International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 01 | Jan - 2025 SJIF Rating: 8.448 ISSN: 2582-3930

AUTOMATIC WEAPON DETECTION FROM REAL TIME IMAGES AND VIDEOS

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ABSTRACT

The main objective of the Project is that Security cameras and video surveillance cameras have become an important part of public safety. However, in many cities, these systems still manually detect high-risk situations. Understaffing in security services can lead to delays in detecting incidents or unforeseen threats, putting the public at risk. The aim of this project is to develop a low-cost, effective intelligence-based solution for real-time weapons detection and surveillance video analysis in different situations. As can be seen from many statistics, the incidence of gun,knives and dangerous weapon crimes is increasing every year, making it difficult for the police to solve the problem in time. Crimes caused by guns or knives are very common in many places, especially in places where gun laws do not exist. Early detection of crime is critical to public safety. One way to prevent these situations is to use video surveillance to detect the presence of dangerous weapons such as guns and knives. Monitoring and control now also require monitoring and intervention. We use the YOLOv8 (look once) algorithm to detect weapons in live video. YOLO model is an end-to-end deep learning model; it is very popular because it is fast and accurate. Previous methods such as region-based convolutional neural networks (R-CNN) required thousands of network tests to make predictions for an image, which could be time-consuming-Optimization is a laborious and painful process.The YOLO model, on the other hand, passes the image through the neural network only once. Since speed is important in real-time video, we use the YOLOv8 algorithm.

1.INTRODUCTION

Automatic weapon detection from real-time images and videos is a critical application of computer vision and machine learning, with significant implications for public safety and security. This technology involves using computer vision algorithms to identify and detect weapons, such as guns, knives, or explosives, in real-time images and videos, and has numerous applications, including surveillance, law enforcement, and security. Despite challenges such as variability, occlusion, lighting, and context, several approaches have been proposed, including deep learning, object detection, image processing, and sensor fusion. Techniques such as edge detection, feature extraction, template matching, and tracking are used to detect weapons, and datasets have been created to support the development of automatic weapon detection systems. The technology has been deployed in various real-world applications, including smart surveillance systems, security cameras, and police body cameras, and future research directions include improving accuracy, real-time processing, context-aware detection, and explainability, with the ultimate goal of enhancing public safety and security.

In the last few years, deep learning techniques and Convolutional Neural Networks (CNNs) have achieved great results in image detection, classification, segmentation and it's being used inseveral applications .The advancements in technology and the latest innovative detection models such as YOLO,Faster R-CNN, VGG-16 have achieved satisfactory results. The common challenges that are faced while weapon detection is the increase in complexity due to partial or full occlusion of gun deformation and loss of information while transmission.The rate of false-negative and false-positive also is an issue in weapon detection systems due to such sensitives systems being linked to alarms or such devices. Weapon Detection systems need Real-time processing and fast response times due to their critical nature, so the research has to and implement techniques that speed the processing time of weapon detection models. Algorithms play a crucial role in automatic weapon detection, enabling computers to analyze images and videos, detect patterns, and make decisions. Various algorithms have been developed for this purpose, including deep learning-based approaches such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and object detection techniques like YOLO (You Only Look Once). One of the most recent and advanced algorithms is YOLOv8, which is a real-time object detection system that can detect objects in images and videos with high accuracy and speed. YOLOv8 is an improvement over its predecessors, YOLOv7 and YOLOv6, and offers better performance, efficiency, and scalability. It uses a novel approach called "dense detection" which allows it to detect objects at multiple scales and aspect ratios, making it particularly effective for detecting small objects like weapons.YOLOv8 has the potential to revolutionize automatic weapon detection and enable faster and more accurate threat detection in various applications, including surveillance, security, and law enforcement.

2. LITERATURE REVIEW

The literature review on automatic weapon detection reveals a growing body of research focused on developing robust and accurate detection systems. Studies have explored various deep learning-based approaches, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have achieved high accuracy in detecting weapons in images and videos. Object detection techniques, such as YOLO (You Only Look Once), SSD (Single Shot Detector), and Faster R-CNN, have also been widely adopted for automatic weapon detection. Researchers have also investigated the use of transfer learning, data augmentation, and ensemble methods to improve detection performance. Furthermore, studies have highlighted the importance of considering contextual information, such as scene understanding and object relationships, to reduce false positives and improve detection accuracy. Recent advances in real-time object detection, such as YOLOv8, have also shown promising results in detecting weapons in real-time. Overall, the literature suggests that automatic weapon detection is a rapidly evolving field, with ongoing research focused on developing more accurate, efficient, and robust detection systems for various applications, including surveillance, security, and law enforcement.

The detection of weapons in images and videos is a critical task that has gained significant attention in recent years. With the advent of deep learning-based approaches, researchers have been able to develop robust and accurate detection systems. One of the most popular object detection algorithms is YOLO (You Only Look Once), which has been widely adopted for various applications, including weapon detection.Recently, the YOLOv8 algorithm has been proposed, which has shown significant improvements over its predecessors. YOLOv8 uses a novel approach called "dense detection" which allows it to detect objects at multiple scales and aspect ratios. This makes it particularly effective for detecting small objects like weapons.In addition to YOLOv8, other algorithms such as SSD (Single Shot Detector) and Faster R-CNN have also been used for weapon detection. These algorithms have been shown to be effective in detecting weapons in various environments, including surveillance videos and images.However, the detection of weapons is a challenging task due to the variability of weapon types, occlusion, and poor lighting conditions. To address these challenges, researchers have been exploring the use of multimodal fusion, where multiple sensors and modalities, such as visible, infrared, and acoustic sensors, are combined to improve detection performance.Through the use of machine learning and sensor fusion (MALS), automatic weapon detection can help improve accuracy, enhance situational awareness, enable real-time threat detection, increase efficiency, and support better decision-making. As noted in a recent email discussion, "the use of MALS can provide a more comprehensive understanding of the environment, including the location and movement of people and objects, which can help in detecting potential threats."

3.METHODOLOGIES

The methodologies for automatic weapon detection from real-time images and videos encompass a wide range of approaches, including deep learning-based techniques, object detection algorithms, image processing methods, machine learning-based strategies, sensor fusion, real-time processing, transfer learning, data augmentation, multimodal fusion, and explainable AI. Deep learning-based approaches, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, can be employed to detect weapons in images and videos, while object detection techniques like YOLO (You Only Look Once), SSD (Single Shot Detector), Faster R-CNN, and RetinaNet can be utilized to identify objects, including weapons, in images and videos. Image processing techniques, such as edge detection, feature extraction, and template matching, can also be used to detect weapons in images and videos, and machine learning-based approaches.

1. Data Collection and Preparation

- **Data Sources**:
  - Open-source datasets such as COCO, Open Images, or specialized weapon datasets.

    - Custom datasets created by collecting images and videos of various weapon types (guns, knives, etc.).
- **Data Annotation**:
    - Use tools like LabelImg or CVAT to annotate the dataset with bounding boxes and class labels.
- **Data Augmentation**:
    - Apply transformations (rotation, scaling, flipping, brightness/contrast adjustments) to increase dataset diversity.

2. Model Selection

- **Pre-Trained Models**:
    - Choose state-of-the-art object detection models like:
        - YOLO (You Only Look Once): Known for real-time performance.
        - Faster R-CNN: High accuracy but slower than YOLO.
        - SSD (Single Shot MultiBox Detector): Balances speed and accuracy.
- **Custom Models**:
    - Train from scratch or fine-tune pre-trained models to detect weapons specifically.

3. Model Training

- **Dataset Splitting**:
    - Divide the data into training (70%), validation (15%), and testing (15%) sets.
- **Training Process**:
    - Use deep learning frameworks like TensorFlow or PyTorch.
    - Define loss functions (e.g., cross-entropy for classification, smooth L1 for localization).
    - Optimize with stochastic gradient descent (SGD) or Adam optimizer.
- **Hyperparameter Tuning**:
    - Adjust parameters like learning rate, batch size, and number of epochs to maximize performance.

4. Real-Time Detection Pipeline

- **Pre-Processing**:
    - Convert frames from video streams into the required input format (resize, normalize).
    - Use OpenCV or similar libraries to handle video feeds.
- **Inference**:
    - Run the trained model on incoming frames to detect weapons.
    - Extract bounding boxes, class labels, and confidence scores.
- **Post-Processing**:
    - Apply non-maximum suppression (NMS) to remove overlapping detections.
    - Filter predictions based on confidence thresholds.

5. Integration with Real-Time Systems

- **Hardware Optimization**:
    - Use GPUs or edge devices (e.g., NVIDIA Jetson, Coral TPU) for real-time processing.
- **Latency Minimization**:
    - Convert models to lightweight formats (e.g., TensorRT, ONNX) for deployment.
- **Integration**:
    - Embed the detection system in existing surveillance setups or standalone applications.

6. Deployment and Testing

- **Deployment**:
    - Implement the model in a live environment (e.g., surveillance systems, drones).
    - Use REST APIs or MQTT protocols for alerting and integration.
- **Testing**:
    - Validate the system under various conditions (lighting, crowd density, camera angles).
    - Conduct stress tests to ensure reliability.

4ALGORITHMS

Algorithm for Automatic weapon detection from real time images and videos

1. YOLOv8 Detection Algorithm

- **Algorithm**: YOLO (You Only Look Once) is a real-time object detection algorithm. YOLOv8, the latest version, offers improved performance and efficiency.

- **How it works**:
  - The image is divided into a grid.
  - Each grid cell predicts bounding boxes, class probabilities, and confidence scores.
  - Post-processing (e.g., Non-Maximum Suppression) is applied to eliminate overlapping boxes and retain the most confident predictions.
- **Application in Code**:
  - The model detects weapons by predicting bounding boxes and classifying the objects within them.
  - The model.predict() function performs this detection and returns the bounding box coordinates, classes, and confidence scores.

2. Bounding Box Rendering

- **Algorithm**: Simple geometric rendering using image coordinates.
- **How it works**:
  - The coordinates of the bounding box (x1, y1, x2, y2) are used to draw rectangles around detected objects.
  - The labels and confidence scores are rendered near the bounding box using text-drawing utilities in OpenCV.
- **Application in Code**:
  - cv2.rectangle() draws the bounding box.
  - cv2.putText() displays the label with the detected object and confidence score.

3. Email Sending with Attachments

- **Algorithm**: SMTP (Simple Mail Transfer Protocol) via the yagmail library.
- **How it works**:
  - The sender authenticates with an email server using credentials.
  - An email is composed with a subject, body, and attachment (the processed image).
  - The email is sent to the recipient via the SMTP server.
- **Application in Code**:
  - The send_email() method utilizes yagmail to send alerts about detected weapons, attaching the processed image as evidence.

4. Image Processing and Visualization

- **Algorithms**:
  - **Image Reading and Writing**: Uses OpenCV to load and save images.
  - **Visualization**: Draws bounding boxes and labels to visually indicate detected weapons.
- **How it works**:
  - OpenCV reads the image into a matrix of pixel values.
  - The detection results modify this matrix to include visual markers for bounding boxes and labels.
  - The processed image is then saved and optionally displayed to the user.
- **Application in Code**:
  - cv2.imread() reads the image.
  - cv2.imwrite() saves the processed image.
  - cv2.imshow() displays the image in a window.

5. File and Path Handling

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 01 | Jan - 2025 SJIF Rating: 8.448 ISSN: 2582-3930

- **Algorithm**: OS path utilities.
- **How it works**:
  - The os.path.exists() function checks if files or directories exist before attempting to access them.
  - This prevents runtime errors related to missing files.
- **Application in Code**:
  - Ensures the image and model file paths are valid before processing.

6. Confidence Filtering

- **Algorithm**: Thresholding.
- **How it works**:
  - The algorithm filters out predictions with confidence scores below a certain threshold (e.g., 0.5).
  - This helps eliminate weak or unreliable detections.
- **Application in Code**:
  - Predictions with score >= 0.5 are considered valid and are processed further.

How the Algorithm is Used in the Code

1. Data Collection: Collect a large dataset of images and videos containing weapons.

2. Data Preprocessing: Preprocess the data by resizing, normalizing, and augmenting the images and videos.

3. Model Training: Train a YOLOv8 model on the preprocessed data.

4. Model Evaluation: Evaluate the performance of the YOLOv8 model on a test dataset.

5. Real-time Deployment: Deploy the YOLOv8 model in a real-time system, such as a surveillance camera or a smart security system.

5.IMPLEMENTATION RESULT

Analysis of Implementation Results

The uploaded image demonstrates the successful implementation of the weapon detection system. Below is an interpretation of the results based on the image:

1. Detection Output

- **Detected Objects**:
  - **Knife**:
    - Confidence: 0.67 (67% confidence in detection).
    - Bounding box drawn around the knife.
    - Label: "knife 0.67" displayed above the bounding box.
  - **Gun**:
    - Confidence: 0.87 (87% confidence in detection).
    - Bounding box drawn around the gun.
    - Label: "gun 0.87" displayed above the bounding box.

2. Processed Image Visualization

- The processed image includes:

- Red bounding boxes marking the regions where weapons are detected.
- Green labels with the object name and detection confidence score.
- Text message "Weapon Detected and Email Sent Successfully" prominently displayed at the top of the image.

3. Email Alert

- **Status**: The text "Weapon Detected and Email Sent Successfully" confirms that an email alert was sent.
- **Content of the Email**:
  - Subject: "Security Alert".
  - Body:
  - css

ALERT - knife and gun object(s) have been detected!!

Attachment: The processed image (same as the uploaded image) is attached to the email.

4. Performance Insights

- **Detection Accuracy**:
  - The confidence levels for both detections (knife: 67%, gun: 87%) are reasonable and exceed the typical threshold (0.5).
  - Both objects are correctly identified and localized in the image.

Email Notification:

- The email feature appears to have functioned correctly, as confirmed by the success message.

5. Implementation Success

- The uploaded image demonstrates that:
  - The YOLOv8 model is capable of detecting weapons accurately in images.
  - The bounding box and labeling system is functioning as intended.
  - The email alert system successfully communicates the detection results.

6.**Potential Improvements**

- **Confidence Threshold**: Consider increasing the confidence threshold for detections (e.g., from 0.5 to 0.7) to reduce false positives.
- **Blur Feature**: Add functionality to blur detected regions for privacy/security purposes.
- **Multi-Language Alerts**: Support customized messages in different languages.

6.FUTURE WORK

The future of automatic weapon detection from real-time images and videos is expected to undergo significant transformation, driven by ongoing advancements in machine learning, computer vision, and AI technologies. Enhanced deep learning models, including those based on convolutional neural networks (CNNs), transformers, and recurrent neural networks (RNNs), will continue to improve the accuracy of weapon detection, even in challenging environments such as low lighting or crowded public spaces. These systems will process real-time data more efficiently through the use of edge AI and low-latency algorithms, enabling faster detection and response times, especially when deployed in high-risk areas like airports, stadiums, or urban environments.

- Furthermore, the integration of multimodal data from sensors such as thermal cameras, radar, and acoustic sensors (e.g., gunshot detection) will enable more comprehensive threat identification. This will be especially crucial in detecting concealed weapons or distinguishing between threats and benign objects. 3D object recognition and multi-perspective imaging through a network of strategically placed cameras will improve the system's ability to detect weapons from multiple angles and in more complex scenes. Coupled with contextual awareness, where the system can analyze the environment and predict potential threats based on behavior patterns, these technologies will contribute to more proactive and dynamic security solutions.
- In terms of adaptability, future weapon detection systems will incorporate continuous learning

capabilities, allowing them to update and refine their detection models based on new data, including emerging weapon types or unconventional tactics. Transfer learning and synthetic data generation will enable systems to be deployed across diverse environments and regions, improving generalization and performance in varied contexts. Additionally, integration with broader security infrastructure—such as automated drones, surveillance networks, and emergency response systems—will allow for quicker reactions to detected threats and enhance overall situational awareness. And also in preventing threats and ensuring safer environments worldwide.

7.CONCLUSION

The advancement of automatic weapon detection systems represents a significant step forward in enhancing public safety and surveillance capabilities. These systems utilize cutting-edge machine learning algorithms and computer vision techniques to identify weapons such as guns and knives in real-time images and videos, enabling swift and accurate responses to potential threats. By automating the detection process, they reduce reliance on human monitoring, minimizing errors and improving efficiency. With applications ranging from law enforcement and event security to urban surveillance, these systems are versatile and scalable. However, their performance can be influenced by factors such as environmental conditions and dataset quality, and they raise important privacy considerations. Looking ahead, advancements in AI, integration with smart infrastructure, and ethical implementation will further enhance their effectiveness and global adoption. Automatic weapon detection systems hold great potential for creating safer environments, provided their deployment is balanced with considerations for individual rights and data security.

The development of automatic weapon detection systems signifies a transformative leap in modern surveillance and security. By leveraging advanced machine learning algorithms and computer vision, these systems can accurately identify weapons such as guns and knives in real-time images and videos, ensuring immediate threat recognition and response. Their ability to operate autonomously reduces dependence on manual monitoring, minimizing human error and allowing for more efficient use of resources in critical situations. These systems have broad applications, including public safety in crowded areas, transportation hubs, schools, corporate offices, and event venues. The scalability of such technologies makes them adaptable to diverse environments, from localized installations to large-scale urban surveillance networks.

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