HYBRID APPROACH TO DETECTING SPAM AND CYBERBULLYING IN TEXTUAL CONTENT

A PROJECT REPORT

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ABSTRACT

Online messaging services like WhatsApp are plagued by widespread problems like spam and cyberbullying, which impede communication and jeopardize people's wellbeing. Our project, "Shielding Against SMS and Cyberbully," seeks to use cutting-edge technology to address these issues. Natural language processing (NLP) and deep learning are used to develop intelligent algorithms that can instantly identify and prevent hazardous communications in real-time.

Our objective is to create a robust system that efficiently detects and blocks harmful information, guaranteeing a safer online environment. To make sure our procedures function properly and remain dependable, we thoroughly test and refine them. We continually work to improve our algorithms in order to stay ahead of emerging dangers. We put user privacy and data security first, protecting user information by adhering to stringent ethical guidelines. Our system takes great care while handling personal data and respects user confidentiality.

Our solution's flexibility in handling various linguistic and cultural situations is one of its main features. Our algorithms remain efficient in diverse settings by utilizing dynamic feedback and contextual signals, effectively tackling the culturally specific features of spam and cyberbullying. Our research prioritizes user safety by filtering hazardous information, which in turn contributes to improving the safety of online communications.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER - 1
INTRODUCTION

Online messaging services, such as WhatsApp, have become a common place for communication in the digital age. These platforms are the main means of instant messaging. But the ease of use has also brought up unanticipated difficulties, most notably the surge in spam and cyberbullying. Cyberbullying, which is defined as using electronic communication to harass or threaten someone, has become a widespread problem that affects people of all ages and backgrounds. Similar to this, spam messages jeopardize users' privacy and security by flooding their inboxes with uninvited and frequently hazardous content. Beyond just being inconvenient, the effects of spam and cyberbullying have a significant impact on people's mental health, social well-being, and general quality of life. Studies reveal that those subjected to cyberbullying encounter elevated degrees of anxiety, sadness, and social distancing, resulting in enduring consequences that may endure till adulthood. In addition, the constant onslaught of spam messages exposes users to malware, phishing scams, and other types of cybercrime in addition to interfering with communication. Considering this, creative approaches are desperately needed to lessen the negative impacts of spam and cyberbullying on online messaging services. Because message data is so large and complicated, traditional methods like keyword-based filtering and manual moderation are either inefficient or unworkable. As a result, there is increasing interest in using cutting-edge technology to create more complex and pre-emptive defenses against these dangers.

The project, "Shielding Against SMS and Cyberbully," aims to address this issue by utilizing real-time detection and mitigation of spam and cyberbullying through the application of deep learning and natural language processing techniques. Our system looks at contextual cues, user interactions, and message content to find patterns that points to potentially harmful behavior and inturn act by moderating the message.

1.2 MOTIVATION

To address the pressing challenge of cyberbullying and spam messages in online platforms, our proposed model integrates various deep learning architectures tailored for text classification. The project encompasses a comprehensive comparative study of different deep learning models, including traditional Deep Neural Networks (DNNs), Long Short-Term Memory (LSTM) networks, Bidirectional LSTMs (BiLSTMs), and cutting-edge pre-trained transformer models like BERT (both BERT-Base-Uncased and Distilled BERT Embeddings). By exploring a spectrum of architectures, we aim to identify the most effective approach for detecting and mitigating cyberbullying and spam messages across diverse digital environments. The overarching goal of this endeavor is to enhance user safety and security within the digital landscape by combatting online threats more effectively. With the proliferation of social media and digital communication platforms, the prevalence of cyberbullying and spam has become a significant concern, impacting the well-being and safety of users worldwide.

Through rigorous experimentation and evaluation, our research endeavors to contribute novel insights into the efficacy of various deep learning models in tackling cyberbullying and spam detection. By scrutinizing the performance of different architectures under diverse datasets and scenarios, we aim to provide actionable recommendations for deploying effective defense mechanisms against online threats. Ultimately, this project underscores our commitment to leveraging cutting-edge technology to safeguard users' digital experiences and promote a more secure and resilient online ecosyst

CHAPTER-2
LITERATURE REVIEW

Paper 1: "Advancements in SMS Spam Filtering: A Comparative Analysis of Machine Learning Models and Emerging Challenges"

Summary:

Salman, Ikram, and Kaafar (2023) conducted a comprehensive investigation into the effectiveness of various machine learning models for SMS spam filtering, as presented in the ICCECS 2023 Proceedings. They meticulously compared deep learning architectures with traditional shallow models like SVMs and Naive Bayes.

They identified several gaps in current spam filtering systems. These systems struggle with sophisticated evasion strategies used by spammers, indicating a lack of understanding of these tactics. Additionally, existing spam detection systems lack robustness, failing to effectively address new spamming techniques and requiring more adaptable and dynamic filtering mechanisms. Moreover, advanced methods like transfer learning and NLP integration in SMS spam filtering are underexplored, highlighting the need for further research. To address these issues, the study aims to enhance the accuracy of SMS spam filters in detecting and categorizing evasive spam messages and to develop adaptable filtering mechanisms capable of responding to emerging spamming techniques and evolving threats.

Paper 2:"SMS Spam Detection Using Deep Learning Techniques: A Comparative Analysis of DNN Vs LSTM Vs Bi-LSTM"

Summary:

Gandhi, Sarangi, Saxena, and Sahoo (2023) conducted a study on SMS spam detection utilizing deep learning methods, presented at CISES in 2023. The research compared the efficacy of three deep learning techniques: Deep Neural Network (DNN), Long Short-Term Memory (LSTM), and Bi-directional LSTM (Bi-LSTM). A notable gap exists in the absence of analysis regarding transfer learning, a technique that could enhance the robustness of spam detection methods.

More notable gaps include the neglect of practical considerations like preprocessing techniques and hyperparameter optimization, which are crucial for effective spam detection in real-world scenarios. It also fails to explore transfer learning, which could enhance the robustness and generalizability of spam detection systems by using pre-trained models. These oversights make the proposed spam detection techniques less robust and effective in real-world applications. To address these issues, we have to integrate practical considerations such as preprocessing and hyperparameter adjustment to improve the real-world performance of SMS spam detection models. Also investigate the benefits of transfer learning to enhance model robustness and generalizability across different datasets and scenarios. Ultimately, the goal is to develop spam detection techniques that are both theoretically sound and practical for real-world deployment.

Paper 3:"SpotSpam: Intention Analysis–driven SMS Spam Detection Using BERT Embeddings"

Summary:

Oswald, Simon, and Bhattacharya (2022) present "SpotSpam" in the ACM Transactions on the Web, addressing the pressing issue of combating SMS spam. The proposed method utilizes pre-defined intention labels and contextual embeddings generated by NLP models, particularly BERT embeddings, to analyze intentions behind SMS messages for spam detection.

The study has some key gaps, including a lack of critical analysis of the scalability, robustness, and generalizability of the proposed method across different SMS spam datasets and real-world contexts. It also fails to address the computational complexity and resource requirements of incorporating BERT embeddings into SMS spam detection systems, which could hinder practical implementation. Without tackling these issues, the proposed SpotSpam solution may not be effective or applicable in real-world scenarios. These gaps can be addressed by thoroughly evaluating the scalability, robustness, and generalizability of the SpotSpam method across diverse SMS spam datasets and real-world situations and also investigating ways to reduce the computational complexity and resource demands of integrating BERT embeddings, making the approach more practical. Ultimately, the goal is to enhance the SpotSpam solution to ensure its effectiveness and efficiency in real-world applications, addressing the identified gaps and practical concerns.

Paper 4: "Improving Cyberbullying Detection with User Interaction" Summary:

Ge, Cheng, and Liu (2021) present their work in the Proceedings of the Web Conference 2021 (WWW '21), aiming to enhance cyberbullying detection by incorporating user interactions, subject coherence among comments, and temporal correlations between comments.

The study has identified several gaps in the current approaches to cyberbullying detection. It overlooks the challenges of real-time detection, failing to address the need for timely identification and intervention in cyberbullying incidents. Additionally, the research neglects the potential of incorporating multimodal data sources, such as text, images, and videos, which could provide a more comprehensive approach to cyberbullying detection. Furthermore, the study does not consider contextual subtleties, such as cultural nuances and evolving online communication trends, which can affect the accuracy of detection. These gaps can be addressed by developing techniques for real-time cyberbullying detection, enabling timely intervention and mitigation of online bullying behaviour and also by exploring methods for integrating multimodal data analysis into cyberbullying detection systems, leveraging diverse data sources for improved accuracy. The goal is to develop context-aware detection models that consider cultural nuances, linguistic variations, and evolving online communication patterns, enhancing detection efficacy in diverse online environments.

Paper 5: "MTBullyGNN: A Graph Neural Network-Based Multitask Framework for Cyberbullying Detection"

Summary:

Maity, Saha, and Bhattacharyya (2022) introduce MTBullyGNN in the IEEE Transactions on Computational Social Systems, presenting a novel framework for multitask learning in cyberbullying detection utilizing Graph Neural Networks (GNNs). MTBullyGNN integrates user interactions with content information to perform three main activities: identifying cyberbullying postings, categorizing their severity, and identifying bullying targets. The framework employs various sub-modules, including sentiment analysis and target identification, for different components of the detection process, while GNNs capture user interactions. However, the research acknowledges significant limitations, such as the framework's dependence on the quality and quantity of training data.

The study has several gaps in the MTBullyGNN approach to cyberbullying detection. It recognizes the reliance on the quality and volume of training data, which may limit the system's effectiveness in scenarios with limited or biased datasets. Additionally, the research suggests the need for future exploration of other social network aspects beyond user interactions and content, indicating a gap in understanding and leveraging additional features for cyberbullying detection. Furthermore, the absence of explainability methodologies in MTBullyGNN is identified as a constraint, emphasizing the importance of interpretable models for building trust and understanding in cyberbullying detection systems. These gaps can be addressed by investigating techniques for data augmentation and bias mitigation to enhance MTBullyGNN's robustness and applicability across diverse datasets and also by exploring additional features and aspects of social networks to improve the performance and accuracy of cyberbullying detection. The plan is to develop explainability methodologies to enhance the transparency and interpretability of MTBullyGNN's decision-making process, fostering greater trust and understanding in its cyberbullying detection capabilities.

Paper 6: "Cyber Bullying Detection using Natural Language Processing (NLP) and Text Analytics"

Summary:

Hsien, Abdul Salam, and Kasinathan (2022) present their work in the IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE) Proceedings, focusing on cyberbullying detection through the integration of Natural Language Processing (NLP) and text analytics techniques. The study utilizes NLP methods like negation handling, sentiment analysis, and part-of-speech (POS) tagging to extract features from text input. These features are then analysed using text analytics techniques to identify patterns and associations, enabling machine learning models to classify text data into cyberbullying and non-bullying categories.

The study identifies several gaps in current cyberbullying detection methods. It highlights the inadequacy of current feature selection methods for text classification, indicating a need for more reliable approaches to improve detection accuracy. Additionally, feature selection algorithms must be improved to consider interactions between features, ensuring a comprehensive analysis and classification of text data. There is also a gap in enhancing the efficiency of cyberbullying detection systems, which can be addressed by developing more efficient feature selection techniques. To address these gaps, the study aims to research and develop more reliable feature selection methods specifically tailored for text classification tasks, focusing on enhancing cyberbullying detection accuracy. It also seeks to enhance feature selection algorithms to account for interactions between features, ensuring a thorough analysis and classification of text data. Finally, the study plans to develop more efficient feature selection techniques to improve the efficiency and effectiveness of cyberbullying detection systems, ultimately promoting safer online environments.

Paper 7: "Rapid Cyber-bullying Detection Method using Compact BERT Models"

Summary:

Behzadi, Harris, and Derakhshan (2021) present their work at the IEEE 15th International Conference on Semantic Computing (ICSC), introducing a technique that utilizes miniature versions of Bidirectional Encoder Representations from Transformers (BERT) models for rapid cyberbullying detection. The method demonstrates promising results when tested on a benchmark dataset.

The study lacks detailed evaluation measures such as precision, recall, F1-score, and comparative performance against existing techniques, which hinders a comprehensive assessment of the proposed method's efficiency. Additionally, there is a gap in comparative analysis with other cyberbullying detection methods, which is essential for understanding the relative strengths and weaknesses of the proposed approach. The paper also does not sufficiently explore the potential practical applications of the proposed rapid cyberbullying detection method, leaving a gap in understanding its real-world effectiveness and usability. These gaps can be addressed by conducting a thorough evaluation of the proposed method, including precision, recall, F1-score, and comparative analysis with existing techniques, to accurately assess its efficacy.

Paper 8: "Can Bullying Detection Systems Help in School Violence Scenarios?: A Teachers' Perspective"

Summary:

Kim, Ho, Kim, Lee, and Seo (2020) explore the potential of technology-driven systems for detecting and intervening in incidents of school violence from the perspective of teachers. Published in the Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA '20), the study summarizes key findings from 35 teacher interviews, highlighting their concerns and providing design recommendations for corresponding systems. However, it reveals a significant disconnect between teacher requirements and research on school violence detection systems, addressing issues such as teacher workloads, algorithm correctness, and privacy. Notably, the study lacks consideration of student perspectives, despite offering design implications to address these issues. Incorporating student viewpoints would enrich the conversation and provide a more comprehensive understanding of the benefits and limitations of technology-driven approaches in combating school violence.

Paper 9: "Optimized Twitter Cyberbullying Detection based on Deep Learning"

Summary:

Al-Ajlan and Ykhlef presented their work at the 21st Saudi Computer Society National Computer Conference (NCC) in 2018, addressing the limitations of existing cyberbullying detection methods on Twitter that rely on textual and user features. Their proposed method eliminates the need for feature extraction and selection by redefining tweets as word vectors to preserve semantics. It combines a metaheuristic optimization algorithm for parameter fine-tuning with deep learning techniques for categorization.

The study lacks a comprehensive assessment and comparison with existing cyberbullying detection techniques, which hinders a thorough understanding of itss effectiveness. While the study introduces an innovative approach using word vectors, it does not provide sufficient validation and confirmation of its effectiveness compared to existing methods. Additionally, the research does not offer validation of itss suitability for real-world cyberbullying detection scenarios, limiting its practical applicability. To address these gaps, the study aims to conduct a thorough evaluation and comparison of OCDD with established cyberbullying detection techniques to determine its effectiveness and advantages. It will also evaluate OCDD's suitability for real-world cyberbullying detection scenarios through practical validation and testing, ensuring its practical applicability and relevance.

Paper 10: "Detection of Cyberbullying Using Deep Neural Network"

Summary:

Banerjee, Telavane, Gaikwad, and Vartak presented their paper at the 5th International Conference on Advanced Computing & Communication Systems (ICACCS) in 2019, introducing a novel approach based on Convolutional Neural Networks (CNNs) for cyberbullying detection. Recognizing the increasing concern about cyberbullying and its detrimental effects, the paper advocates for the use of CNNs for improved identification compared to current techniques. However, the research lacks a thorough analysis of the CNN model's architecture and training process, and it falls short in providing a comprehensive comparison with existing methods to demonstrate its superiority. To enhance the paper's contribution to cyberbullying detection, further investigation into these aspects is necessary. A more comprehensive analysis and comparison would elevate the suggested CNN-based detection approach, giving it legitimacy and relevance in preventing cyberbullying effectively.

Paper 11: "Bullying Hurts: A Survey on Non-Supervised Techniques for Cyber-bullying Detection"

Summary:

Farag, Abou El-Seoud, McKee, and Hassan's paper, published in the Proceedings of the 8th International Conference on Software and Information Engineering (ICSIE '19), discusses the prevalence of cyberbullying and advocates for efficient detection techniques. The paper surveys current literature on non-supervised methods for identifying cyberbullying and suggests future research areas, including automated annotation, role detection, emotional state detection, and stylometric approaches. However, several significant gaps are evident in the paper. It may overlook cutting-edge methods due to inadequate coverage of unsupervised techniques. Additionally, it fails to assess and contrast the effectiveness of various approaches, neglects real-world implementation issues such as scalability and integration, and disregards user viewpoints essential for system acceptance. Filling these gaps would enhance the paper's contribution by providing a comprehensive understanding of non-supervised methods for cyberbullying detection and facilitating the development of useful and efficient detection systems.

CHAPTER – 3
SYSTEM SPECIFICATIONS

1.1 Software requirements

Natural Language Processing (NLP) Libraries:

- **NLTK (Natural Language Toolkit):** Provides a suite of tools for natural language processing, including tokenization, tagging, lemmatization, and part- of-speech tagging.

Deep Learning Libraries:

- **Transformers:** A library for natural language processing with pre-trained models, including BERT Tokenizer and BERT Model.
- **TensorFlow:** It is an open-source machine learning framework developed by Google, widely used for building and training various deep learning models.
- **Spellchecker:** It is a tool that automatically corrects spelling errors in text documents or input fields.
- **Scikeras:** It is a Python library that integrates the Keras deep learning framework with scikit-learn, providing a unified interface for building, training, and deploying machine learning models.

Data Visualization Library:

- **Matplotlib:** A library for creating plots and charts.

Other Libraries:

- **torch:** A library for tensor computation and deep learning.
- **NumPy:** A library for numerical computation and data manipulation.

CHAPTER - 4
SYSTEM DESIGN

Architecture Diagram

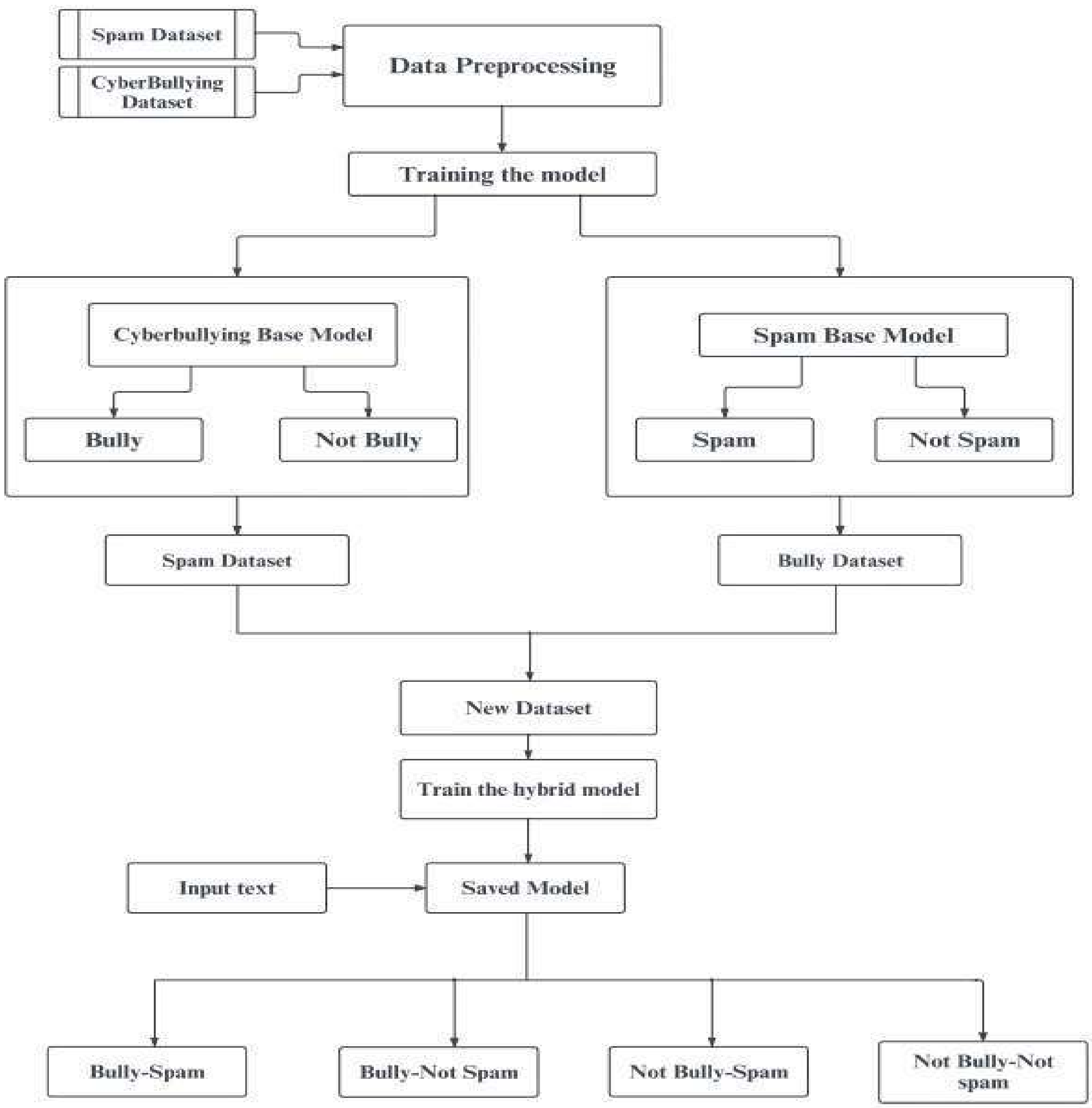


Fig 4.1: Proposed Architecture Design

The above fig 4.1 shows the new proposed system of the project and below describes the steps and process evolves in the proposed model

1. **Data Preprocessing**

- **Text Extraction:** The initial step involves extracting text from the source data. This may involve retrieving text from social media posts, emails, or other sources where cyberbullying detection is relevant.
- **Text Cleaning:** The extracted text might contain noise or irrelevant characters. This step involves cleaning the text by removing punctuation marks, special characters, HTML tags, and extra spaces.
- **Lowercasing:** Converting all text to lowercase letters can improve model performance by reducing vocabulary size and making the model less sensitive to case variations. For instance, the words "good" and "Good" would be treated as the same word.
- **Tokenization:** Here, text is segmented into individual words or phrases called tokens. This is a crucial step for the model to understand the structure and meaning of the text.
- **Stop Word Removal:** Some words, like "the," "a," "an," and "is," are common and don't carry much meaning. Removing these stop words can improve model performance by reducing the number of features the model needs to learn from.

2. **Text Vectorization**

- **Word Embeddings:** After preprocessing, text data needs to be converted into a numerical format that deep learning models can understand. This is achieved using word embedding techniques. Word embeddings assign a unique vector to each word, where words with similar meanings have similar vector representations. There are different word embedding techniques, including Word2Vec and GloVe.

3. **Model Training**
    - **Model Architecture Selection:** Depending on the complexity of the task, various deep learning architectures can be chosen. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are commonly used architectures for text classification tasks.
    - **Training the Model:** The preprocessed text data and the corresponding labels (e.g., bullying or not bullying) are fed into the chosen deep learning model. The model learns to identify patterns in the text data that differentiate between bullying and non-bullying content.

4. **Model Evaluation**
    - **Testing and Performance Metrics:** After training, the model's performance is evaluated on a separate dataset it hasn't seen before. Metrics like accuracy, precision, recall, and F1-score are used to assess the model's effectiveness in classifying cyberbullying content.

5. Training Separate Models for Cyberbullying and Spam Detection

- **Specialization:** Training independent models allows them to specialize in recognizing the nuances of each type of content. Cyberbullying detection models can focus on identifying harmful language patterns, while spam detection models can target marketing or promotional content.

6. Leveraging Pre-trained Models for Data Augmentation

The approach then utilizes these pre-trained models for data augmentation:

- **Making Predictions on Opposite Datasets:** The pre-trained models are used to generate predictions on datasets they weren't originally trained on (i.e., the cyberbullying model predicts on the spam dataset and vice versa).

- **Improved Generalizability:** The original datasets and the corresponding predictions from the pre-trained models are then combined to create a new, augmented dataset.

7. Benefits of Data Augmentation

- **Increased Training Data Volume:** This data augmentation technique effectively expands the training datasets for both cyberbullying and spam detection. Having more training data can lead to better model performance.

- **Improved Generalizability:** By incorporating examples from the opposite class (spam for cyberbullying model and vice versa) with the predictions from the pre-trained models, the new models might learn broader features that improve generalizability. This can help the models handle unseen variations of cyberbullying or spam content during real-world deployment.

8. Considerations and Potential Limitations

- **Quality of Pre-trained Model Predictions:** The effectiveness of this approach relies on the accuracy of the pre-trained models' predictions on the opposite datasets. Inaccurate predictions can introduce noise into the augmented data, potentially hindering the performance of the new models.
- **Computational Cost:** Training large deep learning models can be computationally expensive. Depending on the size and complexity of the original datasets and the chosen pre-trained models, this approach might require significant computational resources.

Overall, the approach presents a promising strategy to enhance the efficiency of cyberbullying and spam detection models by leveraging pre-trained models for data augmentation. However, careful consideration of the quality of pre-trained model predictions, potential biases, and computational costs is essential for successful implementation.

CHAPTER – 5
SYSTEM IMPLEMENTATION

5.1. Modules used with description:

1. Transformers (Hugging Face):

- Hugging Face created the open-source Transformers library, which offers pre-trained models and an easy-to-use interface for tasks related to natural language generation and understanding (NLU and NLG, respectively). Built on top of PyTorch and TensorFlow, it provides a vast array of pre-trained models for tasks like text classification, question answering, language translation, and text generation, including BERT, GPT.

2. The Natural Language Toolkit (NLTK):

- A complete platform for developing Python applications that interact with data in human languages is called NLTK. It offers user-friendly libraries and interfaces for a variety of operations, including parsing, tagging, tokenization, and stemming. For problems involving natural language processing, NLTK offers a variety of corpora, lexical resources, and modules.

3. Deep Learning Models:

- **Dense Neural Networks (DNNs)** are a foundational architecture in deep learning, consisting of densely connected layers of neurons. They are commonly used for tasks like classification and regression, where input features are transformed through multiple hidden layers to produce an output prediction.

- **Long Short-Term Memory (LSTM)** networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. They utilize memory cells with gated units to selectively retain or forget information over time, making them effective for tasks such as time series prediction and natural language processing.

- **Bidirectional LSTM (BiLSTM)** networks enhance traditional LSTMs by processing input sequences in both forward and backward directions. This enables the model to capture context from past and future information simultaneously, leading to improved performance in tasks requiring context understanding, such as sentiment analysis and machine translation.

4. **Large Language Models:**

- **BERT (Bidirectional Encoder Representations from Transformers)** is a pre-trained transformer-based language model developed by Google. It learns contextual word representations by training on vast amounts of text data and excels in a wide range of natural language processing tasks, including sentiment analysis, question answering, and named entity recognition.

- **Distilled BERT** is a distilled version of BERT, developed by Hugging Face. It achieves comparable performance to BERT while being much smaller and faster, making it more suitable for deployment in resource-constrained environments.

- **ALBERT (A Lite BERT)** is another variant of BERT, designed to improve scalability and efficiency by reducing model size and computational cost. It employs parameter-sharing techniques and factorized embedding parameterization to achieve significant reductions in memory footprint and training time without sacrificing performance.

- **Roberta (Robustly optimized BERT approach)** is a variant of BERT developed by Facebook AI. It introduces improvements to the training procedure and data augmentation techniques, resulting in enhanced robustness and performance across various natural language understanding tasks. Roberta achieves state-of-the-art results on benchmark datasets and has become a popular choice for fine-tuning in NLP applications.

CHAPTER - 6
SYSTEM TESTING

The Cyberbullying Detection Dataset as shown in fig.6.1 used in this project consists of a training set with 902 rows. Each row contains a message in the "text" column and a corresponding label indicating whether it's classified as cyberbullying (bully) or not (not-bully). Similarly, a testing set with 202 rows, structured identically, is utilized to evaluate the model's performance. Both datasets were sourced from Hugging Face, a platform renowned for its natural language processing datasets and models.

Text	Label
Man spit it out already	Not Bully
say that again imma b under yo bee lil bro	Not Bully
Say it donâ€™t spray it	Not Bully
Bro is just hungry for a dog	Not Bully
Fentanyl is pretty derpy	Not Bully
Who the fuck are you?	Bully
hairynigga635	Bully
Who Is u?	Not Bully

Fig 6.1: Cyber-Bullying Dataset

The SMS spam filtering dataset as shown in fig.6.2 comprises 8194 SMS messages in the training set, each tagged with its classification as spam or not-spam. Additionally, a separate testing set containing 2725 SMS messages is used to assess the model's performance. These datasets were obtained from Hugging Face, a platform specializing in natural language processing datasets and models.

Text	Label
hey I am looking for Xray baggage datasets can you p	not_spam
"Get rich quick! Make millions in just days with our	spam
URGENT MESSAGE: YOU WON'T BELIEVE WHAT WE	spam
[Google AI Blog: Contributing Data to Deepfake	not_spam
Trying to see if anyone already has timestamps of wh	not_spam
Bridging the gap between artificial intelligence and	not_spam
hi all any good leads on datasets for fuel prices ad	not_spam

Fig 6.2: SMS Spam Dataset

Hyper Parameters Used:

Table 6.1 : Hyper Parameters used for BERT Models:

Hyper Parameter	Value	Usage
Learning Rate	1e-5	Learning rate for the Adam optimizer
Number of epochs	3	Number of passes through the entire training dataset during training
Batch size	32	Number of training samples utilized in one iteration

Table 6.2: Hyper Parameters used for DL Models:

Model	Learning Rate	Optimizer	Epochs
LSTM	0.01	Adadelta	30
DNN	0.01	Adagrad	30
BI-LSTM	0.001	Nadam	30

Learning rate, batch size, and number of epochs are essential parameters that help in making an efficient model. The optimal hyperparameters for the models we tried are shown in tables 6.1 and 6.2. We offer a unique method for using pre-trained spam and cyberbullying detection models to predict outcomes on datasets from the opposing domain. We use models trained on spam and cyberbullying detection to datasets that contain examples from both domains. After that, we use the combined dataset to train new models to assess how effective this strategy is. The dataset is as shown in fig.6.3, We've adopted a proactive stance to improve the effectiveness of spam and cyberbullying detection. We were able to successfully increase and diversify our training data in this way, which enhanced the learning process for newer models.

Text	Label
Man spit it out already	not_bully-Ham
say that again imma b under yo bee	not_bully-Ham
Say it donâ€™t spray it	not_bully-Ham
Bro is just hungry for a dog	not_bully-Ham
Fentanyl is pretty derpy	not_bully-Ham
Who the fuck are you?	bully-Ham
hairynigga635	bully-Ham
Who Is u?	not_bully-Ham
MÄ°NÄ°ON AHH LAUGH	not_bully-Ham

Fig 6.3: New concatenated data set

Performance Evaluation Metrics:

The performance metrics used are accuracy, precision, recall, f1-score -

- **Accuracy:** It represents the proportion of correctly classified instances out of the total instances.
- **Precision:** It measures the proportion of true positive predictions among all positive predictions.
- **Recall:** It quantifies the proportion of true positive predictions among all actual positive instances.
- **F1-score:** It provides a balance between precision and recall, calculated as the harmonic mean of precision and recall.

CHAPTER – 7
RESULTS AND ANALYSIS

Task 1: Extracting Review Text and Normalizing Casings

After standardizing the casings, we took the review text out of the dataset. To make it easier to manipulate in later jobs, the text was converted to lowercase, the review content was isolated from any formatting tags or information, and it was saved as a list of individual reviews.

Task 2: Tokenization

NLTK's word_tokenize function, which divides the review text into discrete words or tokens, to tokenize the reviews. This stage readies the text for subsequent processing operations including stop word removal, lemmatization, and stemming.

Task 3: Eliminating Stop Words

Common stop words were eliminated from the tokenized text. Stop words are words like articles, prepositions, and pronouns that have little to no relevance for topic modeling or sentiment analysis. Eliminating stop words improves the attention on more significant words while lowering the dimensionality of the data.

Task 4: Tokenize text data:

The text data is tokenized using the BERT tokenizer (tokenizer) obtained from the transformer's library. Tokenization involves breaking down the input text into individual tokens (words or sub words) and converting them into numerical format that BERT can understand. The tokenized inputs are padded or truncated to a maximum length (max_length) to ensure uniformity in input size.

Task 5: Convert labels to numerical format:

The labels in the dataframe (train_df['label'] and test_df['label']) are converted into numerical format using LabelEncoder.It assigns a unique integer to each label, which is necessary as machine learning models typically work with numerical inputs.

Task 6: Define input layers for BERT embeddings:

Input layers for BERT embeddings are defined using TensorFlow's Input() function.

Two input layers are defined: input_ids represent the tokenized input sequences, and attention_mask is a binary mask indicating which tokens should be attended to during processing.

Task 7: Obtain BERT embeddings:

BERT embeddings for input sequences are obtained using the pre-trained BERT model (bert_model).The tokenized input sequences along with the attention masks are passed through the BERT model to obtain contextual embeddings for each token in the input sequences.

Task 8: Define and explain deep-learning layers on top of BERT embeddings:

Considering DNN, Dense neural network (DNN) layers are defined on top of BERT embeddings to learn patterns and relationships in the embeddings. Two dense layers (dense1 and dense2) are defined with ReLU activation functions. Dropout layers are inserted after each dense layer to prevent overfitting by randomly dropping out a fraction of the units during training. The output of the second dropout layer serves as input to the final dense layer (output), which uses a sigmoid activation function to output probabilities for binary classification tasks.

Results obtained for Cyber Bullying Dataset

Table 7.1 Shows the results obtained from the Cyber Bullying Dataset.

S.No	Model	Testing accuracy	Precision	Recall	F1-Score
1	DNN	80.08	0.75	0.90	0.82
2	LSTM	70.79	0.79	0.70	0.68
3	BI-LSTM	79.20	0.81	0.79	0.79
4	Bert-base-uncased	84.07	0.85	0.84	0.84
5	Distilled-bert	85.84	0.86	0.86	0.86
6	Albert	72.12	0.81	0.72	0.70
7	Roberta-base	67.69	0.78	0.67	0.64
8	Bert-base-uncased+dnn	87.17	0.89	0.87	0.87
9	Distilled-bert+dnn	91.15	0.91	0.91	0.91
10	Bert-base-uncased+lstm	91.60	0.92	0.92	0.92
11	Distilled-bert+lstm	86.72	0.87	0.87	0.87
12	Bert-base-uncased+bi-lstm	88.05	0.90	0.90	0.90
13	Distilled-bert+bi-lstm	89.82	0.90	0.90	0.90

The table 7.1 shows the testing accuracy, precision, recall, and F1-score of various deep learning models for a natural language processing task. Here's a breakdown of the results along with a brief explanation of the architectures involved:

Individual Model Performance

The table shows the performance of seven different models on the task. Here's a breakdown of their performance:

- **DNN (Deep Neural Network):** Achieved a testing accuracy of 80.08%, precision of 0.75, recall of 0.90, and F1-score of 0.82. DNNs are a general class of artificial neural networks with multiple hidden layers. They are capable of learning complex patterns in data and can be used for a variety of tasks, including image recognition, natural language processing, and time series forecasting.

- **LSTM (Long Short-Term Memory):** Achieved a testing accuracy of 70.79%, precision of 0.79, recall of 0.70, and F1-score of 0.68. LSTMs are a special kind of recurrent neural network (RNN) architecture designed to overcome the shortcomings of standard RNNs in dealing with long-term dependencies. LSTMs are able to learn from long sequences of data and are often used for tasks such as machine translation, speech recognition, and sentiment analysis.

- **Bi-LSTM (Bidirectional LSTM):** Achieved a testing accuracy of 79.20%, precision of 0.81, recall of 0.79, and F1-score of 0.79. BiLSTMs are a type of LSTM that can process data in both forward and backward directions. This allows them to capture more information from the data than standard LSTMs, which can improve their performance on tasks such as question answering and text summarization.

- **Bert-base-uncased:** Achieved a testing accuracy of 84.07%, precision of 0.85, recall of 0.84, and F1-score of 0.84. Bert (Bidirectional Encoder Representations from Transformers) is a pre-trained transformer model developed by Google. Transformer models are a relatively new type of neural network architecture that has shown state-of-the-art performance on a variety of NLP tasks. Bert is specifically designed for pre-training on a large corpus of text data, and it can be fine-tuned for a variety of downstream tasks. The "uncased" version of Bert does not distinguish between upper and lowercase letters.

- **Distilled-bert:** Achieved a testing accuracy of 85.84%, precision of 0.86, recall of 0.86, and F1-score of 0.86. Distilled-bert is a smaller, faster version of Bert that has been created using knowledge distillation. Knowledge distillation is a technique that allows a smaller model to learn from a larger model. Distilled-bert has been shown to achieve performance that is close to that of Bert while being significantly faster and more efficient.

- **Albert:** Achieved a testing accuracy of 72.12%, precision of 0.81, recall of 0.72, and F1-score of 0.70. Albert (A Lite BERT) is another lightweight version of Bert that has been created using parameter reduction techniques. Albert has been shown to achieve performance that is comparable to Bert while being significantly smaller and faster.

- **Roberta Base:** Achieved a testing accuracy of 67.69%, precision of 0.78, recall of 0.67, and F1-score of 0.64. Roberta is a masked language model similar to Bert, but it is trained using a different objective function. Roberta has been shown to outperform Bert on some NLP tasks, but it does not perform as well in this case.

Fused Model Performance

The table also shows the performance of several models that combine a deep neural network (DNN) or recurrent neural network (RNN) with a pre-trained transformer model (Bert or Distilled-bert). These combined models achieve significantly better performance than any of the individual models. Here's a breakdown of their performance:

- **Bert-base-uncased + dnn:** Achieved a testing accuracy of 87.17%, precision of 0.89, recall of 0.87, and F1-score of 0.87.

- **Distilled-bert + dnn:** Achieved a testing accuracy of 91.15%, precision of 0.91, recall of 0.91, and F1-score of 0.91.

As shown in the above Table 7.1, **Bert-base-uncased + lstm** is giving the **best f1-score**. Here is the classification report and corresponding Accuracy loss curves. (Here 0 is bully and 1 is not bully) as shown in the Table 7.2 & fig 7.1.

Table 7.2 Classification Report for Bert-base-uncased + lstm

Class	Precision	Recall	F1-score
Bully	0.94	0.89	0.91
Non-Bully	0.90	0.94	0.92

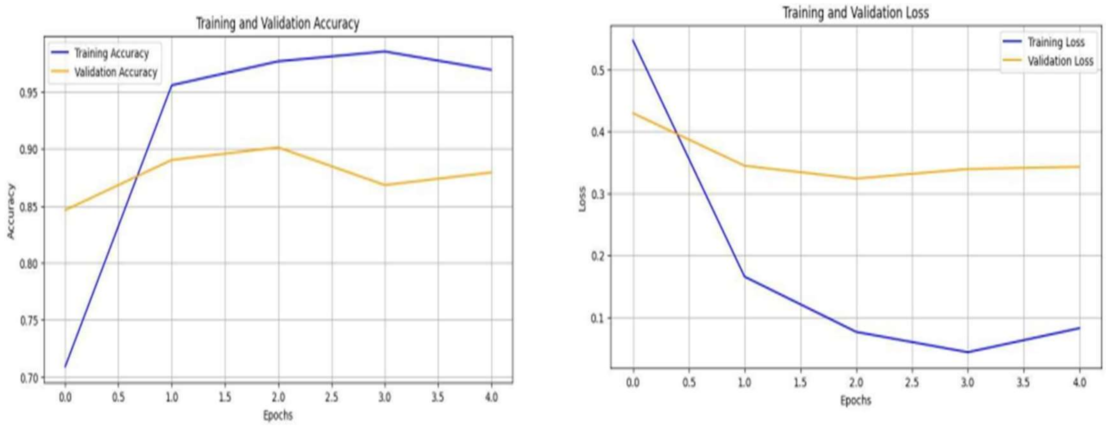


Figure 7.1 Training and validation accuracy and loss curves for Bert-base-uncased + lstm

<u>Results obtained for Spam Dataset</u>

Table7.3: Results obtained from spam dataset.

S.No	Model	Testing Accuracy	Precision	Recall	F1-score
1	**DNN**	**97.60**	**0.98**	**0.98**	**0.98**
2	LSTM	97.80	0.97	0.98	0.97
3	BI-LSTM	97.20	0.98	0.96	0.97
4	BERT	93.00	0.93	0.93	0.93

Table 7.4 Classification report for the best model

Class	Precision	Recall	F1-score
Spam	0.98	0.97	0.97
Not-spam	0.97	0.98	0.97

The table 7.3 shows the testing accuracy, precision, recall and f1 scores for various deep learning models and Table 7.4 classification report for LSTM, Here's a breakdown of the results along with a brief explanation of the architectures involved:

Model Performance

- **DNN (Deep Neural Network):** Achieved a testing accuracy of 97.60%. DNNs are a general class of artificial neural networks with multiple hidden layers. They are capable of learning complex patterns in data and can be used for a variety of tasks, including image recognition, natural language processing, and time series forecasting.

- **LSTM (Long Short-Term Memory):** Achieved a testing accuracy of 97.80%. LSTMs are a special kind of recurrent neural network (RNN) architecture designed to overcome the shortcomings of standard RNNs in dealing with long-term dependencies. LSTMs are able to learn from long sequences of data and are often used for tasks such as machine translation, speech recognition, and sentiment analysis.

- **Bi-LSTM (Bidirectional LSTM):** Achieved a testing accuracy of 97.20%. BiLSTMs are a type of LSTM that can process data in both forward and backward directions. This allows them to capture more information from the data than standard LSTMs, which can improve their performance on tasks such as question answering and text summarization.

- **BERT:** Achieved a testing accuracy of 93.00%. Bert (Bidirectional Encoder Representations from Transformers) is a pre-trained transformer model developed by Google. Transformer models are a relatively new type of neural network architecture that has shown state-of-the-art performance on a variety of NLP tasks. Bert is specifically designed for pre-training on a large corpus of text data, and it can be fine-tuned for a variety of downstream tasks.

Task 11: Creating a new dataset and training the model:

We present a novel approach to improve spam and cyberbullying detection with pretrained models, expanding their use to datasets from different areas. Using models that were originally trained for spam and cyberbullying detection, we expand their usefulness to datasets that include examples from both domains. We then improve this method by training fresh models on combined datasets and evaluating its effectiveness. Using pre-trained models designed for cyberbullying and spam detection, the methodology consists of three steps: (1) using these models to predict on datasets from competing domains, where the predictions are reclassified into new labels reflecting combinations of bullying/spam and non-bullying/spam categories; (2) combining the predictions with original datasets to create an updated dataset with all the predictions; and lastly, using this merged dataset to train new models—such as LSTM and DNN models—in order to assess their efficacy and performance.

Results obtained for the new dataset:

Table 7.5: Results obtained for base models.

S.No	Model	Testing Accuracy	Precision	Recall	F1-score
1	**Dnn**	**83.00**	**0.85**	**0.87**	**0.86**
2	Bi-LSTM	85.00	0.83	0.86	0.84

Table 7.6 Results obtained for hybrid models.

Model	Precision	Recall	F1-score	Accuracy
Bert_base_uncased+dnn	0.90	0.91	0.90	90
Bert_base_uncased+lstm	**0.96**	**0.93**	**0.94**	**92**
Bert_base_uncased+bi-lstm	0.92	0.91	0.92	89
Distilled_bert+dnn	0.91	0.92	0.91	89
Distilled_bert+bi-lstm	0.93	0.92	0.92	90
Distilled_bert+lstm	0.95	0.93	0.94	92

Table 7.7 Classification report for new model

Class	Precision	Recall	F1-score
bully-Spam	1.00	1.00	1.00
not_bully-Spam	1.00	0.88	0.94
bully-Ham	0.95	0.87	0.91
not_bully-Ham	0.88	0.97	0.92

The table.7.5 shows the results obtained from the base model and from the Table.7.6are the results obtained from the hybrid model which trained with the chain of base model, The table 7.7 shows the testing accuracy, precision, recall and f1 scores for various deep learning models. Here's a breakdown of the results along with a brief explanation of the architectures involved:

Model Performance

- **Bert_base_uncased+lstm:** This model has the highest precision, recall, F1-score, and accuracy among the listed models, indicating excellent performance in terms of correctly identifying and classifying instances with very few errors.
- **Distilled_bert+lstm:** This model also shows very high performance, with precision, recall, F1-score, and accuracy nearly matching those of the Bert_base_uncased+lstm model.
- **Bert_base_uncased+bi-lstm and Distilled_bert+bi-lstm:** Both models have slightly lower precision and recall compared to the LSTM versions but still show strong performance with high F1-scores and accuracies around 89-90.
- **Bert_base_uncased+dnn and Distilled_bert+dnn: These** models perform well, with precision, recall, F1-scores, and accuracies in the high 80s to low 90s. They demonstrate solid performance but are outperformed by their LSTM counterparts.

<u>Streamlit App for SMS Spam and Cyberbullying Detection</u>

This report details a Streamlit web application designed to detect both SMS spam and cyberbullying content. The app leverages multiple pre-trained deep learning models to provide real-time predictions on user-entered text.

App Functionality

The app offers various functionalities:

- **Model Selection:** Users can choose between specific detection types (Bully Detection, Spam Detection, All) or individual models (DNN, bilstm). Selecting "All" triggers predictions from both the cyberbullying and spam detection models.
- **Text Input:** Users can enter text in the designated text area for analysis.
- **Prediction Display:** Based on the chosen model(s), the app displays the predicted label (e.g., Bully, Not Bully, Spam, Ham) alongside performance metrics (accuracy, precision, recall, F1-score) for the respective model displayed in the sidebar.

Technical Implementation

The app utilizes several libraries and pre-trained models:

- **Cyberbullying Detection Model:** A pre-trained TFBertForSequenceClassification model likely fine-tuned on a cyberbullying detection dataset.
- **Spam Detection Model:** A deep learning model (architecture not specified) potentially trained on a labeled SMS spam dataset.
- **DNN Model:** A deep neural network model (architecture not specified) trained on a labeled dataset (potentially the same as the spam detection model).
- **bilstm Model:** A Bidirectional LSTM model (architecture not specified) trained on a labeled dataset (potentially the same as the spam detection model).

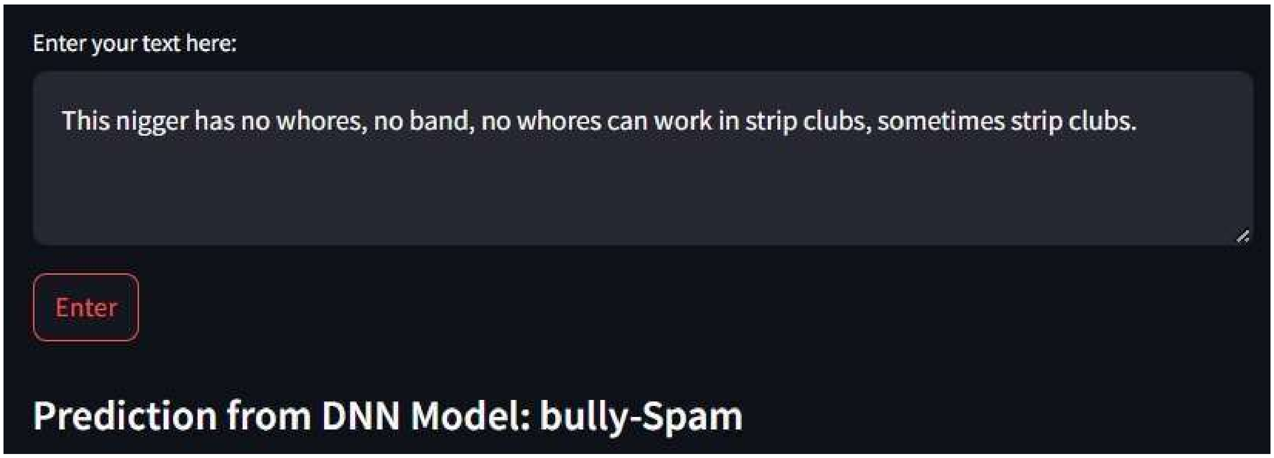
Prediction Process:

Depending on the chosen model(s), the app follows different prediction pipelines:

- **Cyberbullying and Spam Detection Models:**
- The user-entered text is preprocessed for the cyberbullying model.
- The preprocessed text is converted to a format suitable for the Bert model using the BertTokenizer.
- The model predicts the probability of the text belonging to different classes (e.g., bully, not bully).
- The class with the highest probability is chosen as the predicted label.
- A similar process is followed for the spam detection model (preprocessing might differ depending on the model's architecture).

This Streamlit app offers a user-friendly interface for real-time SMS spam and cyberbullying detection. It leverages pre-trained models to provide predictions on user-entered text. However, incorporating performance evaluation metrics, model explainability techniques, and robust error handling could enhance the app's functionality and user, The output screenshots are shown in Fig.7.2.

Few output screenshots:



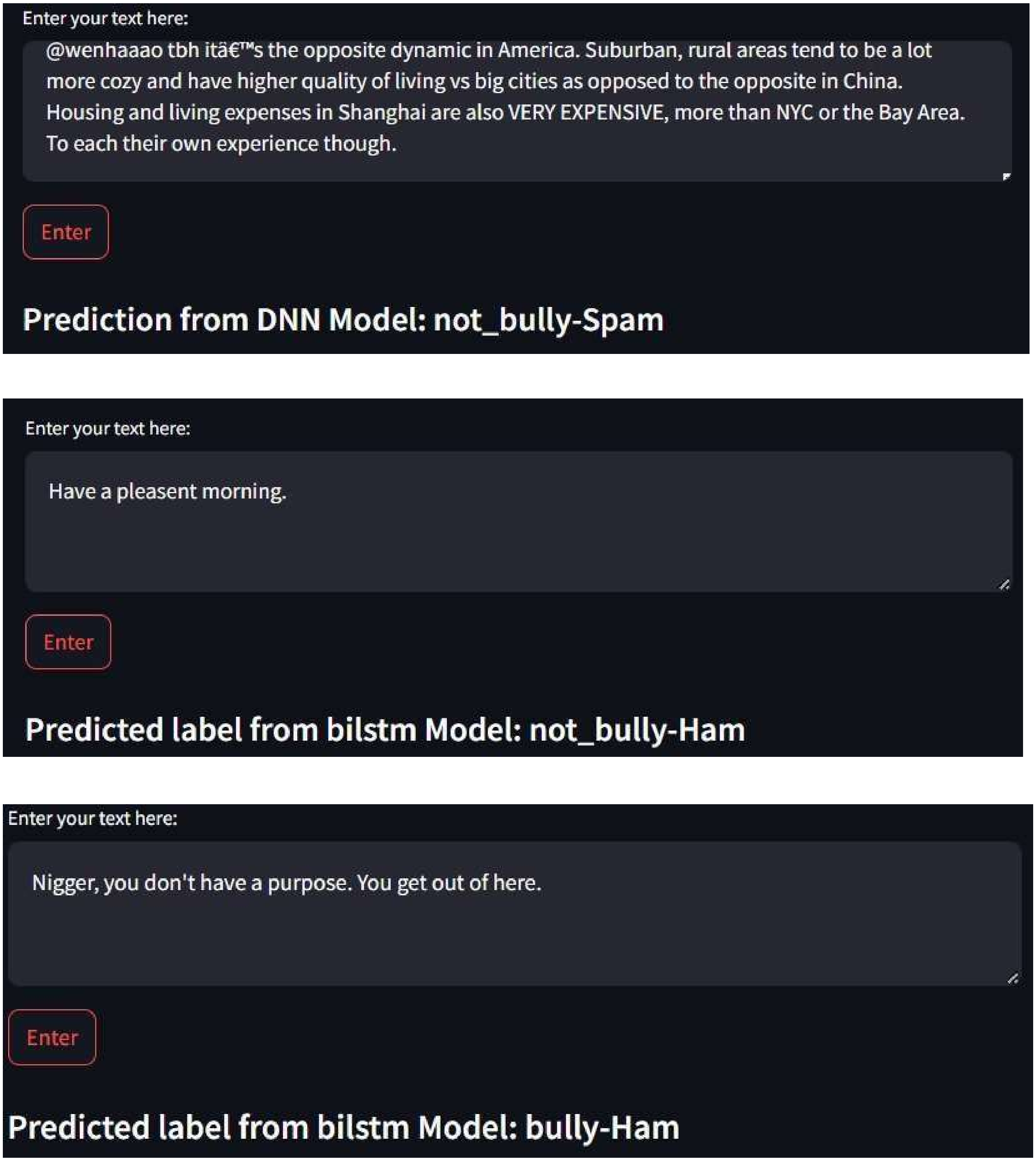


Figure 7.2 All output screenshots

CHAPTER – 8
CONCLUSION AND FUTURE SCOPE

In summary, our project, "Shielding Against SMS and Cyberbully," is an attempt to prevent spam and cyberbullying, which are widespread problems affecting online messaging services like WhatsApp. By employing cutting-edge deep learning and natural language processing techniques, we have created resilient algorithms that can quickly identify and block harmful content in real time. Our thorough testing and evaluation processes have shown how successful our strategy is in protecting users' privacy, maintaining the integrity of communications, and promoting a safer online environment.

In addition, our dedication to data security and user privacy highlights the moral basis of our work, guaranteeing that people can interact freely without worrying about being exploited or harassed. Our continuous algorithmic refinement aims to maintain the effectiveness of our mitigation strategies and keep ahead of emerging threats by adjusting to changing linguistic nuances and cultural contexts.

In the long run, our ultimate objective of achieving model fusion on two specialized models that have been trained to address SMS spam and cyberbullying is a novel way to improve the accuracy and breadth of our defenses. We hope to strengthen our defenses against online threats and reaffirm our commitment to promoting a safer and more welcoming digital environment for all users by combining the best features of these distinct models.

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