Comparative Study of Machine Learning Algorithm on Linguistic Distinctions over Text Related to Human Trafficking and Sexual Exploitation

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***Abstract*— Human trafficking and sexual exploitation (HTSE) are grave global issues that demand comprehensive understanding and effective countermeasures. In total, this issue—also known as modern slavery—affected an estimated 49.6 million people in 2021 and earns traffickers at least $150 billion annually, making it one of the world's most profitable crimes. This crime can penetrate our daily life through internet advertisement, trying to trap non-tech savvy people. Automated analysis for such adverts is essential. It can be used for identifying linguistic patterns in human trafficking and sexual exploitation-related adverstisements. This research employs various machine learning algorithms (i.e., Naïve Bayes, Random Forest, Decision Trees) to classify benign and HTSE advertisements. From our experiments, Random Forest performed best, achieving a high F1 score (0.962), balancing Precision and Recall effectively. Naïve Bayes also showed promising results, while Gradient Boosting had variable F1 scores, and the Tree algorithm scored the lowest. This analysis provides insights into algorithm capabilities and limitations in addressing linguistic distinctions related to human trafficking and sexual exploitation, contributing to better detection systems. By applying these algorithms to a diverse dataset, we aim to enhance our understanding of linguistic cues in addressing these societal challenges and consider potential solutions, policy implications, and future research.**

Keywords—Human Trafficking, Sexual Exploitation, Text Analysis, Linguistic Distinctions, Naïve Bayes, Random Forest, Trees

I. INTRODUCTION

Human trafficking (hereafter trafficking) involves people being moved within, through or between countries for the purposes of exploitation: as such, it is a fundamentally spatial phenomenon. Human trafficking and sexual exploitation stand as deeply distressing global concerns that violate human rights and devastate lives. With the proliferation of digital communication, traffickers and exploiters often employ online platforms to facilitate their activities, necessitating innovative technological approaches for detection and intervention. Textual content, such as advertisements, posts, and messages, plays a pivotal role in these operations, providing crucial insights into the strategies and intentions of traffickers. Analyzing linguistic distinctions within such texts can offer valuable clues for identifying potential instances of human trafficking and sexual exploitation.

This research paper employs advanced machine learning algorithms to explore linguistic nuances in texts associated with these issues. We conducted a comparative analysis of different algorithms, i.e., Naïve Bayes, Random Forest, and Decision Trees. These algorithms are chosen due to their efficacy in text classification tasks, as demonstrated in previous research. Our aim is to enhance the accuracy and efficiency of automated detection systems, providing law enforcement agencies and relevant organizations with powerful tools to combat human trafficking and sexual exploitation more effectively.

Through a diverse dataset sourced from various online platforms, we apply these algorithms to discern patterns in language usage that distinguish between legitimate content and potentially exploitative material. This study's findings have the potential to inform policy decisions, shape law enforcement strategies, and empower organizations in their efforts to safeguard vulnerable populations from the horrors of human trafficking and sexual exploitation. We examine and attempt to address the following questions in the research:

(i) How can machine learning algorithms, including Naïve Bayes, Random Forest, Gradient Boosting, and the Tree algorithm, be effectively employed to identify and analyze linguistic distinctions within texts associated with human trafficking and sexual exploitation?

(ii) To what extent do these machine learning algorithms demonstrate their capabilities in capturing the intricate nuances of language usage related to human trafficking and sexual exploitation, and how do they compare in terms of their classification performance?

(iii) How can the insights gained from the analysis of linguistic patterns within these texts contribute to the development of robust computational tools for detection, prevention, and intervention efforts aimed at combating human trafficking and sexual exploitation?

In the subsequent sections of this paper, we present the methodology used for data collection and preprocessing, provide an overview of the machine learning algorithms employed, present and discuss our results, and conclude with implications for future research and practical applications.

II. RELATED WORK

Hernandez et al in [1] proposed a machine learning-based approach to detect tweets related to sex trafficking. The paper achieved reasonable precision in detecting tweets related to sex trafficking of underage girls. Moreover, a natural language processing and image processing-based approach to detect human trafficking ads in Twitter [2]. The paper achieves high accuracy in detecting human trafficking ads. Authors in [3] n automated classification approach to detect human trafficking from online customer reviews of massage businesses. The paper achieves high accuracy in detecting human trafficking.

Esfahani et al in [4] utilizes context-specific language modeling for human trafficking detection from online advertisements. Finally, authors of [5] a machine learning-based approach to detect sex trafficking circuits in the US through analysis of online escort advertisements. The paper achieves high accuracy in detecting sex trafficking circuits.

Furthermore, there exist some works in detection over human trafficking area. Authors in [6] proposes a semi-supervised learning approach to detect human trafficking using online advertisements. The paper uses a combination of supervised and unsupervised learning to identify patterns in the data and detect potential cases of human trafficking. In [7], natural language processing is utilized to detect human trafficking using online advertisements. The authors use language models to identify patterns in the data and detect potential cases of human trafficking. Hundman et al in [8] proposes an automated classification approach to detect human trafficking from online customer reviews of massage businesses. This work achieves high accuracy in detecting human trafficking. A work in [9] proposed a feature selection approach to improve the accuracy of human trafficking detection models. The authors use machine learning to identify the most relevant features for detecting human trafficking from online advertisements.

There also some works that exist and discuss about sex trafficking detection using machine learning. Data analysis and pattern recognition are utilized in [10] to identify potential cases of human trafficking and predict the path of the traffickers. Moreover, Wang et al in [11] proposed an ordinal regression neural network-based approach to detect sex trafficking. The work uses machine learning to identify patterns in the data and detect potential cases of sex trafficking.

III. METHODOLOGY

The following steps were carried out to achieve the goal of this paper, which is to effectively detect offensive and human trafficking in text-based ads. The diagram in Figure 1 presents the framework used in the study.

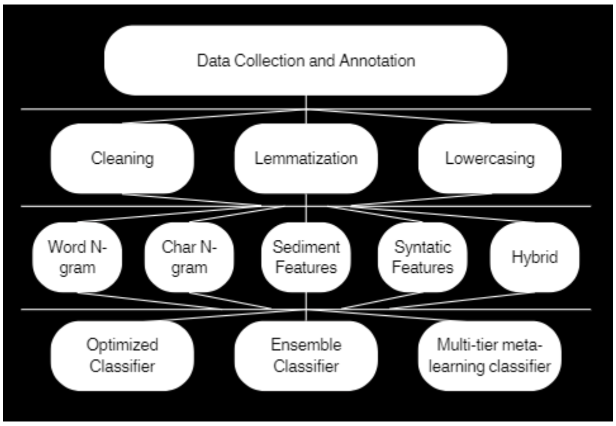

Figure 1. Framework for trafficking speech detection in Text-Based Ads

A. Data Collection and Annotation

A comprehensive methodology was employed to gather a dataset comprising 6,398 text-based ads from Kaggle [12][13]. The integration of these diverse sources ensured the inclusion of a wide spectrum of text-based ads, enhancing the richness and representativeness of the dataset for robust research analysis.

Furthermore, to enhance the integrity of the dataset, certain refinements were implemented. Repeated ads and those devoid of any word characters were excluded from consideration. In order to ensure the precision of the annotations we manually categorized the ad corpus into distinct classes: either as "Traffic Language/Offensive Language" denoted by 'OF', or as the normative category 'N' signifying "Normal". We classified an ad as HTSE if it:

- Directly promotes or advocates human trafficking or related illegal activities.
- Includes language endorsing the exploitation, sale, or coercion of individuals for forced labor or sexual purposes.
- Displays elements that suggest recruitment, advertisement, or facilitation of human trafficking

We label an ad as normal if it does not contain any content that falls under the criteria for human trafficking speech nor convey information, messages, or opinions that do not involve promoting or advocating illegal activities, particularly human trafficking.

Some examples of text-based ads and their annotations are presented as follows:

- Turtle Beach - Ear Force Recon 50X Stereo Gaming Headset - Xbox One (compatible w/ Xbox One controller w/ 3.5mm headset jack) and PS4 (N)
- i'm sara, exotic mix juicy booty with doll face. i'm based in bcdo you want to enjoy an er0tic time with me, i offer online services video calls avail on facetime, whatsapp, snapchat, skype pre made videos & custom videos xxx pics sexting & phone sex toys, heels, outfits, role play, feet fetish, dom, fetish panties, lingerie & clothing items 4 $ale verified by leolist real no scam no autodeposit follow my social media for extra verification snapchat @saradoll4576 instagram / twitter @thicksaradoll call / text / whatsapp 647.493.4576 (OF)
- The all new Ford Freestar. If you haven't looked at Ford lately. Look again. (N)
- baby if your longing for touch and attention and if you want to have the fun call or message me!!! sasha 4374219108 80hh 160hour (OF)

TABLE I. THE CORPUS STATISTICS

Parameters	Value
Total Number of Unique Words	6,000
Average Words Per Ad	23.76
Average Length of Text-Based Ads	142.75

The corpus statistics, as depicted in Table I, offer a comprehensive overview of the total and average distribution of words and characters within the dataset.

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B. Tokenization and Data Pre-processing

The extraction of syntactic and sentiment-related count indicators occurred prior to the tokenization and preprocessing of text-based ads, as detailed in (IV-C). The subsequent cleaning and formatting procedure encompassed the following sequential steps:

- Utilization of Tokenizer from Orange for effective tokenization, adeptly managing emoticons, HTML tags, URLs, reads, user mentions, and Unicode characters.
- Implementation of stemming through the wordnet lemmatizer [21] in NLTK10.
- Elimination of usernames to enhance text clarity.
- Removal of punctuations to streamline text content.
- Omission of special characters and symbols, encompassing emoticons and emojis.
- Exclusion of hash symbols from hashtags.
- Elimination of English stop words, while preserving those of other languages to account for potential meaningful cues in English and offensive contexts.
- Conversion of all text to lowercase for uniformity in analysis.

C. Feature Extraction

All the features used in with modifications were used for our analysis.

1) Word N-gram features

Word n-gram features comprise the enumeration of sets consisting of sequential N words per advertisement, where N spans the spectrum of words present within the ads, ranging from 1 to N. For this investigation, our focus lay on assessing unigram (n = 1) and bigram (n = 2) word features, a choice rooted in their noteworthy performance in previous research endeavors.

To further enhance their efficacy, we harnessed term frequency-inverse document frequency (TF-IDF) weighting for the n-grams [2]. TF-IDF normalization involves compensating for the number of occurrences of a word within a document by gauging its frequency (term) across an entire corpus. The TF-IDF value for a given term 't' in a document (ad) 'd' is mathematically defined as follows:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) * \text{IDF}(t) \quad (1),$$

when $\text{IDF}(t) = \log [\, n / (\text{DF}(t) + 1]$

n = total number of documents in the document set

DF(t) = document frequency of t

The weighted n-gram is given as:

$$W(t,d) = \text{NGram}(t,d) \times \text{TF-IDF}(t,d) \quad (2)$$

2) Character N-gram features

Character n-gram features, commonly referred to as char n-grams, encompass the quantification of sequential sets comprising N alphanumeric characters within each ad. Here, N represents the count of alphanumeric characters inherent to the ad, spanning a range from 1 to N. In the context of this study, we opted to assess trigram (n = 3) and four-gram (n = 4) character features due to their demonstrated efficacy in prior research [10]. To enhance the representation, TF-IDF weighting was applied to the n-grams, in alignment with the methodology discussed earlier. Consequently, the utilization of character n-gram features gave rise to a feature space encompassing 10,466 trigram and 59,573 four-gram character tokens.

3) Syntactic-based features

We gathered the subsequent syntactic details as they constitute linguistic attributes crucial for unraveling the inherent grammatical framework of sentences and documents in the English language. To ensure a more vivid contextual understanding, we opted for their count indicators (frequency of occurrence) as opposed to binary indicators.

- capital letters such as A, B, . . . , Z
- small letters such as a, b, . . . , z
- uppercase words such as COME, RIGHT
- lowercase words such as dog, land
- length of ads including spaces
- alphanumeric words such as Red, black, White
- exclamation marks such as !
- question marks such as ?
- full stops such as.
- quotes such as ‘‘’’, ‘’
- special characters such as @, #, $, %, ^, &, ∗, _,etc
- hash tags marked with characters such as #callme

4) Negative Sentiment-Based Features

Human trafficking is often marked by negative meanings. Negative terms such as negative polarity scores and lexicons, emoticons and emojis have been used for sentiment analysis. In the context of human trafficking detection, count indicators of the negative sentiment features except negative polarity score.

- negations
- negative words based on Opinion Lexicon
- negative emoticons based on Urban Dictionary
- negative emojis based
- Hatebase slur words

D. Classification

We conducted a systematic literature review inventorying studies to answer the three research questions outlined in the introduction. The methodology used for this systematic review was guided by the Orange data software. This section outlines the comprehensive methodology employed in our research to dissect and understand linguistic distinctions embedded in texts pertaining to human trafficking and sexual exploitation. Leveraging the power of machine learning, we delve into the intricate nuances of these texts, employing a suite of advanced algorithms: Naïve Bayes, Random Forest, Gradient Boosting, and the Tree algorithm. Our analysis unfolds within the Orange data mining software framework, facilitating the seamless execution, evaluation, and comparison of these algorithms.

(i) Naïve Bayes: Naïve Bayes, rooted in probabilistic reasoning, forms the cornerstone of our methodology. This algorithm operates on the principles of Bayes' theorem, estimating the probability of an instance belonging to a particular class based on observed features. The "naïve" assumption of feature independence simplifies computations, making it particularly well-suited for text analysis.

Naïve Bayes strives to classify text instances as indicative or non-indicative of human trafficking and sexual exploitation. It is this algorithm that lays the initial groundwork for understanding linguistic patterns within the textual context of our study.

(ii) Random Forest: The intricacies of language are multifaceted, often defying linear analysis. To address this complexity, we incorporate the Random Forest algorithm into our methodology. As an ensemble learning technique, Random Forest constructs a multitude of decision trees by leveraging different subsets of the dataset.

The amalgamation of these trees amalgamates diverse perspectives and increases predictive accuracy. The model's adaptability to complex relationships makes it an invaluable tool for capturing the nuanced linguistic markers embedded within texts related to human trafficking and sexual exploitation.

(iii) Gradient Boosting: Delving deeper, we engage the Gradient Boosting algorithm, an iterative technique that progressively refines predictions by focusing on previously misclassified instances. This algorithm's essence lies in its ability to build a strong predictive model by consecutively emphasizing instances that proved challenging to classify in earlier iterations.

The process continues until a stopping criterion is met. Gradient Boosting unveils the intricate interplay of linguistic nuances, effectively adapting to the multifarious ways in which language signifies instances of human trafficking and sexual exploitation.

(iv) Tree Algorithm: While the previous algorithms showcase sophistication, the Tree algorithm, in its simplicity, offers insights into basic patterns. Operating by recursively partitioning data into homogenous subsets based on feature attributes, the Tree algorithm is a fundamental component of our methodology.

It grants insight into initial classification processes and highlights the basic linguistic cues that can signify potential instances. Though elementary, it provides a baseline for comparison against the more intricate algorithms, offering an understanding of their comparative performance in capturing the complexities of linguistic patterns.

By embracing this comprehensive methodology, our objective extends beyond merely shedding light on linguistic distinctions. Our aim is to make a meaningful contribution to the advancement of robust computational tools that are dedicated to identifying and combatting the grave issues of human trafficking and sexual exploitation. Through our rigorous exploration and meticulous evaluation of machine learning algorithms, we aspire to empower the ongoing endeavors to create effective measures against these pressing challenges.

IV. Experimental results and analyses

In adherence to the delineated methodology, the assessment of model performance was meticulously undertaken through the utilization of the Orange data mining software, a pivotal instrument within our analytical toolkit. This choice of tool facilitated a comprehensive examination of the algorithms' capabilities, enabling us to gain deeper insights into their efficacy.

Our evaluation was centered around the deployment of machine learning algorithms to distinguish between two primary classes: the positive class, encompassing instances related to human trafficking and sexual exploitation, and the negative class, comprising instances unrelated to these themes. The intricacies of this binary classification were further elucidated through metrics such as F1 score, Area Under the Curve (AUC), Precision, and Recall, each serving a distinct purpose in the evaluation process.

By employing these metrics, we achieve a holistic evaluation of our models. F1 score and AUC provide a comprehensive snapshot of the model's predictive prowess, while Precision and Recall offer nuanced insights into its ability to classify instances accurately and identify relevant cases. Through this methodical evaluation, we gain a deep understanding of each algorithm's strengths and limitations, thereby enabling us to draw meaningful conclusions that contribute to the advancement of detection systems in combating human trafficking and sexual exploitation.

The outcomes stemming from the initial series of experiments, which concentrated on the Naïve Bayes algorithm, have been meticulously documented in Table II. Each reported value has been rounded to three decimal places, ensuring precision in our presentation. Amid the ensemble of algorithms subjected to scrutiny, the Naïve Bayes algorithm emerges as the resounding frontrunner, securing the highest F1 score. Of particular significance is its commendable equilibrium between Precision and Recall, a defining attribute pivotal in the discernment of pertinent instances while concurrently quelling the occurrence of spurious outcomes. This distinctive characteristic amplifies its efficacy in both capturing and categorizing pertinent instances while concurrently minimizing the potential for both false negatives and positives.

TABLE II. Model Performance Metrics for Naïve Bayes

F1	Precision	Recall
0.961	0.964	0.961

Continuing our investigative journey, buoyed by the recurrent prevalence of favorable outcomes, we proceeded to replicate the experiments, this time on a configuration utilizing the Random Forest model. The ensuing results, elegantly depicted in Table III, elucidate these outcomes with values rounded to the nearest three decimal points, preserving clarity in our representation.

TABLE III. Model Performance Metrics for Random Forest

Number of Trees	F1	Precision	Recall
5	0.937	0.941	0.938
7	0.954	0.956	0.954
10	0.957	0.959	0.957
12	0.962	0.963	0.962

Subsequently, upon deploying the gradient boosting model, we observed a discernible variability in F1 Scores across the samples under scrutiny. This variance is starkly reflected in the scores, which depict noteworthy reductions in both Precision and Recall. This serves as an indicator of the model's comparatively diminished aptitude in adeptly harmonizing the identification of pertinent instances with the efficient curbing of spurious outcomes. These results, as embodied in Table IV, illuminate the intricacies and challenges associated with employing the gradient boosting model.

TABLE IV. MODEL PERFORMANCE METRICS FOR GRADIENT BOOSTING

Number of trees	Learning Rate	F1	Precision	Recall
80	0,05	0.914	0.921	0.914
80	0,1	0.932	0.937	0.932
80	0,15	0.944	0.948	0.944
100	0,05	0.920	0.926	0.920
100	0,1	0.941	0.946	0.940
100	0,15	0.951	0.954	0.950
120	0,05	0.923	0.930	0.923
120	0,1	0.945	0.949	0.945
120	0,15	0.952	0.955	0.952

In contrast, the Tree algorithm, when evaluated, presented the lowest performance, underscored by its suboptimal scores across all three metrics. This stark observation in Table V underscores the hierarchy inherent to algorithmic performance, reaffirming the potential trade-offs between varying aspects of model performance within the confines of this specific research context.

TABLE V. MODEL PERFORMANCE METRICS FOR TREE ALGORITHM

Min Number of Instance	Maximal Tree Depth	F1	Precision	Recall
2	75	0.930	0.931	0.930
2	100	0.930	0.931	0.930
3	75	0.929	0.930	0.929
3	100	0.929	0.930	0.929
4	75	0.927	0.928	0.927
4	100	0.927	0.928	0.927

In conclusion, the meticulously constructed methodology outlined in this study has steered our investigation into the assessment of model performance, leveraging the robust capabilities of the Orange data mining software. The initial exploration, anchored by the Naïve Bayes algorithm, as illuminated by the results laid out in Table II, highlights values rounded to three decimal places. Amongst the cohort of algorithms subjected to rigorous scrutiny, Naïve Bayes emerges as the pinnacle, its prowess evident in attaining the highest F1 score. The attribute of note, its remarkable equilibrium between Precision and Recall, stands as a keystone feature, engendering the astute identification of pertinent instances while concurrently stifling the rise of misleading outcomes. This unique trait elevates its ability to adeptly capture, categorize, and accurately classify relevant instances while simultaneously mitigating the potential for errors in both positive and negative categorizations.

The path of inquiry then led us to replicate these experiments, this time configuring the exploration within the Random Forest model. The ensuing Tabel III encapsulates these results, rounded to the nearest three decimal points for lucidity. Building upon this trajectory, we extended our scrutiny to the gradient boosting model, unraveling a landscape of F1 Score variability across the studied samples. This variability, laid out in Table IV, brought to the fore notable declines in both Precision and Recall. These observed dynamics shine a light on the gradient boosting model's nuanced potential and limitations.

Lastly, the Tree algorithm's performance took center stage in our evaluation, as indicated by its underwhelming scores across all three metrics, a fact starkly illustrated in Table V. This observed variance further underscores the intricate interplay of algorithmic aptitude and its potential limitations. In summation, this comprehensive evaluation of diverse machine learning algorithms yields a rich tapestry of insights into their distinctive capabilities and constraints within the landscape of linguistic distinctions tethered to human trafficking and sexual exploitation. These nuanced insights invigorate the ongoing drive towards robust detection systems and technology-powered countermeasures to combat these pressing challenges.

V. CONCLUSION

In our meticulous study of linguistic distinctions in texts related to human trafficking and sexual exploitation, we employed a precise methodology, with model performance assessment at its core. The Orange data mining software served as a crucial analytical tool. Our initial focus on the Naïve Bayes algorithm revealed its dominance, achieving the highest F1 score and an exceptional balance between Precision and Recall, effectively distinguishing crucial instances from spurious outcomes. Subsequent experiments with the Random Forest model yielded promising results, while Gradient Boosting exhibited variable F1 scores. In contrast, the Tree algorithm consistently scored lower across all metrics, illustrating the interplay of algorithmic strengths and limitations.

In summary, our exploration of machine learning algorithms in the context of linguistic distinctions related to human trafficking and sexual exploitation offers valuable insights for detection systems. However, this study acknowledges potential complexities in linguistic patterns and data bias. Future research avenues include hybridizing algorithms, integrating advanced classifiers, and exploring deep learning techniques to enhance model effectiveness. As the field continues to evolve, it holds the promise of transformative breakthroughs in combating these societal challenges.

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