WEAPON DETECTION AND ALERT SYSTEM IN ATMs

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Abstract- **Security is always a main concern in every domain, due to a rise in crime rate in a crowded event or suspicious lonely areas. Abnormal detection and monitoring have major applications of computer vision to tackle various problems. Due to growing demand in the protection of safety, security and personal properties, needs and deployment of video surveillance systems can recognize and interpret the scene and anomaly events play a vital role in intelligence monitoring. This project implements automatic gun (or) knife detection using a yolo convolution neural network (CNN) based algorithm. The trained model will be able to detect gun or knife based on the prê-trained yolo file and alert via buzzer and sends an alert to preset authorized user or police station. Victim can also alert via voice whenever there is treat, victim should press the emergency button and say help this voice is recognized and immediately alert will be sent with captured scene.**

Keywords: **Security, crime rate, abnormal detection, monitoring, computer vision, video surveillance systems, anomaly events, intelligence monitoring, automatic gun detection, knife detection, YOLO, convolution neural network, trained model, alert, buzzer, authorized user, police station, victim, emergency button, help, voice recognition, captured scene.**

I. INTRODUCTION:

. Gun violence is a serious problem worldwide that threatens human rights and freedom. According to statistics, around 500 people die every day due to gun violence, and over 44% of assassinations worldwide involve guns. In mid-2012, more than 1.4 million deaths were attributed to firearms violence.

Anomaly or weapon detection involves identifying irregular or unusual events or items that do not conform to standard patterns in a dataset. Object detection algorithms use feature extraction and learning to recognize instances of different categories of objects. The proposed implementation focuses on accurate gun detection and classification, with a balance between accuracy and speed being crucial to avoid false alarms. The methodology for weapons detection using deep learning involves extracting frames from input videos, applying frame differencing algorithms, creating bounding boxes, and detecting objects.

II. LITERATURE REVIEW

In [1]. The "P.R. Dhumal and S.D. Lokhande worked together on a scholarly article titled "ATM Security using Image Processing and GSM" which was published in Volume 4, Issue 4 of the International Journal of Advanced Research in Computer Engineering & Technology in April 2015. The article presented a clever strategy for protecting ATMs from thefts and robberies using image processing techniques and GSM technology; any weapon seized could be quickly seen through di If the system notices any unauthorized user attempting entry, a notification will be sent directly to the relevant authorities, allowing for quick intervention.

In [2]. In their research article "An Intelligent ATM Security System Using Face Detection and Recognition," M.A. Bhuyan and S.S. Saha fairly state ways in which deep learning algorithms can be utilized creatively within automated teller machine (ATM) settings by looking at potential methods of detecting or recognizing people trying their best to abuse these machines' power for personal gain without authorization explicitly granted promptly. This study was published in the International Journal of Computer Science &Information Technologies, highlighting essential considerations about safely keeping ATMs secure.

In [3]. "Robbery Detection System in ATM Using Image Processing" by A. H. Sawant and S. S. Gaikwad, International Journal of Engineering Research & Technology (IJERT), Volume 6, Issue 07, July 2017.
This paper proposes a robbery detection system in ATMs using image processing techniques. The system uses deep learning algorithms to detect the presence of weapons or suspicious objects on ATM premises. If such objects are detected, the system sends an alert to the authorities.

In [4]. A groundbreaking paper published by A.S.Kulkarni and S.D.Lokhande in the International Journal of Computer Applications (Volume180 - No.20 ,December2018) has unveiled a sophisticated real-time robbery detection mechanism at ATMs via cutting-edge image processing technologies coupled with complex deep learning algorithms.The implementation's underlying architecture employs neuronal systems known as "deep convolutional neural networks," and is designed to identify suspicious objects and potentially dangerous weapons in ATM spaces. Upon their discovery, the system sends a prompt alert to relevant authorities to prevent potential harm.

In [5]. "An Intelligent Robbery Detection System in ATM using Machine Learning" by A. V. Amlathe and A. N. Kulkarni, International Journal of Recent Technology and Engineering (IJRTE), Volume 8, Issue 2S6, November 2019.
This paper proposes an intelligent robbery detection system in ATMs using machine learning techniques. The system uses a combination of deep learning algorithms and support vector machines (SVMs) to detect the presence of weapons or suspicious objects on ATM premises. If such objects are detected, the system sends an alert to the authorities.

In [6]. The algorithm proposed by Grega et al. caters to identifying knives and firearms in CCTV images autonomously while notifying security guards or operators accordingly [16]. The researchers prioritized limiting false positives while furnishing a real-time mechanism exhibiting improved specificity rates of nearly 95% for knife detection as well as almost 97% for fire detection albeit possessing lesser - around 36%- sensitivity rates.

In [7]. The video classifier was conducted by Mousavi et al. Histogram of Directed Tractlets is the term used to refer to it, and it can identify irregular conditions in complex scenes. Traditional approaches, using optical flow which only measures edge features from two subsequent frames, are compared with this method which is developed over long-range motion projections called tractlets. As a result, spatiotemporal cuboid footage sequences are statistically gathered on the tracks that move through them.

In [8]. shave presented findings from a study focused on automating handgun detection through advanced deep learning approaches meant for visual surveillance systems. The authors employed the cutting-edge deep learning techniques of YOLO V3 algorithmizing alongside Faster RCNN as a means of limiting false positives/false negatives whilst increasing accuracy rates within said systems. With YOLO algorithm trained via use of real-time images coupled with ImageNet dataset, researchers compared their findings with those garnered from reliance upon Faster CNN by analysing four distinct video samples achieving accelerated detection speeds using YOLO V3 as opposed to relying upon traditional approaches alone alluding towards significant societal benefits.

In [9]. In their study, Pang et al. discussed the usage of passive millimeter wave imagery for real-time concealed object detection under human dress with metallic guns on human skeletons. Their experiment applied the YOLO algorithm to a small-scale dataset and evaluated the efficacy of the Single MultiBox Detector algorithm, YOLOv3-13, SSDVGG16, and YOLOv3-53 on the PMMW dataset. The results showed a weapon detection accuracy of 95% mean average precision with 36 frames per second detection speed.

In [10]. Ji and colleagues created a security system that uses convolutional neural nets (CNNs) to automatically detect human behavior in security footage. They built a deep learning model that operates directly on the raw inputs to identify patterns in the data. To achieve efficient classification, they implemented a 3D CNN model that regularizes the outputs with high-level characteristics. Additionally, the system integrates observations from various models to improve accuracy. This research addresses mathematical problems in engineering and highlights the potential of deep learning algorithms to enhance security systems.

III. METHODOLOGY

Pre-processing is an essential step that involves transforming raw data before feeding it into machine learning or deep learning algorithms. If this step is skipped, it can lead to poor performance. Centring and scaling techniques can be used to speed up training. Image processing, also known as digital image processing, is used frequently in the domain of computer vision. Although both image processing and computer vision algorithms take an image as input, the output in image processing is also an image, while in computer vision, it can be some features/information about the image. Raw data is not fit to be used directly in applications due to various reasons. Pre-processing is performed to analyse and prepare the data for further use. For example, if we were to build a cat classifier, we would collect cat images and resize/pre-process them all to a standard size. This is one of many reasons why image processing is crucial in any computer vision application.

TRAINING: Neural network architectures are frequently used in deep learning models, also known as deep neural networks. Deep neural networks, in contrast to conventional neural networks, can have up to 150 hidden layers. These models are trained utilising massive, labelled datasets and neural network architectures that automatically extract features from the data. In this project, we'll make use of the pre-trained model for finding weapons called YOLO.

TESTING: Once the model is trained the model is ready to detect the weapons from detected images via surveillance. In this phase the model extracts the frames and feed to yolo classifier, the classifier detects the weapons and alerts via buzzer and sends an email alert to the authorized persons/ any authority.

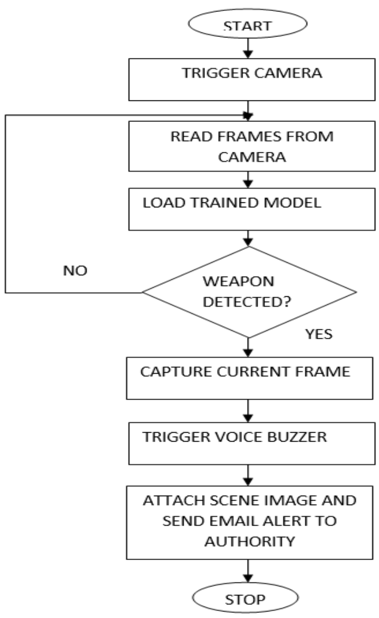

Fig 3.1 Flow diagram of the system

IV. PROPOSED SYSTEM

The deep learning-based weapon/voice detection and alarm system in ATMs is a security system created to deter thefts and crimes in ATM booths. Convolutional Neural Networks (CNNs), a sort of network architecture for deep learning algorithms, are used by the system to identify weapons or dangerous circumstances. CNNs are employed primarily for image recognition and pixel data processing activities.

The technology is able to identify a variety of weapons, including knives, firearms, and other sharp items. Additionally, it can identify any suspicious actions or vocal patterns that might pose a threat to the people using the ATM. The device sends out an alert when it discovers a weapon or suspicious activities, and it also sounds a loud buzzer to warn.

V. CONCLUSION

For detecting weapons, the cutting-edge YOLO V3 object detection model was implemented and trained on the data we had gathered. We suggest a model that gives a machine or robot the ability to recognise dangerous weapons and can also notify a human administrator when a gun or other firearm is clearly visible in the vicinity. The experimental findings demonstrate that the trained YOLO V3 model performs better than the YOLO V2 model and requires less computational resources. Updated surveillance capabilities with better resources are immediately required to support monitoring the efficiency of human operators. With the increasing availability of low-cost storage, video infrastructure, and better video processing technologies, smart surveillance systems would completely replace existing infrastructure. In time, the digital

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