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WEAPON RECOGNITION IN INVESTIGATION SYSTEM USING DEEP LEARNING

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Abstract:
Weapon detection software is an effective technique to keep an eye on the streets and notify the operator only when someone is carrying a weapon, such as a gun or knife, this paper presents the concept of our weapon detection in surveillance systems using deep learning, which can be identified and examined with the use of the "You Only Look Once" (YOLO) and CNN object identification algorithm. Gun detection is a crucial demand nowadays, and our effort focuses on creating a secure environment using CCTV video as a source to find dangerous weapons. YOLO has a potential future in the field of improving surveillance through the use of real-time object detection systems.
Keywords- Weapon detection, CNN, YOLO

1.Introduction:

Security apps leverage deep learning methods for weapon detection. These vision-based algorithms can identify and comprehend situations from video from surveillance systems. In conventional video surveillance, security personnel must view security tape to visually identify the presence of weapons in the monitored scenes and make choices as rapidly as possible. Processing the real-time video stream of security cameras using deep learning algorithms is one of the most efficient ways to overcome the drawbacks of manual analysis and automate weapon identification with improved accuracy.

Modern science and technology have made it possible for individuals to employ surveillance cameras in a variety of settings to deter crime. Security guards must keep an eye on a variety of camera systems that have been put in various locations. Security officers often respond to a crime scene after it has occurred, verify the footage, evaluate it, and gather the required evidence. At the crime site, a proactive mechanism must be put in place. In this case, quick action may be done to deter the potential criminal from committing a crime if the program instantly warns the security personnel after recognizing hazardous things. As a result, it is crucial to develop a system that can recognize dangerous things.

Deep learning's contribution to enhancing task performance in security control systems is well acknowledged. Machine learning has a subfield called deep learning. It employs numerous layers of non-linear processing units for feature conversion, feature extraction, and deep learning. The deep learning framework enables the learning of data at several feature levels. CNN is a deep learning is based on gaining knowledge from how the primary data is represented. A vector of density values per pixel or characteristics like edge clusters and custom shapes may be thought of as the representation of an image, with certain features performing better as data representation than others.

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Deep learning has dominated the fields of object identification, classification, and picture segmentation during the last few years. For conventional image processing issues, including picture segmentation, classification, and detection, YOLO s have so far produced the greatest results.

The majority of crimes committed nowadays are committed using handguns. Numerous studies have shown that the primary criminal tools used in a wide range of crimes, including theft, unlawful hunting, and terrorism, are handguns. Installing a surveillance system or control cameras will enable security personnel to respond appropriately and early to such illegal activity. Due to the many intricacies involved, weapon identification is difficult. Self-occlusion and similarities between objects and backdrop structures provide the biggest challenges in weapon detection. When a portion of the gun is obstructed on one side, self-occlusion happens. When diverse items, such as hands and garments, resemble weapons, there is an object similarity. Problems with the background are those that are connected to the setting in which the gun is positioned.

2. Literature Review:

Pang et al. In a real-time disguised item detecting system for clothing was demonstrated. For passive millimeter wave photography using the YOLO method on a small dataset, metallic weapons on human bones were employed. The Single MultiBox Detector algorithm, YOLOv3-13, SSD-VGG16, and YOLOv3-53 are then compared on the PMMW dataset. Additionally, the weapon detection accuracy estimated a detection speed of 36 frames per second and an average precision of 95%.

Warsi A et al. implement the YOLO V3 algorithm with Faster Region-Based CNN (RCNN) by comparing the number of false negatives and false positives, taking real-time images and incorporating them with the ImageNet dataset before training it with the YOLO V3 algorithm. This has helped to automatically detect the handgun in visual surveillance. They used four separate films to test Quicker RCNN with YOLO V3, and the results showed that YOLO V3 provided faster speed in a real-time scenario.

Grega et al. presented an algorithm that warns the security guard or operator when knives and guns are detected automatically in CCTV images. The algorithm, which has a 94.93 percent specificity and an 81.18 percent sensitivity for knife detection, is primarily focused on reducing false alarms and providing a real-time application. Additionally, the specificity for a fire alarm system is 96.69 percent, while the sensitivity for various items in the film is 35.98 percent.

The Histogram of Directed Track lets, a video classifier also used to identify irregular circumstances in complicated scenes, was developed by Mousavi et al. in. Descriptors have been growing across long-range motion projections known as track lets, as opposed to conventional methods using optical flow that only assess edge characteristics from two consecutive frames. On the track lets that traverse them, spatial-temporal cuboid film sequences are statistically collected.

3. Weapon Detection Dataset:

There is no standard dataset for detecting weapons, we have selected videos or

Images from CCTV our own image dataset containing guns with different position and orientation and merged it with Image dataset. To successfully recognize and identify real-world weapons, downloaded weapon photos must be of high quality and from several perspectives. Additionally, unnecessary items in each weapon image were eliminated in order to improve the generated neural network model's success accuracy. As a result, each downloaded image of a weapon was inspected, and various computer application programs were using to alter each image's appearance in accordance with the content, including padding, masking, background cleaning, scaling, and rotation.

4. Methodology:

The most vital and important component of every application is having a desired and appropriate dataset to train the machine learning models on. As a result, we manually gathered a substantial number of photographs from Google. We gathered at least 80 images, with a few image examples for each type of weapon. One of the greatest ways to gather photographs for creating one's own dataset is by using Google Images Download. We then added those pictures to the "images" folder. Images must be saved in ".jpg" format; if they are saved with another extension, training will be a little more difficult and prone to mistakes. Alternately, because the pictures are processed in batches, all of the CNN's image sizes are changed to the same width and height of 416 pixels before training.

The primary connection between object detection and computer vision is the ability to identify items in digital pictures. Recent advances in deep learning have greatly aided the field of object recognition. In essence, YOLO is a trained object detector. CNN is a deep learning system that can take in a raw input image and give various elements and objects in the image learnable weights and biases. A convolutional layer in the CNN model extracts high-level features such as edges from the input image. These feature maps show the existence of features that were identified in the input.

5. Results:

The results of the detected weapon from the video frame for each of the 3 classes of weapon detection from the video frame are presented in a table along with the accuracy and type of the weapon identified. This indicates that our approach for detecting firearms in real-time surveillance videos is fairly accurate.

CNN (Convolutional Neural Network):

CNN is a term frequently used in image processing. The strength of the CNN is dependent on how many hidden layers are used between the input and output layers. Each layer extracts a collection of characteristics. To produce feature maps, a number of filters are applied to the input. After processing the whole input, each filter multiplies its weights by the input values. A Rectified Linear Unit (ReLU), sigmoid, or activation function receives the outcome. A loss function is used to evaluate the collection of weights. The feature maps that the filters create draw attention to certain facets of the input.

Depending on the Faster R-CNN base architecture's intended use, the CNN should be chosen. The highly deep architecture used by many CNNs is used to achieve improved accuracy at a higher computational expense. On the other hand,

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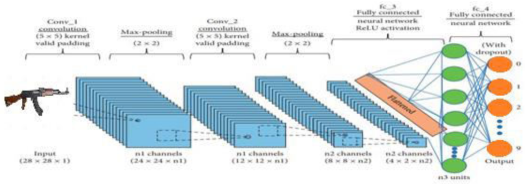
different architectures can be utilized to provide models that can be included in embedded devices while sacrificing accuracy. The categorization of one particular item in an image is an example of an image. However, object localization involves identifying at least one item in an image and delineating a growing box around it. shows how to identify a gun in an animated film. The detection kernel's shape is calculated using the formula 1 × 1 × (bb x (4 + 1 + nc)). Therefore, nc is the number of classes, bb is the number of bounding boxes, "4" is for the 4 bounding box coordinate points, and 1 is object confidence. The input picture is down sampled for three scale predictions using strides 32, 16, and 8. Three components make up the loss function over here. location error (Lbox), confidence error (Lcls), and classification error (Lobj), as presented.



Convolutional neural network (CNN)

Yolo Algorithm:

YOLO is a Convolutional Neural Network (CNN) that can quickly identify objects. CNNs are classifier-based systems that can analyze incoming pictures as organized arrays of data and spot patterns in those patterns (view image below). The benefit of YOLO is that it is quicker than other networks while still maintaining accuracy. Because it enables the model to view the entire image during testing, its predictions are influenced by the image's overall context. Convolutional neural network methods like YOLO "rank" areas according to how closely they resemble predetermined classes.

Regions that score highly are reported as positive detections of the class that they most closely match. For instance, using a live traffic feed, YOLO may be using to identify various. The main benefit of adopting YOLO is its outstanding speed; it can process 45 frames per second. In contrast to previous techniques that scan images using a sliding window, YOLO passes the entire image through a CNN and predicts the result in a single pass. A pre-trained CNN network from Alexey Darknet53 on the image classification challenge is utilized in the background for object recognition using Yolov3. By adding our layers to a trained model, we are using the Transfer Learning approach. So, we download the darknet53. conv.74 pre-trained weights. In contrast to randomly initialized weights, our custom model will be trained using these pre-trained weights, which will save a significant amount of time and calculations.

According to YOLO v2 frequently has trouble detecting tiny objects. This is a result of the layers' down-sampling of the input, which resulted in the loss of fine-grained features. In order to collect low-level features, YOLO v2 uses an identity mapping by concatenating feature mappings from a preceding layer. The design of YOLO v2 was deficient in key important components that are included in the majority of cutting-edge algorithms. Early models lacked up sampling, skip connections, and residual blocks. However, YOLO v3 integrates every one of these. It is possible to notice the identification of tiny items from the

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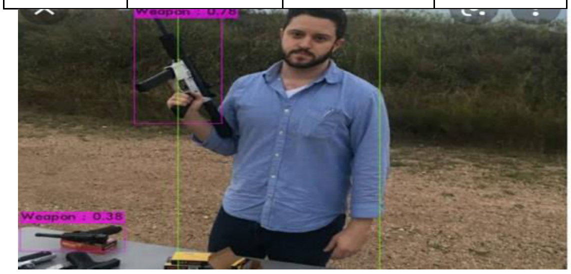
cumulative findings shown in Figure 8. YOLO V2 and YOLO V3.

Table: YOLO V3, Faster RCNN and CNN VGG

SNO	MODELS	DATASET	ACCURACY (%)
1	Trained model YOLO V3	Video or Image dataset collected for present research	98.88
2	Faster RCNN (23)	Stream video	95.6
3	CNN VGG-16 (21)	IMDB	93



Weapon detected object category GUN

Weapon detected object category GUN

Weapon detected object category GUN

Cumulative result of detecting weapon

Conclusion and Future Work:

In today's conditions, wherever criminal activity is on the rise, it is crucial to automatically identify if a person is carrying a weapon based on images captured by security cameras. To stop criminal activity before it starts and to enable the right parties to take the required action, weapon detection and recognition are crucial. Weapons carried or carried in hand are used in the majority of criminal actions. The most crucial tools used in many crimes, including stealing, unlawful hunting, and terrorism, are handheld or carried guns.

For the purpose of detecting weapons, the cutting-edge YOLO V3 and CNN object recognition model was developed and trained. We provide a model that gives a machine or robot the ability to recognize dangerous weapons and can also notify a human administrator when a pistol or other weaponry is clearly seen in the vicinity. According to the experimental findings, the trained YOLO V3 model performs better than the YOLO V2 model and requires less computing power. Improving the surveillance capabilities with more resources is urgently required to enable monitoring the efficiency of human operators. With the increasing accessibility of low-cost storage, video infrastructure, and superior video processing capabilities, smart surveillance systems would completely replace existing infrastructure. With the eventual availability of low-cost computers, video infrastructure, high-end technology, and faster video processing, digital monitoring systems in the form of robots will completely replace present surveillance systems. When it comes to object detection in surveillance systems, speed is key to swiftly detecting an item and notifying the appropriate authorities. In comparison to the earlier systems, this effort was able to accomplish the same goal more quickly.

In future studies, To process data in real-time using security control systems and to improve classification accuracy, an infrastructure inquiry might be conducted on robot soldiers that can automatically monitor, evaluate, and transmit alerts to security forces. Additionally, research should be conducted to identify coated weapons

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