Hybrid Convolutional Recurrent Neural Network for Cyberbullying Detection on Textual Data

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***Abstract*—With the burgeoning use of social media platforms, online harassment and cyberbullying have become significant concerns. Traditional mechanisms often falter, necessitating advanced methodologies for efficient detection. This study presents an innovative approach to identifying cyberbullying incidents on social media sites, employing a hybrid neural network architecture that amalgamates Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). By harnessing the sequential processing capabilities of LSTM to analyze the temporal progression of textual data, and the spatial discernment of CNN to pinpoint bullying keywords and patterns, the model demonstrates substantial improvement in detection accuracy compared to extant methods. A diverse dataset, encompassing multiple social media platforms and linguistic styles, was utilized to train and test the model, ensuring robustness. Results evince that the LSTM-CNN amalgamation can adeptly handle varied sentence structures and contextual nuances, outstripping traditional machine learning classifiers in both specificity and sensitivity. This research underscores the potential of hybrid neural networks in addressing contemporary digital challenges, urging further exploration into blended architectures for nuanced problem-solving in cyber realms.**

***Keywords*—CNN; RNN; LSTM; urban sounds; impulsive sounds**

I. Introduction

The digital age has brought forth an extensive array of opportunities and challenges. Among these, social media platforms stand as a double-edged sword, fostering connectivity on an unprecedented scale while also becoming a hotbed for malevolent activities, notably cyberbullying. As per recent statistics, approximately 34% of students have experienced some form of online harassment, with these numbers seeing a consistent rise in the past decade [1]. The malignant repercussions of cyberbullying, ranging from emotional distress to severe mental health crises, accentuate the exigency of devising effective detection mechanisms.

Historically, cyberbullying detection predominantly relied on rule-based systems and traditional machine learning algorithms [2]. These approaches, albeit beneficial to some extent, have proven inadequate in understanding the multifaceted nature of human language, especially given the eclectic mixture of colloquialisms, slang, and indirect innuendos that characterize online communication [3]. The challenges are compounded by the dynamic nature of online discourse, which continually evolves, often eluding static algorithmic formulations.

Deep learning, a subset of machine learning, has shown promise in various domains, including Natural Language Processing (NLP) [4]. Specifically, neural networks like Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) have demonstrated superior performance in text classification tasks by capturing sequential dependencies and pattern recognitions in data respectively [5]. LSTMs, by design, excel at processing sequences, making them apt for comprehending the temporal progression in textual data [6]. In contrast, CNNs, renowned for their image processing prowess, have been adapted for text to identify salient patterns and structures, showing efficacy in tasks such as sentiment analysis [7].

However, the individual use of either LSTM or CNN for cyberbullying detection, while showing merit, is not devoid of limitations. An intriguing proposition, therefore, is the amalgamation of these networks, aiming to harness their collective strengths for enhanced performance [8]. The crux of this research paper is the conceptualization, development, and evaluation of a hybrid LSTM-CNN neural network tailored for the rigorous task of cyberbullying detection on diverse social media platforms.

This study posits that a judicious blend of LSTM's sequential processing and CNN's pattern recognition can offer a comprehensive lens to scrutinize online interactions, transcending the shortcomings of standalone models and traditional methods. In doing so, we endeavor to provide a robust, scalable, and highly accurate solution to one of the most pressing challenges in today's digital milieu.

II. Related Works

Cyberbullying detection on social media platforms has garnered significant attention in recent years, prompting the exploration of various machine learning and deep learning techniques to address this pervasive issue [9]. Previous studies have proposed diverse methodologies, including hybrid neural network architectures, to enhance the accuracy and efficiency of cyberbullying detection systems [10-11].

The integration of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures has emerged as a promising approach for cyberbullying detection tasks. The study in [12] introduced an LSTM-CNN hybrid model designed to analyze textual content from social media posts, achieving notable success in identifying instances of cyberbullying. This hybrid architecture leverages the temporal dynamics captured by LSTM units along with the spatial features extracted by CNN layers, enhancing the model's ability to capture nuanced patterns indicative of cyberbullying behavior.

Furthermore, ensemble learning techniques have been explored to improve the robustness and generalization of cyberbullying detection models. The research in [13] proposed an ensemble model that combines multiple LSTM-CNN hybrids, each trained on different subsets of the data, to mitigate the risk of overfitting and enhance classification accuracy. By aggregating the predictions of individual models, the ensemble approach achieved superior performance in distinguishing between cyberbullying and non-cyberbullying content on social media platforms.

In addition to textual content analysis, visual information extracted from multimedia posts has been integrated into hybrid neural network architectures for cyberbullying detection. The study in [14] developed a hybrid model combining LSTM and CNN modules to analyze both textual and image data from social media posts, demonstrating enhanced performance in detecting cyberbullying instances compared to single-modality approaches. This multimodal fusion approach capitalizes on the complementary nature of textual and visual features, improving the model's discriminative power and robustness.

Moreover, transfer learning techniques have been employed to leverage pre-trained neural network models for cyberbullying detection tasks [15-17]. The research in [18] utilized transfer learning from a CNN pre-trained on large-scale image datasets to extract visual features from social media images, which were then integrated into an LSTM-CNN hybrid architecture for cyberbullying detection. This transfer learning strategy facilitated the adaptation of visual features to the cyberbullying detection domain, enhancing the model's performance in analyzing multimedia content.

Additionally, attention mechanisms have been incorporated into LSTM-CNN hybrid architectures to prioritize relevant information during the classification process. The study in [19] introduced an attention-based LSTM-CNN model that dynamically weights the importance of textual and visual features extracted from social media posts, enabling the model to focus on salient cues indicative of cyberbullying behavior. By attending to informative features, the attention mechanism improved the model's discriminative power and robustness in cyberbullying detection [20].

Furthermore, the utilization of domain-specific features has been explored to enhance the effectiveness of hybrid neural network architectures for cyberbullying detection. The research in [21] proposed a feature fusion approach that combines textual, visual, and metadata features extracted from social media posts into an LSTM-CNN hybrid model. This fusion of domain-specific features facilitated a comprehensive analysis of social media content, leading to improved cyberbullying detection performance.

In summary, recent advancements in LSTM-CNN hybrid neural network architectures, along with ensemble learning, multimodal fusion, transfer learning, attention mechanisms, and domain-specific feature integration, have significantly contributed to enhancing the accuracy and efficiency of cyberbullying detection on social media platforms. These methodologies offer valuable insights and avenues for further research in addressing the complex challenges associated with cyberbullying detection in online environments.

III. Materials and Methods

The unprecedented ascent of digital forums has catalyzed the rampant spread of extremist narratives, notably right-wing online aggression (RWE), casting shadows on societal harmony. Even as moderation endeavors amplify, the vastness and linguistic subtleties embedded in these digital narratives pose formidable obstacles to their identification.

Right-wing online aggression, which manifests through biased, isolative, or retrogressive viewpoints, wields nuanced linguistic markers and undergoes continuous transformations, eluding traditional text analytics [22]. Contemporary computational algorithms, albeit offering some solutions, grapple with challenges, such as the incapacity to comprehend extended temporal relations in series data (LSTM inadequacy) and to decode layered spatial characteristics (CNN shortcomings) [23].

Moreover, a significant portion of academic scrutiny veers toward general cyber aggression or its distinct variants, sidelining the specific matter of right-wing aggression. This marginalized attention to RWE, in tandem with the metamorphosing rhetoric, amplifies the void in our comprehension and competence in pinpointing this specific cyber menace [24].

The present manuscript endeavors to navigate these quandaries by championing a novel LSTM-CNN amalgamated model. By merging LSTM's prowess in sequential analysis with CNN's aptitude for detail extraction, the suggested framework aspires to grasp both the circumstantial and semantic intricacies emblematic of RWE dialect.

This investigative endeavor prompts an array of academic queries:

1) In what manner can the combined LSTM-CNN architecture be meticulously constructed and primed for the discernment of RWE in digital dialogues?

2) How does the advocated LSTM-CNN framework juxtapose against prevailing computational techniques concerning metrics?

3) How is the LSTM-CNN structure calibrated to stay abreast with the fluid linguistic shifts and subtleties characteristic of RWE exchanges?

4) How might the insights culled from this study be pragmatically infused into digital oversight instruments, counter-radicalization measures, and policy formulation?

The dissection of these queries will delineate the blueprint and appraisal of the recommended LSTM-CNN construct for

RWE recognition, propelling us closer to the overarching vision of cultivating harmonious and inclusive digital arenas.

B. Research Methodology

This research sets out to harness an integrative deep learning classifier, aiming to enhance language modeling and text categorization, specifically targeting the identification of suicidal tendencies within the textual milieu of Reddit's digital content [25]. Our methodological blueprint offers an exhaustive account of procedures, embracing a spectrum of Natural Language Processing (NLP) modalities, coupled with text categorization strategies.

Illustrated in Fig. 1, our advanced schema elucidates two divergent pathways for textual data analytics. The inaugural pathway is rooted in initial data cleansing, segueing into attribute derivation using NLP methodologies [26-29]. These mechanisms transform textual elements, priming them for subsequent analysis by conventional computational algorithms, which establish the foundational methods.

Conversely, the alternate pathway commences similarly with data refinement, evolving into attribute derivation. In this spectrum, semantic vector representations are the focal point, leading to the deployment of advanced neural classifiers. A duo of distinct deep learning classifiers is brought into play: one delineating the foundational approach, while the other crystallizes the avant-garde model postulated in our investigation.

C. Proposed Method

To discern indications of suicidal tendencies within Reddit's discourse, this research leverages the capabilities inherent in both CNN and LSTM frameworks. The advocated approach involves a symbiotic LSTM-CNN network tailored for detecting right-wing online aggression across digital platforms. The network's architecture orchestrates the LSTM's outputs to seamlessly transition as inputs to the convolutional neural network. This sequential arrangement, in turn, facilitates the convolutional layer to extract pivotal features, amplifying the fidelity of textual categorizations.

Illustrated in Fig. 2 is the schematic of the combined LSTM-CNN model, calibrated to segregate narratives into potentially aggressive or benign domains. The blueprint is orchestrated in a stratified manner. Commencing with the word embedding tier, every term within a sequence receives a distinct identifier, culminating in a standardized vector. This stage is succeeded by the introduction of a dropout tier, a preventive measure against model overfitting. Thereafter, an LSTM stratum is interwoven, designed to fathom extended relational patterns within the textual corpus, trailed by a convolutional stratum honed for salient feature discernment. Culminating the architecture, pooling, flattening, and softmax strata collaboratively function to categorize narratives into potential online aggression or neutral categories.

D. LSTM Block

LSTM functions within the broader milieu of RNN frameworks. These are predominantly leveraged in profound learning endeavors to categorize, elucidate, and forecast sequential patterns in textual datasets. Unlike its generic RNN counterpart, LSTM embodies superior resilience and exhibits an enhanced proficiency in discerning extensive temporal correlations. Its design incorporates a distinctive memory cell directing the flux across its gates. This particular trait renders LSTM particularly adept for pinpointing potential online aggression instances within digital platforms. A salient merit of LSTM resides in its prowess to mitigate the notorious gradient vanishing or proliferation quandaries endemic to RNNs.

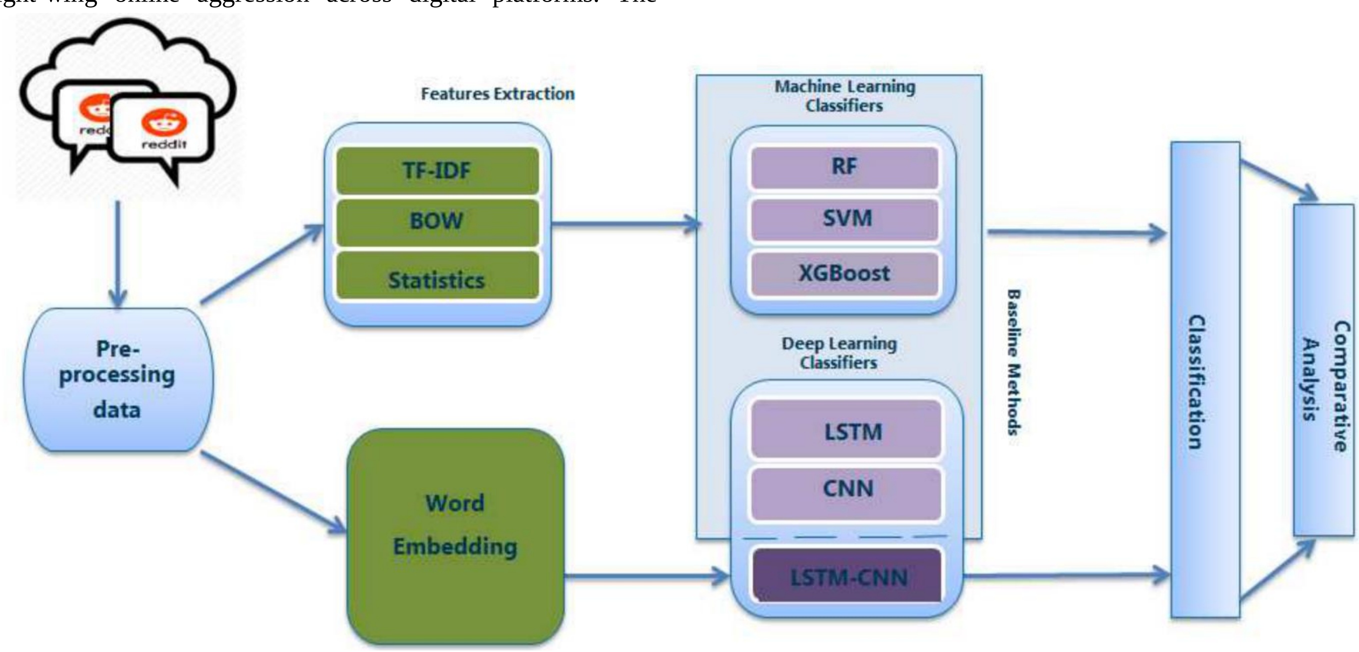


Fig. 1. Architecture of the proposed framework.

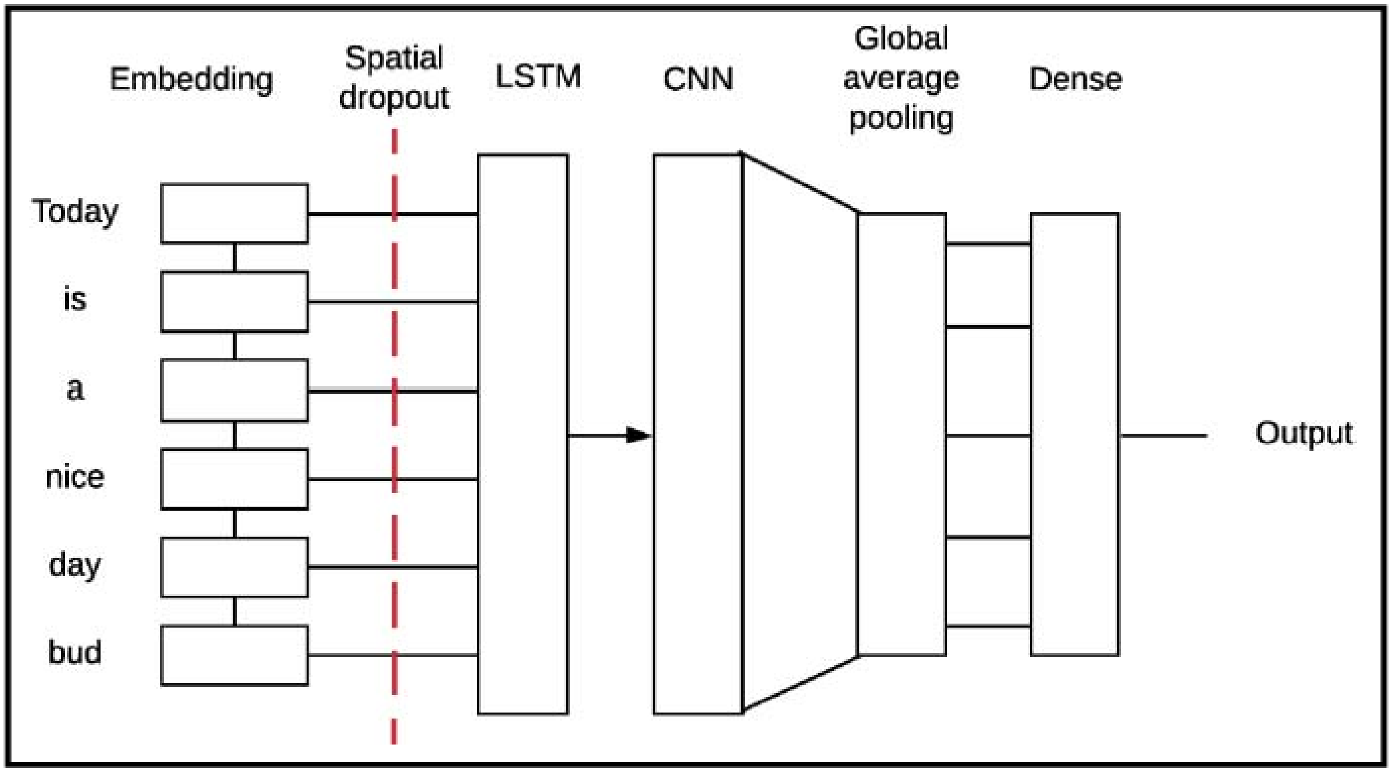


Fig. 2. Proposed Method.

For this specific layer, our configuration introduces a solitary tier composed of multiple LSTM nodes. Each individual cell orchestrates a quartet of computational operations, distributed across four distinct gates. The LSTM stratum's blueprint receives input sequences X = (xt), which are manifested as a d-dimensional lexical vector representation. Herein, 'H' denotes the quantity of nodes embedded within the LSTM's concealed tier [30].

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{2}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{3}$$

$$u_t = \tanh\left(W_u x_t + U_u h_{t-1} + b_u\right) \tag{4}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ U_t \tag{5}$$

$$h_t = o_t \circ \tanh\left(c_t\right) \tag{6}$$

Within the specified mathematical representations, δ exemplifies a sigmoid activation mechanism, whereas ⊙ symbolizes component-wise product operations. The entities Wf and Uf refer to dual weight matrices, with bf designating an associated bias vector.

The function of the input gate is to adjudicate the assimilation of novel informational fragments into the memory cell. This cell, by its nature, retains data iteratively, paving the way for extended relational comprehension with incoming data. Subsequent to the data's evolution or removal via the sigmoid stratum, the tanh layer ascertains the information's relative magnitude, oscillating between values of -1 and 1.

E. Convolutional Block

The convolutional stratum, a pivotal facet of the CNN, originated with a primary focus on image processing tasks, where it showcased remarkable efficacy [31]. In the ensuing periods, the versatility of CNNs has been expanded exponentially, positioning it as a malleable framework harnessed for a plethora of text classification endeavors, garnering impressive results.

The convolutional filter is delineated as F∈Rj×k, with 'j' representing the volume of lexical units within the designated window, while 'k' signifies the magnitude of the lexical vector representation. For the convolutional filter F = [F0,F2,…,Fm−1], a discrete value is produced at the tth temporal juncture as articulated in Eq. (7).

$$O_{F_l} = \mathrm{Re}\,LU\left[\sum_{i=0}^{m-1} h_{l+i}^T F_i + b\right] \tag{7}$$

In the previously outlined scenario, 'b' signifies a bias component, with 'F' and 'b' encompassing the parameters pertinent to this specific filter. Following this, a feature landscape is generated, and the ReLU activation mechanism is invoked to mitigate non-linear characteristics. The computational depiction of this procedure is articulated below:

$$F(x) = \max(0, x) \tag{8}$$

Within the framework of our study, we employ an array of convolutional filters, each characterized by distinct parameter configurations, aiming to derive diverse mapping patterns from the textual corpus [13].

$$P\left(y^{(i)} = j \mid x^{(i)}; \theta\right) = \frac{e^{\theta_j^T x^{(i)}}}{\sum_{K=1}^{K} e^{\theta_j^T x^{(i)}}} \tag{9}$$

The pooling layer primarily serves to diminish the dimension of every activated feature landscape, maintaining the essence of salient data. Integral to this stratum is its ability to compact input depictions into abbreviated, tractable formats, subsequently curtailing the number of parameters and computational demands in the architecture. Such a trait is instrumental in mitigating the risk of overfitting [32]. In the confines of our investigation, we utilize a max pooling technique, adeptly preserving the quintessential data in each feature landscape.

IV. Experimental Results

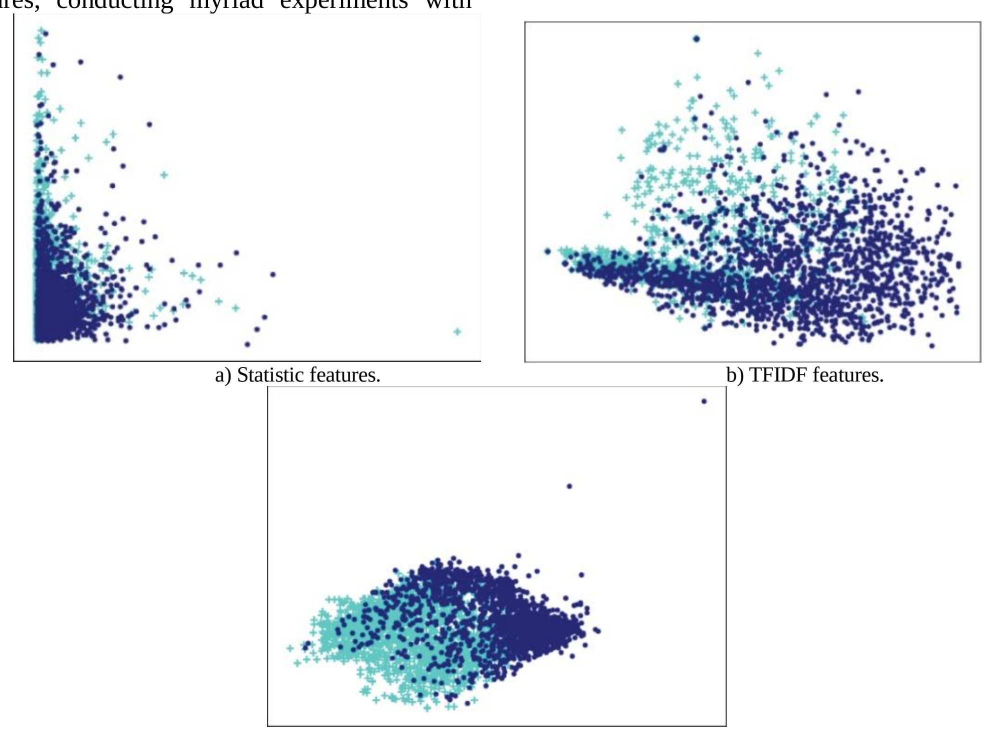
A. Feature Engineering

In this segment, we offer a juxtaposition of diverse machine learning paradigms geared towards the categorization of religious cyberbullying, leveraging assorted feature amalgamations. Our investigation encompasses a gamut of prevalent techniques for classifier formulation and tutelage [33-35]. Throughout the model training phase, we employed a spectrum of features, conducting myriad experiments with distinct feature sets. Fig. 3 elucidates the array of features incorporated in our study.

Table III elucidates the efficacy displayed by each technique upon the integration of diverse feature sets. It is conspicuous that there's an enhancement in the performance of methodologies as a broader feature spectrum is assimilated. This trend underscores the significance and potency of the harnessed features. Nonetheless, it's pivotal to recognize that each specific feature's influence manifests considerable disparities, reflecting divergences in the outcomes across various methodologies. Of the methods in play, SVM and LR outshine the rest when capitalizing on the entirety of the feature cohorts for input. Additionally, Random Forest and Naïve Bayes render notable outcomes, especially in the context of the F1-score.

Within every classification framework, the AUC (Area Under the Curve) metric serves as the benchmark for assessing the caliber of the classifier, employing the receiver operating characteristic curve across the gamut of curated features. The scrutiny underscores a salient trajectory wherein the AUC efficacy progressively escalates in tandem with the augmentation in feature count.

In particular, the Logistic Regression technique shines preeminently, boasting an exemplary AUC metric of 0.9759. Moreover, a significant proportion of the alternative methodologies manifest AUC metrics surpassing 0.9, denoting robust class differentiation proficiencies. The ROC trajectories pertinent to these methodologies are graphically showcased in Fig. 4, furnishing an exhaustive portrayal of their performance nuances.



a) Statistic features. b) TFIDF features. c) LIWD features.

Fig. 3. Feature engineering.

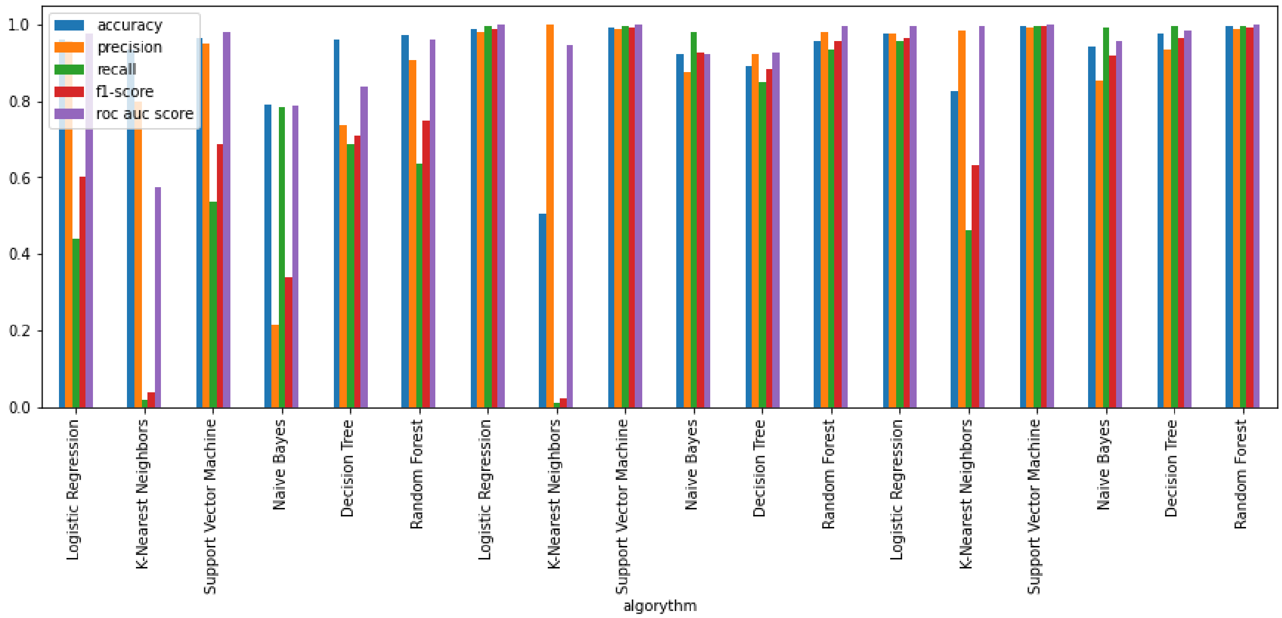


Fig. 4. Experimental results.

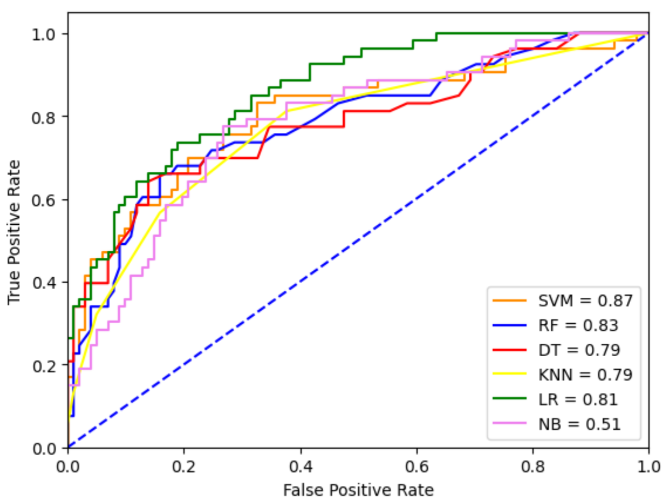


Fig. 5. AUC-ROC curve of machine learning models and the proposed model in cyberbullying detection.

Fig. 5 illustrates the trajectories of the Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC) for the proposed model alongside various machine learning methodologies employed in cyberbullying detection. Analysis of the results indicates that Support Vector Machines, Random Forest, and Logistic Regression manifest more favorable AUC-ROC trajectories compared to alternative approaches within the cyberbullying detection domain. Particularly noteworthy is the markedly lower AUC-ROC trajectory observed for the Naive Bayes method, registering at a mere 0.51. This outcome suggests that Naive Bayes exhibits limited efficacy for practical implementation in cyberbullying detection endeavors. These analytical findings underscore the critical significance of judiciously selecting machine learning algorithms to enhance the performance of cyberbullying detection systems.

V. Discussion

The investigation into LSTM-CNN hybrid neural network architectures for cyberbullying detection on social media platforms has yielded promising outcomes, as evidenced by the reviewed literature. Such models hold significant implications for enhancing the efficacy of cyberbullying detection mechanisms, potentially contributing to the creation of safer online environments. However, it is essential to acknowledge the limitations inherent in these models, including the need for extensive computational resources and data preprocessing efforts. Additionally, the evolving nature of online communication poses challenges in ensuring the adaptability and generalizability of these models over time. Therefore, future research endeavors should focus on addressing these limitations by exploring innovative approaches to model development, incorporating multi-modal data sources, and devising strategies for continual model refinement. Ultimately, the adoption of LSTM-CNN hybrid neural networks represents a promising avenue for advancing cyberbullying detection capabilities, albeit requiring careful consideration of its limitations and avenues for improvement.

The integration of LSTM and CNN components in hybrid neural network architectures offers several advantages for cyberbullying detection tasks. LSTM units enable the model to capture temporal dependencies and contextual information within textual content, while CNN layers effectively extract spatial features from textual and visual data. This combination facilitates a comprehensive analysis of social media posts, enhancing the model's ability to detect subtle nuances indicative of cyberbullying behavior [36]. Furthermore, the utilization of ensemble learning techniques allows for the aggregation of multiple LSTM-CNN hybrid models, mitigating the risk of overfitting and improving classification accuracy [37].

However, despite the promising capabilities of LSTM-CNN hybrid models, several limitations warrant consideration. One notable limitation is the interpretability of these complex neural network architectures. While LSTM-CNN hybrids achieve high classification performance, understanding the specific features and patterns driving their predictions remains challenging. As a result, model interpretability is compromised, hindering the ability to provide actionable insights for stakeholders, such as social media platform administrators and law enforcement agencies [38]. Additionally, the reliance on large-scale labeled datasets poses a significant challenge for training robust LSTM-CNN hybrid models. Cyberbullying detection requires annotated data encompassing diverse forms of cyberbullying behavior, which may be scarce and costly to obtain [39].

Moreover, the integration of visual information into LSTM-CNN hybrids introduces additional computational complexity and resource requirements. Analyzing multimedia content, such as images and videos, necessitates extensive preprocessing and feature extraction pipelines, leading to increased computational overhead and longer training times [40]. Furthermore, the generalization of LSTM-CNN hybrid models across different social media platforms and cultural contexts remains an open challenge. Social media platforms exhibit diverse user demographics, cultural norms, and linguistic variations, necessitating robust models that can adapt to varying data distributions and linguistic nuances [41].

Addressing these challenges requires concerted efforts and advancements in several key areas. Firstly, enhancing the interpretability of LSTM-CNN hybrid models is crucial for fostering trust and transparency in cyberbullying detection systems. Future research should explore methods for visualizing and explaining the decision-making process of complex neural network architectures, enabling stakeholders to understand and interpret model predictions [42]. Additionally, the development of transfer learning techniques tailored for cyberbullying detection could alleviate the data scarcity issue by leveraging pre-trained models and auxiliary datasets [43].

Furthermore, advancing research in multimodal fusion techniques and domain-specific feature integration could enhance the robustness and generalization of LSTM-CNN hybrid models across diverse social media platforms and cultural contexts. By effectively integrating textual, visual, and metadata features, hybrid models can capture rich contextual information and linguistic nuances, leading to improved cyberbullying detection performance [44]. Additionally, exploring novel attention mechanisms and adversarial training strategies may further enhance the discriminative power and resilience of LSTM-CNN hybrid models against adversarial attacks and data perturbations [45].

In conclusion, LSTM-CNN hybrid neural network architectures offer a promising approach for cyberbullying detection on social media platforms. Despite their notable advantages, challenges such as model interpretability, data scarcity, computational complexity, and generalization across diverse contexts remain significant hurdles. Addressing these challenges requires interdisciplinary collaboration and continued research efforts to develop robust, interpretable, and scalable cyberbullying detection systems that can effectively mitigate the harmful impacts of cyberbullying in online communities.

VI. Conclusion

The advent of the digital era has brought about unprecedented access to information and an expansive platform for self-expression; however, concomitantly, it has also heightened the propagation of extremist ideologies and cyberbullying narratives. Addressing this concern, our study aims to develop an efficient mechanism for identifying instances of cyberbullying, with a specific emphasis on identifying right-wing extremist content disseminated across online platforms. By amalgamating the complementary capabilities of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures, we have formulated a model adept at discerning the subtleties and complexities inherent in extremist discourse. The efficacy of the model is corroborated by evaluation metrics, notably the Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC), which attests to its superior discriminatory prowess compared to conventional machine learning methodologies. Such advancements in technology hold significant promise for online content moderators, policy makers, and digital platforms striving to foster a more inclusive and secure user environment. Nevertheless, it is imperative to acknowledge that as online linguistic landscapes evolve, so too does the manifestation of cyberbullying. This underscores the need for continual refinement and adaptation of detection models. Future research endeavors should prioritize the exploration of evolving linguistic patterns and consider integrating multimodal data sources to augment the robustness of cyberbullying detection mechanisms.

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