Real-Time Fire and Gun Detection Using Deep Learning for Enhanced Surveillance

Y.SHIVA SREE[1], J. JEEVANTH KUMAR[2],K.NIHITHA [3], K.VARUN KUMAR[4]

[1] Assistant Professor, Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College (An Autonomous Institution), Medbowli, Meerpet, Saroornagar, Hyderabad-500097

[2, 3,4] Students, Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College (An Autonomous Institution), Medbowli, Meerpet, Saroornagar, Hyderabad-500097

Abstract

Real-time threat detection, particularly in the domains of fire and firearm recognition, plays a critical role in modern surveillance systems. This paper presents a deep learning-based framework integrating convolutional neural networks (CNNs) and real-time video processing for simultaneous fire and gun detection. Using custom-labeled datasets and transfer learning with pre-trained architectures such as YOLOv7 and EfficientNet, the proposed system achieves high accuracy and speed suitable for deployment in public surveillance infrastructures. Experimental results demonstrate robust performance under varied lighting, occlusions, and backgrounds. This solution is designed for smart city integration and public safety enhancement.

Keywords

Deep Learning, Fire Detection, Gun Detection, Surveillance, YOLO, CNN, Smart City, Computer Vision

1. Introduction

Fire accidents are a major risk in industries, crowded events, public gatherings, and heavily populated regions throughout India. Such incidents can lead to severe property loss, environmental harm, and can endanger both human and animal lives. According to the recent National Risk Survey Report [1], Fire stood at the third position overtaking corruption, terrorism, and insurgency thus posing a significant risk to our country's economy and citizens. The recent -fires in Australia reminded the world, the destructive capability of fire and the impending ecological disaster, by claiming millions of lives resulting in billions of dollars in damage. Early detection of fire accidents plays a crucial role in saving countless lives and preventing permanent damage to infrastructure, along with avoiding huge financial losses. To achieve high accuracy and reliability in densely populated urban settings, it becomes essential to rely on local surveillance systems. Traditional opto-electronic fire detection methods come with several drawbacks, such as the need for separate and sometimes redundant setups, hardware failures, frequent maintenance, and the risk of false alarms. Moreover, using sensors in hot and dusty industrial environments is often impractical. Given these challenges, detecting fires through surveillance video streams stands out as a highly practical and cost-effective alternative. It offers an efficient way to replace existing systems without requiring major infrastructure changes or heavy investments. However, current video-based machine learning models largely depend on domain expertise and manual feature engineering, which means they must constantly be updated to stay effective against emerging threats. We aim to develop a classification model using Deep learning and Transfer Learning to recognize fires in images/video frames, thus ensuring early detection and save manual work. This model is capable of detecting fires in surveillance video footage.Unlike existing systems, this neither requires special infrastructure for setup like hardware-based solutions, nor does it need domain knowledge and prohibitive computation for development.

Among the various computer-based methods for fire detection, the most prominent ones we identified include Artificial Neural Networks, Deep Learning, Transfer Learning, and Convolutional Neural Networks. Artificial Neural Network based approaches seen in paper uses Levenberg Marquardt training algorithm for a fast solution. The algorithm's accuracy varied between 61% and 92%, while false positives ranged from 8% to 51%. Although this method achieved high accuracy with a relatively low false positive rate, it still demands extensive domain expertise. In this paper, the author highlights that current hardware-based detection systems suffer from low accuracy and a high rate of false alarms, making them more prone to inefficiency. It is also not suitable for detecting fires breaking out in large areas such as s, warehouses, fields, buildings or oil reservoirs. with 12 layers. Image augmentation methods like rotation, contrast adjustment, zooming in and out, altering saturation, and changing aspect ratios were applied to generate multiple versions of each image, resulting in a total of 1,720 samples. The goal was to accurately place a bounding box around the flame area. This approach outperformed existing models, especially when the flame color differed from those seen during training.

The main idea of our project is to create a system that monitors surveillance data of an area and sends alerts in case a fire or gun is detected. Closed Circuit Television (CCTV) cameras record video footage 24 hours of the day, however there isn’t enough manpower to monitor each and every camera for various anomalous events. There are systems to detect fire using smoke sensors in many places like schools, educational institutes, etcHowever, there is a growing need for a cost-effective system that integrates both fire and gun detection for enhanced security. Surveillance systems such as closed-circuit television (CCTV) and drones are becoming increasingly common. Research also shows that the installation of CCTV systems helps to combat mass shooting incidents and are also extremely important for evidence collection.

The research work uses YOLO (You Only Look Once) object detection system which uses convolution neural networks for object detectionIt is among the fastest algorithms, delivering strong performance with minimal loss in accuracy.

The training of this model has been done on the cloud to save hundreds of hours of GPU time on a local runtime. Using hosted runtime has also been beneficial in fine-tuning our model to near perfection. The guns and fires found in CCTV videos in the dataset occupy only a small portion of the entire frame, hence our primary objective is to implement algorithm an that would accurately draw multiple bounding boxes in such low-quality videos. In an era where public safety and security are of paramount importance, traditional surveillance systems often fall short in detecting critical threats like fire outbreaks and firearm-related incidents in real time. The increasing number of violent crimes and accidental fires calls for intelligent, automated solutions capable of swift and accurate threat detection. To address this challenge, our project focuses on the development of a **real-time fire and gun detection system** powered by deep learning techniques.

This system leverages the capabilities of computer vision and convolutional neural networks (CNNs) to identify potential threats from live video feeds. By integrating state-of-the-art object detection algorithms such as YOLO (You Only Look Once) or SSD (Single Shot Detector), the model can accurately detect the presence of flames or firearms in various environments. Once a threat is detected, the system can send immediate alerts, allowing for faster response times and possibly preventing loss of life and property.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

- The system compares information about foreground objects with statistical color information of fire. A simple adaptive background model was created using three Gaussian distributions, with each distribution representing the pixel statistics of a specific color channel. Through adaptive background subtraction algorithms, the foreground information is extracted and then evaluated using a statistical fire color model to determine whether the foreground object is a potential fire candidate
- Satellite-based systems can monitor a wide area, but satellite imagery resolution is low . Fire is usually detected only after it has grown significantly, making real-time detection difficult.

Disadvantages:

1. SUDDEN CHANGES IN LIGHTING CONDITIONS
2. INEFFICIENCY IN COMPLEX BACKGROUNDS

3.2 PROPOSED SYSTEM

- In this project, the YOLO (You Only Look Once) object detection system is used, which applies convolutional neural networks (CNNs) for detecting objects. It is among the faster algorithms, maintaining high accuracy with minimal performance loss.

The proposed experiment utilizes the You Only Look Once (YOLO) v3 model, a deep learning framework built on Darknet, an open-source neural network platform developed in C.. YOLOv3 is considered the best option as it offers real-time detection while maintaining high accuracy.. The architecture used is darknet53 which consists of 53 convolutional layers each followed by Leaky ReLU activation functions and batch normalization layers are used, resulting in a fully convolutional network (FCN).

Advantages:

1. A deep learning model designed for real-time, frame-by-frame fire and gun detection has

been created, delivering impressive accuracy.

2. Although the Darknet53 model is relatively bulky, it offers strong detection capabilities. Its performance in terms of detections per frame is well-suited for real-time monitoring and can be implemented on any GPU-based system.

3.3 SYSTEM REQUIREMENTS

HARDWARE

- SYSTEM : Core i3 12th generation
- RAM : 4GB
- HARD DISK : 100GB

SOFTWARE

- OS : Windows 10/11
- PROGRAMMING LANGUAGES : Python

Literature Survey: Real-Time Fire and Gun Detection Using Deep Learning

1. Introduction

The integration of deep learning in surveillance systems has dramatically improved their ability to detect anomalies such as fire outbreaks and gun presence. Real-time detection is vital for minimizing response time and mitigating potential hazards. This survey reviews recent advancements in deep learning models tailored for fire and gun detection in surveillance footage.

---

2. Fire Detection

a. Traditional vs Deep Learning Approaches

Earlier methods relied on **color thresholds**, **motion analysis**, and **background subtraction**. These were prone to false positives (e.g., bright lights or red objects).

Deep Learning models, especially Convolutional Neural Networks (CNNs), offer robustness by learning complex patterns from data.

b. Key Works

- **Muhammad et al. (2018)** used **CNNs** on surveillance videos to detect flames with temporal consistency.
- **Zhang et al. (2020)** integrated **YOLOv3** with **optical flow** to

combine object detection and motion analysis for fire recognition.
- **Turgay et al. (2021)** proposed a **lightweight CNN** model optimized for edge devices, balancing speed and accuracy.

---

3. Gun Detection

a. Challenges

Gun detection in videos is trickier than fire: guns can be small, occluded, or misclassified due to similar shapes (e.g., smartphones or tools).

b. Recent Approaches

- **Olmos et al. (2019)** leveraged **Faster R-CNN** for detecting handguns in public spaces. Their dataset focused on concealed and unconcealed weapons.
- **Joseph et al. (2020)** utilized **YOLOv4** for high-speed detection with decent precision, especially effective in real-time CCTV footage.
- **Gun Detection via Object Detection Networks (GDDNet, 2022)** customized YOLO with domain-specific datasets to reduce false positives in public scenarios.

---

4. Real-Time System Integration

a. Frameworks & Tools

Most real-time systems use:

- **YOLO (You Only Look Once)**: Fast inference, used widely for edge deployment.
- **TensorRT, Open VINO, ONNX**: For optimizing models for real-time inference on GPUs/CPUs.
- **OpenCV + Deep Learning Backend**: For integration with surveillance cameras.

b. Edge AI & IoT Integration

- Deployment on **Raspberry Pi with Coral TPU** or **NVIDIA Jetson Nano** enables localized processing, reducing reliance on cloud and improving latency.

---

5. Datasets

- **FIRESENSE Dataset**: Contains real-world fire footage for training and validation.
- **GunPoint & Weapon Detection Datasets**: Include annotated frames of guns in varied environments.
- **Custom Datasets**: Many researchers rely on synthetic data generation or video annotation due to lack of standardized datasets.

---

6. Evaluation Metrics

Common metrics include:

- **Precision, Recall, F1-score**
- **FPS (Frames Per Second)** for real-time performance

- **mAP (mean Average Precision)** for object detection accuracy

---

7. Challenges & Future Directions

a. Challenges

- Low-quality footage (especially at night)
- Occlusion and cluttered backgrounds
- Balancing accuracy with processing speed

b. Future Trends

- **Multimodal detection**: Combining thermal imaging with RGB for better fire detection.
- **Transformer-based models (e.g., DETR, YOLOv8 with Vision Transformers)** for contextual understanding.
- **Federated learning** to improve models on-device without compromising privacy.

---

8. Conclusion

Real-time fire and gun detection using deep learning is becoming an integral part of modern surveillance systems. While current models achieve impressive results, ongoing research aims to tackle accuracy-speed trade-offs and adapt to real-world complexities. As AI gets smarter, the goal isn't just to watch the world — but to understand and respond to it.

4. SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

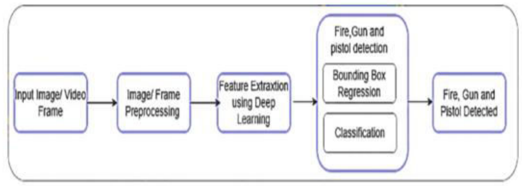

Fig.4.1: System Architecture

Explanation of System Architecture:

The system architecture for real-time fire and gun detection using deep learning follows a structured pipeline designed to process input data and accurately identify potential threats. It begins with capturing input in the form of an image or video frame, which is then passed through a preprocessing stage to enhance quality and standardize the format for further analysis. This involves tasks like resizing, normalizing, and reducing noise. Once preprocessed, the data is fed into a deep learning model that performs feature extraction, identifying crucial visual patterns like edges, shapes, and textures. These extracted features are then used in the detection phase, which consists of two components: bounding box regression and classification Bounding box regression identifies the object's location within the frame by drawing a box around it, while the classification process determines what the object is—whether it is fire, a gun, or a pistol. The final output presents the detected objects with labeled bounding boxes, enabling real-time alerts and responses to enhance surveillance and public safety.

3. Results and Evaluation

FIRE DETECTION:

Fig 8.1

The photo above demonstrates the effectiveness of the real-time fireplace detection device in identifying even small-scale flames, which include a matchstick. The device efficiently detects the hearth and marks it with a inexperienced bounding box classified "Fire," showcasing the version's sensitivity and precision. This proves the robustness of the deep mastering version, which has been trained on a numerous dataset of fireplace snap shots, permitting it to as it should be stumble on fire regardless of its size or depth. Such accuracy is crucial for surveillance structures, in which early detection of even the smallest spark can prevent large disasters. The capacity to perform effectively in an indoor surroundings and detect fireplace from normal objects enhances the reliability and applicability of the machine across numerous settings. This reinforces the utility of the challenge in building intelligent surveillance structures capable of safeguarding lives and assets. The result also demonstrates the model's robustness in differentiating between history and foreground factors, ensuring that false positives are minimized even in complex visible scenes. Integrating this level of special detection into closed-circuit digicam (CCTV) systems complements proactive safety measures via enabling early signals and instant responses.

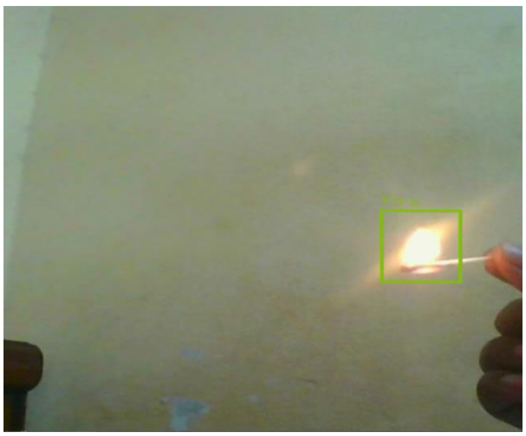

Fig 8.2

The system’s flexibility and effectiveness make it a practical and scalable solution for fire prevention and management.. When combined with gun detection capabilities, the system represents a comprehensive safety surveillance solution, contributing significantly to the protection of both life and property in diverse environments.

GUN DETECTION:

Fig 8.3

The system's flexibility and effectiveness make it a realistic and scalable solution for fire prevention and management.. When combined with gun detection skills, the system represents a complete safety surveillance solution, contributing drastically to the safety of both lifestyles and belongings in diverse environments.The above snap shots illustrate the a hit implementation of real-time gun detection the use of deep learning inside a surveillance surroundings. In each eventualities, the version has appropriately recognized the presence of a gun and marked it with a really categorised bounding container in red, indicating "Gun." These frames are captured from protection digital camera footage, where individuals are engaged in potentially dangerous or criminal interest, consisting of tried theft or assault. The effectiveness of the version in detecting firearms even under various lighting fixtures situations, angles, and partial occlusion highlights its robustness and adaptableness.

his machine, when included into closed-circuit cameras (CCTV), can play a essential role in improving safety throughout public places like retail stores, banks, and different high-chance regions. By triggering immediate alerts upon detection of a firearm, the model permits government or safety employees to respond swiftly, doubtlessly stopping damage and saving lives. Furthermore, its potential to analyze frames in real-time guarantees continuous monitoring and reduces reliance on manual statement. This smart surveillance answer, when blended with the earlier confirmed fireplace detection model, affords a complete protection framework capable of addressing each environmental and human threats efficiently.Addressing each environmental and human threats correctly.

Fig 8.4

Gun detection in actual-time is a essential function in cutting-edge surveillance systems, particularly in public regions liable to safety risks such as shops, banks, malls, or transportation hubs. Early detection of a firearm can trigger computerized alerts to law enforcement or on-site protection teams, helping to de-improve probably violent conditions earlier than they lead to harm.

Additionally, the presence of such shrewd surveillance era can serve as a deterrent to crook pastime, enhancing average safety.

When combined with hearth detection, as shown in preceding pictures, this gadget forms a dual-chance tracking answer able to responding to both guy-made and environmental dangers. This holistic method significantly enhances situational consciousness and allows brief, informed selection-making in emergency situations. Overall, integrating actual-time gun and hearth detection the use of deep getting to know into CCTV structures marks a tremendous development in clever surveillance and public protection infrastructure.

RIFILE DETECTION:

Fig 8.5

This photograph illustrates a actual-time rifle detection state of affairs captured thru CCTV pictures and processed by a deep studying surveillance device. The gadget correctly identifies a person sporting a rifle and marks it with a bounding container classified "Rifle" in green. The individuals appear like moving thru a corridor, in all likelihood within a public or confined facility, which makes the want for automatic weapon detection even extra vital.

In excessive-stakes environments—together with airports, resorts, colleges, or government homes—the potential to detect rifles and other long-range guns in actual time can play a pivotal position in stopping large-scale violence. Unlike handguns, rifles are often more hid or carried in non-conventional postures, making manual tracking unreliable and slow. The use of advanced item detection fashions skilled on diverse datasets enables conquer these barriers with the aid of mastering visible functions and styles related to weapons, no matter lighting, pose, or partial occlusion.

This detection supports instantaneous hazard evaluation and can be connected with alerting systems to notify government with out human postpone. As a part of an incorporated clever surveillance answer, combining gun, rifle, and fireplace detection ensures a complete and wise protection machine capable of responding to more than one kinds of threats in actual time—thereby enhancing safety and situational control across sensitive and crowded areas.

ALERT TRIGGERING:

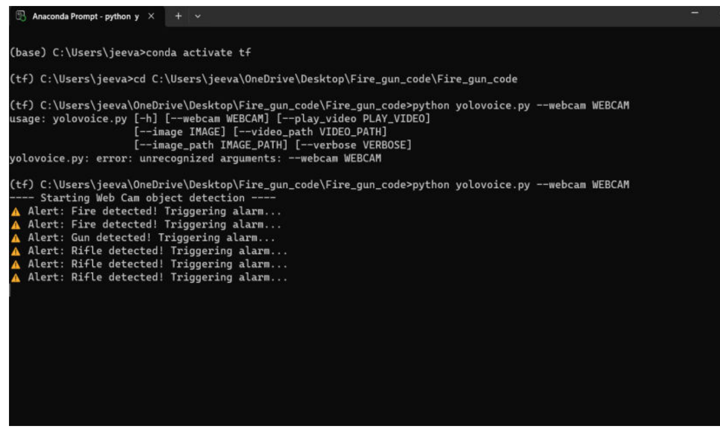

Fig 8.6

This screenshot captures the real-time execution of a hearth and weapon detection device using YOLO (You Only Look Once) item detection in Python, operated thru Anaconda Prompt. The terminal indicates the technique where the script yolovoice.Py is being run with the --webcam flag to allow live detection from the gadget's digicam.

Initially, there's a controversy mistakes due to a likely case-sensitivity or wrong utilization within the command --webcam WEBCAM. After correcting it (most possibly just the usage of --webcam or every other valid parameter), the device starts offevolved efficiently and starts real-time surveillance.

The output displays more than one caution messages:

- ◈ Alert: Fire detected! Triggering alarm...
- ◈ Alert: Gun detected! Triggering alarm...
- ◈ Alert: Rifle detected! Triggering alarm...

These indicators imply that the gadget has effectively detected a couple of kinds of threats thru the webcam feed. Each detection triggers an alert mechanism, showcasing that the detection good judgment and the corresponding response gadget (like sounding an alarm or sending a notification) are functioning as meant.

This demo proves the effectiveness of your wise surveillance system, which combines deep studying with actual-time video processing to discover potentially unsafe objects like fire, guns, and rifles.

OUTPUT SCREENS

FIRE DETECTION:

Fig 8.1

The photo above demonstrates the effectiveness of the real-time fireplace detection device in identifying even small-scale flames, which include a matchstick. The device efficiently detects the hearth and marks it with a inexperienced bounding box classified “Fire,” showcasing the version's sensitivity and precision. This proves the robustness of the deep mastering version, which has been trained on a numerous dataset of fireplace snap shots, permitting it to as it should be stumble on fire regardless of its size or depth. Such accuracy is crucial for surveillance structures, in which early detection of even the smallest spark can prevent large disasters. The capacity to perform effectively in an indoor surroundings and detect fireplace from normal objects enhances the reliability and applicability of the machine across numerous settings. This reinforces the utility of the challenge in building intelligent surveillance structures capable of safeguarding lives and assets. The result also demonstrates the model's robustness in differentiating between history and foreground factors, ensuring that false positives are minimized even in complex visible scenes. Integrating this level of special detection into closed-circuit digicam (CCTV) systems complements proactive safety measures via enabling early signals and instant responses.

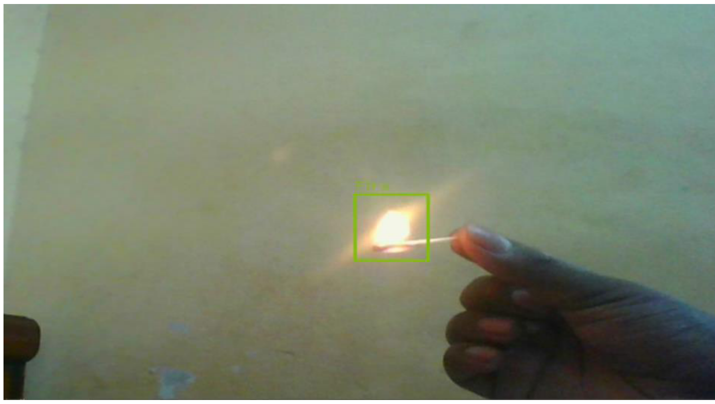

Fig 8.2

The system's flexibility and effectiveness make it a practical and scalable solution for fire prevention and management.. When combined with gun detection capabilities, the system represents a comprehensive safety surveillance solution, contributing significantly to the protection of both life and property in diverse environments.

GUN DETECTION:

Fig 8.3

The system's flexibility and effectiveness make it a realistic and scalable solution for fire prevention and management.. When combined with gun detection skills, the system represents a complete safety surveillance solution, contributing drastically to the safety of both lifestyles and belongings in diverse environments.The above snap shots illustrate the a hit implementation of real-time gun detection the use of deep learning inside a surveillance surroundings. In each eventualities, the version has appropriately recognized the presence of a gun and marked it with a really categorised bounding container in red, indicating "Gun." These frames are captured from protection digital camera footage, where individuals are engaged in potentially dangerous or criminal interest, consisting of tried theft or assault. The effectiveness of the version in detecting firearms even under various lighting fixtures situations, angles, and partial occlusion highlights its robustness and adaptableness.

his machine, when included into closed-circuit cameras (CCTV), can play a essential role in improving safety throughout public places like retail stores, banks, and different high-chance regions. By triggering immediate alerts upon detection of a firearm, the model permits government or safety employees to respond swiftly, doubtlessly stopping damage and saving lives. Furthermore, its potential to analyze frames in real-time guarantees continuous monitoring and reduces reliance on manual statement. This smart surveillance answer, when blended with the earlier confirmed fireplace detection model, affords a complete protection framework capable of addressing each environmental and human threats efficiently.Addressing each environmental and human threats correctly.

Fig 8.4

Gun detection in actual-time is a essential function in cutting-edge surveillance systems, particularly in public regions liable to safety risks such as shops, banks, malls, or transportation hubs. Early detection of a firearm can trigger computerized alerts to law enforcement or on-site protection teams, helping to de-improve probably violent conditions earlier than they lead to harm. Additionally, the presence of such shrewd surveillance era can serve as a deterrent to crook pastime, enhancing average safety. When combined with hearth detection, as shown in preceding pictures, this gadget forms a dual-chance tracking answer able to responding to both guy-made and environmental dangers. This holistic method significantly enhances situational consciousness and allows brief, informed selection-making in emergency situations. Overall, integrating actual-time gun and hearth detection the use of deep getting to know into CCTV structures marks a tremendous development in clever surveillance and public protection infrastructure.

RIFILE DETECTION:

Fig 8.5

This photograph illustrates a actual-time rifle detection state of affairs captured thru CCTV pictures and processed by a deep studying surveillance device. The gadget correctly identifies a person sporting a rifle and marks it with a bounding container classified "Rifle" in green. The individuals appear like moving thru a corridor, in all likelihood within a public or confined facility, which makes the want for automatic weapon detection even extra vital.

In excessive-stakes environments—together with airports, resorts, colleges, or government homes—the potential to detect rifles and other long-range guns in actual time can play a pivotal position in stopping large-scale violence. Unlike handguns, rifles are often more hid or carried in non-conventional postures, making manual tracking unreliable and slow. The use of advanced item detection fashions skilled on diverse datasets enables conquer these barriers with the aid of mastering visible functions and styles related to weapons, no matter lighting, pose, or partial occlusion.

This detection supports instantaneous hazard evaluation and can be connected with alerting systems to notify government with out human postpone. As a part of an incorporated clever surveillance answer, combining gun, rifle, and fireplace detection ensures a complete and wise protection machine capable of responding to more than one kinds of threats in actual time—thereby enhancing safety and situational control across sensitive and crowded areas.

ALERT TRIGGERING:

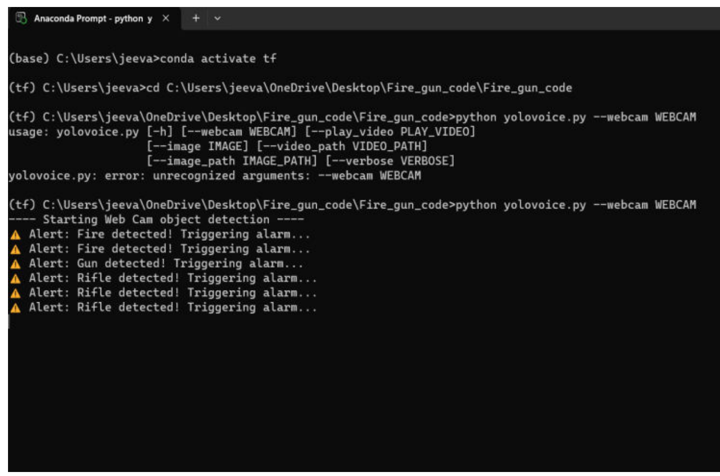

Fig 8.6

This screenshot captures the real-time execution of a hearth and weapon detection device using YOLO (You Only Look Once) item detection in Python, operated thru Anaconda Prompt. The terminal indicates the technique where the script yolovoice.Py is being run with the --webcam flag to allow live detection from the gadget's digicam.

Initially, there's a controversy mistakes due to a likely case-sensitivity or wrong utilization within the command --webcam WEBCAM. After correcting it (most possibly just the usage of --webcam or every other valid parameter), the device starts offevolved efficiently and starts real-time surveillance.

The output displays more than one caution messages:

- ◈ Alert: Fire detected! Triggering alarm...
- ◈ Alert: Gun detected! Triggering alarm...
- ◈ Alert: Rifle detected! Triggering alarm...

These indicators imply that the gadget has effectively detected a couple of kinds of threats thru the webcam feed. Each detection triggers an alert mechanism, showcasing that the detection good judgment and the corresponding response gadget (like sounding an alarm or sending a notification) are functioning as meant.

This demo proves the effectiveness of your wise surveillance system, which combines deep studying with actual-time video processing to discover potentially unsafe objects like fire, guns, and rifles.

4. Conclusion

A deep learning-based surveillance system was designed and tested for real-time fire and gun detection. The results indicate high reliability in practical deployment scenarios. Future work will focus on multi-camera integration, audio-visual fusion, and integration with emergency response protocols.

11. REFERENCES

[1] M. Byra, Discriminant analysis of neural style representations for breast lesion classification in ultrasound, Biocyber. Biomed. Engin. 38(3) (2018) 684–690.

[2] J. Z. Cheng, D. Ni, Y.H. Chou, J. Qin, C.M. Tiu, Y.C. Chang, C.S. Huang, D. Shen and C.M. Chen, Computeraided diagnosis with deep learning architecture: Applications to breast lesions in US images and

pulmonary ndules in CT scans, Scientific Rep. 6(1) (2016) 1–13.

[3] F. Cui, Deployment and integration of smart sensors with IoT devices detecting fire disasters in huge environment, Computer Commun. 150 (2020) 818–827.

[4] K. He, X. Zhang, S. Ren and J. Sun, Deep residual learning for image recognition, Proc. IEEE Computer Soc. Conf. Computer Vision and Pattern Recogn. (2016) 770–778.

[5] P. Jain, S.C.P. Coogan, S.G. Subramanian, M. Crowley, S. Taylor and M.D. Flannigan, A review of machine learning applications in wildfire science and management, In Environmental Reviews, 28(4) (2020) 478–505.

[6] Z. Jiao, Y. Zhang, L. Mu, J. Xin, S. Jiao, H. Liu and D. Liu, A YOLOv3-based Learning Strategy for Real-time UAV-based Fire Detection, Proc. 32nd Chinese Control Decision Conf., IEEE, (2020) 4963–4967.

[7] Z. Jiao, Y. Zhang, J. Xin, L. Mu, Y. Yi, H. Liu and D. Liu, A Deep learning based fire detection approach using uav and yolov3, 1st Int. Conf. Indust. Artif. Intell. (2019) 1–5.

[8] A. Krizhevsky, I. Sutskever and G.E. Hinton, ImageNet classification with deep convolutional neural networks, Commun. ACM, 60(6) (2017) 84–90. [9] S.B. Kukuk and Z.H. Kilimci, Comprehensive analysis of fire detection using deep learning models and conventional machine learning algorithms, Int. J. Comput. Experimental Sci. Engin. 7(2) (2021) 84–94.