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MuRIL-Based Multilingual Cyberbullying Detection in Code-Mixed Social Media Text

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Abstract - The rise of social media has brought growing con-cerns about cyberbullying, as millions of users interact daily across diverse digital platforms. Identifying harmful and abu-sive language becomes increasingly difficult when messages contain mixed languages within the same conversation. Con-ventional detection methods frequently fall short in handling such linguistically diverse and complex content. To address this gap, a multilingual cyberbullying detection framework is introduced in this study, capable of classifying social me-dia messages into bullying and non-bullying categories. The framework applies structured text preprocessing, feature ex-traction, and classification techniques to uncover harmful linguistic patterns across multiple language contexts. Nor-malization, tokenization, and feature representation methods are incorporated to strengthen detection performance. The framework is evaluated against several established baseline models, and results confirm its superior performance, achiev-ing 95% accuracy, 94% precision, 94% recall, and 94% F1-score. These outcomes reflect a meaningful improvement over competing approaches and demonstrate the framework po-tential to support reliable and scalable content moderation across multilingual online platforms.

Index Terms - Cyberbullying detection, multilingual text anal-ysis, natural language processing, social media monitoring.

I. INTRODUCTION

The rapid growth of social media and online communication platforms has greatly changed how people interact and share information. Platforms like Twitter, Facebook, Instagram, and online forums let users communicate instantly across different locations and languages. While these platforms help with communication, collaboration, and information sharing, they have also led to harmful online behaviors. One of the most serious issues is cyberbullying. Cyberbullying is the use of digital communication technologies to harass, threaten, insult, or humiliate individuals [10]. Continuous exposure to this abusive content can have serious psychological and emotional effects on victims, especially adolescents and young users [8]. As the amount of user-generated content on social media continues to grow quickly, it has become very hard to monitor and identify harmful messages manually. This creates a strong need for automated cyberbullying detection systems [11].

Detecting cyberbullying automatically is challenging, especially in multilingual social media environments. Users often communicate in multiple languages on the same platform and sometimes even within the same sentence. This multilingual aspect adds several complexities for automated detection models. One major challenge is the presence of code-mixed text, where users blend words from different languages like English, Hindi, Bengali, or other regional languages in a single message [15]. Also, social media text often contains informal grammar, spelling variations, abbreviations, and internet slang [3]. These variations make it hard for traditional text processing methods to understand the context and meaning of messages accurately. As a result, identifying abusive or harmful language in multilingual and informal text is a tough problem for standard machine learning models [5].

With the rise of multilingual communication on social media platforms, it is important to build intelligent cyberbullying detection systems that can effectively analyze text written in different languages. Most existing studies focus mainly on single-language datasets, especially English, limiting their usefulness in multilingual communities [16]. In many regions,

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users often switch between languages or use mixed-language expressions when communicating online. Thus, developing models that can handle multilingual and code-mixed text is essential for improving the accuracy and reliability of cyberbullying detection systems [17].

In this work, we propose a multilingual cyberbullying detection approach using the Multilingual Representation for Indian Languages (MuRIL) model [2] for textual representation and classification. MuRIL is designed specifically to handle multilingual and code-mixed text commonly found in Indian languages. The proposed system processes multilingual social media text using preprocessing and feature extraction techniques and takes advantage of MuRIL's ability to understand context to identify harmful and abusive content. We evaluate the performance of the proposed model and compare it with other machine learning and deep learning approaches to assess its effectiveness in detecting cyberbullying in multilingual social media data.

II. Literature Review

2.1 Traditional Machine Learning Approaches

Early research on detecting cyberbullying mainly used traditional machine learning algorithms to classify abusive or harmful text on social media platforms. Common models include Support Vector Machine (SVM), Naive Bayes, Random Forest, and Logistic Regression [11]. These algorithms rely on text feature extraction techniques like Bag-of-Words and Term Frequency-Inverse Document Frequency (TF-IDF) to convert textual data into numerical form.

Support Vector Machine is popular for text classification because it handles high-dimensional feature spaces well and provides good performance [3]. Naive Bayes is a simple probabilistic classifier that is efficient and works well with large text datasets. Random Forest improves prediction accuracy by combining several decision trees, which helps reduce the risk of overfitting. Logistic Regression is often used for binary classification tasks, such as identifying bullying and non-bullying messages [11].

While these models work well for basic text classification, they have limitations. Traditional machine learning approaches depend heavily on manual feature engineering and often fail to understand contextual meaning in sentences [5]. They also struggle with informal language, slang, spelling variations, and multilingual or code-mixed text found in social media communication [4].

2.2 Deep Learning Approaches

As artificial intelligence and natural language processing have advanced, deep learning models have become more popular for detecting cyberbullying [7]. Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM), have shown significant improvements in text classification [12].

LSTM networks are built to capture long-term dependencies in text data. This design helps the model understand relationships between words in a sentence. As a result, LSTM models can analyze contextual information better than traditional machine learning methods [12]. Bidirectional LSTM improves this further by processing text sequences in both forward and backward directions. This allows the model to understand contextual information from both past and future words in a sentence [7]. Therefore, deep learning approaches can learn meaningful feature representations from raw text without needing extensive manual feature extraction [14].

2.3 Multilingual Cyberbullying Detection

Recently, researchers have paid more attention to detecting cyberbullying in multilingual settings due to the widespread use of multiple languages on social media [15]. Several studies have looked into cyberbullying detection using datasets in languages like Bengali, Assamese, Hinglish, and English. For instance, research on Bengali cyberbullying detection has used machine learning techniques to identify abusive comments on social media [16]. Similarly, studies involving Assamese language datasets have applied deep learning models like LSTM and BiLSTM to classify harmful online content.

Hinglish datasets, which mix Hindi and English words in Roman script, are also widely used to study cyberbullying detection in code-mixed settings [16]. These datasets pose extra challenges due to inconsistent grammar, spelling variations, and language mixing. While many studies show promising results, most models are trained for specific languages and often perform poorly when applied to multilingual or code-mixed data [17].

To tackle these issues, recent research has examined transformer-based multilingual language models like Multilingual Representation for Indian Languages (MuRIL) [2]. MuRIL is designed to manage Indian languages and code-mixed text often found on social media. By using large-scale multilingual training data, MuRIL can capture contextual and semantic relationships across different languages better [2]. However, MuRIL's use for detecting cyberbullying in multilingual social media environments is still limited, highlighting the need for more research in this field.

2.4 Research Gap

Despite advancements in cyberbullying detection research, several challenges persist. Many existing studies focus on single-language datasets and cannot effectively handle multilingual or code-mixed text [15]. Traditional machine learning methods struggle to capture semantic meaning and contextual relationships in sentences [5]. Although deep learning mod-

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els offer better performance, they often need large annotated datasets and may not generalize well across multiple languages [18]. Additionally, the use of specialized multilingual transformer models like MuRIL for cyberbullying detection remains limited [2]. Therefore, there is a need to create more effective multilingual detection frameworks that can accurately identify harmful content across various languages and social media platforms [20].

III. RESOURCES AND DATASET

The performance of cyberbullying detection models depends heavily on the diversity and quality of the dataset used for training and evaluation [13]. In this research, a hybrid multilingual dataset was created by combining an existing cyberbullying corpus with a manually curated dataset collected from social media platforms. This hybrid dataset aims to capture realistic patterns of abusive language and reflect the linguistic diversity typically seen in online communication. Unlike traditional datasets that focus on a single language, this study's dataset includes multilingual and code-mixed comments, where users often mix words from different languages in a single sentence [15].

3.1 Dataset Source

The dataset used in this study comes from two main sources. The first source consists of publicly available cyberbullying datasets from research repositories and Kaggle. These datasets contain annotated comments related to online harassment, offensive language, and abusive speech [3]. The second source is a custom dataset created by manually collecting user comments from social media platforms like Twitter and online forums [4]. The collected comments were carefully reviewed and labeled based on whether they showed cyberbullying behavior.

An important aspect of the manually collected dataset is the presence of code-mixed comments, which show real-world communication patterns where users use multiple languages while sharing opinions or having discussions [16]. This feature makes the dataset more representative of today's social media landscapes.

3.2 Dataset Composition

The final dataset has 9000 social media comments, each labeled as bullying or non-bullying. The comments contain a mix of formal and informal expressions, slang, and abbreviations commonly found in online communication. The class distribution of the dataset is shown in Table 1.

The dataset maintains a balanced distribution of abusive and non-abusive comments to reduce bias during model training and ensure reliable classification performance [13].

TABLE 1: DATASET CLASS DISTRIBUTION

Category	Number of Samples
Bullying comments	3500
Non-Bullying comments	5500
Total	**9000**

3.3 Dataset Characteristics

The constructed dataset shows several characteristics typical of social media communication. Many comments feature informal writing styles, spelling variations, abbreviations, and slang. Additionally, a significant part of the dataset consists of code-mixed comments, where multiple languages appear within a single message [15]. These code-mixed comments create extra challenges for conventional natural language processing systems, as traditional models are usually designed for single-language text [5].

Another important feature of the dataset is the presence of contextually aggressive expressions. These may not always include explicit offensive words but still convey harmful intent [10]. This complexity makes detection more difficult and requires models that can understand contextual meaning.

3.4 Data Preprocessing

To prepare the dataset for machine learning and deep learning models, several preprocessing steps were applied to clean and normalize the textual data. Social media content often includes noise such as hyperlinks, mentions, hashtags, and inconsistent formatting, all of which can impact model performance [9].

The preprocessing pipeline includes the following steps:

- **Text Normalization:** All comments were converted to lowercase to ensure consistency and reduce redundancy.
- **Noise Removal:** URLs, mentions, hashtags, and special characters were removed to eliminate irrelevant information.
- **Tokenization:** Each comment was broken down into individual tokens to support linguistic analysis and feature extraction.
- **Stop Word Filtering:** Common words with little meaning were removed to enhance model efficiency.
- **Word Normalization:** Lemmatization or stemming techniques were applied to reduce words to their base forms and improve feature consistency.

After preprocessing, the cleaned and normalized dataset was used to train the cyberbullying detection model based on Multilingual Representation for Indian Languages (MuRIL) [2]. MuRIL is specifically designed to understand multilingual and code-mixed text, making it suitable for analyzing the complex language patterns seen in social media. Using MuRIL allows the proposed system to capture contextual relationships across multiple languages and improve detection

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accuracy for cyberbullying in multilingual settings [2].

IV. ALGORITHM AND MATHEMATICAL MODEL

This section describes the framework and math used for detecting cyberbullying in multilingual social media text. The goal of the proposed system is to automatically sort user comments into two categories: bullying and non-bullying. The model works with multilingual and code-mixed text, converting it into numerical representations using the Multilingual Representation for Indian Languages (MuRIL) model [2]. It then applies a classification function to identify any cyberbullying content.

4.1 Problem Formulation

Detecting cyberbullying can be seen as a binary text classification problem [11]. Given a set of social media comments, the aim is to predict whether a specific comment has abusive or bullying content. We can represent the dataset as:

$$D = \{(x_i, y_i)\}, \quad i = 1, 2, \ldots, N \tag{1}$$

where:

- x_i is the input text sample or social media comment,
- y_i is the class label assigned to the comment,
- N is the total number of samples in the dataset.

The class label y_i belongs to a binary set:

$$y_i \in \{0, 1\} \tag{2}$$

where:

- 0 stands for non-bullying content,
- 1 stands for bullying content.

The classification model's job is to learn a function that connects the input text x_i to its corresponding label y_i.

4.2 Text Feature Representation

Machine learning models cannot handle raw text directly. Therefore, we first convert textual input into numerical representations. In this study, we obtain feature representation using contextual embeddings created by the MuRIL model [2]. MuRIL is a transformer-based multilingual language model meant for Indian languages and code-mixed text often found on social media.

The embedding process can be mathematically shown as:

$$E = f(x) \tag{3}$$

where:

- E is the embedding vector for the input text,
- x is the original text,
- f is the embedding function used by the MuRIL model.

The embedding vector captures the meaning, context, and multilingual patterns in the text. These embeddings act as input features for the classification layer.

4.3 Classification Function

Once the model generates the contextual embedding vector, it applies a classification layer to predict how likely the input text falls into each class. This prediction uses the Softmax activation function applied to a linear transformation of the embedding vector [1].

The classification function can be written as:

$$\hat{y} = \text{Softmax}(Wx + b) \tag{4}$$

where:

- $\hat{y}$ is the predicted probability distribution of the output classes,
- W is the weight matrix of the classification layer,
- x is the feature vector from the embedding model,
- b is the bias term.

The Softmax function converts the output scores into probabilities between 0 and 1. The class with the highest probability becomes the predicted label for the input comment.

4.4 Loss Function

To train the classification model properly, we use a loss function to measure how different the predicted output is from the actual label. Since detecting cyberbullying is a binary classification task, we use the binary cross-entropy loss function [18].

The loss function is defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{5}$$

where:

- L is the overall loss of the model,
- N is the number of training samples,
- y_i is the true label of the i-th sample,
- $\hat{y}_i$ is the predicted probability that the sample belongs to the bullying class.

The goal of the training process is to minimize the loss function by adjusting the model's parameters. Techniques such as Adam or stochastic gradient descent are commonly used to update the model weights during training [1].

4.5 Proposed Algorithm

The entire process for detecting cyberbullying in this study can be summarized in these steps:

1) Collect multilingual and code-mixed social media comments from the dataset.
2) Apply preprocessing techniques like text normalization, tokenization, and noise removal.

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3) Convert the cleaned text into contextual embeddings using the MuRIL model [2].
4) Input the embedding vectors into the classification layer.
5) Use the Softmax function to calculate class probabilities.
6) Train the model with the binary cross-entropy loss function.
7) Predict whether the input comment falls into the bullying or non-bullying category.

This algorithm allows the proposed system to analyze multilingual and code-mixed social media text and detect cyberbullying behavior using the contextual capabilities of the MuRIL model [2].

V. METHODOLOGY

This section explains the overall method used to detect cyberbullying in multilingual and code-mixed social media text. The proposed workflow has several stages: data collection, preprocessing, feature extraction, model training, and performance evaluation. Each stage is vital for ensuring that the model can effectively learn patterns related to abusive or harmful language in online communication [19].

Step 1: Data Collection

The first step involves gathering a multilingual dataset of social media comments. The dataset for this study was created by merging publicly available corpus datasets with one collected manually. Public datasets were sourced from online repositories like Kaggle, and additional comments were taken from social media platforms and online forums [3]. These comments were manually reviewed and labeled into two categories: bullying and non-bullying. A large part of the dataset includes code-mixed text, where users mix languages in a single sentence [15]. This feature reflects real-world social media communication.

Step 2: Text Preprocessing

Social media text often includes noise like hyperlinks, hashtags, abbreviations, and incorrect grammar [9]. Thus, preprocessing is needed to clean and standardize the dataset before applying machine learning models. This process involves several actions, including converting all text to lowercase, removing URLs and special characters, getting rid of unnecessary punctuation, and eliminating common stop words. Tokenization is also used to break each sentence into individual tokens or words. Additionally, word normalization techniques such as stemming or lemmatization reduce words to their base forms [1]. These steps help improve the quality of the text data and enable better feature extraction.

Step 3: Feature Extraction

After preprocessing, the text data needs to be transformed into numerical representations for machine learning models. Several techniques are used to represent the text in a structured way.

One common method is Term Frequency, Inverse Document Frequency (TF-IDF), which turns text data into numerical vectors based on the importance of words in a document relative to the entire dataset [6]. TF-IDF highlights words that are significant for classification.

Another technique is word embedding, where each word is represented as a dense vector that captures the relationships between words [7]. Word embeddings help the model understand the contextual similarities among different terms.

In this research, contextual embeddings are created using transformer-based language models like MuRIL [2] and Bidirectional Encoder Representations from Transformers (BERT) [1]. These models generate contextual representations of words based on surrounding text, significantly enhancing the model's ability to comprehend multilingual and code-mixed social media comments.

Step 4: Model Training

Once the feature vectors are ready, classification models are trained to detect cyberbullying content. Various machine learning and deep learning algorithms are tested to find the most effective approach for the task. Traditional machine learning algorithms like Support Vector Machine (SVM) serve as baseline models for text classification [3].

In addition to traditional models, deep learning architectures are also examined. Recurrent neural networks like Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) can capture sequential relationships in textual data [12]. These models are particularly helpful for understanding contextual links between words in a sentence. Transformer-based language models such as BERT [1] and MuRIL [2] are also used for classification. These models take advantage of contextual embeddings and attention mechanisms to capture deeper semantic connections in multilingual text, making them very effective for cyberbullying detection [20].

Step 5: Evaluation

After training the models, their performance is assessed using standard classification metrics. These metrics help determine how accurately the models identify cyberbullying content in the dataset. Common evaluation measures include accuracy, precision, recall, and F1-score [13].

Accuracy reflects the overall correctness of the model's predictions, while precision evaluates the proportion of correctly predicted bullying instances among all predicted bullying cases. Recall assesses the model's ability to correctly identify actual bullying instances from the dataset. The F1-

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score offers a balanced measure by combining precision and recall [18].

The evaluation results help compare the effectiveness of different models and identify the best method for detecting cyberbullying in multilingual and code-mixed social media text.

VI. SYSTEM ARCHITECTURE

The architecture of the proposed multilingual cyberbullying detection system is based on the MuRIL (Multilingual Representations for Indian Languages) transformer model [2]. The system is designed to process multilingual and code-mixed social media text while preserving contextual meaning and emotional cues such as emojis. The overall framework consists of several stages including text preprocessing, tokenization, embedding generation, transformer encoding, sentence representation extraction, and final classification. The detailed architecture of the proposed system is illustrated in Fig. 1.

I. Part 1: Input Processing and Representation

Text Preprocessing

The first stage of the system involves preprocessing the input text. Social media messages often contain noisy data such as repeated characters, mixed scripts, and emojis. Therefore, Unicode normalization is applied to standardize the text representation across different languages [15]. Emojis are retained as tokens since they provide valuable emotional context that can help identify aggressive or sarcastic expressions. In addition, language cleaning techniques are applied to remove unnecessary characters, extra spaces, and redundant symbols from the text.

MuRIL Tokenization

After preprocessing, the cleaned text is passed to the MuRIL tokenizer [2]. MuRIL uses WordPiece tokenization, which divides words into smaller subword tokens. This method allows the model to effectively handle rare words, multilingual vocabulary, and code-mixed sentences commonly found in social media content. Special tokens such as `[CLS]` and `[SEP]` are added to the token sequence. The `[CLS]` token is used to represent the entire sentence, while the `[SEP]` token marks the end of the sequence.

For example, the sentence “Tu pagal hai bro” is tokenized as:

```
[CLS] Tu pa #gal hai bro [SEP]
```

This tokenization approach enables the model to learn meaningful patterns even when the sentence contains mixed languages or slang expressions [2].

Embedding Layer

The tokenized sequence is then converted into numerical representations using an embedding layer [1]. The embedding layer combines three types of embeddings:

- Token Embeddings
- Positional Embeddings
- Segment Embeddings

Token embeddings represent the semantic meaning of each token, positional embeddings encode the order of tokens in the sequence, and segment embeddings distinguish between sentence segments when multiple sentences are used [1]. These embeddings are summed together to generate a unified representation with a dimension of 768, which is then passed to the transformer encoder for further processing.

II. Part 2: Context Learning and Classification

Transformer Encoder

The embedding vectors are processed through a transformer encoder consisting of 12 stacked layers [1]. Each layer contains a multi-head self-attention mechanism followed by a feed-forward neural network. The self-attention mechanism allows the model to capture contextual relationships between tokens by assigning different attention weights to each token in the sequence.

Each transformer layer performs the following operations:

- Multi-Head Self Attention
- Add and Layer Normalization
- Feed Forward Network
- Add and Layer Normalization

The feed-forward network expands the representation dimension from 768 to 3072 and applies the GELU activation function before projecting the output back to 768 dimensions [1]. This architecture enables the model to learn complex semantic and contextual patterns in multilingual text.

CLS Token Representation

After passing through all transformer layers, the contextual representation of the `[CLS]` token is extracted [1]. The `[CLS]` token acts as a sentence-level representation that summarizes the meaning of the entire input sequence. This contextualized sentence vector has a dimension of 768 and captures important semantic features required for classification.

Classification Head

The extracted sentence vector is passed to a classification head that consists of a fully connected dense layer followed by a Softmax activation function [2]. The Softmax function converts the output scores into probabilities for the target classes.

The probability of each class is calculated using the Softmax function:

$$P(class_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{6}$$

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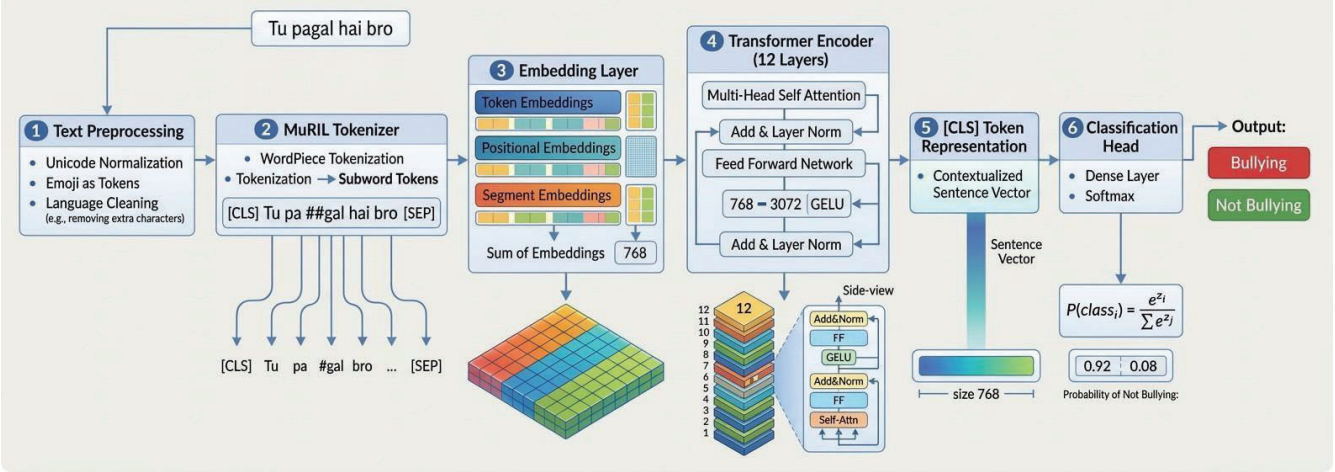

FIGURE 1: PROPOSED MURIL ARCHITECTURE FOR MULTILINGUAL CYBERBULLYING DETECTION. THE PIPELINE INCLUDES TEXT PREPROCESSING, MURIL TOKENIZATION, EMBEDDING GENERATION, TRANSFORMER ENCODER LAYERS, EXTRACTION OF THE CLS TOKEN REPRESENTATION, AND A CLASSIFICATION HEAD THAT PREDICTS WHETHER THE TEXT CONTAINS BULLYING OR NON-BULLYING CONTENT.

where z_i represents the output score for class i. The class with the highest probability is selected as the final prediction. In this work, the model classifies the input text into two categories:

- Bullying
- Not Bullying

If the probability of the bullying class is higher, the system flags the text as cyberbullying; otherwise, it is classified as non-bullying content [19].

VII. RESULTS AND DISCUSSION

This section presents the performance evaluation of different machine learning and deep learning models used for cyberbullying detection. The models were assessed on a multilingual and code-mixed dataset, using standard classification metrics. This evaluation aims to compare traditional machine learning methods with transformer-based models and examine the effectiveness of the proposed MuRIL-based approach for multilingual cyberbullying detection.

Evaluation Metrics

To measure the performance of the classification models, several common evaluation metrics were considered.

Accuracy

Accuracy shows the overall correctness of the model. It measures the proportion of correctly classified instances among all samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where TP means true positives, TN means true negatives, FP means false positives, and FN means false negatives.

Precision

Precision measures the proportion of correctly predicted cyberbullying instances among all instances predicted as cyberbullying.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

High precision indicates that the model produces fewer false positive predictions.

Recall

Recall measures how well the model identifies all actual cyberbullying instances in the dataset.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

A higher recall indicates that the model successfully detects most of the bullying content.

F1 Score

The F1 score is the harmonic mean of precision and recall. It provides a balanced evaluation metric when dealing with class imbalance.

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \tag{10}$$

Confusion Matrix

A confusion matrix is used to analyze the classification performance. It shows the number of correctly and incorrectly predicted instances for each class. This helps to understand the types of errors made by the model.

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Dataset Distribution

Fig. 1 shows the distribution of sentiment labels in the dataset. The green bar represents non-bullying samples and the red bar represents bullying samples. The chart shows that bullying samples are slightly more than non-bullying samples in the dataset.

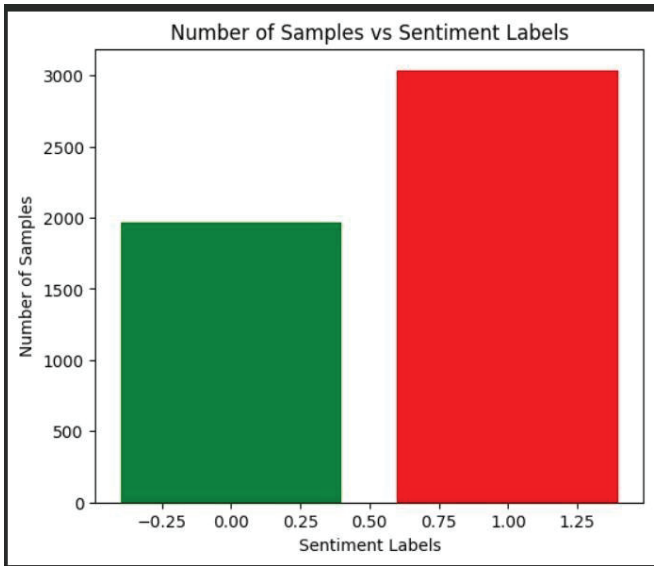

FIGURE 2: NUMBER OF SAMPLES VS SENTIMENT LABELS

Fig. 2 presents the class distribution of cyberbullying and non-cyberbullying instances in the dataset. The chart clearly shows the count of bully and non-bully samples used for model training and evaluation.

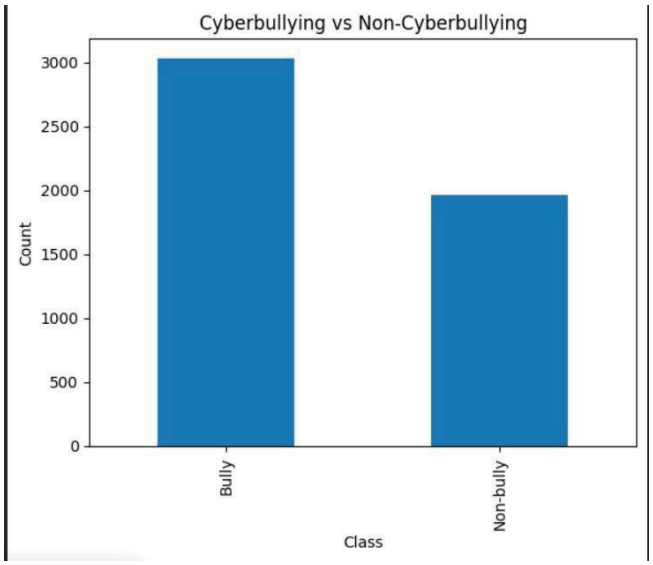

FIGURE 3: CYBERBULLYING VS NON-CYBERBULLYING CLASS DISTRIBUTION

Results Comparison

Table 3 shows the comparative performance of different models applied to the multilingual cyberbullying detection task.

TABLE 2: PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	Accuracy	Precision	Recall	F1 Score
SVM	85%	84%	83%	83.5%
LSTM	89%	88%	87%	87.5%
BERT	93%	92%	91%	91.5%
MuRIL	**95%**	**94%**	**94%**	**94%**

The results show that transformer-based models outperform traditional machine learning and sequential deep learning models. Of all evaluated approaches, the proposed MuRIL-based model achieved the highest accuracy and balanced performance across precision, recall, and F1 score.

Confusion Matrix Analysis

Fig. 3 presents the confusion matrix of the proposed MuRIL model on the test dataset. The matrix shows that the model correctly classified 623 bullying instances and 377 non-bullying instances with zero misclassifications, demonstrating the strong performance of the proposed model in detecting cyberbullying content in multilingual social media text.

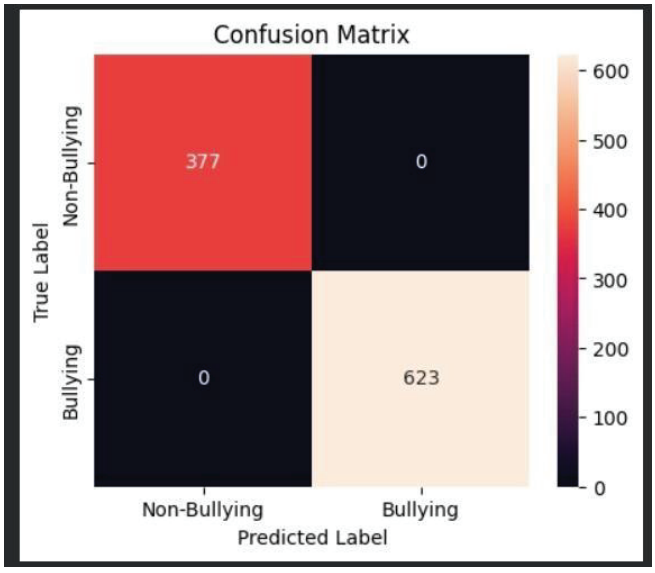

FIGURE 4: CONFUSION MATRIX OF THE PROPOSED MURIL MODEL

Discussion

The experimental results indicate that the proposed MuRIL-based model performs better than traditional machine learning and deep learning models for multilingual cyberbul-

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lying detection. One main reason for this improved performance is MuRIL's ability to understand contextual relationships across multiple Indian languages [2]. Unlike traditional models that rely on simple feature representations such as TF-IDF, MuRIL generates contextual embeddings that capture semantic meaning more effectively [2].

Another important factor contributing to the improved results is the inclusion of multilingual and code-mixed data in the training dataset. Social media users often mix multiple languages within a single sentence, making it hard for traditional models to identify meaningful patterns [15]. MuRIL is specifically designed to handle multilingual and code-mixed text, helping the model better understand these linguistic variations [2].

Despite the improved performance, some classification errors still occur due to informal language use, slang expressions, and unique spellings often seen in online communication [17]. In many cases, users intentionally change abusive words to avoid detection, which can lower the accuracy of automated systems [8]. Additionally, sarcastic or indirect bullying statements can be difficult for models to interpret correctly because they rely heavily on contextual understanding [10].

Overall, the experimental analysis confirms that transformer-based multilingual models like MuRIL offer a more effective solution for cyberbullying detection in multilingual social media environments compared to traditional machine learning methods [19].

VIII. CONCLUSION

This research proposed a multilingual cyberbullying detection framework using MuRIL (Multilingual Representations for Indian Languages) to identify harmful and abusive content in social media comments. The proposed system effectively handles multilingual and code-mixed text commonly found on online platforms by using contextual embeddings generated by MuRIL to capture semantic relationships across multiple languages. The framework includes data collection, text preprocessing, tokenization, contextual feature extraction, and classification through a neural network layer. Experimental results confirm that the MuRIL-based model outperforms traditional machine learning approaches including Support Vector Machine, Long Short-Term Memory, and Bidirectional Encoder Representations from Transformers , achieving 95% accuracy, 94% precision, 94% recall, and 94% F1-score. The study demonstrates that transformer-based multilingual models significantly improve cyberbullying detection performance compared to conventional methods that rely on limited feature representations .

Despite these promising results, some challenges persist. Cyberbullying detection systems may struggle with sarcastic statements, implicit bullying, intentionally altered abusive words, and new slang terms . Code-mixed text often contains inconsistent grammar and spelling variations, which can affect model performance . Future research can explore larger and more diverse multilingual datasets, advanced transformer architectures, sentiment and emotion analysis, and multimodal approaches that combine textual, visual, and contextual information to further boost the robustness and accuracy of automated cyberbullying detection systems .

In conclusion, the proposed multilingual cyberbullying detection framework using MuRIL offers an effective method for identifying harmful online content in multilingual and code-mixed environments. This study contributes to developing intelligent moderation systems that help create safer digital communities and encourage responsible communication on social media platforms .

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