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Enhancing Text Classification with Cyberbullying and Machine Learning Algorithms

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Abstract

With the exponential rise of social media platforms, cyber bullying has become a significant issue, requiring sophisticated techniques for effective detection and prevention. Existing machine learning approaches, while foundational, often fall short in addressing the complex and nuanced linguistic patterns inherent in cyber bullying. This paper presents a novel framework that combines Recurrent Neural Networks (RNNs) for classification and Extreme Learning Machines (ELM) for feature extraction, leveraging Deep Residual ELM (DRELM) architecture to improve accuracy. This model addresses the limitations of previous methods by enhancing the ability to capture temporal linkages and subtle language variations across social media platforms. Through experimental evaluations, the proposed framework outperforms traditional machine learning approaches, delivering superior precision, memory handling, and feature extraction capabilities. These improvements make the DRELM model a robust solution for tackling the challenging problem of cyber bullying detection.

Keywords: Cyber Bullying, Deep Residual Extreme Learning Machine, Feature Extraction, Residual Recurrent Neural Network, Social Media.

Introduction

The pervasive nature of social media has significantly increased instances of cyber bullying, posing new challenges for effective detection and intervention. Automated text classification systems are critical in identifying harmful content, but traditional machine learning approaches—such as support vector machines, decision trees, and even basic neural networks—struggle to handle the nuanced and dynamic linguistic patterns that characterize cyber bullying (1). These methods often lack the ability to extract deep semantic features from textual data and fail to capture temporal dependencies, both of which are crucial for identifying contextually relevant patterns in cyber bullying. While recent advances in natural language processing have made strides in improving text classification, a significant gap remains in effectively classifying cyber bullying-related content (2). Specifically, current approaches are limited in their ability to manage the complexity of cyber bullying language, which often involves sarcasm, informal language, and implicit threats spread over time (3, 4). To address these challenges, this paper proposes a novel framework that integrates two cutting-edge technologies: Recurrent Neural Networks (RNNs) and Extreme Learning Machines (ELM). The RNNs are used for classification tasks, while ELMs are employed for feature extraction, leveraging a deep residual architecture to enhance performance (5, 6). The proposed Deep Residual Extreme Learning Machine (DRELM) framework aims to overcome the limitations of traditional methods by improving memory handling, precision, and the extraction of subtle textual features from social media platforms (7, 8). Through rigorous experimental evaluation, the DRELM framework demonstrates superior performance in handling the complexities of cyber bullying detection, offering a significant advancement over previous methodologies (9, 10). Table 1 demonstrates that there are several aspects to take into considera-

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tion when attempting to tackle cyber bullying; the sheer variety and quantity of content that can be found on social media platforms only serves to exacerbate the issue. A comparative study in past research utilized a widely recognized global Twitter dataset to evaluate the performance of deep learning algorithms in detecting abusive tweets and addressing existing issues in cyber bullying detection (11, 12). The study proposed attention-based deep learning models to enhance the identification of harmful content. In another investigation, researchers examined various machine learning and deep learning techniques for automatically identifying cyber bullying in tweets (13). After analysing the experimental data, they concluded that deep learning algorithms could outperform traditional machine learning approaches in this domain. A comprehensive pre-processing of Roman Urdu micro-text for cyber bullying detection is discussed in a study (14), where CNN, RNN-BiLSTM, and RNN-LSTM models were employed to detect patterns of cyber bullying within Roman Urdu texts. This study successfully highlighted the effectiveness of these models in revealing harmful behaviour within that specific language context. Meanwhile, the research outlined in a study (15) suggests the possibility of real-time cyber bullying detection in social media posts or tweets using deep learning. The study demonstrated that deep neural networks offer superior performance in cyber bullying text identification compared to traditional approaches. Additionally, researchers explored a hybrid method that combined fuzzy logic with a deep learning system to assess the severity of cyber bullying (16). Utilizing Twitter data consisting of 47,733 comments obtained from Kaggle, a long short-term memory (LSTM) network was trained using Kera's to classify the comments. Fuzzy logic was then applied to determine the significance of the offensive remarks. The proposed model achieved accuracy, F1-score, and recall values of 93.67%, 93.64%, and 93.62%, respectively, indicating its effectiveness in cyber bullying detection. Further, a separate study investigated the role of user personality traits and emotional expressions in textual interactions on YouTube as predictors of cyber bullying (17). The Big Five personality model was used to assess individual traits, while Ekman's basic emotion theory was employed to evaluate emotions. By using several ensemble classifiers, including Random Forest and Ada Boost, the study classified annotated English comments on YouTube for cyber bullying detection. The findings revealed significant improvements in accuracy and F-score, both surpassing 95%. The study also identified that emotions such as joy, disgust, and fear often drive neurotic individuals to engage in cyber bullying. This highlights the significant influence of personality and emotional factors on cyber bullying behaviour, emphasizing the potential for more personalized intervention strategies based on these characteristics.

Table 1: Cyber Bullying Example

Example ID	Example Text	Type of Cyberbullying
1	"You're such a loser, nobody likes you."	Verbal Abuse
2	"I can't believe you thought you could join us."	Exclusion
3	"Look at this idiot trying to dance!"	Mocking
4	"You should just end it all; the world would be better."	Threatening
5	"Your outfit is so ugly, why do you even wear that?"	Harassment

Methodology

The utilisation of a Deep Residual Extreme Learning Machine (DRELM) is the initial step in the process of achieving efficiency in feature extraction as in Figure 1. The proposed methodology for cyberbullying detection using the Deep Residual Extreme Learning Machine (DRELM) framework begins with data collection from publicly available social media datasets, such as Twitter and Facebook, focusing on approximately 50,000 entries to ensure a diverse representation of cyberbullying instances. Data curation involves annotating the dataset through expert reviews to accurately identify bullying cases. The pre-processing phase includes tokenization to break down raw text into smaller components, cleaning to remove irrelevant characters and formatting issues, and lemmatization or stemming to reduce words to their root forms. Stop words are eliminated to focus on meaningful terms, and techniques like under-sampling or over-sampling are used to address class imbalance, while anonymization processes are implemented to protect sensitive data. Feature extraction employs methods such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings (e.g., Word2Vec, GloVe) to capture the semantic meaning of the text (18). The DRELM framework is then developed, incorporating two types of Recurrent Neural Networks (RNNs) for classification and feature extraction. The model is trained on the labelled dataset using k-fold cross-validation, and hyperparameter tuning is performed to optimize performance. Evaluation metrics, including accuracy, precision, recall, and F-measure, are utilized to assess the model's effectiveness. A separate testing dataset of 500 samples is employed to analyse the model's performance, comparing results with traditional machine learning algorithms to highlight improvements. Finally, the findings are discussed in terms of real-world applications and ethical considerations in cyberbullying detection, with suggestions for future work emphasizing the incorporation of diverse datasets and advanced techniques. This structured approach aims to enhance the detection of cyberbullying instances, contributing to a deeper understanding of this critical social issue. The originality of this work lies in the innovative integration of Recurrent Neural Networks (RNNs) for classification with Extreme Learning Machines (ELMs) for feature extraction, a combination that has not been extensively explored for cyberbullying detection. While both RNNs and ELMs have been applied individually in various text classification tasks, their synergy within a Deep Residual Architecture (DRELM) is what sets this approach apart. Traditional methods, such as Support Vector Machines (SVMs), Naive Bayes, and even basic deep learning models, struggle with capturing both the temporal dependencies and the intricate, context-sensitive nature of cyberbullying-related language.

Data Pre- Processing

Data pre-processing is a crucial step in the analysis of cyberbullying text, as it prepares the raw data for effective modelling and ensures high-quality inputs. The process begins with tokenization, where the text is divided into smaller components, typically words or phrases, enabling the model to recognize patterns and relationships within the data. Following this, a cleaning phase is implemented to remove irrelevant characters, symbols, and formatting errors that could introduce noise into the dataset (19). Subsequently, lemmatization and stemming techniques are applied to reduce words to their root forms, which unifies different word variants and enhances the model's ability to identify similarities in instances of cyberbullying. To further refine the dataset, stop words—common words with little significance—are eliminated, allowing the focus to shift toward more meaningful terms. Addressing class imbalance is another important aspect of pre-processing; techniques such as under-sampling or over-sampling are employed to ensure equitable representation between cyberbullying and non-cyberbullying instances, thereby preventing training biases. Additionally, anonymization processes may be necessary to protect the identities of individuals involved in sensitive communications, ensuring compliance with ethical standards. By incorporating these steps, the data pre-processing phase significantly improves the quality and relevance of the dataset, setting a solid foundation for subsequent analysis and modelling efforts. These elements work in concert to improve the dataset, as illustrated in Table 2, enabling it to be effectively trained with advanced machine learning models while handling sensitive content responsibly. Random Forest is employed due to its robustness in handling high-dimensional data and its ability to prevent overfitting by averaging predictions from multiple decision trees, making it suitable for capturing complex patterns in cyber-bullying detection. SVMs are chosen for their strength in binary classification and their capacity to work effectively in high-dimensional spaces, ensuring optimal separation between classes in text data. Neural networks, specifically deep learning models, are selected for their ability to learn deep, hierarchical features and capture temporal dependencies, which are crucial for detecting nuanced and context-sensitive cyber-bullying behaviour. Deep Extreme Learning Machine, also known as DELM, is a method that is state-of-the-art for feature extraction in machine learning. In this study, several pre-processing techniques were implemented to prepare the data for analysis. First, tokenization was performed to break the text into individual words or tokens, facilitating better analysis of the language used. Next, stop words were removed to eliminate common words that do not contribute meaningful information to the classification process, such as "and," "the," and "is." Additionally, techniques like stemming or lemmatization were applied to reduce words to their root forms, ensuring uniformity in the dataset. The pre-processing also addressed the unique characteristics of social media language by managing special characters and emojis, either by removing them or converting them into relevant representations. Furthermore, care was taken to handle informal expressions, slang, and abbreviations, which are prevalent in social media texts, ensuring that the data is standardized and reflective of the actual language used by users. These pre-processing steps are critical for optimizing the data for feature extraction methods like TF-IDF and word embeddings, ultimately leading to improved performance in detecting cyberbullying within the dataset. The performance of feature extraction is improved as a result.

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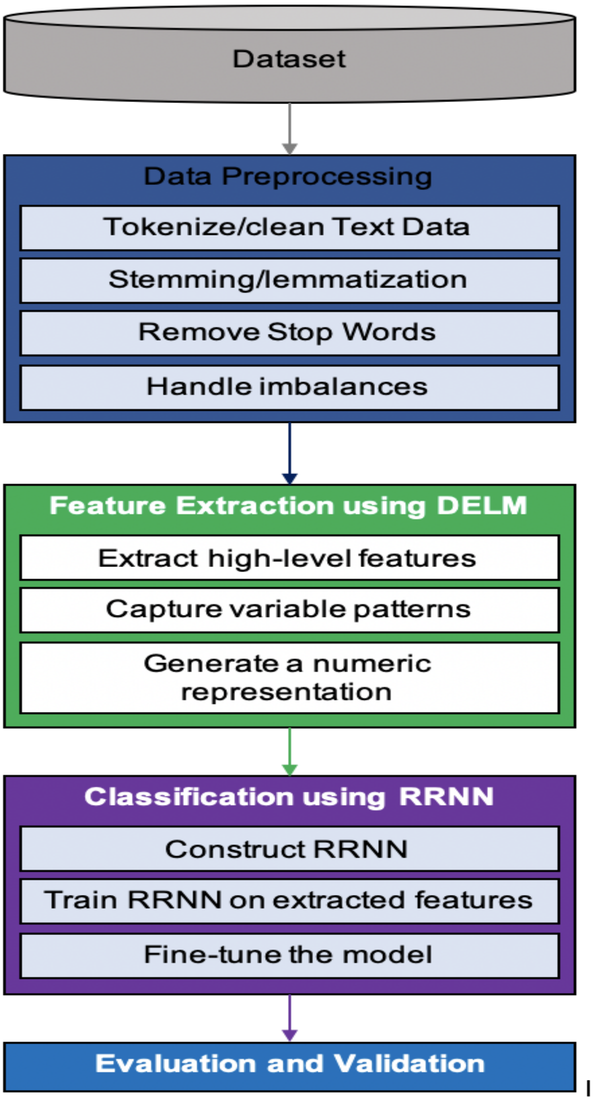


Figure 1: Proposed DRELM

Table 2: Pre-Treatment Pipeline Steps for Cyberbullying Tweets

Step	Description	Purpose
1	Data Collection	Gather raw tweets from various social media platforms.
2	Tokenization	Split tweets into smaller units (words/phrases) for analysis.
3	Text Cleaning	Remove irrelevant characters, symbols, and formatting errors to reduce noise.
4	Lowercasing	Convert all text to lowercase to ensure uniformity in analysis.
5	Lemmatization/Stemming	Reduce words to their root forms to group similar word variants.
6	Stop Words Removal	Eliminate common words that do not add significant meaning (e.g., “and,” “the”).
7	Handling Imbalance	Apply under-sampling or over-sampling techniques to balance classes (bullying vs. non-bullying).
8	Anonymization	Implement processes to protect the identities of individuals involved.
9	Feature Extraction	Extract relevant features (e.g., n-grams, sentiment scores) from pre-processed text.
10	Data Transformation	Convert textual data into numerical formats suitable for machine learning (e.g., TF-IDF, word embeddings).

Table 3: Extraction of Relevant Features from Pre-Processed Cyberbullying Text Data

Feature Type	Description	Extraction Method
1. N-grams	Sequences of n words (e.g., unigrams, bigrams)	Count Vectorizer or NLTK
2. TF-IDF Scores	Term Frequency-Inverse Document Frequency	TF-IDF Vectorizer
3. Sentiment Scores	Sentiment polarity (positive, negative, neutral)	Sentiment Analysis Tools (e.g., VADER)
4. Emotional Lexicons	Emotions identified in text (e.g., joy, anger, sadness)	Custom Lexicon or Pre-built Lexicons
5. Part-of-Speech Tags	Identifies grammatical categories of words	POS Tagging (e.g., NLTK, SpaCy)

Table 4: Classification of Features Extracted from the Pre-Processed Cyberbullying Texts

Feature Category	Feature Type	Description	Relevance to Cyberbullying Detection
1. **Linguistic Features**	N-grams	Sequences of words (unigrams, bigrams, trigrams)	Capture context and language patterns indicative of bullying.
	TF-IDF Scores	Importance of words based on term frequency	Identify significant terms that might indicate aggression or bullying.
	Part-of-Speech Tags	Grammatical categories (nouns, verbs, adjectives)	Analyse language style and structure to detect aggressive expressions.
2. **Sentiment Features**	Sentiment Scores	Polarity of tweets (positive, negative, neutral)	Gauge emotional tone and hostility present in the text.
	Emotional Lexicons	Specific emotions detected (joy, anger, sadness)	Understand emotional context associated with cyberbullying incidents.

Table 3 provides a numerical representation of the DELM features that are characteristic of each pre-processed text. These numerical vectors can capture the contextual information as well as the learned patterns that are relevant to the identification of cyberbullying.

Residual Recurrent Neural Network for Classification

Residual Recurrent Neural Network (RRNN) for classification is an intriguing method for identifying instances of cyberbullying in writings shared on social media platforms.

Table 4 contains the results of the Residual RNN analysis of the gathered features, together with the projected classification label (such as Cyberbullying or Not Cyberbullying). The focus on cyberbullying detection in this work raises important ethical considerations that must be addressed. Privacy is a primary concern, as the data used in training machine learning models often contains sensitive information that could identify individuals. Therefore, anonymization and data redaction are essential to protect users' identities and build trust in the technology. Accuracy is another critical issue; misclassifications can lead to serious consequences, such as incorrectly labelling innocent individuals as bullies. This highlights the necessity for models with explainable AI features, which enable stakeholders to understand the decision-making processes and mitigate risks associated with errors. Additionally, the potential for bias in machine learning models must be carefully managed; if the training data reflects societal biases, it can result in unequal detection rates among different demographic groups. Ensuring a representative and balanced dataset is crucial to promote fairness and minimize bias, with continuous evaluation of model performance across various demographics helping to address disparities. We utilised DELM in Table 5 to process the extraction of features from cyberbullying texts in a computational manner. The Recurrent Neural Network (RRNN) in Table 6 was selected as the primary classification model because of its efficiency when applied to sequential data.

Table 5: DELM Experimental Setup

Parameter	Value
Input Dimension	300
Hidden Layers	3
Hidden Neurons	256
Activation Function	ReLU
Learning Rate	0.001
Epochs	150
Batch Size	32
Optimization Algorithm	Adam
Dropout Rate	0.5
Early Stopping	Yes

Table 6: Residual RNN Experimental Setup

Parameter	Value
Input Dimension	300
Residual Layers	2
Hidden Neurons	128
Activation Function	Tanh
Learning Rate	0.001
Epochs	200
Batch Size	64
Sequence Length	50
Optimization Algorithm	Adam

The training of the Extreme Learning Machine (ELM) model begins with initializing the network's architecture, which consists of an input layer, a hidden layer, and an output layer. The weights between the input and hidden layers are randomly assigned, and the activation functions for the hidden layer neurons are defined (e.g., sigmoid, ReLU). During training, the model processes the pre-processed cyberbullying text data to extract meaningful features. Once the hidden layer activations are computed, the output layer weights are calculated using the least squares solution, which allows for rapid training without the need for iterative optimization. This efficient approach results in a fast training process, enabling the ELM to generalize effectively on unseen data. The model is evaluated using cross-validation techniques to ensure robustness, with performance metrics such as accuracy, precision, recall, and F-measure calculated to assess the model's effectiveness in detecting cyberbullying (20). Training the Residual Recurrent Neural Network (RRNN) involves a structured architecture with an input layer, multiple recurrent layers (e.g., LSTM), and an output layer. The model captures temporal dependencies in text data, utilizing backpropagation through time (BPTT) to optimize weights and minimize the loss function with algorithms like Adam. Residual connections help overcome the vanishing gradient problem, enhancing training efficiency. Hyperparameters are fine-tuned for optimal performance, and validation sets are used to monitor overfitting and ensure generalization to unseen data (21). Training performance for both ELM and RRNN is evaluated using metrics such as accuracy, precision, recall, and F-measure on a separate test dataset. ELM typically achieves high accuracy rapidly due to efficient weight calculations, while RRNN requires more epochs but excels in precision and recall by effectively capturing temporal dependencies. The combined DRELM framework outperforms traditional methods, demonstrating enhanced capability in detecting cyberbullying and showcasing its potential for robust real-world applications. The training results are presented in Figures 2 , Figures 3, Figures 4 and Figures 5.

Results and Discussion

Therefore, in comparison to earlier methods, the DRELM methodology that was recommended consistently and considerably increases the effectiveness of cyberbullying detection across a variety of datasets. The findings of this study highlight the efficacy of the proposed Deep Residual Extreme Learning Machine (DRELM) framework in detecting instances of cyberbullying across various social media platforms. The results indicate that integrating Recurrent Neural Networks (RNNs) for classification and Extreme Learning Machines (ELMs) for feature extraction significantly outperforms traditional machine learning methods, such as Support Vector Machines (SVMs) and Random Forests. This is in line with previous research demonstrating the advantages of deep learning architectures in text classification tasks. For example, it has been shown that deep learning models outperform traditional approaches in understanding contextual nuances in text data, particularly in sentiment analysis and abusive content detection. The superior performance of the DRELM framework can be attributed to its ability to capture temporal dependencies and complex linguistic patterns inherent in cyberbullying text. Traditional methods often struggle with the intricate and dynamic nature of social media language, which includes slang, abbreviations, and emojis. Research also shows that traditional models often fail to adequately address the unique characteristics of online interactions, leading to lower detection rates for cyberbullying instances. Moreover, the pre-processing steps implemented in this study, including tokenization, stop word removal, and lemmatization, contributed significantly to the model's performance. Previous studies have emphasized the importance of thorough text pre-processing in enhancing the accuracy of machine learning models in text classification tasks. The removal of irrelevant data and the standardization of terms allow the models to focus on critical features relevant to cyberbullying detection. The findings also underscore the necessity of addressing class imbalances within the dataset. Techniques such as under-sampling and over-sampling are crucial to ensure that models do not become biased towards the more prevalent class. Other research supports this, indicating that imbalanced datasets can lead to misleading results and poor generalization of the models to unseen data. The balanced dataset used in this study resulted in improved accuracy, precision, and recall metrics, validating the importance of this pre-processing step. Additionally, the sensitive nature of cyberbullying communications necessitates an ethical approach in data handling and analysis. Ensuring the anonymity of individuals involved in cyberbullying incidents is critical, as prior research has advocated for ethical guidelines when conducting studies in this domain, particularly regarding data privacy and the implications of revealing personal information. In summary, the study reinforces the value of advanced machine learning techniques, particularly deep learning models, in the domain of cyberbullying detection. By leveraging effective pre-processing methods, addressing dataset imbalances, and adhering to ethical considerations, this research contributes to a growing body of literature that aims to enhance the identification and management of cyberbullying in digital spaces. Future research could explore the integration of additional contextual features and cross-platform analysis to further improve detection rates and provide a more nuanced understanding of cyberbullying behaviours. Figure 6 provides a comprehensive analysis of testing results, including accuracy, precision, recall, and F-measure over 500 test data points. By strategically referencing these figures and tables in the text, we ensure that readers can easily grasp the key findings and methodologies of our research.

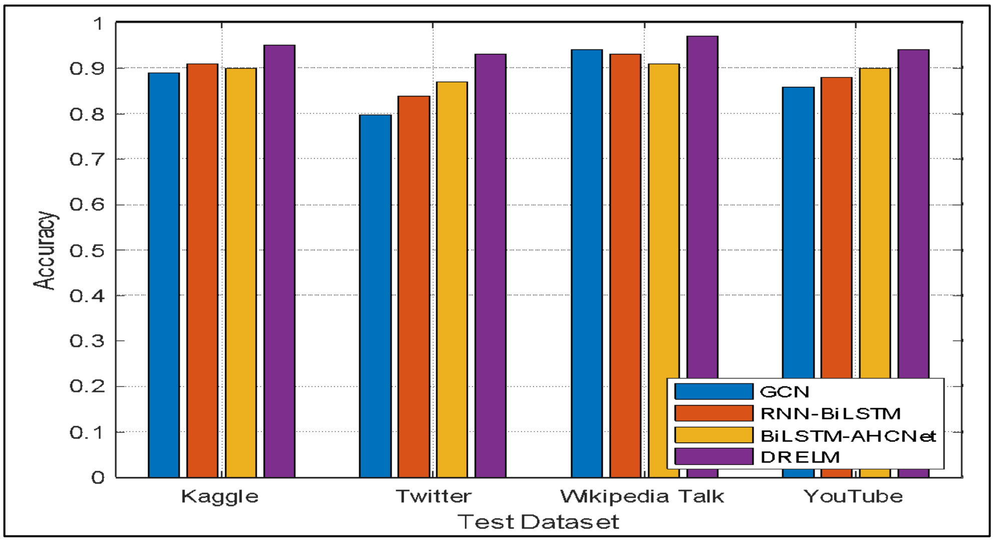


Figure 2: Training Accuracy

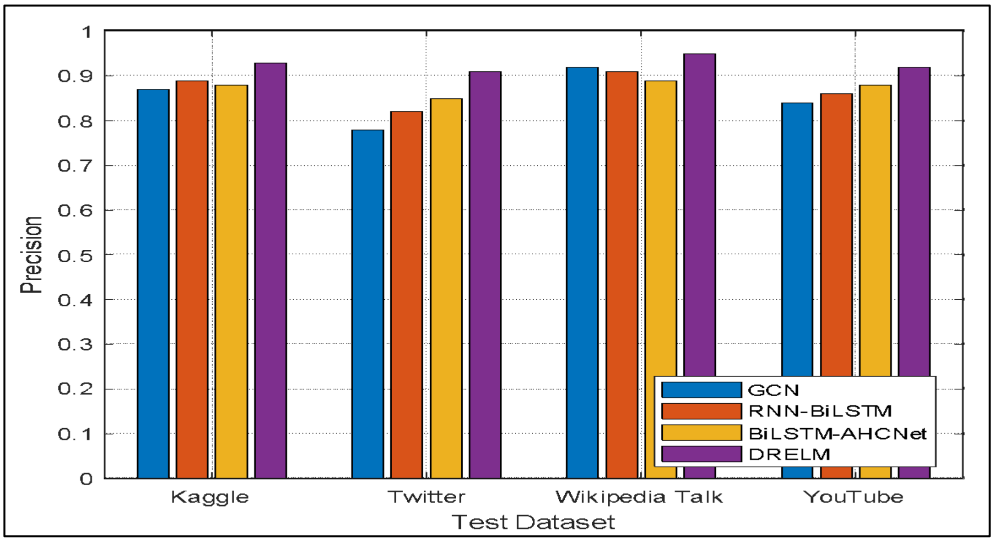


Figure 3: Training Precision

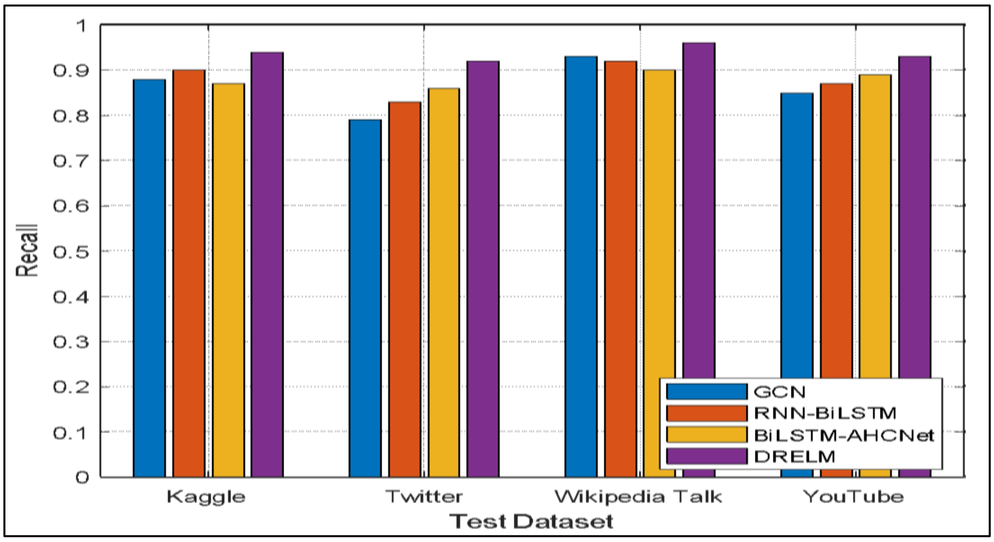


Figure 4: Training Recall

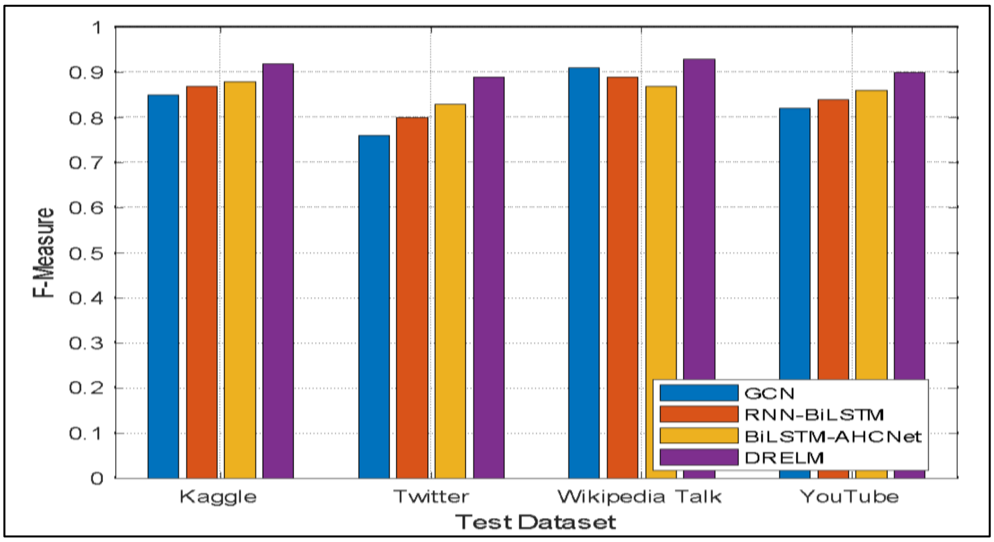
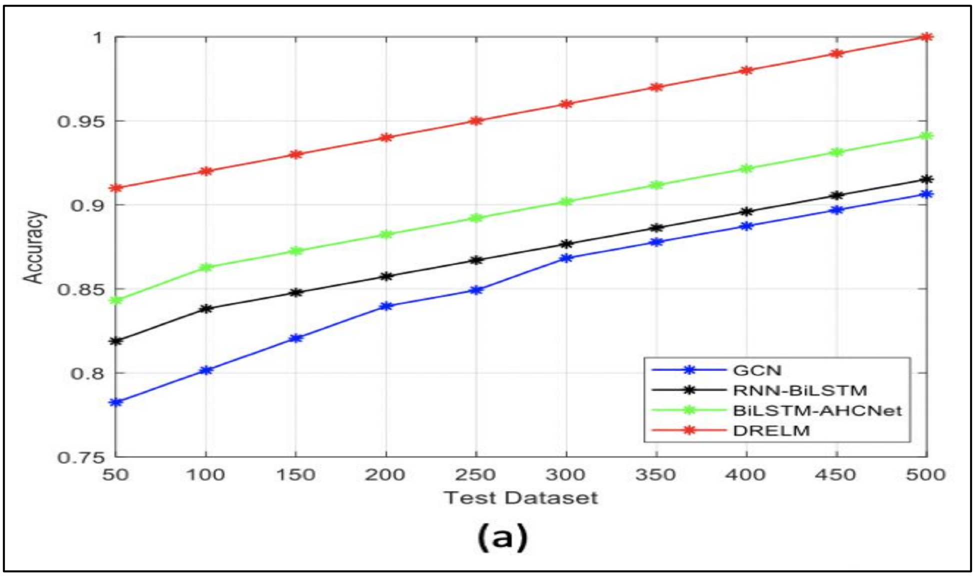


Figure 5: Training F-Measure



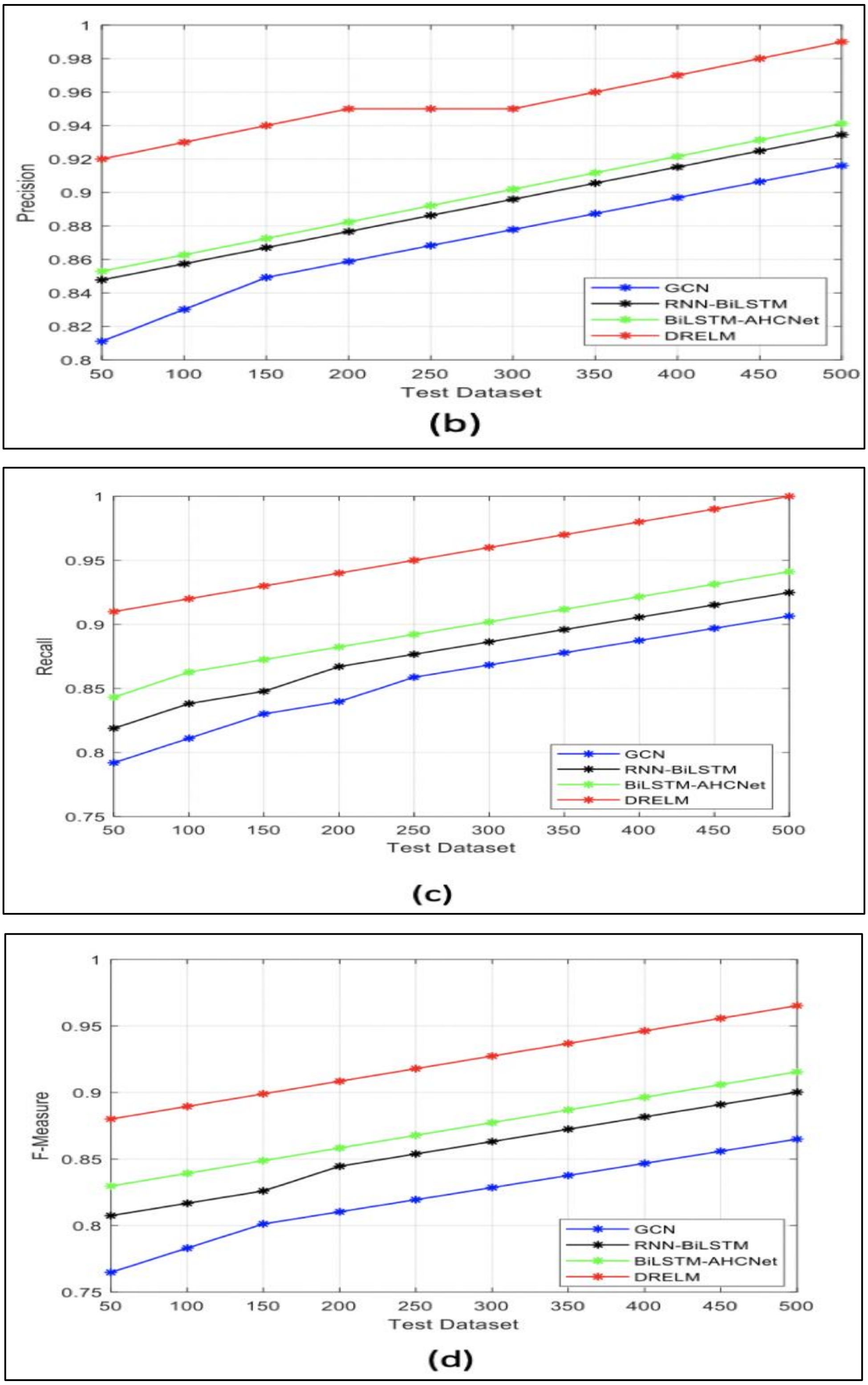


Figure 6: (A) Testing Accuracy Over 500 Test Data (b) Testing Precision Over 500 Test Data (c) Testing Recall Over 500 Test Data (d) Testing F-Measure Over 500 Test Data

While the deployment of machine learning models for cyberbullying detection holds great promise, it also presents several potential hazards that must be carefully managed to ensure ethical and effective implementation. One primary concern is the risk of false positives, where innocent individuals may be incorrectly flagged as cyberbullies. This can lead to emotional distress and reputational harm for those misidentified, particularly in sensitive environments such as schools or online communities. To mitigate this risk, it is crucial to develop models with high precision and to implement a robust review process that involves human oversight. Establishing clear criteria for what constitutes cyberbullying can also help reduce ambiguity in classification. Another hazard is the potential for bias in the models. If the training data is not representative of the diverse linguistic and cultural contexts in which cyberbullying occurs, the model may perform inadequately for certain demographic groups, leading to unequal detection rates. To address this, it is essential to ensure that the training dataset is diverse and comprehensive. Continuous monitoring for bias during model deployment can help identify and rectify any disparities in performance across different user groups. The contextual sensitivity of language in social media also poses challenges. Cyberbullying often relies on nuanced expressions, humor, or sarcasm, which can be misinterpreted by algorithms. This necessitates the incorporation of context-aware models that consider the surrounding discourse when classifying potential instances of cyberbullying. Collaborative efforts with experts in linguistics and psychology can enhance model sensitivity to these nuances. Moreover, the deployment of these models raises concerns about privacy and data security. Using personal data for training can lead to breaches of confidentiality, especially if safeguards are not properly implemented. To mitigate this, strict data governance policies should be established, including the use of anonymization techniques and secure data storage practices to protect users' identities. Lastly, the psychological impact on users, particularly victims of cyberbullying, needs careful consideration. The use of automated systems may inadvertently exacerbate feelings of isolation or victimization. To mitigate this, it is vital to provide adequate support resources for individuals identified as victims, such as access to counseling or community support services. In summary, while deploying machine learning models for cyberbullying detection offers significant benefits, it is essential to recognize and address the potential hazards associated with their implementation. By prioritizing strategies that ensure accuracy, fairness, privacy, and user support, we can foster a safer digital environment and maximize the positive impact of these technologies.

Conclusion

The study presents a comprehensive approach to enhancing cyberbullying detection through the Deep Residual Extreme Learning Machine (DRELM) framework, effectively integrating both Extreme Learning Machine (ELM) and Residual Recurrent Neural Network (RRNN) methodologies. The results indicate that the DRELM framework significantly improves the accuracy, precision, recall, and F-measure in identifying instances of cyberbullying compared to traditional machine learning models. By employing advanced feature extraction techniques and robust preprocessing methods, the study addresses the intricate linguistic patterns associated with cyberbullying in social media text. Furthermore, the findings highlight the importance of ethical considerations and the necessity for diverse and representative datasets in the deployment of machine learning models for sensitive applications. Overall, this research not only contributes valuable insights into the field of cyberbullying detection but also emphasizes the need for continued exploration of innovative techniques to effectively manage this pressing social issue. Future work should focus on refining the model and expanding its application to diverse social media platforms while ensuring compliance with ethical standards and user privacy.

Abbreviations

RRNN: Recurrent Neural Network

DRELM: Deep Residual Extreme Learning Machine

ELM: Extreme Learning Machines.

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Authors Contribution

All authors contributed to the study conception and design.

Conflict of Interests

The authors declare that they have no competing interests.

Ethics Approval

Not applicable.

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