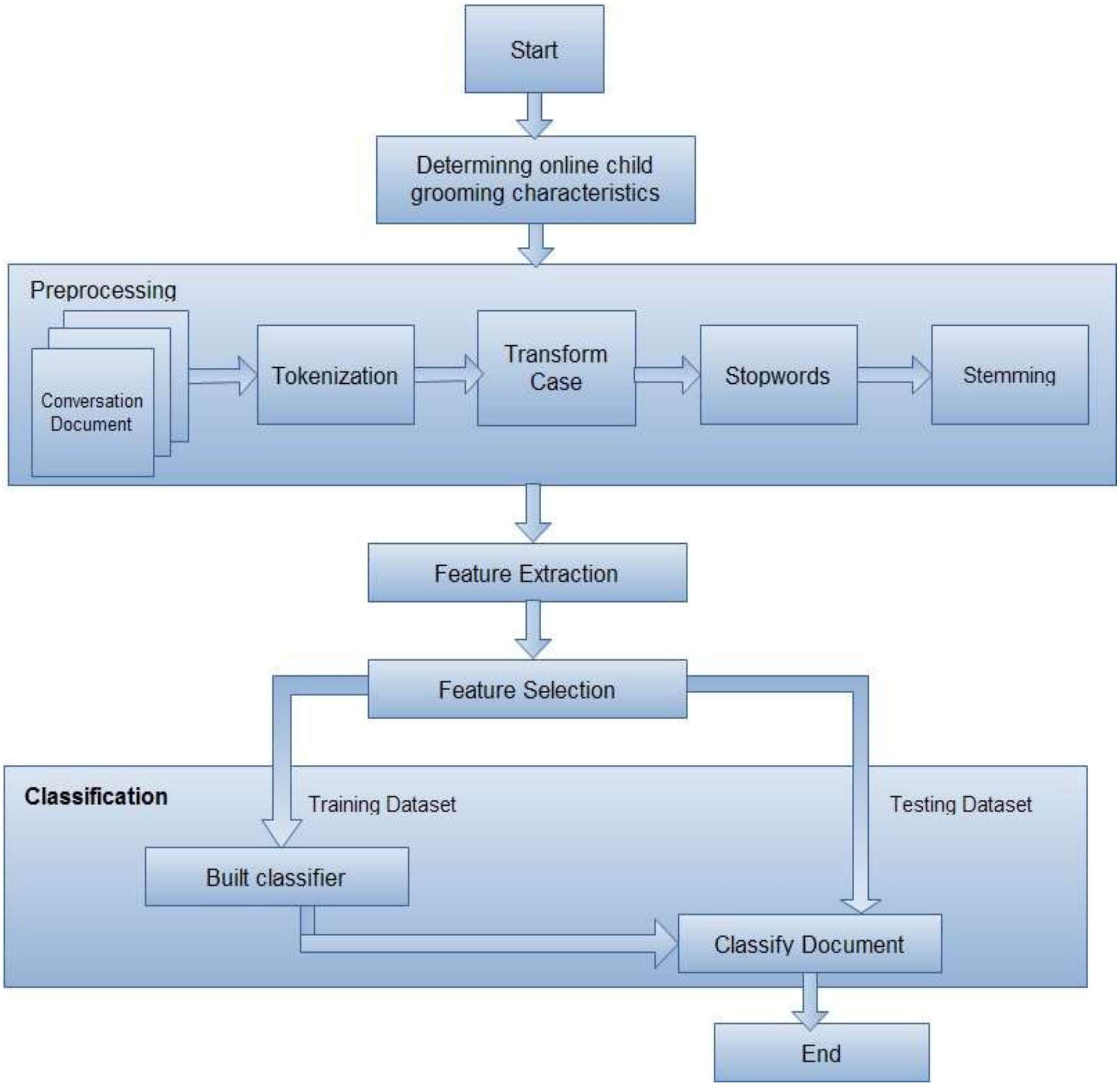

Fig -1: Process of Research.

In lowercase. Stopword Elimination: Words that are often present in a document, but are not significantly useful. Stemming: the words in the document will be reduced or minimize at their root using the porter algorithm. Creating a 3-gram: The words in the document will be made into a 3-gram of 1 continuous sequence made up of 3 words from the document. Then comes the one of the important method in grooming technic to identify the online grooming attacks in conversation.

3.3 Feature extraction

Texts that are preprocessed will be transformed into a vector space model (VSM). Attributes are words or combinations of words that make up a wordlist. The word list is shown with T1, T2. . . , Tt. The feature extraction result from the document (dm) is converted to the vector dm = {wT1, m, wT2, m,. . , wTt, m}.
Where, $m \epsilon M, M$ is the number of documents and wTi, m, is the load calculation result from feature i using the TF-IDF that represents how important features are in the document m and all documents in the dataset.

3.4 Feature selection

Feature extraction results from each document in VSM will be used to create a grooming attribute vector. The features used are 15 features.

In Table 1, the vector is defined as Cm = {cm, 1, cm, 2, cm, 3. . . , Cm, 15} where $m \epsilon M$ and $c_{m,j}$ is a value that indicates whether or not the attribute j in the document m. If the document m does not have the attribute j, then $c_{m,j} = 0$. If the document m has the attribute j, then $c_{m,j} = 1$. To determine the attribute j value in the document m cm, j, of the attributes of extraction The database that stores the words or combinations will be selected accordingly.
Words that describe each grooming feature. The value of the attributes that have been selected will be expressed. If the result is 0 then $c_{m,j} = 0$ and if the result is greater than 0, the attribute value j in the document $c_{m,j} = 1$.

3.5 Classification

Classification will be performed using SVM (see Subscription II-B), k-NN (see Subscription II-C) and our proposed method, which is based on the characteristics of grooming in the document.

4. Results and Discussion

We have analyzed around 130 conversation texts, including 95 embellished conversations, randomly taken from www.perverted-justic.com, and 65 non-grooming conversations randomly from www.literotika.com has gone. We have identified seventeen grooming characteristics by considering previous works and learning those grooming conversations. Those features are then represented in a vector space. These characteristics and the frequency of occurrence in their grooming and non-grooming are presented in Table 3. The automatic classification makes it difficult that non-grooming conversations also show grooming characteristics as shown by Table 3. For example, the most prevalent features, which are the 13th features, are "biology, the use of the word about the body, intersecting parts, and category" appearing in 95 grooming text conversations and 39 non-grooming text conversations.
Another insight shown by the table is that two features, namely the 14th features, "asking the hot picture", and the 7th features, "asking questions to find out the risk of interaction," are rarely visible. We hypothesize: Two characteristics may not significantly contribute to the performance of document automatic performance. This will be evaluated empirically.

Here as the given below, we are going to do discussion about the results in term of classification accuracy for different classification methods and without 7th or 14th grooming characteristics. The training set consists of 70 grooming and 30 non-grooming conversations. The test set consists of 35 grooming and 15 non-grooming conversations. For the first research results, we compare the level of accuracy of the results by several SVM kernel functions, such as RBF, quadratic, polynomial, and linear functions. The results, on average accuracy, are shown in Table 4.

Here, these results reveal some interesting events, some expected, some unexpected. We expect that the highest level of accuracy will be achieved using all grooming characteristics. This expectation is physical for three types of SVM kernels: polynomial, quadratic and linear. Using the RBF kernel, the results are unpredictable: Accuracy without 7th and 14th attributes is better than using all attributes. It is expected that the 7th and 14th grooming features will only slightly affect the level of accuracy, physicized for only three kernels: polynomial, quadratic, and linear. The accuracy level through the SVM method is within the range of 83–98% depending on the selection, using all the grooming characteristics.

Table -3: Fifteen Grooming Characteristics and their occurrences of Grooming and Non Grooming Texts.

No.	Characteristics of Grooming	Frequencies	
		G	N
1.	Asking profile	97	2
2.	Contact in another way	101	10
3.	Asking photo	102	10
4.	Praising	96	22
5.	Talking about activity, favorites, hobbies, school	104	28
6.	Speaking of friend and relationship	95	16
7.	Asking questions to find the risk of negotiation	44	0
8.	Recognizing Doing wrong	99	15
9.	Asking if the child is single or alone or an teen	84	0
10.	Trying to build mutual trust	98	27
11.	Using words like fall in love	70	7
12.	Using words to express emotion	105	42
13.	Using words about biology, body, intimate parts and erotic category	105	43
14.	Hot picture asking	13	0
15.	Introducing sexual phase	101	34

G= Grooming, N=Non grooming

Table -4: Fifteen Grooming Characteristics and their occurrences of Grooming and Non Grooming Texts.

Grooming Characteristics	The SVM kernel type			
	RBF	Polynomial	Quadratic	Linear
All Fifteen	82.8	97.6	98.6	98.6
Without the Fourteen	86.4	97.6	98.6	98.6
Without the Seven	88.4	96.6	97.4	97.8

In comparison to the method of using logistic regression models, see Ref. [1], three kernels Provide slightly better accuracy. The RBF kernel produces lower accuracy than the logistic model. For other research results, we also compare the level of accuracy using a different classifier, which is the k-NN method, with values for k, 1, 3 and 5. On average, the results are shown in Table 5 below.

Table -5: Fifteen Grooming Characteristics and their occurrences of Grooming and Non Grooming Texts.

Grooming Characteristics	k-value		
	1	3	5
All Fifteen	96.0	96.8	96.2
Without the Fourteen	96.0	96.8	96.2
Without the Seven	95.8	97.2	95.8

These results completely agree with our expectation. The highest average level of accuracy is obtained using all the grooming characteristics. This result is physical for all values of k. The expectation that 7th and 14th grooming characteristics will slightly affect the level of accuracy is materiality for all values. The average level of accuracy in classification without 14th characteristics is the same with using all aesthetic attributes. The all grooming characteristics usage, the moderate level of accuracy through the k-NN method is within the range of 95.8–96.8% depending on the k value. However, it is unclear whether increasing the k value will decrease or increase the level of accuracy.

We evaluate the method by varying the threshold value from 1 to 15. If the amount of number of grooming attributes in a document is less than the threshold, the conversation will most probably classified as a non-grooming conversation and with vice versa as well. The results of the average accuracy are indicated in Table 6. These empirical data indicate that the highest average level of accuracy has been attained at a threshold value of 11. The best range provides an accuracy level of 95.8%. The expectation that Seventh and Fourth grooming characteristics will only quite slightly disturb or affect the level of accuracy is physical threshold values for all included.

Finally, we compare the level of accuracy of the three classification methods: K-NN, SVM (Support Vector Machine) and our proposal. For the SVM method, we only include the results of using the linear kernel because they are the best among the method. For the same reason, for the k-NN method, we only include the case of k = 3.. The comparison is presented in Table 6 as below.

All methods we see here that is all three support the hypothesis that the accuracy will be slightly reduced when the Seventh and Fourteenth grooming characteristics are excluded. Furthermore, these results suggest that the SVM classifier is best able to classify in term of accuracy. The proposed method, despite its simplicity, performs rather well.

Table -6: The Differentiable comparison of Avg. level of Classification Accuracy using K-NN, SVM and Current Proposed Methods.

Grooming Characteristics	Method of Classification		
	K-NN	SVM	Proposed Method
All Fifteen	97.60	96.80	95.80
Without the Fourteen	97.60	96.80	95.80
Without the Seven	96.80	96.20	95.00

5. CONCLUSIONS

Automated systems for detecting online child grooming have an important role in the analysis of large amounts of conversational texts. For this reason, several studies have been performed using different pattern detection schemes. In the present work, seventeen features of interaction are identified and used for classification. Here the two good and traditional classification methods are used: SVM (Support Vector Machine) and K-NN. In addition, this work proposes a simple classification method based on the existing grooming characteristics in the interaction. Numerical analysis using empirical data shows that the SVM method with linear kernel is the best method among others with an average level of accuracy of 97.6%. Our proposed method, despite its simplicity, also performs well with an average level of 95.8% accuracy. Empirical studies also suggest that two of the seventeen attributes are unimportant for classification accuracy.

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