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Identifying Online Child Sexual Texts in Dark Web through Machine Learning and Deep Learning Algorithms

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Abstract

Predators often use the dark web to discuss and share Child Sexual Abuse Material (CSAM) because the dark web provides a degree of anonymity, making it more difficult for law enforcement to track the criminals involved. In most countries, CSAM is considered as forensic evidence of a crime in progress. Processing, identifying and investigating CSAM is often done manually. This is a time-consuming and emotionally challenging task. In this paper, we propose a novel model based on artificial intelligence algorithms to automatically detect CSA text messages in dark web forums. Our algorithms have achieved impressive results in detecting CSAM in dark web, with a recall rate of 89%, a precision rate of 92.3% and an accuracy rate of 87.6%. Moreover, the algorithms can predict the classification of a post in just 1 microsecond and 0.3 milliseconds on standard laptop capabilities. This makes it possible to integrate our model into social network sites or edge devices to for real-time CSAM detection.

Keywords

Child sexual exploitation material, CSEM, CSAM, text content, artificial intelligent, forums

1. Introduction

In general, Child Sexual Abuse Material (CSAM) includes any visual, written or audio material that depicts or describes sexual abuse of children. This can include photographs, videos, stories, chats, comments, drawings or any other media¹. The production and distribution of CSAM has negative impacts on victims and society. Victims can live with long psychological, emotional, and physical harm [1]. A high volume of CSAM is created and shared daily on both surface web platforms such as social network sites and dark web forums. It is not viable for human experts to investigate, detect and prevent CSAM manually [2]. However, automatically detecting and analysing online CSA text can be extremely challenging and time-consuming, due to language complexity, contextual ambiguity, dynamic nature of language and large volume of data. This is particularly the case for CSAM shared on the dark web, where privacy and anonymity are prioritized. Moreover, perpetrators often use code words, slang, or other forms of obfuscation to avoid detection and hide their activities.

In this context, we propose a CSAM detection intelligence model based on both classical Machine Learning (ML) and Deep Learning (DL) techniques. Our CSAM detection model can be used to monitor and remove CSA texts on online platforms in real-time and with high accuracy, providing better protection for children. We have also created a manually labelled dataset of CSAM and non-CSAM content that can be used to train and test CSAM detection algorithms. In the future, our model will be able to detect perpetrator behaviours, collect forensic evidence, and extract valuable knowledge for child agencies, hotlines, education programs and policy makers.

The remainder of the paper is organised as follows. In the Section 2 we review the related work. Section 3 presents our system architecture and the machine learning and deep learning algorithms. The evaluation methodology and experimental results for the system are shown in Section 4. Finally, we conclude and give some future directions in Section 5.

2. Related Work

Research works [3], [4], [5], [6] and [7] applied deep convolutional neural network models or deep perceptual hashing algorithms with the goal of removing CSAM from social media sites. With the exception of [3], papers [4], [5], [6] and [7] used datasets from third-parties to train and test their models. However, these papers only considered CSA images and not text. Similar to our work, research works [8], [9], [10], [11] and [12] applied ML and DL models to process CSA text. In [8], Naive Bayes (NB), Support Vector Machine (SVM) and Random Forest

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¹<https://www.inhope.org/EN/articles/child-sexual-abuse-material>,

<https://www.hotline.ie/what-to-report/csam>, <https://www.rainn.org/news/what-child-sexual-abuse-material-csam>

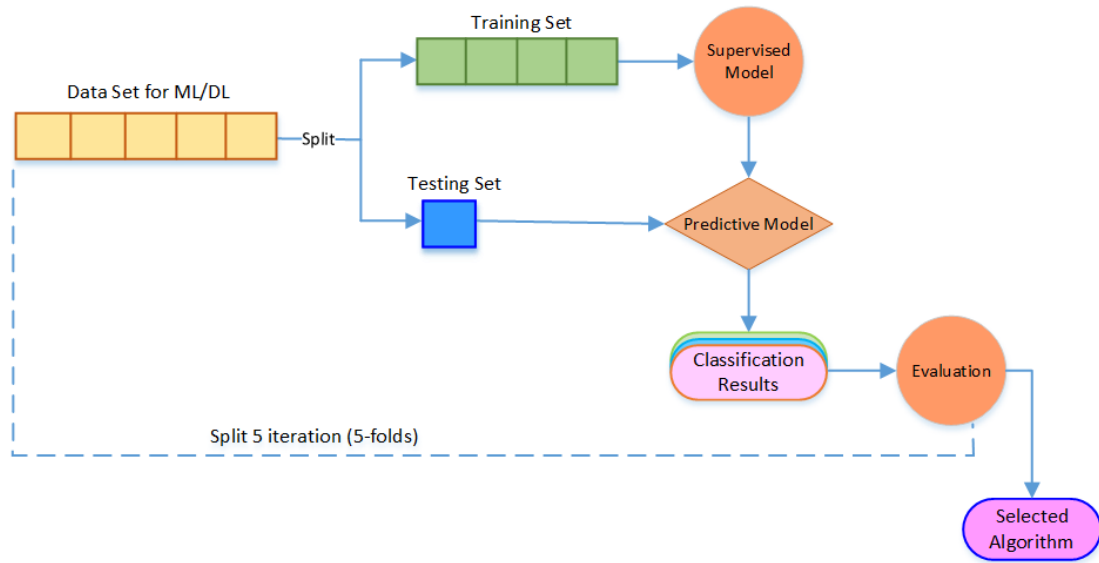


Figure 1: The system architecture for CSAM classification algorithm

(RF) were applied to detect online abusive and bullying comments on Facebook and Twitter. In [9], the histogram gradient boosted decision trees were exploited for predatory chat conversation detection. In [10], Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) were applied for YouTube comments. In [11], deepWalk model and graph embedding representations were used to detect abuse chat logs in French on the SpaceOrigin game. In [12], Logistic Regression (LR), XG-Boost and Multi Layer Perceptron (MLP) were exploited to detect sexual predatory chats in social networks. To train and test ML/DL models, the papers [8] and [11] created their own datasets and the papers [9], [10] and [12] used datasets of third-parties. However, these papers considered the clear web not the dark web.

Dark web data was also processed in [13], [14], [15], [16] and [17]. However, the approaches did not automatically detect CSA text on the dark web by using post contents and artificial intelligence. In [13], the 450 authorised hidden service sites were manually classified. In [14], the authors analysed seven popular dark web sites to monitor the sites by using their metadata, e.g. the number of users, site names and common users in sites. In [15], the authors statistically analysed some simple metadata e.g. victim ages and the number of CSAM reports per year. In [16], K-Means algorithm was applied to cluster the forum comments into the selected seven labels, i.e. breach, financial, drug, vendor, account, product and other. In [17], the authors manually analysed transcripts of 53 anonymous suspects in United Kingdom to understand suspects' interaction behaviors and sexual interests.

3. System Architecture and Algorithms

3.1. System Architecture

Supervised learning in classical ML and DL is a popular method for text classification based on learning patterns from labelled training samples [18, 19]. Every supervised learning algorithm has its strengths and weaknesses. Therefore, to find a suitable algorithm to classify CSAM post contents, we apply the two most popular classical ML algorithms, NB and SVM, and the two most popular DL algorithms, LSTM and BERT (Bidirectional Encoder Representations from Transformers). More details can be found in Section 3.2.

Figure 1 shows our system architecture used to design and implement our novel algorithm for CSAM text classification. In that, the Supervised Method component implements NB, SVM, LSM and BERT algorithms. The algorithms tokenizes the post texts and transforms them into vector representation using TF.IDF² (in NB and SVM) or embedding layers³ (in LSTM and BERT).

The Evaluation component is used to determine the execution times (i.e., training time and prediction time) and the classification performance metrics (i.e., precision, recall and accuracy) of each combination of algorithms. To avoid overfitting, we apply 5-fold cross-validation of our dataset. Then the algorithm uses 4 folds for the train-

²https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

³https://www.tensorflow.org/api_docs/python/tf/keras/layers/Embedding

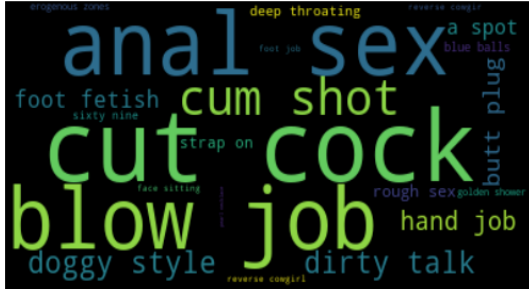


Figure 3: sexual abuse two-word-phrases in dark web forums

(64-bit) on a Dell laptop with an Intel Core i7 CPU (3.00 GHz) and 16 GB memory.

For the purpose of measuring the quality of the predicted classes of posts compared to the correct classes, we apply the most commonly used metrics namely accuracy, precision and recall ([24, 25]). The metrics are derived from four categories in the confusion matrix: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) as follows:

- TP: Posts in which the algorithm predicted CSAM and the correct class was also CSAM.
- FP: Posts in which the algorithm predicted CSAM, but the correct class was non-CSAM.
- TN: Posts in which the algorithm predicted non-CSAM and the correct class was non-CSAM.
- FN: Posts in which the algorithm predicted non-CSAM, but the correct class was CSAM.

Accuracy (ACC) in binary classification is defined as a ratio between the correctly classified samples to the total number of samples: $ACC = \frac{TP+TN}{TP+FP+TN+FN}$. The accuracy puts the same emphasis on all these factors. However, when categorising pairs, there is usually a bias: it is much easier to identify true negatives correctly, due to their large number. So, we also look at the the precision $P = \frac{TP}{TP+FP}$ and the recall $R = \frac{TP}{TP+FN}$.

4.2. Results

Using the 5-fold cross-validation methodology, each experimental round includes a training set of 3,680 posts (2,000 CSAM and 1,680 non-CSAM) and a testing set of 920 posts (500 CSAM and 420 non-CSAM). Table 1 presents the average training time, average prediction time, average precision, average recall and average accuracy of four algorithm combinations as follows:

- NB: The training time and prediction time were 0.5 and 0.001 seconds, respectively. The precision was 76.1%, recall was 89% and accuracy was 78.8%.

Table 1

Average execution time and binary classification performance of the algorithms

Results	Algorithms			
	NB	SVM	LSTM	BERT
Training time ¹	0.5	1.8	32.5	4,261
Prediction time ¹	0.001	0.27	1.01	215.3
True Positive	445	421	428	415
False Positive	140	35	46	68
True Negative	280	385	374	352
False Negative	55	79	72	85
Precision	76.1%	92.3%	90.2%	86%
Recall	89%	84.2%	85.5%	83%
Accuracy	78.8%	87.6%	87.1%	83.4%

¹ second.

- SVM: The training time and prediction time were 1.8 and 0.27 seconds, respectively. The precision was 92.3%, recall was 84.2% and accuracy was 87.6%.
- LSTM: The training time and prediction time were 32.5 and 1.01 seconds, respectively. The precision was 90.2%, recall was 85.5% and accuracy was 87.1%.
- BERT: The training time and prediction time 4,261 and 215.3 seconds, respectively. The precision was 86%, recall was 83% and accuracy was 83.4%.

The combination of the NB algorithm has the fastest execution time, taking only about 1 microsecond to detect a post on our laptop’s capabilities. The second best performing algorithm is SVM, which takes about 0.3 milliseconds. These fast prediction times make our models well-suited for processing CSA text in real-time on social networks. Additionally, our models can run on edge devices with limited computational resources and power supply.

In terms of classification precision, the SVM combination performs the best with 92.3%, followed by LSTM and BERT as the second and third-best performers, respectively. Meanwhile, the NB combination has the highest recall rate of 89%, followed by LSTM as the second-best performer. When it comes to accuracy, SVM is the best with 87.6% which is slightly higher than LSTM with 87.1%. The BERT algorithm has long training and prediction times, and it is not suitable for binary classification of CSAM posts in dark web.

5. Conclusion and Future Work

We proposed and implemented a novel algorithm based on machine learning and natural language processing to automatically detect and classify CSAM text post content in dark web. In the experimental evaluation on the

dataset of 4,600 CSAM and non-CSAM posts with 5-fold cross-validation, the combination of NB algorithm performed the best in terms of classification recall and execution time. On the other hand, the SVM combination performed the best in terms of classification precision and accuracy, and was the second-best in execution time. The choice of NB and SVM depends on the specific goals and requirements of the CSAM classification task. NB is maximize the number of true positives which could be useful identifying and removing CSAM posts from online platforms to protect potential victims. On the other hand, SVM is minimize false positives which could be useful for identifying CSAM posts to extract information about potential predators and victims for investigative purposes.

As part of our future work, functional APIs will be implemented to create a user-friendly web application. Furthermore, we aim to leverage the metadata associated with CSAM posts to identify the characteristics, conversation and behaviours of perpetrators. This information can be valuable in developing more effective models for preventing and addressing CSA text on social media platforms. We also will recognise named entities in CSA text to supply important concepts for ML models [26].

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