e-ISSN:2582-7219

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH

IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 7, Issue 5, May 2024

INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.521

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly Peer Reviewed & Referred Journal |

| Volume 7, Issue 5, May 2024 |

| DOI:10.15680/IJMRSET.2024.0705012 |

Survey on Cyber Bullying Detection on Social Media

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ABSTRACT: The widespread use of the internet and social media has given rise, to a problem known as cyberbullying. This research aims to explore strategies for combating cyberbullying and providing support to those affected by it. To address the complexity of this issue we have developed a computer program that can identify and prevent instances of cyberbullying Our innovative program utilizes machine learning technology serving as an assistant in detecting and addressing cyberbullying incidents on social media platforms. Think of it as an filter that swiftly recognizes and manages such situations.We conducted testing on cases of cyberbullying yielding highly successful out-comes. Combining two technologies called Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) our program surpassed the effectiveness of using LSTM in detecting and managing instances of cyberbullying. Consequently it offers an more approach when dealing with substantial amounts of data.In terms our research focuses on leveraging technology to safeguard individuals from the harmful effects of cyberbullying prevalent, on social media. We have developed an program that boasts enhanced speed and effectiveness in curbing cyberbullying occurrences ultimately creating a safer online environment forall users.

KEYWORDS: Cyberbullying, CNN, LSTM, Machine learningmethod, Machine learning model

I. INTRODUCTION

Cyberbullying, an unfortunate reality of the digital era, poses a significant challenge within the realm of social media. This form of harassment involves individuals using online platforms to intimidate or harm others, creating a pervasive and worrisome issue. Cyberbullying comes in various forms, such as spreading false information, engaging in online harassment, and assuming false identities, often fueled by the anonymity provided by social media platforms. The consequences of suchactions extend beyond the digital space, profoundly impacting individuals on a psychological and emotional level, leading to

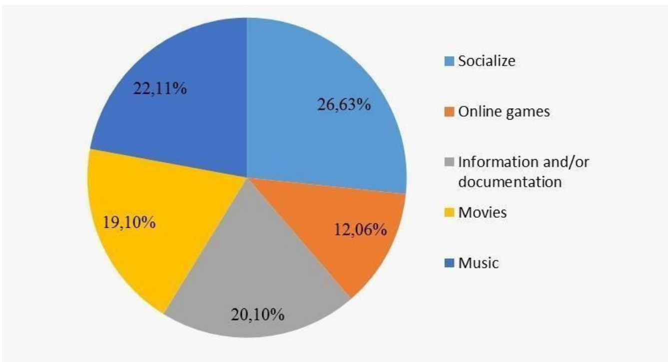

Fig. 1. Various domains where cyberbullying occurs

heightened anxiety and depression.

However, the ripple effects of cyberbullying extend beyond individual experiences, influencing the overall dynamics of online communities. The pervasive fear and tension it fosters hinder open discourse and genuine engagement on social media platforms. Trust among users erodes, making it diffi- cult for these platforms to promote healthy and constructive interactions.

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Tackling cyberbullying necessitates a holistic strategy that integrates preventive measures and responsive interventions in a cohesive manner. Social media platforms play a cru-cial role in this endeavor by swiftly moderating content, implementing robust reporting mechanisms, and conducting educational campaigns to raise awareness about responsibleonline behavior. Additionally, cultivating a culture of empathy,tolerance, and digital literacy is fundamental to addressing the root causes of cyberbullying.

In the interconnected era we live in, collective action is essential to foster social media environments that are not only inclusive and supportive but also conducive to positive human interactions. By recognizing the severity of cyberbullying, implementing effective measures, and promoting a culture of respect and empathy online, we can work towards creating a safer and more positive digital space for everyone.

II. LITERATURE SURVEY

In the paper proposed by Teoh Hwai Teng and Kasturi Dewi Varathan entitled as ”Cyberbullying Detection in Social Networks: A Comparison Between Machine Learning and Transfer Learning Approaches”[1] , this study, a comprehensive evaluation of cyberbullying detection models is undertaken, employing a combined approach to establisha benchmark through comparisons with past models. The methodology intricately examines various models using the F-measure, with a specific focus on textual analysis, sentiment analysis, emotion analysis, and the utilization of DistilBert embeddings. This thorough evaluation encompassesa comparison between conventional machine learning and transfer learning techniques. The accuracy assessment highlights DistilBert as the top performer, demonstratinga balanced perspective by acknowledging instances of misclassification. However, a notable drawback surfaces inthe form of limited technical insight into the inner workings of the models and the feature engineering process. While the analysis is extensive, the study faces criticism for lacking empirical evidence that substantiates the proposed improvements in cyberbullying detection. To bolster the credibility of the suggested methodologies, there is a clear call for a more detailed exploration of technical aspects and the incorporation of empirical evidence in future research endeavors.

As outlined in the document authored by Mohammed Al- Hashedi et al. entitled as ”Cyberbullying Detection Based on Emotion”[2], the study delves into the realm of Cyberbullying Detection Models (CDMs), introducing a novel approach that incorporates emotion features for heightened efficacy. The comprehensive methodology covers crucial steps from meticulous data preparation to the implementation of deep learning models, placing a strong emphasis on utilizing high-quality datasets. Addressing challenges like sparsity and label imbalance, the study leverages the toxic dataset from Conversation AI and Twitter, employing sampling techniques. The extracted textual features encompass a spectrum, including syntactic, semantic, contextual, emotion, and sentiment features. Notably, the study upholds privacy by excluding perpetrator demographics from the analyzed features. The resultant Emotion Detection Model (EDM), leveraging BERT for pre-trained word representation, outshines its counterpart using BERT alone in cyberbullying detection precision. Specifically, the integration of emotion contribute significantly, achieving a recall of 0.88, marketing a substantial 0.6 enhancement over the baseline model. This research underscores the effectiveness of incorporating emotion features in cyberbullying detection, contributing valuable insights to the evolving landscape ofonline safety.

According to the research paper presented by Belal Ab- dullah Hezam Murshed et al. entitled as ”DEA-RNN: A Hy- brid Deep Learning Approach for Cyberbullying Detection in Twitter Social Media Platform”[3],The proposed methodology introduces a novel approach by initializing a hybrid model, DEA-RNN, combining the Differential Evolution Algorithm (DEA) with an Elman Recurrent Neural Network (RNN) struc- ture for cyberbullying detection. The model is initialized with population parameters and a specified RNN dimension size. The training process involves iterative procedures, continuing until the Mean Squared Error (MSE) meets a predefined stop- ping criterion. The DEA determines optimal RNN weights, employing feed-forward processing, error computation, and optimization in each iteration. This encompasses generating new DEA locations, eliminating poor solutions, finding re- placements, and evaluating fitness functions. Training persists until convergence, updating final weights and biases for opti- mal performance.The evaluation phase showcases the DEA- RNN hybrid model’s superiority in cyberbullying detection accuracy, achieving approximately 90.45 percent. This out- performance is notable when compared to baseline models such as Bi-LSTM, RNN, SVM, MNB, and RF. However, the proposed methodology exhibits sensitivity to dataset speci- ficity, potential challenges with larger datasets, limited analysisof user behavior, and a need for further clarity on real- time stream processing efficiency. These findings highlight both the strengths and areas for improvement, contributing valuable insights to the domain of cyberbullying detectionmethodologies.As shown in the fig1

In the scholarly article suggested by Nagwan Abdel Samee et al. entitled as ”Safeguarding Online Spaces: A

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PowerfulFusion of Federated Learning, Word Embeddings, and Emotional Features for Cyberbullying Detection”[4], the employed methodology initiates with dataset acquisition, focusing on undersampling to address class imbalance,and meticulous preprocessing of textual data. Feature engineering incorporates the utilization of word embeddings and the extraction of emotional features. Notably, the methodology adopts a privacy-conscious approach tocyberbullying detection through Federated Learning. This involves global model initialization, client selection, local training, aggregation, broadcasting, and iterative rounds. However, there is a notable absence of details regarding hyperparameters, evaluation metrics, and validation specific to Federated Learning, potentially hindering reproducibility. While the methodology effectively addresses challenges such as dataset imbalance, textpreprocessing, and the incorporation of features to enhance accuracy, the lack of specificity on critical aspects within Federated Learning poses a limitation, impacting the comprehensive understanding and replicability of the proposed approach.

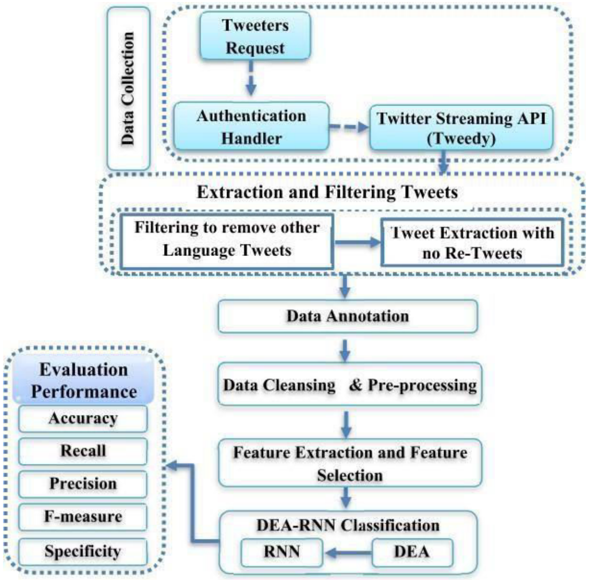

Fig. 2. Methodology of the paper entitled as DEA-RNN: A Hy-brid Deep Learning Approach for Cyberbullying Detection in Twitter Social MediaPlatform

As per the publication recommended by Fatma Elsafoury et al. entitled as ”When the Timeline Meets the Pipeline: A Survey on Automated Cyberbullying Detection”[5] ,the study undertook a comprehensive exploration of a cyberbullying detection model originally developed by Wulczyn et al., extending its application to diverse datasets encompassing platforms like Twitter and Kaggle-insults. The testing process showcased varied performance outcomes, unveiling the model’s adaptability to different contexts. Notably, the study delved into potential enhancements by fine-tuning BERT and incorporating slang-based word embeddings, achieving consistently high accuracy rates. However, amidst the successes, there emerged concerns related to performance variability, particularly evident across datasets of varying sizes and when employing Multilayer Perceptron (MLP) models. Despite the fine-tuned BERT model demonstrating superior performance, the study lacks an in-depth analysis of underperforming models on distinct datasets, which limits the extraction of valuable insights for potential improvements and optimizations. Addressing these nuances could contribute to a more nuanced understanding and refinement of the cyberbullying detection model.

In the manuscript put forth by Ravuri Daniel et al. entitled as ”Ensemble Learning With Tournament Selected Glowworm Swarm Optimization Algorithm for Cyberbullying Detection on Social Media”[6],the methodology implemented the EDL-TSGSO algorithm, a fusion of Natural Language Processing (NLP) and ensemble learning techniques, to tackle cyberbullying detection specifically on Twitter. Core procedures involved NLTK-based preprocessing, leveraging Glove word embedding, ELSTM-AB classification, and hyperparameter tuning via TSGSO. Impressively, the model exhibited a high level of accuracy in identifying instances of cyberbullying, showcasing its robustness across various splits within the dataset. However, concerns regardingits generalizability surfaced due to the specificity of the dataset used for evaluation, potentially limiting its broader applicability to different contexts. Additionally, the study fell short in thoroughly exploring hyperparameter optimization possibilities, which could have enhanced the model’s performance. Moreover, the research lacked in-depth investigation into the reasons

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behind underperformance on diverse datasets, which restricts the depth of insights necessary for substantial improvements in cyberbullying detection methodologies.

Expounding upon the idea in the paper proposed by Mohammed Hussein Obaid et al. entitled as ”Cyberbullying Detection ans Severity Determination Model”[7], the implemented cyberbullying detection model, constructed using Python and LSTM, achieved a remarkable accuracy rate of 93.6 percent when applied to a dataset comprising 47,733 tweets.This impressive accuracy highlights its effectiveness in precisely detecting instances of bullying present in social media content.. Such robust performance positions the model as a promising tool for practical applications in moderating social media content and combating cyberbullying. However, despite its success, the model’s limitations are evident. Its sole reliance on text-based analysis neglects the detection of cyberbullying within image or video content, indicating a significant blind spot. Additionally, the model’s development and evaluation solely on a dataset of tweets potentially limit its generalizability to other social media platforms, raising concerns about its adaptability in different online environments. To address these limitations and further enhanceits applicability, future endeavors might focus on integrating multimedia detection capabilities and conducting tests across diverse social media platforms, thereby broadening themodel’s scope and effectiveness in identifying cyberbullying across varied online landscapes.

Building upon the framework introduced in the study authored by Jamshid Bacha et al. entitled as”A DeepLearning-Based Framework for Offensive Text Detection in Unstructured Data for Heterogeneous Social Media”[8],The methodology revolved around constructing the KAU-Memes dataset by overlaying offensive tweets onto prominent images, a process that encompassed various stages such as comprehending text nuances, meticulous data refinement, and precise labeling. Evaluation of models like YOLOv4, YOLOv5, and SSD MobileNet-V2 was conducted utilizing performance metrics such as mean Average Precision (mAP), F1-Score, and Precision-Recall. YOLOv5 emerged as the standout performer, boasting an impressive accuracy rate of 88.50percent along with notably faster training and processing speeds compared to its counterparts. Nevertheless, the evaluation highlighted several challenges. Notably, difficulties in detecting small text within memes, limitations in effectively handling offensive text across languages beyond English, and the identification of specific memes posed considerable hurdles. Furthermore, the model’s proficiency might diminish when confronted with memes requiring classification beyond binary classes, such as distinguishing between harassment or propaganda. To address these limitations, future research priorities were outlined, underscoring the importance of data augmentation strategies and the integration of multilingual support to enhance the model’s capabilities and overcomethese identified challenges effectively

Investigating the methodologies articulated in the paper authored by Lida Ketsbaia et al. entitled as ”A Multi-Stage Machine Learning and Fuzzy Approach to Cyber-Hate Detection”[9],the methodology introduces an innovative strategy by leveraging bio-inspired optimization techniques— specifically Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)—in conjunction with fuzzy logic for detecting hate speech within social media contexts. Evaluation across four distinct datasets involves comparing the efficacy of conventional classifiers like Logistic Regression and Naive Bayes against an optimized fuzzy rule-based system. The study also delves into assessing VADER’s (Valence Aware Dictionary and sEntiment Reasoner) effectiveness in capturing the nuances of social media language. Notably, while demonstrating enhanced performance, particularly with LR-Fuzzy-GA, compared to traditional classifiers, the research confronts significant challenges. These challenges encompass the intricacies of establishing precise guidelines for the fuzzy logic model, introducing uncertainty throughpredicted probabilities, and managing imbalances within datasets. These complexities underscore the necessity for continued exploration and refinement in tackling linguistic subtleties and uncertainties inherent in hate speech detection across diverse social media platforms. Addressing these challenges is critical for improving the accuracy and reliability of hate speech detection systems on social media.

Discussing the implications of the research work put forth by Fatima Shannaq et al. entitled as ”Offensive Language Detection in Arabic Social Networks Using Evolutionary-Based Classifiers Learned From Fine-Tuned Embeddings”[10],in an effort to identify offensive Arabic tweets, the study adopted a meticulous two-step approach. Initially, word features underwent refinement using ArCybC, followed by the optimization of classification techniques using SVM or XGBoost through GA-based methods. The study focused on specific domains within Twitter and conducted manual annotation post filtering of offensive content. While the research showcased advancements in accuracy across multiple phases—starting from base classifiers to fine-tuning embedding models and employing GA-based optimization—it encountered hurdles attributed to a relatively small training dataset and vocabulary limitations within pre-trained models. Key limitations revolved around the size of the dataset and the constraints of pre-existing models, highlighting the necessity for more expansive and varied datasets, as well as specialized models tailored to the nuances of offensive language detection within Arabic tweets. Addressing these limitations becomes

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pivotal for enhancing the efficacy of offensive language detection in Arabic social media contexts.

Unpacking the concepts in the literature proposed by Rahul Ramesh Dalvi et al. entitled as ”Detecting a Twitter Cyberbullying using Machine Learning”[11],the method adopted for cyberbullying detection involves collecting tweets, initial preprocessing utilizing NLTK, and subsequently employing TFIDF for feature extraction. Binary classification is conducted using Support Vector Machines (SVM) and Naive Bayes algorithms, where SVM demonstrates superior performance with an accuracy of 71.5 percent. However, this approach faces several limitations, notably its dependence on fixed thresholds, concerns regarding dataset representativeness, and ethical considerations surrounding biases within the data. To ensure practicality and accuracy in real-world applications, continuous refinements are deemed imperative. Critical drawbacks encompass the fixed threshold’s impact on adaptability, potential biases inherent in the dataset, and the lag in real-time implementation. Addressing ethical concerns is paramount, particularly in mitigating biases to enhance the model’s reliability. Ongoing refinement remains essential not only for accuracy improvements but also to ensure the model’s ethical and practical applicability in real-world settings.

Interpreting the findings as per the contribution made in the paper by John Hani entitled as ”Social Media Cyberbullying Detection Using Machine Learning”[12] ,the Sentiment Informed Cyberbullying Detection (SICD) framework is a sophisticated approach designed to identify instances of cyberbullying within the landscape of social media. It relies on sparse learning techniques, effectively modeling various aspects such as social media content, user-post relationships, and sentiment indicators crucial for detecting cyberbullying. Utilizing proximal gradient descent, SICD aims to minimize the complex objective function F(W), encompassing content- label alignment, weight sparsity (W), and sentiment parameters (and). Across assessments conducted on datasets from platforms like Twitter and MySpace, SICD consistently surpasses established benchmarks like LS, Lasso, MF, POS, and USER, showcasing its robustness even with varying training ratios. The framework’s performance gains are validated through rigorous statistical testing, demonstrating significant improvements at a confidence level of = 0.01. Notably, SICD exhibits an upward trajectory in accuracy as the volume of training data increases, indicating potential for

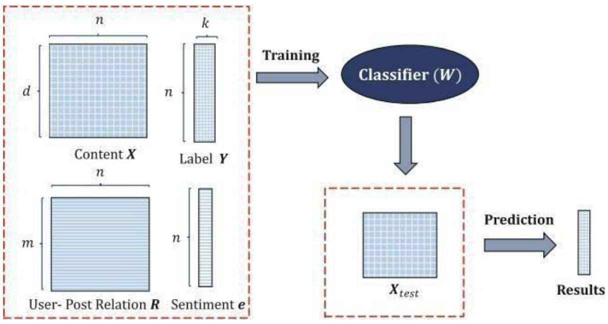

Fig. 3. Strategy outlined in the paper under the title Harsh Dani et al. entitled as ”Sentiment Informed Cyberbulling Detection In Social Media

further refinement with more extensive datasets. However, limitations surface, notably the subgradient descent method’s slow convergence rate, potentially hindering its real-world application. Addressing scalability concerns by accessing larger datasets is crucial, while exploring deep learning techniques emerges as a promising avenue to bolster the framework’s adaptability to evolving cyberbullying patterns.

Reflecting on the implications highlighted in the publication proposed by Harsh Dani et al. entitled as ”Sentiment Informed Cyberbulling Detection In Social Media”[13],the Sentiment Informed Cyberbullying Detection (SICD) framework relies on sparse learning to model social media content, user-post relationships, and sentiment cues for effective cyberbullying detection. Its optimization strategy involves proximal gradient descent to minimize the comprehensive objective function F(W), which accounts for content-label fitting, sparsity regularization of weights (W), and sentiment parameters (represented by symbols and). Across Twitter and MySpace datasets, SICD consistently outperforms several established baselines such as LS, Lasso, MF, POS, and USER, showcasing robustness even under varying training ratios. Rigorous statistical tests validate these improvements, underscored by a confidence level of = 0.01. Moreover, SICD demonstrates a gradual improvement in accuracy with increased training data. However, challenges linger, notably the slow convergence rate of the subgradient descent method, potentially limiting its practical application. Addressing scalability concerns by acquiring larger datasets is recommended, while

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exploring deep learning techniques emerges as a promising avenue to adapt to evolving cyberbullying behaviors and enhance detection capabilities.As shown in the fig2.

In the written work recommended by Learning Rupesh Kumar et al. entitled as ”Detection of Cyberbullying using Machine Learning”[14],the cyberbullying detection methodology outlined follows a systematic process, commencing with text preprocessing involving tokenization, lowercase conversion, and the integration of Microsoft Bing’s Word Correction API to enhance text quality. Feature extraction incorporates TFIDF for word significance evaluation, emotional analysis, and N- Gram processing across different word sequences. Classifica- tion relies on Support Vector Machine (SVM) and Neural Net-work algorithms, with SVM showcasing efficacy in identifyingcyberbullying patterns. Nevertheless, limitations arise from a limited training dataset and specific challenges within Arabic contexts, impacting accurate detections. This underscores the necessity for refined methodologies and acknowledges the im- portance of cross-linguistic applicability for future explorationto enhance model robustness across various languages and cul-tural nuances. Despite promising aspects, ongoing refinement remains imperative for the continual evolution of culturally sensitive and effective cyberbullying detection solutions.
Examining the insights provided in the publication recom- mended by Nanlir Sallau Mullah 1,2, and Wanmohd Nazmee Wan Zainon entitled as ”Advances in Machine Learning Algorithms for Hate Speech Detection in Social Media: A Re- view”[15],the machine learning-driven hate speech detection methodology provides a structured approach involving data collection, feature extraction, and model selection. However, its theoretical underpinnings lack validation from real data experiments, possibly constraining its practical effectiveness. Notably, it overlooks particular hate speech elements, such as symbols and numeric characters, impacting its abilityto achieve comprehensive coverage. Moreover, by assuming universal applicability without considering cultural nuances, it risks introducing biases in detection processes. The methodol- ogy’s heavy reliance on theory without substantial empirical testing may hinder its accurate assessment and practical imple- mentation, especially when confronted with real-world com- plexities. Addressing these limitations—validating theories with real data, recognizing diverse hate speech elements, and accounting for cultural nuances—would enhance its potential for reliable and unbiased hate speech detection across various contexts.

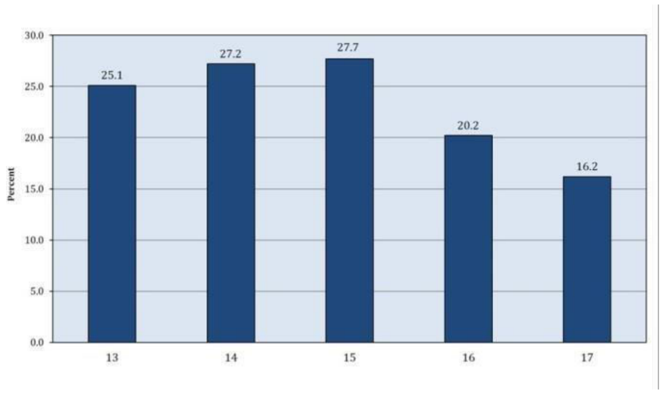

Fig. 4. Recent Cyberbullying Victimization by Age

Table1: Comparision Table

Reference Number	Authors	Advantages	Disadvantages
[1]	**Teoh Hwai Teng et al**	**Versatile, well -established techniques**	**Limited generalization to new data**
[2]	**Mohammed Al-Hashedi et al**	**Emotion captures context.**	**Emotion not always.**
[3]	**Belal Abdullah Hezam Murshed et**	**Deep Learning: Captures intricate data**	**Computational complexity and resource-intensive training.**

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	al	patterns.	
[4]	Nagwan Abdel Samee et al	Privacy, local training.	Federated learning complexity.
[5]	Fatma Elsafoury et al	Automated bullying detection.	Limited technique exploration.
[6]	Ravuri Daniel T et al	Enhanced generalization: model fusion.	Quality and diversity crucial.
[7]	Mohammed Hussein Obaid et al	Detects and determines.	Labels may needed.
[8]	Jamshid Bacha et al	Deep Learning: Captures complex patterns	Resource-intensive training, potential overfitting.
[9]	Lida Ketsbaia et al	Multi-stage enhances accuracy.	Complex process management.
[10]	Fatima Shannaq et al	Adaptable language classifiers.	Cultural/offensive language adaptation.
[11]	Rahul Ramesh Dalvi et al	Ethical bias mitigation.	Threshold, representation limitations.
[12]	John Hani et al	Deep learning scalability.	Training data limitations.
[13]	Harsh Dani et al	Gradual accuracy improvement.	Slow convergence rate.
[14]	Shreyas Parakh et al	Cross-cultural model robustness.	Arabic detection refinement.
[15]	NANLIR SALLAU MULLAH et al	Text data structuring.	Theory lacks validation.

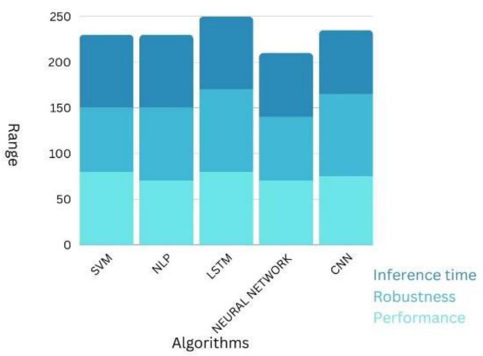

Fig. 5. Performance comparison with the Algorithms

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| Volume 7, Issue 5, May 2024 |

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III. DISCUSSION AND CONCLUSION

The comparison evaluates various algorithms such as SVM, NLP, LSTM, Neural Network, and CNN based on accuracy, reliability, and prediction speed. LSTM excels in performance and reliability, particularly with ordered data, while CNNs are reliable for image-related tasks but may have slower prediction speeds. SVM and NLP offer a balance between accuracy and real-time usefulness. However, the assessment lacks details on datasets and parameter tuning, limiting the applicability of results. Practical implementation depends on data distribution and available computing resources. Addressing cyberbullying, our research proposes a proactive approach through an innovative computer program. Leveraging advanced machine learning, the program acts as a vigilant assistant, detecting and addressing cyberbullying instances on social media. This initiative aims to mitigate the impact of cyberbullying and foster more positive digital interactions. Further real-world testing is crucial for informed decision-making.

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