DEEP LEARNING APPROACH FOR
EVENT MONITORING SYSTEM

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ABSTRACT

With an increasing number of extreme events and complexity, more alarms are being used to monitor control rooms. Operators in the control rooms need to monitor and analyze these alarms to take suitable actions to ensure the system's stability and security. Security is the biggest concern in the modern world. It is important to have a rigid surveillance that should guarantee protection from any sought of hazard. Considering security, Closed Circuit TV (CCTV) cameras are being utilized for reconnaissance, but these CCTV cameras require a person for supervision. As a human being, there can be a possibility to be tired off in supervision at any point of time. So, we need a system to detect automatically. Thus, we came up with a solution using YOLO V5. We have taken a data set and used robo-flow framework to enhance the existing images into numerous variations where it will create a copy of grey scale image, a copy of its rotation and a copy of its blurred version which will be used to get an enlarged data set. This work mainly focuses on providing a secure environment using CCTV live footage as a source to detect the weapons. Using YOLO algorithm, it divides an image from the video into grid system and each grid detects an object within itself.

KEYWORDS

Convolutional Neural network (CNN), YOLO algorithm, Kaggle, Support vector machine (SVM).

1. INTRODUCTION

Weapon or Anomaly recognition deals with the concept of detecting items that can be sporadic, unexpected, and hazardous. Object detection highlights models to recognize cases of shifted classification of items. Security is the greatest worry in the advanced world. Manual checking of surveillance cameras isn't sufficient to recognize and respond to any perilous circumstances. In the past two or three years, profound learning methods and Convolutional Neural Networks (CNN's) have accomplished extraordinary heights in picture identification, order, division and it's being utilized in a few applications. The progressions in innovation and furthermore the most recent imaginative identification models like YOLO [1], Faster R-CNN [2], have accomplished acceptable outcomes.

Weapon Detection frameworks need Real-time dealing with faster response times considering their fundamental nature, hence the assessment should find complete methodology that speeds the stretch of time area models [3]. The principal issues like the enormous number of misdirecting negatives and counterfeit up-sides happen due to the challenges like relative shape and treatment of non-weapon objects which are consistently handheld. Another critical test is ensuring that the model doesn't forget to distinguish the weapon and solidifies an incredibly low counterfeit negatives rate. The model should attempt to have the choice to avoid misdirecting up-sides from the underpinning of those photos and accounts [4].

Figure 1. Weapon Detection

To achieve this goal, this review progresses a model that could benefit models like YOLO which take less time in distinguishing proof velocities. The responsibilities of this work integrate diminishing how much counterfeit up-sides and negatives inside the space of Weapon Detection by using Gaussian cloudiness to discard the establishment and simply address significant expert in the space of Interest and its solidified use with YOLO v5 by SGD (Stochastic inclination plummet) [5].

2. LITERATURE SURVEY

2.1. Existing System

In the existing system, there are few systems which are based on weapon detection, security-based literature and other are irregular shaped object Detection and supporting literature. Weapon detection and Security based literature are practically identical investigation prompted for weapon area consolidates the work done RCNN and VGG-16 [6] on different informational collections, accounts from YouTube and test the window approach. The speed of acknowledgment shows up at 0.19 s per frame with the high precision rate. While other examination works attempt client pre-processing utilizing double cameras to obscure the foundation using Global Block Matching calculation, following the area of premium procedure which builds their precision and brings down the bogus positive rate that adds velocity of the model. The investigation work presented by CNN based model, on the speed of acknowledgment to the extent that weapons like knives and blades [7], this was strong for indoor applications at any rate extraordinary lighting conditions and reflections cut down the precision inside the external application.

 Irregular Shaped Object Detection and Supporting Literature is Utilization of different strategies and profound learning approaches for the identification of different articles, among the one research centers around the smoke delivered by the Gunfire to distinguish the arrangement of the discharged gun. Other examination work incorporates utilizing the Faster-RCNN model to recognize items and people on foot. Support vector machine (SVM) [8][9] was implemented to do continuous apparel acknowledgment from reconnaissance recordings. The assessment work revolves around face disclosure of terrible quality pictures using the facial credits presents inside the image [10]. Other evaluation bases on multi-facet CNN consolidates and taking advantage of the equivalent attributes to incorporate it for picture retrieval.

3. PROPOSED METHODOLOGY

We propose video-based perception structure that might perform steady event recognizable proof. We intend to diminish the speed of bogus negatives and misleading up-sides in weapon identification while keeping the speed of recognition as a main boundary. The proposed approach is implemented using You Only Look Once (YOLO) and Area of Interest (AOI). At first, the models take pre-handled outlines where the foundation is eliminated by the usage of the Gaussian haze calculation. It's promising to be utilized in the circle of safety and weapon identification.
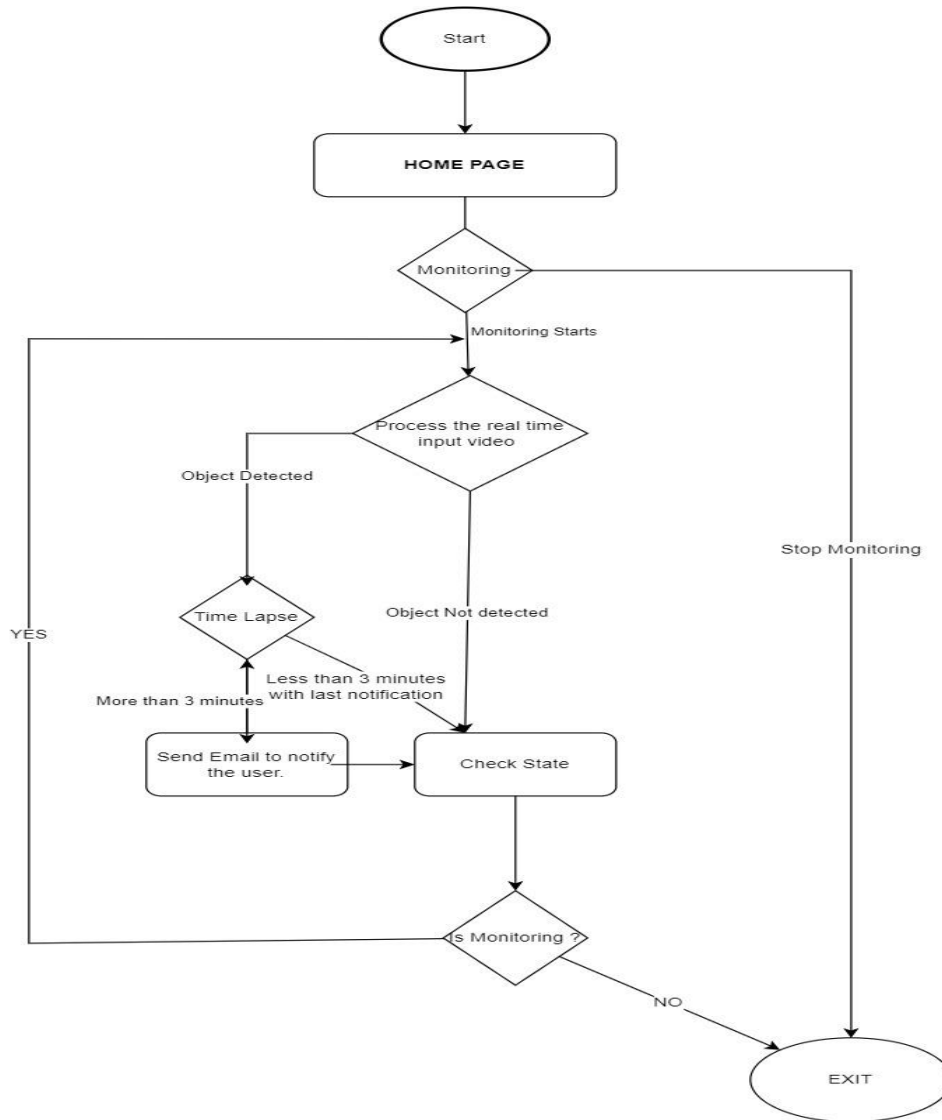

Figure 2. Flow Chart

We have implemented weapon detection as one of the events from several event detection. In this, we used the YOLO v5 algorithm for object detection, and the process flows as follows: Once the user login, the user is redirected to the home page then the user can be able to see two buttons those are start monitoring and stop monitoring. Once user clicks on Start monitoring, it takes the video, processes in the real time frame and detects the object(weapon). [11] Once the

object is detected, it sends a notification to the user and timer start from the mail sent. The processing of video continues if the object is detected once again and if the time is less than 3 minutes then it won't notify to the user, whereas if the time is greater than 3 minutes then it notifies to the user again. It continues unless the user clicks on stop monitoring. You Only Look Once is referred to as YOLO in an abbreviation. Version 5, released in June 2020, is now the most sophisticated object detection algorithm on the market. It is a cutting-edge convolutional neural network that accurately detects objects in real-time. This method processes the entire image using a single neural network, then divides it into parts, forecasts bounding boxes and probabilities for each component. The predicted probability weighs these bounding boxes. The technique "only looks once" at the image means that it only does one forward propagation loop through the neural network before making predictions. After non-max suppression (which guarantees that the object detection method is working properly), it then delivers discovered objects.

4. IMPLEMENTATION

4.1. Introduction to YOLO Algorithm

YOLO is a framework that utilizes brain organizations to supply constant item discovery. This detection is famous because of its speed and exactness. It's been used in different applications to identify traffic lights, individuals, stopping meters, and creatures. Object discovery could be a peculiarity in PC vision that includes the location of differed objects in computerized pictures or recordings. some of the items identified incorporate individuals, vehicles, seats, stones, structures, and creatures. [12] YOLO is an abbreviation for the term 'You Only Look Once'. This is an algorithm that distinguishes and perceives different items in an image (progressively). Object identification in YOLO is done as a relapse issue and gives the class probabilities of the recognized pictures. YOLO calculation utilizes Convolutional Neural Network (CNN) to recognize objects progressively. As the name recommends, the calculation requires just a solitary forward proliferation through a brain organization to recognize objects. This implies that expectation in the whole picture is done in a solitary calculation run. The CNN is utilized to anticipate different class probabilities and bouncing boxes all the while.

4.2. Residual Blocks

To begin with, the picture is partitioned into different matrices. Every network has an element of N x N. The accompanying portrait shows how an info picture is separated into matrices. In the picture below, there are numerous lattice cells of equivalent aspect. Each network cell will identify objects that show up inside them.

Figure 3. Residual Blocks

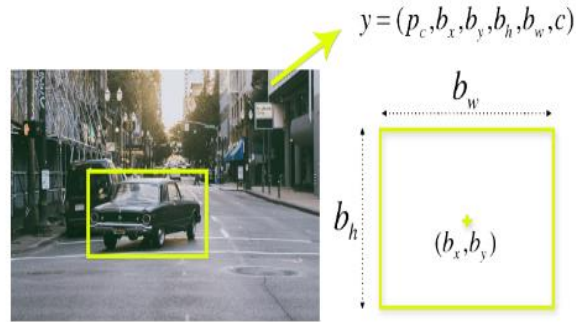## 4.3. Predict Localization Boxes

Figure 4. Localized Blocks

The figure above shows an illustration of a jumping box. The predict localization box has been addressed by a yellow framework. The predict localization box is a diagram that features an item in figure.

Each predict localization box confine the picture comprises of the accompanying credits:
Breadth (bw)
Tallness (bh)
Class (for instance, individual, vehicle, traffic signal, and so on)- This is addressed by letter c.
Predict localization box focus (px, py).

4.4. Intersection Over Union (IOU)

Intersection over union (IOU) is a peculiarity in object discovery that portrays how boundaries cross-over [13]. YOLO purposes IOU to impeccably give a result box that encompasses the articles. Every framework cell is liable for anticipating the bounding boxes and their certainty scores [14]. The IOU is equivalent to 1 if the anticipated bouncing box is equivalent to the genuine box. This component disposes predict localization boxes that are not equivalent to the genuine box [15].
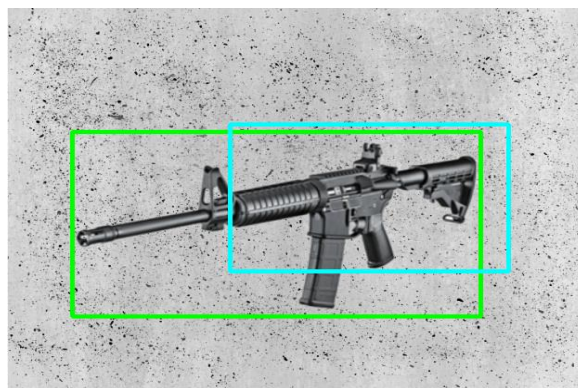

Figure 5. Intersection Over Union

4.5. Mix of Three Methods

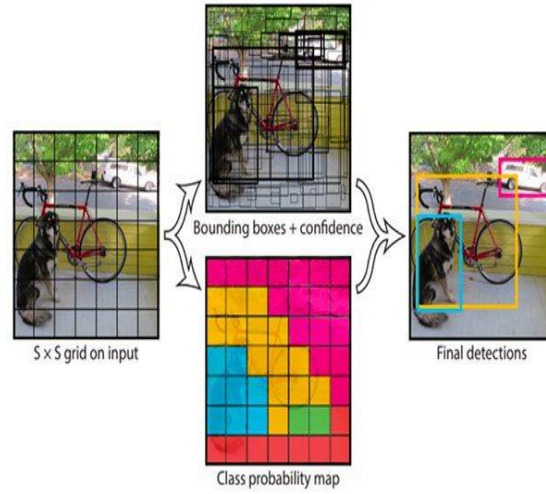The accompanying picture shows how the three procedures are applied to deliver the end results.

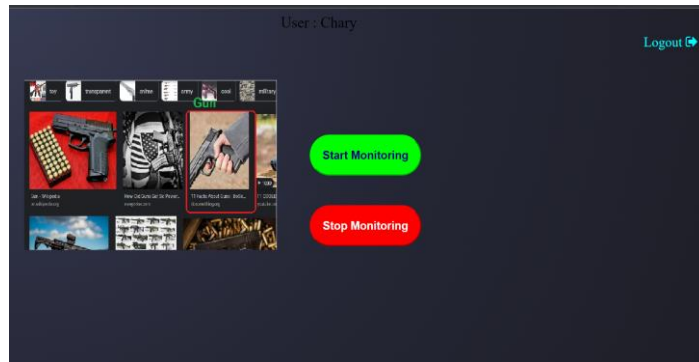Figure 6. YOLO Detection

5. EXPERIMENTAL RESULTS
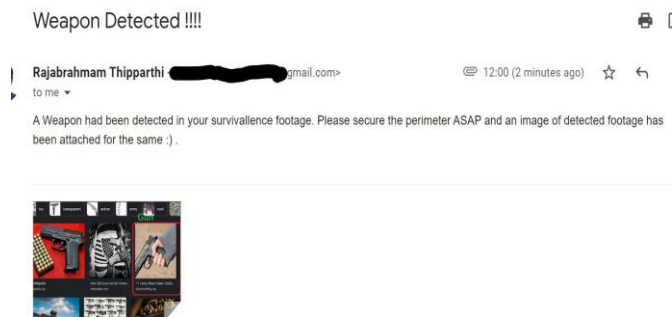

Figure 7. Object Detection

Figure 8. Email Notification

6. CONCLUSION AND FUTURE WORK

In this work, we have proposed a model to distinguish the weapons by handling the ongoing video and advising the client by means of an email and this can be utilized with caution-based frameworks in utilization of observation. We exploited one of the most up to date models, for example, YOLO v5s which had extremely powerful outcomes and speed, we involved them for the undertaking of weapon recognition. We further utilized the pre-handling strategy of obscuring the foundation with Gaussian haze to improve our F1 score. The most encouraging outcomes are acquired from the YOLO-v5 model prepared on the 3000-gun picture data-set with the option of 12,000 negative class pictures further as tried on YouTube recordings, our most prominent outcomes accomplished 93% accuracy and 94% review on the video, these outcomes are superior to the outcomes accomplished by comparative exploration, particularly the review score of our model, moreover in light of the fact that the speed per outline with 0.01s which is quicker than the Faster R-CNN model utilized by any other examination. This exploration is utilized in mix with an email notice to supply powerful weapon recognition. In future, we will pivot upon this model by utilizing other pre-processing methods like splendor control, we additionally found few regions where the presentation of the model is frequently expanded by taking care of the issues such as weapons which fluctuate from the nonexclusive look of guns, for which we can develop strategies that help recognize moulded objects which are key difficulties inside the area of weapon location.

We framed the title of the project as "Deep Learning Approach for Event Monitoring System" because there may be several events where we can use the proposed model by YOLO v5. One of the events is Weapon detection which we implemented at present. Some other events such as car theft detection, unauthorized presence in restricted area can be implemented in future.

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