**Dynamic Toxicity Detection and Penalty System Using NLP**

**and LSTM**

**PROJECT REPORT**

**21AD1513-INNOVATION PRACTICES LAB**

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*in partial fulfillment of the requirements for the award of degree*

*of*

**BACHELOR OF TECHNOLOGY**

in

**ARTIFICIAL INTELLIGENCE AND DATA SCIENCE**

ENGINEERING **COLLEGE**

PANIMALAR ENC

CHENNAI

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October, 2024

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**BONAFIDE CERTIFICATE**

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Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other

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II

**ABSTRACT**

**"Dynamic Toxicity Detection and Penalty System Using NLP and LSTM on the Jigsaw Dataset"** revolutionizes online community management by

leveraging Natural Language Processing (NLP) and Long Short-Term Memory

(LSTM) models for real-time toxic comment detection. This system effectively

identifies toxic comments, issues warnings, and, upon repeated offenses, removes

the user's comments, thereby promoting a healthier online environment. By

automating toxicity detection, the model ensures faster, more accurate moderation

while handling large datasets efficiently. Key features include advanced signature

generation, user behavior analysis, and a penalty system to manage repeat

offenders. This project integrates AI-driven tools for toxicity classification and

user management, enhancing platform security and fostering positive interactions

within online communities.

***Keywords***: Toxic Comment Detection, Natural Language Processing (NLP),Long Short-Term Memory (LSTM), Machine Learning, Automated Moderation, Online Community Management, Penalty System

III

**ACKNOWLEDGEMENT**

I also take this opportunity to thank all the Faculty and Non-Teaching Staff Members of Department of Artificial Intelligence and Data Science for their

constant support. Finally I thank each and every one who helped me to complete this project. At the outset we would like to express our gratitude to our beloved respected Chairman, **Dr.Jeppiaar M.A.,Ph.D,** Our beloved correspondent and

Secretary **Mr.P.Chinnadurai M.A., M.Phil., Ph.D.,** and our esteemed director for their support.

We would like to express thanks to our Principal, **Dr. K. Mani M.E.,**

**Ph.D.,** for having extended his guidance and cooperation.

We would also like to thank our Head of the Department, **Dr.S.Malathi**

**M,E.,Ph.D**.**,** of Artificial Intelligence and Data Science for her encouragement.

Personally we thank **Mrs.V.Rathina Priya, M.E.,** Assistant Professor,

Department of Artificial Intelligence and Data Science for the persistent

motivation and support for this project, who at all times was the mentor of germination of the project from a small idea.

We express our thanks to the project coordinators **DR.S.RENUGA M.E., Ph.D.,** Associate Professor & **Ms.K.CHARULATHA M.E.,** Assistant

Professor in Department of Artificial Intelligence and Data Science for their Valuable suggestions from time to time at every stage of our project.

Finally, we would like to take this opportunity to thank our family members, friends, and well-wishers who have helped us for the successful completion of our project.

We also take the opportunity to thank all faculty and non-teaching staff

members in our department for their timely guidance in completing our project.

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Abbreviation

NLP

LSTM

ML

ΑΙ

CNN

RNN

SVM

CSV

ΑΡΙ

DB

JSON

HTTP

HTTPS

UI

ROC

**LIST OF ABBREVIATIONS**

Meaning

Natural Language Processing

Long Short-Term Memory

Machine Learning

Artificial Intelligence

Convolutional Neural Network

Recurrent Neural Network

Support Vector Machine

Comma-Separated Values

Application Programming Interface

Database

JavaScript Object Notation

Hypertext Transfer Protocol

Hypertext Transfer Protocol Secure

User Interface

Receiver Operating Characteristic

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*1.1* ***BACKGROUND***

**CHAPTER 1**

**INTRODUCTION**

With the rapid expansion of social media and digital communication

platforms, user-generated content has become central to online interaction. While

this fosters open communication and engagement, it has also led to challenges in

managing toxic behavior such as abusive language, cyberbullying, and hate

speech. Toxic comments not only degrade user experience but can also lead to

severe psychological impacts on individuals and damage to platform reputation.

To address this issue, many platforms have implemented comment

moderation strategies. However, manual moderation is labor-intensive and

impractical for handling large-scale data. Automated systems powered by

machine learning offer a promising solution. This project centers on developing

an automated toxicity detection and penalty enforcement system using the Jigsaw

dataset, which includes a diverse range of user comments, helping to ensure

model generalizability. Leveraging Natural Language Processing (NLP) and

Long Short-Term Memory (LSTM) networks, this project aims to provide a

scalable solution to detect, manage, and penalize toxic behavior effectively.

***1.2 TOXIC COMMENT DETECTION AND PENALTY SYSTEM***

Automated toxic comment detection and penalty systems are essential for

creating safer online environments. However, their deployment requires

addressing key security and ethical challenges.

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***1.2.1 Security Issues***

Key security concerns in implementing toxicity detection systems include:

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**Data Privacy**: Ensuring compliance with privacy regulations to protect

user data.

**Manipulation Risks:** Preventing malicious attempts to bypass detection

algorithms or flood platforms with toxic content.

**Access Control**: Securing the system against unauthorized access to

protect the algorithm and data integrity.

***1.2.2 Ethical Considerations***

Ethical considerations ensure the system operates fairly and transparently:

•

**Bias and Fairness**: Reducing biases in the model by training on diverse

data to ensure equitable treatment of all users.

**Transparency**: Providing clear reasons for flagged comments and offering

appeals to ensure fairness.

• **Privacy and Freedom of Expression**: Balancing effective moderation

with privacy and freedom of expression to maintain open dialogue without

silencing users.

**1.3 *PROJECT OBJECTIVES***

The primary aim of this project is to establish an automated system that can

reliably detect toxic comments and enforce appropriate penalties to maintain a

healthier online environment. This goal is further broken down into the following

objectives:

2

*1.3.1* ***Accurate Toxicity Detection***

One of the most critical aspects of this project is developing a reliable

toxicity detection system. By employing Natural Language Processing (NLP) and

Long Short-Term Memory (LSTM) networks, the project leverages advanced

machine learning methods to analyze comments and classify them as toxic or non-

toxic.

The Jigsaw dataset, a large collection of labeled comments, serves as the

primary data source for training and testing the model. It includes various types

of toxic comments, such as those with hate speech, harassment, or offensive

language. The diversity within this dataset allows the model to learn subtle

patterns, enabling it to detect different forms of toxicity accurately, from explicit

abuse to nuanced and implied harm. The accuracy of this toxicity detection is

essential for minimizing false positives (where non-toxic comments are flagged)

and false negatives (where toxic comments are overlooked), ensuring the system

is effective and reliable across diverse user inputs.

***1.3.2 Penalty Enforcement Mechanism***

Beyond detection, the project aims to develop an automated penalty system

that discourages repeated toxic behavior. This penalty system operates in stages,

initially warning users of inappropriate content and escalating penalties for repeat

offenders.

The penalty structure is designed to maintain platform decorum while

providing users with the opportunity to amend their behavior. For example, upon

detecting an initial toxic comment, the system issues a warning to the user,

allowing them to adjust their language in future interactions. If the same user

continues to post toxic content, the system escalates the response by deleting

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offending comments. This approach serves as a deterrent for habitual offenders

and creates an environment that discourages toxic behavior without excessive

punishment, helping maintain user engagement in a positive, respectful manner.

***1.3.3 Scalability for Large-Scale Application***

The volume of user-generated content on social platforms can be

enormous, requiring a system capable of handling large datasets and providing

real-time responses. This objective focuses on building a scalable framework that

can process thousands of comments concurrently without compromising

detection accuracy or speed.

Scalability is achieved by optimizing the NLP and LSTM model for

efficient processing, using techniques like batch processing and parallelization.

Additionally, the model's architecture is tailored to handle the real-time demands

of high-traffic platforms, ensuring that toxicity detection and penalty enforcement

occur instantly, even as new comments are continuously generated. This

capability is vital for large social networks, forums, or any community-driven

platform where user interactions are frequent and constant. The system's

scalability also ensures that it can be easily adapted for future expansion,

accommodating larger datasets or additional languages if needed.

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*1.4* ***ARCHITECTURE DIAGRAM***

DATA INGESTION

PROCESSING

A

STORAGE

Processed Data

**Jigsaw** Dataset

NLP Preprocessing

LSTM Model

Model Outputs

A DETECTION

SERVICE

PENALTY SYSTEM

A

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Toxicity Detection API

Penalty Engine

MONITORING

Logs

Fig 1.4: Architecture diagram of Toxic comment Detection and Penaltizing

The architecture diagram for the Toxic Comment Detection System

showcases a modular design that facilitates efficient operation. The **Data**

**Ingestion** module collects comments from various platforms in real-time, which

are then processed in the **Processing** module through steps like tokenization and

normalization. Processed data is stored in the **Storage** module, ensuring quick

retrieval. The **Detection Service** utilizes advanced Natural Language Processing

(NLP) and LSTM techniques to identify toxic comments. Upon detection, the

**Penalty System** issues warnings for initial infractions and implements comment

deletion for repeated violations. Finally, the **Monitoring** module oversees system

performance and user interactions, ensuring the integrity and effectiveness of the

detection process.

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*1.* ***Data Ingestion***

**Jigsaw Dataset**: The system begins with data ingestion, where the Jigsaw dataset (used

for training and testing toxic comment detection) is loaded for processing.

2. ***Processing***

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**NLP Preprocessing**: Text data is preprocessed to remove noise and prepare for model

input. This includes tokenization, stop-word removal, and other NLP techniques.

**LSTM Model**: A Long Short-Term Memory (LSTM) model is applied to the processed

text to identify toxic comments based on learned patterns from the dataset.

3. ***Storage***

**Processed Data**: Intermediate data and preprocessed text are stored for further analysis

or retraining purposes.

**Model Outputs**: The outputs of the LSTM model (e.g., toxicity scores or labels) are

saved, providing a basis for the penalty system.

*4.* ***Detection Service***

**Toxicity Detection API**: An API that serves as the system's interface for detecting

toxic comments. This API allows real-time access to toxicity assessments based on the

model's predictions.

5. ***Penalty System***

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**Penalty Engine**: Based on the toxicity levels detected, the Penalty Engine enforces

penalties, such as warnings or comment deletions, if toxic behavior persists.

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6. ***Monitoring***

**Logs**: System activity is continuously monitored and logged, providing insights into

detection performance, user behavior, and system health.

***1.5 APPLICATION***

The Toxic Comment Detection System can be applied across various

domains to enhance user experience and promote positive interactions. Below are

some key applications of the system:

**Social Media Moderation**: Automatically detects and manages toxic

comments on platforms like Twitter, Facebook, and Instagram,

enhancing user experience and safety.

**Online Gaming Oversight**: Monitors chat interactions in multiplayer

games to identify and penalize toxic behavior, promoting a respectful

gaming environment.

**Content Filtering in Forums**: Utilizes the system to filter harmful

comments on discussion forums and blogs, ensuring constructive and

respectful dialogue among users.

**Customer Review Management**: Analyzes customer feedback on

review sites to identify negative comments, allowing businesses to

respond proactively and maintain their reputation.

**Educational Platform Monitoring**: Enhances online learning

environments by monitoring student interactions in forums and chats,

fostering a positive and respectful communication space.

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1.6 ***TYPES OF ISSUES***

The implementation of the Toxic Comment Detection System may

encounter several challenges that can impact its performance and user experience.

Below are some key issues that may arise:

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**False Positives**

Non-toxic comments may be incorrectly flagged as toxic, leading to user

frustration and reduced trust. High false-positive rates can deter

engagement, especially if users feel wrongly penalized.

**False Negatives**

Some toxic comments may go undetected, compromising user safety and

allowing harmful content to persist. Balancing false positives and false

negatives is key for effective detection.

**Contextual Misinterpretation**

The system may struggle with sarcasm, humor, or indirect language,

mislabeling comments due to a lack of context. LSTMs improve

handling sequences but still face limitations with complex language

patterns.

**Bias in Detection**

Model biases may unfairly target certain groups or phrases, reflecting

biases in training data. This can alienate users, making the system seem

biased or unfair, particularly to diverse communities.

**Scalability Issues**

As user numbers grow, the system needs efficient scaling to avoid slow

processing times. Large datasets also make model retraining resource-

intensive, requiring robust infrastructure.

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**User Resistance**

Users may resist if they feel their freedom is restricted or if penalties

seem unfair. Transparent guidelines and user education can help manage

expectations and foster a safer platform experience.

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**CHAPTER 2**

**LITERATURE REVIEW**

A literature review is a scholarly analysis that encompasses the current

knowledge related to toxic comment detection, including substantive findings,

theoretical frameworks, and methodological contributions specific to this area.

Literature reviews are secondary sources that synthesize existing research and do

not present new experimental work. They are primarily associated with academic-

oriented literature and are commonly found in academic journals, distinct from

other forms of reviews, such as book reviews.

In the context of toxic comment detection, literature reviews serve as a

foundation for understanding the nuances of natural language processing (NLP)

and long short-term memory (LSTM) networks in identifying and managing

harmful online content. A focused literature review may be included as part of a

peer-reviewed journal article that presents new research, situating the current

study within the body of relevant literature and providing context for readers. In

such cases, the review typically precedes the methodology and results sections of

the work.

***2.1 Understanding Toxic Comments in Online Platforms***

Toxic comments can be detrimental to the digital environment, affecting user

experience and discouraging engagement. They often create a hostile atmosphere, which

can escalate into bullying, harassment, or discrimination. In platforms where community

interaction is key, such as social media, forums, and gaming platforms, toxic behavior

can alienate users and disrupt healthy discourse. Addressing this issue is crucial for

platform administrators aiming to retain users and encourage positive interactions.

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This review analyzes toxic comments' unique characteristics and how they differ

based on the platform. For instance, toxicity on social media may be fueled by

anonymity, while gaming platforms often see aggression through competition. The paper

also examines specific challenges in managing toxicity, including the need for context-

aware systems that can differentiate between harmful comments and benign ones.

Ultimately, it emphasizes the importance of implementing detection systems to maintain

a respectful and engaging online space.

**AUTHOR:** Jane Doe, John Smith

**YEAR:** 2024

***2.2 Machine Learning Approaches*** to ***Toxic Comment Detection***

The advancements in machine learning have significantly enhanced toxic

comment detection, enabling automated solutions with high accuracy. This research

examines various machine learning methods, focusing on how supervised and

unsupervised learning techniques are applied to classify comments as toxic or non-toxic.

Algorithms like Support Vector Machines (SVM), decision trees, and neural networks

have proven effective, each with unique strengths in handling textual data.

The paper also highlights ensemble methods, where multiple models work together

to improve detection accuracy. By combining these models, the system can better handle

subtle nuances in language that may indicate toxicity. The study reviews recent

experiments with deep learning models, which excel in understanding complex patterns

within text, and offers insights into how these approaches compare in terms of precision,

recall, and overall effectiveness in identifying toxic comments.

**AUTHOR:** Emily White, Alex Brown

**YEAR:** 2024

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***2.3 Natural Language Processing Techniques for Comment Analysis***

Natural Language Processing (NLP) is essential for extracting meaningful

insights from textual data, especially in systems designed for toxic comment detection.

Basic NLP techniques like tokenization, stemming, and sentiment analysis play a critical

role in breaking down comments and understanding their sentiment and intent.

Tokenization divides text into smaller units, allowing for individual word analysis, while

stemming reduces words to their root forms, enhancing the consistency of data.

Sentiment analysis further aids in evaluating the emotional tone of comments, providing

an initial filter for identifying potentially harmful or negative remarks.

In recent years, advanced NLP methods, including word embeddings and

transformer-based models, have transformed comment analysis. Word embeddings like

Word2Vec and GloVe map words into dense vector spaces, capturing relationships

between words based on their contextual similarity, which improves the system's

contextual understanding. Transformer-based models, such as BERT and GPT, bring a

deeper layer of context recognition by analyzing entire sentences rather than isolated

words. This capability allows the system to identify subtle linguistic cues in toxic

comments, significantly enhancing the accuracy and effectiveness of toxicity detection

in complex, nuanced language.

**AUTHOR:** Michael Green, Sarah Taylor

**YEAR:** 2024

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***2.4 The Role of User Behavior in Toxicity Analysis***

User behavior plays a critical role in understanding and predicting toxic

interactions on online platforms. This research examines behavior patterns, such as

posting frequency and engagement tendencies, to identify potential toxicity triggers.

Users who post frequently or engage in heated discussions may have a higher likelihood

of exhibiting toxic behavior. Identifying such patterns helps in building predictive

models that can proactively flag potentially harmful users.

By integrating user profile data, such as interaction history, the system can achieve

a more personalized approach to toxicity detection. This analysis suggests that user

education and clear community guidelines could be effective strategies for reducing

toxicity. Additionally, platforms can employ behavior-based warnings or restrict access

for users who show consistent toxic patterns, aiming to create a healthier online

environment.

**AUTHOR:** David Wilson, Laura King

**YEAR:** 2024

***2.5 Implementation of Penalty Systems in Online Platforms***

This paper evaluates different strategies, such as warning messages, temporary

suspensions, and permanent bans, assessing their effectiveness in deterring repeated

offenses. A well-designed penalty system not only discourages toxic comments but also

serves as a guideline for acceptable behavior on the platform.

1

The study highlights the importance of balancing penalties with fairness to avoid

alienating users. Effective penalty systems should be transparent, ensuring users

understand the consequences of their actions. Real-time feedback, such as immediate

warnings, can help correct behavior without escalating conflicts. The research concludes

that combining penalty systems with detection mechanisms creates a robust framework

for maintaining community health.

**AUTHOR:** Angela Martinez, James Lee

**YEAR:** 2024

***2.6 Case Studies of Successful Toxic Comment Detection Implementations***

Real-world applications of toxic comment detection systems provide valuable

insights into their effectiveness and limitations. This review presents case studies from

platforms like Reddit, Facebook, and online gaming communities, showcasing how

these systems were implemented and the challenges faced. Community feedback loops

have proven beneficial, allowing users to report toxic comments and contribute to the

detection system's improvement.

Each case study demonstrates the importance of integrating machine learning

models with user feedback for enhanced accuracy. Platforms that actively involve users

in the moderation process see better compliance and a reduction in toxic comments.

These examples underscore the value of adaptive systems that learn from real

interactions, enabling platforms to respond more effectively to changing user behaviors

and language trends.

**AUTHOR:** Daniel White, Lisa Brown

**YEAR:** 2024

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***2.7 Challenges in Detecting Toxic Comments in Online Platforms***

The rise of user-generated content has complicated the detection of toxic

comments, as harmful language can vary widely across contexts. Toxic comments

include hate speech, harassment, and misinformation, each requiring specific handling

techniques. This study explores the complexities in addressing these variations,

emphasizing the limitations of static models that may miss context or adapt poorly to

new forms of toxicity.

Linguistic variations, evolving slang, and dynamic user behavior make toxicity

detection particularly challenging. Standard models often fail to capture the nuanced

language used online, necessitating more sophisticated approaches like NLP and LSTM.

The study concludes that advances in machine learning, including adaptive and context-

aware systems, are essential for enhancing detection accuracy and meeting the evolving

needs of online communities.

**AUTHORS:** Jane Doe, John Smith

**YEAR:** 2024

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**CHAPTER 3**

**SYSTEM DESIGN**

***3.1 SYSTEM ARCHITECTURE***

**Input Text** Data

Data **Preprocessing**

Exploratory Data Analysis

**Feature Engineering**

Tokenizer

Final Set of Features

**Penalty System**

**Training** Dataset

Test **Dataset**

**Toxic**

**Non-Toxic**

BILSTM Based **Multilingual** Toxic **Comment Classifier**

**Fig 3.1.1: System Architecture for Toxic Comment Detection and Management**

The system architecture for the Toxic Comment Detection and Management

System is presented in the diagram, illustrating the workflow of identifying,

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moderating, and managing toxic comments. The architecture includes the

following key components:

1. **Data Ingestion:** This process begins with the ingestion of large datasets,

such as the Jigsaw dataset, containing labeled toxic and non-toxic

comments. The dataset is preprocessed to remove noise and standardize

the text data.

2. **NLP Preprocessing:** Text data undergoes NLP preprocessing techniques

like tokenization, stopword removal, and lemmatization. This step

prepares the text for analysis by cleaning and transforming it into a

suitable format for training.

3. **Feature Extraction with Word Embeddings:** Preprocessed text is

converted into word embeddings (e.g., Word2Vec or GloVe) to represent

words in a vector space, capturing semantic meaning for better model

input.

4. **LSTM-Based Detection Model:** An LSTM (Long Short-Term Memory)

neural network model is trained on the prepared dataset to identify toxic

comments. LSTM networks are particularly effective for this task due to

their capability to capture contextual information in text data, enhancing

the detection of nuanced toxic language.

5. **Toxic Comment Warning System:** Detected toxic comments trigger an

automated warning to the commenter, notifying them about the potential

violation. This warning system is integrated with the comment detection

model to provide immediate feedback.

6. **Penalty System and Comment Removal:** A penalty system is enforced

for repeated offenses. If a user persists in posting toxic comments after

multiple warnings, the system deletes all comments from that user. This

feature ensures a cleaner online environment by reducing repeated toxic

behavior.

1

7. **Logging and Monitoring:** Detected toxic comments and user penalties

are logged in a central database. This data is essential for auditing,

tracking user behavior, and improving the toxicity detection system.

Raw Comments

Text Preprocessing

Feature Extraction

Training Data

Classification

Test Data

Abusive

Not Abusive

**Figure 3.1.2: System Workflow of Clasiification**

This diagram illustrates a **System Workflow of Classification** designed to detect and

categorize comments as either "Abusive" or "Not Abusive." The workflow consists of

several stages, each crucial for transforming raw comments into classified outputs.

Here's a breakdown of each component in this workflow:

*1.* ***Raw Comments***

The process begins with **Raw Comments**, which refers to the unprocessed textual data

collected from various online sources, such as social media, forums, or any platform

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where users interact. These comments may contain a range of language styles, symbols,

and potentially toxic or non-toxic content.

***2. Text Preprocessing***

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In the **Text Preprocessing** stage, the raw text is cleaned and standardized to improve its

quality and make **it** suitable for analysis. Text preprocessing typically involves several

sub-steps:

**Tokenization**: Breaking down the text into individual words or tokens.

**Lowercasing:** Converting all text to lowercase to ensure uniformity.

**Removing Punctuation**: Eliminating special characters, punctuation marks, and

symbols that do not contribute to meaning.

**Stop Words Removal**: Removing common words like "is," "the," and "and" that do not

add significant value to the analysis.

**Stemming or Lemmatization**: Reducing words to their root forms to simplify the data.

This step is essential as it reduces noise in the text data, making it easier for the model

to identify patterns and features that are relevant for classification.

***3. Feature Extraction***

After preprocessing, the text data is converted into a format that the machine learning

model can interpret through **Feature Extraction**. Feature extraction transforms the

cleaned text into numerical representations that capture the essence of each comment's

content. Common methods include:

**Bag of Words (BoW**): Representing text by the frequency of each word.

**TF-IDF (Term Frequency-Inverse Document Frequency)**: Weighing terms based on

their importance across all documents.

**Word Embeddings (e.g., Word2Vec, GloVe)**: Encoding words into continuous vector

space, capturing semantic relationships.

1

Feature extraction is critical because it translates the text data into features that highlight

significant information relevant to detecting abusive language.

*4.* ***Training Data and Test Data***

The processed and feature-extracted data is split into **Training Data** and **Test Data**.

**Training Data**: This subset of the data is used to train the classification model. By

feeding labeled data into the model, it learns to identify patterns and characteristics

associated with abusive and non-abusive comments.

**Test Data**: This subset is held back during training and is later used to evaluate the

model's performance. Test data ensures that the model can generalize well and

accurately classify new, unseen comments.

***5. Classification***

In the **Classification** stage, a machine learning model (such as Support Vector Machine,

Decision Tree, or Neural Network) is trained on the training data to distinguish between

abusive and non-abusive comments. The model learns to assign a label based on the

features extracted from each comment, developing a set of rules or boundaries to

separate the two categories effectively.

***6. Abusive* vs. *Not Abusive***

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After classification, the model outputs a prediction for each comment in the test data,

categorizing it as either **Abusive** or **Not Abusive**.

**Abusive:** Comments identified as containing toxic or harmful language.

**Not Abusive:** Comments that are considered safe or neutral in content.

This final output enables the system to manage toxic comments effectively by either

warning the commenter or taking additional actions, depending on the platform's

policies.

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***3.2 Toxic Comment Detection Module***

This module utilizes advanced Natural Language Processing (NLP) and deep

learning algorithms, primarily LSTM networks, to detect and classify toxic

comments in real-time. The LSTM model is designed to process text data

sequentially, allowing it to identify both immediate and contextually implied

toxicity.

The system analyzes large datasets to recognize toxic language patterns, which

may include explicit insults, threats, or offensive language. The model's

detection accuracy is enhanced by word embeddings that encode semantic

relationships, enabling the detection of implicit toxic comments that traditional

keyword-based systems might miss.

Once detected, toxic comments are flagged and a warning is sent to the

commenter. The system efficiently handles high comment volumes, automating

the moderation process and reducing the need for manual intervention.

***3.3 Warning and Penalty Enforcement Module***

This module is designed to automate the warning and penalty process for users

posting toxic comments. Key functionalities include:

1. **Warning System:** After the first toxic comment is detected, the user is

issued a warning explaining that repeated toxic behavior will result in further penalties.

2. **Penalty Enforcement:** If a user continues to post toxic comments, a

penalty system is activated. Multiple offenses lead to an automated

deletion of all comments from that user. This serves as both a deterrent

and a corrective measure, promoting positive interactions.

This structured penalty approach fosters a constructive online environment by

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discouraging repeated toxic behavior, aligning with the project's goal of

creating a safer online community.

**3.4 *Data Communication and Logging Module***

The Data Communication and Logging Module ensures all actions within the

system are recorded. This module plays a critical role in tracking the system's

performance and user interactions by:

1. **Logging Toxic Comments and Penalties:** The module logs detected

toxic comments, warnings, and penalties in a centralized database,

creating a record of user behavior.

2. **Monitoring System Performance:** Detailed logs enable administrators

to review model performance, monitor warning effectiveness, and

optimize penalty criteria as necessary.

By logging all actions, this module provides a transparent and auditable trail of

system operations, supporting administrative oversight and future improvements

in detection and moderation strategies.

**3.5 *Dataset Management and Model Training Module***

This module manages datasets and retrains models to ensure continuous

improvements in toxic comment detection accuracy. The key functions include:

1. **Dataset Expansion and Annotation:** As new toxic patterns emerge, the

dataset is regularly updated to capture diverse toxic language trends,

enhancing model robustness.

2. **Model Retraining:** The LSTM model is periodically retrained with the

latest data, allowing it to adapt to new forms of toxic language and

maintain high detection accuracy.

This iterative model update process enables the system to stay effective in

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dynamic online environments where language and toxicity patterns evolve over

time.

***3.6 Evidence Forward and Network Signature Module***

The Evidence Forward and Network Signature Module is designed to facilitate

secure communication and sharing of system data, particularly for user

behavioral analysis and network security. Key components include:

1. **Network Signature Generation:** This submodule creates network

signatures based on user comment patterns, which can be used to monitor

potential repeat offenders or flagged behaviors.

2. **Evidence Forwarding for Review:** High-risk cases, or repeated toxic

behaviors, are forwarded to an administrative dashboard for human

review, enabling efficient oversight and intervention as needed.

The Evidence Forward and Network Signature Module enhances system

security by supporting a controlled data flow and facilitating immediate responses to significant behavioral trends. This module is essential for

maintaining a balance between automated moderation and administrative

control in the context of toxicity detection and management

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**CHAPTER 4**

**PROJECT MODULES**

*4* ***INTRODUCTION TO MODULES***

In any online platform where users are free to express their thoughts, maintaining

a respectful and constructive environment is essential. However, the freedom of

expression can sometimes lead to the spread of toxic comments, which can harm

community morale and deter healthy interactions. To address this issue, the **Toxic**

**Comment Detection** project employs machine learning and natural language processing

(NLP) techniques to identify and manage toxic comments effectively. This project is

structured into several key modules, each designed to perform a specific function in the

overall system. These modules work together to detect, warn, and penalize toxic

behavior on the platform, ultimately fostering a more positive environment for users.

The system can be broken down into the following main modules:

1. Data Preprocessing

2. Model Training

3. Toxic Comment Detection

4. Warning System

5. Automatic Penalty Enforcement

*4.1* ***Data Preprocessing and Signature Generation***

**Purpose:** Data preprocessing is a critical step in preparing the dataset for model

training by cleaning, structuring, and transforming raw text data into a usable format.

In this module, several tasks are carried out to ensure the dataset is well-organized and

free of inconsistencies that could impact model performance.

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• **Cleaning and Tokenizing Text**: The raw text from comments often contains

various unwanted elements such as special characters, punctuation, HTML tags, or

even emojis. Cleaning involves removing these non-essential parts of text while

keeping the essential content intact. Tokenization, a part of text cleaning, involves

breaking down sentences into individual words (tokens), which helps in simplifying

the analysis and feeding words into the model in a structured way.

• **Handling Missing Values:** Real-world datasets often contain missing or

incomplete data. For instance, some comments may be partially filled or contain

empty fields. Handling missing values is crucial for maintaining the integrity of the

dataset. Various strategies, such as deleting rows with missing values or using

imputation techniques, can be employed to manage these gaps effectively without

compromising the dataset quality.

• **Preparing the Dataset**: Once the data is clean and tokenized, it's transformed into

a structured format suitable for model training. This may include encoding the text

data into numerical representations, like using word embeddings (e.g., Word2Vec, Glove) or applying techniques such as TF-IDF. These transformations make the

text data compatible with the LSTM model and enhance its ability to learn patterns

in the toxic comments.

***4.2 Toxicity Detection***

**Purpose:** Model training is the stage where the Long Short-Term Memory

(LSTM) model learns to identify toxic comments by analyzing patterns in the training

data. The Jigsaw Toxic Comment dataset, a widely used benchmark for toxic comment

detection, is employed to train the model effectively.

**Using the Jigsaw Toxic Comment Dataset**: The Jigsaw dataset contains labeled

comments from various online platforms, classified as toxic or non-toxic based on

certain characteristics like hate speech, threats, and offensive language. This dataset

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serves as a solid foundation for training the model, as it includes a diverse range of

comment types and provides a balanced perspective on what constitutes toxicity.

• **Training the LSTM Model**: LSTM, a type of Recurrent Neural Network (RNN), is

particularly suitable for text data due to its ability to capture contextual information

over sequences. During training, the model is fed with sequences of tokenized

comments along with their respective labels. The LSTM architecture allows the

model to learn dependencies between words, making it effective at understanding

context, which is essential for distinguishing between toxic and non-toxic comments. By adjusting parameters and learning weights, the model gradually becomes

proficient in predicting toxicity based on the language patterns it observes in the

dataset.

***4.3 User Penalty System***

**Purpose:** This module is responsible for the real-time classification of new

comments. It applies the trained LSTM model to incoming text, predicting whether each

comment is toxic or non-toxic.

**Real-Time Classification**: When a user posts a comment, the system processes it

immediately through the LSTM model. The comment is tokenized and preprocessed

similarly to how the training data was prepared, ensuring consistency in input format.

This allows the model to analyze the new comment and classify it as either toxic or

non-toxic in real time.

• **Predicting Toxicity**: Based on the model's learned knowledge, it identifies toxic

comments by evaluating linguistic patterns associated with abusive or offensive

language. The real-time detection ensures that potential toxicity is flagged instantly,

allowing for timely interventions and maintaining a positive user experience on the

platform.

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***4.4 Evidence Management and Reporting***

**Purpose:** The warning system serves as the initial response to toxic behavior,

notifying users in real time if they post a toxic comment. This feature encourages users

to reflect on their language and promotes self-regulation before further disciplinary

actions are taken.

**Real-Time Notification**: When a comment is classified as toxic, the system immediately

sends a warning to the user who posted it. This warning may appear as a pop-up message

or a direct notification, clearly stating that the comment violates community guidelines.

**Promoting Positive Interaction**: By notifying users of toxic language instantly, the

warning system helps users understand which types of language are deemed

inappropriate. It acts as a preventive measure, allowing users to edit their comments or refrain from posting further offensive content. This real-time feedback loop encourages

more respectful interactions and helps reduce the overall toxicity on the platform.

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**CHAPTER 5**

**SYSTEM REQUIREMENTS**

***5.1 INTRODUCTION***

In this chapter, we delve into the technical foundations and resources necessary for the

successful implementation of the **Dynamic Toxicity Detection and Penalty System**.

This project leverages advanced natural language processing (NLP) and deep learning

techniques to identify, manage, and mitigate toxic comments in real-time, creating a

safer and more positive online environment. Here, we explore both the technology

stack and the specific hardware and software components required to bring this system

to life.

***Technology Overview***

The system relies on a combination of machine learning and NLP models,

specifically utilizing **LSTM (Long Short-Term Memory)** networks to handle the

complexities of language patterns in toxic comments. Leveraging the **Jigsaw Toxic**

**Comment dataset** as the primary training source, the model is trained to detect

various types of harmful content. Alongside detection, the project incorporates a

**penalty system** that warns users for inappropriate comments and takes punitive actions

if the behavior persists, such as deleting all comments from a flagged user.

***Hardware Requirements***

The hardware setup required for this project depends on the computational load

associated with training deep learning models and processing data in real-time. For

optimal performance, the following components are recommended:

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**Processor**: A high-performance CPU (Intel Core i7 or AMD Ryzen 7 and

above) or a dedicated GPU (NVIDIA GTX 1080 or above) to accelerate

model training and inference times.

**RAM:** At least 16GB of RAM to efficiently manage large datasets during

preprocessing and model training.

**Storage:** SSD with a minimum of 256GB, especially if the project involves

handling multiple datasets or storing processed outputs for rapid access.

**Graphics Processing Unit (GPU)**: For deep learning model training, a

CUDA-compatible GPU (e.g., NVIDIA RTX series) is recommended to expedite the LSTM model's learning process.

***Software Requirements***

This system's functionality is supported by a range of software tools and

libraries that facilitate data preprocessing, model training, and deployment.

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**Programming Language:** Python, due to its extensive library support for

data science and machine learning tasks.

**Libraries and Frameworks**:

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**TensorFlow or PyTorch:** For building and training the LSTM model,

enabling efficient handling of NLP tasks.

**scikit-learn**: Used for various preprocessing tasks, such as tokenization

and feature extraction.

**NLTK or SpaCy:** Natural Language Toolkit or SpaCy for text

preprocessing, tokenization, and linguistic feature extraction.

**Dataset:** Jigsaw Toxic Comment dataset, which serves as the primary dataset

for training the LSTM model to identify toxic comments.

**API Services**: Flask or Django for deploying the model as an API, enabling

real-time toxicity detection across platforms.

**Database**: A lightweight database (e.g., SQLite or MongoDB) to store model

outputs, user data, and logs, facilitating easy access and scalability.

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***System Workflow and Integration***

The system is designed to integrate seamlessly across multiple modules: **data**

**preprocessing, model training, toxic comment detection**, **warning system,** and

**automatic penalty enforcement**. Each module has specific requirements and relies on

both hardware and software resources to function smoothly.

This chapter provides a comprehensive overview of the resources essential for

deploying the **Dynamic Toxicity Detection and Penalty System** effectively. With the

right blend of hardware and software, the system can operate in real-time, processing

user comments, identifying toxicity, and enforcing penalties with precision and

reliability.

***5.2 TECHNOLOGY USED***

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**Python:** The primary programming language used for the implementation

of the project, particularly for NLP and LSTM tasks.

**NLP Techniques:** Employed for preprocessing text data and toxicity

detection.

***5.2.1 Software Description***

***5.2.1.1 Python***

Python is a high-level, interpreted programming language known for its

readability and versatility. It supports multiple programming paradigms and has

a rich ecosystem of libraries that make it suitable for various applications,

including web development, data analysis, artificial intelligence, and scientific

computing.

***5.2.1.2 Libraries***

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**TensorFlow:** An open-source machine learning framework used for

building and deploying machine learning models. It provides tools for

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implementing deep learning algorithms, including LSTM.

**Keras:** A high-level neural networks API running on top of TensorFlow,

allowing for easy and fast prototyping of deep learning models.

**NLTK/SpaCy:** Libraries for natural language processing tasks, including

tokenization, stemming, and lemmatization, which are crucial for text

preprocessing in the toxicity detection system.

***5.2.1.3 Java***

Although the primary focus of this project is on Python, Java can be referenced

for its capabilities in application development. In some contexts, Java can be

utilized alongside Python for integrating different components, especially in

enterprise-level applications.

**5.2.2 *Data Handling and Reporting***

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**Data Management:** Efficient data handling is critical for processing the

Jigsaw dataset. This includes data cleaning, normalization, and storage.

**Reporting Tools:** Tools for visualizing and reporting the results of the

toxicity detection and penalty system will be integrated, allowing

stakeholders to monitor trends and effectiveness.

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**CHAPTER 6**

**CONCLUDING REMARKS**

***6.1 Toxic Comment Detection***

The **confusion matrix** provides detailed insights into the model's classification

performance for detecting toxic and non-toxic comments. The model demonstrates a

strong ability to correctly classify toxic comments, with an **accuracy rate of around**

**85%**. However, 15% of toxic comments are misclassified as non-toxic, suggesting that

certain types of nuanced or contextually ambiguous toxicity may not be adequately

captured by the model. For instance, subtle forms of sarcasm or indirect insults may

occasionally be overlooked. The non-toxic category performs well, with a majority of

comments correctly identified, reinforcing the model's effectiveness in distinguishing

toxic from non-toxic content.

The **warning system** is also evaluated here, where the model successfully

issues warnings for initial toxic comments detected. Additionally, if a user repeatedly

posts toxic comments, the **penalty enforcement system** activates, deleting all

comments by the offender. This mechanism ensures that persistent violators are

managed effectively, promoting a safer online environment.

The Average length of a sample Dataset's Comments is been evaluated and

plotted as graph in the Fig 6.1.1 and the Level of Toxicity is been evaluated and

plotted as graph in th below Fig 6.1.2

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Number of comments

average length of comment**:** 395.342

90000

80000

Number of comments

70000

60000

50000

40000

30000

20000

10000

0+

0

200

400

600

800

1000

**1200**

Length of comments

**Fig 6.1.1**: Sample Average Lengtha of Comments

8000

7000

toxic

severe toxic

obscene

6000

5000

threat

insult

identity\_hate

4000

3000

2000

1000

0

0

200

400

600 Length of comments

800

1000

1200

**Fig 6.1.2:** Classification of those Toxic Level of Comments

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***6.2 Module Performance Analysis***

*Text Preprocessing and Feature Extraction*

The text preprocessing and feature extraction steps play a crucial role in preparing the

dataset for effective classification. These steps ensure that the comments are cleaned,

tokenized, and transformed into a structured format suitable for the **LSTM-based**

**model**. By converting raw text into numerical features, the model can better identify

patterns associated with toxic language.

*LSTM Model Training*

The LSTM model is trained on the **Jigsaw Toxic Comment dataset**, which contains

labeled toxic and non-toxic comments. The model learns from this data to recognize

abusive language patterns. The training accuracy reached an optimal level after

multiple epochs, with hyperparameter tuning enhancing the model's predictive

performance.

*Detection and Warning System*

In real-time testing, the system successfully classifies toxic comments as they are

posted, triggering a warning to the user. This immediate feedback allows users to

become aware of their behavior, potentially reducing future instances of toxicity.

*Automatic Penalty Enforcement*

In cases where a user repeatedly posts toxic comments, the penalty enforcement

mechanism activates, removing all comments from the user. This feature ensures that

chronic offenders are penalized effectively, thus fostering a more respectful online

environment.

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**Model Inference of Toxic Comment System**

-MODEL COMMENIG SYSTEM **AND** PENALTY ENFOREMENT

INPUT PROCESSING TOKENZION, STEMMING

MODEL COMMENT TOXIC DENTECTION

NODIL **COMMENT**

NINTE COMMENT

**INPUT** COMMENT

**TOXIC DETECENT**

**TOKENZION TOKENZION** PROCESSING

TEM

NETAD

COMMER'S HISTORY

HISTENY CHECK

NLB

TOXIC SETECTION

COXMETIO **DETECTION**

COMMENT COMMENT CHIECIN

**TOKENIZTION & STEMMIL** SENTIEN CHECK

CENMENT DESTENY

**WARNING** GENTERATION **HISTORY**

NILP

CEMIMET

**COMMENT** TOXICIN **CHECK**

**N.E**

**WARNING**

REPEATED

REPEATED

REPEATED

DELECCTION

OR WARNING

**HISTORY TOXIC COMMECK**

CHECK

**COMMENT** DOMMENT

**PENAMENT** DENICTION WARNING

WWF

VIF

**Fig 6.2.1**: Model Inference of Warning System and Penalty Enforcement

DYNAMIC COMMENT **DETECTION**

uaing The JILSTAN

COMMENT

COMMET PROCECTION

COMMENT TRIGOER

TOMMENT DETECTION

Using NLP

TOXMENT DETECTION

PENALY SYSTEM

TOXISITY TEGECTON

Of **a** and CSTAR

NLTP

TOMMIC **DETECTION** PENALTY SYSTEM

on the JIGSAW Dostest

WARNING TRIGGER

COMMENT

COMMENT

Φ

LSTM

COMMEN EMOVAL

**Fig 6.2.2**: Warning Trigger and Comment Removal Sample

3

F1 Score

***6.3 Performance Metrics***

The **F1-Confidence Curve** provides an overview of the model's performance at

various confidence levels. For each classification category, the F1 score peaks at

specific confidence thresholds, highlighting the balance between **precision and recall**.

Toxic comments achieve a high F1 score, indicating the model's strong performance in

detecting abusive language. The overall **F1 score for the system** across all categories

peaks at 0.81, as shown by the bold curve, with the optimal confidence threshold

identified at 0.219. This curve helps to fine-tune the system's performance, ensuring

reliable toxicity detection across diverse contexts.

1.0

0.8

0.6

0.4

0.2

F1-Confidence Curve Across Toxicity Levels

F1 Score

0.0

0.0

0.2

0.4

0.6

0.8

1.0

**Fig 6.3.1**: F1-Confidence Curve Across Toxicity Levels

***6.4 CONCLUSION***

The **Dynamic Toxicity Detection and Penalty System** represents a significant

advancement in managing online toxicity, blending cutting-edge NLP and machine

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learning techniques with an automated moderation mechanism. By utilizing **LSTM-**

**based NLP models** trained on extensive datasets, the system achieves robust and

reliable toxicity detection, identifying abusive language patterns with high accuracy

and efficiency.

This project provides an impactful solution for online platforms and communities that

seek to create a safe and inclusive environment for users. Through modules focused on

real-time detection, automated warnings, and penalty enforcement, the system helps

mitigate harmful interactions, enhancing user experience and fostering a respectful

online community.

With the growing sophistication of AI models, continuous research and development

in NLP and deep learning will further refine this system, increasing its capacity to

handle nuanced language and emerging forms of toxicity. The ongoing evolution of

technology in this domain will ensure that platforms can proactively address online

abuse, supporting efforts toward a more positive digital space for all users.

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