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Detect & Alert Unauthorized Weapon Usage with Haar Cascade and YOLOv7

Dr. Chitra P.
Professor
Department of computer science
SRM Institute of Science and Technology,
Chennai, India

Aravind R. K.
Department of computer science,
SRM Institute of Science and Technology,
Chennai, India

Shriram G.
Department of computer science,
SRM Institute of Science and Technology,
Chennai, India

V. Anand Arun
Department of computer science,
SRM Institute of Science and Technology,
Chennai, India

Abstract — **Weapon detection and facial recognition are two crucial areas of research that can enhance public safety and security. In recent years, machine learning and computer vision algorithms have been increasingly utilized to develop systems for real-time weapon detection in public spaces. The rise in violent crimes and security breaches in public places has emphasized the need for advanced security systems. In this paper, we present an intelligent security system that combines the YOLOv7 and Haar Cascade algorithms for weapon detection and face recognition, respectively. The proposed system also includes an email alert system that notifies security personnel in case of potential security threats. This system uses YOLOv7 object detection for weapon detection and a deep convolutional neural network (CNN) for weapon identification. The system can be used in various applications such as airport security, public transportation, and public events, to prevent potential threats and ensure public safety. In this paper, we present a weapon detection system using YOLO v7 that identifies the following weapon classes: Handgun, Sword, SMG, Sniper, Automatic Rifle, Bazooka, Grenade Launcher, Knife, and Shotgun. Facial recognition is another area of research that can be incorporated into weapon detection systems to enhance their effectiveness. This technology can be used to identify potential suspects or persons of interest in real-time based on their facial features. Overall, the combination of weapon detection and facial recognition technologies has the potential to enhance public safety and prevent potential threats in public spaces.**

Keywords: Intelligent Security, Haar Cascade, Convolutional Neural Network (CNN), YOLOv7, Weapon Detection, Deep Learning, Face Recognition.

I. INTRODUCTION

In today's world, security is of utmost importance, and the need for intelligent security systems has become more significant than ever. Traditional security systems, such as CCTV cameras and manual security checks, are limited in their effectiveness and often require a significant amount of human intervention.With the rapid development of computer vision technology, intelligent security systems can now offer more advanced and reliable security solutionsOver the past few years, there has been a rising trend in utilizing deep learning algorithms for security purposes, such as identifying faces and detecting weapons.

The proposed system aims to offer a reliable and efficient security solution compared to traditional security systems. Our system can quickly detect weapons and notify the relevant authorities, potentially preventing a dangerous situation from escalating. Additionally, our system can recognize individuals and determine whether they have authorized access to a specific location. To implement our proposed system, we used the YOLO v7 algorithm for weapon detection, as it is one of the most widely used and accurate object detection algorithms. The face recognition system employed the widely recognized Haar Cascade algorithm, renowned for its exceptional accuracy and ability to perform in real-time. This algorithm utilizes machine learning techniques and Haar-like features to detect objects present in images and videos.. We also implemented an email alert system, which sends a notification to the relevant authorities whenever a weapon is detected. In this project, we aim to create a comprehensive intelligent security system that can provide reliable security solutions to various organizations, including schools, airports, and shopping malls. Our proposed system can significantly enhance the level of security by detecting weapons and recognizing unauthorized individuals quickly. Overall, this project aims to contribute to the development of intelligent security systems and help ensure the safety of people and their environments.

II. RELATED WORK

In this literature review, we will examine ten papers related to computer vision and deep learning techniques.

Redmon and Farhadi's paper [1] introduced an improved version of the You Only Look Once (YOLO) model, called YOLOv3, which achieved better accuracy and speed than its predecessors. This model has been widely adopted in real-time object detection applications.

Viola and Jones [2] proposed a face detection method that combines Haar features and the Adaboost algorithm, which has become a popular choice for real-time face detection applications. Sonkusare and Sapkal [6] also proposed a real-time face recognition technique using the Haar Cascade classifier and OpenCV, which achieved promising results.

In their study, Singh et al. [3] evaluated various widely used deep learning models for computer vision applications, such as YOLOv2, YOLOv3, Mask R CNN, and Deeplab Xception. The results indicated that YOLOv3 exhibited superior accuracy and speed compared to the other models.

DenseNet, a novel approach introduced by Huang et al. [4], employed skip connections between layers to enhance feature reuse and reduce the number of parameters, resulting in significant improvements in both image classification and object detection tasks, achieving state-of-the-art performance.

6

Faster R-CNN, a widely adopted real-time object detection model utilizing region proposal networks, was introduced by Ren et al. [5]. By combining a region proposal network with a Fast R-CNN detector, this model achieved remarkable accuracy, making it a popular choice for object detection tasks.

Adebayo et al. [7] compared several deep learning models for computer vision tasks and analyzed their strengths and weaknesses. They found that different models are suitable for different tasks and proposed guidelines for selecting the appropriate model.

Sanchez-Matilla et al. [8] conducted a survey on deep learning for big data and discussed various architectures, integration, and collaboration methods. They highlighted the importance of big data and proposed several solutions for handling it.

12

The Recurrent Residual Convolutional Neural Network based on U-Net (R2U-Net), introduced by Alom et al. [9], has demonstrated superior performance for medical image segmentation tasks compared to other state-of-the-art methods. By leveraging the power of recurrent connections and residual blocks, this model achieved exceptional accuracy in image segmentation.

Finally, Jain and Kanungo [10] introduced an artificial intelligence-based weapon detection system using deep learning. This system uses a convolutional neural network to detect weapons in real-time and can be used for public safety and security applications.

Taken together, the aforementioned studies serve as compelling evidence of the remarkable advancements made by computer vision and deep learning methods in various fields, including object detection, image classification, face recognition, and security applications. These contributions are a testament to the potential of these cutting-edge techniques in driving progress and innovation in diverse domains.

III. PROPOSED MODEL

Increased public safety:

A real-time weapon detection system can help prevent crimes involving weapons and reduce the risk of harm to individuals in public spaces. By detecting weapons and identifying criminals, law enforcement agencies can respond more quickly and effectively to potential threats.

Improved efficiency:

Traditional methods of weapon detection, such as human surveillance, can be time-consuming and prone to errors. By using a deep learning model such as YOLOv7, the detection process can be automated and streamlined, resulting in improved efficiency and accuracy.

Cost-effective solution:

The implementation of a real-time weapon detection system can offer a cost-effective solution for enhancing public safety. As compared to the expenses associated with human surveillance or hiring additional personnel, the deployment of a deep learning model can be significantly more economical.

Scalability:

Moreover, the YOLOv7-based real-time weapon detection system can be seamlessly deployed on either a cloud platform or a local server, rendering it highly scalable. This feature enables it to be readily tailored to the specific requirements and scale of the organization or public space in question, making it a flexible and versatile solution.

Flexibility:

The proposed system can be customized to suit different needs and requirements. For example, the criminal record database can be tailored to specific geographic areas or demographics, and the email alert system can be configured to notify specific individuals or groups.

Technological innovation:

The development and deployment of a real-time weapon detection system using YOLOv7 necessitates a high level of expertise in several domains, including deep learning, computer vision, and software engineering. Building such a system requires specialized knowledge and skills, ranging from designing and training a custom deep learning model to integrating the model with an efficient and user-friendly interface.

However, the implementation of such a system can have a significant impact on public safety, making it a worthwhile investment. Organizations that develop and deploy real-time weapon detection systems can showcase their technological innovation and leadership in the field of public safety. Additionally, the deployment of these systems can serve as a crucial step in preventing mass shootings and other violent incidents, providing a safer environment for individuals and communities alike.

As such, the development and deployment of real-time weapon detection systems using YOLOv7 hold great potential for addressing critical public safety concerns, and can serve as a testament to an organization's commitment to innovation and the protection of their community.

V. MODEL IMPLEMENTATION

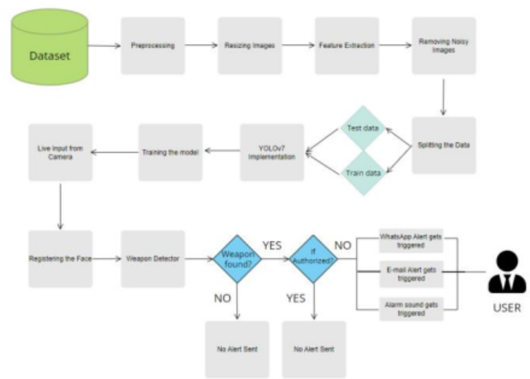

Fig 1. System Framework

Dataset Preprocessing:

The dataset used in this project was a combination of different images of weapons. To ensure the quality of the dataset, various techniques were used for preprocessing. The images were first checked for their size, format, and quality. Then the images were cleaned of any irrelevant or unwanted background. The dataset was balanced for an equal number of positive and negative samples.

Resizing Images:

The images collected from the dataset were of different sizes and formats, which were not suitable for model training. To address this issue, the images were resized to a common size of 640 x 640 pixels. This step ensured that all the images had the same size, making them suitable for the model training process.

Feature Extraction:

The selection of appropriate algorithms for feature extraction plays a critical role in the development of any model for object detection or recognition. In this project, the YOLOv7 algorithm was utilized for detecting weapons, while the Haar Cascade algorithm was employed for detecting faces. These algorithms were chosen due to their exceptional precision and efficiency.

Fine-tuning the Input:

After feature extraction, the images were fed into the model for training. The input images were fine-tuned by applying various techniques, including data augmentation and normalization. Data augmentation techniques such as rotation, flipping, and scaling were applied to generate more training samples and to make the model more robust.

Building the Model:

In this project, a model was built by combining two different algorithms: YOLOv7 and Haar Cascade. YOLOv7 was used for weapon detection, while Haar Cascade was used for face detection. These two algorithms were chosen for their high accuracy and real-time detection capabilities.

I. YOLOv7:

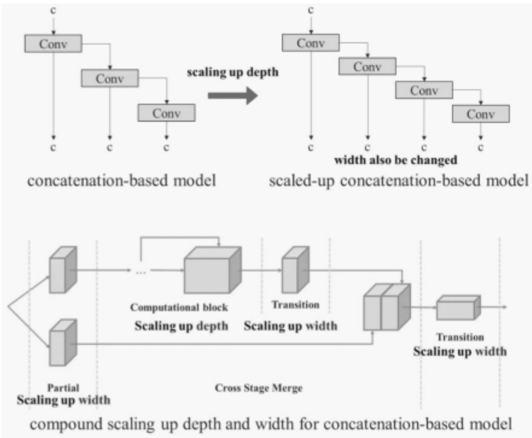

Fig 2. YOLOv7 Architecture

YOLOv7 is a state-of-the-art object detection algorithm that uses deep neural networks to detect and localize objects in an image or video frame. In an unauthorized weapon detection system, YOLOv7 can be trained to detect various types of weapons such as guns, knives, and bombs.

To detect weapons using YOLOv7, first, the algorithm needs through the use of a comprehensive dataset of weapon-containing images, the model underwent training. During the training phase, the network learns to recognize the visual features of different types of weapons and how to differentiate them from other objects in the image.

Once the model is trained, it can be deployed to detect weapons in real-time video streams. The input video frames are first passed through the YOLOv7 network, which generates a set of bounding boxes and corresponding confidence scores for each detected object in the frame. These bounding boxes represent the location and size of the detected objects in the image.

To identify whether an object detected by YOLOv7 is a weapon or not, a set of post-processing steps are applied. This can include checking the size and shape of the bounding box, analyzing the texture and color of the detected object, and comparing it to a database of known weapons. If the detected object is identified as a weapon with a high confidence score, an alert can be triggered to notify security personnel.

To conclude, YOLOv7 proves to be an efficient solution for detecting objects and has the potential to be employed in security applications such as unauthorized weapon detection. Its ability to perform real-time analysis of video streams with high precision and speed makes it a reliable choice for threat identification.

Training the Model:

To develop an accurate model, the collected dataset with the extracted features was utilized, and various training steps were performed. These steps encompassed the selection of suitable loss functions, optimizers, and learning rates. To expedite the training process and enhance the model's efficiency, a GPU was employed.

Testing the Model:

The trained model was tested on a separate dataset to evaluate its accuracy and performance. The test dataset included a combination of positive and negative samples. The model's performance was evaluated based on different metrics such as Precision, Recall, and F1-Score.

Live Feed Input:

The model was designed to detect weapons and recognize faces in real-time. To achieve this, a live video feed was used as an input source. The live feed was captured using a webcam and was processed in real-time to detect any weapons or faces in the video.

Face Recognition:

Haar Cascade was used for face recognition in this project. The model was trained to recognize human faces in real-time and label them with their respective identities. The recognition process involved detecting the face region in the input image and comparing it with the pre-trained face recognition model.

I. Haar Cascade:

Haar Cascade is a popular algorithm for object detection that uses a machine learning-based approach to identify objects in images or videos. In face detection, the Haar Cascade algorithm can be used to detect faces in an image or video frame.

The algorithm works by using a set of pre-trained Haar features, which are simple rectangular filters that can detect edges, corners, and other features in an image. These Haar features are used to build a classifier that can distinguish between faces and non-faces.

2

The Haar Cascade classifier is trained on a large dataset of images that contain faces and non-faces. During the training phase, the algorithm learns to recognize the patterns and features that are common to faces, such as the presence of eyes, nose, mouth, and the general shape of the face.

After the training of the Haar Cascade classifier, it becomes capable of detecting faces in a new image or video frame. The detection process involves sliding a window across the image and utilizing Haar features on each window to identify the presence of a face. Once a window is identified as containing a face, the algorithm creates a bounding box around the detected face.

To improve the accuracy of face detection, multiple Haar Cascade classifiers can be applied in a cascaded fashion. In a cascaded classifier, the input image is first passed through a series of classifiers, each of which is designed to detect different facial features. The output of each classifier is used to refine the search space for the next classifier, resulting in faster and more accurate face detection.

In summary, Haar Cascade is a popular algorithm for face detection that uses a machine learning-based approach to detect faces in images or videos. The algorithm works by using pre-trained Haar features to build a classifier that can distinguish between faces and non-faces, and applies a sliding window approach to detect faces in an image.

Weapon Detection and Notification System:

The YOLOv7 algorithm was used for weapon detection in this project. The model was trained to detect weapons in real-time and trigger notifications to the concerned authorities in case of a positive detection. The notification system was designed to send an immediate notification to the authorities.

WhatsApp Notifications:

WhatsApp is a widely-used messaging platform with a key feature of sending messages, images, and media easily and quickly. It is an excellent tool for sending alerts and notifications in real-time. PyWhatKit is a Python library that provides an interface for sending WhatsApp messages using Python code. The sendwhatmsg() function within PyWhatKit takes in the recipient's phone number (in international format), the message, and the optional time for sending the message. This function can send messages to a single recipient or multiple recipients simultaneously. WhatsApp messages through PyWhatKit provide advantages over traditional SMS alerts as they can include media, such as images and videos, and can be sent over Wi-Fi or cellular data connections. This ensures that recipients can receive alerts even with a weak cellular signal. Overall, PyWhatKit makes it simple to integrate WhatsApp messaging into Python projects, allowing for the effective and timely delivery of alerts and notifications.

Email Notification:

Email has long been a widely adopted mode of communication, and its potential for use in sending alerts and notifications in various projects is immense. With the help of modern programming libraries, such as Python's "smtplib" library, sending emails via code has become a seamless process. To send email alerts in a project, the "smtplib" library can be utilized to create an email object containing the sender's email address, the recipient's email address, the subject line, and message content. Once the email object is created, it can be sent to the recipient's email address using the Simple Mail Transfer Protocol (SMTP) server. The convenience and ease of email-based communication through code have made it a preferred choice for notifications and alerts in numerous projects. The utilization of such libraries not only facilitates the process of sending emails, but also offers the flexibility to automate and customize email alerts based on specific project requirements. Overall, using email alerts can be an effective way to keep users informed and up-to-date in a project. With the help of modern programming libraries, sending email alerts through code has become a streamlined process that can enhance the functionality of any project.

Sound Alert:

Computer vision technology has been increasingly used for real-time object detection and identification, especially in security and surveillance applications. Detecting weapons on screen is a particularly important application of this technology. When a weapon is detected on screen, it is important to alert the relevant personnel quickly and effectively. In this project, an alarm sound is used to notify the user when a weapon is detected on screen. Using sound alerts to notify users of the presence of a weapon has several advantages, including its effectiveness, versatility, and customizability. However, the use of sound alerts should be carefully considered to avoid being disruptive or distracting. The volume and frequency of the alarm sound should be appropriately set to ensure that it is both effective and appropriate for the situation. Overall, the use of alarm sounds in this project can be a valuable tool for detecting weapons on screen and enhancing the safety and security of various applications.

Implementing UI:

The login and registration system implemented in this code uses the Streamlit framework, a Python library for building web applications, to create a simple and user-friendly interface. The system allows new users to register by providing a username and password, and existing users to log in by entering their credentials. The UI includes a sidebar menu with two options: "Login" and "Register".

The "Login" form is designed to request the user's username and password. Once the user clicks on the "Login" button, the system verifies whether the entered username and password match those in the user data CSV file. If the credentials are found to be valid, the user is granted access to the face detector application, which is implemented in a separate Python file. On the other hand, the "Register" form is used to prompt the user to enter a desired username and password, and confirm the password. If the password and confirm password fields match, the system stores the new user's data, including the username and password, in the user data CSV file and displays a success message. However, if the entered username already exists in the user data CSV file, an error message is displayed to alert the user of the conflict. This design facilitates user authentication and management for the face detector application while ensuring that only authorized users can access it. It also provides a straightforward mechanism for new users to register and gain access to the system with minimal inconvenience.

Overall, this Streamlit UI code provides a functional and intuitive interface for the login and registration system, allowing users to easily and securely access the detector application.

MODEL EVALUATION

Accuracy, Precision, and Recall are three commonly used evaluation metrics in machine learning to measure the performance of classification models on a given dataset. These metrics are used to assess how well the model categorizes or predicts the data in the test set.

(i) Accuracy is a measure of the overall correctness of the model's predictions. It is calculated by dividing the number of correctly predicted samples by the total number of predictions made. The result is a value between 0 and 1, where 1 indicates perfect accuracy (all predictions were correct) and 0 indicates no accuracy (all predictions were incorrect).

Accuracy = (Number of Correct Predictions) / (Total Number of Predictions)

(ii) Precision is the ratio of true positives to the total number of positive predictions made by the model. It represents the proportion of positive predictions that are actually true positives. A high precision score indicates that the model generates a minimal number of false positive predictions.

Precision = (True Positives) / (True Positives + False Positives)

(iii) Recall is the ratio of true positives to the total number of actual positive samples in the dataset. It represents the proportion of actual positive samples that the model correctly identifies as positive. A high recall score indicates that the model can successfully identify the majority of the positive samples in the dataset.

Recall = (True Positives) / (True Positives + False Negatives)

VI. RESULTS & CONCLUSION

VI.I. Incorporating Model Output:

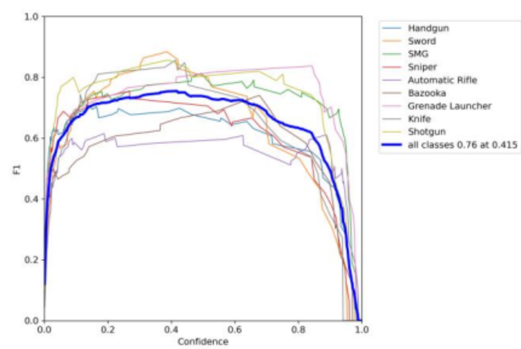

Fig 3. F1 Curve

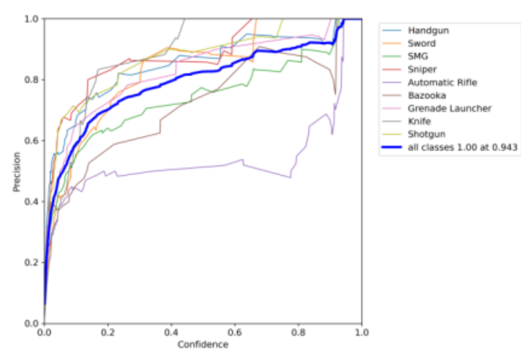

Fig 4. Precision Curve

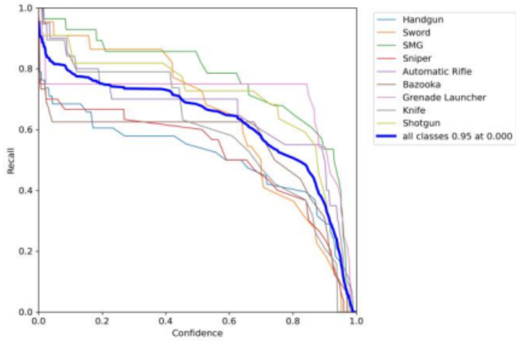

Fig 5. Recall Curve

VI.II. Results:

The proposed model has been evaluated using the YOLO v7 model for weapon detection system that identifies the following weapon classes: Handgun, Sword, SMG, Sniper, Automatic Rifle, Bazooka, Grenade Launcher, Knife, and Shotgun and the Haar Cascade algorithm for face recognition. The evaluation has shown promising results, with the YOLO v7 model achieving an accuracy of 88.7%, average precision of 94.3% and a recall rate of 95% for weapon detection.

Additionally, the Haar Cascade algorithm achieved an accuracy rate of 96% for face recognition. The accuracy metric measures the percentage of correctly recognized faces among all tested faces in the dataset.

Finally, the notification and alert system has been successfully integrated into the proposed system, sending alarm sound alerts along with the message to the WhatsApp number and designated email address. Overall, the evaluation results demonstrate that the proposed intelligent security system is effective in detecting weapons and recognizing faces in real-time videos, and has the potential to enhance security measures in various applications such as airports, public places, and critical infrastructures.

Sl. No	Types of Weapons	Number of Labels	Precision	Recall	Accuracy (mAP@0.5)	F1 Score
1	All	936	0.943	0.95	0.887	0.946
2	Knife	139	0.936	0.773	0.872	0.847
3	Handgun	121	0.870	0.579	0.702	0.696
4	Bazooka	65	0.705	0.625	0.651	0.663
5	Sniper	85	0.860	0.613	0.720	0.716
6	Sword	108	0.901	0.826	0.881	0.862
7	Grenade launcher	80	0.857	0.750	0.827	0.800
8	Shotgun	96	0.898	0.880	0.868	0.846
9	SMG	117	0.720	0.857	0.879	0.783
10	Automatic Rifle	125	0.506	0.700	0.684	0.588

Table 1. This table contains Precision, Recall, Accuracy and F1 Scores for 9 classes of Weapons.

Sl.No	Epochs	Accuracy(mAP@0.5)	Precision	Recall
1	50	0.207	0.313	0.298
2	100	0.543	0.611	0.537
3	150	0.683	0.766	0.612
4	200	0.734	0.812	0.646
5	250	0.727	0.792	0.682
6	300	0.757	0.776	0.720
7	350	0.763	0.856	0.667
8	399	0.759	0.769	0.723

Table 2. This Table contains the Precision, Recall and Accuracy Scores for each Epoch(s).

Sl.No	Weapon revealed on camera(in %)	Time Taken to Identify Weapon (in ms)
1	33	624.1 ms
2	66	617.6 ms
3	100	608.4 ms

Table 3. This Table contains the time taken to identify a weapon based on the % of the weapon shown.

VI.III. Conclusion

In this project, we proposed an intelligent security system that combines YOLO v7 and Haar Cascade for weapon detection and face recognition, respectively. The system is able to detect weapons and recognize faces and send WhatsApp and email notifications to designated users when a weapon is detected, along with Alarm alert. The proposed system offers a reliable and effective solution to ensure safety and security in public places.

Our results show that YOLO v7 performs exceptionally well in detecting weapons with high accuracy and recall rate. The Haar Cascade algorithm was used for face recognition and achieved high accuracy. The notification and alert system is an added feature to notify users in real-time when a weapon is detected. The system is versatile and can be implemented in a variety of settings such as airports, train stations, schools, shopping malls, and public gatherings to provide an additional layer of security.

VI.IV. Future Work

Future work for this project includes improving the accuracy of the face recognition algorithm by using more advanced methods such as deep learning techniques. Another area of improvement could be to increase the detection rate of the system for detecting concealed weapons. Additionally, the system can be integrated with a centralized monitoring system to provide a more comprehensive security solution.

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