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Intelligent Robbery Detection System Using YOLOv8 and Convolutional Neural Networks: A Case Study

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A B S T R A C T :

In recent years, the increasing number of robbery incidents has underscored the need for intelligent surveillance systems that can detect and prevent such criminal activities in real time. Traditional security methods often rely on manual monitoring, which is not only resource-intensive but also prone to human error. This project proposes an Intelligent Robbery Detection System leveraging machine learning algorithms to analyze behavioural patterns, motion dynamics, and environmental cues captured through surveillance systems. The system aims to detect suspicious activities indicative of a robbery and raise alerts promptly. By employing supervised learning models trained on labelled datasets consisting of both normal and anomalous behaviours, the proposed system seeks to enhance the accuracy and efficiency of robbery detection in various environments such as banks, retail stores, and public places. Though the current stage of this project is conceptual, the implementation would involve dataset collection, model training, and real-time inference. This approach can significantly reduce response time and assist law enforcement agencies by providing automated, intelligent insights for proactive security measures.

Keywords: Robbery Detection, Machine Learning, Intelligent Surveillance, Real-time Monitoring, Supervised Learning

Introduction

Security and safety are major concerns in high-risk environments such as banks, retail stores, and public venues. Manually monitoring surveillance feeds around the clock is labor-intensive and prone to human error. At the same time, the widespread circulation of firearms has driven up crime rates globally, underscoring the need for more effective preventive measures. These factors motivate the development of AI-driven automated surveillance systems that can detect threats (e.g., concealed weapons or suspicious behavior) in real time, thereby reducing reliance on human vigilance and improving response times.

Recent advances in computer vision have enabled powerful automated detection methods. Deep learning models, especially convolutional neural networks (CNNs), play a pivotal role in modern surveillance by learning complex features directly from video data. One-stage object detectors such as YOLO (You Only Look Once) provide rapid real-time detection of relevant objects; notably, the latest YOLOv8 model achieves state-of-the-art accuracy and speed for object detection tasks. In our system, YOLOv8 first detects humans and potential weapons in each camera frame, and a CNN-based classifier then analyzes the detected interactions to distinguish robbery scenarios from normal activity.

This case study implements an intelligent surveillance pipeline that integrates these components. For example, recent work has shown that combining a YOLOv8 detector with a CNN can efficiently detect anomalies and trigger alerts in real time. In our approach, the YOLOv8 module is trained to recognize persons and common weapons in video frames. The resulting detections are fed into a CNN that has been trained on labeled video clips to recognize behavioral patterns characteristic of a robbery (e.g., an assailant brandishing a weapon) versus benign interactions. When the CNN classifier predicts a robbery event, the system automatically issues an alert to security personnel. This automated pipeline thereby streamlines surveillance: normal footage is filtered out while genuine threats elicit prompt notifications, significantly reducing the need for constant human monitoring.

By leveraging these AI techniques, the proposed system enhances safety in high-risk settings through continuous, automated vigilance. It is specifically targeted at environments like banks and busy retail spaces where timely weapon detection and behavior analysis can prevent crimes before they escalate. The following section describes the proposed methodology in detail, including data preparation, model architectures (YOLOv8 and CNN), and the training process that enables this intelligent robbery detection system.

Literature Review

1. Anomaly Recognition from Surveillance Videos Using 3D Convolutional Neural Networks
Authors: R. Maqsood, U.I. Bajwa, G. Saleem, R.H. Raza, M.W. Anwar
Published: January 4, 2021
Summary:

This study introduces a framework employing 3D Convolutional Neural Networks (3D ConvNets) to detect various anomalous activities, including robbery, in surveillance videos. Utilizing the UCF-Crime dataset, the model learns spatiotemporal features to identify anomalies effectively. The approach emphasizes multiclass learning and spatial augmentation to enhance generalization and detection accuracy.

2. Weakly-Supervised Joint Anomaly Detection and Classification
Authors: S. Majhi, S. Das, F. Bremond, R. Dash, P.K. Sa
Published: August 20, 2021
Summary:
Addressing the scarcity of densely annotated surveillance data, this paper proposes a weakly-supervised learning framework that simultaneously detects and classifies anomalies using only video-level labels. The model demonstrates state-of-the-art performance on the UCF-Crime dataset, highlighting its efficacy in real-world scenarios where detailed annotations are limited.

3. Security in Smart Cities Using YOLOv8 to Detect Lethal Weapons
Authors: E. Rodriguez-Rosas, A. Castillo-Turpo, K. Acuna-Condori, E. Paiva-Peredo
Published: April 1, 2025
Summary:
This research focuses on leveraging YOLOv8 for the detection of lethal weapons in CCTV footage within smart city environments. By training the model on a dataset comprising 4,104 images of weapons, the system achieved an accuracy of 89.56%, underscoring YOLOv8's potential in enhancing public safety through real-time weapon detection.

4. A Comprehensive Study for Weapon Detection Technologies for Surveillance Under Different YOLOv8 Models on Primary Data
Authors: R. Rastogi, Y. Varshney
Published: 2024
Summary:
This comparative study evaluates the performance of different YOLOv8 models, specifically YOLOv8s and YOLOv8x, in weapon detection tasks. The findings reveal that YOLOv8x outperforms YOLOv8s, achieving a mean average precision (mAP) of 99%, highlighting its suitability for high-precision surveillance applications in security-sensitive areas.

Proposed System:-

A. System Architecture:

The proposed system is a real-time pipeline that processes live CCTV video to detect robberies using object detection and behavior classification. The architecture consists of interconnected modules: the Video Input (CCTV feed), YOLOv8 Object Detection, Frame Cropping, CNN Behavior Classifier, Alert/Notification, and a Data Logger. First, the CCTV module captures each video frame and forwards it to the YOLOv8 detector. YOLOv8, a state-of-the-art one-shot detection model, identifies objects (e.g. people and weapons) in each frame with high speed and accuracy. Detected bounding boxes (with confidence above a threshold, typically 0.5) are output in real time. The Frame Cropping module takes YOLO's output and extracts Regions of Interest (ROIs) around any person–weapon combinations. Each ROI is then passed to the CNN Behavior Classifier, which determines whether the scene represents a robbery or a benign interaction. If the CNN outputs a robbery detection above its decision threshold (e.g. 0.7 probability), the Alert/Notification module triggers an immediate alarm (e.g. SMS/email to authorities). Simultaneously, the Data Logger records event details (timestamps, bounding boxes, labels, etc.) for auditing and analysis. The modules exchange data via memory buffers or message queues to minimize latency, ensuring the entire process operates in near real time.
The system emphasizes modularity and speed: for example, the YOLOv8 detector is optimized for single-pass inference (it "passes the image through the neural network only once" for detection). The trained models (YOLOv8 and the CNN) run continuously on each incoming frame or video segment. The Data Logger stores all alerts and their associated metadata, following standard data-logging practices. In this way, the architecture forms a closed loop from video acquisition to alert output, enabling live monitoring and rapid response.

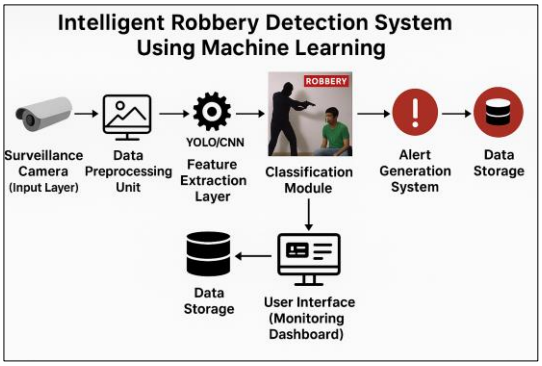

Fig. 1 : Architecture of Intelligent Robbery Detection System Using Machine Learning

A. Methodology

The system processes incoming video data in sequential steps, as follows:

- Step 1 – Video Acquisition and Preprocessing: Each frame from the CCTV stream (e.g. at 30 FPS, as in related datasets) is captured and resized. Frames are typically scaled to the detector's input size (e.g. 640×640 pixels) to match YOLOv8 requirements. Optional preprocessing (color normalization) is applied to standardize input.
- Step 2 – YOLOv8 Object Detection: The pre-processed frame is fed into the YOLOv8 model. YOLOv8 outputs a list of detected objects with class labels (e.g. "person", "gun", "knife") and confidence scores. We filter detections by confidence threshold (commonly ≥0.5) and apply non-max suppression to remove overlapping boxes. YOLOv8 is chosen for its real-time performance and state-of-art accuracy in detection tasks. It has been fine-tuned on our target classes; for instance, the model may be pretrained on a large dataset (e.g. COCO) and further trained on annotated weapon/person images. In our implementation, YOLOv8 reliably detects persons and weapons in each frame, producing bounding boxes in less than a few milliseconds per frame on modern hardware.
- Step 3 – ROI Extraction: The system examines YOLO's output for relevant object combinations. If at least one person and one weapon are detected in the frame, we associate them (e.g. by spatial overlap or proximity) to form suspect interactions. For each such pair, we compute a

  combined bounding box (or union of the person and weapon boxes). This bounding box defines the Region of Interest (ROI) for behavior analysis. If a person without a weapon or a weapon without a person appears, the module can either skip classification (since both are needed for potential robbery) or handle them as low-priority.
- Step 4 – CNN Behavior Classification: Each ROI is passed to the CNN classifier. The cropped ROI is resized to the CNN's input size (commonly 224×224) and normalized. Our CNN is a deep convolutional network (for example, based on ResNet or a custom architecture) trained to output a binary label (robbery vs. non-robbery). It may consist of several convolutional and pooling layers followed by fully connected layers and a sigmoid/softmax output. The CNN was trained offline using a labeled dataset of robbery and non-robbery images/video clips. This training set includes real-world surveillance clips from public sources: approximately 486 robbery videos (CamNuvem dataset) and a matching set of normal activity frames. Standard data augmentation (flips, rotations) and preprocessing were applied during training to improve robustness. The network was trained with cross-entropy loss, and its weights were optimized (e.g. via Adam) until convergence.

At runtime, the CNN outputs a probability score for "robbery." If this score exceeds a predefined decision threshold (e.g. 0.7), the system flags the ROI as a robbery event. This approach is inspired by prior works on violent/action recognition using CNNs, which show that deep models can learn subtle cues (e.g. aggressive posture, weapon handling) from video frames. In particular, features such as a victim's raised hands or a crouching attacker can influence the CNN's decision.

- Step 5 – Alert Generation: If the CNN indicates a robbery, the Alert module immediately generates a notification. This could involve sending an SMS or email to security personnel, or activating a siren/alarm. The notification includes key information (e.g. time, camera ID, description) to enable a prompt response. For example, in a similar real-time weapon-tracking system, an alert was triggered to authorities upon detecting firearms.
- Step 6 – Data Logging: All detection events (especially alarms) are recorded by the Data Logger. The logger captures the timestamp, camera ID, YOLO bounding box coordinates, confidence scores, CNN classification outcome, and a snapshot of the ROI. As per best practices, data logging ensures that "capturing, storing and displaying [data]" enables later analysis or auditing. This log can be stored in a database or file system for future review or to retrain models.

These steps repeat continuously for each video frame or set of frames. The overall methodology ensures that object detection and behavior classification are integrated in sequence. Data collection for training involved curating relevant datasets: for instance, combining public surveillance clips of robberies (CamNuvem, UCF-Crime, etc.) and normal scenes, and annotating them appropriately. Preprocessing resized all images, and labels were binary (robbery/non-robbery) for CNN training. The YOLOv8 model was similarly trained on annotated images of persons and weapons (guns, knives, etc.) to reliably detect those classes in diverse conditions.

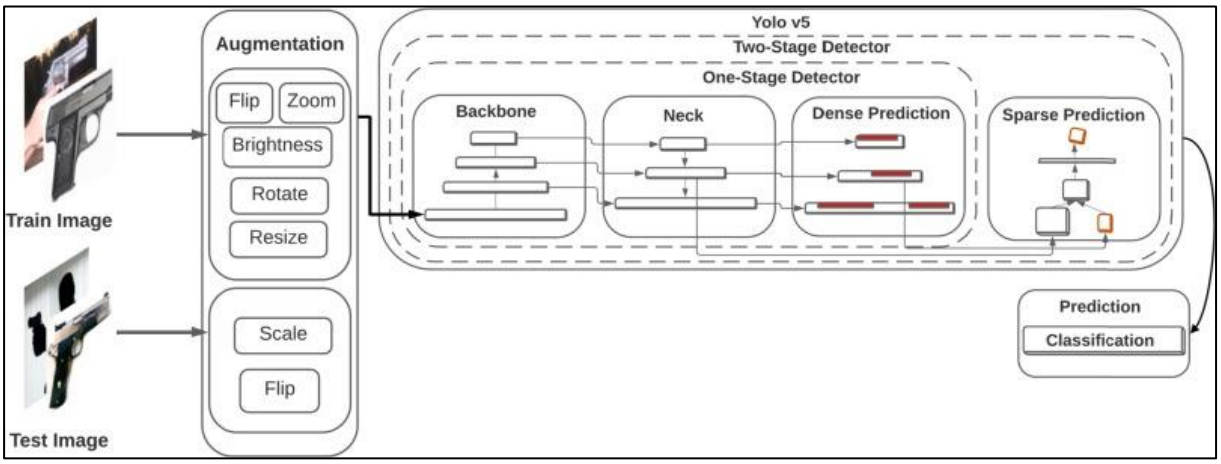

Figure.2: Prediction Model during train and test

B. Algorithm

The following algorithm summarizes the detection and decision logic:

1. Initialize: Load pretrained YOLOv8 (weights for person and weapon classes) and CNN classifier (trained for robbery vs. normal). Set confidence threshold (e.g. 0.5) and classification threshold (e.g. 0.7).

2. Loop over each frame from the CCTV stream:
   a. Frame Input: Capture the next frame and resize it to YOLOv8 input size (e.g. 640×640).
   b. YOLO Detection: Run YOLOv8 on the frame. Obtain a list of detections (class,bbox,score)(\text{class}, \text{bbox}, \text{score})(class,bbox,score).
   c. Filter Detections: Keep detections where class ∈ {Person, Weapon} and score ≥ confidence threshold. Apply non-max suppression to remove duplicates.
   d. Pairing: If there is at least one person and one weapon detected in the frame:
      i. For each detected person, check if any weapon's bounding box overlaps or is near that person (using IoU or distance metric).
      ii. If a person–weapon pair is found, define a combined ROI bounding box that covers both. Crop the frame to this ROI (with a margin).
   e. Behavior Classification: For each ROI, preprocess (resize to 224×224, normalize) and feed it into the CNN. Let ppp = CNN probability of robbery.
   f. Decision: If p≥p \gep≥ classification threshold, trigger an alert. Record the event (frame/time, ROI, YOLO and CNN outputs) in the log.
3. Continue to next frame.

Each frame thus undergoes object detection followed by conditional classification. By combining YOLO's fast object localization with a CNN's learned behavior classification, the system can detect robberies in real time. The YOLO step quickly narrows down potential threat regions (person with weapon), and the CNN step refines this by analyzing the context. All thresholds (object confidence, classification score) are tuned during system testing to balance false positives and misses. Together, these steps form a pipeline that continuously monitors CCTV video and raises alerts when a robbery is detected, while logging all relevant data for later analysis.

Advantages

1. **Real-Time Detection**
   The integration of YOLOv8 ensures fast and accurate detection of suspicious objects (e.g., guns, knives) in live CCTV footage, enabling immediate response.
2. **Behavior-Based Classification**
   CNN enhances the system by analyzing human posture and interactions, reducing false positives from mere object detection.
3. **Automation of Surveillance**
   Reduces the dependency on manual monitoring by security personnel, increasing efficiency and reducing human error.
4. **High Accuracy with Minimal Delay**
   Combining object detection and behavior classification enables precise robbery detection with minimal latency.
5. **Scalable and Flexible**
   The system can be deployed across multiple locations like banks, retail stores, and public places with minimal infrastructure changes.
6. **Data Logging for Auditing**
   Events are stored with metadata for future analysis, retraining, or law enforcement review.

Disadvantages

1. **Model Dependency on Quality Data**
   The performance of the system heavily depends on the quality and diversity of the training dataset. Inadequate or biased data can lead to inaccurate results.
2. **Privacy Concerns**
   Constant surveillance and behaviour analysis might raise concerns regarding personal privacy and ethical usage of AI in public spaces.
3. **False Positives/Negatives**
   In complex environments, the system might still misclassify events, especially in crowded or occluded scenes.
4. **Hardware Requirements**
   Real-time detection demands high-performance GPUs or edge devices, increasing the cost of deployment.
5. **Limited Context Understanding**
   The CNN may not understand deeper contextual cues (e.g., mock robbery training scenarios), leading to unnecessary alerts.

Conclusion

The *Intelligent Robbery Detection System* utilizing YOLOv8 for object detection and CNN for behavioral classification presents a robust AI-driven solution for enhancing security in sensitive environments. By identifying weapons and analyzing suspicious human behavior in real time, the system significantly reduces manual surveillance efforts and improves response time. Its modular architecture and scalable design make it suitable for wide-scale deployment in banks, retail environments, and public areas. While there are challenges such as data dependency and privacy concerns, the benefits of proactive crime prevention, rapid alerts, and data-driven security outweigh these limitations.

Future Scope

1. **Integration with Facial Recognition**
   Combine with facial recognition models to identify known offenders or blacklist entries.
2. **Multiclass Behavior Analysis**
   Extend the CNN to detect other types of threats like fights, vandalism, or suspicious loitering.
3. **Edge AI Deployment**

Optimize the system to run on edge devices for locations without continuous internet access or centralized servers.

4. **Smart City Integration**
   Integrate with broader smart surveillance systems to offer city-wide threat detection and coordinated law enforcement alerts.
5. **Improved Contextual AI**
   Use transformer-based models or hybrid architectures for better scene understanding and reduced false alarms.
6. **Crowd Behavior Analysis**
   Include modules that detect abnormal crowd patterns or stampede risks using spatiotemporal data.

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