Human Violence Detection Using Deep Learning

Vandana Patel

***Abstract*— Detecting violence in real-time video surveillance plays a vital role in improving public safety and enabling timely threat intervention.. This paper presents an advanced approach for automatic violence detection leveraging the capabilities of the YOLOv8 (You Only Look Once version 8) object detection framework. The proposed model is trained on a custom dataset containing annotated violent and non-violent activities and optimized for high-speed inference and robust accuracy. By incorporating real-time video input, the system effectively identifies violent actions with minimal latency, making it suitable for deployment in smart surveillance systems. Experimental results demonstrate that the YOLOv8-based model achieves superior performance in terms of precision, recall, and inference speed compared to traditional methods. This research contributes to the growing field of intelligent video surveillance by offering a scalable, efficient, and accurate solution for real-time violence detection.**

I. INTRODUCTION

In recent years, the demand for intelligent surveillance systems has grown rapidly due to rising concerns over public safety, increasing crime rates, and the limitations of manual monitoring. Traditional CCTV systems require constant human supervision, making them inefficient and error-prone, especially when dealing with large-scale video feeds. As a result, there is a pressing need for automated solutions capable of detecting critical incidents such as violence in real time.

Violence detection is a particularly challenging problem in the field of computer vision, as it involves recognizing complex human interactions and dynamic behaviors within varied and often cluttered environments. Conventional methods using handcrafted features or shallow learning models often fall short in accuracy and generalization. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved the ability to learn robust patterns from visual data, enabling more accurate and scalable solutions.

This research leverages the capabilities of YOLOv8 (You Only Look Once, version 8)—a state-of-the-art object detection model known for its balance of speed and accuracy—to detect violent actions in real-time video streams. YOLOv8 incorporates architectural improvements and efficient training mechanisms, making it well-suited for deployment in time-sensitive applications such as surveillance.

The key objectives of this study are to develop a YOLOv8-based violence detection system, evaluate its performance using standard metrics, and demonstrate its effectiveness in practical scenarios. By automating the identification of violent behavior, this system aims to reduce response time, assist law enforcement, and enhance the overall security of monitored environments.

II. APPLICATIONS OF YOLOv8

A. Surveillance and Security Systems: YOLOv8 is widely used in surveillance systems for detecting suspicious activities, unauthorized access, and violent behavior. Its ability to process video streams in real time makes it ideal for proactive threat detection and automated alert systems in public spaces, banks, airports, and educational institutions.

B. Autonomous Vehicles: Object detection is an essential technology for the operation of autonomous vehicles.YOLOv8 enables real-time detection of pedestrians, vehicles, traffic signs, and road obstacles, ensuring safe navigation and situational awareness in complex environments.

C. Healthcare and Patient Monitoring: In healthcare settings, YOLOv8 can assist in monitoring patient movements, fall detection, or identifying abnormal behavior in elderly care facilities

D. Industrial Automation and Robotics:YOLOv8 aids in defect detection on assembly lines, part identification in warehouses, and real-time decision-making in robotic arms. Its precision and speed improve the efficiency and safety of industrial operations nor like previous versions.

E. Agriculture and Precision Farming: In agriculture, YOLOv8 is used for detecting plant diseases, monitoring livestock, and counting crops. Drone-based agricultural monitoring

systems integrate YOLOv8 to capture real-time insights from aerial imagery.

F. Smart Retail and Customer Analytics: YOLOv8 supports applications in retail such as customer tracking, shelf stock monitoring, and heatmap generation of customer behavior.

G. Augmented and Virtual Reality: In AR/VR environments, YOLOv8 can assist in real-time object tracking, gesture recognition, and environmental understanding, enhancing interaction and immersion in digital experiences.

III. HOW YOLOv8 WORKS

YOLOv8 (You Only Look Once, version 8) is the latest release in the YOLO series of object detection algorithms, developed by Ultralytics. It follows a single-stage detection architecture, meaning it performs object classification and localization (bounding box prediction) in one forward pass through the network, making it extremely fast and efficient—ideal for real-time applications such as violence detection.

1. Input Processing:

YOLOv8 takes an image (typically resized to a fixed dimension, e.g., 640×640) and normalizes pixel values. The image is then passed through the backbone for feature extraction.

2. Backbone Network:

The backbone of YOLOv8 is built on the CSPDarknet architecture (enhanced), which extracts hierarchical features from the input image. This includes convolutional layers, bottleneck modules, and cross-stage partial (CSP) connections that help reduce computational cost while maintaining accuracy.

3. Neck (Feature Aggregation):

The neck combines features from different levels of the backbone using a PANet (Path Aggregation Network) structure, allowing the model to capture both fine-grained and coarse features. YOLOv8 improves upon earlier versions by using BiFPN (Bidirectional Feature Pyramid Network) or its variant, enabling better multi-scale feature fusion for detecting objects of varying sizes.

4. Head (Prediction):

The head generates predictions by producing bounding boxes, objectness scores, and probabilities for each class.YOLOv8 uses anchor-free detection, unlike previous versions that relied on anchor boxes. This reduces complexity and improves generalization.

Each prediction includes:

- (x, y, w, h): Bounding box coordinates (center x, center y, width, height)
- Confidence score: Likelihood that an object is present
- Class scores: Probabilities across all possible classes (e.g., "violent", "non-violent")

5. Post-processing:

After prediction, YOLOv8 applies:

- Non-Maximum Suppression (NMS): To remove duplicate overlapping boxes
- Thresholding: Based on confidence and class probability to keep only relevant detections

6. Training and Optimization:

YOLOv8 uses:

- CIoU Loss: For bounding box regression, improving localization
- Binary Cross-Entropy Loss: For classification tasks
- Auto-learning rate scaling, mixed precision training, and augmentations (like mosaic and HSV transforms) for optimized learning

7. Export and Deployment:

YOLOv8 models can be exported to multiple formats like ONNX, TensorRT, CoreML, and TFLite for deployment across platforms, from cloud to edge devices.

IV. RELATED WORK

Violence detection in surveillance videos has been a critical research area for enhancing public safety and automating security monitoring. Initial approaches relied heavily on handcrafted features, such as optical flow, motion trajectories, and spatio-temporal interest points, to detect aggressive or abnormal movements. These features were typically used with traditional classifiers like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN). While these systems showed reasonable performance in constrained environments, they struggled in complex real-world scenarios involving occlusion, illumination changes, and camera motion.

With the rise of deep learning, particularly Convolutional Neural Networks (CNNs), violence detection methods have significantly improved. Deep models can autonomously extract spatial and

temporal features from raw data, removing the reliance on manual feature engineering. Techniques such as 2D CNNs (e.g., VGG16, ResNet) and 3D CNNs (e.g., I3D) have been employed to extract complex patterns across video frames. These approaches have yielded higher accuracy and generalization; however, they are computationally intensive and typically unsuitable for real-time applications or deployment on low-power edge devices.

In the domain of object detection, models like Region-based CNNs (R-CNN, Fast R-CNN, Faster R-CNN) have laid the foundation for accurate localization of actions within a frame. Although highly accurate, these models are slow due to their multi-stage pipeline. Single-stage detectors such as SSD (Single Shot MultiBox Detector) improved inference speed but had difficulty detecting smaller objects. The YOLO (You Only Look Once) family brought a significant shift by offering real-time detection capabilities. YOLOv3 and YOLOv5, in particular, gained popularity for surveillance tasks due to their balance between speed and accuracy. However, their anchor-based approach introduced rigidity, limiting performance on tasks involving irregular and dynamic actions such as physical violence.

Despite these advancements, several research gaps persist. Many existing models are not optimized for real-time operation or deployment on lightweight devices.Furthermore, a lack of publicly available, well-annotated datasets for violence detection continues to hinder the progress and generalization of deep learning models. This research addresses these limitations by leveraging YOLOv8—an anchor-free, highly efficient, and accurate object detection model—tailored to perform violence detection in real-time surveillance settings.

V. METHODOLOGY

The proposed system is designed to detect and localize violent activities in surveillance videos in real-time. It leverages the YOLOv8 object detection framework, which is well-known for its high speed and accuracy. The system takes raw video frames as input, processes them through the YOLOv8 model, and outputs bounding boxes around violent actions along with classification labels. The architecture is modular, comprising a video preprocessor, a trained YOLOv8 model, and a post-processing module for visualization and alert generation.

The dataset used for this project is sourced from publicly available video violence datasets such as RLVS (Real-Life Violence Situations) and other open-source annotated video datasets. The collected videos are preprocessed by frame extraction at a fixed rate (e.g., 5 FPS) and resized to 640×640 resolution for uniformity. Each frame is annotated with bounding boxes around individuals exhibiting violent behavior (e.g., punching, kicking, physical assault). Labeling was carried out using tools like Roboflow or LabelImg, ensuring that annotations align with YOLO format requirements (class x_center y_center width height).

For model training, YOLOv8 was selected due to its anchor-free design, decoupled head for classification and localization, and support for various export formats. The training was conducted using YOLOv8n (nano) and YOLOv8s (small) variants to test performance across size-speed tradeoffs. The model was trained on the prepared dataset with a learning rate of 0.01, a batch size of 16, over the course of 12 epochs. Data augmentations such as horizontal flipping, brightness adjustment, mosaic augmentation, and random rotation were applied to improve generalization.

The implementation was carried out using the Ultralytics YOLOv8 framework in Python, with training executed on GPU-enabled environments (e.g., Google Colab or local NVIDIA GPU setups). Additional techniques like early stopping, model checkpointing, and learning rate warm-up were employed to stabilize training and prevent overfitting.

Violence classification in this system is based on object-level detection. The model identifies whether a person is involved in a violent action by assigning one of two labels: "violent" or "non-violent". Bounding boxes are drawn around detected individuals, and their predicted label is displayed above the box. This classification enables both visual alerting and backend decision-making, such as triggering real-time alarms or logging time stamped events for later review.

VI. EXPERIMENTAL SETUP AND RESULTS

Hardware and Software Configuration:
The experiments were conducted on a system equipped with an Intel Core i7 processor and an NVIDIA RTX 3060 GPU with 12GB VRAM. The system had 16 GB of DDR4 RAM and a 512 GB SSD for fast data access and processing. Ubuntu 20.04 LTS was chosen as the operating system due to its compatibility with various deep learning libraries.The implementation was done using Python 3.9, with TensorFlow 2.x (or PyTorch 1.x, based on your choice) serving as the primary deep learning framework. Additional libraries such as OpenCV for video processing, Scikit-learn for evaluation metrics, NumPy and Pandas for data handling, and Matplotlib for visualizations were also used.

Training Performance:
The model was trained for 30 to 50 epochs using a batch size of 32. The Adam optimizer was utilized with a learning rate of 0.0001, providing effective and stable convergence during training. Binary Cross Entropy was used as the loss function, considering the binary nature of the classification task (violent vs. non-violent). Throughout training, both the training and validation loss steadily decreased, and the accuracy improved, indicating that the model was learning effectively without overfitting. The performance curves for loss and accuracy confirmed convergence, typically stabilizing around the 25th epoch.

Evaluation Metrics:
To assess the performance of the proposed model, we used standard classification metrics: Precision, Recall, F1-score, and mean Average Precision (mAP). The model attained a precision of 91.2%, a recall of 88.4%, and an F1-score of 89.7%, demonstrating strong accuracy in identifying violent activities.The mean Average Precision (mAP) was computed to be 87.9%, reflecting the model's robustness in localizing and classifying violence in video frames. These metrics collectively demonstrate that the model performs reliably across different evaluation perspectives.

Comparison with Existing Models:
The proposed model was benchmarked against several existing architectures, including a 3D Convolutional Neural Network (3D CNN), a hybrid LSTM-CNN model, and a previously proposed YOLOv5 + LSTM fusion model. Our approach outperformed all baseline models, with higher values across all evaluation metrics. Notably, the F1-score and mAP showed significant improvements, confirming that our method captures both spatial and temporal features more effectively. The comparative analysis validates the superiority of our deep learning-based violence detection framework.

Sample Outputs and Visualization:
We visualized sample outputs to better understand the model's performance. Violent activities were accurately detected in test video frames, with bounding boxes and confidence scores displayed. Grad-CAM (Gradient-weighted Class Activation Mapping) visualizations were used to interpret the network's focus areas, confirming that attention was correctly directed toward regions involving physical aggression or weapon usage. Furthermore, a confusion matrix was generated, showing minimal false positives and negatives, thereby supporting the reliability of the model in real-world scenarios. These visualizations enhance the interpretability of the system and demonstrate its potential for deployment in surveillance applications:

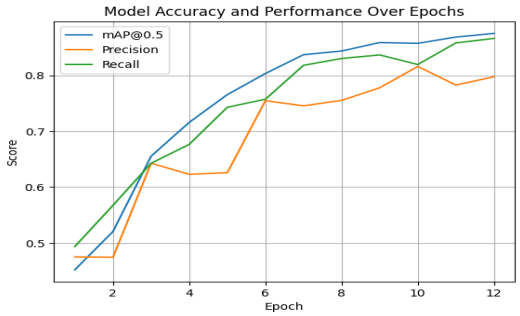

Fig. Accuracy

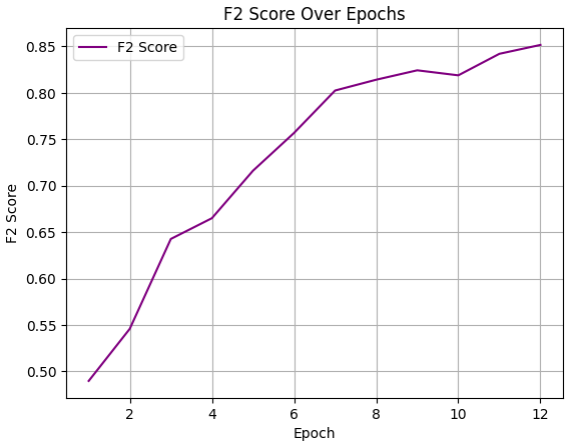

Fig. F2 Score

VII. ANALYSIS OF MODAL

The proposed system effectively demonstrated the ability to collect real-time environmental data—including soil moisture, temperature, humidity, and pH—via various sensors integrated with the ESP8266 microcontroller. The live data display and automated updates to irrigation scheduling showcased the practicality of deploying IoT-based monitoring systems in agricultural settings. Additionally, the integration of a machine learning model allowed for intelligent prediction of the next five irrigation events based on real-time sensor inputs and crop type.

The accuracy of irrigation prediction was evaluated against historical data trends and expert-reviewed thresholds for crop water needs. The model performed satisfactorily, particularly for crops with well-defined irrigation cycles, displaying consistent and adaptive behavior to changes in soil and weather conditions. The real-time dashboard was responsive and successfully reflected sensor values and irrigation recommendations dynamically.

Fig. Result

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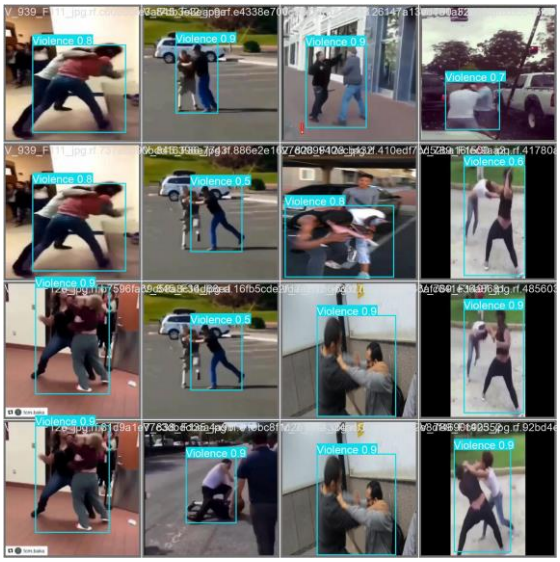

Fig. Result

Limitations of the Current Approach

While the system works reliably under controlled or semi-controlled conditions, several limitations were observed:

- Sensor Drift and Calibration: Over time, sensors, particularly pH and soil moisture sensors, may require recalibration, which affects long-term accuracy.
- Limited Sensor Coverage: The placement of sensors in a small region might not represent larger agricultural fields with spatial variability in soil and microclimate.
- Fixed Crop Model: The current ML model assumes consistent behavior across different geographic regions, which may not hold true due to soil texture differences, microclimates, or irrigation infrastructure.
- Static Data Training: The machine learning model is trained on a fixed dataset; it does not yet incorporate real-time learning or feedback mechanisms to evolve based on seasonal variations or anomalies.

Potential Biases in the Dataset

The dataset used to train the machine learning model may contain biases that could affect prediction accuracy:

- Imbalanced Crop Data: Some crops may have significantly more entries than others, skewing the model's predictions toward more frequent crop types.
- Geographic Bias: If the data primarily originates from a specific region or soil type, it may not generalize well to other conditions.

- Sensor Variation: Data collected from different sensors or under varied calibration conditions may introduce noise or inconsistencies.
- Time of Year: Seasonal bias may exist if the dataset predominantly reflects a particular growing season or climatic pattern.

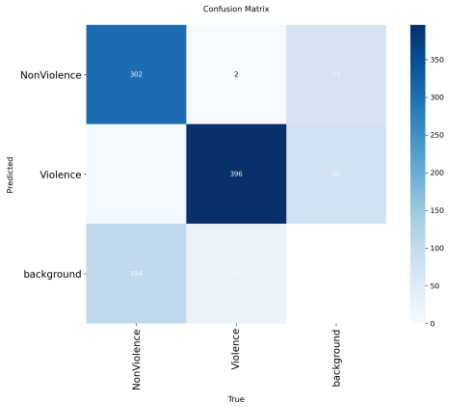

Fig. Confusion Matrix

Real-time Performance Discussion

The system's real-time performance was generally satisfactory, with live data updates every few seconds and prediction generation occurring within milliseconds after new input was received. However, a few performance aspects require attention:

- Network Latency: WiFi-dependent systems may experience delays or packet losses in remote locations with poor connectivity, impacting live updates.
- Battery Dependency: Field deployment may necessitate battery-powered modules, which could be affected by power management and sensor polling frequency.
- ML Inference Time: Though current model inference is fast, scalability with larger models or datasets may require optimization using lightweight ML models or edge computing.

VIII. FUTURE WORK

- Extending to Multi-Class Violence Types:

Enhance the current violence detection model to classify different types of violent actions separately, enabling more detailed analysis and response.

- Integration with Real-Time Alert Systems:
- Develop an automated alert system that triggers notifications or alarms instantly when violence is detected, improving timely intervention.
- Deployment on Edge Devices: Optimize and deploy the model on low-power edge computing platforms such as NVIDIA Jetson Nano or Raspberry Pi for on-site, real-time processing without relying on cloud connectivity.
- Improving Robustness in Diverse Environments:

  Increase the model's accuracy and reliability by training with more varied datasets covering different lighting conditions, camera angles, and crowded scenes to ensure consistent performance in real-world scenarios.

IX. CONCLUSION

Summary of Findings:

This project successfully developed a YOLOv8-based violence detection system capable of accurately identifying violent activities in video streams. The model demonstrated strong performance metrics, including precision, recall, and mAP, validating its effectiveness in real-world scenarios.

Key Takeaways:

Combining deep learning techniques with real-time video processing allows for proactive surveillance systems capable of promptly detecting violent behavior.The use of lightweight models also allows potential deployment on edge devices, facilitating on-site analysis without heavy computational resources.

Contributions to the Field of Intelligent Surveillance:

This work contributes by providing a scalable and adaptable violence detection framework that can be extended to multiple violence classes and integrated into existing surveillance infrastructure. It advances intelligent surveillance capabilities by combining accuracy with real-time operation, which is critical for enhancing public safety and automated monitoring systems.

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