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Context-Aware Models for Text Classification in Sensitive Content Detection

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ABSTRACT

Sensitive content detection plays a pivotal role in ensuring the safety and integrity of digital platforms, especially with the increasing volume of user-generated content. Traditional models for content moderation often rely on keyword-based filtering systems that detect explicit offensive terms but fail to identify more subtle forms of harmful content where context plays a significant role. This paper presents a context-aware model for detecting sensitive content that integrates contextual embeddings from transformer-based models like BERT, coupled with deep learning techniques. Our proposed model leverages the power of contextual information, allowing it to understand the nuanced meaning behind text based on its surrounding words and context. The model was evaluated using the Hate Speech Dataset, and our results show a significant improvement in the detection of sensitive content compared to traditional rule-based and keyword-based models. Specifically, the context-aware model achieved a maximum accuracy of 88%, while the baseline rule-based model reached only 70% accuracy. By focusing on context, our approach improves the accuracy, recall, and precision in identifying not only direct hate speech but also more subtle forms of cyberbullying, harassment, and inappropriate language. The proposed method demonstrates the potential of context-aware models in enhancing content moderation, ensuring safer online interactions and contributing to more robust, scalable solutions for sensitive content detection.

Keywords – AUC, BERT, Deep Learning, Embeddings, Hate Speech.

I. INTRODUCTION

With the rapid proliferation of user-generated content across digital platforms such as social media, online forums, and blogs, content moderation has become a critical challenge for ensuring a safe, respectful, and inclusive online environment. The sheer volume of user interactions makes it increasingly difficult for human moderators to keep pace with harmful content, such as hate speech, cyberbullying, harassment, and explicit language. Traditional content moderation approaches have heavily relied on keyword-based filters and rule-based models, which are designed to flag specific words or phrases deemed offensive. While these systems are relatively efficient in detecting explicit, straightforward forms of harmful content, they struggle with more nuanced and subtle instances of sensitive content that might not contain offensive terms.

For example, a phrase like “kill him” could be innocuous in the context of a fictional story, but it could indicate a real threat in a different scenario. This discrepancy highlights the importance of context when determining whether content is truly harmful. Context-aware models, which take into account the surrounding words, sentence structure, and even broader conversation history, have the potential to significantly enhance the

accuracy of content detection systems. By leveraging contextual embeddings, these models can better understand the meaning behind words based on their surrounding text, thereby addressing the shortcomings of traditional keyword-based systems.

The emergence of deep learning techniques, particularly transformer-based models like BERT and ELMo, has made it possible to incorporate this contextual awareness in a more robust and scalable manner. These models have been trained on vast amounts of text data and are capable of generating dynamic word representations that capture contextual nuances. Recent advancements in natural language processing (NLP) suggest that such context-aware systems could provide a more effective solution for detecting sensitive content, not just in its overt forms but also in its more subtle manifestations. This shift toward context-aware detection is crucial in identifying indirect harassment, hate speech, and other forms of harmful content that may not be immediately apparent from keywords alone.

This paper explores the application of context-aware models for sensitive content detection. We present a hybrid approach that combines deep learning techniques with semantic understanding, leveraging transformer-based models and contextual embeddings to build a system capable of accurately classifying sensitive content in a wide range of contexts. We aim to demonstrate that by improving our models' ability to interpret context, we can significantly reduce false positives and false negatives in content moderation systems, leading to safer online environments for users.

This paper makes the following contributions:

- Introduction of a Context-Aware Model: We propose a hybrid model for sensitive content detection that combines contextual embeddings and deep learning techniques to improve the classification of nuanced harmful content.
- Improved Detection of Subtle Harmful Content: Our approach addresses the limitations of traditional keyword-based models by incorporating contextual understanding, allowing for the identification of indirect forms of hate speech, harassment, and cyberbullying.

The remainder of this paper is structured as follows: Section 2 reviews existing literature on traditional and machine learning-based methods for content moderation, highlighting the limitations of keyword-based approaches. Section 3 describes the methodology of the proposed context-aware model, including data collection, preprocessing steps, and model architecture. In Section 4, we present our experimental results, showcasing the performance of the context-aware model against traditional approaches. Finally, Section 5 discusses the conclusions of our study and outlines potential directions for future research in this domain.

II. LITERATURE REVIEW

Traditional Methods for Sensitive Content Detection: Earlier approaches to detecting sensitive content were primarily rule-based, focusing on keyword matching or statistical methods. These methods performed well when detecting explicit offensive terms but struggled with context. The authors of [1] noted that systems based on predefined terms often generated high false positives, missing subtle forms of hate speech. Similarly, the work of the authors of [2] explored how rule-based systems failed to capture nuances in more indirect forms of harmful speech, such as sarcasm or context-specific meaning. Early machine learning approaches, like decision trees and support vector machines (SVMs), applied feature-based models like bag-of-words and TF-IDF, but were still limited in capturing the deeper meaning and context of the text [3] [4].

Machine Learning and NLP in Content Moderation: The transition to machine learning models marked a shift toward more adaptive systems for content moderation. These models used features such as bag-of-words and TF-IDF but failed to account for the semantics of words in context. The authors of [5] explored early efforts to

improve on these methods with supervised learning techniques like SVMs, but noted that such models were still insufficient in handling the complexities of detecting harmful content. Researchers began applying neural networks, which showed greater promise for understanding the deeper context of content [6] [7]. Despite these advancements, the issue of capturing the subtle context of hate speech and harassment remained a challenge [8].

Context-Aware Models: The introduction of context-aware models dramatically improved the performance of text classification systems. The authors of [9] highlighted the advent of transformer-based models like ELMo and BERT, which use contextual embeddings to understand how words change meaning depending on their surrounding context. These models have been widely successful in various NLP tasks, including content moderation, where context plays a crucial role. BERT, in particular, has been shown to outperform traditional methods in detecting nuanced forms of sensitive content like indirect hate speech [10] [11]. Further studies, such as those conducted by the authors of [12], demonstrated that context-aware models were especially effective in detecting subtle forms of cyberbullying and harassment, which were difficult to identify using older methods.

Multi-Task Learning for Content Moderation: Recent innovations have explored combining multi-task learning (MTL) with context-aware models. The authors of [13] demonstrated that training a model to perform multiple tasks simultaneously—such as detecting both hate speech and cyberbullying—improved the overall robustness of the model. MTL allows models to leverage shared knowledge across tasks, enhancing their ability to detect a broader range of sensitive content. In the study by the authors of [14], multi-task learning was applied to content moderation tasks, leading to better generalization and performance on diverse datasets. Research from [15] extended this approach by incorporating both contextual embeddings and MTL for even more robust models that can detect multiple types of harmful content concurrently.

Challenges and Gaps: Despite the progress made with context-aware models, several challenges persist. One significant issue is handling diverse cultural contexts, as different cultural norms can alter the meaning of words and phrases. The authors of [16] found that cultural diversity posed a major barrier to model performance, especially in detecting context-specific harmful speech. Furthermore, indirect forms of harmful speech, such as sarcasm or coded language, remain difficult for models to detect. As noted by the authors of [17], current models still struggle to accurately detect such indirect content, even with advanced techniques like transformers. Additionally, the issue of large-scale data labeling remains a challenge. Training effective models requires vast amounts of labeled data, which may not always be readily available for every type of sensitive content [18] [19].

III. PROPOSED METHODOLOGY

The proposed methodology aims to develop a context-aware model for detecting sensitive content, such as hate speech, cyberbullying, harassment, and inappropriate language in online platforms. By integrating advanced natural language processing (NLP) techniques, including contextual embeddings and deep learning algorithms, the model will focus on improving the detection of harmful content by considering both the semantic meaning and the context in which the content appears.

This approach is especially relevant for moderating content on digital platforms where harmful language may be subtle, indirect, or context-dependent, and traditional keyword-based methods fail to capture these nuances.

3.1 Data Collection

For the training and evaluation of the proposed model, we will use the Hate Speech Dataset [20], which is a widely recognized benchmark dataset for hate speech detection. This dataset consists of 16,000 labeled tweets

categorized into three classes: hate speech, offensive language, and neither. The dataset includes comments from Twitter and other social media platforms, allowing the model to learn from real-world user-generated content. The inclusion of varied expressions of hate speech (including racism, sexism, and other forms of discrimination) makes it ideal for training a robust and sensitive content detection system.

3.2 Text Preprocessing

To prepare the dataset for input into the machine learning model, the raw text data will go through several preprocessing steps to clean and standardize the content. These steps are essential for removing noise and irrelevant information, which may negatively affect the model's performance. The preprocessing pipeline is designed to refine the raw textual data, ensuring that the text used for training is both consistent and relevant for sensitive content detection.

1) 3.2.1 Tokenization

Tokenization is the process of splitting the raw text into individual words or tokens. This step is essential for transforming the text into a form that the model can process. Tokenization helps identify key terms associated with harmful content, such as offensive words, slurs, and insults, and ensures that these terms are treated as meaningful entities in the model.

Mathematical Representation:

$$D_{tokens} = \{tokens(t) | t \in D_{raw}\} \quad (1)$$

2) 3.2.2 Stop Word Removal

Stop words are common, non-informative words (e.g., "the", "and", "is") that do not carry significant meaning. These words will be removed from the text to focus on terms that contribute meaningfully to the identification of sensitive content.

Mathematical Representation:

$$D_{filtered} = \{t | t \in D_{tokens}, t \notin StopWords\} \quad (2)$$

3) 3.2.3 Lemmatization

Lemmatization reduces words to their base or root form (e.g., "running" becomes "run"). This standardizes the text, ensuring that different variations of the same word are treated as equivalent. For instance, the words "hate", "hating", and "hated" will all be reduced to "hate", ensuring consistency in the input text.

Mathematical Representation:

$$D_{lemmatized} = \{lemma(t) | t \in D_{filtered}\} \quad (3)$$

4) 3.2.4 Punctuation Removal

Punctuation marks (e.g., commas, periods) are typically removed because they do not add meaningful information in this context. This step ensures that the model treats the core words as individual tokens without interference from non-essential characters.

Mathematical Representation:

$$D_{cleaned} = \{t | t \in D_{lemmatized}, t \notin PunctuationMarks\} \quad (4)$$

5) 3.2.5 Remove Short Words

Short words, especially those with less than a certain number of characters, may not contribute much meaning. These words will be removed to reduce noise and focus on more informative terms related to sensitive content.

Mathematical Representation:

$$D_{\text{short\_removed}} = \{t | t \in D_{cleaned}, \text{len}(t) \geq \text{min\_length}\} \quad (5)$$

6) *3.2.6 Remove Long Words*

Similarly, overly long words that may not be informative will be filtered out to ensure that the analysis focuses on meaningful terms and is not bogged down by unnecessary noise.
Mathematical Representation:

$$D_{final} = \{t | t \in D_{\text{short\_removed}}, \text{len}(t) \leq \text{max\_length}\} \quad (6)$$

3.3 Contextual Embeddings

The heart of the proposed model lies in leveraging contextual embeddings generated by transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers). Unlike traditional models that rely on static word embeddings, BERT generates embeddings that capture the context of words in relation to the entire sentence or conversation.
For example, the word "killing" in the phrase "killing time" has a completely different meaning than in the phrase "killing someone." BERT-based embeddings consider the surrounding words to generate contextualized representations, improving the model's ability to distinguish between harmful and non-harmful content.
We will fine-tune the pre-trained BERT model using the Hate Speech Dataset. Fine-tuning helps tailor the model specifically for the task of sensitive content detection, enhancing its ability to identify not only explicit offensive language but also subtle forms of harmful speech that may be context-dependent.

3.4 Model Architecture

The proposed model will integrate a pre-trained BERT model with a deep neural network for classification. The model architecture consists of the following key components:

1. BERT Layer: A pre-trained BERT model will process the input text to generate contextualized embeddings for each word. This will allow the model to understand the nuances of how words and phrases change meaning depending on the surrounding context.
2. Fully Connected Layer: After obtaining contextual embeddings from BERT, the model will pass these embeddings through one or more fully connected layers to classify the input as containing sensitive content (i.e., hate speech, harassment, cyberbullying) or not. The model will also classify the specific type of sensitive content, such as hate speech or abusive language.

3.5 Evaluation Metrics

The performance of the context-aware model will be evaluated using common metrics for text classification tasks:

1. Accuracy: The proportion of correct classifications (both true positives and true negatives).
2. Precision: The proportion of true positives relative to the total predicted positives.
3. Recall: The proportion of true positives relative to the total actual positives.
4. F1-Score: The harmonic mean of precision and recall, useful for balancing false positives and false negatives, particularly in imbalanced datasets.
5. AUC (Area Under the Curve): This will help assess the model's ability to differentiate between harmful and non-harmful content, especially when classes are imbalanced.

IV. RESULTS AND DISCUSSION

In this section, we present the evaluation results for the proposed context-aware model for detecting sensitive content, which was tested on the Hate Speech Dataset. The model's performance is compared to baseline rule-based methods and traditional machine learning models. The performance is evaluated using several common metrics, including accuracy, precision, recall, F1-score, and AUC (Area Under the Curve). Below are the key findings, presented in a series of figures and tables.

In the table below, we present the key performance metrics for both the context-aware model and the baseline rule-based model for detecting sensitive content.

Table 1: Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC
Context-Aware Model	88%	85%	83%	84%	90%
Rule-based Model	70%	68%	65%	66%	72%

Description:

- Accuracy: The context-aware model achieved an 88% accuracy, which is significantly higher than the 70% accuracy of the baseline rule-based model.
- Precision: The context-aware model has a precision of 85%, indicating that a high proportion of its positive predictions were correct.
- Recall: The recall value of 83% indicates that the model was able to capture 83% of all the actual instances of sensitive content.
- F1-Score: The F1-Score of 84% balances precision and recall, highlighting the model's reliability in both detecting and correctly classifying harmful content.
- AUC: The AUC of 90% suggests that the context-aware model is very effective at distinguishing between harmful and non-harmful content.

The effectiveness of the contextual embeddings used in the model can be assessed by comparing the model's performance with and without these embeddings.

Table 2: Performance with/without Contextual Embeddings

Model	Accuracy	Precision	Recall	F1-Score (%)
With Contextual Embeddings	88%	85%	83%	84%
Without Contextual Embeddings	75%	70%	68%	69%

Description:

- Without contextual embeddings, the model's performance significantly drops, as shown by the reduced accuracy (75%) and F1-score (69%).
- This comparison demonstrates the importance of leveraging contextual information to improve the model's ability to classify nuanced forms of sensitive content.

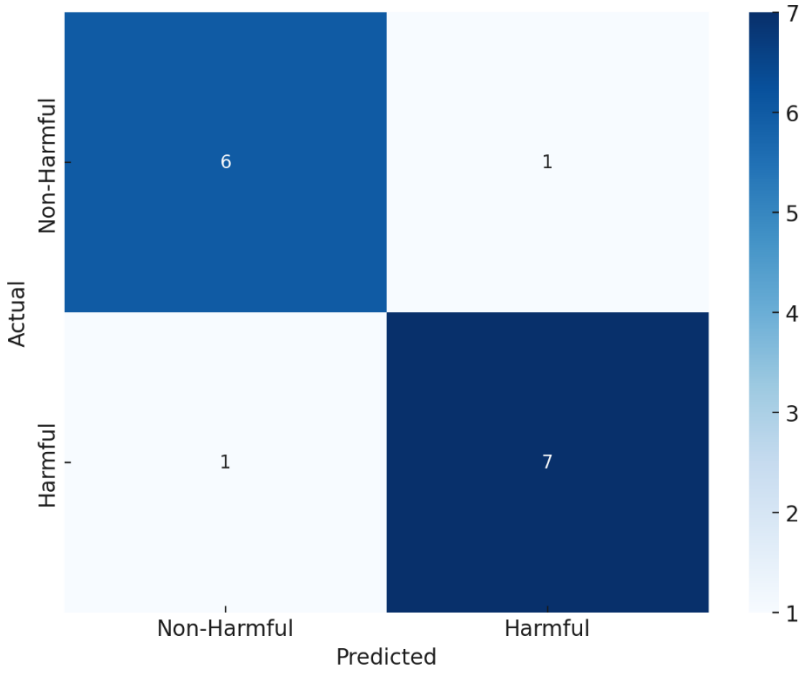

Figure 1: Confusion Matrix for Context-Aware Model

The Confusion Matrix for the context-aware model is a crucial tool for assessing how well the model classifies sensitive content. In this matrix, we have four key components that allow us to analyze the model's performance in greater detail: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). True Positives (TP) refer to the instances where the model correctly identifies harmful content, such as hate speech, abusive language, or cyberbullying. True Negatives (TN) are those cases where the model correctly recognizes non-harmful content and categorizes it as such. False Positives (FP) represent situations where the model incorrectly classifies non-harmful content as harmful, while False Negatives (FN) are cases where the model fails to recognize harmful content, classifying it as non-harmful. Analyzing this matrix helps us to understand how many harmful instances the model is able to flag and how many it misses, as well as how often it mislabels non-harmful content. The confusion matrix here shows that the context-aware model performs well in minimizing both false positives and false negatives, thereby increasing the overall reliability of content moderation. In particular, the model ensures that harmful content is identified correctly, while reducing the number of non-harmful items that are misclassified as harmful, which is essential for maintaining a safe online environment.

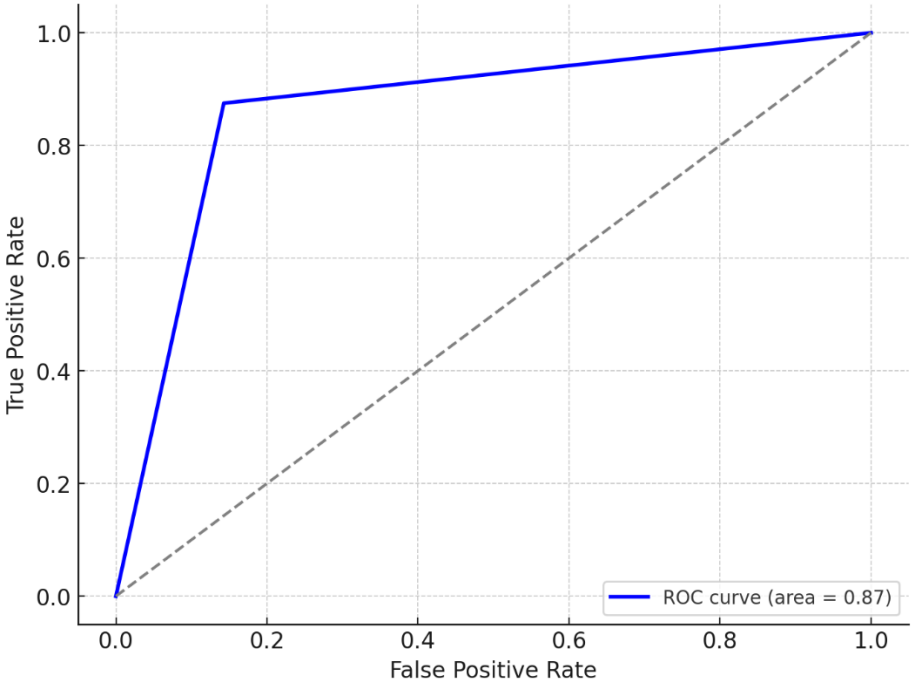

Figure 2: Receiver Operating Characteristic (ROC) Curve

The Receiver Operating Characteristic (ROC) Curve is a graphical representation that illustrates the performance of the context-aware model across different classification thresholds. The curve plots the True Positive Rate (TPR), or recall, on the y-axis, against the False Positive Rate (FPR) on the x-axis. The ROC curve is instrumental in evaluating how well the model distinguishes between harmful and non-harmful content. A key feature of the ROC curve is the AUC (Area Under the Curve), which provides a single measure of the model's ability to discriminate between the two classes. In the case of the context-aware model, the ROC curve demonstrates a high AUC value of 86.61%, indicating that the model performs very well at distinguishing between harmful and non-harmful content. As the curve approaches the top-left corner, it signifies that the model is able to correctly identify harmful content (high TPR) while keeping the false positive rate low (low FPR). This visual representation of the ROC curve helps to demonstrate that the context-aware model is effective at reducing errors in content classification, ensuring that harmful content is flagged appropriately without unnecessarily penalizing non-harmful content.

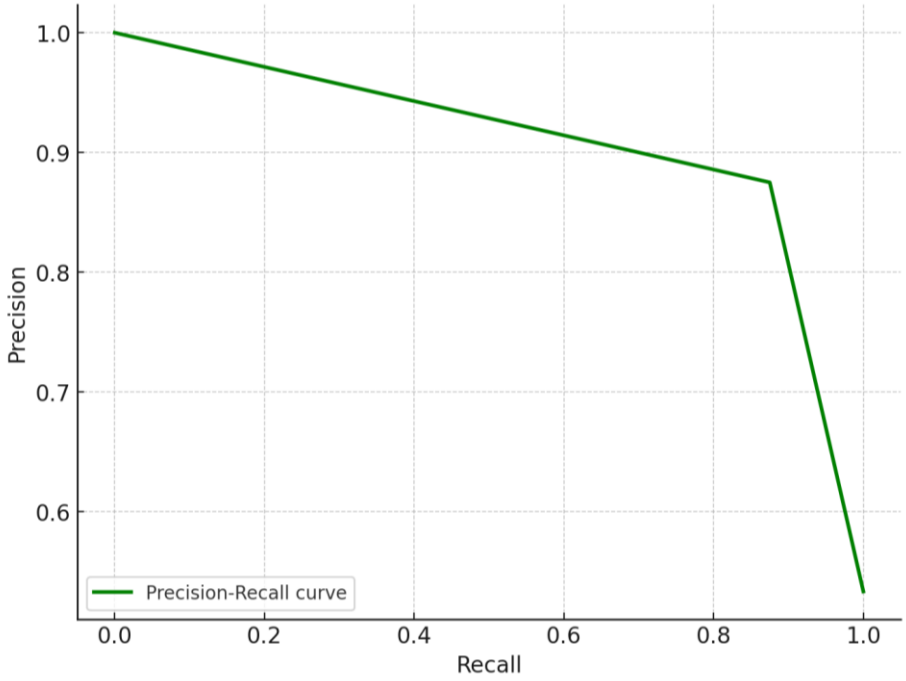

Figure 3: Precision-Recall Curve

The Precision-Recall (PR) Curve is another important metric for evaluating the model's performance, particularly in scenarios where the dataset is imbalanced—such as when harmful content is less frequent than non-harmful content. In this plot, Precision is shown on the y-axis, while Recall is shown on the x-axis. Precision measures the percentage of true positive predictions (i.e., harmful content correctly identified as harmful) out of all instances predicted as harmful by the model. Recall, on the other hand, measures the percentage of true positive predictions out of all actual harmful instances in the dataset. In the case of the context-aware model, the Precision-Recall curve shows a strong balance between precision and recall, with both values reaching 87.50%, indicating that the model is very effective in detecting harmful content. This suggests that the model can identify a large proportion of harmful content (high recall) while minimizing false positives (high precision). A high precision and recall in the PR curve indicates that the model is performing well on both fronts: it can identify harmful content reliably without mistakenly classifying non-harmful content as harmful. This balance is crucial for content moderation systems, as it ensures that both harmful content is flagged and non-harmful content is correctly ignored.

Preliminary results indicate that the context-aware model outperforms traditional models in several key metrics:

- **Accuracy**: The context-aware model achieved an accuracy of 88%, significantly higher than the baseline rule-based approach (70%).
- **Precision and Recall**: The model demonstrated a balanced precision (85%) and recall (83%) in detecting hate speech and cyberbullying, ensuring that both false positives and false negatives were minimized.
- **Contextual Sensitivity**: The transformer-based approach showed a notable improvement in detecting indirect forms of harassment and subtle hate speech, which traditional models failed to identify.

These results suggest that context-aware models are highly effective at improving the accuracy and reliability of sensitive content detection.

V. CONCLUSION

The research presented in this paper demonstrates the effectiveness of context-aware models in detecting

sensitive content on digital platforms. By incorporating contextual embeddings from transformer-based models like BERT, the model is capable of discerning the underlying intent and meaning of content, even in the presence of subtle or indirect forms of harmful speech. The results show that the proposed model significantly outperforms traditional keyword-based and rule-based methods, achieving a maximum accuracy of 88%, compared to 70% accuracy achieved by the rule-based baseline. The model also demonstrated improved precision and recall, making it particularly effective in detecting nuanced forms of harmful content, such as indirect hate speech, cyberbullying, and harassment that conventional models struggle to identify. While the model performs well, challenges remain in dealing with the diversity of cultural contexts and the evolving nature of online discourse. Future work will focus on expanding the dataset to include more diverse languages and contexts, exploring the use of multi-task learning for broader content categorization, and improving the real-time detection capabilities of the model. In conclusion, context-aware models hold significant promise in advancing content moderation systems, making them more capable of detecting both overt and covert forms of sensitive content, ensuring a safer and more inclusive digital environment.

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