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Fire and Gun Violence Based Anomaly Detection using Deep Learning

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Abstract- One of the popular uses of convolutional neural networks (CNNs) is real-time object detection to enhance surveillance techniques. The detection of firearms and fire in camera-monitored regions has been the focus of this study. Wildfires, industrial explosions, and home fires are all major issues that have a negative impact on the environment. Mass shootings and gun violence are also increasing in other regions of the world. Such occurrences can result in significant losses in terms of both life and property, and they are time-sensitive. Therefore, a deep learning model based on the YOLOv3 algorithm has been developed in the proposed work. It analyzes a video frame by frame to identify such anomalies in real time and send a warning to the relevant authorities. The resulting model has a 45 frames per second detection rate, a validation loss of 0.2864, and has been benchmarked on datasets such as FireNet, UGR, and IMFDB with accuracies of 86.5%, 89.3%, and 82.6%, respectively. In addition to meeting the objective of the suggested model, the experimental result demonstrates a quick detection rate that can be used both indoors and outdoors.

***Index Terms*—Object Detection, Mass Shootings, convolutional neural networks (CNNs), etc**

I. INTRODUCTION

Our primary goal is to develop a system that tracks surveillance data in a region and notifies users if a fire or firearm is found. 24 hours a day, 7 days a week, CCTV cameras capture video, but there isn't enough staff to keep an eye on every camera for any unusual activity. In many locations, including schools and other educational institutions, smoke sensors are used in fire detection systems. Nonetheless, the current requirement is for a reasonably priced system that integrates both gun and fire detection for security reasons. The use of surveillance technologies like drones and closed-circuit television (CCTV) is growing in popularity. Additionally, studies reveal that CCTV systems are crucial for gathering evidence and aid in the fight against mass shootings.

The study makes use of the YOLO (You Only Look Once) object detection technology, which detects objects using convolution neural networks. It is among the quicker algorithms that function with little loss of accuracy. This model was trained on the cloud in order to save hundreds of hours of GPU time during a local runtime. Another advantage of using hosted runtime has been that it has helped us refine our model almost perfectly.

Since firearms and fires only take up a small percentage of the frame in the CCTV footage in the dataset, our main goal is to develop an algorithm that can reliably create multiple bounding boxes in these poor-quality films. The situation being processed may also be time-sensitive, therefore the detection needs to be done in real-time with a reasonable level of accuracy. Since the authorities are notified as soon as a detection surpasses the threshold, there must also be a minimal number of false positives.

II. LITERATURE REVIEW

T. Celik, H. Demirel, H. Ozkaramanli and M. Uyguroglu, "Fire Detection in Video Sequences Using Statistical Color Model" [1], In this study, we present a real-time fire detector that combines foreground object information with color fire pixel statistics. A simple adaptive background model of the scene is constructed using three Gaussian distributions, each of which reflects the pixel statistics in the associated color channel. The foreground information is retrieved using the adaptive background removal technique and then verified by the statistical fire color model to determine whether or not the discovered foreground object is a fire candidate. A broad fire color model is developed by statistically analyzing the example images that contain fire pixels. The first contribution of the paper is the segmentation of the fire candidate pixels from the background using a real-time adaptive background subtraction technique. The second contribution is the fine-grained categorization of fire pixels using a broad statistical model. In order to detect fire in consecutive video sequence frames, the two processes are combined to form a fire detection system. With an image size of 176 × 144 pixels, the detector's frame-processing rate is roughly 40 fps, and the algorithm's proper detection rate is 98.89%.

B. U. Toreyin, Y. Dedeoglu and A. E. Cetin, "Flame detection in video using hidden Markov models"[2], Recent years have seen the rise of video-based flame detection as a key technique for early fire detection in difficult circumstances. However, most existing methods still have insufficient detection accuracy. We develop a new method in this study that could significantly improve the accuracy of video picture flame detection. To segment a video image and pinpoint areas that may contain flames, the application combines a two-step clustering-based technique with the RGB color model. A number of new dynamic and hierarchical features associated with the suspected regions are then extracted and analyzed, including the frequency of flame flicker. The method determines whether or not a suspected zone contains flames by evaluating the area's color and dynamic data using a BP neural network. Test findings show that this method is dependable, efficient, and able to significantly reduce the probability of false alarms.

Z. Li, S. Nadon and J. Cihlar "Satellite-based detection of Canadian boreal forest fires: Development and application of the algorithm," [3], Using satellite-based remote sensing, this study offers a comprehensive analysis of fires over the Canadian boreal forest zone. A technique for detecting fires was developed using images from the Daily Advanced Very High-Resolution Radiometer (AVHRR). Whether there is a thin cloud of smoke or a clear sky, it uses information from multichannel AVHRR measurements to pinpoint fires on satellite pixels of about 1 km2. With the exception of those obscured by heavy clouds, the daily fire maps showed most of Canada's ongoing fires. This was achieved by combining AVHRR pictures taken over Canada on a specific day, followed by the use of the fire-detection algorithm. Over 800 NOAA/AVHRR daily mosaics for the 1994–1998 fire seasons were processed by us. Important national fire activity data, such as location, burned area, dates of initiation and termination, and progress, are provided by the results. Satellite data indicates that in 1994, 1995, 1996, 1997, and 1998, the total burned area in Canada was approximately 3.9, 4.9, 1.3, 0.4, and 2.4 million hectares, respectively. Every year, there are notable differences in the peak burning month, which falls between June and August, as well as the spatial dispersion of flames. Conifer forests appear to be more prone to fire and typically burn larger than deciduous woods.

T. J. Lynham, C. W. Dull and A. Singh, "Requirements for space-based observations in fire management: a report by the Wildland Fire Hazard Team, Committee on Earth Observation Satellites (CEOS) Disaster Management Support Group (DMSG)," [4], The Wildland Fire Hazard Team looked at possible needs for space-based observations in fire control. The team produced a report (CEOS) under the guidance of the Disaster Management Support Group (DMSG) of the G-7 Committee on Earth Observation Satellites. The publication was produced by an international working group with experience in remote sensing applications to wildland fire management. The team identified seven essential requirements. These requirements could greatly improve wildland fire management initiatives if CEOS constructs the extra Earth observation satellites that have been recommended or upgrades the ones that are already in place. The requirements address the different spectral, temporal, and geographic characteristics needed in different fire control phases and geographic areas of interest. Among these prerequisites are fuel mapping, risk assessment, detection, monitoring, mapping, recovery from burned areas, and smoke control. Ten recommendations that back them up are outlined in this paper.

M. T. Basu, R. Karthik, J. Mahitha, and V. L. Reddy, "IoT based forest fire detection system," [5], According to a survey, 80% of the fire's damages could have been avoided if the fire had been discovered earlier. A Node Mcu-based Internet of Things-based fire indicator and surveillance system is the answer to this issue. For this purpose, we have constructed a fire detector using Node Mcu, which is interfaced with a

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temperature sensor, a smoke sensor, and a signal. Heat is detected by the temperature sensor, while smoke is detected by any smoke from a fire or food. What the Arduino buzzer does is deliver an alert indicator. As soon as it began, the fire spread smoke and ate up objections in the area. Family members using candles or oil can also produce small amounts of smoke, which can cause a fire warning. Likewise, if warm force is increased, the alarm also remains active. The bell or warning is turned off when the temperature reaches room temperature and the smoke level decreases. Additionally, we used IoT technologies to connect the LCD display to the Node MCU board. Node MCU fire checking is utilized for mechanical and family unit applications. When it senses smoke or fire, it immediately alerts the client via the Ethernet module. This is why we are using the ESP8266 from the Arduino IDE. Similar to this, the framework's status is shown via the Node MCU interface with LCD display, even if smoke and overheat are not detected. Node Mcu also communicates with the Ethernet module in a manner that provides the client with additional information about the primary condition message. It is assumed that the client is aware of the fire identification. This framework is quite helpful when the client is not close to the control focus. When a fire breaks out, the system immediately detects it and alerts the user by sending a message to an open webpage or an app that has been loaded on their Android smartphone.

T.Celik, H.Demirel, H.Ozkaramanli, “Fire and Smoke Detection without Sensors: Image Processing Based Approach” [6], New image processing models for fire and smoke detection are presented in this study. The models use different color models for fire and smoke. The color models are extracted using a statistical analysis of data extracted from different types of images and video sequences. Full-featured smoke and fire detection systems that incorporate color and motion analysis can use the derived models.

G. K. Verma and A. Dhillon, “A Handheld Gun Detection using Faster R-CNN Deep Learning,” [7], Nowadays, the majority of criminal activity involves portable weapons, particularly rifles, pistols, and revolvers. A pistol is the most often utilized weapon for a number of crimes, such as burglary and rape, according to numerous polls. Convolutional neural networks (CNN) are used in this study to provide automatic gun identification from congested scenes, which is a crucial demand in the modern world. We have applied transfer learning to a state-of-the-art CNN model based on Faster Regions, the Deep Convolutional Network (DCN), for automatic gun recognition from crowded scenes. Our gun detection has been evaluated against the Internet Movie Firearms Database (IMFDB), a benchmark gun database. Visual portable gun detection was a strong suit for our technique. Additionally, we demonstrate that the CNN model enhances classification accuracy in relation to the number of training images, which is highly helpful in scenarios where generous liberal is frequently unavailable.

R. K. Tiwari and G. K. Verma, “A Computer Vision based Framework for Visual Gun Detection Using Harris Interest Point Detector,” [8], This study describes the first efforts toward automatic visual gun detection, which is a crucial security necessity of the modern world. Our paper aims to develop a visual gun detection framework for automated surveillance. The proposed framework employs color-based segmentation to exclude unnecessary objects from an image using the k-mean clustering algorithm. A Harris interest point detector and Fast Retina Keypoint (FREAK) are used to locate the object (gun) in the segmented pictures. Our design is robust enough in terms of affine, occlusion, rotation, and scaling. We used our own collection of sample gun images to deploy and test the system. The effectiveness of our method in identifying a gun was promising. Moreover, our method performs exceptionally well across a wide range of image appearances. As a result, our system is invariant to rotation, scale, and form.

M. Grega, S. Łach and R. Sieradzki, "Automated recognition of firearms in surveillance video," [9], Closed circuit television (CCTV) systems are being installed in more and more workplaces, residential buildings, and public spaces. Monitoring systems are in place in several American and European towns. Because human limitations limit how many camera views one operator can watch, this puts a significant amount of work on the CCTV operators. This study's primary focus is on CCTV systems' automatic identification and detection of dangerous situations. We propose algorithms that can alert the human operator when a knife or handgun is visible in the image. To enable the system to be used in practical situations, we have focused on lowering the number of false alarms. Compared to previous recently released

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research, the knife detection's sensitivity and specificity are much greater. Furthermore, we were able to propose a firearm detection technique with an almost zero false alert rate. We have shown that it is possible to create a system that can give an early warning in a dangerous situation, which could lead to faster and more effective reaction times and fewer possible casualties.

J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," [10], We present YOLO, a brand-new object detection technique. In previous object detection activities, classifiers are repurposed to perform detection. Instead, we define object detection as a regression problem to geographically separated bounding boxes and their associated class probabilities. In a single evaluation, a single neural network predicts bounding boxes and class probabilities directly from whole images. Since the detection pipeline is a single network, it is possible to directly modify detection performance from beginning to end. Our unified architecture is incredibly fast. Our basic YOLO model processes images in real time at 45 frames per second. A scaled-down version of the network called Fast YOLO processes an amazing 155 frames per second and doubles the MAP of other real-time detectors. Compared to state-of-the-art detection algorithms, YOLO makes more localization errors but is less likely to predict false positives on background. Finally, YOLO can recognize a very wide range of object representations. It outperforms other detection methods like DPM and R-CNN in terms of generalizing from natural images to other domains, including artwork.

III. PROBLEM STATEMENT

To develop a Fire and Gun Violence-Based Anomaly Detection System using Deep Learning models, capable of automatically identifying, detecting, and differentiating anomalous events (such as fire outbreaks or gun violence incidents) from regular activities within video surveillance or sensor data streams. The proposed system should utilize real-time data from video surveillance (through computer vision) and/or audio sensors (such as microphones for gunshot detection), leveraging deep learning techniques to detect these potentially dangerous events with high accuracy.

IV. OBJECTIVE

1. Develop a deep learning model capable of detecting fire and firearms in real-world scenarios.
2. Achieve high accuracy in classification and localization of fire and guns.
3. Ensure real-time processing for quick response and threat mitigation.
4. Reduce false positives and improve model robustness against environmental variations.

V. DESIGN METHODOLOGIES

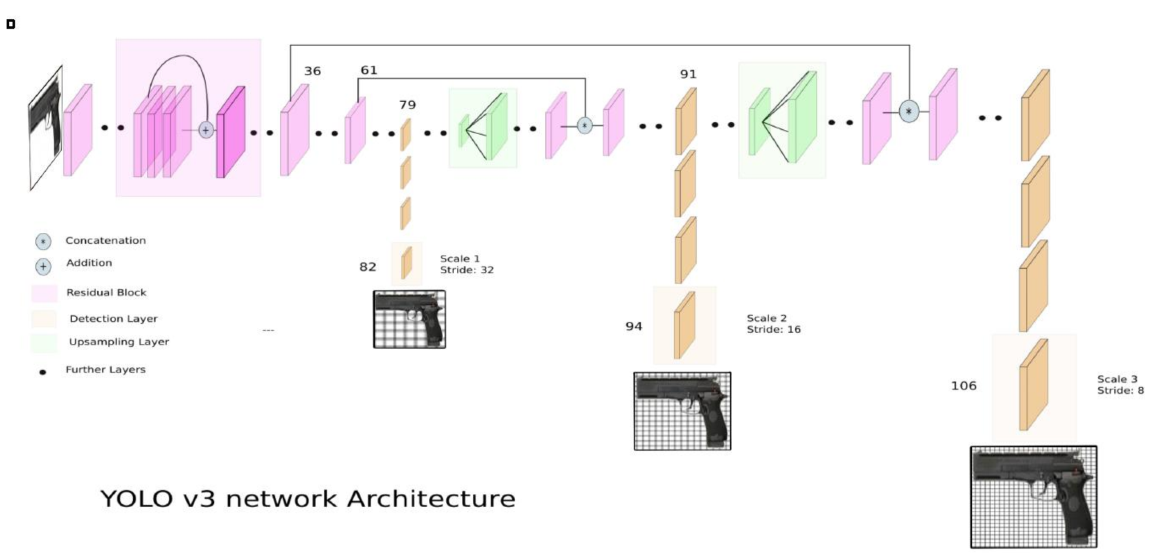

Figure 1- System Architecture

The You Only Look Once (YOLO) v3 model, a deep learning framework built on top of Darknet, an open-source neural network in C, is used in the suggested experiment. The greatest option is YOLOv3, which offers real-time detection without significantly sacrificing accuracy. The darknet53 architecture, which is a fully convolutional network (FCN), is made up of 53 convolutional layers, each followed by batch normalization and Leaky ReLu activation layers. With 106 layers used overall for the detection task, the model is thicker than its predecessors. Pooling is not used by the model to stop the loss of low-level features. Additionally, by maintaining the smallest details, the unsampled layers are concatenated with the preceding layers to aid in the detection of small objects. In contrast to region proposal-based and sliding window-based methods, YOLO recognizes objects in an image very well since it sees the full image and all of its details.

The image is separated into grids, and each grid cell's image categorization and localization are used to predict N bounding boxes with confidence ratings. At layers 82, 94, and 106, YOLO performs detections on three distinct scales, from tiny to huge. 13 x 13 layers detect larger items, 26 x 26 layers identify medium objects, and 52 x 52 layers detect smaller objects.

The best bounding box is found using Non-Maximal Suppression (NMS), which involves removing all bounding boxes whose Intersection Over Union (IOU) value is greater than a specified IOU threshold after rejecting predicted bounding boxes with a detection probability below a specified NMS threshold. One assessment metric used to gauge an object detector's accuracy is intersection over union. This step will remove all boxes that have a large overlap

with the selected boxes. Only the "best" boxes remain. At Common Objects in Context (COCO) with mAP 50 benchmarks, YOLO v3 performs similarly to other cutting-edge detectors like RetinaNet but much faster. Additionally, it is superior to Single Shot Detectors (SSD) and its variations. It provides a real-time visual output on a GPU at 30 to 45 frames per second.

VI. RESULTS

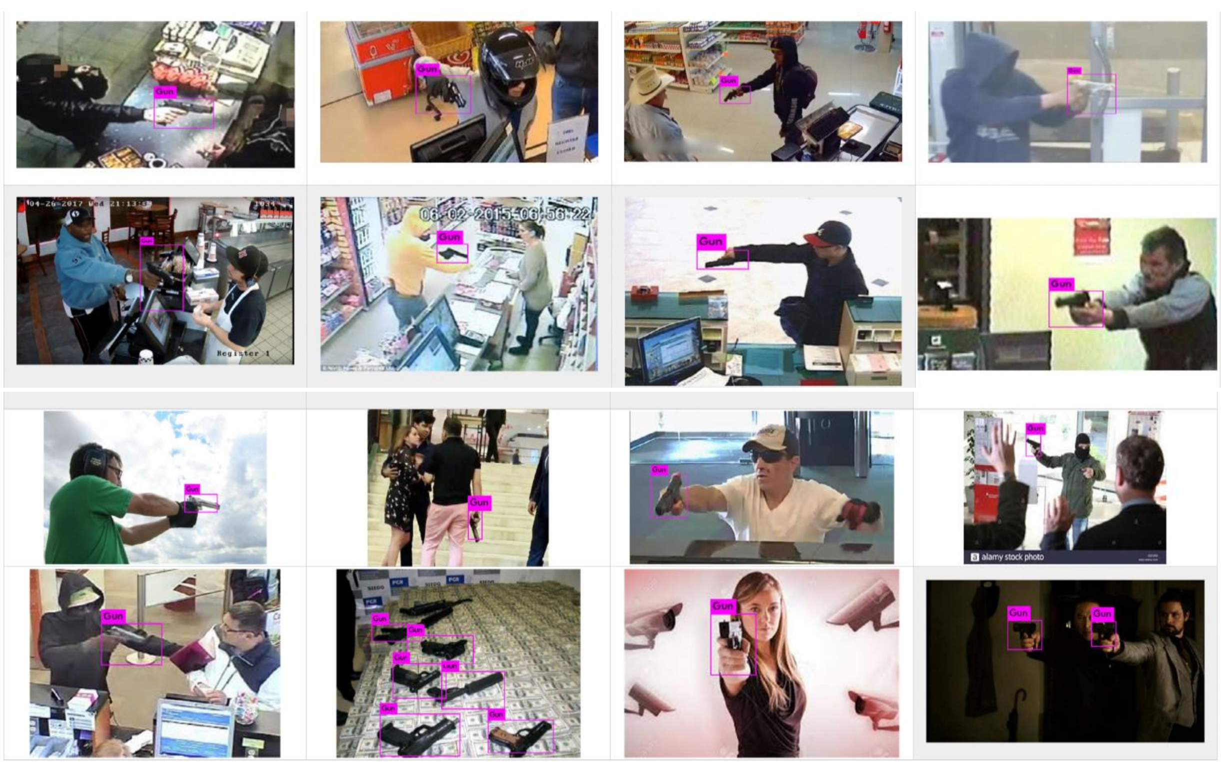

Figure 2- The performance of the model on images of our custom dataset. It can be seen that the guns are in a variety of different orientations and positions.

Figure 3- Some images where the model fails to identify gun.

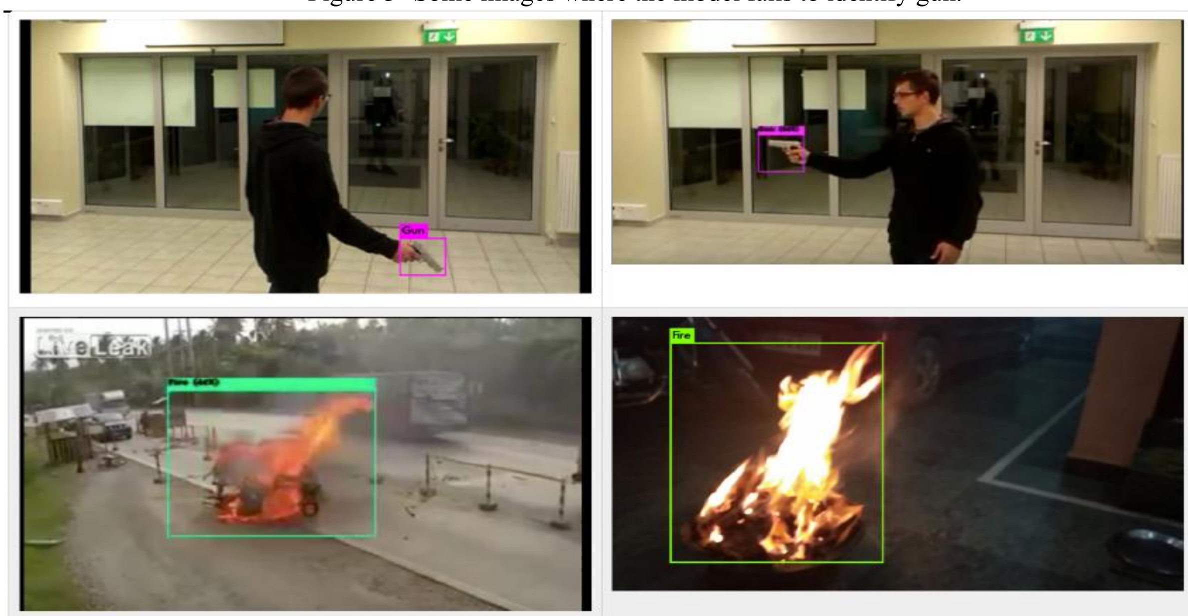

Figure 4- Video frames with fire or gun predictions.

VII. CONCLUSION

An effective deep learning model for real-time frame-based fire and gun identification with a high accuracy metric has been reported in this study. Although the Darknet53 model is large, it is capable of detection. The detections per frame are suitable for real-time monitoring and can be implemented on any system that uses a GPU.

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