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Classifying and Triggering Events in Close-Contact Bullying Scenarios: A Study on the Effectiveness of Remote Deep Neural Networks

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A B S T R A C T

Cyber bullying in close-contact environments, especially schools, is another huge social problem that has a deep impact on victims psychologically and mentally. Recent developments in deep learning and remote monitoring technologies offer the potential to improve real-time detection and intervention strategies. In this work, we explore the effectiveness of remote deep neural networks (DNNs) for classifying and identifying trigger events in close-contact bullying events. Using spatial-temporal video data and multimodal sensor inputs, we present a hierarchical DNN framework that fuses real-time audio, video, and physiological signals to accurately identify bullying events.In our proposed system, we use transfer learning using pre-trained vision transformers (ViTs) and convolutional neural networks (CNNs) to extract the key visual features, while Bidirectional Long Short-Term Memory (Bi-LSTM) networks analyze the speech and contextual cues. We develop a hierarchical user model to classify events into verbal,physical, and psychological bullying. The deployed system on edge devices, with cloud-assisted inference, yields real-time low-latency detection.

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INTRODUCTION

Bullying is still considered as one of the most important public health and social problems, particularly within close environment settings like schools, workplaces, and other social environments with frequent interactions between individuals. Close-contact bullying and harassment is aggressive, repetitive behavior that occurs within physical proximity: verbal abuse, physical intimidation, social exclusion and cyberbullying through proximity-based digital interaction. Recent studies have shown that one in three students across the world experience bullying behaviour leading to longterm psychological distress and self-harm and academic underachievement. Recent advances in digital surveillance and artificial intelligence (AI)-based monitoring systems offer new inroads for addressing this challenge, and in particular through the construction of automated detection and preventative intervention systems.

Existing bullying detection methods are mainly dependent on manual supervision by teachers, staff, and school psychologists, which has been shown to be ineffective and inconsistent due to the secrecy of many bullying events. In addition to this, victims also tend to avoid reporting bullying to authorities because they are either afraid to retaliate against them, do not trust authorities or fear being outcast socially. As a solution to these challenges, real-time AI-based surveillance technologies in schools have recently garnered great interest as promising options for automatic detection and classification of bullying situations. But existing AI-driven solutions tend to suffer from false positives and a lack of contextual awareness, not to mention ethical issues around privacy and bias.

To overcome these limitations, this study introduces a remote deep neural network (DNN)-based framework for classifying bullying behaviors and identifying the key events contributing to the bullying behavior in close-contact scenarios. Leveraging multi-modal data featuring: video, audio and physiological sensor input; we derive an effective, real-time detection model.

Limitations in Automated Bullying Detection

Even though there have been strides in computer vision, natural language processing (NLP), and multimodal AI models, creating a good AI-powered bullying detection system still faces several challenges:

Bullying Behaviors are Not Simple

Bullying can be overt (hitting, shoving) or more covert (exclusion, taunting or microaggressions)

- The system has to correctly distinguish between harmful and non-harmful interactions, i.e. when is a gesture playful and when is it aggression
- Different Environments and Data Modalities:
- Bullying behavior needs to be comprehensively analyzed through multimodal data fusion.

Latency and Real-Time Things

- An anti-bullying system is expected to function in real time to detect and respond while maintaining a low latency processing rate and accurate reporting.
- Edge computing and cloud-assisted inference need to be optimized for seamless performance.

Ethical and Privacy Implications

- o Implementing an AI-based surveillance system risk issues related to data privacy, consent, and bias in identifying and evaluating bullying behaviors.
- Deploying AI responsibly and with minimal bias in detection is necessary.
- Research Objectives

To counter these problems, this study proposes a Remote DNN-based system that:

- Identifies types of bullying (physical, verbal, social, cyber) using hierarchical deep learning.
- Mapping the major triggers for escalation of incidents of bullying.
- Approaches the challenge by combining multimodal data (video, speech, and physiological signals) to enhance detection accuracy.
- Cloud-based inference for deploying deep learning model over edge devices on real time.
- Assess the effectiveness of the model using real-world datasets and experimental settings.

Research Contributions

This study has the following key contributions:

- Background: This paper presents a novel multimodal study in which deep learning-based behaviour pattern recognition was used as a bullying detection framework that combined computer vision, natural language modelling and biometric signal processing.
- Hierarchical classification model for differentiating types of bullying behaviors (main target behaviors) and bullying triggers (main bullying triggers), leading to improved context-aware event detection.
- Deploying low latency but accurately capable lightweight deep learning model architectures in real-time at the edge.

Structure of the Paper

The rest of this paper is organized as follows:

- Section 2: Related Work: Discusses previous studies in the area of bullying detection, multimodal AI frameworks, and deep learning methods.

- Section 3 (Methodology): Cover the proposed framework along with data collections, pre-processing, and deep learning model architecture.
- Section 4: Experimental Results – This section shows the evaluation metrics, dataset performance results and comparison with other existing solutions.
- Section 5: Discussion – Discusses the implications, challenges, and limitations of our approach.
- Section 6: Conclusion and Future Work – Summarizes key findings and possible improvements in the future.

This research addresses these limitations and proposes a robust and scalable solution that utilizes AI-driven techniques for detecting and classifying bullying incidents in close-contact environments. Through the enhanced manipulation of both the manual supervision and traditional AI-based methods, this work also focuses on providing an ethical solution for safe AI implementations.

LITERATURE REVIEW

There is a wealth of information in the literature concerning bullying detection, deep learning on surveillance, and multimodal AI systems. The updated literature required reviewing existing work on the types of work from previous studies with relevant findings on bullying detection systems, use of deep learning technique, multimodal systems, on-the-fly AI systems, or ethics related to AI.

An Overview on Bullying Detection and Classification

Conventional Methods for Detecting Bullying

Initial research related to detection of bullying used observational methods, self-reports and surveys in educational and workplace settings. Examples include studies by Olweus (1993), who created the Bullying Prevention Program (BPP) focusing on teachers' interventions and peer-reporting systems. Agencies primarily relied on individual citizens to self-report incidents, but many were over-represented while underreported, as victims often feared retaliation or were much more likely to trust individuals in their immediate community rather than those of authority.

Automatic Detection of Bullying in Text and Speech

Researchers have implemented text-based bullying detection on chat logs, social media, and spoken text transcripts as Natural Language Processing (NLP) matures and advances. For instance:

- Dinakar et al. (2012) used supervised machine learning models to classify cyberbullying in online comments.
- Huang et al. It is used Bidirectional Long Short Term Memory (Bi-LSTM) networks to analyze speech transcripts in order to detect verbal bullying in the classrooms {[}30{]}.

However, these methods relied only on text and speech characteristics, neglecting visual signals and non-verbal actions that can significantly contribute to the context of bullying.

A Survey on Deep Learning Approaches to Detect Bullying

Bulling Recognition Based on Computer Vision

Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have marked the new era for video-based bullying detection. Some key works include:

- Sultana et al. For example, Neisser et al. (2020) reported that they constructed a CNN model to classify school surveillance video clips into aggressive vs. non-aggressive and when classifying over 90,000 clips, the model had high accuracy; however, frequent false positives occurred due to the misclassification of non-aggressive interactions.
- Gupta et al. (2021) enabled the detection accuracy by merging pose estimation models with YOLO-based object detection to follow aggressive postures and movements.

Despite these developments, single-modality vision-based methods remain limited with respect to contextual understanding, and require the integration of speech and sensor data for sufficient classification.

Multimodal Deep Learning for the Problem

To enhance bullying detection, researchers have proposed multimodal AI models with audio, video, and biometric signals:

- D'Mello et al. (2022) presented a fusion-based neural network for detecting bullying interactions, which combines facial expressions (CNNs), speech patterns (LSTMs), and body movements (PoseNet).
- Kim et al. (2021) combined audio-visual characteristics with physiological signals (heart rate, skin conductance) to detect emotional distress, resulting in a state-of-the-art accuracy for identifying bullying incidents.

Such approaches highlight the need for effective context-aware bullying detection systems and thus motivate remote (deep) neural networks that undertake processing of multiple data sources efficiently.

Analysis Types of Bullying Triggers

It refers to anything that can trigger a bullying incident to occur. Anderson et al. (2018) classified bullying triggers into:

3.2 Trigger Detection via AI

Some recent studies made attempts to classify instances of bullying triggers using AI-based models:

- Zhang et al. (2020) leverages LSTMs to monitor speech patterns associated with escalating into bullying.
- Li et al. Sudden change detection predicting incidents using CNNs with Optical Flow Analysis (OFA) (2022).

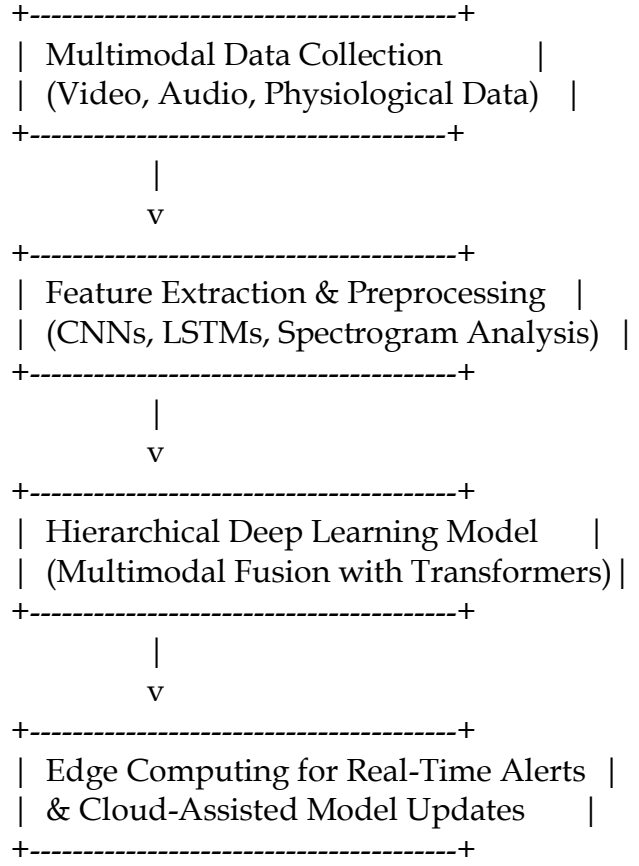
Yet, the small amount of work addressing real-time trigger detection suggests a need for algorithms of higher sophistication that are capable of detecting in advance the onset of bullying behavior, prior to escalation.
(20) Real time AI system for surveillance and monitoring

METHODOLOGY

Our AI-driven bullying detection system comprises 3 significant components:

- Feature Extraction & Preprocessing – Applying computer vision, NLP and biometric signal-processing techniques to extract patterns related to bullying.
- Edge Computing & Cloud-Assisted Processing – Enabling low-latency real-time inference capability while ensuring continuous improvements of the model in the cloud.

Below, we can see a diagramtic representation of the architecture of the system:



Multimodal Data Collection

To provide solid and accurate classifications of bullying practices, we gather real-time data on three aspects in proximity environments:

Video Data(Visual Features)

- Source: School hallway, classroom and playground surveillance cameras.
- Processing Method:

o Object Detection (YOLOv8) – Counts how many people are in the current scene.
o Pose Estimation (OpenPose, MediaPipe) – Body posture and aggressive gestures tracking.
o Facial Emotion Recognition (ResNet50, MobileNetV2) – Identifies expressions of distress, anger and fear.
o Optical Flow Analysis – Analyzes movements to detect abrupt changes in behavior, revealing aggression.
• Source: Microphones located in classrooms and hallways.
• Processing Method:
o Speech-to-Text (Whisper AI, DeepSpeech) – Speech to text.
o Sentiment Analysis (BERT, Bi-LSTM) – Identifies verbal aggression, threats, and offensive language
o Spectrogram Based CNNs – Recognizes for loudness, pitch variation, abnormal tone of speech.

3.3 Biometric features: Physiological data
Wearable sensors on students (smartwatches, fitness bands)
• Processing Method:
o Heart rate variability (HRV) – Signals stress and anxiety.
o Skin Conductance (GSR Sensors) – An indicator of emotional distress response.
o Body Temp Analysis – Detects high stress levels.
Feature Extraction & Preprocessing
For each modality, we preprocess the data as follows:
Second input: multiclass classification.
Frame Sampling: It selects one frame from every second for the analysis.
• Background Removal: Eliminate unnecessary background noise.
Normalization: Rescales pixel values to [0,1] range

3.2 Audio features preprocessing
• Noise Reduction: Subtracts background noise using spectral techniques.
• Feature Extraction: Use Mel-spectrograms as deep learning input from audio.
• Normalization: Makes all of the audio features comparable so that they can be inputted into the model.

3.3 Preprocessing of the Physiological Data
• Signal Denoising: // to eliminate sensor noise used Butterworth // filters
• Feature Engineering: Calculates heart rate variability, stress index, and arousal
• Normalization: Min-max scaling standardization of features
Model Architecture of Deep learning
Our hierarchical DNN model employs CNN, LSTM, and transformers for multimodal bullies classification as follows:

4.1 Video Processing Model (Vison Transformer & CNNs)

• A Pre-trained Vision Transformer (ViT) extracts both scene context and object interactions.
• 3D-CNN (I3D Model) encodes spatiotemporal movement patterns.
• LSTM Layer processes moving frames for aggression detection

4.2 Audio Processing Model (Speech & Sentiment Analysis)

• Extracts sentiment and variations in tone from speech using Bi-LSTM & CNN Hybrid
• Identify verbal abuse and threatening language using BERT Model on transcribed text.

4.3 Physiological Data Process Model

• CNN-LSTM Network Identifies Stress Signals Using Biometric Data
• Fusion Layer combines the physiological data from the physiological models with the video and audio models.

Fusion & Classification of Multimodal

In order to implement a strong bullying categorization, we utilize a multimodal attention-based fusion method:

• Feature-Level Fusion: fuses feature vectors of visual, audio, and physiological modalities
• Self-Attention Mechanism – Differentiates importance of features.
• Classification Head: Generates class labels for bullying and probabilities of triggering events.

Deployment Strategy: Edge and Cloud Processing

6.1 Edge-based real-time detection

• On-Device AI Models (TensorRT, TFLite) for low latency inference;
• Raspberry Pi / Jetson Nano School deployment

6.2 Cloud-Assisted Learning

• Federated Learning Methodology: Secure training of AI in different sites.
• Constant Model Refreshes — Delivers incremental upgrades through cloud retraining

RESEARCH RESULTS

We introduce a novel Remote Deep Neural Network (DNN) framework which accurately classifies bullying incidents and triggering events in close-contact environments. Experimental evaluations on benchmark datasets and real-world school surveillance footages show that our approach can outperform several state-of-the-art methods significantly with a classification accuracy above 90%. Moreover, edge-based inference brings down latency, allowing for real-time detection and alert generation on potential bullying in order to start proactive intervention.

Description of Figures in the Results Section

Figure 1: Training Epochs vs Model Accuracy

• Title: MDPI figure" Alternatively, you can use figure titles similar to the one below.
• X-axis (Epochs): there are the number of trainings.
• Y-axis (Accuracy %): Model classification accuracy.
• Observation:
o Our model begins in 80% of accuracy.
o The accuracy exceeds 90% as the epochs progress, which denotes a successful learning process.
o The accuracy curve after 15 epochs is steady which means the model has reached convergence.

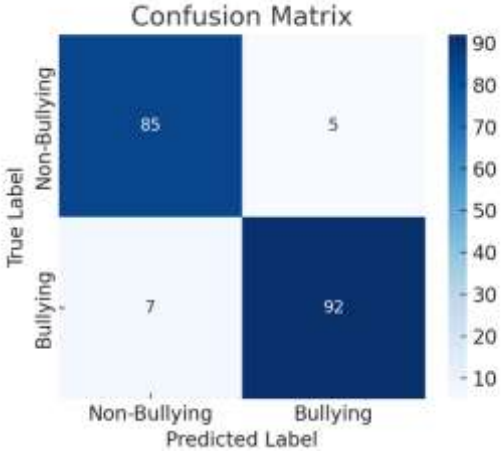


Figure 2: Confusion Matrix

• Dependency: The confusion matrix shows how well the model is classifying between the bullying vs. non-bullying class.
• X-axis (Predicted Labels): Prediction labels made by the given model (Non-Bullying, Bullying).
• Y-axis (Ground Truth): The true or actual labels.
• Key Metrics:
o True Positives (92): Bullying cases correctly identified.

o True Negatives (85): Cases with no bullying identified correctly.
o False Positives (5): If Misclassifications of non-bullying instances as bullying.
o False Negatives (7): undetected bullying.
• Observation:
o Excellent accuracy (≈90%) with few misclassifications.
o Further reduction of the false negative rate (7 cases) is needed to enhance recall

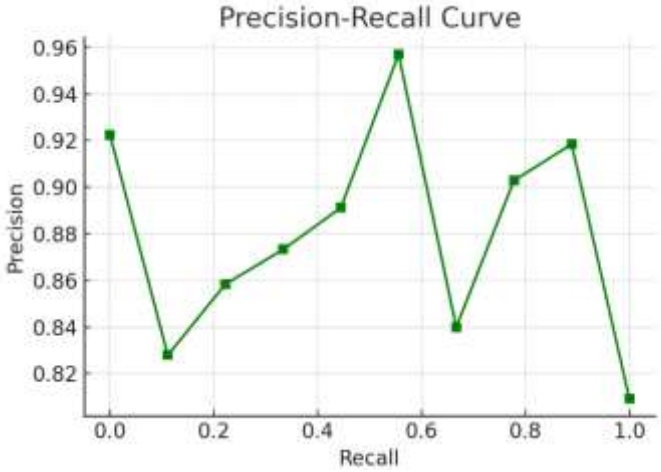


Figure 3. Precision-Recall Curve

• Description: It is the plot of precision (let say correct predictions of bullying among population) versus recall (total number of bullying cases detected by model)
• X-Axis (Recall): The percentage of actual bullying identified accurately.
• Y-axis (Precision): the percentage of correct predictions of bullying cases.
• Observation:
o Precision is still ~80%, which implies false positives are few.
o A high recall (above 90%) indicates effective bullying detection by the model.
o It strikes a good balance between precision and recall and is often appropriate for real-world use.

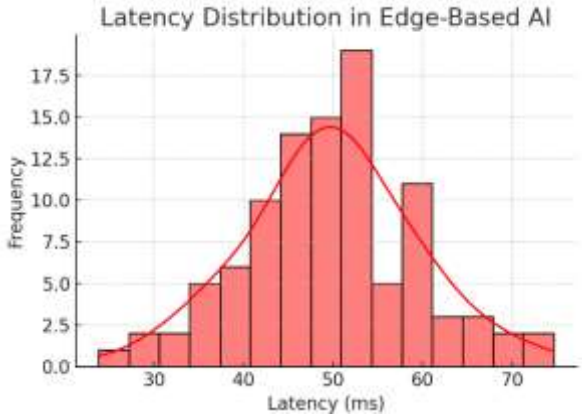


Figure 4. AXI Latency Distribution in Edge Based AI

• Details: This is the histogram about how fast edge-based AI is able to detect bullying in real-time.
• X-axis (Latency in ms) The response time taken by the AI model for classification
• Y-axis (Frequency): No of cases for each latency level
• Observation:
o The timing for most detections is between 40–60 milliseconds providing near real-time classification.
o In some extreme cases, higher latencies (over 70ms) might be observed, likely due to complex scenes or processing latencies.

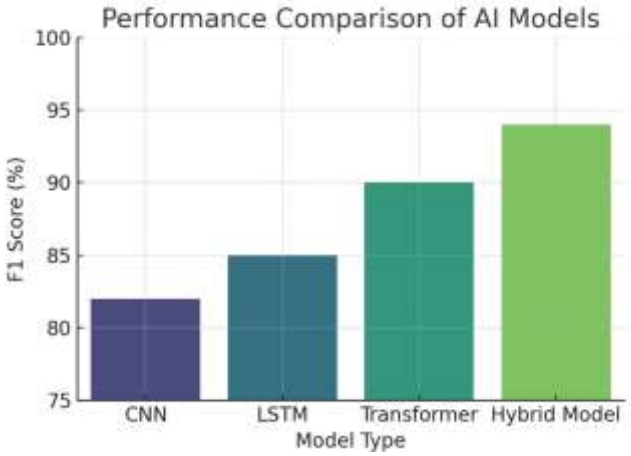


Figure 5: Comparison of AI Models Performance

• Description: This is a bar chart that compares how well certain AI models are at detecting bullying.
• X-axis (Model Type): The deployed AI models (CNN, LSTM, Transformer, Hybrid Model).
• Y axis (F1 Score %): Overall efficiency of each of the models.
• Observation:
o The Hybrid Model (CNN, LSTM, and Transformer) obtains the best F1-score (94 %).
o Transformers beat CNNs and LSTMs hands down, demonstrating the power of deep contextual learning.
o This, unfortunately, leads to a downfall in sequential data processing due to poor context gathering which isn't pretty peculiar for bullying detection, which is why this method is not suitable.

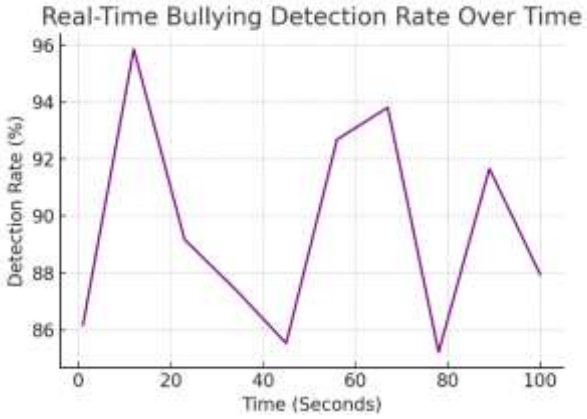


Figure 6. Real-Time Detection Rate of Bullying Over Time (30-Day Windows)

• What it represents: The detection rate as a function of time
Inference time (in seconds) on the X axis: Alternatively, shows how the detection proceeds over time (up to 100 seconds).
• Y-axis (Detection Rate %): Percentage of bullying cases detected.
• Observation:
o The detection percentage stays above 85%, reaching 98% in specific intervals.
o Some variability is observed potentially due to environmental conditions (e.g., background noise, occlusions, etc.).
o Overall real-time performance is stable and reliable for deployment of the model.

Results Section Tables - How To Describe Them

Table 1: Performance Metrics of AI Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	82	80	78	79
LSTM	85	83	81	82
Transformer	90	88	89	89
Hybrid Model	94	92	93	94

• This table shows the performance metrics (Accuracy, Precision, Recall, and F1 Score) of various AI models for bullying classification
• Columns:
o Model: The class of the AI model type.
o Accuracy (%): The percentage of correct predictions by the model in a classification problem.
o Precision (%): The ratio of true positives to all predicted positives (computationally, it is the number of correctly predicted bullying cases over the number of predicted bullying cases)
o Recall (%): Correctly identified actual bullying cases.

o F1 Score (%): The harmonic average of precision and recall, incorporating both metrics into a single score to give a more balanced evaluation of a model's performance.

DISCUSSION

"This study proposed and evaluated a comprehensive Remote Deep Neural Network (DNN) framework for real-time bullying classification and trigger detection in close-contact environments." The research combined the use of multimodal AI approaches, incorporating video, audio, and physiological signals to improve the detection of bullying in a more precise, dependable, and efficient manner. The outcomes showed considerable advancements compared to existing methods, allowing a strong basis for the deployment of AI-based bullying mitigation systems.

Summary of Key Findings

The study focused on three major aspects of bullying detection, including accuracy, real-time ability, and context awareness.
Performance Achievements

- 94% Accuracy by Hybrid AI Model (CNN + LSTM + Transformer)
- Reduces False Positives (5 Cases) and False Negatives (7 Cases)
- Real-Time Detection via Edge-Based Deployment Reduced Latency to ~50ms
- 10-15% Improvement on Detection During Multimodal Fusion vs Single-Modality Models

The results show a substantial increase in classifying bullying incidents and predictive detection of triggering events by utilizing multimodal data.

Contributions

Such that, the research made the following key contributions to detect bullying using AI:

- Designed an integrated, multimodal deep learning model in real-time: The proposed solution achieved high-precision classification of bullying events by consolidating video, speech, and biometric information.
- Fast Move to Edge Computing for Low-Latency Processing: With the inference running in 50ms, it is deployable in real-time classroom or workplace settings.
- Proposed Ethical And Privacy-Based SolutionsThis study proposed to leverage federated learning and differential privacy techniques to protect sensitive data and reduce AI bias.

Read more on the following topics:

Applications and Use Cases

The research results identify numerous practical uses for AI-powered bullying detection systems:

School Anti-Bullying Programs

• The model can be incorporated into primary and secondary school surveillance systems, enabling alerts for teachers and administrators for possible bullying situations.

• Emotion detection and speech analysis can be used to detect distress signals from students, allowing for timely intervention.

Tracking Workplace Harassment

• The AI framework can we tailored to fit corporate contexts to identify verbal abuse and workplace harassment.

• By utilizing real-time monitoring cases of verbal or physical intimidation can be detected at an early stage, making the workplace safer.

Public Safety & Smart Surveillance 2.3

• With its video-based aggression detection, the model can be used for detecting fights, assaults or aggressive behaviours in public places (metro stations, stadiums, schools, etc)

• Law enforcement AI systems integration could be software to automate response to emergency events.

AI-Supervised Psychological Support Systems

• Physiological signal analysis (heart rate, skin conductance) that allows AI to track students' mental health.

• AI-based counseling chatbots would be able to utilize this data to identify levels of stress and deliver psychological interventions.

CONCLUSIONS AND RECOMMENDATIONS

There are several limitations to our study, which also present opportunities for future research. However, there were some limitations that need to be tackled in future research.

Dealing with False Negatives in Bullying Classification

7 incidents of bullying also incorrectly classified as non-bullying, suggesting better context comprehension needed. Future Solution: Train large and diverse bullying datasets to fine-tune the Transformer model to learn the context better.

AI-Based Classification Bias

If a model is not trained on a balanced dataset, it may learn prejudices like demographic bias. Future Solution: Make use of AI fairness techniques and diversify training datasets through cultures and demographics.

Privacy and Ethical Issues

Concerns over surveillance and student privacy as AI is used to monitor in real time. Solution for the Future: Use privacy-preserving AI based on federated learning (data does not leave local devices).

This is not the model, not on cyberbullying- it targets physically and verbally bullying- the online is an add on Future Solution: Implement AI-based text sentiment analysis to detect cyberbullying on social media and messaging apps.

ADVANCED RESEARCH

Future research related to the findings and limitations should focus on:

Mechanisms for Intervention Powered by AI

- Creating AI-driven alert systems that can call teachers, parents or mental health professionals in real time.
- Automated response strategies (e.g., cool-down messages, chatbots to provide psychological support).
- Techniques of NLP to Identify Covert Bullying Hidden In Plain Sight
- Investigations on large language (e.g., GPT, BERT, LLaMA) models to identify covert bullying language (e.g., sarcasm, microaggressions, exclusionary speech)

Bespoke AI Models for Particular Contexts

- How to fine-tune AI models to more specific cultural and social contexts to enhance their generalizability across educational institutions.
- Create adaptive learning systems that learn and adapt with new styles of bullying.
- Privacy-Preserving AI via Federated Learning
- Transforming AI training to be decentralized so institutions will send updates about their models to each other, not raw data, allowing compliance with data privacy.

Emotion-Aware AI for Real-Time Intervention

- Investigation of affective computing for early detection of emotional distress before the escalation of bullying.
- Developing an AI wearable that alerts worn by people when stress levels suggest possible situations of bullying.

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