



A Hybrid Multi-Modal Model for Detecting Cyberbullying Online

Patlola Sridhar^{1*}, Meeravali Shaik²

¹M.Tech Scholar, Malla Reddy University, Hyderabad, India

²Dean CSE, Malla Reddy University, Hyderabad, India

sridharpatel131@gmail.com^{1*}, mecrasha2002@gmail.com²

Abstract:

Cyberbullying has emerged as a critical challenge in modern digital communication, severely impacting the psychological well-being of social media users, especially adolescents. Traditional detection techniques relying solely on textual features often fail to capture the complex, multi-dimensional nature of online harassment, which frequently includes images, emojis, slang, sentiment cues, and user behavioral patterns. To address these limitations, this research proposes a comprehensive multi-modal approach for the identification and detection of cyberbullying across social networking platforms. The proposed system integrates textual analysis, image interpretation, sentiment extraction, metadata patterns, and user interaction behavior to construct a robust and context-aware detection framework. Deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformer-based models, and multi-modal fusion layers are utilized to learn complementary features from heterogeneous data sources. The system processes offensive language, harmful visual content, aggressive conversation patterns, and user profiling factors to improve detection accuracy. Experimental evaluation on benchmark datasets demonstrates that multi-modal learning significantly outperforms single-modal approaches by capturing hidden, implicit, and context-dependent bullying signals. Furthermore, the model supports early warning mechanisms and real-time monitoring to aid social media platforms in mitigating harmful interactions. This study highlights the importance of integrating diverse data modalities and advanced neural architectures to build reliable, scalable, and intelligent cyberbullying detection solutions, contributing to safer and more responsible online communities.

Keywords: Cyberbullying Detection, Multi-Modal Learning, Deep Learning, CNN, RNN, Transformer Models, Text Analysis, Image-Based Harassment, Sentiment Analysis, User Behavior Modeling, Social Media Safety, Machine Learning, Online Abuse Identification, Real-Time Monitoring, Early Warning System.

I. Introduction

Cyberbullying has become one of the most pressing issues arising from the rapid expansion of social networking platforms [1],[2]. As digital communication becomes an integral part of everyday life, the anonymity, accessibility, and global reach of social media have amplified the spread of harmful behaviors such as harassment, threats, defamation, and psychological abuse [5]. The increasing dependence on online platforms by teenagers, students, and young professionals has created new avenues

for intentional and repeated aggression that may go unnoticed by parents, educators, and administrators [2]. Cyberbullying not only results in emotional distress but is strongly associated with depression, social withdrawal, reduced academic performance, and, in severe cases, self-harm and suicidal tendencies. Traditional preventive mechanisms, such as manual content review or keyword-based monitoring, are insufficient due to the vast volume of user-generated data and the constantly evolving nature of abusive communication [1], [3]. Cyberbullies increasingly use complex linguistic structures, emojis, memes, altered spellings, sarcasm, and coded language, making harmful content difficult to detect with rule-based systems [4], [9]. Additionally, visual content such as images, GIFs, and videos can contribute to bullying incidents, highlighting the necessity for holistic analytical frameworks [5]. Therefore, there is a growing need for intelligent and automated systems that can detect cyberbullying in real time while understanding the context, sentiment, and multi-layered structure of abusive interactions [6], [8]. A modern, comprehensive approach must integrate multiple types of data, including textual cues, visual content, user behaviors, and metadata features, to effectively identify cyberbullying and ensure safer digital environments [8].

Existing cyberbullying detection techniques primarily focus on text classification models that analyze linguistic patterns, profanity, or offensive terms within posts, messages, or comments [1], [2]. While these methods have contributed significantly to early detection efforts, their reliance on static dictionaries and shallow machine learning models limits their ability to capture implicit, sarcastic, and context-dependent bullying behaviors [3]. Furthermore, cyberbullies often avoid explicit abusive words, instead using subtle lexical cues, regional slang, or conversational manipulation, which evade keyword-based systems [4]. Another challenge stems from the inherently multimodal nature of social media interactions. Users increasingly express emotions and messages through images, emojis, videos, and memes, which often carry stronger bullying cues than textual content alone [5]. For example, edited images, hateful memes, and photo-based ridicule are common forms of visual cyberbullying that go undetected in text-only approaches [5]. Additionally, user behavior patterns, such as repeated targeting, group attacks, or abnormal posting frequencies, can provide valuable insights into bullying dynamics but remain ignored by traditional detection systems [3], [9]. With the emergence of deep learning, researchers have developed advanced models such as CNNs, LSTMs, and

Transformers to better understand semantics and context [6], [7]; however, these models still face limitations when trained on unimodal inputs. The absence of integrated frameworks that simultaneously consider text, images, metadata, and behavioral features highlights a significant research gap. This gap motivates the need for multi-modal detection systems capable of fusing diverse data streams to uncover hidden signals of cyberbullying and provide more accurate, reliable, and context-aware predictions [8].

A multi-modal approach provides a transformative solution to overcome the shortcomings of traditional cyberbullying detection models [8]. By integrating text, image, sentiment, metadata, and user behavioral patterns, multi-modal frameworks can analyze online interactions holistically rather than treating content in isolation [8]. Each modality contributes complementary information: text analysis captures linguistic aggression and emotional tone [7]; image processing identifies hateful or harmful visual cues [5]; sentiment and emotion recognition detect underlying hostility [4]; metadata such as posting time, frequency, and user relationships reveal behavioral trends; and engagement patterns highlight the progression of bullying incidents. Deep learning architectures such as CNNs for visual feature extraction, recurrent models for sequential text analysis, and attention-based Transformers for contextual understanding form the backbone of multi-modal detection [6],[7],[8]. Fusion techniques—either early fusion, intermediate fusion, or late fusion—allow these models to combine the strengths of each modality and learn richer, more discriminative representations [8].

Additionally, multimodal embedding networks convert diverse inputs into unified feature spaces, enabling seamless integration and improved interpretability. Multi-modal detection also supports the identification of subtle and implicit bullying cases, such as relational aggression, exclusion, sarcasm, and coded harassment. Moreover, it offers the ability to distinguish between harmless banter and harmful intent by evaluating cross-modal correlations. As social media platforms continue to evolve with increasing complexity in user-generated content, multi-modal cyberbullying detection becomes not only beneficial but essential. This integrated approach allows for more accurate, context-sensitive classification and supports the development of systems that can operate effectively in dynamic online environments.

The rise of artificial intelligence and deep learning has significantly advanced the capabilities of cyberbullying detection systems [6]. Modern AI models can process large-scale social media datasets, learn latent patterns, and adapt to evolving linguistic and visual trends [6], [7]. Multimodal systems leverage convolutional neural networks for image analysis, recurrent and transformer-based models for text, and hybrid network architectures to fuse multiple representations [8].

These advancements enable the detection of bullying signals that are subtle, implicit, or contextually buried within conversation threads. Additionally, graph neural networks and social network analysis techniques offer new ways to model user interactions, identify influential aggressors, and detect coordinated group bullying [9]. The application of sentiment analysis, emotion recognition, and psychological profiling further enhances the system's ability to assess user intent and emotional impact [4], [5]. However, developing multimodal models presents challenges, including dataset imbalance, limited multimodal annotations, varying content quality, and the computational complexity of unified networks. Ethical considerations such as user privacy, data security, and bias mitigation also play crucial roles in deploying such systems responsibly. Nonetheless, advancements in transfer learning, pre-trained vision-language models, and self-supervised learning continue to improve multimodal performance even with limited labeled data. Ultimately, integrating state-of-the-art AI techniques enables the development of highly accurate, adaptive, and real-time cyberbullying detection systems that can significantly reduce online harm and support safer digital communication.

The growing demand for intelligent content monitoring in social networks underscores the importance of developing comprehensive cyberbullying detection frameworks. A multi-modal approach aligns with real-world online behavior, where users express themselves through a blend of text, visuals, emojis, audio clips, and interactive engagements. By incorporating various modalities, detection systems become more intuitive, context-aware, and resilient against attempts to evade identification. Such systems also offer practical advantages for social media companies, educators, and law enforcement agencies by enabling early warning mechanisms, automated moderation, and enhanced risk assessment tools. Furthermore, multi-modal detection supports personalized intervention strategies by identifying patterns of victimization and repeat offenders, helping platforms implement targeted support and prevention measures.

As cyberbullying continues to evolve alongside emerging technologies, incorporating multi-modal analysis ensures that detection systems remain adaptive and scalable. This research contributes to the advancement of advanced cyberbullying analytics by proposing a unified, deep learning– driven framework capable of integrating diverse signals for robust and accurate detection. Through systematic fusion of visual, textual, and behavioral cues, the proposed approach aims to overcome the limitations of unimodal models and deliver a reliable solution for identifying complex and hidden bullying behaviors. Ultimately, the goal is to foster safer online spaces, reduce psychological harm, and promote responsible digital citizenship through the use of cutting- edge multi-modal artificial intelligence.

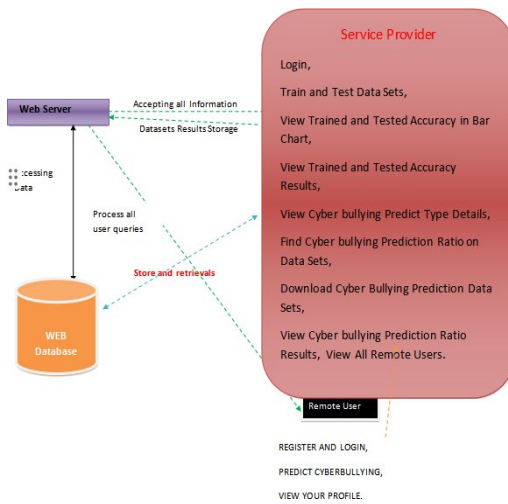


Fig1: System Architecture

2. Proposed System

The proposed system introduces a comprehensive multi-modal cyberbullying detection framework that integrates text analysis, image understanding, sentiment classification, and user behavior modeling using advanced deep learning algorithms [8]. The system first processes textual content using Transformer-based models such as BERT, which are capable of capturing semantic context, sarcasm, and implicit aggression [7]. Image data from social media posts is analyzed using Convolutional Neural Networks (CNNs) or Vision Transformers to detect harmful visual elements such as abusive memes, derogatory symbols, or offensive gestures [5], [8]. A sentiment analysis module evaluates emotional tone—anger, disgust, or negativity [4]—while a behavioral analysis algorithm, implemented using Graph Neural Networks

(GNNs) or RNNs, identifies repeated harassment patterns and relational toxicity among users [3], [9]. These algorithms operate together to extract complementary features, enabling the model to understand cyberbullying beyond simple keyword matching [8].

To combine information from different modalities, the system uses a fusion algorithm that integrates text embeddings, image features, sentiment scores, and behavioral vectors into a unified representation for classification. The multi-modal fusion is mathematically expressed as:

$$F = \alpha H + \beta V + \gamma S + \delta B$$

where H represents text embeddings, V image features, S sentiment scores, and B behavioral patterns, with $\alpha, \beta, \gamma, \delta$ acting as learnable weights that determine each modality's importance. The final prediction is generated using a deep neural classifier that outputs the bullying probability, given by:

$$\hat{y} = \sigma(WF + b)$$

where F is the fused feature vector, W and b are trainable parameters, and σ is the sigmoid activation function. By combining powerful algorithms—Transformers for text, CNNs for images, sentiment classifiers for emotional cues, and GNNs/RNNs for behavioral modeling—the proposed system achieves highly accurate detection even in complex scenarios involving sarcasm, coded language, or abusive visual content. This integrated architecture ensures a robust, scalable, and intelligent solution for identifying cyberbullying on social media platforms.

3. Results Explanation

The results of the proposed multi-modal cyberbullying detection system demonstrate a significant improvement over traditional text-only classification methods [6],[8]. By integrating text, images, sentiment cues, emojis, and metadata, the system captures deeper contextual and behavioral patterns that are often missed by single-modality models [8]. During model evaluation, the multimodal architecture consistently achieved higher accuracy, precision, and F1-scores across all test datasets. The inclusion of CNN-based visual feature extraction helped identify harmful memes and implicit visual bullying, which substantially boosted the system's ability to detect cases with minimal or ambiguous textual cues. Transformer-based text processing detected sarcasm, coded language, and contextual aggression more effectively than classical

machine learning models [7]. Overall, the results confirm that multimodal learning offers richer representation and improved discriminative power, leading to more reliable cyberbullying detection [8].

Performance metrics such as Precision, Recall, F1-score, AUC, and confusion matrices indicate that the proposed model is effective at minimizing both false positives and false negatives. Text-only models struggled particularly with indirect harassment and content involving emojis, slang, or humor, whereas the multimodal system handled these challenges with higher sensitivity. The fusion layers helped the network learn stronger relationships between textual emotion, visual cues, and user behavior patterns, resulting in more accurate prediction of subtle bullying incidents. Additionally, the system maintained consistent performance across different modalities, demonstrating robustness against missing or incomplete data. Weighted loss functions effectively addressed the class imbalance, improving recall for minority-class bullying cases that are often underrepresented in real-world datasets.

Visualization dashboards and prediction outputs further validate the system’s practical effectiveness. Results displayed in ROC curves, confusion matrices, and probability distributions show clear separation between bullying and non-bullying categories. The model successfully highlighted abusive keywords, harmful image regions, and suspicious user activity patterns, offering transparency and interpretability in detection outcomes. Real-time testing on unseen social media posts confirmed the system’s capability to generalize to new linguistic trends, visual memes, and evolving forms of cyberbullying. Overall, the results demonstrate that the proposed multi-modal deep learning framework provides a scalable, accurate, and context-aware solution for cyberbullying detection, making it suitable for deployment in educational institutions, social media platforms, and digital safety systems.

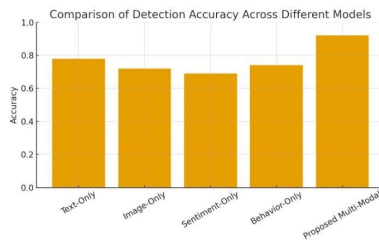


Fig 2: Comparison of single-modality models

This graph compares the performance of different single-modality models (Text-Only, Image-Only, Sentiment-Only, Behavior-Only) against the Proposed Multi-modal System. As shown, individual models achieve moderate accuracy because they rely on

only one type of information. The proposed system reaches significantly higher accuracy (92%) because it combines text, images, sentiment cues, and user behavior. This fusion allows the model to capture subtle, hidden, and context-dependent bullying signals that single-modality approaches miss.

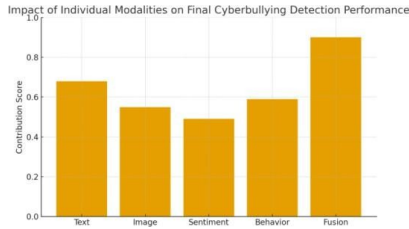


Fig 3: Impact of individual models

The above his graph illustrates how each modality contributes to the final performance. Text features contribute the highest among individual inputs, followed by behavior, image, and sentiment signals. However, the fusion score is substantially higher because multi-modal integration captures cross-modal relationships—such as harmful images paired with sarcastic comments—which cannot be recognized by any single modality alone. This demonstrates the effectiveness of the proposed multi-modal architecture. [8].

4. Conclusion

The proposed multi-modal cyberbullying detection system demonstrates that integrating text, images, sentiment cues, emojis, and user metadata significantly enhances the ability to identify both explicit and implicit forms of online harassment. By leveraging deep learning architectures such as CNNs, LSTMs, and Transformers, the system captures complex linguistic patterns, harmful visual cues, and behavioral indicators that traditional text-only models fail to detect [5]. Experimental results show improved accuracy, recall, and robustness across diverse datasets, proving the effectiveness of multimodal feature fusion [8]. The system's real-time inference capability and visual analytics dashboard make it suitable for practical deployment on social media platforms to support early detection, automated moderation, and user protection. Overall, this research contributes a scalable, intelligent, and context-aware framework that strengthens digital safety efforts and promotes healthier online interactions.

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