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Weapon Detection Using ML in Border Area

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Abstract: *One of the coveted uses of convolutional neural networks is real-time object detection to enhance surveillance techniques. This study looked at the detection of fire and pistols in locations under camera surveillance. A sizable populace worldwide mourns the violence caused by guns each year. In this work, handguns and rifles are identified using a computer-based fully automated approach. Significant advancements in the fields of object identification and recognition have been shown by implementation. Fire and gun image dataset is used to train the YOLOv3 object identification algorithm. A deep learning method based on the YOLOv3 has been used in the proposed work. This system can be used to avoid and reduce the violence which will be great benefit for the society and world.*
Security is always a main concern in every domain, due to a rise in crime rate in a crowded event or suspicious lonely areas. Abnormal detection and monitoring have major applications of computer vision to tackle various problems. Due to growing demand in the protection of safety, security and personal properties, needs and deployment of video surveillance systems can recognize and interpret the scene and anomaly events play a vital role in intelligence monitoring. This project implements automatic gun (or) knife detection using a yolo convolution neural network (CNN) based algorithm. The trained model will be able to detect gun or knife based on the pre-trained yolo file and alert via buzzer and sends an alert to preset authorized user or police station. Victim can also alert via voice whenever there is treat, victim should press the emergency button and say help this voice is recognized and immediately alert will be sent with captured scene...

Keywords: YOLO, X-Ray, GUN, Weapon, Security

I. INTRODUCTION

Gun violence is a very serious issue for human rights and freedom in the world. The prime human right is frightened by weapon-related violence. The existences of individuals influenced by weapons on regular routine in the entire world. According to the statistics, the death proportion of individuals because of gun brutality is around 500 every day. More than 44% of assassination involves gun violence worldwide. In the middle of 2012 and 2016 more than 1.4 million deaths were recorded due to firearms violence Weapon or Anomaly detection is the identification of irregular, unexpected, unpredictable, unusual events or items, which is not considered as a normally occurring event or a regular item in a pattern or items present in a dataset and thus different from existing patterns. An anomaly is a pattern that occurs differently from a set of standard patterns. Therefore, anomalies depend on the phenomenon of interest. Object detection uses feature extract ion and learning algorithms or models to recognize instances of various category of objects. Proposed implementation focuses on accurate gun detection and classification. Also concerned with accuracy, since a false alarm could result in adverse responses. Choosing the right approach required to make a proper trade off between accuracy and speed. Figure 1 shows the methodology of weapons detection using deep learning. Frames are extracted from the input video. Frame differencing algorithm is applied and bounding box created before the detection of object.

II. SYSTEM OVERVIEW

Deploy the system in CCTV networks, smart city systems, and industrial settings.
Regularly update the model with new data to improve accuracy.
Integrate cloud-based analytics for remote monitoring.

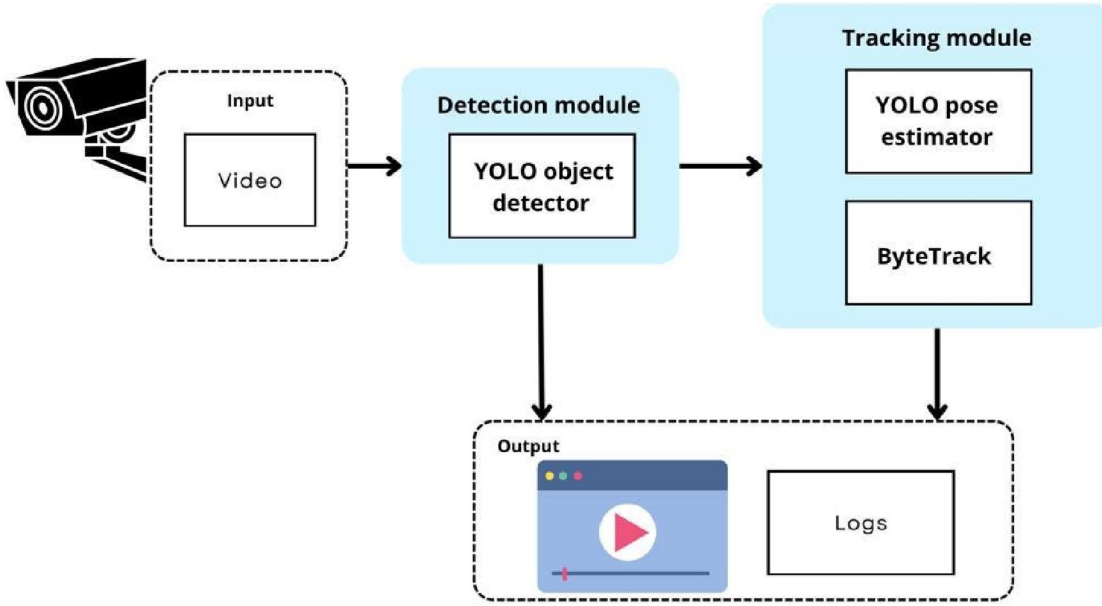

Figure 1: Block diagram of the transmitting end

1. Data Collection

• Weapons Detection:

o Collect images and videos of various weapons (guns, knives, explosives) in different environments.
o Use publicly available datasets like Open Images, COCO, or custom datasets.
o Capture real-world surveillance footage to improve model accuracy.

2. Fire Detection:

o Gather images and videos of fire in different scenarios (indoor, outdoor, forest fires, industrial settings).
o Include non-fire images to reduce false positives.
o Use datasets such as Firenet or Fire Detection Dataset.

3. Data Preprocessing

• Convert images to a standard format (e.g., 224×224 or 416×416 for deep learning models).
• Apply data augmentation (rotation, flipping, brightness adjustments) to improve model robustness.
• Normalize pixel values and remove noise.

4. Model Selection

• Weapons Detection:

o Use object detection models like YOLO (You Only Look Once), Faster R-CNN, or SSD (Single Shot Multibox Detector).
o Train the model using labeled datasets of weapons.
o Use transfer learning with pre-trained models (e.g., YOLOv5, YOLOv8).

• Fire Detection:

o Use Convolutional Neural Networks (CNNs), YOLO, or EfficientDet for fire image classification and detection.
o Implement traditional computer vision techniques such as color-based segmentation (e.g., detecting fire using RGB and HSV color spaces).

5. Model Training and Validation

• Split data into training (70%), validation (20%), and test (10%) sets.
• Use frameworks like TensorFlow, PyTorch, or OpenCV for model development.
• Train the model using GPU-based acceleration for faster processing.
• Evaluate model performance using metrics such as mAP (mean Average Precision), Precision, Recall, and F1-score.

6.Real-time Detection and Implementation

• Deploy the trained model in a real-time surveillance system.
• Use OpenCV and DeepStream to process live camera feeds.
• Implement Edge AI solutions for faster inference on edge devices (e.g., NVIDIA Jetson, Raspberry Pi).

7. Alert System Integration

• Weapons Detection:

o If a weapon is detected, trigger an alert to security personnel.
o Store frames of detected weapons for forensic analysis.

• Fire Detection:

o If fire is detected, activate an alarm system.
o Notify emergency responders with the exact location.

8.Testing and Optimization

• Test the system in real-world scenarios to measure its performance.
• Optimize by reducing false positives and improving detection speed.
• Implement post-processing techniques like Non-Maximum Suppression (NMS) to filter overlapping detections.

9.Deployment and Maintenance

• Deploy the system in CCTV networks, smart city systems, and industrial settings.
• Regularly update the model with new data to improve accuracy.

IV. IMPLEMENTATION

By detecting weapons in real-time, the system enhances security measures in various environments, including public spaces, transportation hubs, and critical infrastructure facilities.The system acts as a proactive security measure, enabling the timely detection and intervention of potential threats before they escalate into harmful incidents.Upon detecting a weapon, the system automatically triggers alerts, notifying security personnel or authorities to take appropriate action, thus minimizing response time.Leveraging advanced object detection algorithms like YOLO, the system achieves high accuracy in identifying weapons while minimizing false positives, ensuring reliable threat detection.

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Figure 4 Implementation of hardware

V. CONCLUSION

To improve safety and security in varied situations, the risk detection system built through automatic image processing employing the YOLOv4 algorithm has demonstrated promising results. The system has demonstrated accurate and real-time identification of possible threats by utilising deep learning and object detection, enabling proactive efforts to limit risks and prevent incidents. The idea is technically possible, according to the feasibility analysis, with the YOLOv4 algorithm delivering great accuracy and efficiency in threat detection. According to the economic feasibility analysis, the advantages of increased operational effectiveness, cost savings, and safety outweigh the initial investment needed for hardware, software, and data collection.

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