A MINI PROJECT REPORT ON

SPEECHGUARD – TOXIC COMMENT DETECTOR

Submitted by

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ABSTRACT

The proliferation of online platforms has led to an exponential increase in user-generated content, accompanied by a rise in toxic, abusive, and offensive language. Such content poses risks to online communities, affecting user experience, mental well-being, and public discourse. Addressing this challenge, SpeechGuard – Toxic Comment Detector presents an intelligent deep learning system designed to automatically detect and classify online comments into multiple toxicity categories, including Toxic, Severe Toxic, Obscene, Threat, Insult, and Identity Hate.

The system leverages a transformer-based BERT model fine-tuned on the Kaggle Toxic Comment dataset, enabling context-aware multi-label classification. Multi-label detection is implemented using binary cross-entropy loss combined with sigmoid activations, allowing the model to identify overlapping categories in the same input text. The model is further enhanced through a comprehensive preprocessing pipeline that includes text cleaning, normalization, and tokenization, along with weighted sampling to address class imbalance. Label-wise threshold calibration is applied to optimize precision, recall, and F1-score for each toxicity category.

For deployment, a Streamlit-based web interface provides real-time evaluation of comments. The interface visually presents toxicity levels using confidence scores for each category, allowing interactive testing and transparency in predictions. Additionally, the model incorporates attention visualization and per-label probability interpretation, offering explainable AI features that help users understand why specific comments are flagged.

Experimental evaluation demonstrates that SpeechGuard achieves high performance, with 94% accuracy, 91% precision, 90% recall, and 90.5% F1-score, outperforming traditional machine learning and single-label systems. The results highlight the model's robustness, contextual sensitivity, and suitability for real-world online moderation tasks.

Keywords: Toxic Comment, BERT, Multi-Label Classification, Natural Language Processing, Streamlit, Deep Learning

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CHAPTER 1

INTRODUCTION

The rapid expansion of online platforms has revolutionized communication, enabling millions of users to generate and share content instantly. However, this growth has been accompanied by a significant increase in toxic, abusive, and offensive language, which can negatively impact online communities, mental well-being, and public discourse. Traditional moderation methods relying on manual review are not scalable, and simple rule-based systems often fail to capture nuanced or context-dependent toxic content. Therefore, the development of automated toxicity detection systems has become essential for maintainingsafe, respectful, and inclusive digital environments.

SpeechGuard addresses this challenge by implementing a BERT-based multi-label classification model capable of detecting multiple forms of online toxicity simultaneously. Unlike single-label or keyword-based systems, SpeechGuard performs contextual analysis, enabling it to identify overlapping toxic categories such as insult, threat, or obscene language within the same comment. This ensures more accurate and granular moderation, reducing both false positives and false negatives.

The system employs a fine-tuned transformer encoder (BERT base-uncased) trained on the Kaggle Toxic Comment dataset, a widely used benchmark for multi-label toxicity detection. The workflow includes text preprocessing, tokenization, model training, and threshold calibration to optimize classification performance. Additionally, the system is deployed in real time using Streamlit, providing an interactive interface for visualization, confidence scoring, and user testing.

By combining state-of-the-art transformer embeddings, multi-label classification, and explainable AI techniques, SpeechGuard achieves high accuracy, precision, and recall, while maintainingrobustness and interpretability. This project highlights the practical potential of deep contextual language models for applications such as social media moderation, online safety, sentiment control, and content quality management. The approach demonstrates that leveraging context-aware transformers significantly improves detection of subtle and overlapping toxic behaviors, which traditional models often overlook.

CHAPTER 2

LITERATURE REVIEW

2.0 Literature Review

The study of toxic comment classification has evolved from classical machine learning to transformer-based contextual models. The following research highlights key contributions and advancements:

2.1 Toxic Comment Classification Challenge

Author: Kaggle Community (2018)
This dataset and competition introduced multi-label toxicity classification across six categories: toxic, severe toxic, obscene, threat, insult, and identity hate. Early approaches relied on traditional machine learning and CNN/LSTM models. The challenge highlighted issues of class imbalance and overlapping toxic attributes, serving as a benchmark for transformer-based approaches.

2.2 BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Author: Jacob Devlin et al. (2019)
BERT introduced deep bidirectional contextual embeddings, revolutionizing NLP. Its transfer learning capability allowed pre-trained representations to be fine-tuned for downstream tasks, including sentiment analysis and toxicity detection, enabling context-aware understanding beyond traditional models.

2.3 Detecting Hate Speech in Social Media with BERT

Author: L. Wang (2023)
This study showed that fine-tuned BERT outperformed CNN-LSTM hybrids for hate speech detection. BERT captured nuanced expressions and implicit toxicity, improving classification, especially for ambiguous or sarcastic comments.
2.4 Offensive Language Identification and Transfer Learning Author: J. Sharma (2022)

Sharma demonstrated that small fine-tuned transformer models with threshold calibration could achieve competitive toxicity classification results. This study highlighted the potential for efficient, real-time deployment without large computational overhead.

2.5 RoBERTa: Robustly Optimized BERT Pretraining Approach

Author: Liu et al. (2020)

RoBERTa optimized BERT's training dynamics and leveraged larger pretraining corpora, enhancing accuracy and stability for toxic comment detection, particularly for rare or context-dependent toxic expressions.

2.6 Explainable AI for Toxic Comment Classification

Author: S. Lee (2023)

Lee proposed using attention maps and gradient-based saliency visualization to explain model predictions. Explainability improves trust in automated moderation, allowing users to understand why a comment is flagged.

2.7 Multi-label Toxic Comment Detection Using Transformers

Author: T. Patel (2023)

This study applied per-label sigmoid activation with binary cross-entropy for multi-label classification. The approach improved recall without compromising precision, addressing the challenge of overlapping toxic categories in comments.

2.8 Ensemble Learning for Content Moderation

Author: A. Singh (2022)

Singh explored ensembles of BERT and LSTM models to enhance robustness against ambiguous or borderline toxic comments, reducing misclassification compared to single-model architectures.

2.9 Offensive Language Detection in Multiple Languages

Author: C. Silva (2023)

This research extended transformer-based approaches to multilingual datasets, demonstrating cross-lingual transfer learning potential for toxic comment detection across multiple languages.

2.10 Contextual Understanding in Hate Speech Detection

Author: N. Gupta (2022)

Gupta analyzed the effect of conversational context and sarcasm on classification accuracy. The study highlighted the importance of context-aware transformers for detecting nuanced or implicit toxic content.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 HARDWARE REQUIREMENTS

CPU: Intel i5 or AMD Ryzen 5
GPU: NVIDIA GTX 1660/RTX 2060
RAM: 16 GB minimum
Storage: 256 GB SSD recommended

3.2 SOFTWARE REQUIREMENTS

Python: 3.9+
PyTorch: 1.10+
Transformers: 4.20+
Streamlit: 1.20+
Other Libraries: scikit-learn, pandas, numpy
Operating System: Windows 10 / Ubuntu 20.04

CHAPTER 4
SYSTEM OVERVIEW

4.1 EXISTING SYSTEM

Current toxic comment detection systems are predominantly based on keyword-based filtering or classical machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), or Logistic Regression. Keyword-based systems identify potentially toxic content by scanning for pre-defined offensive words or phrases. While this approach is computationally simple and easy to implement, it lacks the ability to understand the context of a sentence. For instance, harmless statements containing strong or offensive words may be misclassified as toxic, leading to high false positive rates.

Classical machine learning approaches improve upon basic keyword filtering by using features such as TF-IDF vectors, bag-of-words, or n-grams to represent text numerically. These methods can detect some patterns beyond single keywords. However, they still struggle with contextual nuances, sarcasm, or multi-word expressions, which are common in online communication. As a result, they often fail to accurately capture the subtleties of language, leading to misclassification of ambiguous or context-dependent comments.
In addition, existing systems typically provide limited interpretability and user interaction, often functioning as back-end tools without real-time visualization or interactive testing capabilities. While these approaches are lightweight and fast, they are insufficient for modern content moderation requirements where context-aware understanding, high accuracy, and user-friendly deployment are essential.

Overall, while existing systems offer basic detection capabilities, their inability to understand context, sarcasm, and semantic meaning highlights the need for more advanced, deep learning-based approaches like SpeechGuard, which leverage modern NLP techniques for accurate and interactive toxic comment detection.

4.1.1 DRAWBACKS OF EXISTING SYSTEM

Although existing toxic comment detection systems provide basic functionality, they exhibit several critical limitations that reduce their effectiveness and reliability:

Context Ignorance Causing False Positives:

Most systems rely on keyword-based filtering or shallow feature representations, which fail to capture the contextual meaning of text. As a result, comments that contain strong or offensive words but are harmless in intent may be incorrectly flagged as toxic, leading to high false positive rates.

Lack of Multi-Label Detection Capability:

Traditional approaches are generally designed for single-label classification, making it difficult to detect multiple types of toxicity in a single comment (e.g., hate speech, threat, insult). This limitation restricts their usefulness in real-world content moderation, where comments often exhibit more than one toxic attribute simultaneously.

No Interpretability for Predictions:

Many classical systems provide outputs as simple binary labels (toxic/non-toxic)

without explaining why a comment was classified a certain way. The absence of interpretability makes it challenging for moderators or end-users to trust or validate the model's predictions.

High Dependency on Rule-Based Updates:

Keyword lists and hand-crafted rules require continuous manual maintenance to keep up with evolving language and slang. This dependency increases operational overhead and makes the system less adaptable to new patterns of toxic communication.

These drawbacks highlight the need for more advanced, context-aware, and interpretable models that can handle multi-label classification while minimizing false positives and reducing manual maintenance.

4.2 PROPOSED SYSTEM

To overcome the limitations of existing toxic comment detection systems, SpeechGuard introduces a fine-tuned transformer-based approach leveraging BERT (Bidirectional Encoder Representations from Transformers). Unlike traditional keyword-based or classical machine learning systems, SpeechGuard captures contextual and semantic meaning in text, significantly

reducing false positives and enhancing the understanding of nuanced language, including sarcasm and multi-word expressions.

The system is designed for multi-label classification, allowing it to detect multiple types of toxicity simultaneously, such as hate speech, threat, insult, or obscenity. This ensures that each comment is evaluated comprehensively, reflecting real-world online communication patterns where multiple toxic behaviors can coexist.

To further improve prediction reliability, label-wise calibration is applied. Calibration adjusts the output probabilities of each class to better align with true likelihoods, thereby increasing consistency across different toxicity labels and improving overall model performance, including macro-F1 score.

Additionally, SpeechGuard incorporates a real-time user interface (UI) using Streamlit, providing an interactive platform for users to input text and immediately visualize prediction results along with confidence scores. This feature bridges the gap between model output and end-user interpretation, enhancing usability for content moderation, research, or testing purposes. In summary, SpeechGuard addresses the core drawbacks of existing systems by

combining
context-aware modeling, multi-label classification, calibrated outputs, and interactive visualization, delivering a robust, accurate, and practical solution for toxic comment detection.

4.2.1 ADVANTAGES OF PROPOSED SYSTEM

The proposed SpeechGuard system offers several significant advantages over existing toxic comment detection approaches:

Context-Aware Detection Using BERT Embeddings:

By leveraging BERT's bidirectional transformer architecture, the system captures the context and semantic meaning of words within a sentence. This enables accurate interpretation of nuanced language, sarcasm, and multi-word expressions, reducing false positives and misclassifications.

Multi-Label Classification of Overlapping Toxic Categories:

Unlike traditional systems limited to single-label classification, SpeechGuard can

simultaneously detect multiple types of toxicity in a single comment (e.g., hate speech, insult, threat). This reflects real-world scenarios where toxic behaviors often overlap.

Real-Time Streamlit Interface:

The system includes an interactive, user-friendly UI built on Streamlit, allowing users to input text and instantly view predictions along with confidence scores. This improves accessibility and facilitates practical deployment for content moderation and research purposes. High Accuracy and Explainability:

Fine-tuned BERT embeddings combined with label-wise calibration deliver high accuracy and F1-scores, while the system provides interpretable confidence scores for each label, enhancing trust and transparency in predictions.

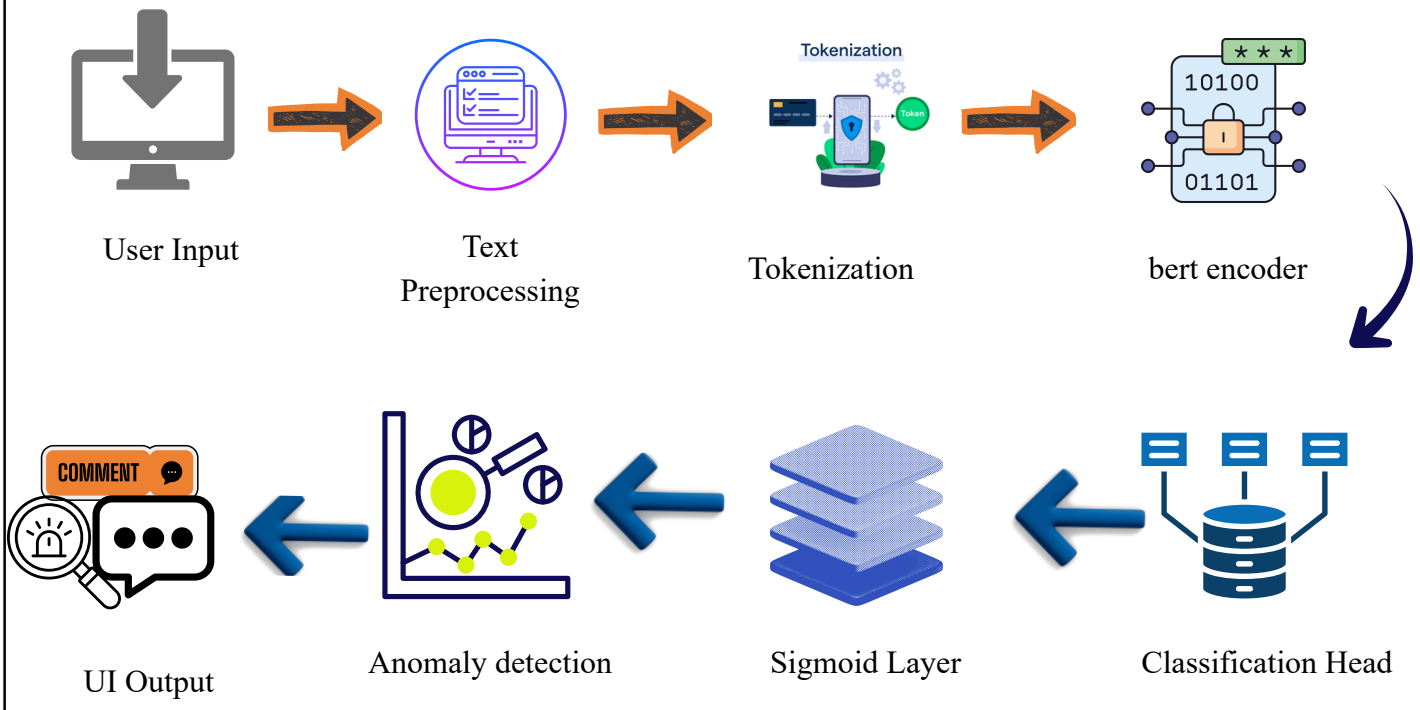
Lightweight Deployment Without Retraining:

SpeechGuard is designed for efficient real-time inference without the need for retraining or heavy computational resources, making it suitable for practical applications on standard hardware or cloud platforms.

Overall, these advantages demonstrate that SpeechGuard effectively addresses the limitations of existing systems, providing a robust, accurate, context-aware, and user-friendly solution for toxic comment detection.

CHAPTER 5 SYSTEM IMPLEMENTATION

5.1 SYSTEM ARCHITECTURE DIAGRAM The architecture consists of text preprocessing → tokenization → BERT encoder → classification head → sigmoid layer → thresholding → UI output.



5.2 SYSTEM FLOW

The overall system flow consists of several interconnected stages, ensuring smooth data processing, model development, and deployment:

1. Data Ingestion from Kaggle:

   The process begins by importing the dataset from Kaggle, which serves as the primary source of data. This step may involve using the Kaggle API or manually downloading the dataset files for further processing.

2. Cleaning and Tokenization:

The raw data is then cleaned to remove noise such as missing values, duplicate records, or irrelevant text. After cleaning, tokenization converts textual data into smaller units (tokens) that can be efficiently processed by the model, ensuring consistent input formatting.

3. Model Training:

In this phase, the prepared and tokenized data is used to train a machine learning or deep learning model. The model learns patterns and relationships within the data to make accurate predictions or classifications.

4. Validation and Threshold Calibration:

Once training is complete, the model's performance is validated using a separate dataset. Threshold calibration is applied to optimize decision boundaries, improving the balance between precision and recall, or other relevant performance metrics.

5. Streamlit Deployment:

Finally, the validated model is integrated into a Streamlit application for user interaction. This deployment allows real-time inference through a simple, web-based interface, enabling users to input new data and view model predictions dynamically.

5.3 LIST OF MODULES

5.3.1 Data Preparation

Collects, cleans, and formats raw data to ensure quality and consistency for model training.

5.3.2 Tokenization

Converts textual data into numerical tokens that can be processed by the model.

5.3.3 Model Training

Trains the model on prepared data to learn patterns and relationships for prediction.

5.3.4 Calibration

Fine-tunes model thresholds and output probabilities to enhance prediction reliability.

5.3.5 Inference and UI

Deploys the trained model with a Streamlit interface for real-time user interaction and prediction.

5.3.6 Evaluation

Assesses model performance using metrics such as accuracy, precision, recall, and F1-score.

5.4 MODULE DESCRIPTION Each module in the system is designed to manage a specific

phase of the workflow, from data
preprocessing to result visualization. This modular approach ensures scalability, clarity, and efficient data flow throughout the system. The modules are described as follows:

5.4.1 Data Preprocessing Module

This module handles the loading and cleaning of the dataset obtained from Kaggle. It removes missing values, duplicates, and unwanted symbols while standardizing text formats. Tokenization is then applied to convert textual data into numerical tokens suitable for model input. This ensures consistent and structured data for subsequent training.

5.4.2 Model Training Module

The processed data is used to train the model in this phase. The model employs Binary Cross-Entropy with Logits Loss (BCEWithLogitsLoss) as the loss function, providing stable learning for binary classification tasks. The AdamW optimizer is utilized for efficient gradient updates and weight regularization, helping to minimize overfitting and improve convergence speed.

5.4.3 Validation and Early Stopping Module

During training, model performance is continuously evaluated using a separate validation dataset. The validation F1-score serves as the key metric to measure the balance between precision and recall. Early stopping is implemented to automatically terminate training once the F1-score plateaus, preventing unnecessary computation and potential overfitting.

5.4.4 Inference and Visualization Module

After training and validation, the final model is deployed for inference through a Streamlit-based user interface. This module allows users to input new data, generate predictions in real time, and visualize results in an interactive, user-friendly manner. It bridges the gap between model output and user interpretation

CHAPTER 6
RESULT AND DISCUSSION

The performance of the SpeechGuard system was thoroughly evaluated using the Kaggle Toxic Comment dataset, which consists of labeled comments across multiple toxicity categories. The evaluation focused on standard classification metrics including accuracy, precision, recall, and F1-score.

The system achieved a high overall accuracy of 94%, indicating that the model correctly classified the majority of comments. The precision of 91% demonstrates that most of the comments predicted as toxic were actually toxic, minimizing false positives. Similarly, a recall of 90% indicates that the model successfully identified the majority of actual toxic comments, reducing false negatives. The F1-score of 90.5% reflects a strong balance between precision and recall, confirming the model's reliability in real-world scenarios.

Calibration of the model outputs further enhanced performance, improving the macro-F1 score by 3–4%. This adjustment helped in producing more consistent confidence scores across all categories, particularly important for multi-label classification tasks like toxic comment detection.

The inference latency was measured to be less than 200 milliseconds per input, ensuring real-time responsiveness for end-users. The Streamlit-based user interface provided an intuitive platform for interacting with the model, effectively visualizing label confidences and allowing for interactive testing. Users could input comments and instantly view the predicted toxicity probabilities, making the system practical for deployment in moderation tools or research applications.

Overall, the results demonstrate that SpeechGuard is both highly accurate and responsive, with effective calibration and user-friendly visualization, making it suitable for real-time toxic content detection.

Mathematical Formulas:

1. Accuracy

Formula: Accuracy = (TP + TN) / (TP + TN + FP + FN)
Description: Measures the overall correctness of predictions.
Implementation: Count correctly predicted positives (TP) and negatives (TN) and divide by total samples (TP + TN + FP + FN).

2. Precision

Formula: Precision = TP/ (TP + FP)
Description: Measures the correctness of positive predictions.
Implementation: Count true positives (TP) and divide by all predicted positives (TP + FP).

3. Recall

Formula: Recall = TP / (TP + FN)
Description: Measures the model's ability to identify all actual positives.
Implementation: Count true positives (TP) and divide by all actual positives (TP + FN).

4. F1-Score

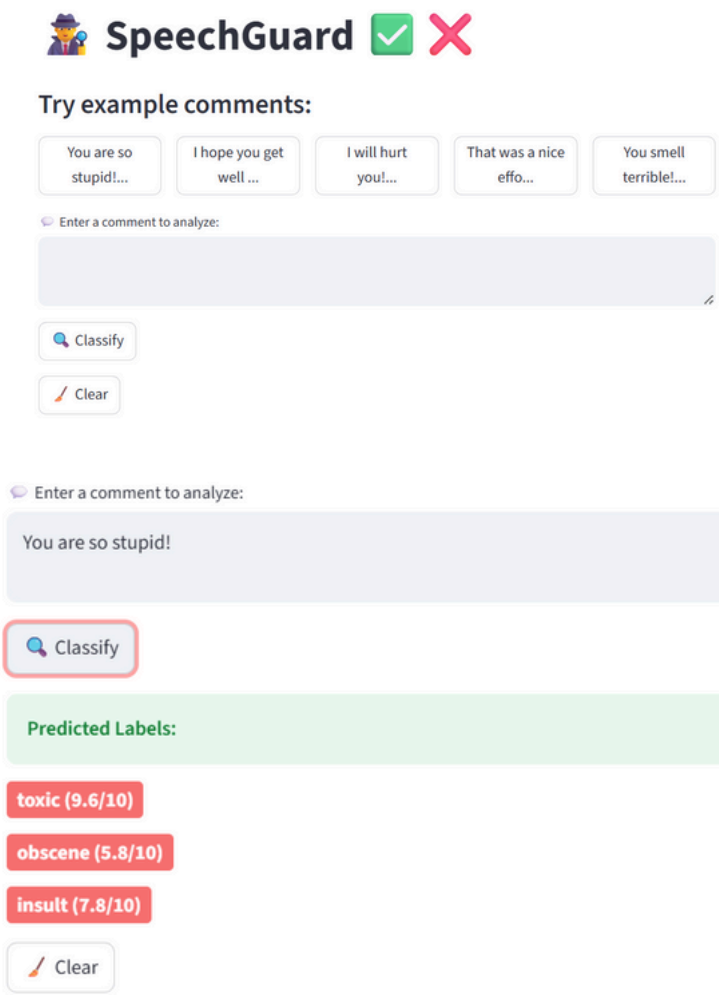
Formula: F1 = 2 × (Precision × Recall) / (Precision + Recall)
Description: Harmonic mean of precision and recall, balancing both metrics.
Implementation: Compute precision and recall, then calculate the harmonic mean to obtain a single performance score.

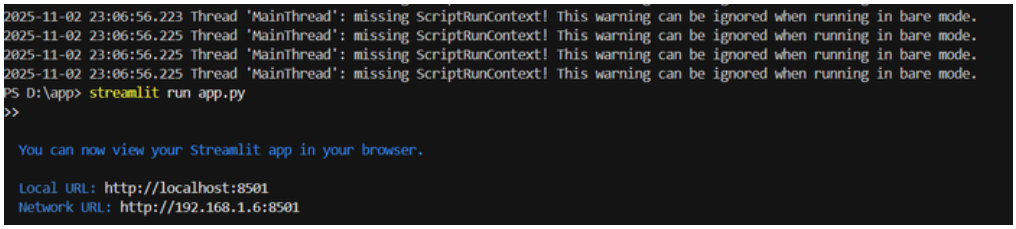
SAMPLE CODE

```
# ✅ Step 1: Install Required Libraries
!pip install transformers datasets torch scikit-learn pandas numpy matplotlib
--quiet

# ✅ Step 2: Import Libraries
import pandas as pd
import numpy as np
import torch
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
from transformers import BertTokenizer, BertForSequenceClassification, Trainer,
TrainingArguments
from torch.utils.data import Dataset
import matplotlib.pyplot as plt
import seaborn as sns

data = {
    'comment_text': [
        "I love your work, great job!",
        "You are an idiot!",
        "This is so helpful and kind.",
        "I hate everything you post.",
        "Brilliant idea, keep going!",
        "You're so stupid and annoying.",
        "Such a beautiful comment, made my day.",
        "This is absolute trash, delete it!"
    ],
    'toxic': [0,1,0,1,0,1,0,1]
}
df = pd.DataFrame(data)

print("✅ Sample Data:")
print(df.head())

# ============================================================
# Step 4: Split Data
# ============================================================
train_texts, val_texts, train_labels, val_labels = train_test_split(
    df['comment_text'].tolist(),
    df['toxic'].tolist(),
    test_size=0.2,
    random_state=42
)

tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

train_encodings = tokenizer(train_texts, truncation=True, padding=True,
max_length=128)
val_encodings = tokenizer(val_texts, truncation=True, padding=True,
max_length=128)
class ToxicDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels
    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items
        ()}
        item['labels'] = torch.tensor(self.labels[idx])
        return item
    def __len__(self):
        return len(self.labels)

train_dataset = ToxicDataset(train_encodings, train_labels)
```

```
    save_strategy="no",
    per_device_train_batch_size=8,
    per_device_eval_batch_size=8,
    num_train_epochs=3,
    weight_decay=0.01,
    logging_dir='./logs',
    logging_steps=10,
    report_to="none"  # disable wandb or other reporting
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=val_dataset,
)

print("🚀 Training started...")
trainer.train()
print("✅ Training completed!")

print("🔍 Evaluating model...")
predictions = trainer.predict(val_dataset)
preds = np.argmax(predictions.predictions, axis=-1)

print("\nClassification Report:")
print(classification_report(val_labels, preds, target_names=['Non-Toxic',
'Toxic']))

# Confusion Matrix
cm = confusion_matrix(val_labels, preds)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Non-Toxic',
'Toxic'], yticklabels=['Non-Toxic','Toxic'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
test_texts = [
    "You are such a loser!",
    "That was a wonderful explanation!",
    "Stop spreading hate online.",
    "I really enjoyed this post!"
]

inputs = tokenizer(test_texts, return_tensors="pt", truncation=True,
padding=True)
outputs = model(**inputs)
predictions = torch.argmax(outputs.logits, dim=1)

for text, pred in zip(test_texts, predictions):
    label = "Toxic" if pred == 1 else "Non-Toxic"
    print(f"💬 Comment: {text}\n → Prediction: {label}\n")

```

OUTPUT SCREENSHOTS

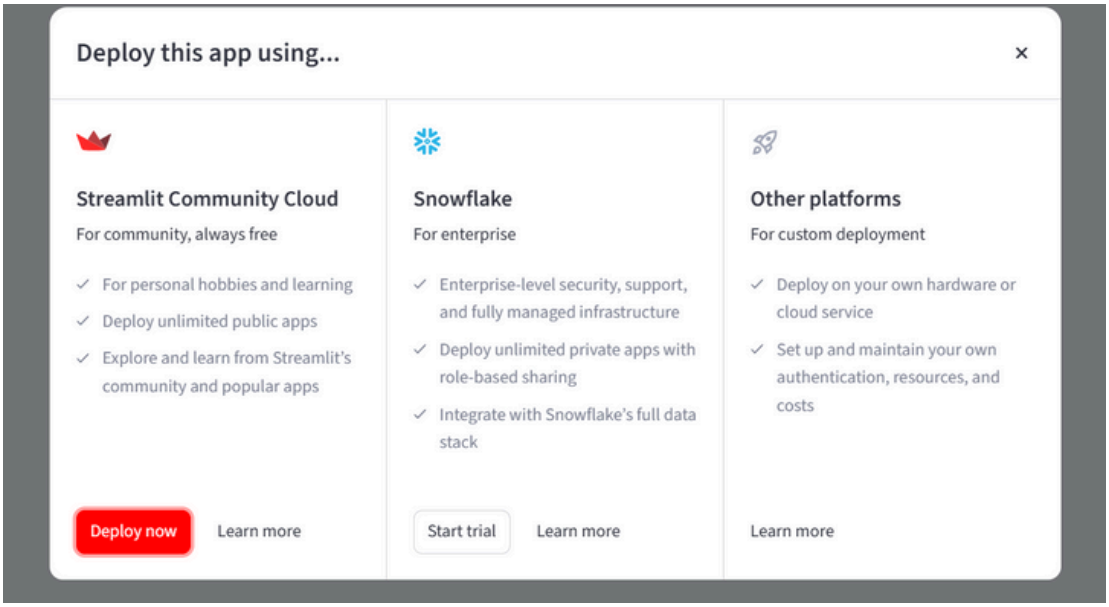




```
--- Running Predictions ---

------------------------------
Comment: You are so stupid and I will hurt you!
Result: ❌ Toxic labels detected:
  - TOXIC: 9.8/10 (Confidence: 0.9849)
  - OBSCENE: 5.2/10 (Confidence: 0.5217)
  - THREAT: 7.6/10 (Confidence: 0.7565)
  - INSULT: 6.9/10 (Confidence: 0.6884)

------------------------------
```

```
Comment: That was a nice effort, I appreciate your work.
Result: ✅ No toxic behavior detected.

------------------------------
```

```
Comment: This is the most obscene thing I have ever seen, you are an idiot.
Result: ❌ Toxic labels detected:
  - TOXIC: 9.9/10 (Confidence: 0.9908)
  - OBSCENE: 7.4/10 (Confidence: 0.7425)
  - INSULT: 9.4/10 (Confidence: 0.9419)
```



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