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WEAPON DETECTION USING DEEP LEARNING

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Abstract-Withinthisproject,Duetothefactthatcrimetendstoincreaseatmajoreventsorinisolated,unsettlingareas, security is always the first priority in every industry involved in this project. Computer vision addresses a variety of problemsandiswidelyutilizedinanomalydetectionandmonitoring.Videosurveillancesystemsthatcanrecognizeand analysesituationsandunexpectedactionsarebecomingmoreandmore Researchperformsautomatedgun(orweapon) identificationusing FasterRCNN andConvolutionNeuralNetwork(CNN)basedSSDalgorithms.Two distincttypesof datasets are utilized in the proposed methodology. There were two datasets: one comprised a list of manually labelled photographs, and the otherhad pre-tagged images.When combined, the findings demonstrate the excellent accuracy of both methods; nevertheless, their practical use may be contingent on how well speed and accuracy are matched [1].

Keywords–Gundetection,deeplearning,objectdetection,artificialintelligence,computervision,RCNN,SSD

I. INTRODUCTION

WeaponorFindinganomaliestheprocessofdetectingevents or objects thatare anomalous, unexpected, unpredictable, or that do not fit into a pattern or are present in a dataset and hencedeviatefrompre-existingpatterns.Anirregularpattern from a set of accepted patterns is called an anomaly. As a result, anomalies are dependent upon the relevant phenomenon. Feature extraction and learning techniques or models are used in object identification to identify occurrences of different object categories the suggested implementation aims to achieve precise gun detection and classification.Anotherreasonaccuracymattersisthatafalse alarm might have unintended consequences. Selecting the appropriatestrategynecessarytoappropriatelybalancespeed and precision. It's an illustration of the deep learning-based technique for detecting weapons. From the video input, frames are extracted. The frame differencing procedure workstoproducetheboundingboxpriortoobjectdetection. The process of object detection and trailing ends after the dataset has been generated, trained, and sent to the object detection algorithmic program. Application-appropriate detection can be enabled for the algorithmic program (rapid RCNN or SSD) chosen for gun detection. The method encompasses abroad spectrumof detectionand exploitation tasks for various machine learning models, including Single Shot Detection (SSD) and Region Convolutional Neural Network (RCNN) [1]. Artificial intelligence and Deep Learningalgorithmsareappliedtobringaboutaparadigm change. This technology uses the capacity of contemporary neuralnetworkstoidentifythepresenceofweaponsnotonly more efficiently and accurately than previous methods, but alsomoreeffectively.Inshort,thissystemappliesBounding Box obtained by detection of an object based on images or videos and algorithm applied to the system compared with faster RCNN. The target Convolutional neural network-based detections separated into one-stage target detection algorithm and two-stage target detection [8].

II. AIMSANDOBJECTIVE

a) Aim:

This project's goal to improve public safety and security by developing an accurate and efficient weapon detection system via the use of deep learning and AI.

b) Objective:

The principal aim of this project is to enhance public safety by developing a strong weapon detection system via the utilizationartificialintelligenceanddeeplearning.Themain goalwillbetocreateandapplyadeepAlearningmodelthat is efficient and specifically designed for precise weapon detection.Avariety of datasets will be employed to instruct themodel,enablingoptimizationtoreachhighaccuracyand efficiency it basically contains 5 objectives.

- **DataCollection:**Gatheradiversedatasetofimagesand videos featuring various environments where weapons might be present.

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- **Data Preprocessing**: Clean and preprocess the data. Thismightentailenhancingthedataset'svarietythrough augmentation, standardization, and image resizing.
- **Model Development:** Create and use deep learning models for weapon detection tasks, such as CNNs, YOLO, or SSD.
- **Training and Evaluation:** Train the models using annotated data and evaluate their performance using metrics like precision, recall, and F1-score
- **Integration and User Interface**: Develop a user-friendlyinterfaceandintegratethesystemwithexisting.

III. LITERATURESURVEY

Paper1:(SSD)SingleShotMultiBoxDetector:

We only discuss one deep neural network method for object identification in photos. Our technique, which werefer toas SSD,discretizestheboundingboxoutputspace intoagroup ofstandardboxesthatspandifferentaspectratiosbyscaling each feature map point. In terms of prediction length, the network creates scores for every kind of item found in the default box and modifies the box to better suit the shape of theobject.Moreover,thenetworkintegratespredictionsfrom many feature map strategies to manage items of natural different sizes. Compared to methods that need object proposals,ourSSDvariantofferseasiertouseasitunifiesall processing into a single network and completely eliminates proposaldevelopmentandtheensuingstepofpixelorfeature resampling. Due to SSD is easy to train and integrate into systemsthatrequireadetectingcomponent.Investigationson the ILSVRC, PASCAL VOC, and MS COCO databases demonstrate that SSD provides a single framework for both inferenceandtraining,andthatitisbothsubstantiallyquicker than and as accurate as approaches requiring an extra item proposal step [6].

Paper 2: Scalable Object Detection Using Deep Neural Networks:

The ImageNet Large-Scale Visual Recognition Challenge (ILSVRC-2012)isoneoftheimagerecognitionbenchmarks onwhichrecently,deepconvolutionalneuralnetworkshave shownstate-of-the-artcapabilities.Anetworkthatpredictsa singleboundingboxandaconfidencescoreforeachcategory of elements in the image emerged as the winner in the localization subtask.

Despite being able to capture the contextoftheentireimagearoundtheobjects,themodelcan manage many instances of the same object in the image without needlessly reproducing the number of outputs for each instance. It suggest using a neural network model for saliency-based detection. It allocates a single bounding box and predicts a quantity of enclosing boxes independent of class [7].

Paper 3:Anomaly Detection in Videos for Video Surveillance Application Using Neural Network:

Duetoanincreaseincrimeinbusyplacesandshadyisolated regions, security is always a top priority in all fields. An extensive array and problems are addressed by computer vision, which is extensively employed in anomalous detection and monitoring. The increasing need to safeguard people's safety, security, and property has produced a need for video surveillance systems that can recognize and comprehendsituationsandunusualactivities.Thesesystems are essential for intelligence monitoring. Using a technique known as anomaly detection, one can discern between differentpatterns and pinpointoddpatternsthat appear fora shortwhile;these patternsareknown asoutliers.Surveillance film may catch a wide range of probable oddities.Anomaly Invideosurveillance,detectionentailsdismantlingtheentire process into three stages: activity detection, image processing, and video labelers. Therefore, when it comes to real-time settings, anomaly identification in footage for use in security applications provides guaranteed outcomes. Bb - Inthiswork,anomalieswereidentifiedinpicturesandvideos with a 98.5% accuracy rate [3].

IV. EXISTINGSYSTEM

Theprocessofweaponryortheabilitytoidentifyanomalies involves identifying anomalous, erratic, unexpected, or strangeoccurrencesorobjectsthatdonotfitintoapatternor are present in a dataset and hence deviate from pre-existing patterns.Ananomalyrepresentsapattern thatdiffersfroma collection of recognized patterns.As a result, anomalies are dependentupontherelevantphenomenon.Featureextraction and learning techniques or models are used in object identification to identify occurrences of different item categories [1]. It basically 2 Disadvantages.

- This systemis not entirely automated.An administrator will confirm each gun detection alert.
- R-CNN algorithm used.

Table1:ComparativeAnalysis

SR NO.	PAPERTITLE	AUTHOR NAME	Technology	Purpose
1.	WeaponDetectionusingArtificialIntelligenceand DeepLearningforSecurity Application	HarshJain	SSD AlgorithmFasterR_CNN	SSDSelf-CreatedImagedataSet
2.	SSD:SingleShot MultiBoxDetector	WeiLiuetal.	Singledeep neuralnetwork	SSDisSignificantlyMoreAccurate,EvenwhenTheinputImagesizeis Less.
3.	ScalableObject DetectionUsing DeepNeural Networks	D.Erhanetal.	DeepNeuralNetworks	Modelcapturesthewhole-image context around the objects.
4.	AnomalyDetectioninVideos for VideoSurveillance ApplicationUsing NeuralNetwork	RubenJ Franklin et.al.	NeuralNetworks	Anomalieswereidentifiedinpicturesandmovieswitha98.5% accuracyrate.

VI. PROBLEMSTATEMENT

Effectively identifying and reducing possible risks posed by concealed weapons is a major concern facing public safety today.Theabilityoftraditionalsecurityscreeningtechniques to quickly and precisely detect hidden weapons in real-time situations is frequently compromised. This discrepancy necessitates the development of an advanced artificial intelligence and deep learning weapon detection system. Because the current systems are not sophisticated enough to offereffectiveandtrustworthythreatdetection,theremaybe weaknesses in different security configurations. By creating a reliable and moral weapon detection system A device capableofpreciselyidentifyingweaponryandmonitorthem in real time, our project seeks to close this crucial gap in public safety protocols and reduce the risks that come with bringing a hidden weapon in an array of contexts.

VII. PROPOSEDSYSTEM

Precise gun detection and categorization are the main goals of the proposed implementation. Another reason accuracy matters because a false alarm might have unintended consequences.Selectingtheappropriatestrategyisnecessary to appropriately balance speed and precision. The deep learning-basedweaponsidentificationalgorithmisdepicted. Fromthe inputvideo,frames are taken off. Before an object isdetected,theframedifferencingprocedureworkstocreate the bounding box. The SSD algorithm achieved unprecedentedlevelsofaccuracyandperformancedetection [1].SSDspeedsuptheprocess bydoingawaywiththeneed for a region-specific proposal network. SSD introduces severalmethods,includingasstandardboxesand many scales features, to address the accuracy drop. With these enhancements, SSD can now match the Faster R- precision even with images of lower quality, it increases speed even further. Around 74% on MAP and 59 fps on COCO datasets represent the average scoring.

VIII. ALGORITHM

The general idea of working of proposed system algorithms is given as follows:

ConsensusAlgorithm:

```
importcv2
importnumpyasnp
from deep_learning_model import load_model,
predict_object
# Function to load the pre-trained deep learning model for
object detection
def load_model():
  #Implementthemodelloadinghere pass
#Functiontoprocesseachframeandperformobject detection
defprocess_frame(frame,net): #
  Set parameters
  confThreshold=0.5#Confidencethresholdforbounding box
predictions
  maskThreshold=0.3#Maskthresholdforbinarymasks #
  Extract frame dimensions
  frameH,frameW=frame.shape[:2] #
  Create blob from the frame
  blob =cv2.dnn.blobFromImage(frame)
  #PasstheblobasaninputtotheConvNets net.setInput(blob)
  # Perform forward pass
  detections=net.forward()
  #Extracttheboundingboxanddrawtheboxforeach detected
object
  for i in range(detections.shape[2]):
    confidence=detections[0,0,i,2]
    #Checkifconfidenceisabovethethreshold if
    confidence > confThreshold:
      box=detections[0,0,i,3:7]*np.array([frameW, frameH,
frameW, frameH])
      (startX, startY, endX, endY) = box.astype("int")
      color=(0,255,0)#Greencolorforboundingboxes
      cv2.rectangle(frame,(startX,startY),(endX,endY),
color, 2)
 returnframe
#Mainfunction def
main():
  #Loadthepre-traineddeeplearningmodel net
  = load_model()
  #Initializevideocapture
  vs=cv2.VideoCapture(".../weapon_video.mov")          #
Loadingthevideo while
  True:
    #Readframefromthevideostream
    grabbed, frame = vs.read()
    #Checkifframeissuccessfullycaptured if
    not grabbed:
      break
    #Processeachframeandperformobjectdetection
    frame_with_boxes = process_frame(frame, net)
    # Display the frame with bounding boxes
    cv2.imshow('WeaponsDetection',frame_with_boxes)
    # Check for exit command
    ifcv2.waitKey(1)&0xFF==ord('q'): break
  #Releasethevideocaptureobjectandcloseallwindows
  vs.release()
```

cv2.destroyAllWindows()
ifname=="main": main()
End

IX. MATHEMATICALMODEL

EllipticCurve Cryptography:

A mathematical model of weapon detection using deep learning and artificial intelligence involves determining the crucial components and steps engaged in the process of detecting.Thefollowingsimplemathematicalrepresentation of the weapon detection process:

1. Input:

-LetXbetheinputspacerepresentingvideo frames

-Xirepresentsanindividualframeinthevideosequence, where i is the frame index.

2. Preprocessing:

- Define a preprocessing function P that transforms the raw input frames: Preprocessed Frame i = P(xi)

3. ModelRepresentation:

-LetMrepresentthedeeplearningmodelusedforobject detection.

- Forthei-thpreprocessedframe,Yiisthemodel'soutput:Yi =M(Framethathasbeenprepped)

4. Frame Differencing:

-DefineaframedifferencingfunctionDtoidentifyregionsof motion between consecutive frames:

-DiffFramei=D(PreprocessedFramei,Preprocessed Frame i-1)

5. ObjectFiltering:

- DefineafunctionFtofilterdetectedobjectsbasedon relevant classes (e.g., guns): Filtered Objects i = F(Yi)

6. BoundingBoxDrawing:

- Define a function B to draw bounding boxes around the filteredobjects:Framewith Boxes i=B(Xi,FilteredObjects i)

Output:

The result includes a series of frames showing the weapons' bounding boxes that were found:

Frame with Boxes 1, Frame with Boxes 2, and Frame with Boxes n] is the created film.

In security applications, it's critical to iterate on the model architecture,trainingdata,andevaluationmetricsinorderto optimizeperformanceandensureaccurateweapondetection. Moreover, privacy and ethical issues must be considered while putting these devices in place in public spaces.

X. SYSTEM ARCHITECTURE

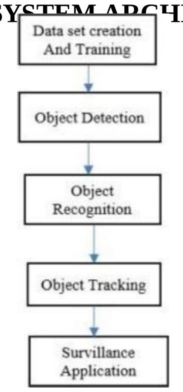

Figure1:SystemArchitecture

Description:

Intheproposedarchitecture,theflowofobjectdetectionand tracking as shown in figure 1. the implementation of the system begins with training data using image processing techniques. Initially, preprocessing and feature extraction mechanismsareappliedtothedata,whichisthenstoredina database. Subsequently, sample data is provided for the detection method, wherein the system raises an alert upon spotting a weapon. The primary objectives of implementing this system include accurate gun identification and categorization, withaparticular emphasisonachievinghigh accuracy to avoid false alarms, which could lead to undesirable consequences. Achieving a When choosing the best deployment plan, finding the ideal balance between speed and precision is essential. Deep learning serves as the foundation for the weapons identification technology. The process involves extracting frames from input videos, and while both algorithms are effective and yield satisfactory results, for real-time applications, accuracy and speed must be tradedoff [1].Thepre-labelled dataset(AK47) yields the bestaverageaccuracy,asseeninFigure3. Figure4displays the accuracy of 74% and 91% gun identification using the cam Faster R-CNN method.

XI. ADVANTAGES

- **HighAccuracy:**Deeplearningmodelsachievesuperior accuracy in recognizing weapons.
- **Real-Time Processing:** Enables swift identification of weapons in live video feeds or images.
- **Scalability:** Can be deployed across various platforms and scales, from small cameras to large-scale security systems.
- **Adaptability:** Easily updated to recognize new threats or variations in weapon designs
- **Cost-Effectiveness**: Once deployed, AI-based weapon detection systems can operate autonomously with minimal human intervention, leading to long-term cost savings compared to traditional security measures that require constant manpower.

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- **Integration with Existing Infrastructure**: AI-based weapon detection solutions can be integrated with existing security systems, including CCTV networks, access control systems, and alarm systems, facilitating seamless implementation without requiring significant infrastructure overhaul.

XII. DESIGNDETAILS

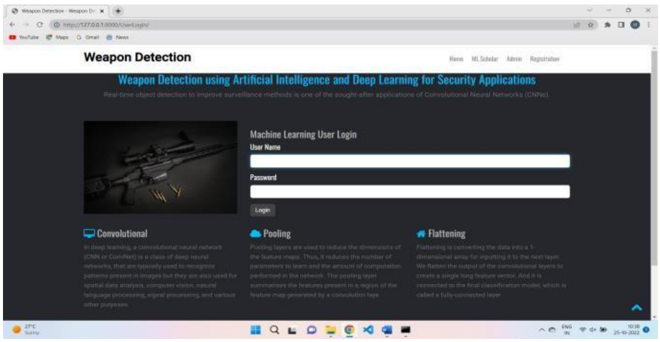

Figure2:UserLoginPage

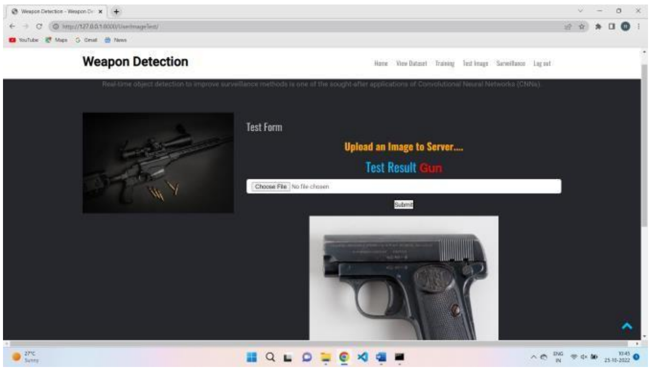

Figure3:FileAccessResult

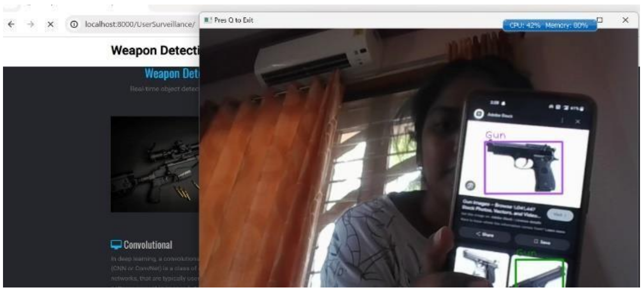

Figure4:WeaponDetectwebcam

XIII. CONCLUSION

We have attempted to put into practice **"Harsh Jain., "WeaponDetectionusingArtificialIntelligenceandDeep LearningforSecurityApplication",IEEE,July.2020**"in practice. The objective of weapon (gun) detection, pre-labelledandself-createdimagedatasetsareusedtosimulate Faster SSD and RCNN algorithms. While both algorithms are effective and produce good results, using them in real time requires balancing speed and accuracy. With 0.736 s/frame, the SSD algorithm provides faster speed. Faster RCNN, on the other hand, only achieves 1.606 s/frame, which is slower than SSD [2]. Faster RCNN provides improved accuracy, coming in at up to 84.6%. In contrast, SSD provides up to 73.8% accuracy, which is subpar when comparedtoRCNN'sspeed.SSD'squickerspeedmadeit possibleforreal-timedetection,butquickerRCNN'sgreater accuracy was achieved. Additionally, by employing GPUs and expensive DSPand FPGApackages for training, it may be applied to larger datasets [1].

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