FIRE AND GUN DETECTION SYSTEM USING DEEP NEURAL NETWORKS

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ABSTRACT

Systems for detecting anomalies are essential for ensuring public safety, particularly in area significant risk of fire and violent entertainment. According to the study, we present a real-time fire and gun detection system that uses deep neural networks to identify anomalous events. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) implemented in combination with the suggested system, which uses video surveillance data as input to identify anomalies. While the RNNs record the temporal dependencies between frames, the CNNs takes the responsisbility of extracting spatial features from the input frames. The proposed system are viewd against a benchmark dataset of actual surveillance footage after being trained using a sizable dataset of fire and gun violence-related events. The outcomes show that our system achieves high detection accuracy and outperforms existing state-of-the-art methods. Object detection is a different program in computer vision applications such as surveillance, autonomous driving, and robotics. Deep neural networks have shown promising results in object detection, but real-time performance is often a challenge due to the large computational requirements of these models. According to this report, we present a real-time object detection system based on a deep neural network architecture. The proposed system uses a combination of convolutional neural networks (CNNs) and region proposal networks (RPNs) to detect objects in the current world. The system is evaluated on a benchmark dataset and compared with state-of-the-art methods. The results demonstrate that our system achieves high detectionaccuracy and real-time performance.

I. INTRODUCTION

According to many applications, including public safety, surveillance, and intrusion detection, anomaly detection is a different program. There are two different types of incidents that can seriously endanger public safety are fires and gun violence. Real-time detection of unusual fire and gun violence incidents can help avoid accidents and save lives. According to the study, we present a deep neural network-based anomaly detection system that uses video surveillance data to identify occurrences connected to fire and gun violence.

The problem in computer vision are called object detection is finding and identifying things in an image or video. The other uses for object identifying, in surveillance, driverless vehicles, robots, and augmented reality. Deep neural networks have made significant strides in object detection in recent years. However, due to these Models' high computational demands, real-time performance is still a problem. According to the paper, we suggest a deep neural network-based real-time object detection system.

Our main goal is to create an algorithm that would accurately generate numerous bounding boxes in like low-quality films because the weapons and flames seen in theCCTV recordings in the dataset only occupy a small percentage of the total frame. Furthermore, since the scenario which has gone through might be time-sensitive, the detectionneeds to be made in the current world with a fair amount of accuracy. Additionally, since the authorities are changed once a detection above the threshold is ready, there must be atleast minimal things are false positives. The main objective of our project is to create a system that scans a location's surveillance data and sends alerts when a fire or gun is spotted CCTV. Even with the cameras continuously recording video, there are not enough employees to monitor each one for strange activity. Many places, including schools and other educational institutions, have smoke sensor-based fire detection systems. However, the current demand for security necessitates a system that integrates fire and gun detection while also being reasonably priced. Dronesand closed-circuit television (CCTV) are two popular types of surveillance equipment.Furthermore, studies show that installing CCTV systems can aid in the prevention of mass shootings.

II. Existing Problem

- **Number of Attributes used to define an anomaly** − The question asked there is an object is anomalous depends on an individual attribute is a question of whether the object's value for that attribute is unknown. Because An object may possessmultiple characteristics, it can have anomalous values for several conditions, butoriginal values for many attribute.

- **Global versus Local Perspective** − An object can appear unusual concerning all things, but not concerning objects in its local neighbors. For instance,a person whose height is 6 feet 5 inches is extremely tall concerning the generalcitizens, but not giving importance to professional basketball players.
- **The degree to which a point is an Anomaly** − The assessment of an object as an anomaly is documented by some methods in a binary fashion: An object is an anomaly or it is not. Generally, this does not reflect the reality that some objects things are more numerous anomalies than others. Therefore, it is fascinating to have multiple assessments of the degree to which an object is anomalous. This assessment is called the anomaly or outlier score.

- **Identifying One Anomaly at a Time versus Many Anomalies at Once** − In some methods, anomalies are cancelled one at a time; i.e., the most examples are recognized and removed, and then the procedure repeats. For multiple techniques, a set of anomalies identified all together.

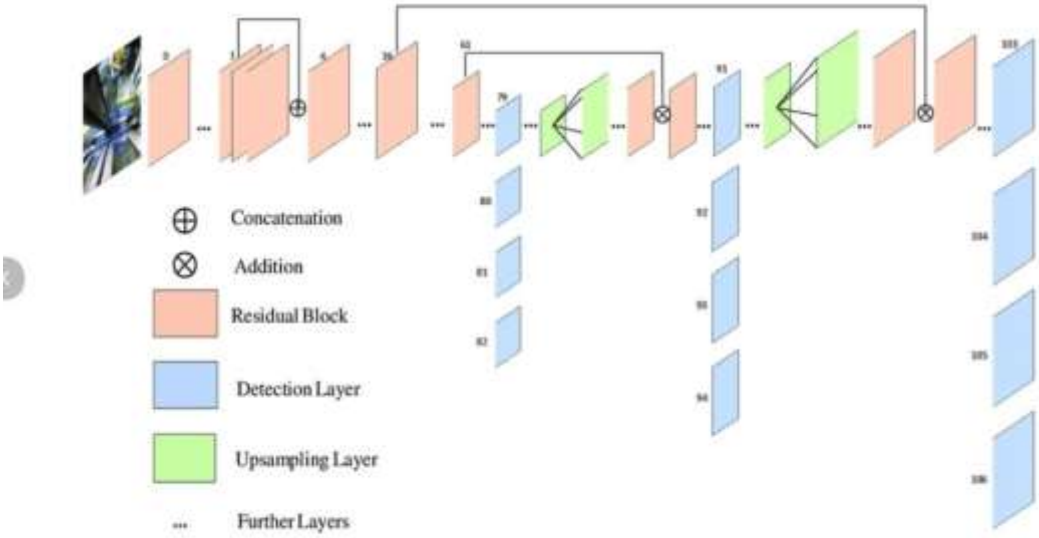
- **Efficiency** − There are differences in the computational cost of severalanomaly detection schemes. Classification-based schemes can need essential resources to make the classification model but are generally inexpensive to use. Likewise, statistical methods generate a statistical model and can categorize an element in constant time.

III. Proposed Solution

You Only Look Once (YOLO) v3 model, a deep learning framework built on Darknet, an open-source neural network written in C [14], is utilized in the suggested experiment.

The best choice is YOLOv3 since it provides real-time detection without significantly lowering accuracy. The darknet53 was used; it is a fullyconvolutional network (FCN) composed of 53 CNN layers,individually followed by batch normalization and Leaky ReLu activation layers. The amount of layers used overall for the detection task is 106, which takes the model bulkierthan its prior iterations. Due to prevent the loss of low-level characteristics, the model does not use pooling. Additionally, the unsampled layers are combined with the preceding layers to preserve the features, which aids in the identification of small objects. Likely to the slide window and region proposal-based techniques, YOLO detects objects in an image very well as it gets every detail about the whole picture and the object by seeing the entire image.

Grids implemented to divide the image, and image classification is used to predict N bounding boxes with confidence ratings and localization on each grid cell. YOLO detection on deffering on three different scales, from small to large atlayer to layer number 82, 94, and 106. The larger objects are detected by 13 x 13 layers, medium objects by 26 x 26 layers, and smaller objects by 52 x 52 layers. YOLOv3 (You Only Look Once version 3) is a deep learning method for detecting objects.Due to accuracy and speed, it is superior to its forerunners, YOLO and YOLOv2. The Darknet-53 backbone and 75 convolutional layers make up the YOLOv3 architecture. The three distinct output scales or detection layers of the YOLOv3 network enable it to recognize objects of various sizes. The image are divided into grids by the CNN, and each grid cell forecasts the bounding boxes of any objects that are visible in that cell. Each bounding box prediction includes the box's x, y, width, and height as well as a confidence score that indicates how likely it is that the grids contain an object. For each object in the bounding boxes, the network also forecasts the class probabilities, and it usesthese probabilities to establish the object's final classification. The final output of the YOLOv3 network is a list of bounding boxes and their corresponding class probabilities. Overall, the great accuracy and quick processing speeds of YOLOv3 have made it a well-liked technique for real-time object recognition.



Network architecture of YOLOv3.

To apply Non-Maximal Suppression (NMS), predicted bounding boxes with detection probabilities below a specified threshold are first rejected. All bounding grids whose Intersection Over Union (IOU) value exceeds a particular IOU thresholdare then cancelled after the NMS threshold. The accuracy of an object detector is evaluated using a measure known as intersection over the union.

IV. DATASET DESCRIPTION

A 3000 gun picture dataset from the UGR handgun dataset was used to train our model. Various angles, positions, and orientations of guns are depicted in the dataset. A further 500 fire-related photos that were retrieved from Google and labeled with the image annotation application LabelImg were used.

We are using the IMFDB dataset and the UGR handgun testing dataset to test the detection of guns. There are about 4000 photos of different guns, rifles, shotguns, and other weapons in the IMFDB dataset. These depict different movie moments. The dataset's negative images include pictures of items like hair dryers, drills, and other things that resemble guns in shape. We are using the photos in the FireNet Dataset to evaluate the effectiveness of our algorithm on fire-related image datasets. Additionally, we created a customized dataset of19 Google images that includes CCTV images of people holding handguns and various other angles as well as adding a few videos from the Gun movies database and Firenet Dataset. Our dataset is called the fire-Gun dataset.

V. IMPLEMENTATION

The goal of anomaly detection is to identify objects that are distinct from otherobjects. As a result of their location on a scatter plot of the data, which is far from other data points, anomalous items are frequently referred to as outliers. Because anomalous objects typically have attribute values that differ significantly from expected or typical attribute values, anomaly detection is also referred to as deviation detection or exception mining because anomalies are exceptional in many ways.

Visual Recognition

Complex data representations are amenable to learning by deep learning models, enabling them to achieve state-of-the-art performance in tasks suchas image classification, object detection, and face recognition.

The YOLO parameters listed in the table have been used to train our model. Label 0 stands for firearms, while Label 1 represents fire.

Table I. Training Parameters

Parameters	Description
Max Batches	4000
Steps	3200, 3600
Filters	21
Classes	2

VI. OUTPUT

Each prediction takes around 0.7 seconds when running on CPU and 44 milli-seconds onGPU.

- Prediction on an image on the UGR dataset.

The UGR handgun testing dataset contains 304 images with guns and 304 images without a gun. The table below shows the model's good performance on the UGR testing dataset. This is also owing to the positive photos in the dataset only including focused shots of handguns.

	Actual Positive	Actual Negative
Predicted Positive	303	64
Predicted Negative	1	240

Table: Confusion Matrix of Model on UGR Dataset

- Prediction on an image in the FireNet dataset

We chose 200 photos from the Firenet dataset—200 with and without fore—to test our model's fire detection efficiency. The table below displays the model's performance. A fewinstances of fore-detection using the suggested model are shown in the image.

	Actual Positive	Actual Negative
Predicted Positive	159	13
Predicted Negative	41	187

Table: Confusion matrix of the model on Firenet Dataset.

VII. CONCLUSION

A real-time frame-based effective fore and gun detection deep learning model has been shown in this proposed system with a high accuracy metric. Despite being large, the Darknet53 model has good detection abilities. Any GPU-based system can use the detection per frame, which is suitable for real-time monitoring.

VIII. REFERENCES

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