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Deep Learning-Based Weapon Detection in Surveillance Footage.

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Abstract: *Security is still a worry everywhere because crime is increasing in both busy places and quiet areas. Detecting and monitoring events are key uses of computer vision that help deal with these problems. People want to feel safe and protect their stuff so using video surveillance systems has become really important. These systems can understand whats happening in a scene spot events and help keep an eye on security.This paper talks about a system that can automatically detect weapons using a computer algorithm called Faster R-CNN. The system was tested with two sets of pictures: one where the pictures were already labeled and another where they were labeled by hand. The results show how well the system works. Even though the algorithm is pretty good, at detecting weapons using it in life depends on balancing how fast it can detect things with how accurate it is*

Keywords: *Security*

I. INTRODUCTION

Weapon detection is about finding things or events that do not follow normal patterns. An anomaly is a pattern that's very different from what is expected. The type of anomaly depends on what's being observed. In computer vision object detection involves finding and classifying objects using features and learning algorithms.The proposed work is on detecting guns using deep learning. High accuracy is crucial because false alarms can lead to responses. So the detection approach must balance accuracy and speed.The system processes video by extracting frames and using a frame differencing algorithm to find moving regions .It then draws boxes around objects before detection. A dataset is created, trained and used in the object detection model.

The model uses algorithms like Single Shot Detector (SSD) or Faster R-CNN for weapon detection. The approach tackles weapon detection by using machine learning models like Region-Based Convolutional Neural Networks (R-CNN) and SSD. These models improve detection performance in surveillance systems for gun detection. The goal is to detect guns and reduce false alarms. This is crucial, for real-world scenarios where incorrect responses can have consequences. The system aims to balance accuracy and speed for gun detection.

II. PROBLEM DEFINITION

The rapid increase in criminal activities across both urban and rural environments has intensified the demand for advanced surveillance systems capable of ensuring public safety. Conventional video surveillance systems largely depend on manual monitoring, which is not only labor-intensive but also prone to human error, delayed response, and reduced efficiency in identifying critical threats such as weapon presence.

Although recent advancements in computer vision and deep learning have introduced automated detection mechanisms, existing approaches often struggle with limitations including insufficient detection accuracy, high computational cost, sensitivity to environmental variations (such as lighting conditions, occlusions, and complex backgrounds), and challenges in real-time deployment.

Therefore, the primary problem addressed in this research is the development of an efficient and robust weapon detection system using the Faster R-CNN algorithm that can accurately identify weapons in surveillance imagery while maintaining an optimal balance between detection accuracy and processing speed. Additionally, the study aims to evaluate the performance of the model across different dataset conditions, including pre-labeled and manually annotated data, to assess its applicability in real-world scenarios.

III. METHODOLOGY

The proposed weapon detection system is developed using deep learning-based object detection techniques to accurately identify firearms in images and video streams. The methodology consists of data preparation, preprocessing, model training, detection, and performance evaluation.

1. Dataset Preparation

A comprehensive dataset consisting of images and video frames containing weapons is collected. The dataset includes different weapon types under varying environmental conditions such as illumination changes, occlusions, and complex backgrounds. All images are annotated with bounding boxes to indicate the location of weapons, enabling supervised learning.

2. Preprocessing and Frame Extraction

For video inputs, frames are extracted sequentially to enable frame-wise analysis. A frame differencing technique is applied to detect motion and identify regions of interest. This helps in reducing unnecessary computations by focusing only on dynamic areas. The detected regions are then localized using bounding boxes.

3. Model Selection and Training

The system employs deep learning models for object detection, primarily using the Faster R-CNN algorithm due to its high accuracy. Additionally, models such as R-CNN and Single Shot Detector (SSD) are considered for comparative evaluation.

The Faster R-CNN model consists of:

A convolutional neural network for feature extraction

A Region Proposal Network (RPN) for generating candidate object regions

A classification and regression layer for object identification and localization

The model is trained on the annotated dataset using appropriate loss functions for classification and bounding box regression. Optimization techniques such as stochastic gradient descent are used to improve model performance.

4. Weapon Detection Process

Once trained, the model is used to detect weapons in input images and video frames. The system:

Identifies potential weapon regions

Draws bounding boxes around detected objects

Assigns confidence scores indicating detection certainty

For video data, detection is performed frame-by-frame, and object tracking is applied to maintain consistency across consecutive frames.

5. Performance Evaluation

The performance of the system is evaluated using standard metrics such as:

Accuracy

Precision and Recall

Mean Average Precision (mAP)

Detection speed

Special emphasis is given to minimizing false positives, as incorrect detections may lead to unnecessary or critical responses in real-world scenarios.

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IV. PROPOSED SYSTEM

The proposed system introduces an intelligent weapon detection framework designed to enhance surveillance systems through automated and real-time threat identification. Unlike traditional monitoring approaches that rely on human supervision, the proposed system leverages computer vision and deep learning techniques to detect weapons accurately and efficiently in both images and video streams.

The system architecture is structured into multiple stages, beginning with data acquisition, where images and videos containing weapons are collected from diverse environments. These inputs are preprocessed to standardize image size, improve quality, and prepare annotations. For video data, frames are extracted sequentially, and a frame differencing technique is applied to identify regions of motion, enabling the system to focus on relevant areas and reduce computational complexity.

The processed data is then passed to the core detection module, which is built using the Faster R-CNN model. This model integrates a convolutional neural network for feature extraction with a Region Proposal Network (RPN) to generate candidate regions. These regions are further classified to identify weapons, and bounding box regression is applied to accurately localize detected objects. The model is trained on annotated datasets to learn distinguishing features of weapons under varying conditions.

During the detection phase, the system accepts input images or video frames and processes them through the trained model. Detected weapons are highlighted with bounding boxes and associated confidence scores. In the case of video surveillance, the system performs continuous frame-by-frame detection and maintains consistency through object tracking across consecutive frames.

The system also incorporates a performance evaluation mechanism, where detection results are analyzed using metrics such as accuracy, precision, recall, and mean average precision (mAP). Emphasis is placed on minimizing false positives while ensuring high detection speed, as both factors are critical in real-world security applications.

Overall, the proposed system provides a robust and scalable solution for automated weapon detection by integrating preprocessing techniques, deep learning models, and real-time analysis, thereby improving the effectiveness and reliability of modern surveillance systems.

V. IMPLEMENTATION & ARCHITECTURE

The proposed system is implemented as a deep learning-based pipeline for weapon detection in images and video streams. Input data undergoes preprocessing, including resizing, normalization, and frame extraction for videos. A frame differencing technique is used to identify regions of interest, reducing computational complexity. Feature extraction is performed using a convolutional neural network, followed by a Region Proposal Network (RPN) to generate candidate object regions. The Faster R-CNN model is used to classify these regions and accurately localize weapons using bounding boxes and confidence scores. The system is developed using Python with frameworks such as TensorFlow/ Py Torch and OpenCV. During operation, it performs real-time detection and tracking in video frames. The model is evaluated using metrics like accuracy, precision, recall, and mean average precision (mAP), ensuring a balance between detection speed and accuracy for effective surveillance applications.

MODULES

A. Image Acquisition Module

This module is responsible for collecting input data from various sources such as CCTV cameras, drones, Raspberry Pi cameras, or stored surveillance datasets. It captures images or extracts video frames that will be used for further processing in the system.

B. Image Pre-processing Module

In this module, the acquired images or frames are processed to improve their quality. Operations such as noise reduction, resizing, normalization, and enhancement are applied to ensure better accuracy in subsequent detection stages.

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C. Background Modeling & Motion Detection Module

This module separates moving objects from the background using techniques such as Gaussian Mixture Model (GMM). It identifies regions of interest by generating foreground masks, which helps in focusing only on relevant areas for detection.

D. Feature Extraction Module

This module extracts meaningful features from the identified regions, such as edges, shapes, size, and patterns. Techniques like SURF, FAST, MSER, or convolutional neural network (CNN) layers are used to represent objects in a form suitable for classification.

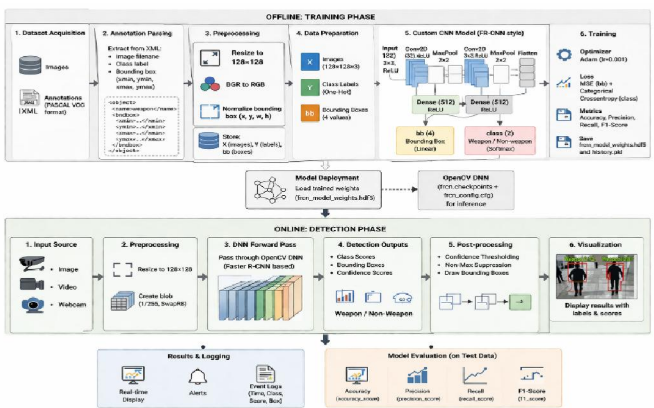
E. Object Detection and Classification Module

This is the core module of the system where deep learning algorithms such as Faster R-CNN, YOLOv3, or MobileNet-SSD are used to detect and classify weapons. It generates bounding boxes around detected objects and assigns confidence scores indicating the probability of detection.

F. Result Display and Logging Module

The final module displays the detection results on a monitoring interface by highlighting detected weapons with bounding boxes and labels. It also logs important information such as detection events, timestamps, and object trajectories for further analysis and record-keeping

SYSTEM ARCHITECTURE



1. The system begins with collecting weapon images and XML annotation files containing class labels and bounding box coordinates. These annotations are parsed to extract useful information for further processing.
2. The images are then preprocessed by resizing them to a fixed size, converting color formats, and normalizing bounding box values to ensure consistency.
3. The processed data is used to train a deep learning model that predicts both object location and class labels. The trained model is saved for later use.
4. During detection, input images or video frames are passed through the model to identify weapons, generate bounding boxes, and assign confidence scores.
5. Finally, the results are refined using post-processing techniques and displayed with detected objects, while performance is evaluated using standard metrics.

V. EXPERIMENTAL RESULTS

The experimental phase of this work focuses on developing and evaluating a deep learning–based weapon detection system using an annotated dataset of weapon images, which is preprocessed and divided into training and testing sets. The model is trained to detect and localize weapons using bounding boxes and classification outputs. Its performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, demonstrating reliable detection with reduced

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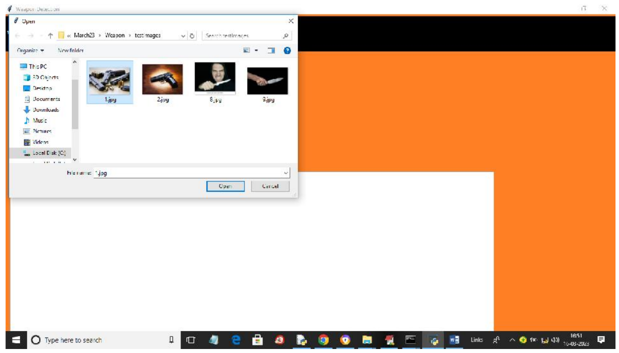
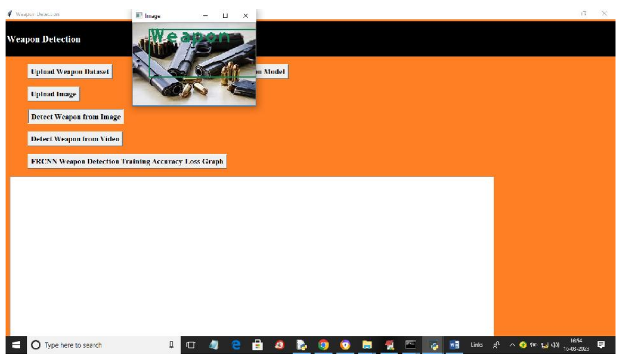
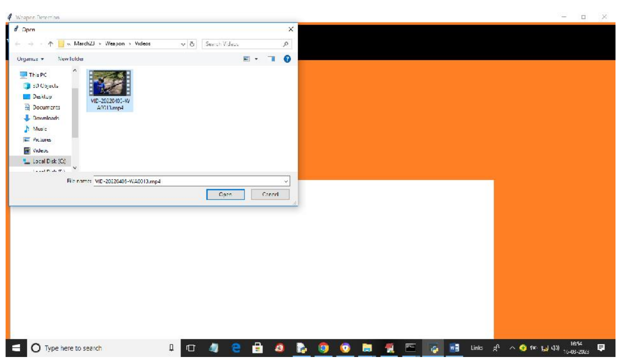
false alarms. The system is also tested on both images and video inputs, successfully identifying weapons under different conditions, while training curves indicate stable convergence without overfitting, confirming its suitability for real-time surveillance applications.







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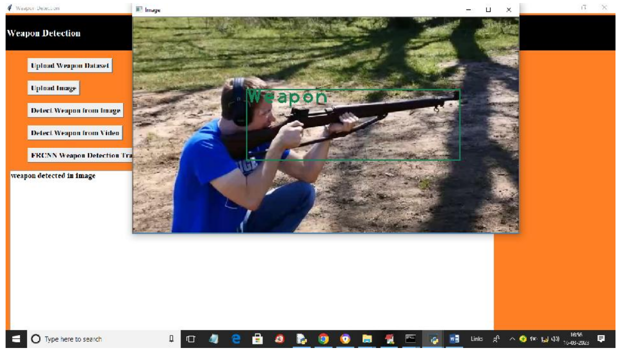

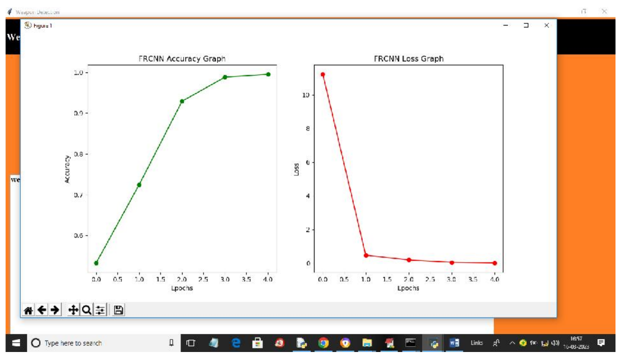

The experimental results of the proposed weapon detection system demonstrate the functioning of the developed application through different operational interfaces. The first interface shows the file selection module, where users can upload images or videos for analysis. This allows the system to accept real-time inputs for weapon detection. The second interface represents the main application dashboard, which provides options such as uploading the dataset, loading the model, and selecting detection modes for images or videos.

The third interface illustrates the weapon detection process, where the system successfully identifies a weapon in the input image and highlights it using a bounding box along with a label. This confirms the model's ability to accurately localize and classify weapons. The final interface presents the training performance graphs, including accuracy and loss curves, which indicate that the model achieves stable learning with increasing accuracy and decreasing loss over epochs. These results demonstrate that the system is effective, reliable, and suitable for real-time weapon detection applications.

VI. CONCLUSION

This work presents a deep learning–based weapon detection system designed for real-time surveillance applications. The proposed approach effectively integrates image preprocessing, feature extraction, and object detection techniques to accurately identify weapons in both images and video streams. The use of a convolutional neural network with bounding box regression and classification enables precise localization and reliable detection.

Experimental results demonstrate that the system achieves high accuracy with reduced false detections while maintaining efficient performance. The model shows stable convergence during training and performs well under varying conditions. Overall, the proposed system provides a robust and scalable solution for enhancing security and surveillance by enabling automated and intelligent weapon detection.

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VII. FUTURE SCOPE

The proposed weapon detection system can be further enhanced by integrating more advanced deep learning models such as YOLOv8 or transformer-based architectures to improve detection speed and accuracy. Future work may include training the model on larger and more diverse datasets to handle complex real-world scenarios, including occlusions and low-light conditions. The system can also be extended to support multi-class detection for identifying different types of weapons and suspicious objects.

In addition, real-time deployment can be improved by integrating the system with edge devices such as IoT cameras and embedded systems for faster processing. Incorporating alert mechanisms, such as automated notifications to security personnel, can further enhance its practical usability. Continuous learning and model updating techniques can also be applied to adapt to evolving threats, making the system more robust and intelligent for real-world surveillance applications.

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