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SURVEY PAPER ON FIRE AND GUN VIOLENCE BASED ANOMALY DETECTION SYSTEM

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ABSTRACT
One of the most sought-after uses of various techniques 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, home fires, and industrial explosions 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. In order to identify such anomalies in real-time and send a warning to the relevant authorities, the proposed study has developed a deep learning model based on the YOLOv3 algorithm that analyzes a video frame-by-frame.

Keywords:
Object Detection, Camera-Monitor, Mass Shootings, Gun Violence.

I. Introduction
The primary goal of our project is to develop a system that tracks surveillance data in a region and notifies users when a gun or fire is spotted. All day and night, closed circuit television (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. However, the current demand is for a system that is both affordable and combines 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.
Convolution neural networks are used in the research project's YOLO (You Only Look Once) object detection system. It is among the fastest algorithms with minimal accuracy deterioration. To save hundreds of hours of GPU time on a local runtime, this model was trained on the cloud. It has also helped us refine our model to almost perfection by using hosted runtime. Since the firearms and fires in the CCTV footage in the dataset only take up a small percentage of the frame, our main goal is to put in place an algorithm that can precisely construct several bounding boxes in these poor-quality movies. Additionally, because the situation being processed may be time-sensitive, the detection needs to be done in real-time with a comparatively high degree of precision. Additionally, since the authorities are notified as soon as a detection surpasses the threshold, there must be few false positives.

II. Literature
T. Celik, H. Demirel, H. Ozkaramanli and M. Uyguroglu, "Fire Detection in Video Sequences Using Statistical Color Model" [1], In this research, we offer a real-time fire detector that integrates color fire pixel statistics with information about foreground objects. Three Gaussian distributions are used to create a basic adaptive backdrop model of the scene, each of which represents the pixel statistics in the corresponding color channel. To ascertain if the detected foreground object is a fire candidate or not, the adaptive background removal technique is used to retrieve the foreground information, which is subsequently confirmed by the statistical fire color model. The example photos with fire pixels are statistically analyzed to create a general fire color model. The use of a real-time adaptive

background subtraction technique to help segment the fire candidate pixels from the background is the paper's initial contribution. Using a general statistical model for fine-grained fire-pixel categorization is the second contribution. The two procedures are integrated to create a fire detection system, which is used to identify fire in successive video sequence frames. The algorithm's proper detection rate is 98.89%, and the detector's frame-processing rate is approximately 40 fps with an image size of 176 × 144 pixels.

B. U. Toreyin, Y. Dedeoglu and A. E. Cetin, "Flame detection in video using hidden Markov models"[2], Video-based flame detection has emerged as a significant method for early fire detection in challenging situations in recent years. Nevertheless, the majority of current techniques still have inadequate detection accuracy. In this work, we create a novel algorithm that may greatly increase the precision of video picture flame recognition. The program uses the RGB color model in conjunction with a two-step clustering-based method to segment a video image and identify regions that might contain flames. After that, several fresh dynamic and hierarchical characteristics linked to the suspected areas—such as the flame flicker frequency—are taken out and examined. The technique uses a BP neural network to assess the area's color and dynamic data in order to determine whether or not a suspected zone includes flames. According to test results, this algorithm is reliable, effective, and capable of drastically lowering the likelihood 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], This study provides a thorough examination of fires using satellite-based remote sensing throughout the Canadian boreal forest zone. Daily Advanced Very High-Resolution Radiometer (AVHRR) photos were used to create a fire detection system. Using data from multichannel AVHRR measurements, it locates fires on satellite pixels of roughly 1 km2 whether there is a clear sky or a thin cloud of smoke. The majority of Canada's current fires were displayed on the daily fire maps (except from those hidden by dense clouds). This was accomplished by first applying the fire-detection algorithm after compositing AVHRR scenes that were obtained over Canada on a particular day. We processed around 800 NOAA/AVHRR daily mosaics for the 1994–1998 fire seasons. The findings offer important national data on fire activity, including location, burned area, dates of initiation and termination, and progress. According to satellite data, the total burned area in Canada was roughly 3.9, 4.9, 1.3, 0.4, and 2.4 million hectares in 1994, 1995, 1996, 1997, and 1998, respectively. Both the spatial distribution of flames and the peak burning month, which occurs between June and August, vary significantly from year to year. Compared to deciduous woods, conifer forests generally seem more susceptible to fire and tend to burn larger.

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], Potential needs for space-based observations in fire management were examined by the Wildland Fire Hazard Team. Under the direction of the G-7 Committee on Earth Observation Satellites' Disaster Management Support Group (DMSG), the team created a report (CEOS). An international working group with expertise in remote sensing applications to wildland fire management created the document. Seven key requirements were determined by the team. If CEOS builds additional Earth observation satellites as suggested or enhances current satellites, these criteria might significantly enhance wildland fire management programs. The requirements cover the various temporal, geographical, and spectral properties required in various geographic areas of interest and fire control phases. Fuel mapping, risk assessment, detection, monitoring, mapping, burned area recovery, and smoke management are some of these prerequisites. This report outlines ten proposals that support them.

M. T. Basu, R. Karthik, J. Mahitha, and V. L. Reddy, “IoT based forest fire detection system,” [5], According to a poll, if the fire had been detected sooner, 80% of the losses brought on by fire would have been prevented. The solution to this problem is an IoT-powered fire indicator and observation system based on Node Mcu.Using Node Mcu, which is interfaced with a temperature sensor, a smoke sensor, and a signal, we have put together a fire detector for this task. The smoke sensor picks

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up any smoke from fire or consumption, while the temperature sensor picks up warmth. An alert sign is provided by the Arduino buzzer. As soon as the fire started, it consumed nearby protests and released smoke. Small amounts of smoke from oil or candlelight used by family members can also trigger a fire warning. Similarly, the alert also continues if warm force is elevated. When the smoke level drops and the temperature reaches normal room temperature, the bell or warning is killed. Additionally, we have connected the LCD display to the Node Mcu board.with the help of innovations in IoT.Node MCU fire checking is used for both family unit and mechanical purposes. Through the Ethernet module, it instantly notifies the client of the fire whenever it detects smoke or fire. Because of this, we are using the Arduino IDE's ESP8266. Similarly, the Node Mcu interface with LCD display is used to display the framework's status, regardless of whether smoke and overheat are detected. Additionally, Node Mcu interfaces with the Ethernet module in a way that helps the client learn more about the main condition message. The client is implied to be aware of the fire identification. When the client is not in the proximity of control focus, this framework is quite beneficial. When a fire occurs, the system automatically detects it and notifies the user by sending an alert to an app that has been installed on their Android smartphone or a webpage that is open online.
T.Celik, H.Demirel, H.Ozkaramanli, “Fire and Smoke Detection without Sensors: Image Processing Based Approach” [6], This research presents new image processing models for smoke and fire detection. For smoke and fire, the models employ distinct color models. A statistical analysis of samples taken from various kinds of photos and video sequences is used to extract the color models. The derived models can be applied to full-featured fire and smoke detection systems that integrate motion analysis and color information.
G. K. Verma and A. Dhillon, “A Handheld Gun Detection using Faster R-CNN Deep Learning,” [7], Nowadays, handheld weapons, especially guns, pistols, and revolvers, are used in the majority of criminal activity. According to multiple surveys, the most common weapon used for a variety of crimes, including rape and burglary, is a handgun. Consequently, automated gun detection is a critical need in the modern world, and this research uses convolutional neural networks (CNN) to offer automatic gun detection from cluttered scenes. For automatic gun recognition from congested scenes, we have used transfer learning to the Deep Convolutional Network (DCN), a cutting-edge Faster Region-based CNN model. We have tested our gun detection against the benchmark gun database, the Internet Movie Firearms Database (IMFDB). In terms of visual portable gun detection, our technology performed well. Furthermore, we show that the CNN model improves classification accuracy when compared to the quantity of training photos, which is very useful in situations 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], Automatic visual surveillance is a critical security requirement of the modern world, and this paper outlines the initial steps toward automatic visual gun detection. Creating a visual gun detection framework for automated surveillance is the aim of our paper. Using the k-mean clustering algorithm, the suggested framework uses color-based segmentation to remove irrelevant objects from an image. To find the item (gun) in the segmented images, Fast Retina Keypoint (FREAK) and a Harris interest point detector are utilized. In terms of affine, occlusion, rotation, and scaling, our architecture is sufficiently resilient. We have deployed and evaluated the system using our own collection of sample gun photos. Our system's performance in detecting a gun was encouraging. Furthermore, our technique works incredibly well with a variety of image appearances. Our system is therefore scale, form, and rotation invariant.
M. Grega, S. Łach and R. Sieradzki, "Automated recognition of firearms in surveillance video," [9], An increasing number of offices, apartment complexes, and public areas are using closed circuit television (CCTV) systems. Many cities in Europe and America have installed monitoring systems. This creates a huge workload for the CCTV operators because human factors restrict how many camera views one operator can watch. The automatic identification and detection of hazardous

circumstances for CCTV systems is the main topic of this study. When a knife or firearm is visible in the image, we suggest algorithms that can notify the human operator. We have concentrated on reducing the quantity of false alerts so that the system may be employed in real-world scenarios. The knife detection's sensitivity and specificity are noticeably higher than those of other recently published studies. Additionally, we were able to suggest a method for detecting firearms that has a nearly zero false alarm rate. We have demonstrated that it is feasible to develop a system that can provide an early warning in a risky scenario, perhaps resulting in quicker and more efficient reaction times as well as fewer potential casualties.
J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," [10], We introduce a novel method for object detection called YOLO. Classifiers are repurposed to carry out detection in earlier object detection operations. Rather, we formulate object detection as a regression issue to bounding boxes that are geographically separated and the class probabilities that go along with them. Bounding boxes and class probabilities are directly predicted from complete images in a single evaluation by a single neural network. The detection pipeline may be directly adjusted end-to-end on detection performance because it is a single network. The speed of our unified architecture is really high. At 45 frames per second, our fundamental YOLO model processes images in real time. Fast YOLO, a scaled-down variant of the network, achieves double the mAP of other real-time detectors while processing an incredible 155 frames per second. While YOLO is less likely to forecast false positives on background, it makes more localization errors than state-of-the-art detection algorithms. Lastly, YOLO picks up extremely broad object representations. When it comes to generalizing from natural images to other domains, such as artwork, it performs better than other detection techniques like DPM and R-CNN.

III. Proposed System

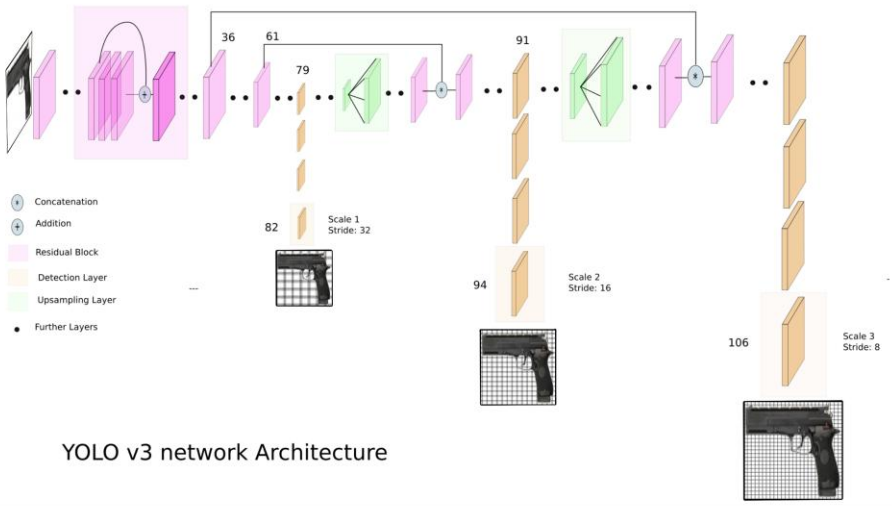

Figure 1- System Architecture

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.

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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.

IV. Conclusion

This research examines various approaches for a violence-based anomaly detection system. A high accuracy metric has been demonstrated for the effective deep learning model for real-time frame-based fire and gun detection. Despite its size, the Darknet53 model has a strong detecting capability. The detections per frame can be implemented on any GPU-based system and are suitable for real-time monitoring.

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