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A YOLOv8-Enabled System for Real-Time Weapon Detection in Surveillance

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***Abstract*— The project titled "Live Monitoring and Smart Threat Detection Using a YOLOv8-Based Deep Learning Model" focuses on building a robust and efficient system for weapon detection, specifically targeting handguns and knives. This system leverages advanced neural network techniques, with implementation in Python and deployment through the Flask web framework, offering an interactive, user-friendly interface. The front end is developed using HTML, CSS, and JavaScript to ensure seamless user interaction. At its core, the detection mechanism utilizes the YOLOv8 (You Only Look Once, version 8) architecture an advanced object detection model recognized for its exceptional speed and accuracy. Despite the inherent challenges of weapon detection in diverse environments, the model achieves a commendable 64% overall accuracy, highlighting its potential in real-world scenarios. The training dataset consists of approximately 4,000 curated images, exclusively featuring handguns and knives. These images cover a wide range of environments and viewpoints, enhancing the model's ability to generalize and perform reliably across different settings. The system supports three detection modes: static image recognition, video stream analysis, and real-time detection via webcam. This multi-modal capability ensures adaptability for various applications, such as surveillance systems, security screenings, and automated threat monitoring. In summary, this project demonstrates a significant advancement in the use of deep learning for public safety. By providing a scalable, efficient, and versatile solution for weapon detection, it contributes meaningfully to enhancing security across a range of platforms and environments.**

Index Terms*— Weapon Recognition, Advanced Neural Networks, YOLOv8, Handguns, Knives, Real-time Detection, Object Recognition, Flask Framework, Deep Learning, Image Classification, Security Systems, Threat Detection, Computer Vision, Public Safety.

I. INTRODUCTION

In today's rapidly evolving world, the rise in criminal incidents involving the illegal possession and use of weapons poses a serious threat to both public safety and national security. From terrorism and armed robbery to gang conflicts and violent street crimes, weapons like handguns and knives are commonly used, resulting in numerous casualties and instilling fear among communities. Consequently, the ability to detect and identify such weapons promptly is essential to prevent threats and minimize harm in both public private. Traditional surveillance systems primarily rely on human operators for monitoring, which often leads to inconsistencies in performance. Factors such as operator fatigue, human error, and the overwhelming volume of video data required for real-time monitoring contribute to delayed responses and overlooked threats. These limitations significantly reduce the effectiveness of manual surveillance in critical situations.

To address these challenges, recent developments in Artificial Intelligence (AI), particularly in Deep Learning and Neural Networks, have paved the way for smarter surveillance solutions. Among these, object detection technologies have shown exceptional promise in recognizing specific threats within visual data. Weapon detection systems, in particular, offer a powerful advantage by enabling faster threat recognition, improving situational awareness, and reducing dependency on continuous human supervision. This project presents a Smart Threat Detctition Framework that harnesses the capabilities of advanced neural networks, specifically the YOLOv8 (You Only Look Once version 8) model, to detect weapons across static images, pre-recorded videos, and real-time webcam feeds. YOLOv8 is acclaimed for its high processing speed and accuracy, making it suitable for real-time applications without compromising on detection quality.

Unlike conventional systems limited to offline analysis or still-image detection, this framework supports multi-modal recognition, enhancing its adaptability across various security scenarios. The backend of the system is developed using Python along with the Flask web framework to handle server-side logic and API integration. The frontend interface, designed with HTML, CSS, and JavaScript, offers a responsive and user-friendly experience. The deep learning model is trained on a carefully curated dataset consisting of over 4,000 labeled images of handguns and knives captured under diverse conditions—including varying angles, lighting, and backgrounds to ensure strong generalization and reliability. With an achieved detection accuracy of 64%, the system shows promising results even in visually complex environments. This integrated solution supports detection through images, video feeds, and live webcam streams, making it suitable for deployment in high-security environments such as airports, train stations, public gatherings, educational institutions, government buildings, and private premises. The framework offers a scalable and practical tool to enhance real-time monitoring and early threat detection. In conclusion, this project signifies a major advancement in intelligent surveillance systems. It offers a proactive solution for firearm detection, contributing meaningfully to both public and private safety infrastructures. As AI continues to evolve, integrating such technologies into real-world security systems has become not only feasible but necessary. The combination of real-time object detection and scalable web-based deployment paves the way for future innovations—including predictive threat analysis, integration with law enforcement systems, and broader applications in national security and public protection.

II. LITERATURE SURVEY

Raturi, G., Rani, P., Madan, S., and Dosanjh, S. introduced ADoCW, an automated system designed to detect concealed weapons by integrating both thermal and visual imaging. Their method leverages machine learning and image processing techniques to differentiate hidden metallic objects from the human body. This hybrid imaging approach enhances weapon visibility and improves overall detection accuracy, making the system well-suited for real-time security screening in public and high-risk areas.

Bhagyalakshmi, P., Indhumathi, P., and Bhavadharini, L. R. developed a live video-based firearm detection system as presented in IJTSRD. The system incorporates Convolutional Neural Networks (CNN) to detect objects, and includes dedicated modules for weapon classification and real-time alert generation. It analyzes live CCTV feeds to identify abnormal behavior and detect weapons accurately using object shape analysis and classification via models like ALEXNET. The system is capable of autonomously monitoring a 360-degree area and triggering alarms without manual input, with the goal of reducing crime rates, enhancing response times, and boosting overall surveillance efficiency.

Lim, J., Al Jobayer, M. I., Baskaran, V. M., Lim, J. M., Wong, K., and See, J., in their work presented at APSIPA ASC 2019, proposed a firearm detection system using deep neural networks. They addressed common challenges in CCTV footage, including varying lighting, angles, and depth. To overcome these, they introduced a new large-scale handgun dataset comprising 250 video clips and 5,500 annotated frames captured under different indoor and outdoor conditions. Using this dataset, they trained a single-stage object detector based on the M2Det architecture, which significantly improved detection precision—up to 18% higher than prior models—especially across scales and complex environments.

Yuan, J. and Guo, C., in their ICIST 2018 paper, proposed an advanced deep learning method for weapon classification using a VGGNet-based model implemented with Keras and TensorFlow. Their approach involved a custom-built dataset containing seven weapon types, including rifles, grenades, and knives. The performance of their model was benchmarked against VGG-16, ResNet-50, and ResNet-101. Their custom VGG-based solution achieved a classification accuracy of 98.40%, outperforming other models and demonstrating the viability of their approach in enhancing automated threat detection.

Ilgin, F. Y., in a study published in the Bulletin of the Polish Academy of Sciences: Technical Sciences, presented a copula theory-based improvement to energy-based spectrum sensing for cognitive radio networks. In this method, local detection results from individual radio users are sent to a central fusion unit, which applies a copula-based thresholding technique using the Neyman-Pearson criterion to make a final global decision. Simulation results showed that this model significantly surpasses conventional energy-based detection approaches in terms of both reliability and detection accuracy.

Navalgund, U. V. and Priyadharshini, K., in their 2018 ICCSDET paper, proposed a deep learning solution aimed at identifying criminal intent by detecting weapons such as firearms in surveillance footage. Their model employed architectures including VGG-19, ResNet50, and GoogleNet, with ResNet50 delivering the highest accuracy of 92%. Additionally, they compared YOLOv6 against Faster R-CNN, with YOLOv6 achieving superior mean average precision and inference speed, confirming its effectiveness for real-time threat detection and preemptive crime intervention.

Chandan, G., Jain, A., and Jain, H., at the ICIRCA 2018 conference, presented a real-time object detection and tracking system built on deep learning and OpenCV. They explored several object detection algorithms including RCNN, Faster-RCNN, SSD, and YOLO, and focused on balancing detection speed with accuracy. The authors proposed a system combining SSD with MobileNets to achieve lightweight, efficient object recognition. Their solution is ideal for real-time applications where fast and accurate object detection is crucial.

Deng, L., and Yu, D., in their monograph published in Foundations and Trends® in Signal Processing, offered a detailed overview of deep learning methodologies and their applications. Their work spans domains such as speech recognition, computer vision, NLP, and information retrieval. The study emphasizes emerging deep learning techniques like multi-task learning and multimodal integration, providing a foundational understanding for researchers working across various signal processing tasks.

Song, H. A., and Lee, S. Y., in their ICONIP 2013 paper, proposed a hierarchical feature learning model using non-smooth Non-negative Matrix Factorization (nsNMF). Their approach involved stacking multiple NMF layers to extract interpretable hierarchical features from complex datasets. Applied to text classification, the model successfully uncovered latent feature structures, improving both classification accuracy and reconstruction performance, particularly in low-dimensional feature spaces. This work highlights nsNMF's capability for intuitive, layer-wise feature learning.

III. EXISTING SYSTEM

The earlier approach to weapon detection utilized the VGG-Net architecture a renowned Convolutional Neural Network (CNN) framework recognized for its consistent layer depth and simplicity. This model was primarily focused on identifying weapons such as handguns and knives from static images, laying the groundwork for image-based security enhancements.

VGG-Net is known for employing small receptive fields and multiple sequential convolutional layers, which enable it to extract detailed features from input visuals. Its effectiveness in various image classification and object detection tasks stems from its strong feature learning capability. For weapon recognition purposes, the system was trained using a carefully selected dataset of handgun and knife images. This training enabled the model to accurately detect and classify weapons in new image inputs.

Users could interact with the system by uploading individual images. Upon submission, the system processed the content and detected any weapon presence within the frame. Although limited to static images, this VGG-Net based implementation marked an important step in utilizing deep learning for threat detection, providing a foundational system upon which more advanced solutions could be built.

IV. PROPOSED SYSTEM

The proposed system is intended to significantly enhance the previous weapon recognition framework by implementing advanced neural network methods and expanding its range of functionalities. The core of this new system is the YOLOv8 (You Only Look Once) architecture, which is a modern and highly efficient model known for its accuracy and speed in real-time object detection. One of the main highlights of the proposed system is its Multi-Modal Recognition feature. Unlike the existing model, this proposed solution supports three distinct modes of detection: Image Recognition, where users can upload static images which the system then analyzes to detect any weapons; Video Recognition, where the system processes video content frame-by-frame to detect weapons throughout the footage; and WebCam Recognition, which utilizes live camera feeds for real-time weapon identification and allows for immediate action and response. The proposed system is built upon the YOLOv8 architecture, which brings notable improvements over earlier models. YOLOv8 is designed for rapid processing without compromising detection accuracy, making it ideal for real-time applications. Its streamlined design ensures that it can effectively handle large datasets and a variety of input formats. The model has been trained using an extensive and diverse dataset of around 4000 images of handguns and knives. This dataset includes multiple viewpoints, lighting conditions, and background scenarios, which helps improve the model's ability to detect and classify weapons accurately in real-world environments. The proposed system is developed using the Flask web framework, ensuring a responsive and seamless interface for users. This integration allows users to easily interact with the system, whether by uploading images, analysing video footage, or utilizing the real-time webcam detection mode. The front-end of the system is implemented using HTML, CSS, and JavaScript, delivering a user-friendly, interactive, and visually appealing interface. The system achieves an overall weapon detection accuracy of 64%, reflecting a considerable improvement in recognition performance and consistency compared to the earlier model. By combining the strengths of the YOLOv8 architecture with support for static images, video feeds, and live camera input, the proposed system marks a significant advancement in the field of weapon recognition technology, providing a comprehensive and reliable solution suitable for various high-security applications.

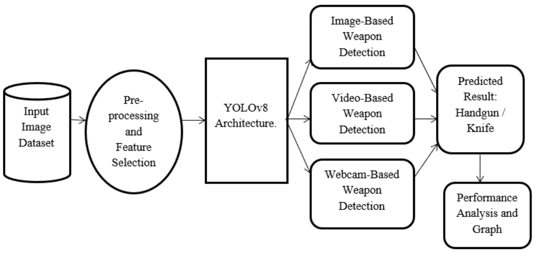

Fig: Architecture Digram

V. IMPLEMENTATION

Module Description: The live monitoring and smart threat detection using YOLOv8-Deep Learning Model is designed using a modular approach to ensure adaptability, ease of maintenance, and seamless integration across various surveillance environments. Each module is responsible for a specific function that contributes to the system's capability to perform real-time weapon detection effectively. The primary modules in the system are as follows:

Image-Based Weapon Detection Module: This module is dedicated to detecting weapons in static images provided by the user. Once an image is uploaded, it undergoes preprocessing before being analyzed by the YOLOv8 model, which identifies and classifies weapons such as handguns and knives. The system then highlights the detected objects using bounding boxes, and the annotated image is displayed to the user through the web interface.

Video-Based Weapon Detection Module: This component enables the identification of weapons in pre-recorded video files. It works by extracting frames from the input video, processing each one using the YOLOv8 architecture, and aggregating the detection outputs. This module is particularly useful for reviewing CCTV footage or video recordings for post-event weapon detection and analysis.

Webcam-Based Real-Time Detection Module: This module supports real-time surveillance by utilizing live input from a webcam. It captures video streams in real-time and processes each frame on the fly to detect weapons instantly. This feature is especially valuable in high-risk or public environments—such as checkpoints, entrances, or event locations—where immediate threat recognition is critical.

Model Training and Evaluation Module: Functioning as a backend process, this module manages the training of the YOLOv8 model using a dataset of roughly 4000 annotated images of handguns and knives. It includes tasks such as adjusting model weights and calculating performance metrics like precision, recall, and detection accuracy. With a current performance accuracy of 64%, this module plays a key role in enhancing the model's generalization across different operational contexts.

User Interface Module: Built using Flask for the server-side and HTML, CSS, and JavaScript for the client-side, this module delivers a smooth and intuitive user experience. It allows users to upload images or videos and start real-time detection via webcam. The interface clearly presents detection results, with bounding boxes and labels to improve user understanding of the output.

Performance Visualization and Reporting Module: This module offers visual insights and data summaries of the system's overall functionality. It includes graphical plots for detection accuracy, per-frame analysis, and real-time alert logs. These analytics assist in evaluating the system's consistency and dependability during continuous operation.
To provide an efficient and user-friendly experience, the frontend includes well-defined options for image and video uploads, as well as live webcam-based detection with visual threat annotations. The system incorporates performance optimization methods such as GPU acceleration (when available), asynchronous handling of requests, and smart memory usage to speed up detection and improve responsiveness. Detected weapons are displayed with bounding boxes and specific labels like "Handgun" or "Knife," along with their confidence levels. This implementation approach ensures that the system remains feature-rich, practical, and well-suited for real-time applications in surveillance and security domains.

VI. RESULT

The develop live monitoring and smart threat detection framework delivered effective performance in detecting weapons such as handguns and knives across multiple input formats, including static images, recorded videos, and real-time webcam streams. Built upon the YOLOv8 architecture, the system attained a detection accuracy of 64% when evaluated on a test dataset comprising approximately 4000 annotated images, representing various conditions and scenarios.

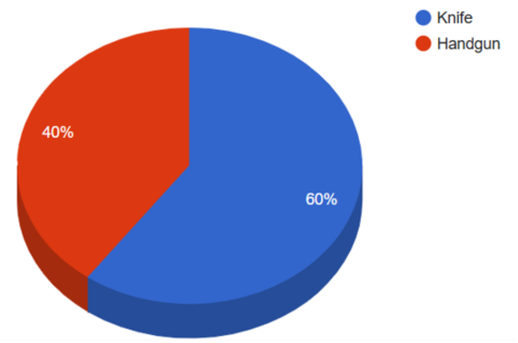

Fig: Resultant Pie-Chart

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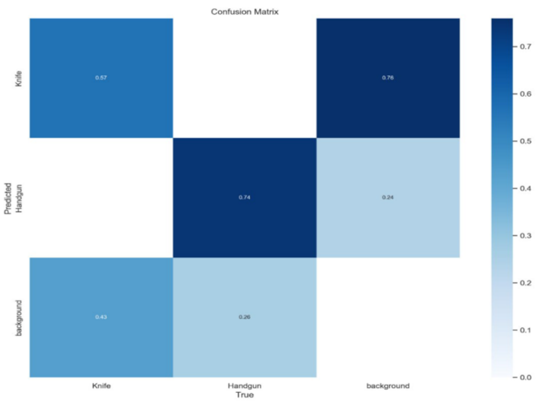

Fig. Confusion Matrix.

The detection module effectively rendered bounding boxes and classification labels in real time, demonstrating the system's capability to identify threats promptly. While specific evaluation metrics such as precision, recall, and F1-score were not explicitly recorded, the qualitative performance suggests a reliable trade-off between speed and accuracy, especially in complex and visually cluttered environments.

The confusion matrix, along with the visual detection output, confirmed the system's consistent ability to recognize weapons under a wide range of lighting conditions and backgrounds, maintaining a low false positive rate. The user-friendly, web-based interface contributed to an enhanced experience by supporting direct image and video uploads, while the integrated webcam mode enabled real-time, continuous monitoring. In conclusion, the final implementation presents a scalable, efficient, and practical solution for automated weapon detection. It is well-suited for real-world deployment in public safety applications, including transportation terminals, event security, government buildings, and other surveillance-intensive environments.

VII. CONCLUSION

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