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Automated Weapon Detection System in CCTV's Through Image Processing

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Abstract. In our study, we aim to detect various weapons through image processing using a combination of traditional machine learning algorithms and deep learning techniques. This would prove beneficial in anticipating unusual occurrences. The utilization of Closed-Circuit Televisions (CCTVs) has become widespread in the security and surveillance industry; however, it requires constant human monitoring to extract useful information, which is both tedious and prone to errors. The base paper deals with identifying only firearms. We intend to utilize machine learning and deep learning methods to recognize different weapons automatically, not only firearms and alert the CCTV monitor to that specific area.

1 . Introduction

Modern technology uses computer vision algorithms and approaches to identify potential risks or dangerous situations in visual data. This is known as danger detection using image processing. This method has drawn a lot of interest in a number of fields, including public safety, business settings, and transportation, thanks to the growing accessibility of digital cameras and surveillance systems.

Automatically analysing photos or video streams and spotting visual indicators linked to potential risks or threats is the main goal of danger detection using image processing[2-5]. This technology may recognise particular patterns or abnormalities that denote harmful conditions by using sophisticated image analysis techniques, such as object detection, motion tracking, and anomaly detection.

Real-time monitoring and alarms are one of the major benefits of risk detection through image processing[8-13]. This technology can quickly spot possible threats by continuously analysing visual data in real-time, and it can send out rapid alerts to the appropriate people or systems. When there is a chance for accidents, dangers to be reduced, or lives to be saved, this competence is essential. Furthermore, image processing-based risk detection can be

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seamlessly integrated with already-installed security networks or surveillance systems. It is feasible to increase the effectiveness and efficiency of safety standards by integrating this technology with video surveillance cameras, drones, or even mobile devices[3]. The proactive monitoring, automatic alerts, and enhanced decision-making processes that can result from this integration give security staff the ability to react quickly and effectively to possible threats.

Overall, the ability to detect danger using image processing is a revolutionary technique with broad applications across many industries. It provides a potent tool for improving situational awareness and minimising dangers in a variety of settings, including public safety, industrial settings, transportation, and more. This technology has the ability to greatly enhance safety precautions and produce safer settings for individuals and communities by utilising the capabilities of computer vision and sophisticated picture analysis algorithms[4].

2 . Literature Review

2.1 Survey Paper 1

S. Ahmed, H. Wang, and Y. Tian, "*Adaptive high-order terminal sliding mode control based on time delay estimation for the robotic manipulators with backlash hysteresis*," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. **51, no. 2, pp. 1128–1137**, (2021).

Approach: In this paper, unknown dynamics of robotic manipulators in the presence of uncertainties, external disturbances and backlash hysteresis are considered. Therefore, further research work suggests that the TDE-based controller can be proposed to design a robust controller under other nonsmooth nonlinearities, such as saturation and dead-zone. Furthermore, the suppression of noise effect in terms of chattering in the control inputs can be considered as future work.

2.2 Survey Paper 2

Warsi, M. Abdullah, M. N. Husen, M. Yahya, S. Khan, and N. Jawaid, *"Gun detection system using YOLOv3," in Proceedings of the 2019 IEEE International Conference on Smart Instrumentation,* Measurement and Application (ICSIMA*),* pp. **1–4**, IEEE, Kuala Lumpur, Malaysia, August (2019).

Approach : Every year, a large amount of population reconciles gun-related violence all over the world. In this paper, we develop a computer-based fully automated system to identify basic armaments, particularly handguns and rifles. Recent work in the field of deep learning and transfer learning has demonstrated significant progress in the areas of object detection and recognition. We have implemented YOLO V3 "You Only Look Once" object detection model by training it on our customized dataset. The training results confirm that YOLO V3 outperforms YOLO V2 and traditional convolutional neural network (CNN).

3 . Implementation

Similar procedures to the preceding response must be followed, with certain modifications unique to weapon detection, when implementing weapon detection using image processing utilising the YOLOv4 algorithm for CCTV surveillance[5]. Here is a detailed manual for implementing weapon detection:

3.1 Data gathering and annotation:

Assemble a collection of photographs with different settings involving guns. Mark the areas of the photographs where there are weapons by annotating them. Make sure the dataset includes a range of lighting situations, angles, and weapon kinds[1].

3.2 Data Preprocessing:

Resize the photos to the correct input scale for YOLOv4. To increase the diversity of the dataset, use data augmentation methods such random cropping, flipping, and rotation.

3.3 Model Selection and Setup:

Get YOLOv4 pre-trained weights for your model selection and setup. The environment, libraries, and dependencies needed for training and inference should be setup. Both TensorFlow and PyTorch offer YOLOv4 implementations that are readily available.

3.4 Model Fine-tuning:

Utilising your annotated dataset, fine-tune the YOLOv4 model. In particular, if class weights are necessary, adjust the hyperparameters. You may wish to prioritise high precision to reduce false positives given the sensitive nature of weapon detection. Post-processing: Use confidence thresholding and non-maximum suppression (NMS) to weed out duplicate and low-confidence detections. Make the post-processing specific to your use case.

3.5 Data file

```
classes=2
train= data/train.txt
valid= data/test.txt
names= data/Multiple_Images.names
backup= backup/
```

Fig. 1. Weapon Detection Data Files

3.6 Names file

```
Knife
Gun
```

Fig. 2. Weapon Detection of Gun and Knife

4. Testing Results

Fig. 3. Weapon Detection of Gun

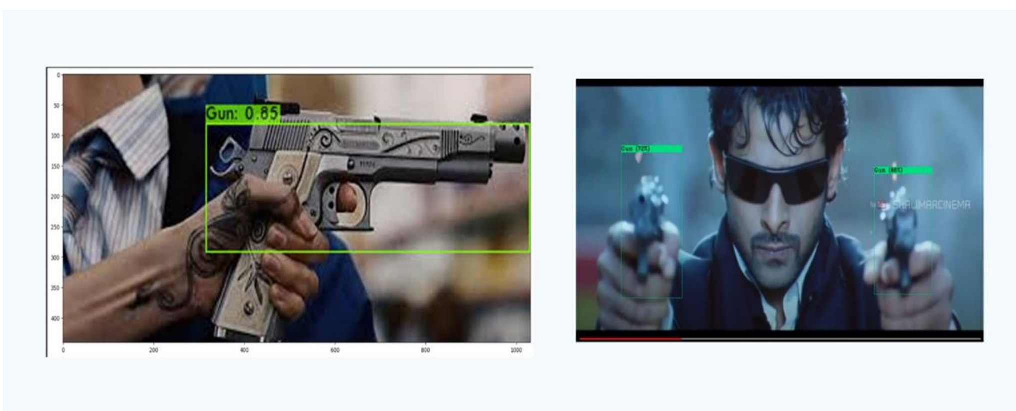

Fig. 4. Weapon Detection and Identification

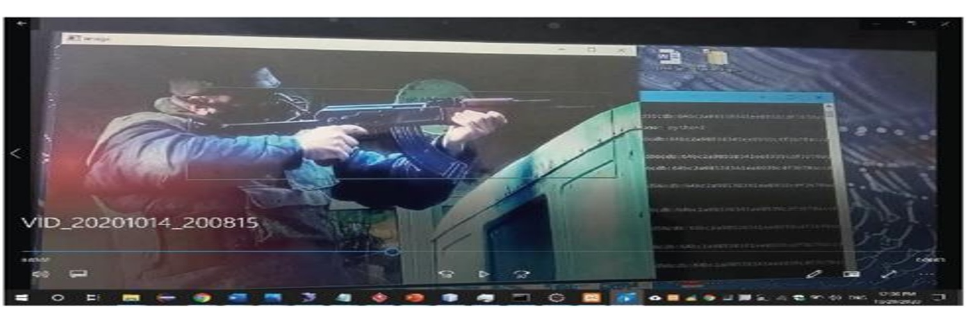

Fig.5. Weapon Detection in Video

5. 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.

6. Further Scope

Although the YOLOv4 algorithm-based risk detection system is a big accomplishment, there are a number of opportunities for further development and improvement: Optimisation and fine-tuning: The YOLOv4 model can be further improved to increase the speed and accuracy of detection. The model's performance in identifying particular kinds of threats can be improved by optimising hyperparameters and fine-tuning it using data from the relevant domains.Integration with other sensors: Combining image processing with other sensor technologies, such thermal cameras or lidar, can create a more thorough detection system that can spot more dangerous situations or different kinds of threats. Real-time video analytics: Increasing the system's capacity to analyse video feeds in real-time can help with proactive threat identification and response, as well as continuous monitoring of dynamic situations. Collaboration with current security systems: The risk detection system can be integrated with current security infrastructure, including access control systems or surveillance networks, to build a full security ecosystem with improved capabilities.Support for numerous cameras: Increasing the system's capacity to handle many camera inputs at once can enhance coverage and make it possible to fully monitor greater regions or challenging settings.

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