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WEAPON DETECTION SYSTEM

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ABSTRACT
This project aims to develop a real-time weapon detection system using CCTV video to enhance public safety by detecting threats early and reducing the requirement for human monitoring. The technology will accurately detect and classify weapons in live video feeds by employing advanced deep learning algorithms, ensuring an early response to any threats. This technology will be integrated with the existing security framework to enhance overall safety protocols and speed up surveillance activities .To achieve high accuracy and low latency in weapon identification, the system will utilize advanced deep learning models, like convolutional neural networks and object recognition frameworks like YOLO or SSD. This approach fosters a more efficient and reactive security environment apart from solving the problems of the current security situation.

Keywords: Gun Detection, Deep Learning, Object Detection, Artificial Intelligence.

I.INTRODUCTION
Public safety has been a pressing matter in the fast-changing world today, particularly in highlypopulated metropolises. Embracing advanced technologies will be required in order to Proactively identify and minimize risk chances, which are on the rise with firearm-related incidents.Response time and fatigue are some of the significant disadvantages of conventional surveillance technologies which are greatly based on human observation. The deep learning-based real-time identifications of weapons hold great promise as a potential solution to this. Using artificial intelligence with the lowest amount of human intervention, these systems automatically scan live CCTV data and detect weapons such as knives and firearms. Deep learning-based weapon detection systems can significantly accelerate reaction times, reduce false alarm rates and enhance public safety by immediately alerting users when a threat is detected. This approach provides a proactive means of preventing violent events from occurring in the first place, which is a significant advancement in security technology.

1.1 GUN DETECTION

A critical innovation in real-time surveillance systems is gun detection which instantaneously detects weapons in video streams and enhances the safety of people. Thesealgorithms will be able to clearly determine the presence of weapons within live CCTV streams by implementing deep learning algorithms. Object identification models like YOLO or Faster R-CNN are used such that the system can identify weapons in various settings and viewpoints, even the most challenging settings such as dark areas or places with a large number of people.The technology alerts the security personnel as soon as it detects a gun and provides them with enough time to respond to the danger. With advanced tracking and identification algorithms, this system reduces human operation needs and false positives while ensuring timely response in dangerous situations. In dangerous areas, therefore, gun detection equipment is vital to preventing bloodshed and ensuring public safety.

1.2DEEPLEARNING

Artificial intelligence (AI) entails deep learning, a process of data and generates patterns for decision-making by simulating the functions of the human brain. It makes use of multi-layered neural networks, which enable computers to process and learn from enormous volumes of data. Deep learning is particularly good at difficult tasks like audio analysis, natural language processing, and picture identification. Deep learning is powerful because it can automatically extract characteristics from unprocessed data without the need for human interaction. Deep learning models offer better accuracy and performance in many applications such as object recognition, self-driving cars, and medical diagnostics, by learning from patterns and improved upon that. Deep learning has emerged as one of the most powerful techniques for solving complex problems in many different industries given the continued increases in computing power and large datasets.

1.3 OBJECTDETECTION

A computer vision technique called object detection makes it possible to identify and locate particular objectswithin a given image or video frame. Object detection differs from basic image classification since, apart from classifying an image, it also gives the exact location of objects through bounding boxes. This technology is crucial for several applications, including augmented reality, surveillance systems, and driverless cars. Because of their superior accuracy and real-time image processing capabilities, YOLO (You Only Look Once) and Faster R-CNN are two of the more well-liked deep learning models in object recognition. +Systems for object detection are crucial for activities requiring the capability of visual perception and situational awareness because they can detect all the objects in a scene, monitor all the movements, report all anomalies, and make decisions accordingly.

1.4ARTIFICIALINTELLIGENCE

The objective of the area of artificial intelligence under computer science involves creating machines that are able to perform tasks that, normally, are characteristic of human intelligence. They are those tasks such as learning, thinking, problem-solving, and understanding natural language. AI systems imitate human thought using data and algorithms in an attempt to find patterns, make decisions, and adapt to new situations.Among the branches of artificial intelligence that support a wide range of applications are robotics, machine learning, deep learning,

nd natural language processing.Artificial Intelligence (AI) is transforming several sectors through process automation, enhanced productivity, and data analysis to provide novel insights. Examples of these industries include autonomous cars, medical diagnostics, and virtual assistants like Siri and Alexa. AI's ability to comprehend and interact with the environment will have a greater and bigger impact on how we live and work as it develops.

II. LITERATUREREVIEW

According to Jesus Salido et al., this method The implementation of preventive measures against shootings and acts of terrorism in public areas with highpedestrian trafficsimportant.Despitethewidespread use of security cameras, automatic detection techniques are still necessary for the round- the-clock monitoring and quick reaction times. In order to automatically identify pistols in security camera footage, this article provides three convolutional neural network (CNN) models as the basis for the study. By integrating posture data related to the pistol grip in the training dataset's image collection,it seeks to determine how to reduce false positives. YOLOv3 achieved the highest precision (96.23%) and F1 score values (93.36%), when trained on the dataset that included pose information, whereas Retina Net, which was optimized with the unfrozen ResNet-50 backbone, had the highest average recall (97.23%) and precision (96.36%). By explicitly taking posture information into account during training, only this final design consistently improved (by about 2%). The Small Arms Survey [1] released statistics in 2017 that showed that civilians owned over 85% of the weapons globally, compared to 13% for the military forces and 2% for law police (refer to Figure 1). With a total of 393,347 firearms registered for a population of 326,474, the United States of America stands out among other nations in terms of firearm ownership.

This translates to 120.5 firearms per 100 people, placing it first in terms of the total number of civilian-owned firearms in addition to the quantity of weaponsfor every 100 individuals. Out of the 227 nations in the aforementioned survey, Spain ranks 103rd with 7.5 weapons per 100 people. These statistics,along with the rise in shootings and terrorist attacks that result in civilian casualties in areas outside of armed conflict, have made it more important than ever to set up surveillance systems, particularly in public areas like transportation hubs and places for education, healthcare, business, and recreation that see high volumes of foot traffic. By pre training on the MS COCO dataset and applying transfer learning, it was feasible to over come the lack of training data and acquire the starting values for the parameters of the models used in experiments without having to start from scratch. In order to determinethe network settings for the particular identification issue, a dataset consisting of 1220 photos was selected using the problem-adapted selection criteria, with "handgun" being the sole class of interest. The eight experiments that were conducted on the 183 test images—which were not viewed during training— wereevaluatedbycomparing the standardized metrics (Table 1) for each model, which include area under the PxR curve, average precision (AP), recall, F1 score, and precision.In this system, Alexey Kotchkoski [2] et al. have presented Many characteristics claim to increase Convolutional Neural Networks' (CNNs') accuracy. Practical testing of these It is necessary to use feature combinations on large datasets, and the results must be theoretically supported. Certain features work only with certain models, issues, or small-scale datasets;on the other hand, The majority of models, tasks, and datasets are compatible with additional features like residual connections and batch normalizationWeighted-residual. Among the universal properties we assume to exist are Connections (WRC), Cross-Stage-Partial-connections (CSP), Cross mini-Batch Normalization (CmBN), Self-adversarial-training (SAT), and Mish-activation. The majority of CNN-based object detectors are only used in recommendation systems, such as accurate but slow models are responsible for finding open parking spots using urban video cameras, whereas quick erroneous models are involved in providing accident alerts for cars. Enhancing the accuracy of real-time object detectors makes them suitable for use in systems that generate recommendations, minimize human input, and manage processes independently.Conventional Graphics Processing Units(GPUs)with real-time object detecting functionality enable inexpensive mass use. Today's most accurate neural networks need a lot of GPUs in order to train with big mini-batch sizes and do not operate in real time. In order to solve these issues, we developed a CNN that uses a single conventional GPU for training and that runs in real-time on one. We provide a cutting-edge detector, that surpasses all other alternative detectors currently in use in terms of accuracy (MS COCO AP50 95 and AP50) and speed (FPS).

Because it can be trained and used on a typical graphics card with 8–16 GB of VRAM, the presented detector has a wide range of applications. One-stage anchor-based detectors were a viable concept from the start. We have chosen which characteristics to use after verifying a vast number of them in order to improve the classifier and detector's accuracy. These features can serve as best practices in future research and development. In this system, cutting edge object identification networks rely on algorithms for region proposal to make educated guesses about item placements, assuggested by Shaoqing Ren [3] et al. The region proposal calculation is now seen as a bottleneck since advances like SPP net [1] and Fast R-CNN [2]Fast R-CNN employs the high-quality region suggestionsthattheRPNgeneratesthroughout its end-to-end training to identify anomalies. By sharing their convolutional features, we further combine RPN and consolidating Fast R-CNN into one network. The unified network is told where to search by the RPN component, using the lately coined notion of neural networks that have "attention" processes.With just300 suggestions each picture, Our detection technique produces cutting-edge object recognition accuracy for the incredibly deep VGG-16 model on the PASCAL VOC 2007, 2012, and MS COCO datasets, all at a frame rate of 5 frames per second (including all stages) on a GPU[3]. R-CNN and RPN are the faster cornerstones of the successful submissions in numerous tracks for the top spot in the 2015 COCO and ILSVRC competitions. The code is available to the general public. The success of region proposal techniques and Developments in object detection have recently been powered by convolutional neural networks that are based on regions (R CNNs). Since pooling convolutions among proposals, region-based CNNs have significantly decreased in cost, while being computationally costly when first devised in [5]. Fast R-CNN [2], the most recent iteration, uses aextremely profoundnetwork to attain rates in close to real time while ignoring the time spent on region suggestions. In current cutting-edge detection systems, suggestions represent the computational bottleneck during testing. Economic inference procedures and inexpensive characteristics are the mainstays of region proposal techniques. One of the most often used techniques, Selective Search, avariciously combines super pixels using cleverly designed low-level properties. However, Selective Search takes an order of magnitude longer in a CPU implementation—2secondsperimage—thaneffective detection networks. At 0.2 seconds per image, Edge Boxes offers the best current trade-off between proposal quality and speed. Still, the region proposal phase takes the same amount of time to operate as the detection networkIn this method, Jan Hosang [4] et al. have presented The best object detectors available today use detection suggestions to direct the search for things, saving time by skipping a thorough sliding window search across all of the pictures. The trade-offsinvolved in applying detection suggestions for object detection are not well understood, despite their extensive usage and popularity. We offer a thorough examination of twelve proposal techniques and ground truth annotation recall using ImageNet, MS COCO, and PASCAL, four baselines for proposal repeatability, and their effects on detection performancefor R-CNN, Fast R-CNN, and DPM. Our data demonstrates that increasing proposal localization accuracy is just as crucial for object identification as increasing recall. We provide a unique the average recall (AR) metric, which corresponds remarkably well with detection performance and rewards both exceptional localization and high recall. Our results highlight the common advantages and disadvantages of the current approaches and offer measurementsand insights for choosing and fine-tuning proposal strategies. The popular "sliding window" paradigm, in which a computationally effective classifier checks for the existence of an item in each possible picture window, was the basis for the most effective object recognition techniques up until recently. As the quantity of windows increases,sliding window classifiers scale linearlyevaluated; for multi-scale detection, the quantity of windows increases by an order of magnitude, whilst single-scale detection needs classifyingaround104–105windowsper pictureThe object aspect ratio prediction is also necessary for contemporary detection datasets [4]–[6], which expandsthe search space to106–107 windows per picture. Figure 1: Why are suggestions for object detection useful? Although the detection quality has improved due to the main classifiers' constant complexity rise, the calculation time per window has grown noticeably as a result.Using "detection suggestions" is one way to resolve the conflict between high detection quality and computational tractability. It is possible to create or train a system that, given an image, generates acollection of proposed areas that are probably goingto includeobjects, assuming that every item of interest have common visual qualities that set themfrom the backdrop. Significant speedups can be obtained, allowing the employment of more complexclassifiers, if high object recall is attained with a significantly smaller number of windows than those required by sliding window detectors.According to Rafael Padilla [5] et al., this method Outstanding recent outcomes in supervised object detection from challenges and contests are frequently linked to certain datasets and metrics. The need for annotated datasets has grown as a result of the assessment of these techniques used in many settings. A lack of agreement on the representation results from annotation tools representing object position and size in different forms. A situation like this frequently makes comparing object detection techniques more difficult. In the following ways, this work mitigates this issue: (i) It gives a summary of the most pertinent evaluation techniques applied in object detection competitions, emphasizing their quirks, benefits, and distinctions; (ii) It looks at the most popular annotation formats, demonstrating how various implementations may affect the evaluation outcomes; and (iii) It offers an innovative open- source toolkit that supports 15 performance metrics and various annotation formats, making it simple for researchers to assess the effectiveness of their detection algorithms in the majority of well-known datasets. Furthermore, based on the spatiotemporal overlap between the ground-truth and detected bounding boxes, this study suggests a new metric— also part of the toolkit—for assessing object detection in films. The human visual system is capable of making good distinctions between objects in a range of settings and circumstances, despite a number of obstacles such dim lighting, color disparities, and occlusions. Furthermore, objects are essential for comprehending the context of a scene, which makes determining their exact placement and classification extremely important. Because of this, computer vision experts have been investigating autonomous object identification for decades, with some quite spectacular achievements in the last few years. Algorithms for object detection look for widespread instances of one or more specified object classes. For example, in a pedestrian detection system, an algorithm searches for every pedestrian that appears in a picture or a video. On the other hand, in the identification job, an algorithm attempts to identify a particular instance of an object class. Anidentification algorithm seeks to identify every pedestrian that has previously been spotted in the pedestrian example.

III. EXISTINGSYSTEM

In today's environment, safety and security are major concerns. A nation has to give investors and tourists a safe and secure environment in order to have a robust economy. Even yet, human oversight and involvement are still necessary when using CCTV (closed circuit television) cameras for monitoring and monitoring actions like robberies. We need technology that can recognize these illegal activities on its own. The majority of contemporary CCTV cameras, fast processing equipment, and cutting-edge deep learning algorithms still have difficulty identifying weapons in real time, despite technological advancements. Taking angle into account makes the task even more challengingvariations and potential occlusions from the firearm's carriage and bystanders. The goal of this effort is to create a safe environment by utilizing CCTV video as a source for cutting-edge open-source deep learning algorithms that can detect dangerous weapons. In order to minimize false positives and false negatives, we have built binarycategorization,using the introducing the pertinent confusion objects inclusion concept and using the pistol class as the reference class. Since there was no pre-existing dataset for a scenario in real time, we developed our own using our own camera, manually collected online photos, extracted information from CCTV footage on YouTube, accessed data from the The Internet Movies Firearms Database (IMFDB) at imfdb.org and the GitHub repositories of the University of Granada.We use region proposal/object detection and sliding window/classification.YOLOv3, YOLOv4, SSDMobileNetV1, Faster-RCNN Inception-ResnetV2 (FRIRv2), VGG16, Inception-V3, and Inception-ResnetV2are a few of the algorithms made use of.We assessed all of these techniques in terms of recall and precision since these two metrics matter more in object detection than accuracy. Yolov4 out performs every alternative algorithm, using an F1-score of 91% and a mean average accuracy that is 91.73% greater than the previous record.

IV. PROPOSEDSYSTEM

The suggested system combines deep learning and CCTV technologies to provide an enhanced real-time weapon detection solution that improves security and safety. The system will continually record video using high-resolution CCTV cameras. A complex deep-learning algorithm will then process the film to detect weapons. Using cutting-edge models such as SSD (Single Shot MultiBox Detector) and YOLO (You Only Look Once), the system will identify firearms in the camera's field of view quickly and accurately. The technology will instantly notify security staff of any danger sit detects, allowing them to take prompt action. This self-learning way will ensure that the threat management approach is more efficient and proactive with much simpler security operations and with a significantly reduced need for constant human monitoring. The continuous learning feature of this system will allow it to adapt to new threats and changing environments while keeping high accuracy and robustness in various environments.

A.CLIENT SIDE(EDGECOMPUTING)

This module is responsible for detecting weapons. It employs algorithms that operate directly on edge devices or local servers, utilizing an edge computing approach. Unlike centralized servers, this system experiences less latency since it processes video data right at the source—near the CCTV cameras. The edge computing module captures and preprocesses video feeds, detects objects in real time, and manages alerts or quick responses locally. This design reduces reliance on network connectivity, optimizes bandwidth usage, and facilitates swift decision-making in dynamic situations.

B.OBJECT DETECTION AND RECOGNITION

The Object Detection and Recognition module is the main part of our system for identifying and categorizing firearms in video footage. This module uses cutting-edge deep learning methods like SSD (Single Shot Multi Box Detector) and YOLO (You Only Look Once) to analyze images or video frames in order to recognize and distinguish between different types of weapons. To pinpoint weapon types and their precise locations effectively, training neural networks on labeled datasets is crucial. Furthermore, to strengthen the system's reliability and enhance the accuracy of weapon detection, we also integrate feature extraction and pattern recognition techniques.

C. MESSAGING

The incident notification system is architected to communicate with the stakeholders registered concerned to weapon detection interactively through Messaging. This system has abilities that can be configured uniquely to interface in real-time with notification and alerts when a weapon is detected that gets pushed to law enforcement or security personnel over email or SMS. In order to send messages at the aforementioned notification time, communication APIs such as Twilio inform the systems of the connection that has been established so that messages can be sent out if needed. It also has the ability to record voice and video of the users in order to perform audits in the future.

D.SERVERSIDE

The Server Side component is in charge of the back-end part of the weapon detection system. This module will establish a smooth data transfer between the front-facing application, object detection algorithms, and edge devices. Also embracing system commands and user session management, the Server Side gathers and forwards detection data and services systematically. It thus ensures the reliability and scalability of the system. The apparatus guarantees continuous performance at several edge devices and underscores a sophisticated mechanism to accommodate for peak activities.

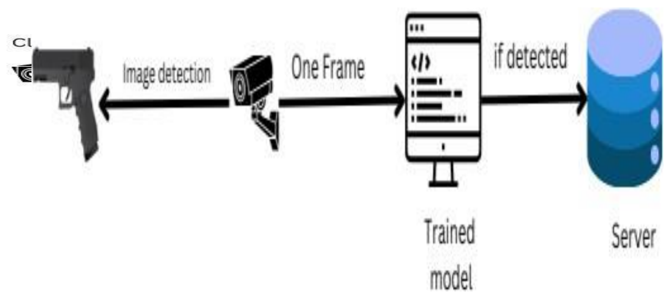
E.DATABASE

The module for the weapon detection system is the 'database' which is meant for data mining and data gathering. It contains things like user accounts, detection logs, videos, configuration files, etc. The system is able to perform queries and retrievals almost instantly, thus making reporting and auditing easier for the analytics head. Moreover, the module attempts to achieve data protection, backup, integrity, and data maintenance in parallel with large amount data set managing. The type of database technology that will be used, relational or non-relational like MySQL or MongoDB, will depend on the performance and scalability requirements of the system.

F.FRONTENDAPPLICATION(DJANGO)

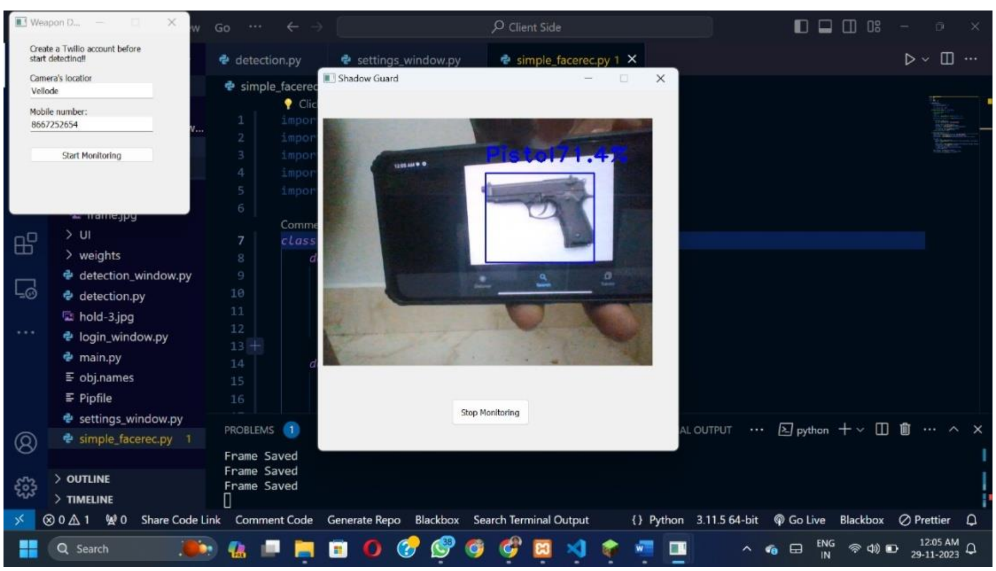
It is also of great significance that the Front End Application Module was developed with the help of the Django framework, as it makes the use of weapon detection system more user friendly. The system allows the users to change system parameters, check current streams of video, and to set alerts. Identification, data representation, and system interaction is an essential part of the Django application permitting easier integration with all subsystems. The design implies that together with the information, the administrative and security staff will also be able to access detection reports, change system parameters, and to check the system's performance from a web browser. The application is also designed and structured in such a manner that it is user friendly, efficient, and easily accessible from most devices.

SYSTEM FLOW DIAGRAM



CLIENT SIDE

V. RESULTANALYSIS



When analyzing the results, system accuracy is checked by watching CCTV footage and comparing it with the classification done by the real-time detection system. Responsiveness of the system alongside the detection and classification rates are major points of consideration. For instance, the effectiveness of the system in sifting real threats from benign objects is evident as well as the ability to identify weapons without ambiguity. The system assumes that as soon as a weapon is detected, the speed with which people such as in authorities are alerted is a measure of responsiveness. As such, the intention is to ensure that there is reduced latency so that a response can be deployed. These strengths are established in the context of other parameters that include how well the system works in different scenarios and cameras position. The objectives of enhancing public safety with minimal direct surveillance are met with improved real-time

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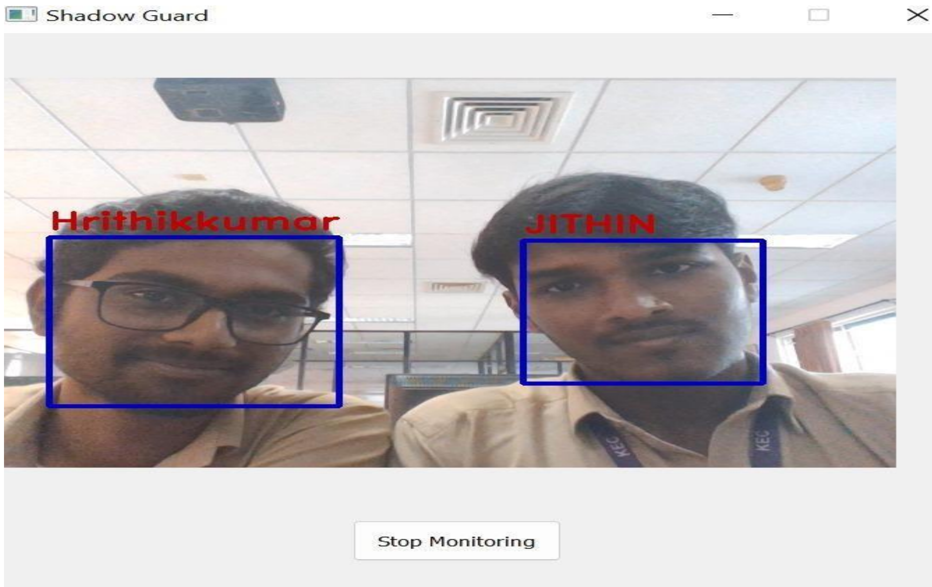
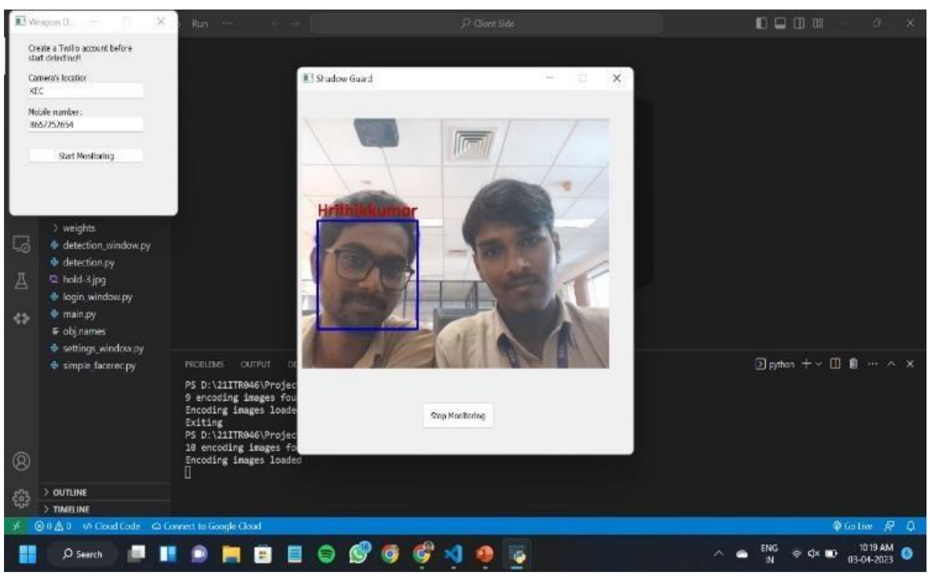
monitoring, automated iterative testing, and detection algorithm refinement, which reduces the need for frequent enforcement.





VI.CONCLUSION

In a nutshell, the weapon detection technology in real-time is one of the major developments toward enhancing public security and speeding up security processes. In this system, cutting-edge deep learning techniques and edge computing technologies are used so that possible dangers may be identified correctly and promptly without constant human monitoring. Together with effective messaging and real-time item detection, security staff is immediately alerted about weapons found so that responses can be swift and properly informed. action. In-depth testing and review have delineated how the system can certainly hold high performance, pointing out its adaptability in a wide scale, varied surroundings and circumstances. The system assures to offer greater dependability and flexibility as it evolves further, incorporating new data and input which leads to an enhanced and safer workplace.

VII. FUTURE WORK

The real-time weapon detection system's functionality and performance can further be improved through future development based on a few key points. A key strategy for improved accuracy and robustness in the detection will be an augmentation of the dataset for the training of the deep learning models, which can comprise a large number of varieties in weapons and conditions.Furthermore, efforts shall be made to improve the algorithms such that it contains fewer false positives and false negatives, especially on congested and complex scenarios. Additional features involving cross-checks from many data sources and synchronizing several cameras might further advance danger identification and situational awareness. Increasing total system dependability might be provided through further investigation of various sensor and technological deployments, even to the application of motion detection and other technologies such as thermal imaging, and new evidence might be accumulated. Constant updates of model implementation based on performance in actual scenarios and newer threats mean adapting and learning incessantly will remain a key. Ensuring optimisation of the system scalability along with integration of the wider security infrastructures beside improvements in the user interfaces and experience ensures easy deployment and operational in diverse environments.

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