CRIME PREDICTION BASED ON PERSON-WEAPONS RELATION USING DEEP LEARNING TECHNIQUES

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Abstract
Crime Scene detection predict the chances of happening the crime without any involvement of human intervention is always the crucial task in the field of artificial intelligence. In this paper crime forecasting based on the weapon detection and tracking with the person can help investigator to understand the sequence of action took place during the crime. The images are manually annotated, which is a process where an expert goes through each images and mark the position and class of object within the image. Object detection and classification algorithms provides the necessary ground to verify data for the algorithms. The models like SSD, YOLO and Faster RCNN are used for weapons detection and mediapipe library is used to generate the human body datapoints and calculate the relation between weapons with the human. The maximum accuracy of Faster RCNN with mediapipe library is 93%.

Keywords:-Machine Learning, Deep Learning, Crime Prediction, Object Detection, Object Classification

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I. INTRODUCTION

Every society's first worry is crime. It affects a society's standard of living and financial well-being. It is essential in deciding whether people should go to a city or nation at a certain time or, if they choose to do so, which regions they should avoid. . It is crucial to take precautions to avoid a physical attack, especially in public settings where it may be more challenging to flee or call for assistance. It is crucial to call the police as soon as a crime is committed. So, a government's first aim has always been to reduce criminal activity. Since crime rates increase globally, law enforcement organizations are always looking for cutting-edge information systems that make use of cutting-edge machine learning methodologies to better protect their communities. Many valuable lives were lost due to street crimes and individual institution attacks. This further proves that manual monitoring systems still require a human eye to see unusual activity, and that it takes time to report such activity to security professionals who may then take appropriate action.

The proposed device intends to help law enforcement officers find and recognize guns in a range of situations, including outdoor locations. Guns, Knives, or any other sharp instrument are mainly used to perpetrate violence, which has a huge negative impact on social costs as well as physiological, psychological, and financial costs. Each year, violence claims many lives. Children who are exposed to high levels of violence in their communities or through the media frequently experience psychological trauma. Whether they are spectators, offenders, or victims, children exposed to violence may suffer harmful psychological repercussions in the short and long term. Many studies have shown that knives and weapons are the main tools used in crimes including robberies, theft, rapes, and break-ins. These crimes can be decreased by spotting disruptive conduct early on and closely monitoring any suspicious activity so that law enforcement officials can respond right away.

II. LITERATURE REVIEW

Object Detection from the Image Scene:

Liang et al. (2019) uses CNN-RsNN hybrid architecture for object detection and shows the relation among the object with the help of PASCALVOC2012 and SYSU (Sun Yat-Sen University) datasets with scene descriptions. They define the entire sentences in phrases of nouns and verbs with the assist of natural processing [1]. Li et al. (2019) uses deep supervision methods by formulating the probabilistic framework to predict improved generalization. They train disorder or partially visible scenes from synthetic CAD renderings in which weights are been calculated and used in the real images of datasets include KITTI, PASCALVOC, PASCAL3D+[3]. The authors predict two-dimension and three-dimension object skeletons in a given single test image by using the deep supervision framework with a novel CNN architecture [3]. G. Kalliatakis et al. (2019) identify the child labor through imagery. They use the HRA (Human Rights Archive) database and CNN (convolution neural Network) [1] [5] for human rights violations. Himanshu and hiren (2018) compare the accuracy of various hybrid method like resfeatt-cnn, resfeat resfeats-152 + pca-svm, resfeats-152 + scnn and resfeats-50 + scnn [6]. They use a unique dataset like caltech-101, caltech-256, MLC, solar, mit-indoor67, scene-15[5]. Mehrdad et al. (2020) detects the salient objects of various sizes in the scene with the help of Multi-scale Attention Guided (MAG). They propose a discriminative feature extraction and integration network, which they discuss with as dfnet, inclusive of elements feature extraction N/W [9] and the feature integration network [6]. Shichao et al. (2019) shows the system for recognizing the traffic signal which will help the ADAS [10] self-reliant vehicles system. Their system includes clustering-orientated characteristic for traffic signs detection and recognition. The gtsrb and btsc are used as datasets [10]. Brais et al. (2020) detects the small object by using STDnet [13]. The stdnet is built on the mechanism, known as region context community (rcn), Region proposal network for deciding the favorable regions, and removing the other region from the scene. Saikia et al. (2016) uses the faster-rcnn for detecting an object in an indoor environment [16]. Chunwei et al. (2019) proposed the network (ADNET), for denoising the scene. Adnet has block-matching, 3-d filtering (bm3d), and dncnn for quantitative and qualitative evaluation [18]. Li (2015) reviewed DNN R-CNN for object detection in smart cities by using Pascal Visual Object Challenge (VOC) 2007 and 2012 datasets [20].

Object Detection from the Motion Scene:

Li and shin (2019) detect the unexpected accident of cars in the tunnel under bad light of CCTV monitoring. They use Faster Regional Convolution Neural Network (Faster R-CNN) for detecting the Objects and Tracking algorithm for surveillance the tunnels for the events, like driving direction, halting, fire, roaming person in the tunnel [4]. Inad and duaa(2018) designed an approach for pedestrian detection. They use vggnet, they will work with is mpeg-4[7]. It improve the overhead of video search interest as well as improve accuracy. Zouhair et al. (2020) reviewed the Driver Behavior (DB) inside the car. The machine learning technique used widely and shows good results in calculating the behavior of the driver while driving [8]. Sreenu and Saleem (2019) survey in detecting the number of people in the big crowd at all conditions. They surveyed various methods like the svas[11] model which offers the automatic detection of such type of activity. IBSTM and Kalman filter [11] is used for object entity in the crowd. Smriti et al. (2017) build the system to detect the fall of a person especially the old age person in the home. Shi-Tomasi algorithm and Pyramidal Lucas-Kanade algorithm are used to detect the fall and not fall [12]. Sachin and Subrahmanyam(2016) defines a motion recognition technique named as weber movement history image (wmhi)[14]. Hanen et al. (2017) introduce a method for identify the object in the motion. They use the SIFT method with BOVW [26][15]. Zhigang et al. (2018) recognize the human movement with the help of feature extraction CNN with a TS-NET [17]. Qaisar et al (2017) contributed the action recognition in a deep learning environment [19]. They overview the CNN, RNN, DBN, DBM, SDA [19]. They show that the deep learning techniques can be applied in human action recognition, gesture and emotion recognition, etc. Muhammad et al. [21] compares various model like VGG16, Inception-V3, Inception-ResnetV2, SSDMobile NetV1, Faster-RCNN, YOLOv3, and YOLOv4 for weapon detection using dataset No standard dataset (weapons images from own camera, internet, extracted data from YouTube CCTV videos, through GitHub repositories). Erssa et al.[22] detects the violent object like gun, pistol and sword from CCTV by using the efficient-net machine learning model and gets the accuracy of 98.12%, They uses the real time dataset for training and testing of model from local surveillance department. Arunnehru et.al. recognize the human action with 3D (CNN) and KTH and Weizmann dataset [26]. Ravinarayana et.al [27] uses LSTM with transfer learning for predicting the crime activity with the help of inputs videos and gets the accuracy of 70%.

III. PROPOSED METHOD

We proposed a model that gives a computer a prescient awareness of dangerous weapons and that can also warn a human administrator when a pistol or knife with a person is clearly on the edge. If possible, we can also share the live image with security personnel so they may move simultaneously by using cameras with GPS position. Also, in preparation for a future catastrophe, we have built an information system for keeping track of all the drills that have an influence on the metropolitan areas. This leads to the establishment of a database that records all activities so that quick action may be taken in the event of a future emergency. In this work, we have tried to create an integrated framework for investigation security that distinguishes the weapons gradually. If the identification is definitely correct, it will warn/brief the security personnel to handle the situation by getting to the scene of the incident using the GPS location of cameras. The workflow of the proposed work can broadly be divided into five phases as shown in figure1.

1. Data acquisition and preprocessing
2. Train the various model like YOLO, SSD and Faster RCNN with the weapons images
3. Test the models
4. Find relation between the detected objects
5. Compare the accuracy between the models

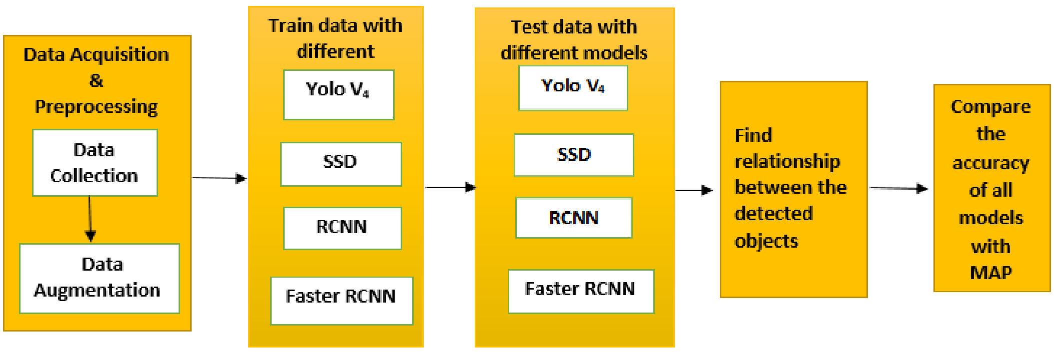

Figure1: The workflow of the proposed work.

A. Data acquisition and preprocessing:

In data acquisition step the images are taken from various sources from internet like kaggle and Roboflow shown in below Figure.2 [30]. After that images are passed for cleaning and enhancement using python code. Then all the images dataset passed for augmentation process where extra images are generated for your classifier through squishing skewing or extraordinary randomize crops. It is the process of expanding the dataset by include more pictures like images from different views and angles from a single image, which might result in a model that is more accurate. The 80% of individual class of guns, knife and person are in the training phase and 20% images are process for testing phase.

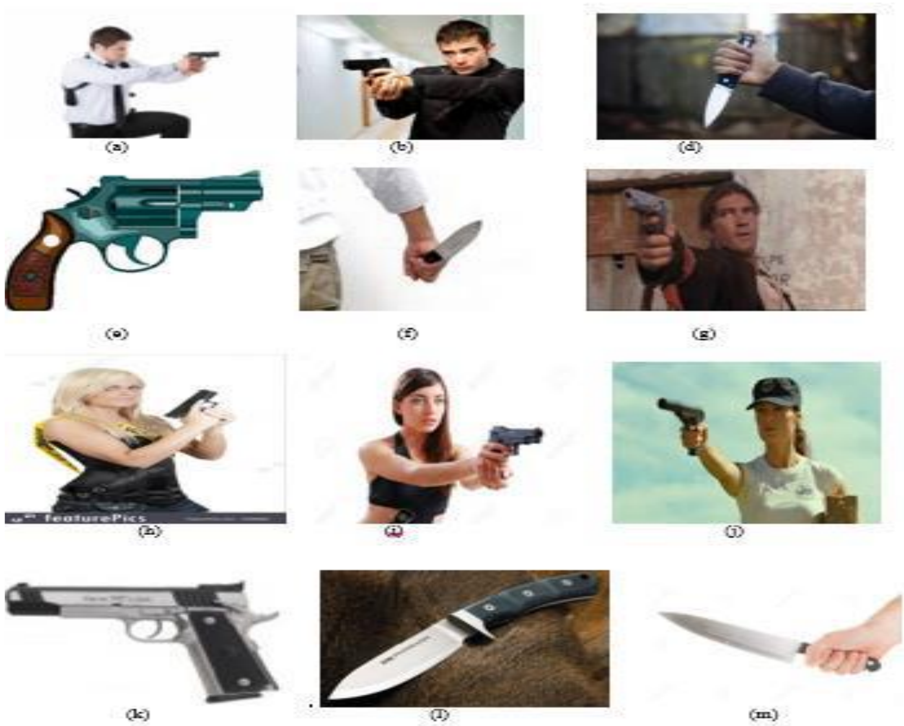

Figure 2: Sample images collected from dataset [30]

B. Training the Images with various Models:

The processed image dataset is now passed to various deep learning models for weapons detection and classification. All models will train with the images of 3 classes i.e. guns, knife and the person, so these models will detect the images of guns , knife and the person from the scene. The 80%of images are processed for the training phase.

1. In YOLOv5, these were the two unified blocks that turned into a single monolithic block.

i. Feature extraction

ii. Object localization

YOLOv5 has three main components namely Backbone, Neck, and Head shown in below Figure.3 [28].

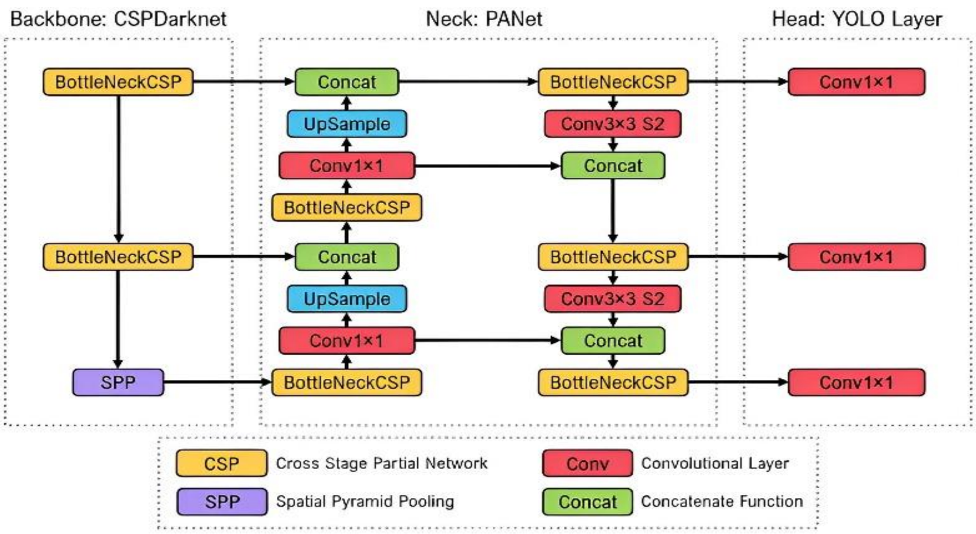

Figure.3. YOLOv5 Architecture [28]

YOLOv5 employs Cross Stage Partial Networks for the purpose of obtaining instructive information from the input image (CSP). The model neck creates feature pyramids (FP). Anchor boxes are used to apply feature class probabilities. In YOLOv5, hyperparameters are used to control the model's architecture, training process, and performance. For YOLOv5 the hyperparameters were 50 along with the Batch size and Learning rate as 16 and 0.001.

2. The SSD architecture is depicted in the below Figure .4[11] comprises additional layers that are built on top of a base CNN network, such as VGG or Mobile Net. The SSD techniques extracted data from each grid cell using a sequence of convolutional and pooling layers. Each grid cell is then subjected to a classifier to forecast. The hyperparameters for SSD algorithm were 150 with similar batch size and learning rate as YOLOv5 algorithm.

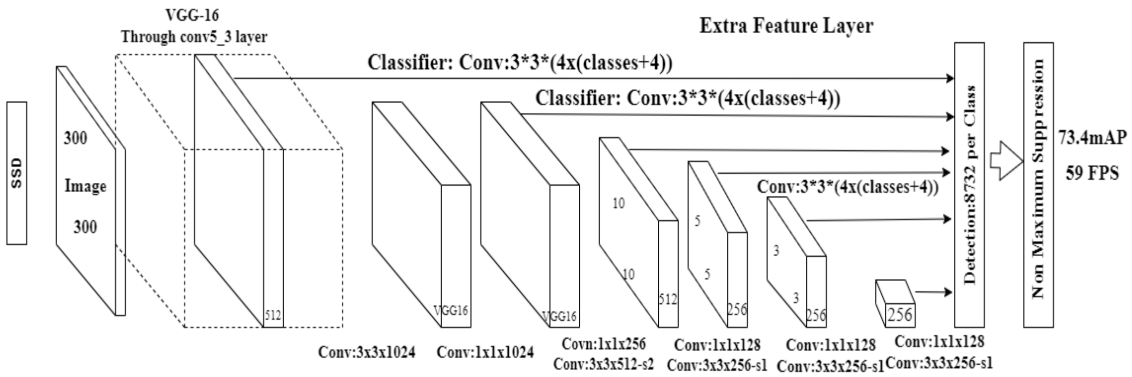

Figure.4. SSD VGG-16 Architecture [11]

3. Faster R-CNN is used for detecting small and prominent objects in a scene. Faster R-CNN is mainly used in object detection. They have the same layers as the basic CNN model, as well as the RCN and RPN networks, and their output is fed into the SVM classifier as shown in Figure.5 [16]. The faster R-CNN has early convolution, which is like the ResNet [8], which is used to extract simple features; it acts as a shallow layer, the next is the RCN which selects the small regions that may contain objects.

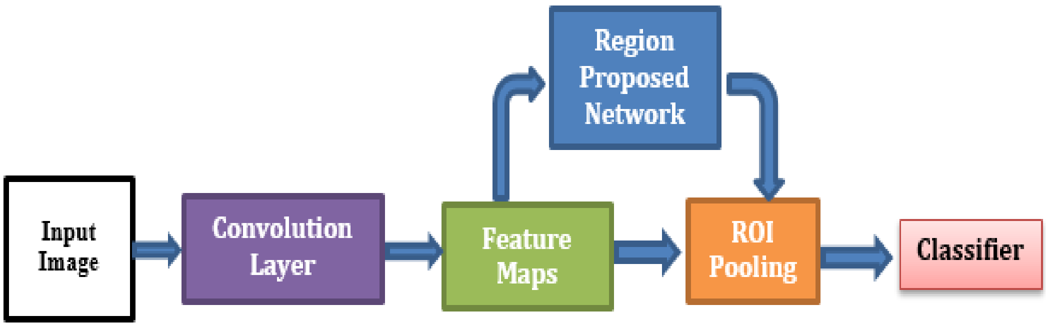

Figure.5. Faster RCNN Architecture [16]

C. Test the models

Testing the Images with various Models: After successful completing the training phase of each models with around 65,046 images of guns, knife and person. The model works well in the training part. The next step is to test each model with around 15,323 images of guns, knife and person. The over fitting and under fitting are also be measured for each model.

D. Find relation between the detected objects

For forecasting the chance of happening the crime based on the object present in the scene is very crucial and it require very high level precision and accuracy. We used the mediapipe library which is provide the facility of datapoints generation. It will create the datapoints in the full body of the person like they create 423 datapoints in only the face of the person, and 21 data point only in hand. We used the datapoints of hand, arm, shoulder, stomach, thigh and legs. The total six datapoints from the person body is detected in the scene, if the weapons is also detected in the hand of the person, then the next step is to calculate the angle between the weapons and the person body with the help of these datapoints. If the angle is between 30 to 120 then there is the high chance of happening a crime if the angle of not in between then there is less chance of happening the crime. If no weapons is detected in the scene then no chance of happening the crime. These data points help in tracing the movement of person also this will provide the information that person is carrying gun or knife along with them or not.

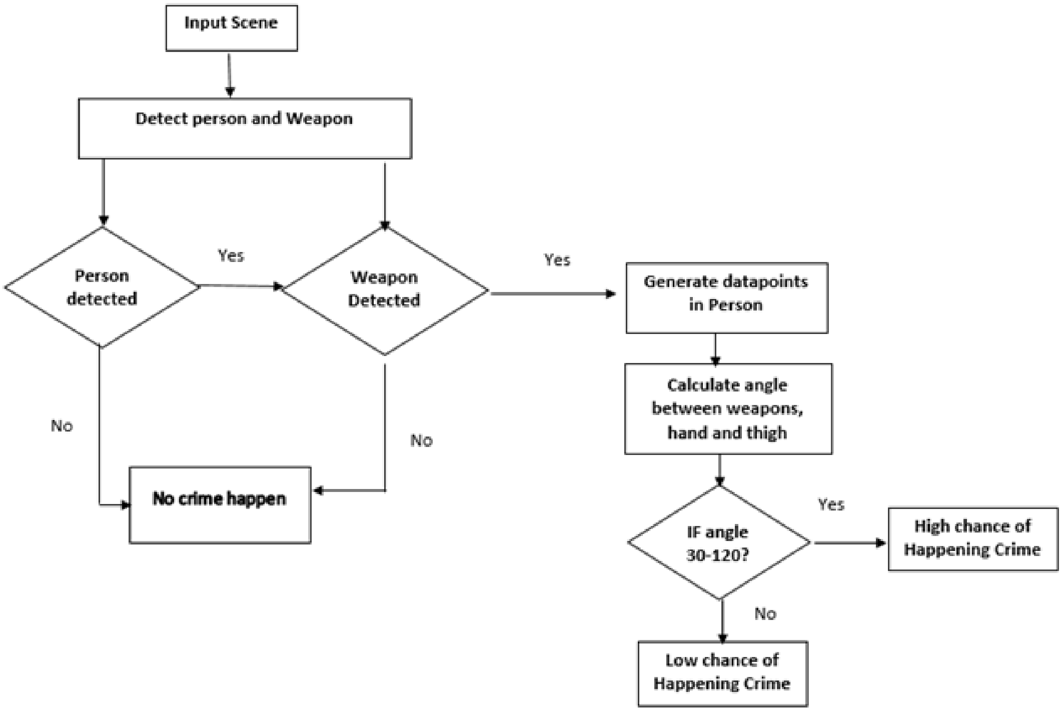

Figure 6: Relation of weapons with the person

IV. EXPERIMENTATION AND RESULT

A. Detection of Weapons SSD Model

This section presents all of the results from the implementations of the Single Shot Detection (SSD), the results of the detected objects from the scene for each of the 3 classes–Guns, Knives, and Person with the accuracy and type of detected object is formulated in a figure.7. The performance of the model is calculated in table1, 2, 3.

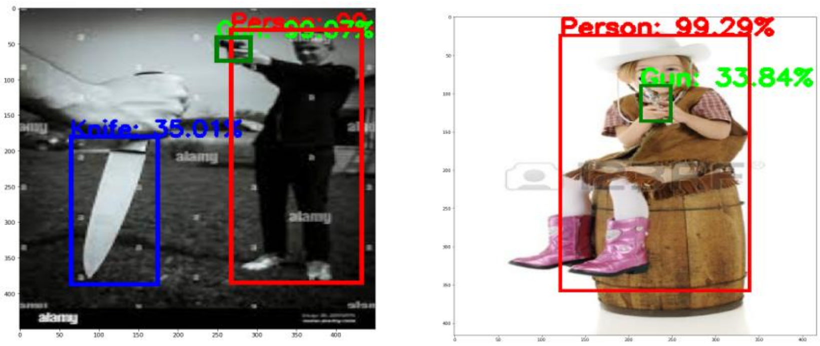

Figure.7. Detection of Objects with SSD Model [30]

B. Detection of Weapons YOLO Model

This section presents all of the results from the implementations of the You only look once (YOLO), the results of the detected objects from the scene for each of the 3 classes–Guns, Knives, and Person with the accuracy and type of detected object is formulated in a Figure.8. The performance of the model is calculated in table1, 2, and 3.

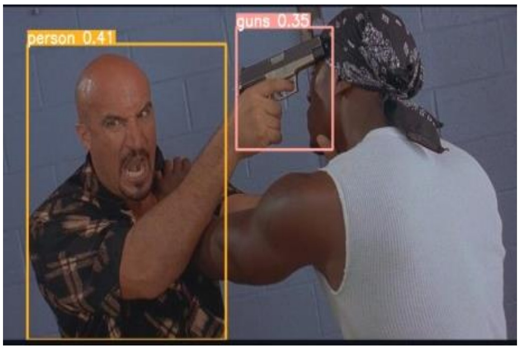

Figure.8. Detection of Objects with YOLO Model

C. Detection of Weapons Faster RCNN Model

This section presents all of the results from the implementations of the Faster Region based Convolution Neural Network (Faster RCNN), the results of the detected objects from the scene for each of the 3 classes–Guns, Knives, and Person with the accuracy and type of detected object is formulated in figure9. The performance of the model is calculated in table1, 2, 3.

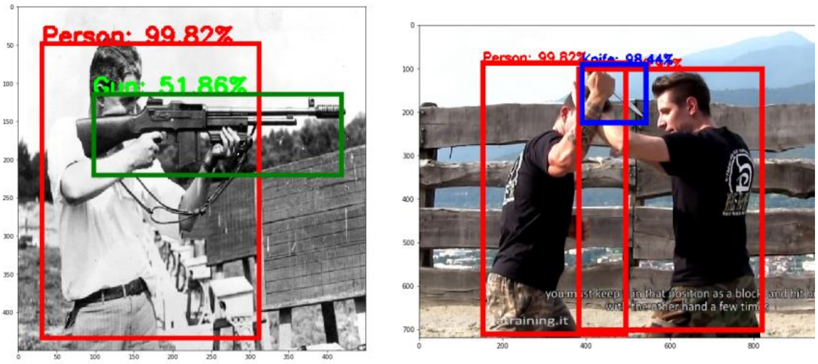

Figure.9. Detection of Objects with Faster RCNN Model

D. Prediction of Happening, Not Happening Crime

This section presents all of the results from the implementations of the Mediapipe library for forecasting the crime prediction based on the datapoints and the angle between the weapons and the person. In figure.10 the angle between the gun, shoulder and hip is 47° which is considered as high chance of happening the crime.

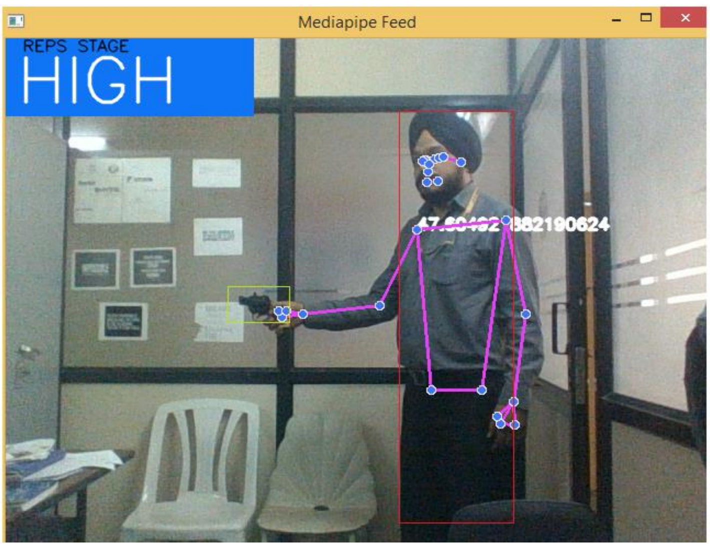

Figure.10. High Probability of the crime with person and gun

In figure11 the angle between the gun, shoulder and hip is 17° which is considered as low chance of happening the crime.

Figure.11. Low Probability of the crime with person and gun

In figure.12 the angle between the Knife, shoulder and hip is 115° which is considered as high chance of happening the crime.

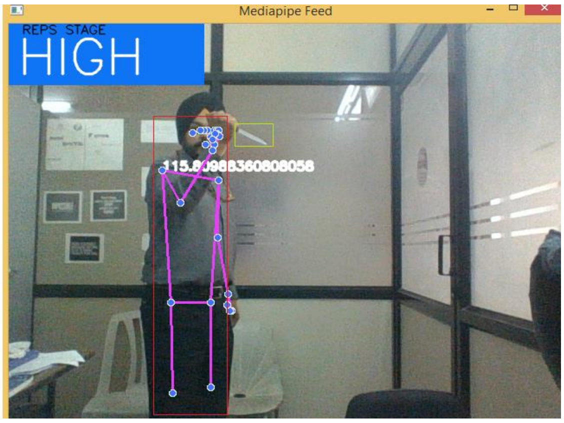

Figure.12. High Probability of the crime with person and Knife

In figure.13 the angle between the Knife, shoulder and hip is 9.3° which is considered as low chance of happening the crime

Fig13. Low Probability of the crime with person and gun

E. Performance Evaluation of various Models with Mediapipe Library:

Table 1: ACCURACY COMPARISON BETWEEN ALL THREE MODELS

Algorithm	Avearge Gun Accuracy	Average Knife Accuracy	Avearge Person Accuracy	Average
SSD	89%	82%	76%	82%
YOLO	92%	89%	87%	89%
Faster	**97%**	**93%**	**90%**	**93%**

Table 2: SPEED COMPARISON BETWEEN ALL THREE MODELS

Algorithm	Testing Time
SSD	**0.25 sec**
YOLO	0.54 sec
Faster RCNN	0.75 sec

Table 3: MAP WITH FASTER RCNN, SSD, YOLO MODELS

Models	Avearge Precision		
	Guns	Knife	Person
SSD	0.78	0.744	0.698
YOLO	0.76	0.72	0.66
Faster RCNN	**0.84**	**0.76**	**0.72**

The four performance matrices such as accuracy, recall, precision, and F1-score as shown in Eqs.1 - 4 and the result are shown in Table 4.

Accuracy = (TN + TP) / (TP +FP +FN +TN) (1)

RECALL = TP / (TP + FN) (2)
PRECISION = TP / (TP+ FP) (3)
F1 SCORE = 2 *(Recall* Precision) / (Recall + Precision) (4)

Table 4: CONFUSION MATRIX WITH ALL THREE MODELS

Models	Accuracy	Precision	Recall	F1 Score	Specificity
YOLO	88	86	90	88	84
SSD	82	82	86	84	84
Faster RCNN	93	92	95	93	90

V. CONCLUSION

In this paper, we compare the performance of SSD, YOLO, and Faster RCNN with different weapons dataset like (knife and gun) and the person dataset. The faster RCNN is shown to have better results in detecting small objects like guns and knives in the scene as compared with SSD and YOLO, Yolo is faster than the faster RCNN, and SSD is faster than YOLO. The accuracy of faster RCNN is 97%, 93%, 90% for guns, knives and person which is better than SSD and YOLO models. Also, SSD requires a higher order resolution layer to detect small objects, accuracy can be increased by increasing the cost of increasing the default bounding box. Once the weapons are detected from the scene, the relation of weapons with person are calculate with help of angle between the datapoints of weapons, elbow and hip of the person. Based on the angle we forecast the probability of happening the crime. The images captured in predetermined and controlled situations made up the dataset that was utilized. Under unfavorable image conditions, like low resolution, blur, position fluctuation, and occlusion, the algorithm's accuracy suffers significantly. It is difficult to increase the accuracy of the majority of the image-based data that is currently accessible because it was collected using low-resolution equipment. The most recent massive datasets made from online images are poorly annotated, which leads to inaccurate people and knife identification. Datasets that are based on video produce superior results because they allow us to record objects from the scene and forecast the likelihood that a crime will occur based on the objects and poses that were observed.

VI. FUNDING

Not applicable

VII. COMPETING INTERESTS

Both authors declare that they have no competing interests.

VIII. ETHICS APPROVAL

Not applicable

IX. CONSENT TO PARTICIPATE

Not applicable

X. CONSENT FOR PUBLICATION

Not applicable

XI. DATA AVAILABILITY AND ACCESS

All dataset used for supporting the conclusion of this manuscript are available in kaggle repository.
Gun Image data were extracted from the Kaggle Data Repository

https://www.kaggle.com/ankan1998/weapon-detection-dataset.
All Knife data were obtained Kaggle Data Repository and Roboflow
https://www.kaggle.com/datasets/shank885/knife-dataset
https://universe.roboflow.com/workspace-zqssx/knife-dataset-new.
All Person data were obtained Kaggle Data Repository
https://www.kaggle.com/datasets/constantinwerner/human-detection-dataset

XII. CODE AVAILABILITY

Not applicable

XIII. AUTHORS CONTRIBUTION STATEMENT

Dr. Hemang Shrivastava coordinate this research work. Mr. Taranpreet singh carried out the designed, experimentation and data analysis of this research work, both authors had participated sufficiently in the work and read and approved the final manuscript

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