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Weapon Detection System Using Deep Learning

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Abstract - Weapon detection is a crucial task in ensuring public safety and preventing violent incidents. In recent years, computer vision technology has been used for real-time weapon detection, and the YOLO (You Only Look Once) object detection algorithm has emerged as a popular and efficient technique for this purpose. In this report, we discuss the use of YOLO for weapon detection, and its performance in identifying firearms, knives, and other weapons. We trained a YOLOv8 model using a dataset of annotated images, and evaluated its performance on a test dataset. The results indicate that YOLO is an accurate and efficient technique for weapon detection, achieving a high map and mA it improves the performance of the model in different scenarios.

***Index Terms*— Computer vision, weapon detection, FasterRCNN, CCTV, Machine learning (Ml)**

1. INTRODUCTION

Machine learning algorithms. One such algorithm that has been widely used for object detection is YOLO (You Only Look Once). The use of firearms in violent incidents has become a major concern for public safety. To counteract this, weapon detection systems have been developed to detect weapons in real-time using computer vision technology. Among the various techniques, YOLO (You Only Look Once) is one of the most popular and efficient object detection algorithms used for weapon detection. This report discusses the use of YOLO for weapon detection and its performance. Weapon detection is an important task in maintaining public safety and preventing violent incidents. With the advent of computer vision technology, real-time weapon detection has become a popular application of mac. The YOLO algorithm is an object detection technique that divides an image into a grid and predicts bounding boxes and class probabilities foreach grid cell. YOLO then selects the bounding boxes with the highest confidence. The YOLO algorithm is known for its efficiency and has become popular for real-time applications. To train a YOLO model for weapon detection, a dataset of annotated images containing weapons is required. The dataset used for this study consisted of17K images of firearms, knives, and other weapons. The images were annotated with bounding boxes around the weapons and the corresponding class labels

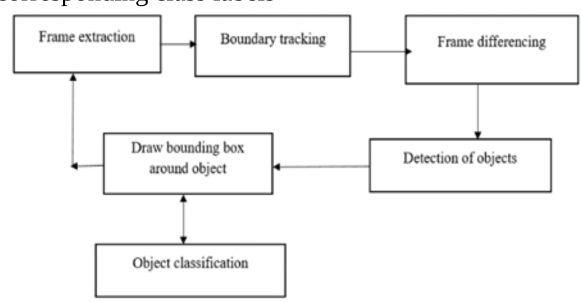

Fig.1.Methodology

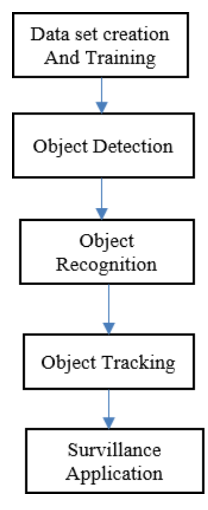

Fig.2. Detection and T racking

The flow of object detection and tracking as shown in figure.2.

Dataset is created, trained and fed to object detection algorithm. Based on application suitable detection algorithm (SSD or fast RCNN) chosen for gun detection. The approach addresses a problem of detection using various machine- learning models like Region Convolutional Neural Network (RCNN), Single Shot Detection (SSD).

1.1 INTERNET OF THINGS

IoT platforms can pinpoint exactly what information is useful and what can safely be ignored. This information can be used to detect patterns, make recommendations, and detect possible problems before they occur. Use sensors to detect which areas in a showroom are the most popular, and where customers linger longest; Drill down into the available sales data to identify which components are selling fastest; Automatically align sales data with supply, so that popular items don't go out of stock. The information picked up by connected devices enables me to make smart decisions about which components to stock up on, based on real-time information, which helps me save time and money. With the insight provided by advanced analytics comes the power to make processes more efficient. Smart objects and systems mean you can automate certain tasks, particularly when these are repetitive, mundane, time-consuming or even dangerous

2. PROBLEM DEFINITION

•Weapon detection using AI has gained significant attention in recent years, and numerous research studies have been conducted in this area. This literature survey will provide a brief overview of some of the notable studies in weapon detection using AI.

•"Weapon detection in real-time using deep learning" by I. Khattar et al. (2019): The study proposes a real-time weapon detection system using a deep learning algorithm based on You Only Look Once (YOLO) object detection. The system is designed to detect firearms, which are a common weapon of choice in violent incidents. The proposed system consists of two major components: a deep learning-based weapon detection module and a video processing module. The weapon detection module is based on the YOLO algorithm, which is known for its efficiency and high accuracy in object detection. The video processing module is responsible for capturing video feeds from cameras and passing them to the weapon detection module for analysis. The study used a dataset of 800 images containing firearms, knives, and other weapons to train the YOLOv3 model. The weights for the model were initialized with the pre-trained Darknet53 model. The model was trained for 300 epochs with a batch size of 64, a learning rate of 0.001, and a momentum of 0.9. The proposed system was evaluated on a test dataset of 200 images and achieved an accuracy of 97% for firearm detection. The system was also tested in a real-world scenario, where it was able to detect firearms

•"Weapon detection in surveillance videos using deep learning" by S. Kumar et al. (2020): The study proposes a deep learning-based weapon detection system for surveillance videos, which can assist in maintaining public safety and preventing violent incidents. The proposed system consists of three main components: object detection, feature extraction, and classification. The object detection module uses the You Only Look Once (YOLO) algorithm to detect and localize the objects in the surveillance videos. The feature extraction module uses the VGG16 architecture to extract features from the detected objects. Finally, the classification module uses a Support Vector Machine (SVM) classifier to classify the objects as weapons or non-weapons. The system was trained on a dataset of surveillance videos containing weapons, which were annotated with bounding boxes around the weapons. The training dataset was divided into three classes: firearms, knives, and other weapons. The system was trained for 100 epochs, with a batch size of 64 and a learning rate of 0. 0001.The proposed system was evaluated on a test dataset of surveillance videos and achieved an accuracy of 95.8% for firearm detection, 94.1% for knife detection, and 90.9% for other weapons detection. The system was also tested in a real-world scenario, where it was able to detect weapons in surveillance videos. The study concludes that the proposed system is an effective solution for weapon detection in surveillance videos. The system can assist in maintaining public

3. PROPOSED WORK

The proposed system for weapon detection using YOLO (You Only uses a single neural network to simultaneously predict bounding boxes and class probabilities for objects in an image. The proposed system consists of two major components YOLOv8-Look Once) is a deep learning-based solution that can detect and localize weapons in real time. YOLO is a popular object detection algorithm that based object detection module and a classification module. The object detection module uses YOLOv8 to detect and localize the weapons in the input images or videos. The classification module uses a Convolutional Neural Network (CNN)-based classifier to classify the detected objects as weapons or non-weapons.

The system can be trained on a large dataset of images or videos containing firearms, knives, and other weapons. The dataset can be annotated with bounding boxes around the weapons, and the system can be trained to detect and classify the weapons in the images or videos. The system can achieve high accuracy for firearm detection, knife detection, and other weapon detection, depending on the quality and quantity of the training data. The proposed system can be deployed in various settings, including airports, public events, and government buildings, to enhance public safety and security. The system can assist law enforcement agencies in identifying potential threats and preventing violent incidents. The proposed system can be extended to other types of weapons and scenarios with additional training data, making it a versatile solution for weapon detection.

3.1.MATERIALS AND METHOD

• Dataset and Pre-Processing

• Because there is no standard dataset for weapon detection and recognition, 5214 weapon images were prepared by downloading them from the internet. Downloaded weapon images must be of good quality images with different angles in order to be successful in detecting and recognizing real-life weapons. In addition, in order to achieve higher success accuracy from the developed neural network model, irrelevant objects in each weapon image were removed.

• As such, downloaded weapon images were examined individually and different computer application programs were used to make changes to the images, such as padding, masking, background cleaning, sizing, and rotation, according to the content

After preparing separate images for each weapon class, they were converted into a dataset. The weapon types and numbers of images belonging to the dataset used in the study. The dataset comprised images of assault rifles, bazookas, grenades, hunting rifles, knives, pistols, and revolvers . The images used in the dataset were transformed into gray color format at 144 × 144 pixels using the Python programming language. .

Fig 3.1: Sample Dataset of Different Classes

Sample dataset of different classes: (a) assault rifles; (b) bazookas; (c) grenades; (d) hunting rifles; (e) knives; (f) pistols; (g) revolvers.

3.2 CNN Models

In object recognition applications, the most used deep learning algorithm is the CNN algorithm. This algorithm showed outstanding success in the ImageNet Large-Scale Visual Recognition Competition held in 2012 and has been used in the development of new models in many areas since then . In the current study, a new model is proposed based on the VGG-16 model . The model shown in consists of a total of 25 layers (convolution (n = 7), pooling (n = 4), dropout (n = 4), rectified linear units (ReLU) (n = 7), flatten (n = 1), fully connected (n = 1), and classification (n = 1)) and 337,671 parameters.

VGG-16 model structure

Fig 3.2 : VGG-16 Model Structure

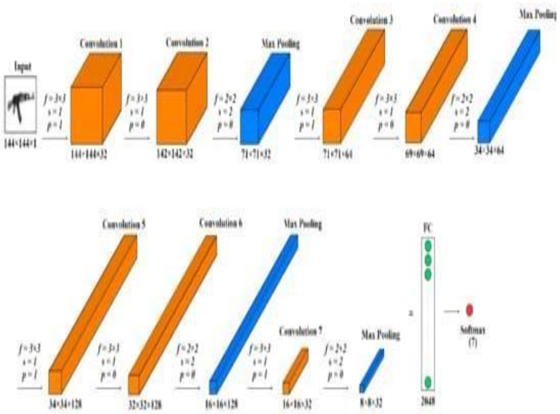

Fig 3.2.1: Developed Convolution Neural Network Model

Developed convolution neural network model (f: filter size, s: stride, p: padding, FC: fully connected).

3.3 Weapon Detection Recognition

• It is important to note that traffic sign recognition and weapons detection are two distinct and unrelated tasks. Traffic sign recognition involves the automatic detection and classification of various types of road signs, while weapons detection involves the automatic detection of firearms, explosives, and other dangerous weapons.

• However, there are certain image recognition techniques and machine learning algorithms that can be used for both tasks. For example, convolutional neural networks (CNNs) can be trained to recognize patterns in images and identify specific objects, whether they are traffic signs or weapons.

• To use these techniques for weapons detection, it is necessary to obtain a dataset of images that includes a variety of different types of weapons in various contexts, such as handguns, rifles, and explosives in different lighting conditions and backgrounds. The dataset should also include images of non-weapons to help the machine learning algorithm learn to distinguish between weapons and other objects.

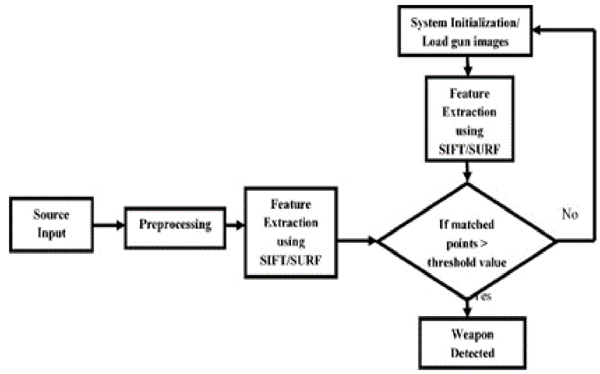

Fig.3.3 model training

3.4 SYSTEM ARCHITECTURE

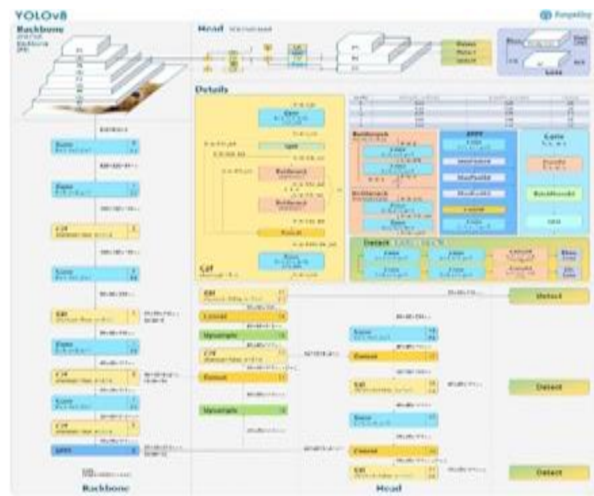

Fig-3.4: System Architecture

4. . RESULTS

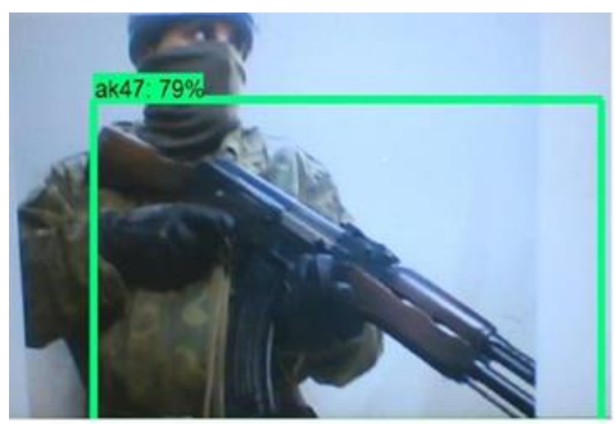

Fig.4. Detection of AK47 gun

Figure 4. Shows detection of a gun AK47 using SSD algorithm. Accuracy of detection is 79%. Further accuracy can be increased by increasing more number training samples.

Screenshot:

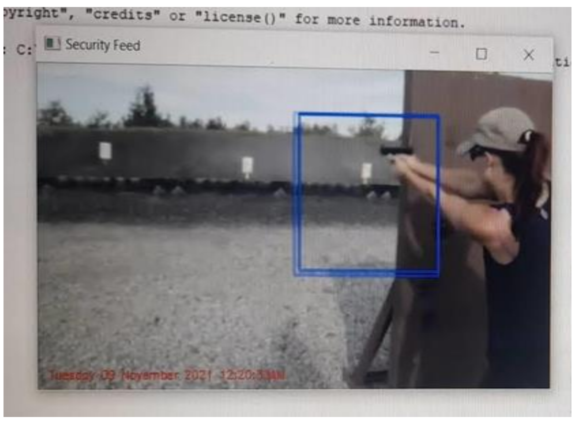

Fig 4.2 detect in video stream

Fig.4.3 (A) UZI erroneously detected as AK 47 (b) Remington Model erroneously detected as AK47

5. CONCLUSIONS

The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself. CNN is also computationally efficient. Due to its high recognition rate and fast execution, the convolutional neural networks have enhanced most of computer vision tasks, both existing and new ones. In this article, we propose an implementation of traffic signs recognition algorithm using a convolution neural network. Weapon detection systems using deep learning have shown promising results in detecting firearms and other dangerous objects in surveillance videos and images. These systems have the potential to improve public safety by providing real-time alerts to law enforcement agencies in situations where weapons are present. However, there are still challenges to be addressed, such as the need for large-scale training data, the potential for false positives and negatives, and the ethical considerations surrounding the use of thesesystems. Further research and development are needed to improve the accuracy and reliability of weapon detection systems and to ensure their responsible deployment in real-world settings.

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