Comparative Analysis of Artificial Intelligence Techniques for the Detection of School Violence

Análisis comparativo de técnicas de inteligencia artificial para la detección de la violencia escolar

DOI: https://doi.org/10.17981/cesta.06.01.2025.04

Review article.
Date of reception: 03/20/2025 Date of acceptance: 06/05/2025

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How to cite:
C. Barrios-Cogollo and M. Reales, "Comparative Analysis of Artificial Intelligence Techniques for the Detection of School Violence", *J. Comput. Electron. Sci.: Theory Appl.*, vol. 6, no. 1, pp. 35-44, 2025. DOI: https://doi.org/10.17981/cesta.06.01.2025.04

Abstract
Introduction: School violence represents a global issue that affects the physical, emotional, and academic well-being of students. It can manifest itself in various forms, including verbal, physical, social, digital, socioeconomic, and sexual abuse. Faced with the growing need for more effective strategies for its prevention and detection, Artificial Intelligence (AI) emerges as a promising tool to address this challenge in educational contexts.
Objective: To analyze and compare different artificial intelligence techniques applied to the early detection of school violence, evaluating their effectiveness and potential integration in hybrid systems.
Method: A systematic literature review was done following the PRISMA protocol and using the Scopus database.
Results: The approach based on natural language processing (NLP) and machine learning achieved an F1 score of 84.2% in identifying at-risk students. The second study, focusing on voiceprint and speech recognition technologies, facilitated real-time harassment detection, although it did not report quantitative metrics. The third approach, which employed computer vision with YOLOv8 and LSTM neural networks, achieved 95.67 % accuracy in identifying violent behavior.
Conclusions: Artificial intelligence techniques applied to school violence offer complementary advantages: computer vision excels in accuracy for direct detection, PLN is helpful for early prevention, and speech recognition enables immediate responses. Integrating these methods into hybrid systems, with an ethical and collaborative approach, emerges as a comprehensive and effective solution to address this problem in the educational environment.

Keywords: Artificial intelligence; Deep learning; Natural language processing; Neural networks; Speech recognition; Violence detection.

Resumen
Introducción: La violencia escolar representa una problemática global que afecta el bienestar físico, emocional y académico de los estudiantes. Esta puede manifestarse de diversas formas, incluyendo abuso verbal, físico, social, digital, socioeconómico y sexual. Frente a la creciente necesidad de estrategias más eficaces para su prevención y detección, la Inteligencia Artificial (IA) surge como una herramienta prometedora para abordar este desafío en contextos educativos.
Objetivo: Analizar y comparar distintas técnicas de inteligencia artificial aplicadas a la detección temprana de violencia escolar, evaluando su eficacia y potencial integración en sistemas híbridos.
Método: Se llevó a cabo una revisión sistemática de la literatura siguiendo el protocolo PRISMA y utilizando la base de datos Scopus. El proceso de selección culminó en la inclusión de tres estudios relevantes que implementan técnicas de IA en distintos tipos de datos de entrada: texto, audio y vídeo.
Resultados: El enfoque basado en procesamiento del lenguaje natural (PLN) y aprendizaje automático logró una puntuación F1 del 84,2 % en la identificación de estudiantes en riesgo. El segundo estudio, centrado en tecnologías de huella vocal y reconocimiento de voz, facilitó la detección en tiempo real de acoso, aunque no reportó métricas cuantitativas. El tercer enfoque, que empleó visión por ordenador con YOLOv8 y redes neuronales LSTM, alcanzó una precisión del 95,67 % en la identificación de comportamientos violentos.
Conclusiones: Las técnicas de inteligencia artificial aplicadas a la violencia escolar ofrecen ventajas complementarias: la visión por ordenador destaca en precisión para la detección directa, el PLN es útil para la prevención temprana y el reconocimiento de voz permite respuestas inmediatas. La integración de estos métodos en sistemas híbridos, con un enfoque ético y colaborativo, se perfila como una solución integral y eficaz para abordar esta problemática en el ámbito educativo.

Palabras clave: Inteligencia artificial; Aprendizaje profundo; Procesamiento del lenguaje natural; Redes neuronales; Reconocimiento del habla; Detección de la violencia.

INTRODUTION

School violence is a critical problem worldwide [1], affecting the well-being and academic performance of students regardless of age, gender, school grade, or socioeconomic level [2], and it can manifest in various forms, each with specific characteristics and adverse effects on the victims [3], [4], [5].

Among these forms, verbal violence includes insults, mockery, and humiliating comments that undermine students' self-esteem and emotional well-being [6]. Physical violence, on the other hand, often leaves visible marks and is manifested through hitting, shoving, assaults with objects or weapons, and destruction of belongings, causing injuries, chronic pain, trauma, and fear [6], [7].

Social violence seeks to isolate and manipulate the victim through threats, rumors, and damage to their reputation, leading to feelings of loneliness, anxiety, and difficulties in socialization [8]. In the digital sphere, cyberbullying includes the dissemination of humiliating content, identity theft, and anonymous threats, causing stress, low self-esteem, and concentration problems [9].

On the other hand, socioeconomic violence occurs when a person is discriminated against due to their economic status, either through mockery, exclusion, or limitation of academic opportunities, reinforcing inequality and social isolation [8], [10]. Sexual violence, in turn, involves assaults based on sexuality, such as insinuations, non-consensual contact, and coercion, with devastating effects such as anxiety, post-traumatic stress, and loss of trust in school authorities [6], [11]. Additionally, there are other forms of violence perpetrated by adults in positions of power, such as teachers who condition grades in exchange for favors [11], [12]. In any of its manifestations, school violence negatively impacts the mental, emotional, and physical health of its victims [7], [9].

Several countries have implemented targeted prevention and mitigation strategies to address the growing concern of school violence. In Norway, the Olweus Bullying Prevention Program has achieved notable success by restructuring the school environment and promoting consistent, school-wide anti-bullying policies. Similarly, Spain has launched the Tutor Police project, which places police officers within educational institutions to prevent and manage incidents of bullying, cyberbullying, and other violent behaviors in coordination with teachers and social services.

At the international level, efforts to combat violence against children have gained momentum. In November 2024, more than 100 governments, alongside the World Health Organization (WHO), made historic commitments to eliminate all forms of violence against children. The United Nations Children's Fund (UNICEF) has also played a key role in promoting cross-sectoral coordination to strengthen child protection systems. A notable example is in Bolivia, where UNICEF has supported collaborative efforts among education, health, and social sectors to enhance student safety and well-being. These examples underscore the importance of multi-level and cross-institutional collaboration in developing sustainable solutions to school violence.

According to the April 2023 report by the Non-Governmental Organization (NGO) Bullying Without Borders, the countries with the highest reported cases of bullying included Mexico with 270,000 instances, followed by the United States with 250,000, Spain with 69,554, Brazil with 66,500, and Argentina with 50,250 cases [13]. These figures already reflected a concerning panorama of school violence on a global scale.

However, the April 2024 update revealed an alarming increase in bullying incidents across several nations. Spain reported a dramatic rise to 300,000 cases, Mexico to 280,000, Argentina to 270,000, the United States to 260,000, and Germany entered the list with 250,000 reported cases [14]. This escalation underscores that, despite ongoing intervention and prevention programs, school violence remains a persistent and growing issue. The data highlights the urgent need to evaluate the effectiveness of current strategies and consider innovative, technology-driven solutions that complement existing efforts to combat bullying and improve student safety worldwide.

Alongside technological development, artificial intelligence has emerged as a promising tool for the early detection of school violence [15] Its ability to analyze large volumes of data, identify behavioral patterns, and generate real-time alerts makes it a solution that could strengthen existing prevention strategies.

This article compares three AI techniques used to identify school violence, evaluating their effectiveness, scope, and limitations. The aim is to determine which approaches have shown better results in the early identification of bullying. Understanding these differences will help strengthen existing strategies and move toward more accurate and efficient solutions for preventing school violence.

RELATED WORK

A recent systematic review classifies computer vision-based violence detection techniques into three groups: traditional methods, SVM, and deep learning. In addition, the processes of feature extraction, the databases used, and the evaluation metrics are analyzed, providing a useful framework for designing automated school monitoring solutions [16].

Traditional approaches have used descriptors such as Violent Flow (ViF) and optical flow analysis to identify aggressive behaviors in video [17], [18]. Some models extract motion vectors directly from compressed streams, enabling faster and more efficient detection without the need to decode the videos, achieving accuracies above 96% fully [19].

With the rise of deep learning, three-dimensional convolutional neural networks (3D-CNNs) have been developed to extract spatiotemporal features directly from sequences. Some studies have exceeded 90% accuracy in fight detection, while hybrid models such as CNN-ConvLSTM have shown improvements in identifying local dynamic patterns [20], [21].

Other works have focused on integrating contextual information to improve detection reliability. For example, including semantic scene understanding and crowd density estimation has helped differentiate between aggressive and non-aggressive interactions in crowded environments [22]. These models leverage attention mechanisms and spatial-temporal relationships to reduce false positives, which is crucial in dynamic school settings.

Recent studies have explored multi-modal fusion techniques, combining audio and visual signals to increase robustness. One approach used synchronized spectrogram features and optical flow inputs within a two-stream neural network architecture, reporting an F1-score of 93.4% in violent behavior detection [23]. Such fusion techniques are particularly effective in noisy or occluded scenarios, where relying solely on visual cues may be insufficient.

Moreover, advancements in transfer learning and pre-trained models have accelerated the development of real-time school violence detection systems. By fine-tuning architecture such as YOLOv7 and EfficientNet, researchers have been able to deploy accurate detectors on edge devices with limited computational resources [24]. These innovations pave the way for scalable, low-latency applications suitable for integration into school surveillance infrastructure.

METODOLOGÍA

This study employs a comparative analytical approach grounded in the PRISMA [25] methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), a widely accepted protocol for ensuring transparency and rigor in systematic literature reviews. The goal is to examine and compare three distinct artificial intelligence (AI) techniques used to detect school violence.

The following PRISMA diagram illustrates the study selection process:

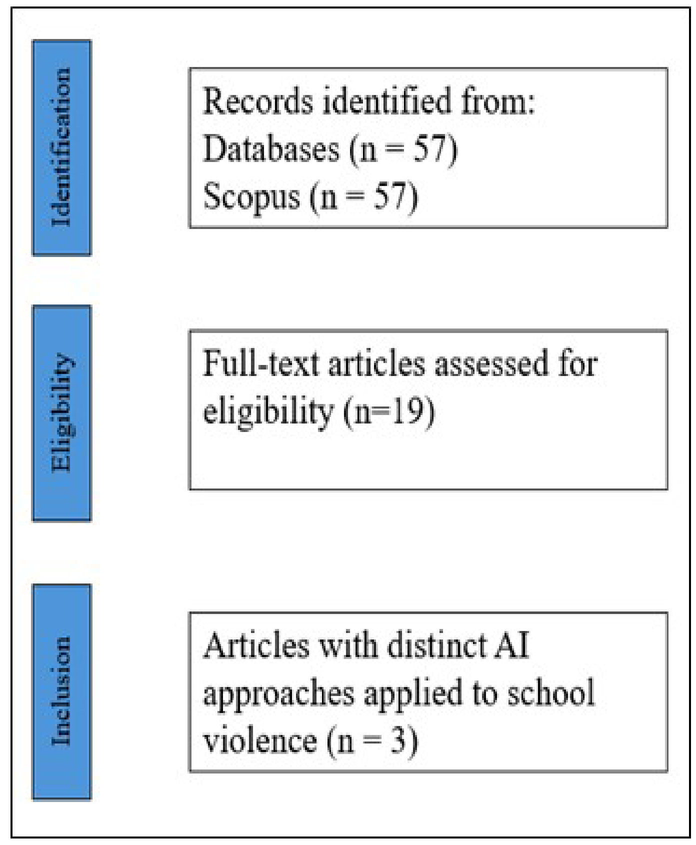

Fig. 1. PRISMA methodology application diagram. Source: Own PRISMA

A systematic literature review was conducted in the Scopus academic database, selected for its comprehensive coverage of peer-reviewed scientific publications. The search used the keywords "School violence" AND technology, yielding an initial pool of potentially relevant articles. The review adhered strictly to predefined inclusion and exclusion criteria, ensuring both the relevance and the methodological robustness of the selected studies

Inclusion criteria were as follows:

- Studies published within the last five years to ensure the timeliness of the data.
- Empirical research articles that implement AI-based approaches for detecting any form of school violence (e.g., verbal, physical, digital).
- Studies reporting quantifiable performance results, including accuracy metrics such as precision, recall, or F1-score.

Exclusion criteria included:

- Duplicate studies or those employing the same AI technique, to avoid redundancy.
- Theoretical reviews or conceptual papers without implementation or experimentation.
- Articles with restricted or no access to complete datasets or results could limit the depth of comparative analysis.

The selection process was conducted in three distinct phases following the PRISMA protocol:

Identification: A total of 57 articles were retrieved from Scopus using the specified search string. Titles and abstracts were screened to eliminate irrelevant studies.

Eligibility: After removing duplicates and screening abstracts, 19 full-text articles were reviewed to assess methodological quality, clarity of objectives, and alignment with inclusion criteria.

Inclusion: Finally, three studies were selected. Each represents a distinct AI approach: natural language processing (text input), voice recognition (audio input), and computer vision (video input), allowing for a comprehensive comparative analysis.

Each selected study was then analyzed based on performance metrics, data types, input modalities, context of implementation, and potential scalability in educational environments.

RESULTS

Se realizó un análisis comparativo de los tres estudios seleccionados, cada uno de ellos abordan el problema de la violencia escolar desde diferentes modalidades de entrada, texto, voz y video, aplicando técnicas de inteligencia artificial específicas para cada caso.

The three selected studies were subject to comparative analysis. Each addresses the problem of school violence using different input modalities, such as text, voice, and video, and specific artificial intelligence techniques for each case.

The first study, "Finding warning markers: Leveraging natural language processing and machine learning technologies to detect risk of school violence," proposes a risk detection system based on language analysis through structured interviews [26]. The system leverages NLP techniques, which allow computers to interpret and analyze human language in context [27]. These techniques are integrated with supervised machine learning algorithms to enhance prediction accuracy. The study evaluates several models, including Logistic Regression (LR), which predicts categorical outcomes [28]. Support Vector Machines (SVM), which classify data by identifying optimal separation boundaries [29]. Artificial Neural Networks (ANN), which mimic the structure of the human brain to detect complex patterns [30]; and Random Forests (RF), which aggregate multiple decision trees for more reliable predictions [31] .

Among the tested models, the combination of NLP with Random Forests produced the best performance, achieving an F1 Score of 0.842 in identifying students at high risk of involvement in school violence. This high score indicates a well-balanced performance in precision and recall, underscoring the model's potential as a reliable tool for early intervention. The study demonstrates the value of proactively integrating language-based analysis with advanced machine learning methods to address school violence through data-driven strategies.

The second study implements an anti-school bullying system based on voice recognition and distributes an intelligent surveillance system using voice recognition technologies to identify real-life bullying situations. It comprises three main modules: a detection terminal, a cloud server, and a mobile application [32]. This system uses voiceprint recognition, a biometric technique that identifies a person by the unique characteristics of their voice, complemented with Vector Quantization (VQ), a method that reduces the dimensionality of signals by encoding key features [33], Hidden Markov Models (HMM), probabilistic models used to represent data sequences where the states are hidden [34], commonly applied in speech recognition [35], and Neural Networks (NN) [33]. It also integrates speech recognition (VQ) to detect sensitive words and speech synthesis to issue automated alerts.

Data processing is partially performed through fog computing, which brings processing closer to local devices to reduce latency [36]. Although the study does not provide quantitative metrics, it describes an architecture capable of triggering alerts when sensitive bullying-related words are detected, recognizing the speaker's identity through voice, and notifying teaching staff in real time via a mobile application.

The third study presents an advanced system for recognizing violent behavior in school by integrating computer vision techniques with deep learning models, specifically YOLOv8 and Long Short-Term Memory (LSTM) networks [37]. The system leverages YOLOv8, a real-time object detection algorithm capable of identifying multiple elements in a single network pass with high efficiency and accuracy [38]. This model is responsible for detecting actions or postures associated with violent conduct. To capture the progression of behavior over time, the system incorporates LSTM networks, a recurrent neural network that excels at modeling temporal dependencies and retaining long-term information [39].

By combining spatial detection from YOLOv8 with the temporal analysis capabilities of LSTM, the system can recognize isolated violent actions and the behavioral patterns that preceded or followed them. The model was evaluated in a multi-camera school environment, demonstrating strong performance with an accuracy of 95.67% in identifying fighting behaviors and 93.65% accuracy when applied across multiple camera views. These results highlight the potential of hybrid deep learning approaches to enhance real-time surveillance and early intervention strategies in educational institutions.

Therefore, vision-based models demonstrate the highest accuracy in detecting violent behaviors, making them highly effective for real-time surveillance in school environments. In contrast, NLP techniques excel in the early identification of at-risk students, offering valuable support for preventive strategies through analyzing language patterns in interviews or written communication. Meanwhile, voice recognition systems contribute significantly to immediate response and continuous monitoring, especially in dynamic or less visually accessible scenarios. However, their effectiveness can be influenced by factors such as audio quality, background noise, and system calibration, which may affect the reliability of detection in real-world conditions.

This diversity of approaches demonstrates that integrating AI could strengthen current prevention and response systems against school violence.

TABLE 1: COMPARATIVE TABLE OF AI TECHNIQUES. SOURCE: OWN ELABORATION

Study	Input Modality	AI Techniques	Metric	Advantage
[23]	Text	NLP+ML (RF, SVM, ANN)	Accuracy: 84.2%	Early detection based on language.
[29]	Audio	Voiceprint recognition + NN + HMM	Not reported	Automated real-time alert.
[35]	Video	YOLOv8 + LSTM + multi-camera	Accuracy: 95.67% (fighting). Accuracy: 93.65% (multi-camera).	High precision in the behavior detection of visible violence.

DISCUSSION AND CONCLUSIONS

The comparative analysis of the reviewed studies reveals significant progress in applying AI techniques to detect school violence. However, various methodological, technological, and ethical challenges remain to be addressed in future research.

The study based on NLP and machine learning identified the need to incorporate structured collateral interviews as part of the automated analysis to enrich the clinical context and reduce errors caused by the lack of complementary information. Likewise, the development of multilevel classifiers is proposed to balance risk and protective factors better, and it is recommended to improve the detection of assertions and narrative coherence in interviews, key aspects for reliable linguistic interpretation [26].

On the other hand, the voiceprint recognition system presents significant challenges for its effective implementation in real school settings. Among the notables are expanding the vocabulary of sensitive words, improving voice recognition accuracy in noisy environments, and optimizing synchronization among voice, image, and data transmission modules, which are crucial elements to ensure real-time alerts to educational staff [32].

Regarding the computer vision-based model combining YOLOv8 with LSTM networks and a multi-camera architecture, limitations were identified in detecting violent behaviors with visual obstructions or blind spots. There were also difficulties in distinguishing between similar actions such as talking, hugging, or fighting, which suggests the need to refine data fusion algorithms and strengthen the system for more diverse and complex school scenarios [40].

Likewise, it is essential to consider the ethical aspects associated with using AI in educational contexts, especially given the involvement of minors. Voice, image, or text data collection must be based on clear informed consent policies, personal data protection, and institutional oversight. Student privacy must always be safeguarded.

Intelligent systems design for school contexts requires technical accuracy and frameworks that facilitate their implementation in educational environments. In this regard, proposals such as INCEPTA [41] offer an integrative approach between agility and structure that can be adapted to developing preventive solutions.

Furthermore, the implementation of these technological systems must be integrated into a broader strategy that includes strengthening the relationship between parents, teachers, and students, promoting trust-based relationships, support, and effective communication [42].

In short, integrating different AI techniques, such as text, voice, and video, can substantially improve prevention and response systems against school violence. However, their effectiveness will depend not only on technical precision but also on ethical and contextualized implementation [43]. Moving toward hybrid models supported by solid ethical frameworks and involving the educational community represents a promising path to address this phenomenon comprehensively.

FUTURE WORKS

Future research should focus on developing hybrid detection systems that integrate text, audio, and video modalities to enhance the comprehensive identification and prevention of school violence. Combining the predictive strengths of NLP, the immediacy of speech recognition, and the high accuracy of computer vision may yield robust, real-time intervention frameworks. Further studies are needed to explore the ethical implications, especially regarding privacy, data security, and the risk of algorithmic bias, ensuring that technological solutions align with educational values and legal standards.

Additionally, future work should involve longitudinal field studies in diverse educational settings to validate the effectiveness of these AI models in real-world conditions. Efforts should also prioritize the development of user-friendly platforms that educators and school counselors can deploy without specialized technical expertise. Lastly, a participatory approach involving teachers, students, and parents in the design and implementation phases could strengthen trust and relevance, ensuring that AI-driven interventions are technologically sound and socially acceptable.

FUNDING

This scientific research article did not receive external funding. The manuscript was developed with institutional support from the Institución Universitaria Tecnológico de Antioquia, the Universidad del Atlántico, and the Universidad de la Costa (CUC), within the framework of the authors' academic and research activities.

AUTHOR CONTRIBUTIONS

Camila Barrios-Cogollo: Manuscript writing, content development, article structuring, and preparation of figures and tables.

Moisés Reales: Critical manuscript review, academic style editing, and validation of the methodological approach.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest regarding the content of this article.

ACKNOWLEDGMENTS

The authors thank the institutions involved for the academic support provided during the development of this article, especially the Institución Universitaria de Barranquilla, the Universidad del Atlántico, and the Universidad de la Costa (CUC), for their support of research initiatives aimed at educational transformation and the prevention of school violence.

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