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DEVELOPMENT OF A CHILD ABUSE MONITORING AND REPORTING SYSTEM USING A NATURAL LANGUAGE PROCESSING MODEL

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Abstract: Child abuse remains a major global concern that threatens the physical, emotional, and psychological development of children. Despite growing awareness and legal frameworks aimed at protecting children, many abuse cases remain undetected or are reported too late due to inadequate monitoring systems, poor data quality, fear of stigma, and ineffective reporting mechanisms. Psychological abuse is often difficult to detect because it does not leave visible physical evidence and is therefore frequently underreported. In addition, the rapid expansion of digital communication platforms has created new avenues through which abusive behaviors such as cyberbullying, harassment, and threats can occur, making traditional monitoring approaches insufficient. This study presents the development of the Child Abuse Monitoring and Reporting (CAMR) System that uses Natural Language Processing (NLP) to enhance the detection, monitoring, and reporting of child abuse cases. The proposed system employs sentiment analysis and Named Entity Recognition (NER) techniques to identify emotional tones and relevant entities in text that may indicate abusive interactions. The system is implemented using the Naïve Bayes algorithm to classify text and detect potentially abusive content.

The system's performance is evaluated using accuracy, precision, recall, and F1-score, along with User Acceptance Testing (UAT), to assess its effectiveness and usability. The study demonstrates that integrating NLP techniques into child protection systems can enhance early detection of abuse, enable automated monitoring of large volumes of textual data, and support timely intervention. The proposed system contributes to improving child protection strategies by providing a scalable and efficient technological solution for monitoring and reporting abuse, particularly within digital communication environments. Ultimately, the system supports government agencies, institutions, and child protection organizations in safeguarding children and responding more effectively to abuse cases.

Keywords: Child Abuse; Child Protection; Abuse Detection; Psychological Abuse; Cyberbullying; Harassment; Threats.

INTRODUCTION

Abuse is a pattern of harmful behavior, often involving control, intimidation, or power imbalances, directed toward an individual or group. It can have wide-ranging effects on mental and physical health, and it occurs across various contexts, including families, workplaces, intimate relationships, and digital spaces. It often involves the misuse of power, control, or authority, in which one person inflicts pain, distress, or deprivation on another. Abuse can occur in many relationships, such as between intimate partners, family members, including children, caregivers, and dependents, and even within professional settings (Ajesafe *et al.*, 2023).

Children are precious gift from the Almighty God. They need to be cared for, loved, cherished, appreciated, and adored reliably. In the African context, children are so regarded in the sense that a family without a child is seen as an incomplete institution. In fact, the Child Rights Act of 2003's Section 277 defines a child as a person who has not attained the age of eighteen (Child Rights Act, 2003). This indicates that the increased violence against young people includes all types of violence that occur for ages between 0 and 18 years old. After conception, children make their family and the people around them happy. As they age, they play a crucial role in their neighborhood and in the country's future leadership. But despite the happiness that comes with having children, many continue to be victims of exploitation, assault, and abuse (Akwara et al., 2010; Olaitan and Idowu, 2016).

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According to the Child Abuse Prevention and Treatment Act of 2003, child abuse is considered any action or inaction by a parent or caregiver that causes death, severe physical or psychological suffering, or sexual abuse or exploitation. Also, Child abuse and neglect refer to any action (physical, sexual, or emotional) by a caregiver that harms, threatens to harm, or endangers a child (Child Welfare Information Gateway, 2022). This term Child Abuse is a word with several definitions given by scholars. First, child abuse and neglect (CAN) have been recognized as a major public health problem impairing the health and welfare of children and adolescents worldwide (Shaw and De Jong, 2012). Although the terms 'maltreatment and abuse' are often used interchangeably in literature, the Centers for Disease Control and Prevention use child maltreatment as a general term that includes both abuse and neglect. It is defined as any act or series of acts of commission or omission by parents or other caregivers that results in harm, potential for harm, or threat of harm to a child. In other words, the World Health Organization (WHO) defines CAN as 'Every kind of physical, sexual, emotional abuse, neglect or negligent treatment, commercial or other exploitation resulting in actual or potential harm to the child's health, survival, development, or dignity in the context of a relationship of responsibility, trust or power' (Leeb *et al*., 2018).

Child abuse is a pervasive global issue that impacts millions of children (Sumitra *et al*.). Child abuse is a practice whereby children are maltreated, battered, or deprived of some basic needs in the home, on the street, in religious houses, or at school by the elderly (Oruche *et al*, 2023). The authors further stated that Child Abuse is a grave societal issue that demands urgent attention. It encompasses various forms of maltreatment and neglect, leading to severe physical and psychological consequences for the affected children. Child Abuse refers to mistreatment, neglect, or harm inflicted upon children, often by adults or caregivers, which can have serious physical, emotional, and psychological consequences. It occurs when a child experiences harm or neglect. Often, the abuser is someone the child knows. It may be a parent, family member, caregiver, or family friend (Crosson-Tower, 2021).

Psychological child abuse, also known as emotional abuse, is defined as a pattern of behavior by a caregiver that results in psychological harm to a child. Unlike physical abuse, which involves overt acts of aggression, psychological abuse encompasses non-physical actions such as verbal assault, isolation, manipulation, and rejection. This form of maltreatment can manifest chronic humiliation, intimidation, or indifference, all of which can severely impair a child's emotional and psychological development (Glaser, 2021).

Psychological child abuse is often underreported due to its subtle and non-physical nature. Recent studies suggest that psychological abuse is one of the most prevalent yet under-recognized forms of child maltreatment. According to (Spinazzola *et al*, 2022), approximately 10-30% of children worldwide experience psychological abuse, often without clear signs or physical evidence, which makes it difficult for healthcare professionals, educators, and social services to identify.

A global report by UNICEF revealed that approximately 300 million children aged between 2 and 4 years' experience psychological aggression and/or physical punishment from their caregivers (UNICEF, 2016). This represents nearly three out of every four children within that age group globally, indicating the widespread nature of emotional and psychological abuse within family environments. Psychological aggression in this context includes behaviors such as shouting, threatening, humiliating, or verbally intimidating children.
Child abuse can have lasting and devastating effects on a child's physical health, mental well-being, and overall development. It can lead to long-term emotional and psychological scars, impairing the child's ability to form healthy relationships and succeed in various aspects of life (Norman *et al., 2012).*

Furthermore, global estimates suggest that about one billion children aged 2–17 years experience physical, sexual, or psychological violence every year (UNICEF, 2016). These alarming statistics highlight the urgent need for effective monitoring, reporting, and prevention mechanisms to protect children from various forms of abuse.
In many developing countries, including Nigeria, the situation is also concerning. Reports show that approximately 6 out of every 10 children experience some form of violence during childhood, which may include emotional or psychological abuse. Many of these cases remain unreported due to fear, stigma, cultural barriers, or lack of accessible reporting systems. A 2023 study conducted in the United States affirmed that 20% of children were reported to have experienced psychological maltreatment, often alongside other forms of abuse (Smith *et al*., 2023). Globally, psychological abuse often accompanies other maltreatment forms like neglect and physical abuse, making its standalone identification more challenging (UNICEF, 2021).

With the rapid growth of digital communication and social media platforms, abuse can also occur in online environments through cyberbullying, harassment, threats, and grooming behaviors. Unfortunately, traditional monitoring systems often struggle to detect such abuse because of the massive volume of online communications.

To address this challenge, modern technological solutions such as Natural Language Processing (NLP) can be applied to automatically analyze online text data and identify patterns related to abusive behavior. An NLP-based child abuse monitoring and reporting system can help detect harmful language, flag suspicious interactions, and support early reporting of abuse cases. This technological approach has the potential to improve child protection efforts by enabling faster detection and response to abuse incidents occurring on online platforms.
Therefore, the development of a Child Abuse Monitoring and Reporting System using an NLP model is an important step toward improving the detection, monitoring, and reporting of abuse cases, thereby contributing to the protection and well-being of children in both offline and online environments.

MATERIALS AND METHODS

Study Design and Methodology
This study adopted the Object-Oriented Analysis and Design Methodology (OOADM) to develop a Child Abuse Monitoring and Reporting (CAMR) system. The approach integrates system analysis, design, implementation, and testing, emphasizing modularity and reusability.

Requirement Specification
A Child Abuse Monitoring and Reporting (CAMR) system facilitates monitoring and reporting without undue burden. To accomplish the task of designing and implementing a CAMR system, it must have the following:
(1) A knowledge of the lexicon that makes up the standard child abuse vocabulary and terms
(2) Appropriate knowledge of the structure of the abusive language.
(3) Every input word is given with its syntax, semantics, and non-standard abusive text. This is the narrative text information about the word identified in the dialogue and its relationship with other texts.
(4) The image associated with each labelled word character must be provided.
(5) Knowledge of the domain of discourse
In the same vein, the annotation or labelling system is also required to have the features and capabilities that allow the reproduction of such a task. Some of the required features of the system are:

i. A lexical database that stores the linguistic information of all words contained in the CAN corpus.
ii. Have an image repository for storing and organizing the images associated with a labelled word.
iii. Methods for deriving the appropriate annotation of an abusive word using the information stored in the lexical database

Data Collection
Secondary textual data were collected from digital sources, including social media platforms (Twitter/X, Facebook, TikTok, Instagram), online forums, chat applications, and emails. A keyword-based web scraping approach was used to retrieve abuse-related content using predefined keywords and hashtags (e.g., #stopchildabuse, "I'm scared at home").

Data Preprocessing
Data cleaning involved removing noise, such as punctuation, stopwords, URLs, and duplicates, while retaining relevant elements, such as emojis, for sentiment cues. Text normalization techniques, including tokenization, stemming, lemmatization, and anonymization, were applied to prepare the dataset for analysis.

Annotation and Feature Extraction
Annotation is a crucial step for preparing language resources, as it provides structured information that algorithms can learn from after data collection. The data is annotated for categories such as type of abuse (Physical, sexual, emotional, neglect); Context: in terms of direct disclosure, indirect hint, joke, awareness campaign. And severity in terms of high risk (e.g., ongoing abuse), moderate, or low risk (general discussion). Annotation often requires domain experts (social workers, psychologists) due to the sensitivity of language, and the output obtained is a labeled dataset suitable for training supervised models.
In feature extraction, there are two (2) main approaches to document representation: bag-of-words and Vector Space. Here, the bag-of-words method was employed in feature extraction, where each word is represented as a separate variable having a numeric weight. In other words, this method converts text into a matrix of token counts, representing each sentence or document as a vector of word frequencies. Each document is represented by a vector using Terms Frequency inverse document frequency (TF-IDF), which is used to evaluate how important a word is to a corpus of text documents, reducing the weight of the common words. Again, in practical terms, word order was ignored, and word frequency in the text was analyzed using n-grams, particularly unigrams, to capture short sequences of words that reveal specific abuse-related phrases. In step 4, a manually defined function was written to double-check the text data preparation and remove any undesirable text. This is to ensure that the data obtained has been cleaned properly.

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Python

```python
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer

binary_term_occurances_vectorizer = CountVectorizer(binary='True')
term_occurances_vectorizer = CountVectorizer(binary='False')
term_frequency_vectorizer = TfidfVectorizer(use_idf='False')
tf_idf_vectorizer = TfidfVectorizer(use_idf='True')
```

Model Development

Supervised machine learning models, particularly Multinomial Naïve Bayes (MNB) and Logistic Regression (LR), were used for text classification. Named Entity Recognition (NER) and sentiment analysis were incorporated to detect entities, emotional tone, and contextual meaning. The dataset was split into training and testing sets (70–80% training, 20–30% testing).

id	class	comments
1	1	you are sick upstairs
2	0	i really dont understand your point it seems that you are mixing apples and oranges
3	0	majority of canadians can and has been wrong before now and will be again unless youre supportive of the idea that nothing is full proof or perfect so you take your c
4	0	ok but i would hope they sign hi am to a one year contract to start with give hi am the chance to be reliable and productive but give themselves the out if all his ti ame c
5	0	yeah and where the fuck are you now
6	1	shut the fuck up you and the rest of your stupid friends should be burned at the stake
7	1	either you are fake or extremely stupid maybe both
8	1	that you are an idiot who understands neither taxation nor womens health
9	0	dont wish hi am injury but it happened on its own and i doubt he is injured he looked embarrassed to me
10	0	be careful brother has a fork with your name on it
11	0	i dont know why you people reason like this
12	0	hmmm perhaps some who are too pigfaced to get laid and therefore have zero chance of getting pregnant from such activity hold something against women who can
13	0	barrettmarson huh her income was 11 her spending was 0 my math puts that at
14	1	for some reason you sound retarded lol damn where have you been negro
15	1	you with the racist screen name you are a piece of shit
16	0	oh cheating as well cup was a cheat fest you still dare to post that comment shame on you lol
17	1	you are such a dickhead
18	1	you are a retard go post your head up your wall
19	0	cant you walk without hi am
20	0	fear short girls they can do and undo
21	0	and you know they burned holes in all the carpeting

Sample dataset

System Architecture

The proposed CAMR system consists of modules for data collection, preprocessing, feature extraction, abuse detection, sentiment analysis, real-time monitoring, alert generation, and reporting. A web-based interface enables interaction between users (students, lecturers) and administrators, with role-based access control.

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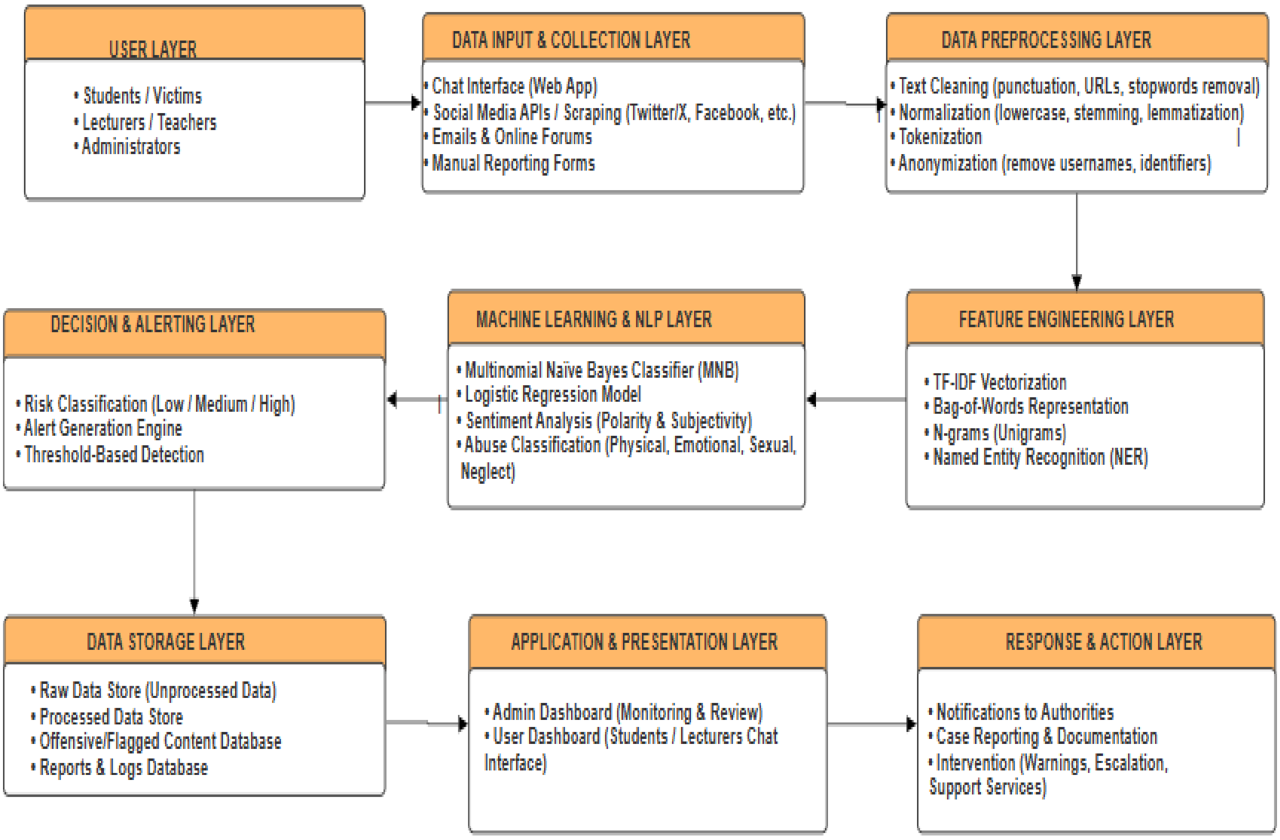

Figure X: System Architecture of CAMR System

User Layer: This layer represents all system users who interact with the platform. It includes students/victims (who report or communicate), lecturers/teachers (who interact and are monitored), and administrators (who oversee and manage the system). They initiate data input and receive system outputs.
Presentation Layer (Web Interface): This is the front-end interface of the system. It provides functionalities such as login/registration, dashboards, chat interfaces, reports, and an admin panel. It enables users to interact with the system in a user-friendly way.
Application Layer (Backend Services): This layer contains the core system services that handle business logic. It manages user accounts, chat and messaging, case/report handling, alert notifications, access control, and API communication between components.
Processing Layer (NLP & ML Engine): This is the intelligence core of the system. It performs:Data preprocessing (cleaning, tokenization, normalization). Feature extraction (TF-IDF, N-grams, entity recognition). NLP analysis (context and entity detection). Sentiment analysis (polarity and subjectivity). Machine learning classification (Naïve Bayes, Logistic Regression). Risk scoring and abuse detection
Data Layer (Database & Storage): This layer handles data storage and management. It stores: User information, raw (unprocessed) data, processed/cleaned data, flagged abuse cases (alerts), generated reports, system logs, and audit trails.
External Data Sources: These are input sources outside the system, such as social media platforms, chat applications, emails, and online forums. They provide raw text data for analysis.
External Authorities & Stakeholders: This layer represents end recipients of system outputs, including child protection services, law enforcement, and social workers. They receive alerts, reports, and notifications for intervention and decision-making.

Data Flow Diagram of the Proposed System

This DFD captures the interaction between users, the various processes, and the data stores in the system, demonstrating the flow of data through the Child Abuse Monitoring and Reporting System using NLP techniques. The data flow diagram (DFD) showing the direction of movement of data in the new system is shown in the figure. 4.1

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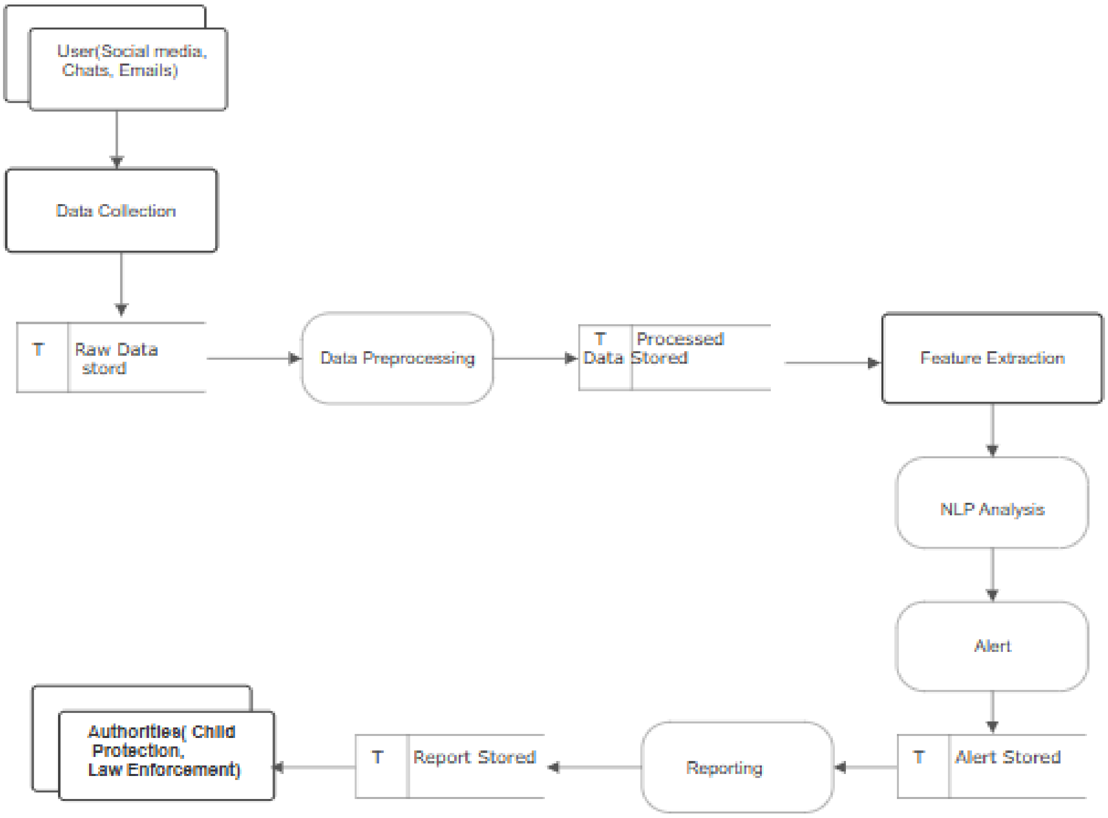

Figure Y: Data flow diagram of the Proposed CAMR system

System Design, Implementation, and Evaluation

Input and Output Specification

The system input consists of real-time textual interactions, particularly chat conversations between students and lecturers. During communication, any abusive or offensive language detected by the system is automatically flagged and stored in a dedicated database along with relevant metadata such as sender, receiver, and timestamp. The output of the system includes classified messages (offensive or non-offensive), flagged alerts, and visual reports accessible via the administrative dashboard for monitoring and intervention.

System Modeling and Design

To ensure clarity in system functionality and interaction, multiple modeling techniques were employed. The **object diagram** illustrates the structural components of the system and their relationships. The **use case diagram** defines system actors (students, lecturers, administrators) and their interactions, highlighting key functionalities such as communication, monitoring, and reporting. Furthermore, the **sequence diagram** captures the dynamic flow of messages and processes, detailing how data moves through the system in a step-by-step manner.

Algorithm Design

The system operates using an NLP-based classification algorithm integrated into a real-time messaging framework. Upon user login, the system assigns roles and grants access to appropriate dashboards. Each message is preprocessed, vectorized, and passed through a trained machine learning model. Messages classified as offensive are stored in a dedicated "offensive_comments" database and flagged for administrative review, while non-offensive messages are stored in a general messages table. Administrators can review flagged content and take appropriate actions such as warnings or escalation.

Data Management and Database Design

A structured database schema supports system operations, including tables for users, administrators, messages, offensive content, and model predictions. The data dictionary defines key attributes such as user identity, message content, timestamps, and classification outputs. This design ensures efficient data storage, traceability, and retrieval for monitoring and reporting purposes.

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System Implementation
The system was implemented using Python as the primary programming language due to its robust ecosystem for machine learning and natural language processing. Key libraries such as NLTK, spaCy, and scikit-learn were utilized, while a web-based interface was developed using frameworks like Flask or Django. The system is designed to be scalable, with defined hardware and software requirements to support efficient performance.

System Testing and Evaluation
Comprehensive testing was conducted through unit, integration, system, and User Acceptance Testing(UAT). The system was evaluated using annotated and unseen datasets to assess its generalization capability. Performance metrics such as **accuracy, precision, recall, and F1-score** were used to measure effectiveness. The confusion matrix analysis demonstrated the model's ability to correctly classify abusive and non-abusive content, with strong predictive performance observed.

Results and Discussion
The developed system effectively classified abusive and non-abusive text using NLP and machine learning techniques. The Multinomial Naïve Bayes classifier demonstrated strong performance in detecting abusive content, supported by high precision and recall values. The system successfully identified emotional cues such as fear and distress through sentiment analysis. Automated alert generation enabled timely reporting of high-risk cases. However, the system is limited to English-language text and may require further enhancement for multilingual and multimodal data processing.

System Limitations
Despite its effectiveness, the system is currently limited to processing text in the English language, which may restrict its applicability in multilingual environments.

Deployment and Security
A phased conversion approach is recommended for system deployment to minimize operational risks. Security measures such as data encryption, role-based access control, and audit logging were implemented to ensure data privacy and system integrity.

Training and Documentation
To facilitate adoption, comprehensive user training and documentation were provided, including user manuals, technical documentation, API guides, and maintenance procedures. These resources ensure ease of use, system sustainability, and effective long-term operation.

Summary, Conclusion, and Recommendations
Summary
This study presents the design and implementation of a **Child Abuse Monitoring and Reporting (CAMR) System** that leverages Natural Language Processing (NLP) and machine learning techniques to detect and classify abusive content in digital communications. The system integrates key components such as real-time monitoring, sentiment analysis, and batch processing to ensure comprehensive identification of abuse-related language.
Advanced algorithms, including **Logistic Regression (LR)** and **Multinomial Naïve Bayes (MNB)**, are employed for text classification, while preprocessing techniques such as tokenization and feature extraction enhance model performance. The system incorporates an interactive user interface featuring dashboards, chat modules, and alert mechanisms to support monitoring and decision-making processes.
Evaluation of the system was conducted using standard performance metrics—precision, recall, and F1-score—demonstrating strong classification capability in identifying abusive content. The architecture is supported by structured system models, including use case diagrams, sequence diagrams, and a well-defined data dictionary, ensuring clarity in system design and implementation. Security measures such as encryption, role-based access control, and audit logging were also integrated to safeguard sensitive data. However, the system is currently limited to processing English-language text.

CONCLUSION

The developed CAMR system demonstrates the practical application of NLP and machine learning in enhancing child protection efforts within digital environments. By enabling real-time detection and classification of abusive language, the system provides a scalable and efficient solution for monitoring online interactions.
Its modular architecture and user-friendly design make it suitable for deployment across multiple sectors, including law enforcement, educational institutions, and child welfare organizations. Despite achieving high accuracy, the system

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requires further enhancements in multilingual processing and contextual understanding to improve its effectiveness across diverse environments. Overall, the system represents a significant step toward leveraging artificial intelligence for proactive child abuse prevention and intervention.

Recommendations

To enhance the system's effectiveness and applicability, the following recommendations are proposed:

- **Multilingual Capability:** Integrate multilingual NLP models to support abuse detection across different languages and regions.
- **Multimodal Expansion:** Extend the system to include **voice and video analysis** for broader abuse detection beyond text.
- **Data Integration:** Incorporate additional datasets and continuously retrain models to improve accuracy and adaptability.
- **Stakeholder Collaboration:** Establish partnerships with social media platforms, law enforcement agencies, and child protection organizations for real-time reporting and intervention.
- **User Training:** Provide structured training programs for end-users such as social workers and law enforcement personnel.
- **Enhanced Security:** Adopt advanced security mechanisms (e.g., blockchain-based systems) to ensure data integrity and confidentiality.

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