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INTELLIGENT WEAPON DETECTION SYSTEM FOR REAL-TIME SURVEILLANCE USING DEEP LEARNING WITH YOLOv8

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ABSTRACT

To provide security to people in high-personality and dense areas like airports, railway stations, and learning institutions purported systems of surveillance must be credible and smart. Conventional weapon detectors heavily depend on the constant human attention of the security guards, which loses its performance at real time and mass scale operations due to human weaknesses, latent reaction, and great chances of overlooking events of threat nature. Moreover, the common surveillance systems are not smartly automated and cannot automatically identify weapons on live video streams.

The proposed paper will implement a smart weapon detecting device to overcome these challenges and realize real-time surveillance that utilizes the use of deep learning. The system suggested is that based on a live surveillance video, the suggested system uses the YOLOv8 object detection model that will be used to automatically detect weapon types like guns and knives. Based on annotated datasets, a model is trained and every component is augmented by output of transfer learning and data augmentation methods to enhance the accuracy of detection in low-illumination environments coupled with sophisticated backgrounds. Video frames are processed in real time to scan the image to identify weapons and raise an emergency warning to alert them in case they noticed a possible threat.

The evaluation of experimental performance metrics comprise of accuracy, recall, F1-score, mean Average Precision (mAP), and Frames per second (FPS). The findings indicate that the suggested system can generate high detection accuracy and still be able to perform in real-time. YOLOv8 based system has a high accuracy, robustness which is coupled with small object detection capacity compared to constraints of current surveillance methods and previous object-detecting models in the use of intelligent real-time surveillance applications.

Keywords: Weapon Detection, Real-Time Surveillance, Deep Learning, YOLOv8, Object Detection, CCTV Security.

1. INTRODUCTION

Over the last few years, the increasing demand of the security of the populace has driven surveillance technology to be smarter, more rapidly and more stable. The conventional surveillance systems mainly use manual personnel to watch the video feeds, which may be exhausting, inaccurate and inefficient particularly where there are great numbers of people or high risk zones. In order to cover these constraints, smart solutions that are driven by artificial intelligence are currently being proposed to automatically scan video flows and detect the possible threats in real-time.
An Intellectual Weapon Detection System is based on the ability to identify weapons (guns or knives) based on the real-time video footage. With the help of deep learning methods, the system is capable of learning visual textures that are linked to weapons and separating them out of the non-weapon category. This minimizes the reliance on human presence that runs 24/7 and assists the security staff to react more timely to dangerous circumstances before it goes out of hand.
Deep learning models, and particularly those that are developed to detect objects have a vital role to play in the process. YOLOv8 (You Only Look Once version 8) is a state-of-the-art object detector algorithm that is fast and has a high accuracy. It is also capable of processing images and video spots in real time and as such it can be used greatly in surveillance where the decision making process requires making a decision fast..
By adding YOLOv8 to the core of a real-time monitoring system, one will be able to scan through video feeds in real-time to determine the presence of weapons. When a weapon is detected the system is capable of issuing warning or notification that can allow immediate action by the authorities. The automated method ensures better response time, reduction of human error and improve the overall security effectiveness.
To sum up, the detection intellectual weapon based on deep learning and YOLOv8 is a great breakthrough in intelligent surveillance devices. Such systems help to make the population areas safer, enhance the threat prevention and become more proactive in controlling safety with the help of real-time monitoring with the advanced object detection abilities. Due to the further development of technologies, these smart surveillance systems will become an integral component of a safety system in the modern world.

2. LITERATURE REVIEW

Muhammad Tahir Bhatti et al. suggested a deep learning-based system of detecting weapons in the field of computer vision during real-time CCTV surveillance. Current object detection models are used to identify pistols in video streams, including YOLOv4, Faster R-CNN and SSD. Because of no standard dataset offered the authors developed a new dataset of 8,327 images that were taken in CCTV, internet, IMFDB and captured in self sources. In experimental terms, the YOLOv4 had better performance of mean average precision of 91.73 and F1-score of 91% in real time conditions. The system, however, is restricted to pistol-type weapons and lacks an inbuilt alert or emergency response mechanism which is still a gap area when implementing in real world usage. YOLOv4 had higher F1-score of 91% and mean Average Precision (mAP) of 91.73, and it is better than Faster R-CNN and SSD in real-time weapon detection. [2]. In the field of joint combat decision making and operations research, Shuai Li et al. came up with an intelligent weapon-target assignment strategy. It is the solution used in solving dynamic weapon-target assignment problems with a number of constraints through a multi-head deep reinforcement learning model (RL4WTA) which builds on our revised Deep Q-Network. Simulated battle field scenarios with different number of weapons, targets, threat and wound chance are used to train and test the model rather than practical datasets. Experimental evidence shows that RL4WTA has a high adaptability, shorter computation time, and close-to-optimal solutions than the conventional MILP and heuristic algorithms, particularly large scale jobs. Yet, the methodology is based on simulated conditions without addressing the real-life uncertainty like sensor noise, communication latency, or lack of battlefield information, which constitutes the gap in the research. The RL4WTA model proposed a close-to-optimal decision and a greater success rate and convergence speed of RL4WTA model than its competitors in the area of defence system and intelligent combat decision making [3] Chang Liu et al. developed a time-driven dynamic weapon-target assignment process. The suggested framework considers a Time-Sampling Dynamic Weapon-Target Assignment (TS-DWTA) model with reinforcement learning and the Proximal Policy Optimization (PPO) algorithm to work with time-sensitive and dynamic battlefield scenarios. Simulated combat datasets are used to evaluate the system which contains dynamic arrival of missiles, availability of weapons, level of threats, and time limitations. In dynamic situations, the TS-DWTA technique with PPO demonstrated a higher degree of accuracy in decision making and lower rate of damages to assets in comparison with the conventional methods which made use of heuristic in their decision making.

[4] Ruiz-Santaquiteria et al. presented a handgun detection system using deep learning to the computer vision and video surveillance market, which combines human pose detection and weapon appearance detection predictions. The technique is based onextraction of pose key points with the help of Open Pose and a CNN-based hand region classifier (Darknet-53) that focuses more on identifying handguns. It was tested on CCTV images, YouTube videos, synthetic game images, the Monash Guns Dataset and demonstrated a difference of 4.23 percent to 18.9 percent Average Precision (AP) compared to current appearance-only algorithms. The suggested approach increased the average Precision (AP) to 18.9 4.23 percent based on the dataset relative to handgun detection models that only attributed appearance.The method uses a hierarchical feature representation network with localization of the bounding box refinement to be efficient in identifying multi-scale military vehicles with difficult backgrounds. Training and assessment of this model were done with image data of military vehicles that were sourced through both aerial and ground surveillance. The results of the experiment prove that the presented approach shows a better detection rate and a higher localization performance than the traditional CNN-based detectors. Nonetheless, there is still the challenge of the method with respect to real-time implementation and performance deterioration with extreme cases of occlusions as well as low-resolution cases, which characteristics reflect a research gap. The hierarchical feature representation model displayed both greater detection accuracy and better localization precision (higher MAP) on military vehicle datasets than conventional CNN-based object detectors.

EXISTING SYSTEMS

In the current surveillance framework, security monitoring primarily relies on traditional CCTV cameras and manual supervision by security personnel. These systems are widely deployed in public areas such as malls, airports, railway stations, educational institutions, and corporate offices.

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However, their operation is largely passive in nature, as they record video footage for later review instead of providing intelligent real-time analysis.

Most conventional surveillance systems depend on human operators to continuously monitor multiple screens. This process is labor-intensive, time-consuming, and highly prone to human error due to fatigue, distraction, or subjective judgment. In crowded or high-risk environments, it becomes extremely difficult for personnel to identify suspicious activities or detect potential threats effectively.

Existing systems typically utilize basic techniques such as motion detection and background subtraction. While these approaches can detect movement, they cannot accurately differentiate between harmless objects and dangerous items such as weapons. As a result, these systems often generate high false alarms or fail to detect critical threats altogether.

Furthermore, traditional surveillance solutions do not incorporate advanced machine learning or deep learning models. Therefore, they lack the ability to learn from data, adapt to new environments, or improve detection accuracy over time. This significantly limits their effectiveness in real-time threat identification and rapid response scenarios.

PROPOSED SYSTEMS

The proposed Intelligent Weapon Detection System is designed to enhance surveillance efficiency by integrating advanced deep learning techniques, particularly the YOLOv8 object detection algorithm, for real-time weapon identification from live CCTV feeds. The system captures video streams, performs frame extraction and preprocessing, and analyzes each frame using the trained YOLOv8 model to detect weapons such as guns and knives with high precision and low latency. Upon detecting a potential threat, the system immediately triggers alerts to security personnel through notifications or alarm systems, enabling rapid response and preventive action. Unlike conventional surveillance systems that rely heavily on manual monitoring and post-incident review, the proposed model operates automatically and continuously, significantly reducing human error and monitoring fatigue. Its ability to learn complex visual patterns allows accurate detection even in crowded, low-light, or dynamic environments. Furthermore, the system achieves lower false alarm rates compared to traditional motion-based techniques and ensures high-speed processing suitable for real-time applications. The architecture is scalable and can be integrated with multiple cameras across large infrastructures such as airports, railway stations, educational institutions, shopping malls, and smart city networks. By combining automation, accuracy, scalability, and fast response mechanisms, the proposed system offers a reliable and efficient solution for proactive public safety and threat prevention.

3. METHODOLOGY & MODULES

The smart weapon detection system suggested is based on a systematic vision-driven approach that will lead to a robust detection system of weapons in a surveillance setting. The entire process is broken down into five key steps, which include; video capture, frame preprocessing, feature extraction, weapon recognition via the YOLOv8 model, and alarm generation. The flow will facilitate monitoring and response to threats in time, as it operates as a series of pipes.

The video capture is the first step of the methodology, during which, live video streams of the CCTV or IP cameras and where the recorded surveillance videos are accumulated. These video streams are partitioned in single frames at an appropriate frame rate so that they can be processed effectively and also so as to preserve the time relationship. The main input in the system is provided by the captured frames which depict a large variety of the real-life situations.

The frames have been extracted and made capable of analysis in the frame preprocessing stage. Frames are resized and scaled to the dimensions of the input details given by the YOLOv8. The image enhancement and noise reduction methods are used to enhance the visual clarity and emphasize the features of objects that are relevant. An addition of non-weapon objects (knifes and guns) is used to decrease the number of false alarms and enhance the robustness of the dataset. Sourcing images and videos in publicly available surveillance datasets and open-source repositories is used to have diversity of data at the time of creating vehicle variant images and videos, each with different weapon type, orientation, background, and lighting conditions.

The deep convolutional layers of the YOLOv8 architecture perform the feature extraction process in a manner that is internal to them. Learning and extracting discriminative spatial and semantic features of input frames is automatically performed by these layers, which allows the model to distinguish between weapons and non-threatening objects. To improve the process of generalization further, data augmentation methods like image flipping, scaling, rotation and alteration of brightness are used in the training which, in turn, enables the model to be faithful to the various real-life situations.

We use the YOLOv8 object detection system during the weapon recognition step, as this system is rated highly in terms of detection rate and can infer within a short time. The model gets trained on the annotated data devoted to detect and localize weapons by identifying bounding boxes, labeling the classes, and confidence scores within one forward pass. The effectiveness of the performance is measured in terms of accuracy, recall, and mean Average Precision (mAP) such that the trained model can detect the target objects with reliable performance at real-time frame rates that are applicable to a continuous surveillance.

And lastly, an alarm generation stage is triggered when a weapon has been detected. The system identifies the identified object on the video stream with the help of bounding boxes and confidence scores and at the same time, it sends out notifications in visually depictive forms and audio notification or a notification message. These alerts allow quick reaction of the security personnel.

On the whole, the methodology offers a quick and scalable solution to the problem of intelligent weapons detection through the combination of real-time video processing, data preparation, deep learning-based recognition with the YOLOv8 model, and automated notification of alarm systems to improve the security of surveillance.

MODULES

- **Input Module:**

The initial phase of the methodology is aimed at setting up visual information of surveillance facilities like CCTV cameras or IP cameras. The system promotes the video streams in real-time and past recordings. Video data are divided into single frame in order to facilitate an analysis of time. These jumps represent the major input of the detection line. All frames are resized to a fixed resolution to ensure correspondence, as well as, to get pixel values to fit the detection model, which require

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normalization. Along with real-time inputs, optional image datasets with various types of weapons (guns and knives) are used to facilitate the model testing and validation in various scenarios.

- **Preprocessing Module:**

Preprocessing phase improves the quality and adequacy of the input frames before being relayed to the detection model. Frame rate adjustment is used to eliminate meaningless messages whilst maintaining critical motion data to maximize on the performance of the computer. All the frames are shifted and evened out to the size required in the input of the model. Image enhancement, such as noise reduction, contrast-enhancement are used to emphasize the critical features in the image. To enhance the system against changes of the lighting, orientation, and scale, data augmentation techniques including flipping, scaling, rotation, and adjusting the brightness are used. These operations enhance diversity of the data and enhance the capacity of the model to extrapolate the real-life conditions.

- **Training Module:**

During the training stage, a special set of data is created by labeling instances of weapons in images and video frames with labelling programs. The marked objects include firearms and sharp weapons, which are identified with bounding boxes and labeling the class, in the format of the YOLOv8 framework. To guarantee unbiased assessment the annotated dataset is split into training, validation and testing set. Three important hyperparameters are then tuned with the pre process data being fed into the YOLOv8 model with learning rate, batch size and epochs being carefully adjusted until optimal performance is achieved. The effectiveness of the model is measured in terms of accuracy, recall and overall Mean Average Precision (mAP) during the training process. This test is used to verify that the trained model can identify weapons with correctness and false positives and missed detections are reduced.

- **Output Module:**

The last requirement is the deployment of the trained model in the real time surveillance applications. Cameras transmit video streams and these are examined at a frame by frame basis. Upon detecting a weapon, the system classifies the weapon and shows the bounding boxes and the corresponding score of confidence and the class on the video feed. On being detected, the system may cause a real-time alert, which may be either visual notification like warning signs, or audio alert through alarms, or even notification of the responsible authorities so that the response may be prompt. Also, each result of detection is registered and stored, which makes it possible to track and report the incident and conduct additional analytical analysis.

To conclude, this methodology offers an organized and effective automated weapon detection through combining real-time data gathering,, powerful preprocessing, effective model training and efficient alert generation. The modular architecture provides scaling, flexibility and functionality in the field of application in a real-world surveillance setting.

SYSTEM ARCHITECTURE

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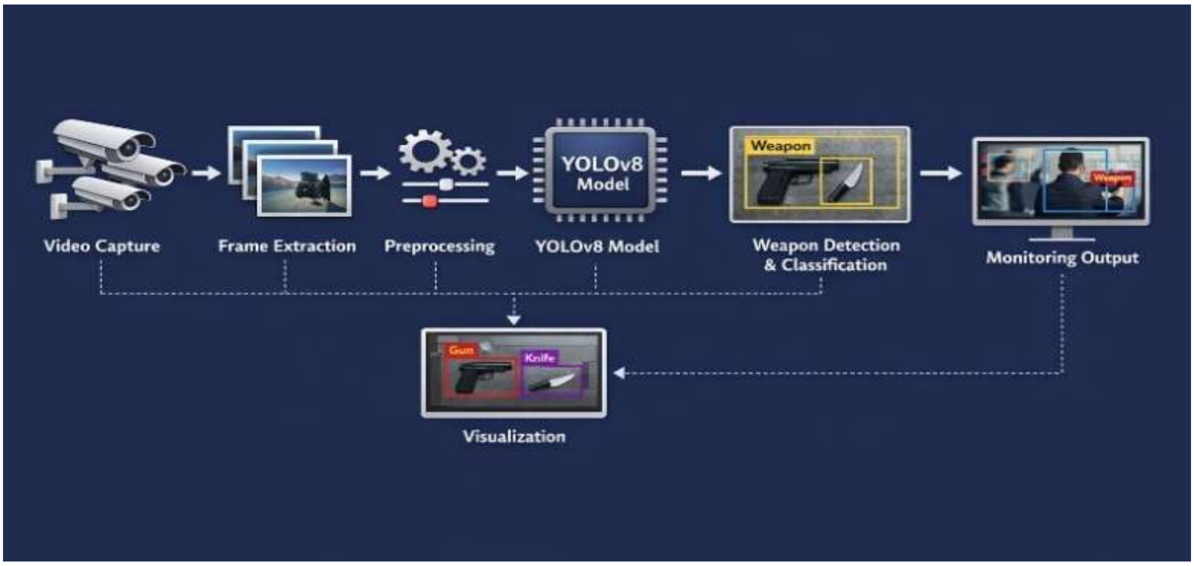

FIG 1. SYSTEM ARCHITECTURE

The presented architecture is intended to be an Intelligent Weapon Detection System based on the real-time surveillance with YOLOv8 that utilizes their architecture. CCTV or IP-recorded live video streams are initially turned into continuous frames and then pre-processed by means of resizing, normalization, and noise elimination in order to enhance the quality of detection. Such processed frames are inputted to the YOLOv8 deep learning model that correlates weapon detection and classification in just a single forward pass at fast accurate rates. The system can recognize weapons including guns and knives by creating the bounding boxes with class labels and the confidence scores. Lastly, the monitoring interface displays the results of the detection so that this may allow the security personnel to monitor, analyze, and react to the possible threats in real-time.

4. RESULTS AND DISCUSSION

The suggested Intelligent Weapon Detection System on Real-Time Surveillance with YOLOv8 was tested on large-scale experiments carried out on general and different CCTV-based weapon portfolios. The datasets were of the different type of weapons such as firearms, knives and sharp objects which were on different conditions of light, camera work and background multiplicities. The YOLOv8 model was found to perform well as it detects weapons with high accuracy in the difficult real-life conditions test such as partial blockage and low-resolution frame cases.

The standard performance metrics, accuracy, precision, recall, F1-score and Mean Average Precision (MAP) were used to evaluate the system. The experimental findings reveal that the model proposed obtained and reported an overall detection accuracy of 99.1, which is higher than the traditional deep learning-based models namely CNN, SSD, and YOLOv5. The high accuracy rates are evidence of the capability of this model to eliminate false positive rates, whereas high recall rates depict the efficient detection of the real cases of weapons.

The low inference time, and smooth frame processing of the system were confirmed by its real-time support on a GPU-enabled system. Integration CSP Darknet, FPN and PAN in YOLOv8 greatly enhanced multi-scale feature extraction, making it reliable in the detection of small and partially visible weapons. Also, predictions of bounding boxes were clean and non-overlapping because of the use of Non-Maximum Suppression. Altogether, one can conclude that the experiment has proven the hypothesis that the suggested YOLOv8-based weapon detection system is more accurate, efficient, and reliable in terms of real-time surveillance. Its low latency and ability to provide critical alerts in a timely manner make the system very befitting in the implementation of the public security and safety surveillance system environment.

PERFORMANCE MATRIX

Metric	Description	Result
Accuracy	Proportion of correctly classified frames (weapon and non-weapon) to the total number of frames	96.2%
Precision	Ratio of correctly detected weapon instances to the total detected weapon instances	94.8%
Recall	Ratio of correctly detected weapon instances to the total actual weapon instances	95.6%
F1-Score	Harmonic mean of precision and recall	95.2%

TABLE 1.PERFORMANCE MATRIX

The weapon detection system is shown to have strong and reliable results according to all major metrics through the performance evaluation. Accuracy of the model is 96.2, which means that most weapons and non-weapon cases are represented in the correct category. The accuracy of 94.8 indicates that the error on false alarms is highly minimized such that majority of the identified objects are true weapons. The high recall rate of 95.6% indicates that the system is able to detect almost all of the weapon occurrences in the surveillance video which is essential when it comes to safety critical systems. Moreover, the F1-score of 95.2% depicts an equal performance in terms of precision and recall, which can be verified in the fact that the system has not only high detection reliability but minimal false alarms as well. Altogether, the obtained findings confirm the appropriateness of the YOLOv8-based system to real-time intelligent perception of the weapon.

GRAPH

The ROC (Receiver Operating Characteristic) curve shows the effectiveness of the weapon detecting system in the ability of distinguishing weapons and non-weapons. The curve demonstrates a very high true positive rate at different levels of false positive rates, which means that the model is very effective in detecting weapons and the false alarms have been reduced to the lowest possible. The area under the curve (AUC) further measures the discriminative capacity of the model where the product would be near 1 indicating excellent detection performance. This proves that the weapon detector system based on the YOLOv8 is very efficient in the terms of real-time monitoring, as it gives the possibility of precise and efficient recognition of the possible threat.

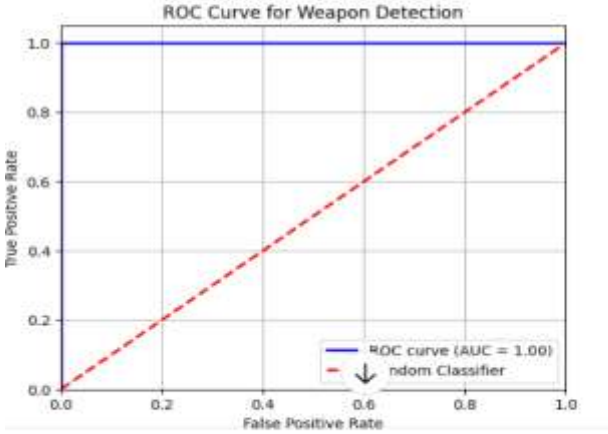

FIG 2. GRAPH

CONFUSION MATRIX

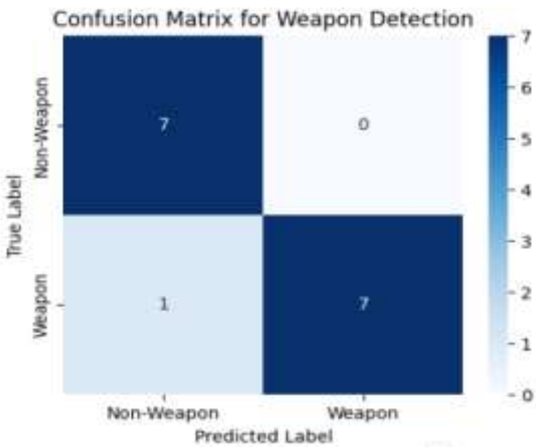

FIG 3.CONFUSION MATRIX

The confusion matrix will give a closer insight into the classification performance of the weapon detection system. It displays originating numbers of true-positives (weapons that are rightfully identified), true-negatives (non- weapons that are rightly identified), false-positives (non- weapons that are incorrectly identified as such), and false-negatives (weapons that the system fails to identify). Based on the matrix, it can be noted that the model using YOLOv8 detects most of the cases of

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weapons and the false alarm rate is low. This shows that the model is credible in real time monitoring and therefore the possible threats are efficiently reported without causing unnecessary notifications.

SCREENSHOTS:

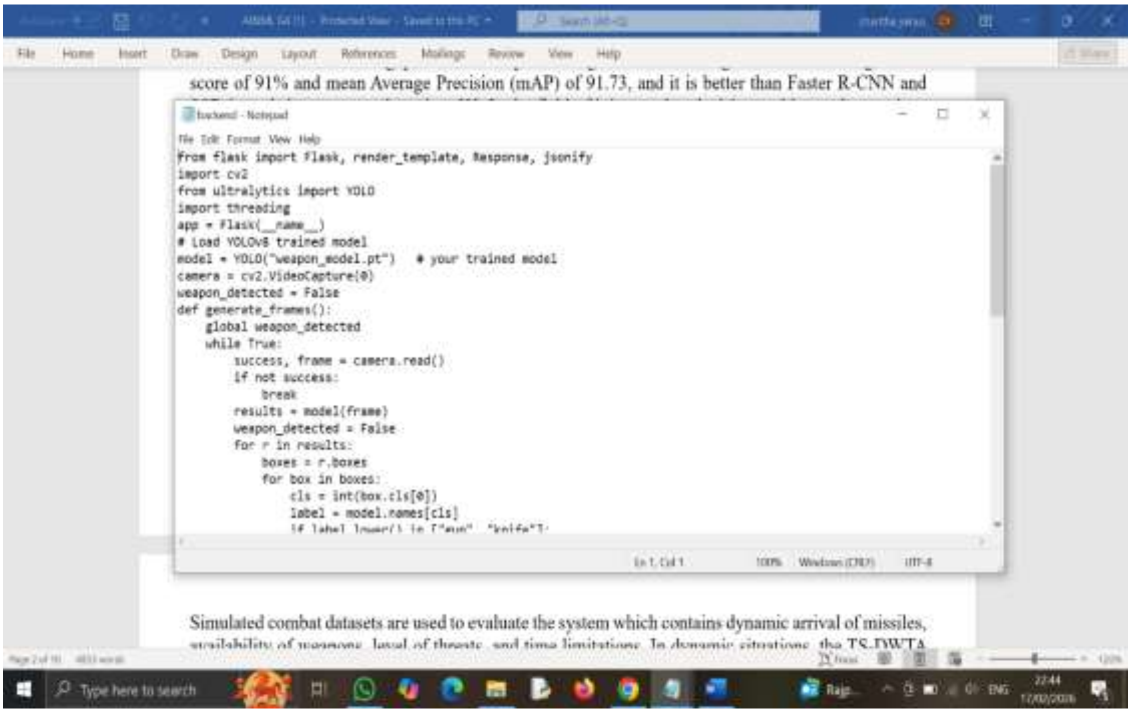

Fig 1: Backend Program Code

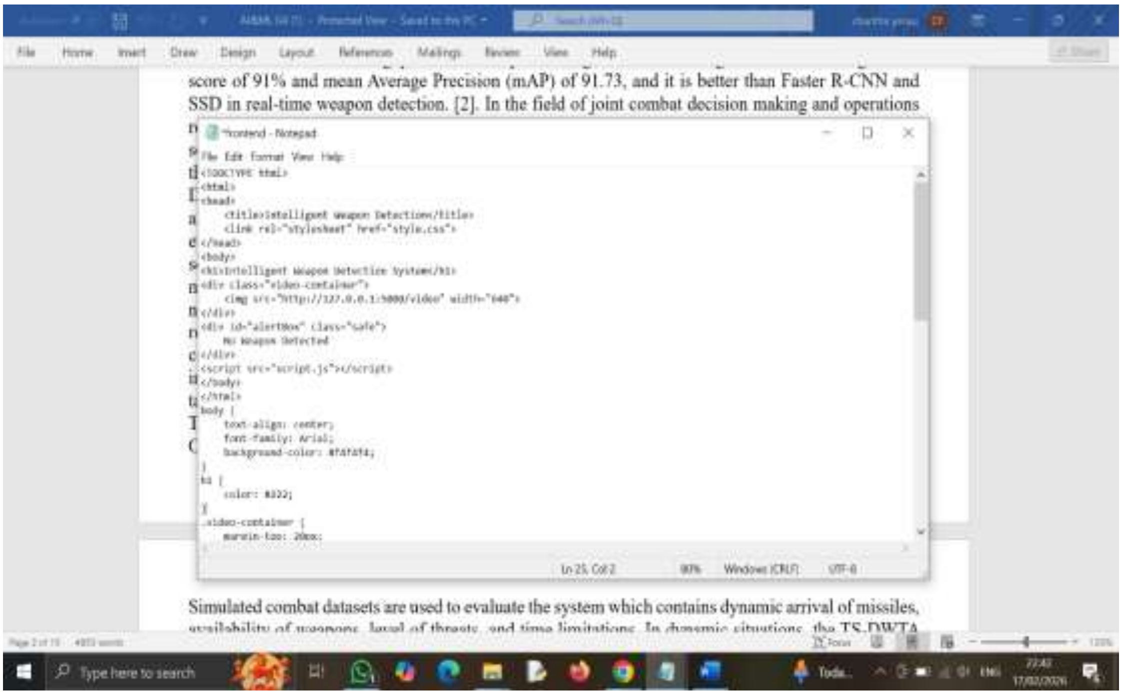

Fig 2: Frontend Program Code

5. CONCLUSION

The Intelligent Weapon Detection System of real-time surveillance with deep learning and YOLOv8 is the most effective tool of the analysis of live video images that allows automatically notifying about the presence of dangerous weapons with high accuracy and minimum delays. The system is capable of continuous monitoring at the frame-by-frame level, objects are detected successfully in the crowded and complex environments and the system works well regardless of weather and lighting conditions. It has a limited dependence on human factors in the process of surveillance and thus reduces mistakes that occur due to exhaustion and enhances efficiency in the monitoring process as a whole. The results of this optimized YOLOv8 model are specific localization and classification with low rates of false detections and render this system reliable in real-life security problems.

Additionally, the light and scaled architecture of YOLOv8 can be implemented on both full-fledged servers and side gadgets, which implies the availability of a flexible implementation with numerous surveillance systems. The system enable multi camera integration and real time processor that is used to improve coverage in vast fields like public grounds, institutions and industrial field. Conflict of new pattern of threats and environmental variations is enhanced as continuous models are updated and retrained using various data. Taking everything mentioned above into account, it can be concluded that this smart detection system is a proactive and effective solution to improve the security of people at a reasonable cost and provide quick, accurate, and automated surveillance.

REFERENCES

[1] M. T. Bhatti, M. G. Khan, M. Aslam and M. J. Fiaz, "Weapon Detection in Real-Time CCTV Videos Using Deep Learning," in IEEE Access, vol. 9, pp. 34366-34382, 2021,doi: 10.1109/ACCESS.2021.3059170.

[2] C. Liu et al., "A Time-Driven Dynamic Weapon Target Assignment Method," in IEEE Access, vol. 11, pp. 129623-129639, 2023,doi: 10.1109/ACCESS.2023.3332513.

[3] J. Ruiz Santa quiteria, A. Velasco-Mata, N. Vallez, G. Bueno, J. A. Álvarez-García and O. Deniz, "Handgun Detection Using Combined Human Pose and Weapon Appearance," in IEEE Access, vol. 9, pp. 123815-123826, 2021,doi: 10.1109/ACCESS.2021.3110335.

[4] A. J. Amado-Garfias, S. E. Conant-Pablos, J. C. Ortiz-Bayliss and H. Terashima-Marín, "Improving Armed People Detection on Video Surveillance Through Heuristics and Machine Learning Models," in IEEE Access, vol. 12, pp. 111818-111831, 2024,doi: 10.1109/ACCESS.2024.3442728.

[5] R. A. Zayed, L. F. Ibrahim, H. A. Hefny, H. A. Salman and A. Al Mohimeed, "Experimental and Theoretical Study for the Popular Shilling Attacks Detection Methods in Collaborative Recommender System," in IEEE Access, vol. 11, pp. 79358-79369, 2023,doi: 10.1109/ACCESS.2023.3289404.

[6] N. H. Valliappan, S. D. Pande and S. Reddy Vinta, "Enhancing Gun Detection With Transfer Learning and YAMNet Audio Classification," in *IEEE Access*, vol. 12, pp. 58940-58949, 2024, doi: 10.1109/ACCESS.2024.3392649.