

# Detection of child exploiting chats from a mixed chat dataset as a text classification task

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## Abstract

Detection of child exploitation in Internet chatting is an important issue for the protection of children from prospective online paedophiles. This paper investigates the effectiveness of text classifiers to identify Child Exploitation (CE) in chatting. As the chatting occurs among two or more users by typing texts, the text of chat-messages can be used as the data to be analysed by text classifiers. Therefore the problem of identification of CE chats can be framed as the problem of text classification by categorizing the chat-logs into predefined CE types. Along with three traditional text categorizing techniques a new approach has been made to accomplish the task. Psychometric and categorical information by LIWC (Linguistic Inquiry and Word Count) has been used and improvement of performance in some classifier has been found. For the experiments of current research the chat logs are collected from various websites open to public. Classification-via-Regression, J-48-Decision-Tree and Naïve-Bayes classifiers are used. Comparison of the performance of the classifiers is shown in the result.

## 1 Introduction

The online chatting has become a popular tool for personal as well as group communication. It is cheap, convenient, virtual and private in nature. In an online chatting one can hide ones personal information behind the monitor. This makes it a source of fun in one hand but possess threat on the other hand. The privacy and virtual nature of this

medium increased the chance of some heinous acts which one may not commit in the real world. O'Connell (2003) informs that the Internet affords greater opportunity for adults with a sexual interest in children to gain access to children. Communication between victim and predator can take place whilst both are in their respective real world homes but sharing a private virtual space. Young (2005) profiles this kind of virtual opportunist as 'situational sex offenders' along with the 'classical sex offenders'. Both these types of offenders are taking the advantages of the Internet to solicit and exploit children. This kind of solicitation or grooming by the use of an online medium for the purpose of exploiting a child may refer to the problem of 'online child exploitation'.

Currently there is no such system that can automatically identify the elements of child exploitation in chat text. It is very difficult for parents or the members of Law and Enforcement Agency (LEA) to watch over the children all the time to protect them from online paedophiles loitering over the vast space of the Internet. An online automatic CE detection system can be useful. Regarding offline, most of the chatting programs have the options of storing the chat-texts in log-archives. According to Krone (2005) and [pjfi.org](http://pjfi.org) chat-logs can be used as evidence to proof a paedophile attempting to exploit children. Therefore after an online child exploitation occur; a LEA member can retrieve those offline archived chat logs from the hard drive of the accused to produce as evidence in the court of law. However manual identification of the evidence is a tedious and time consuming work, as one may have to read hundreds or thousands of pages of chat-texts from different chat-logs. Thus it is prone to error due to exhaustion. Moreover manual process may lead to a biased

decision. Therefore a research to develop such an automatic system will have a significant contribution in both the online and offline situation for the protection of children from exploitation.

This paper introduces the results of the preliminary experiments of an ongoing research aims to develop a novel methodology that can automatically identify the child exploitation in chats through the analysis of the contents of the chat-logs using data-mining and machine learning techniques. For the experiments the chat logs are collected from various websites open to public. Three classifiers, named Classification-via-Regression, J-48-Decision-Tree and Naïve-Bayes classifiers are used from the WEKA data mining tool. Along with term based feature set a new kind of features named psychometric and word categorical information has been used. The LIWC (Linguistic Inquiry and Word Count) is used to get this information of the chat-terms. The result and performances of the classifiers are compared in the experiment and result section.

The contributions of this paper are many fold. First, in the information and language technology field currently it is difficult to find a good number of researches focusing on the issue of detection of internet child exploitation. This paper emphasises on this issue and examines the technical aspects of chat messages that can be used to find a solution. Second, the experiments in the current paper use archived chat logs instead of single chat posts. Single chat posts contain only a few terms, on the other hand a log of chats contain a good number of terms which provides more facility for a machine learning system to learn the prediction function of a class. Third, this research uses psychometric information for the first time to detect CE chats. No other research has been found that is doing the same. This psychometric information seems enriching the feature set that improves the performance of some classifiers.

The remainder of this paper is organized as follows. Section 2 reviews the related works. Section 3 describes the methodology followed in this research. The experimental results are analysed in section 4 while section 5 presents conclusion and future work.

## 2 Related work

In the recent years, IT research community has paid good attention to the chat-text analysis and chat-mining. Different applications evolved in this area though are not perfect in all situations. Literature review suggests that most of the existing techniques have good performance only for its specific context. The context of the current research is particularly unique; it focuses on detecting CE chats. In addition, it uses archived chat logs instead of single chat posts used by others. Therefore the existing works does not match with the current research problem. As any technique that corresponds to the same context is not found, related works on chat messages is discussed in this section.

Following subsections provide a short description of the analysis of unique properties of chat messages, psychological aspect of child exploitation and a brief overview of the related existing work on chat text.

### 2.1 Analysis of Chat messages

The texts in the chat possess some unique characteristics that distinguish them from other literary formal texts (Rosa and Ellen 2009; Kucukyilmaz et al. 2008). Chat-users suppose to type spontaneously and instantly. Therefore the individual post is very brief, as short as a word. Frequently it is confined within a couple of words. Generally the chats do not follow any grammar rules. Therefore the chat-text is grammatically informal and unstructured. This made them more difficult to process by traditional sentence parsers. Chat-users are though typing texts, but are actually trying to talk with each other through it. So the text is typed very quickly, frequently unedited, errors and abbreviations are more common. For example, “ASL” is a common chat abbreviation for Age, Sex and Location asked at the introduction stage. “P911” is a chatting code used by teenagers. It stands for “Parent Alert!”(teenchatdecoder.com). These kinds of previously unseen abbreviations and erroneous texts are difficult to be handled by any currently available text processing techniques.

Chatting is a purely textual communication medium. So for transferring emotional feelings like happiness, sadness and angers, emoticons (emotion + icon = emoticon; a chat jargon) are widely used. These are different sequences of punctuation marks

that display graphical representation of different emotional feelings. For example, “:-)” means “happy” and “:-(” represents “sad”. Another way of emotion transfer is by emphasizing a word with repeating some specific characters. For example, “soryyyyyyyyyyy”. This kind of deliberate misspelling is also frequent in chat text. The emoticons and intentional misspelled words may contain valuable contextual information in a chat text. For example, in the grooming phase the perpetrator may reconstruct relation by an emphasized “soryyyyyyy” when the child felt threatening by any obtrusive language. Another example may be the emoticon for “hug (>:d<)” and “kiss (:-\*)” for a soft introduction of sexual stage. However, preserving such information makes traditional text processing methods (e.g., stemming and part of speech tagging) unsuitable for processing chat text (Kucukyilmaz et al. 2008).

The concern of the current research is child exploiting (CE) chats. This kind of chats is done between an adult perpetrator and a child victim. The perpetrator types the text targeting to entice the child. Therefore this type of chats can be considered as a special type of chats inheriting the above mentioned general properties as well as having special CE properties. Sexually explicit language, though not found in the beginning, may be introduced gradually in the text as the conversation progresses. Matching those words may show some preliminary detection of exploitation, yet this raises some confusions. If the perpetrator is an experienced groomer he may cleverly avoid sexually exploiting words. Instead he may use other words for gentle and soft pressure on the child’s sexual boundaries. On the other hand a chat log between two adults, who have sexual relationship, may also have sexually explicit languages in their intimate private chat sessions. Matching only sexually explicit words does not solve the problem. A robust analysis of the entire chat text is required that may detect the particular child exploiting (CE) profile in the chat log.

## 2.2 Psychological information and LIWC

Rachel O’Connell (2003) identified psychological progressive stages in online child exploitation. The exploitation does not occur instantly. It starts by making an innocent friendship and gradually advances towards the stage of exploitation through

a psychological progression. A perpetrator tends to follow the model of luring communication theory, proposed by Olson et.al. (2007). According to this model a perpetrator builds up a deceptive psychological trust. This indicates that the terms used in the process of exploitation are categorically and psychologically different than the terms used in general chatting. Therefore analysing the psychological and categorical information of the chat terms would be helpful to learn the psychological pattern of the exploitation. To find out the categorical and psychological properties of terms LIWC (Linguistic Inquiry and Word Count) has been used in this current research. According to Pennebaker et al.(2007) LIWC is a text analysis application designed to provide an efficient and effective method for studying the various emotional, cognitive, and structural components present in the terms of a text. The LIWC system counts the number of structural and psychologically significant words in the text. For example it gives the count of the words that contain the following information: social, family, friend, sexual, positive emotion, negative emotion, sad, anger, anxiety etc.

## 2.3 Existing Work on Chat-text

Wu et al. (2005) applied transformation based learning for tagging the chat post. For this purpose the authors used templates incorporating regular expressions. A tag is the type of the post, for example, a statement, a yes no question or a wh-question. The authors provided a list of 15 predefined tags. However the list of the tags does not include any tag that indicate child exploitation.

Adams and Martell (2008) worked on topic detection and topic thread extraction in chat-logs. Each chat post or line is treated as a document. The typical TF-IDF-based vector space model approach along with cosine similarity measure is used. The authors used chat text from the Internet public chat rooms. The focus of the paper was conversation topic thread detection and extraction in a chat session. Attention for the topic of ‘child exploitation’ is not provided.

Text Classification (TC) techniques are used for decades for content based document processing tasks. Besides these applications in formal literary texts, in recent years TC is also been applied into the informal texts like chats. Using text classifiers

Bengel et al. (2004) developed a system that creates a concept-based profile that represents a summary of the topics discussed in a chat room or by an individual participant. Vector space classifiers are used to categorize the concepts of chat message. Though about luring activities in the online chat room is mentioned in this paper as an example of detection of chat topics but neither specific experimental result nor any guideline provided. Moreover no particular result was provided regarding the accuracy of the system.

Kucukyilmaz et al. (2008) worked on authorship attribution and authorship characterization in chat messages. Different supervised classification techniques are used for extracting information from the chat messages. Both term-based and writing-style-based approach is used to identify the author of the chat message. The chat messages were in Turkish instead of English.

Rosa and Ellen (2009) applied traditional text classifiers to categorize military micro-texts. The micro-text is like a post (a line) in a chat among defence personnel. The posts are categorized into different predefined categories of military interest. Child sex exploitation was neither any context of the categorization nor the authors used any civilian chat ; they used only military chat.

Bifet and Frank (2010) used classifiers to analyse sentiment in twitter messages. The twitter messages are small texts somewhat similar to chat messages. Instead of prequential accuracy the authors used Kappa statistics to measure the predictive accuracy of classifiers.

Focuses of the above mentioned researches are different than the focus of current research. Therefore it is very unlikely that any of these researches would be directly applied to solve the problem of the detection of CE chats. This research used supervised machine learning methods i.e. classifiers to learn the distinctive features of CE chats and then applied for the detection.

### 3 Methodology

#### 3.1 Formulation of the Problem of Chat Classification

To understand the problem of detection of child exploitation (CE) one need to look on chats from

the CE point of view. In this view, chats can be defined into the following three categories:

1. CE chat: These are Child Exploiting (CE) chats. An adult perpetrator is involved in this type of chat with a minor. The purpose of the perpetrator is to solicit the child and achieve sexual gratification. The exploitation may occur either online or a physical meeting is arranged for further abuse.

2. Near to CE chat: These chats are Sex Fantasy (SF) chats between two adults. Sexual gratification is one of the common motives in both the CE and the SF types of chats. Similar sexually explicit terms are present in both of them. They may also have similar progression style. As no minor child is involved, these chats are not CE. However both types have some similarity, so we consider SF chats as near to CE type.

3. Far from CE chat: Other general (GN) type of chats which does not have any similarity with CE type chats and easy to distinguish from them. For example chat between a client and an expert to solve a technical problem.

After defining the categories of chats from the CE point of view, the problem of predicting the type of a chat is similar to the text classification problem with careful consideration of the unique characteristics of chat. Using supervised machine learning methods a solution to this problem is to generate a prediction function ( $f$ ) that maps each chat-log ( $D$ ) onto one of the class type ( $C$ ), given as  $f: D \rightarrow C$ . In a binary classification the class type ( $C$ ) includes CE type chats and NonCE type chats. In the case of multi-class classification the suspected CE chats are one of the predefined multiple types. The prediction function ( $f$ ) can be learned by training classification algorithms over a representative set of chat-logs whose types are known. In the experiments of current research two different types of feature sets are used in the supervised machine learning process. First type is the traditional term-based feature set where the vocabulary of the message collection in the chat log constitutes the feature set. Each term corresponds to a feature. For the second type of feature set a new approach has been made in this research. The word categorical and psychometric information from LIWC is used as the feature set. Each chat-log file is considered as a document. By this formulation, the problem of chat classification is reduced to a standard text classification problem.

### 3.2 Procedural Framework

Figure 1 on the next page illustrates the procedural framework followed in the experiments of the current research.

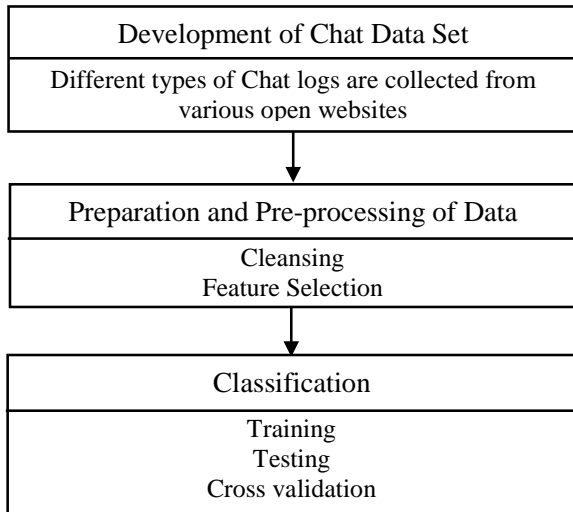


Figure 1: Procedural framework

**Development of Chat Dataset:** Due to the sexually explicit nature of the child exploiting chats, and the surrounding legal and ethical issues, it is difficult to find such data in an authenticated academically available research databases. However, a number of such chat-logs are found in the Perverted Justice Foundation Incorporated (PJFI) website available at <http://pjfi.org>. The PJFI worked with Law and Enforcement Agency (LEA) in a covert operation to catch the online paedophiles. The chat logs contain chat-text between users posing as a child and perpetrators trying to procure children over the Internet for exploitation. The perpetrators involved in those chats are prosecuted according to US law. The chat-texts were used as evidence and finally the perpetrators were convicted. In absence of chats between a real child and a paedophile these chat-texts may work as a benchmark because they contain evidence of child exploitation and the evidence are established in the court of Law. The chat-logs are open for all in the World Wide Web. Permission through email from the administrator of the website has been received to use those chat-logs for the purpose of current research.

For the classification experiments different other kinds of chats are also needed which include SF and GN type chats. Websites like <http://www.fugly.com> and <http://chatdump.com> have a collection of anonymous chats. The chats were provided by volunteers making fun with people online. Some of the chats can be considered as SF type. This type of chats contains elements of sex fantasy. However as the main purpose was only to make fun, in some part of the chat one of the user behave weirdly to make fun out of the already built sex fantasy. For example, after a considerable time of chatting and starting up a romantic relationship, a user appears to be a different person (though he is not) and turns the conversation into a different direction other than sex fantasy. An example excerpt of a turning point is as bellow:

```

Man: Hello?
Man: Who is this?
Man: What the hell do you think you're doing?
Man: cybering with my 10 year old son?
Woman: OMG
Woman: I didn't know he was 10. I'm sooo sorry
Woman: The Profile said he was 26!
Man: This is MY account. NOT his.
  
```

Figure 2: Example of an edited portion of a SF chat

We collected the chats and edited this kind of direction changing parts to keep it as SF. To test the chat-logs are really SF or not, we mixed them with some CE type chat logs and some GN type chat logs to make a collection of 120 chat logs. The collection was sent to an expert researcher of psychology to verify the SF types. The researcher of psychology identified 73 of the collections as SF types. To increase the number of chats in SF type, some of the SF chats are randomly crossed with each other. Finally 85 SF type chats are used in the experiments.

The main objective of this experiment is to observe if the text classifiers are capable of distinguishing CE type chats among different other types of chats. In the experiments the data set consists of text of a number of chat-log files. The logs include child exploiting offensive CE chat-logs, general non offensive (GN) chat-logs and sex fantasy type SF chat-logs. Each log is a member of the data set and is considered as an individual instance. The instances are divided into three classes; CE, SF and

GN. The total number of instances was 392. Among the 392 instances 200 were CE chat-logs, 85 were SF type and 107 were GN type chat-logs.

**Preparation and Pre-processing of Data:** The chat log files were pre-processed by cleansing and feature selection. In cleansing stage the usernames are removed. Then the text is converted into string vectors.

Two types of features are selected for two sets of experiments. In one set of experiment the term-based features are used. The other set of experiment used psychometric and categorical information from LIWC. The categorical counts are used as features in the classifiers.

**Classification:** Three classifiers from WEKA data mining tool are used in the classification experiments. These are Naïve Bayes (NB), J48-Decision Tree (J48-DT) and Classification via Regression (CvR) classifiers. Training, testing and 10 fold cross validations are done. An analysis of the results is given in the following section.

## 4 Experimental Result and Analysis

### 4.1 Result

A number of experiments have been done with different combination of the available chat data set. The combination of the data set is indicated in the corresponding table. The odd numbered tables show the confusion matrices of experiments with term-based feature set whereas the even numbered tables are for experiments with feature set based on psychometric and categorical information from LIWC. For example, the Table 1 corresponds to the results in the Experiment Set-1. It uses 392 instances of chat logs, where 200 are of CE type, 107 are of GN type and 85 are of SF type. Table 1.1, 1.2 and 1.3 show the confusion matrices of the results from Naïve Bayes (NB), J48-Decision Tree (J48-DT) and Classification via Regression (CvR) classifiers respectively. In the confusion matrices the rows specify true class and columns show the prediction of the classifier. Experiment Set-1 does not use psychometric information. It uses term-based feature set. On the other hand, Experiment Set-2 uses psychometric and categorical information as the feature set with the same chat dataset as

of Experiment Set-1. The results of Experiment Set-2 are in Table 2.

### 4.2 Analysis of Result

From the results it can be seen that psychometric and categorical information improves the performance of some classifiers. Table 1.1 and 2.1 shows the result of for Naïve Bayes (NB) classifier. In these tables the correctly detected chats for the CE types are increased by 11.3% (from 168 to 187). Moreover incorrect classification of the CE type chats are decreased by 59.4% (from  $28+4=32$  to  $7+6=13$ ). Similar improvements are found in all results with NB classifiers using psychometric information. Results of Classification via regression (CvR) classifier is also improved in some cases (Table 2.3, 4.3 and 8.3) when psychometric information feature set is used. In those cases it is detecting more CE chats, however at the same time it is predicting more chats as CE which are actually not CE. For the J48-Decision Tree (J48-DT), psychometric information does not make any improvement.

Comparing the results of multiclass classification with binary classification (Table 2 and 4) it is found that the effectiveness of the classifiers are almost same in regards of correctly predicting CE chats. For example, NB classifier correctly detects CE chats 187 times in multiclass classification and 188 times in binary classification. Regarding the false negative case the figure is also very near, 13 and 12. The other two classifiers are also having nearby results.

The results of Experiment Set-5 and 6 (Table-5 and 6) and Experiment Set-7 and 8 (Table 7 and 8) shows that classifiers find more difficulties to distinguish CE vs. SF chats than to distinguish CE vs. GN chats. For example, the result of NB using LIWC (Table 6.1 and 8.1) shows that, incorrectly classified instances in CE vs. SF is 9.8%  $((10+18)/285)$  which is much higher than 4.5%  $((10+4)/307)$  in CE vs GN. Results of other classifiers also support this idea.

The aim of current research is to detect CE chats. Therefore the classifier should not spare any suspected chat-log. It has to be very strict in catching CE chats even if it makes some incorrect prediction about some other non CE chats. That means the classifier can be flexible in Type-I error

**Tables : Confusion Matrices for different Classification Experiments**

Experiments with Term-based feature set										Experiments with feature set of psychometric and word categorical information from LIWC									
<b>Table 1: Confusion Matrices for Experiment Set-1: CE vs. GN vs. SF</b> Total Number of Instances 392; CE = 200, GN = 107, SF = 85										<b>Table 2: Confusion Matrices for Experiment Set-2: CE vs. GN vs. SF</b> Total Number of Instances 392; CE = 200, GN = 107, SF = 85									
Naïve Bayes			J48-Decision Tree			Clas. Via Regression				Naïve Bayes			J48-Decision Tree			Clas. via Regression			
CE	GN	SF	CE	GN	SF	CE	GN	SF		CE	GN	SF	CE	GN	SF	CE	GN	SF	
168	28	4	181	7	12	188	2	10	CE	187	7	6	174	12	14	189	10	1	CE
4	103	0	10	77	20	5	91	11	GN	3	95	9	17	77	13	11	86	10	GN
2	57	26	13	22	50	5	17	63	SF	14	13	58	11	12	62	20	13	52	SF
Table 1.1			Table 1.2			Table 1.3				Table 2.1			Table 2.2			Table 2.3			
<b>Table 3: Confusion Matrices for Experiment Set-3: CE vs. NonCE</b> Total Number of Instances 392; CE = 200, NonCE = 192										<b>Table 4: Confusion Matrices for Experiment Set-4: CE vs. NonCE</b> Total Number of Instances 392; CE = 200, NonCE = 192									
Naïve Bayes			J48-Decision Tree			Clas. via Regression				Naïve Bayes			J48-Decision Tree			Clas. via Regression			
CE	NonCE		CE	NonCE		CE	NonCE			CE	NonCE		CE	NonCE		CE	NonCE		
154	46		183	17		178	22		CE	188	12		170	30		182	18		CE
10	182		19	173		17	175		NonCE	22	170		20	172		37	155		NonCE
Table 3.1			Table 3.2			Table 3.3				Table 4.1			Table 4.2			Table 4.3			
<b>Table 5: Confusion Matrices for Experiment Set-5: CE vs. SF</b> Total Number of Instances 285; CE = 200, SF = 85										<b>Table 6: Confusion Matrices for Experiment Set-6: CE vs. SF</b> Total Number of Instances 285; CE = 200, SF = 85									
Naïve Bayes		J48-Decision Tree		Clas. via Regression						Naïve Bayes		J48-Decision Tree		Clas. via Regression					
CE	SF	CE	SF	CE	SF					CE	SF	CE	SF	CE	SF				
179	21	179	21	188	12					190	10	176	24	185	15				
3	82	18	67	12	73					18	67	17	68	24	61				
Table 5.1		Table 5.2		Table 5.3						Table 6.1		Table 6.2		Table 6.3					
<b>Table 7: Confusion Matrices for Experiment Set-7: CE vs. GN</b> Total Number of Instances 307; CE = 200, GN = 107										<b>Table 8: Confusion Matrices for Experiment Set-8: CE vs. GN</b> Total Number of Instances 307; CE = 200, GN = 107									
Naïve Bayes		J48-Decision Tree		Clas. via Regression						Naïve Bayes		J48-Decision Tree		Clas. via Regression					
CE	GN	CE	GN	CE	GN					CE	GN	CE	GN	CE	GN				
171	29	186	14	185	15					190	10	192	8	188	12				
4	103	11	96	15	92					4	103	14	93	21	86				
Table 7.1		Table 7.2		Table 7.3						Table 8.1		Table 8.2		Table 8.3					

(False positive) but should minimize Type-II error (False negative) as much as possible. Considering this, we try to find out the classifier which is performing best among the three classifiers. In multi-class classifications, in the case of term-based feature set (Table1) CvR is detecting the highest number of CE chats. It is predicting 188 chats as CE whereas prediction by NB is 168 and prediction by J48-DT is 181. Both NB and CvR are competing with each other when psychometric information are used (Table 2). Both of them are detecting almost the same number of CE chats (187 and 189). The number of false negative is also about the same (13 and 11).

In binary classification in Table 3 and 4, NB with psychometric information (Table 4.1), is performing the best. It is detecting 188 CE chats out of 200 and CvR (Table 4.3) is catching 182, whereas J48-DT (Table3.2) catching 183.

## 5 Conclusion and Future Work

Psychometric and categorical information can be used by classifiers as a feature set to predict the suspected child exploitation in chats. The new feature set significantly improves the performance of Naïve Bayes (NB) classifiers to predict CE type chats. In some cases it also improves the performance of Classification via Regression (CvR) classifier. It seems that the chat dataset is enriched by the psychometric and categorical information. However it is interesting that while it is improving the performance of two classifier (NB and CvR), the same enriched dataset does not improve the performance of another classifier (J48-DT). It can be a future scope to look at the profile of CE chats and investigate the interesting behavior of different classifiers.

Though the text classifiers are classifying logs of chat text into predefined suspected CE type they do not provide any particular aspect of the chat that can be used as evidence of the chat being an artifact of child exploitation. Therefore, further analysis is required to detect specific evidences inside the suspected CE chat. This is another future scope of this research.

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