# Motion and Object Recognition for Crime Prediction and Forecasting: a Review

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# Motion and Object Recognition for Crime Prediction and Forecasting: A Review

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***Abstract*- It is fascinating to see how technology is being used to monitor and detect potential threats in our society. Therefore, we propose an algorithm to build a system which detects crime in public places. To overcome this issue and to prevent it, the development of automated surveillance systems which can detect violent, abusive, and abnormal behavior in public is an ensuring step towards public safety. Additionally, crucial to remember is that feature extraction and detection and motion techniques play a crucial role in violence detection and such techniques help to identify specific patterns and behaviors that are indicative of violence and enable the automated system to recognize and respond to such events. Through this we can Prevent violent incidents by enabling early intervention, help law enforcement agencies and other organizations to better understand the patterns and helps understand factors that contribute to violent behavior.**

## I. INTRODUCTION

Machine learning-based object classification and motion detection are versatile and valuable tools with many different applications in various industries, including, surveillance, automotive, security healthcare, and lastly retail. Machine learning has become the present mainstream prediction method for crimes [6]. Criminal activities have a widespread impact on society, damaging the economy and quality of life for residents, and leading to social issues. A range of circumstances, including specific behaviors, motives, human nature, dangerous situations, and poverty, contribute to the occurrence of crime. Contributions such as gender inequality, unemployment, child labor, very high population density, and illiteracy can increase the incidence of violent crimes. The rise in criminal behaviors and activities has made crime prediction an increasingly popular tool in recent years. Taking help from better predictive algorithms and law enforcement agencies can direct police patrols towards potential criminal activity and take timely action [8].

Motion detection is a valuable tool for preventing and detecting criminal activity This can be applied in a number of situations, such as intruder detection, Property Monitoring, Suspicious Behavior Detection, and Traffic Monitoring. In Intruder Detection, motion detection technology can alert security personnel or law enforcement of an intruder's presence. Similarly, in Property Monitoring, motion detection can help monitor a property for any unauthorized activity, triggering an alert that notifies authorities to respond. This shows that motion detection is an excellent way to recognize crime [24].

Our project involves utilizing Python and Computer Vision (CV) to implement Motion Detection, a powerful technique for detecting violence in a video feed. Computer vision-based techniques for violence detection analyze surveillance camera videos, which are increasingly being installed in public spaces such as medical hospitals, educational institutions, markets, stores, banks and streets to keep an eye on people's activities for public safety. Monitoring includes analyzing people's behavior to distinguish between normal and suspicious activities [8].

Initial step is to capture the video feed from a camera using OpenCV, a popular CV library for capturing video frames in Python. Next, we perform background subtraction to identify any moving objects present in the video feed. This is accomplished using OpenCV's background subtraction algorithms, such as MOG2 or KNN, which allow us to extract moving objects from the background. Once we have isolated the moving objects, we can perform motion detection to identify any instances of violent behavior[11].

Detecting suspicious or abnormal behavior among people is an essential aspect of monitoring, which involves analyzing their activities to decide whether they are behaving normally or not. However, detecting such behavior, either in real-time 24/7 monitoring or from the analysis of vast amounts of recorded video data, can be an extremely challenging task. Therefore, we have created many techniques to recognize human activity in actual life situations. These specific techniques will aid in identifying and spotting odd actions in the surveillance videos. [11]. In the detection process to identify violence activity, the first step is to have DATASETS - a collection of data that is organized and stored in a structured format for analysis and processing, PREPROCESSING- process of making the raw data for detailed analysis and modeling. To prepare data for machine learning, it must be cleaned, transformed, and reorganized. The process of choosing and extracting the most pertinent and educational aspects from raw data transformation is the process of changing the shape or structure of data and altering it. It is a critical step in analysis and data processing that helps to clean, normalize, and prepare data for remaining analysis, MODEL TRAINING- Trains the chosen machine learning algorithm using the training data, EVALUATION AND RESULT - give a few testing datasets to test the model, will give the output if its violent or not [24]. Same is shown in Fig 1. we can observe the process for detection of violence.

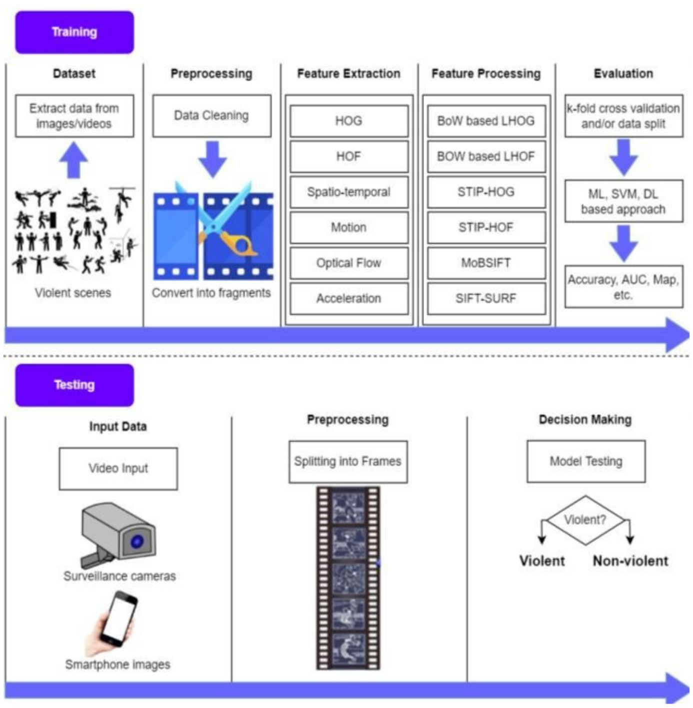


Fig 1. Process of violence detection

## II. LITERATURE SURVEY

The author M. Labayen Esnaola, N. Aginako Bengoa, B. Sierra Araujo, I. G. Olaizola, and J. Flórez *"Machine Learning for Video Action Recognition: a Computer Vision Approach"* published in 2018. The paper discusses the use of techniques involved in machine learning for identifying actions in videos. The authors propose a computer vision strategy that involves extracting features that are visual from a set of video frames, representing these deep neural network characteristics, and using the network to classify actions in the video. The study includes findings from a number of datasets that show how effective and efficient the suggested approach is at identifying a broad range of activities in films. In conclusion, this study can be helpful for scholars and practitioners interested in the topic of video action detection since it sheds light on how to approach this challenge using computer vision and machine learning techniques.

The author X. Zhang, L. Liu, L. Xiao, and J. Ji, *"Comparison of Machine Learning Algorithms for Predicting Crime Hotspots,"* was published in 2020. The use of machine learning algorithms to identify crime hotspots is discussed in the article. On a dataset of crime episodes in a city, the authors examine the effectiveness of a few machine learning methods, such as Random Forest, Support Vector Machine, and Artificial Neural Network. Based on a number of metrics, the authors evaluate the algorithms. Pick the algorithm that, in terms of accuracy, precision, and recall, performs the best in identifying crime hotspots. In summary, this article will be helpful to researchers and professionals interested in applying machine learning to predict and prevent crime because it offers insights into the algorithms and their applicability for different types of crime data.

The author W. Safat, S. Asghar, and S. A. Gillani, *"Empirical Analysis for Crime Prediction and Forecasting Using Machine Learning and Deep Learning Techniques," was* published in 2021. The article examines strategies for forecasting and predicting crime using machine learning and deep learning. Using a dataset of crime episodes in a city, the authors evaluate the prediction capabilities of several deep learning and machine learning algorithms, such as Random Forest, K-Nearest Neighbors, and Convolutional Neural Network. The authors also suggest a brand-new deep learning model for predicting crimes dubbed the Temporal Convolutional Network (TCN) and evaluate its performance against previous models. In general, academics and practitioners interested in Employing deep learning and machine learning techniques, this article beneficial for crime prediction and forecasting, as it provides insights into the performance of different algorithms and the potential of new models like TCN.

The author S. S. Kshatri, D. Singh, B. Narain, S. Bhatia, M. T. Quasim and G. R. Sinha, *"An Empirical Analysis of Machine Learning Algorithms for Crime Prediction Using Stacked Generalization: An Ensemble Approach,"* was published in 2021. The study uses layered generalization, an ensemble learning technique, to provide a quantitative analysis of machine learning methods for predicting crime. The authors evaluate the effectiveness of various machine learning techniques, such as Support Vector Machine, Random Forest, and Decision Trees., using a stacked generalization technique utilizing a dataset of crime episodes in a city. The authors assess the algorithms using a variety of measures, including recall, accuracy, and precision, and they emphasize how the stacked generalization technique effectively enhances the prediction performance of the individual algorithms. It is described how different machine learning algorithms perform, as well as the potential of stacked generalization for increasing predictive accuracy. As a result, this article can be helpful for researchers and practitioners interested in the application of ensemble learning approaches to crime prediction and prevention.

The author Yu, J., Song, W., Zhou, G. et al, *"Violent scene detection algorithm based on kernel extreme learning machine and three-dimensional histograms of gradient orientation",* was published in 2018. In the article, a kernel extreme learning machine (KELM) and three-dimensional gradient orientation histograms are introduced (3DHOG)-based violent scene detection system. The authors' goal is to identify violent scenes in videos, which can be beneficial for many various purposes, including content filtering and surveillance. The authors first extract 3DHOG features from video frames before classifying violent from non-violent scenarios using KELM. They contrast the effectiveness of their strategy with that of already-used methods like random forest (RF) and support vector machine (SVM). Overall, scholars and practitioners may find this paper valuable interested on developing algorithms for detecting violent scenes in videos using machine learning techniques, as it provides insights into the effectiveness of KELM and 3DHOG features for this task.

The authors V. D. Huszár, V. K. Adhikarla, I. Négyesi and C. Krasznay, "*Toward Fast and Accurate Violence Detection for Automated Video Surveillance Applications*" published on 14 February 2023. The amount of video data produced makes it challenging for people to perform real-time analysis makes it difficult to detect aggression in surveillance film. Even manual methods can cause events to be detected later. Automatic violence identification in surveillance footage has generated significant interest from the scientific community as a potential remedy. Machine learning algorithms have advanced, making automatic video recognition jobs like violence detection increasingly possible. 3D convolutions are utilized to record the data's geographical and temporal structure in order to overcome this difficulty. Additionally, effective and precise violence detection in surveillance film is achieved by utilizing the information a trained action recognition model has learned.

The authors K. B. Kwan-Loo, J. C. Ortíz-Bayliss, S. E. Conant-Pablos, H. Terashima-Marín and P. Rad, "*Detection of Violent Behavior Using Neural Networks and Pose Estimation*," published on 16 August 2022. The detecting system is made to automatically process live video from cameras placed outside of buildings or on public roadways. The current approach calls for human security officers to watch numerous video feeds continuously, but this can be taxing and raises the possibility of missed or delayed assault detection. In addition, if a robbery happens, all attention is diverted to that one incident, leaving other places unattended. Human operators' responsibilities can be decreased and their time and attention can be redirected to other crucial activities with a technology that can concurrently detect aggressive behavior across multiple camera sites. The 3D CNN performs convolutions on three-dimensional inputs, allowing it to capture spatiotemporal activities of video data. By analyzing motion and patterns over time, 3D CNNs have proven to be effective in roles like action recognition.

The authors P. Sernani, N. Falcionelli, S. Tomassini, P. Contardo and A. F. Dragoni, "*Deep Learning for Automatic Violence Detection: Tests on the AIRTLab Dataset*," published on 30 November 2021. Violence can be detected Using architectures based on deep learning, such as 3D Convolutional Neural Networks, which have been shown to be effective at extracting spatio-temporal data from videos. However, these architectures could misinterpret rapid, friendly motions like claps, high-fives, and hugs to be violent, leading to false positives. In order to address this problem, we show three models for detecting violence based on deep learning. and assess their performance using the AIRTLab dataset, which was created specially to test how robust algorithms are against false positives.

The authors Wang, Y., Zhu, R., Wang, L., Xu, Y., Guo, D., & Gao, S. "*Improved Vidar and machine learning-based road obstacle detection method*" published on July 2023. Obstacle detection for Vision-based methods offer numerous advantages, such as delivering advanced detection information, being cost-effective, scalable, requiring minimal hardware, and being programmable. These techniques can be separated into three primary groups: those depending on morphology, those depending on machine learning, and those based on motion correction. The limited accuracy of morphology-based approaches in detecting obstacles prevents them from being widely employed. Conversely, machine learning algorithms and methods have demonstrated higher accuracy in identifying specific obstacles, such as pedestrians, vehicles, and dangerous objects, and are therefore more commonly used.

The authors L. Ruotsalainen, A. Morrison, M. Mäkelä, J. Rantanen and N. Sokolova, "*Improving Computer Vision-Based Perception for Collaborative Indoor Navigation*," published on 15 march 2022. For the purpose of tracking the movement of features across multiple photographs of static objects in a scene, we are using a computer vision application. Three key issues complicate the employment of computer vision technologies in our particular application. First, a significant number of clearly visible items must be present in the environment for tracking to be successful, which can be difficult to achieve in poor lighting conditions, such as those encountered at night. As a solution, we plan to install a light on top of the cameras to improve visual quality and ensure proper detection. Secondly, we require small, cost-effective cameras, and we have opted to begin with the typical USB camera used for computers. Thirdly, dynamic objects in the camera's surroundings can hinder view quality. In order to avoid degradation of visual quality and ensure accurate output, we will need to train our model using a vast dataset to minimize potential errors and issues.

The authors Muhammad Ramzan, Adnan Abid, Hikmat Ullah Khan, Shahid Mahmood Awan, Ahsan Mahmood *" A Review on State-of-the-Art Violence Detection Techniques"* on 2019. Computer vision-based techniques for detection of violence analyze surveillance camera videos, which are increasingly being installed in public spaces such as banks, medical institutions, educational institutions, markets, streets and banks to monitor people's activities for public safety. Monitoring includes analyzing people's behavior to distinguish between normal and suspicious activities but detecting suspicious activity 24/7 or in vast amounts of recorded data can be challenging. To overcome this obstacle, researchers have come up with various methods for identifying human activities in real-time and detecting suspicious activities in surveillance videos, including violence detection. These strategies use different input parameters such as flow, time, appearance, and acceleration, and involve dividing videos into sections and frames, detecting objects, extracting features, and detecting anomalous activity. When the distinction between aggression and deviant behavior is noted, this draws the attention of researchers. behaviors that are distinct from daily routines are referred to as abnormal activity, and violent activity includes behaviors like theft, fighting, and beating.

The author Cem Direkoglu "*Abnormal Crowd Behavior Detection Using Motion Information Images and Convolutional Neural Networks"* on 2020. The proposed approach involves techniques and models for detecting abnormal behavior in crowds using computer vision-based methods. An anomalous behavior indicator is a 1D feature vector based on optical flow magnitude and angle difference data. An optical flow dataset is used to generate MIIs and is fed into a convolutional neural network (CNN) to help detect unusual or weird behavior. The Lucas-Kanade algorithm is used to insert into the optical flow into each and every frame, after which the motion information image (MII) is created. When movement is seen at specific pixel locations during a panic situation, the angle difference between the optical flow vectors increases there. The method attempts to be unaffected by changing angles and lighting situations and to be able to distinguish between abnormal and typical events in both local and global contexts.

The authors, Xiang Li, Qixu Wang, Xiao Lan, Xingshu Chen, Ning Zhang, Dajiang Chen,"*Enhancing Cloud-Based IoT Security Through Trustworthy Cloud Service: An Integration of Security and Reputation Approach"* on 2019. The main challenges faced in the IoT context are the resource constraints of IoT devices, which make it difficult to handle activities with very high complex computation and large data storage requirements. Therefore, cloud computing is widely used to store and process data generated by IoT devices. Additionally, choosing the right cloud service providers (CSPs) is essential for guaranteeing the scalability, availability, safety, and protection of cloud-based IoT. According to the numerous cloud service qualities, the cognition of cloud service customers (CSCs) is dependent upon and influenced by the trust evaluation of CSPs. A number of sub-objectives must be met in order to guarantee privacy and security in the IoT network, including reducing the impact of adversarial access requests through request filtration that is based on authentication, maximizing the block chain's scalability and performance, selecting the consensus node with consideration for the trust value, and conducting attribute and user revocation based on time and behavior. By implementing authentication-based request filtering, enhancing the block chain's scalability and performance, taking into account the trust value when choosing the consensus node, and implementing attribute and user revocation based on time and behavior, of adversarial access requests.

The authors Nouar Aldahoul, Hezerul Abdul Karim, Aznul Qalid Md. Sabri, Myles Joshua Toledo Tan, Mhd. Adel Momo, Jamie Ledesma Fermin "*A Comparison Between Various Human Detectors and CNN-Based Feature Extractors for Human Activity Recognition via Aerial Captured Video Sequences"*on 2022. For human detection, a number of object detectors, including YOLOv4, Faster R-CNN, and EfficientDetD7, have been pre-trained using the COCO dataset. YOLOv4 has the benefit of seeing entire images during training, which lowers background errors, and provides a nice striking a balance between rapid inference and high accuracy. In order to extract the features from frames, a block of human patches or ROIs is sliced from the video bits and utilized to extract a pattern of features from a succession of frame ROIs using CNN-based feature extraction. Then, an LSTM is given these features to classify human behavior. The proposed HDAR system is resistant to a range of distortions, including flipping horizontally, blurring, adding Gaussian noise, lightening and darkening, as well as converting RGB to grayscale, by integrating EfficientDetD7 is for feature extraction combined with human detection. The RPN (Region Proposal Network) uses an image of any size to generate a set of rectangles that represent regions. These rectangles are then shared with the detection network for human detection.

The authors Ahlam Al-Dhamari, Rubita Sudirman, Nasrul Humaimi Mahmood,*"Transfer Deep Learning Along With Binary Support Vector Machine for Abnormal Behaviour Detection" on 2020.* This article discusses about abnormal detection frameworks, particularly using SVM and BSVM classifiers. SVM is a type of classifier that can solve linear and nonlinear classification problems and only a few patterns must be trained for optimal detection accuracy for new patterns during testing. BSVM, on the other hand, is the most popular classifier for addressing various classification issues and offers good generalization performance using the structural risk minimization (SRM) approach. Transfer learning is applied with a VGGNet-19 model, which can extract features from challenging and noisy surveillance scenarios, to take motion characteristics out of videos. The five convolutional blocks that make up the VGGNet-19 are referred to as feature extraction layers, while the resulting activation maps are referred to as human motion features. By utilizing descriptive features to boost performance, the goal is to evaluate whether any input video sequence is normal or abnormal.

TABLE 1. FINDINGS AND OBSERVATIONS REGARDING MOTION AND OBJECT DETECTION FOR CRIME

| | |
|---|---|
| Y. Watanabe, M. Okabe, Y. Harada and N. Kashima [30] | • The weakly supervised dataset comprises videos that are classified as either normal or abnormal.<br>• Videos labeled as normal contain only the normal state throughout all frames.<br>• Videos labeled as abnormal contain a mixture of normal and abnormal frames.<br>• This type of dataset eliminates the need to label each frame as normal or abnormal, reducing the amount of labeling required. |
| M. -S. Kang, R. -H. Park and H. -M. Park [13] | • Based on the investigation that people in violent situations usually move actively to produce strong pixel differences between consecutive frames than others<br>• Since violent actions such as punching and kicking usually last for a short time, we propose a method to give 2D CNNs the ability to encode short-term motion information.<br>• We propose a temporal attention module that is very similar to Squeeze-and-Excitation (SE) blocks [51]. The SE block recalibrates channel-wise features, while our temporal attention module deals with time-wise features. |
| P. Machado, A. Oikonomou, J. F. Ferreira and T. M. Mcginnity [28] | • In computer vision, object motion detection is traditionally performed using BS methods, where the foreground (pixels or group of pixels whose light intensity values have suffered an abrupt variation)<br>• are compared with the previous image or background model<br>• BS can be static, subtracting the current image frame from the first image frame, or dynamic, subtracting the current image frame from previous image frame(s) |
| X. Ma, H. Wang, B. Xue, M. Zhou, B. Ji and Y. Li [3] | • As compared to other sensing modalities, camera can provide richer semantic information about the person as well as his/her surrounding environment.<br>• The recently developed extreme learning machine (ELM) has comparable performance to SVM yet it: 1) is extremely fast to compute and 2) has the capacity to deal with highly noisy data. |
| W. Ren, O. Ma, H. Ji and X. Liu [7] | • . Researchers figured out that lack of technology maturity when it comes to safety and comfort of citizens is an impeding society.<br>• . There are two categories of recognition methods: 1) those based on pressure mapping (PM) and 2) those based on visual imaging.<br>• PM sensors are used to recognized to recognize the body posture, but wearing them all the time can be troublesome and burdening to humans. |
| R. Zhang and S. Cao [4] | • CNN, short for Convolutional Neural Network, is a deep learning algorithm commonly used in computer vision tasks, including the detection and classification of human motion behaviors.<br>• CNN is a class of deep and feed-forward neural networks with multilayer perceptrons.<br>• CNN is used as a common classifier for images or visually imagery because of its convolution process emulates the response of an individual neuron to visual stimuli |
| Ye Tao, Peng Xu, Hai Jin [12] | • CECS is a framework that holds great promise for processing IoT data as it allows edge servers to perform real-time processing that stores the data on to a cloud server.<br>• This provides rapid response times to IoT device requests, offers large-scale cloud storage for IoT data, and allows for convenient sharing of data with users.<br>• The fact that cloud servers have abundant storage and computing resources, while edge servers are situated in close proximity to IoT devices gives a great advantage to the framework.<br>• Given that IoT devices generally have limited resources, edge servers are better equipped to respond rapidly to their requests. |

| | |
|---|---|
| [19] Supriya V. Mahadevkar, Bharti Khemani, Shruti Patil | • Convolutional neural networks (CNNs) are widely used for object detection tasks, and feature extraction which are very important in this process.<br>• By processing a large dataset of face photos through supervised learning, a deep CNN can successfully recognize faces<br>• This is achieved through a process of training the network to identify patterns and features in the images that are unique to individual faces.<br>• Once the network has learned to recognize these features, it can then use them to identify and classify new faces with high level of accuracy |
| [13] Umair Muneer Butt, Sukumar Letchmunan, Fadratul Hafinaz Hassan, Mubashir Ali | • Machine learning and Data mining approaches, particularly clustering techniques, had a huge impact on crime hotspot detection.<br>• Techniques involved in Time series analysis and deep learning have been useful in predicting crime trends Including spatial and temporal information in crime datasets have improved the precision and dependability of crime prediction systems.<br>• To make a dataset useful for crime prediction, it should be reliable, accurate, and Spatio-temporal labeled. Some crime events are reported by the police officers and sometimes by the people who are victims<br>• Including spatial and temporal information in crime datasets has improved precision and reliability of crime prediction systems. |

## III. COMPARISON FOR METHODOLOGIES

3D Convolutions - is a mathematical operation that is commonly used in deep learning models for processing and analyzing three-dimensional data such as video, to record the data's geographical and temporal structure [25]. A potent tool for removing spatial information from the input data is 3D convolution. It is feasible to learn hierarchical representations of the input data and use them for tasks like classification, segmentation, and object detection by stacking many layers of 3D convolution in a neural network [26].

The Human Activity Recognition (HAR) system identifies and tracks human body parts in subsequent video frames using image-level descriptors such the Histogram of Oriented Gradients (HOG) or Histogram of Oriented Optical Flow (HOF). [25]. Recognition of Human activity refers to the process of using technology, such as sensors or cameras, to automatically identify and understand human actions and movements in real-time. This can include activities like walking, running, sitting, or even more complex actions like cooking or dancing. The objective of the human activity recognition is to create systems that can interpret and respond to human behavior, such as detecting falls in elderly individuals or tracking athletic performance during training.

Because of its great accuracy and low model complexity, the X3D-M model is a good fit for the job of detection of violence [25]. A reduced version of the X3D standard for describing 3D visuals and interactive information on the web is the X3D-M model, also known as the extended 3D Mobile model. Faster rendering and better performance are possible on mobile devices thanks to the X3D-M model's optimization for use on hardware with restricted processing and memory.

For our objective of detecting aggression, the ResNet 3D backbone, which consists a track record of learning complicated spatio-temporal characteristics, is especially helpful since it enables the model must accurately reflect the dynamic nature of the movies and create trustworthy data visualizations. [25]. ResNet 3D is a deep learning architecture used for video recognition tasks, specifically in the area of action recognition, which involves identifying and classifying human actions in videos. ResNet 3D consists of 3D convolutional layers, which are typically used to extract spatiotemporal features of video frames over time. By addressing the vanishing gradient issue that might arise with deep networks, the residual connections employed in ResNet 3D enable the training of deeper networks. ResNet 3D is able to capture long-term temporal dependencies as a result, which enhances the accuracy of action detection in videos [26].

HSMD stands for Hierarchical Spherical Mixture Distribution, which is a statistical model used for clustering and density estimation of high-dimensional data. The HSMD model is particularly useful for data that are represented as vectors in a high-dimensional space, such as images, speech signals, or genomic data.The HSMD model represents the data as a mixture of spherical Gaussian distributions, where each Gaussian component corresponds to a cluster in the data. Model - Spiking Neuron Models, Input Layer: DBS and Reduction, Pixel Intensities to Currents Encoding, Motion Stability, Motion Detection, Filtering [28].

Convolutional neural network (CNN), an artificial neural network is frequently utilized for processing tasks as well as for video and image identification. By reducing the amount of processing parameters needed, from input data, such as images, it is meant to automatically and adaptively learn spatial hierarchies of features. A CNN is made up of multiple layers, including convolutional, pooling, and fully connected layers. While the pooling layer is used to down sample the data to lessen computational complexity, the convolutional layer applies filters (sometimes referred to as kernels) to the input data to extract pertinent features [13],[4].

The feature selection technique Sequential Forward Feature Selection (SFFS) is utilized in machine learning to identify a subset of features in which its most similar to the prediction task. The goal of feature selection is to reduce the input data's dimensionality while preserving or even improving the prediction's accuracy. Starting with a blank set of features, SFFS iteratively adds one feature at a time, assessing the model's success after each addition. At each iteration, the algorithm adds the feature that produces the largest improvement in performance, until no further improvement can be obtained [29].

SVM (Support Vector Machine) is a type of algorithm used in machine learning to help find the best way to separate things into various groups based on their characteristics. It's like drawing a line between two groups of points on a graph, with the goal of creating the largest possible space between the two groups. SVM can be used for things like image recognition and natural language processing [18]-[20].

K-nearest neighbor (K-NN) is a machine learning approach that is used for classification and regression issues. It is called "k-nearest neighbor" because it finds the K closest data points to the new data point being classified, depending on a distance metric such as Euclidean distance, and assigns its class of majority of these K neighbors to the new data point. Using the feature vector of the instance as an input, K-NN calculates the distance between the new data feature value and training set. After selecting the closest K neighbors, the class is then allocated from the most common class among them[6].

One common classification technique used in machine learning is the Naive Bayes (NB) classifier. Based on Bayesian theory, it makes the independent nature of each feature an underlying tenet. This assumption is how and why it is known as "naïve". The NB classifier calculates the possibility of a data point which can belong to a distinguished class by multiplying the conditional probabilities of each feature. The category with the greatest and highest likelihood is then assigned to the data point [6].

Autoregressive Integrated Moving Average is referred to as ARIMA. It is a well-liked method for forecasting time series values that is applied in econometrics and statistics [8].

CNN operational formulas-

| | |
|---|---|
| Convolution | $z^l = h^{l-1} * W^l$ |
| Max Pooling | $h^l_{xy} = \max_{i=0..s, j=0..s} h^{l-1}(x+i)(y+j)$ |
| Fully-connected layer | $z_l = W_l * h_{l-1}$ |
| ReLu(Rectifier) | $\mathrm{ReLU}(z_i) = \max(0, z_i)$ |
| Softmax | $\mathrm{softmax}(z_i) = e^{z_i} / \sum_j e^{z_j}$ |

SVM math-

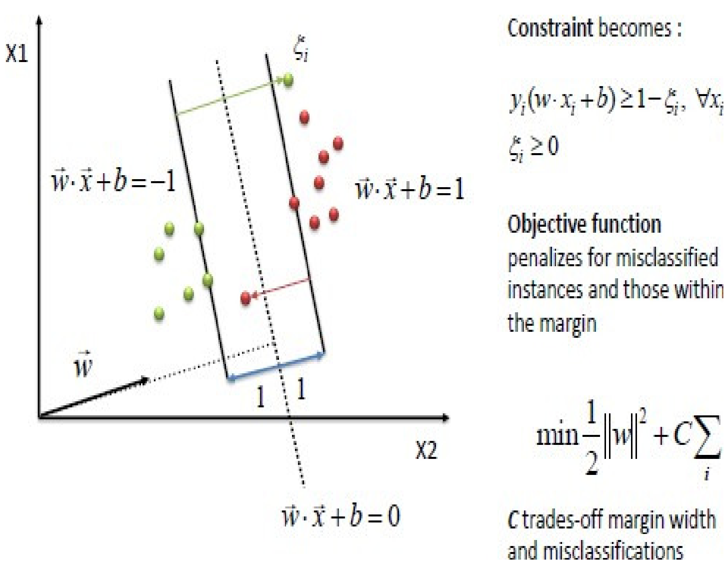


Fig 2. SVM

TABLE 2. ALGORITHMS USED IN DIFFERENT ARTICLES

| | |
|---|---|
| Machine learning | ML |
| deep neural network | DNN |
| computer vision | CV |
| Random Forest | RF |
| Support Vector Machine | SVM |
| Artificial Neural Network | ANN |
| crime prediction and prevention | CPP |
| Deep Learning | DL |
| K-Nearest Neighbors | KNN |
| Convolutional Neural Network | CNN |
| Temporal Convolutional Network | TCN |
| empirical analysis of machine learning algorithms | EAMLA |
| cloud service providers | CSPs |
| Support Vector Machine | SVM |
| kernel extreme learning machine | KELM |

TABLE 3. METHODS USED [11]

| METHOD | OBJECT DETECTION METHOD | FEATURE EXTRACTION METHOD | SCENE TYPE | ACCURACY % |
|---|---|---|---|---|
| real-time detection of violence in crowded scenes (28) | ViF descriptor | Bag of features | crowded | 88% |
| Bag of words framework using acceleration for action detection [3] | Background subtraction algorithms | Ellipse estimation method for consecutive frames. | Less crowded | Approx. 90% |
| GMOF framework with tracking and detection module [10] | Gaussian Mixture model | OHFO for optical flow extraction | Crowded | 82%-89% |
| Multi model features framework on the base of the subclass [30] | Image CNN And ImageNet | Google Net for feature extraction | Less crowded | 98% |
| To determine the occurrence of violent purpose extended form of IFV (Improved Fisher vector) and sliding windows [31] | Spatial pyramids and grids for object detection | Spatio temporal grid technique for feature extraction | Crowded | 96%-99% using different data sets |
| Violence detection using Oriented Violent Flow 32) | Optical Flow method | Combination of ViF and OViF descriptor | crowded | 90% |
| AE and HOG combined framework to recognize the abnormal event in visual motions 34] | AEI technique for Background subtraction | HOG and spatio-temporal methods to extract features | Both crowded and less crowded | 94%-95% |
| The framework includes preprocessing, detection of activity and image retrieval. This work identifies the abnormal event and image from data-based | Optical flow and temporal difference for object detection CBIR method for retrieving images | Gaussian fun tion for video future analysi | Less crowded | 97% |

| | | | | |
|---|---|---|---|---|
| images.[33] | | | | |
| Late Fusion method for temporal perception layers to detect high level activities. Use multiple cameras from \| to N. [35] | A motion vector method to identify in two dimensions | SGT MtPL methoa | Less crowded | 98% |
| Bi-Channel Convolutional neural network for real time detection [36] | ImageNet method of object detection | VGG-f model for feature extraction | Crowded | 91%-94% |
| Solve detecting problem by dividing the Objective in depth and clear format using Con Net [37] | Movement detection and TRof Model | BoW approach | Less crowded | 96% |
| Bag of Words method using the Spatial Temporal method for detection anomalies in the video [38] | Representation of segments and sub Segments. | Using HOF and HOG for acquiring video features | Less Crowded | 84%-91% |

## IV. DATASET COLLECTION:

TABLE 4. DATASETS USED IN DIFFERENT ARTICLES

| | |
|---|---|
| S UT-Interaction Dataset | M. Labayen Esnaola, N. Aginako Bengoa, B. Sierra Araujo, I. G. Olaizola and J. Flórez |
| S Chicago Crime, Crime in Los Angeles | S. S. Kshatri, D. Singh, B. Narain, S. Bhatia, M. T. Quasim and G. R. Sinha |
| A UCF-ARG Dataset | N. Aldahoul, H. A. Karim, A. Q. M. Sabri, M. J. T. Tan, M. A. Momo and J. L. Fermin |
| A UCF 101 | M. Ramzan et al. |
| A WS Dream Dataset | X. Li, Q. Wang, X. Lan, X. Chen, N. Zhang and D. Chen |
| A Chicago Crime Dataset | U. M. Butt, S. Letchmunan, F. H. Hassan, M. Ali, A. Baqir and H. H. R. Sherazi |
| UMN, UCSD-PED1 Datasets | Al-Dhamari, R. Sudirman and N. H. Mahmood |
| UMN, PETS2009 Datasets | C. Direkoglu |
| MUSK1, MUSK2 Datasets | S. V. Mahadevkar et al. |
| UCF Crime, XD Violence Datasets | V. D. Huszár, V. K. Adhikarla, I. Négyesi and C. Krasznay |
| AIRTLab Dataset | P. Sernani, N. Falcionelli, S. Tomassini, P. Contardo and A. F. Dragoni |
| RWF-2000 Dataset | M. -S. Kang, R. -H. Park and H. -M. Park |
| CDnet2012, CDnet2014 Datasets | P. Machado, A. Oikonomou, J. F. Ferreira and T. M. Mcginnity |

The criminal dataset from the Ultimate Fighting Championship (UFC, for short) will be used in this study. Other datasets, such those from AIRTLab, UR-Interaction, XD Violence, and others, may also be used. But because it includes of lengthy, uncut surveillance footage that span 13 real-world abnormalities, we will examine crimes like abuse, arrest, assault, arson, traffic accidents, burglaries, explosions, fighting, robberies, shootings, theft, shoplifting, and vandalism using the UFC crime dataset. Usually, public sources like news stories, court records, and police reports are used to create the dataset. Researchers, writers, and other analysts frequently utilize it to examine trends in criminal behaviors among the UFC community and to pinpoint potential areas of concern. Different datasets used in different articles are present in table 4.

Fig 3. An image containing violence

## V. PROPOSED METHODOLOGY

CNN is referred to as the Convolutional Neural Network in the fields of image recognition and computer vision. It is a deep learning system that use multiple layers of convolutional and pooling algorithms to identify patterns in images or movies. The structure and operation of the human visual system serve as the basis for CNNs. They are made up of numerous layers of interconnected neurons, each of which carries out a particular task such feature detection, feature mapping, or classification. The convolutional layers apply a series of filters to the input image to extract important details, and the pooling layers reduce the input's spatial size by down sampling their output. Here are the steps of CNN:

Data Preparation: Collect and preprocess the input data. This can involve some activities such as resizing images, converting to grayscale, and normalizing pixel values.

Model Architecture: Create the CNN's building plan. Typically, this entails pooling, activation, and many layers of convolutions. The task's complexity will determine the size and number of layers.

Compilation: The loss function, optimizer, and metrics to be used during training should be specified when compiling the model.

Training: Using a suitable approach, such as stochastic gradient descent, train the model on the prepared data. This entails putting input data into the network and adjusting layer weights based on the discrepancies between output predictions and actual output.

Evaluation: Analyze the model's performance in a different validation. dataset to check for overfitting and tune the model parameters accordingly.

Testing: Test the model on a separate test dataset to check its generalization ability and accuracy.

Deployment: Finally, deploy the model for use in real-world applications.

These steps are not quite linear and may involve multiple iterations to fine-tune the model.

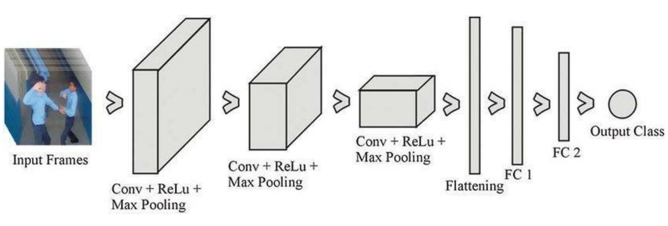


Fig 4. CNN process

Shows how input goes through the steps of pooling, flattening and output to detect violence.

Violence detection with CNN involves using Convolutional Neural Networks to automatically classify images or video frames as containing violent or non-violent content. Here are the general steps involved in building a violence detection system using CNN:

1. Data Collection: Collect a large dataset of images or video frames containing examples of violent and non-violent content. This may involve manual annotation of the images or using pre-labeled datasets.

2. Data Preprocessing: The photos or video frames are resized to a uniform size, converted to grayscale or RGB, and the pixel values are normalized to preprocess the acquired data.

3. Model Architecture: Make a CNN architecture that can precisely capture the characteristics that set violent material apart from other types of media. Convolutional, pooling, and activation layers are often stacked before Layers that are fully connected are used to finish the classification.

4. Model Training: Train the CNN model using the preprocessed data. The data must be separated into training, validation, and testing sets in order to accomplish this. The weights of the network are then updated using backpropagation.

5. Model Evaluation: Use appropriate measures like F1 score, recall, and precision., to evaluate the trained model's performance. In order to do this, the model must be tested using the testing set, and the predicted labels must be compared to the actual labels.

6. Model Optimization: Optimize the CNN model by adjusting the hyper parameters like, to enhance its performance, adjust the epoch count, learning rate, batch size, and layer sizes.

7. Deployment: Use the trained model in practical applications such content moderation systems, social media platforms, and video surveillance systems.

Overall, the amount and quality of the dataset, the architecture of the CNN, and the optimization of its model parameters all affect how well a violence detection using CNN performs.

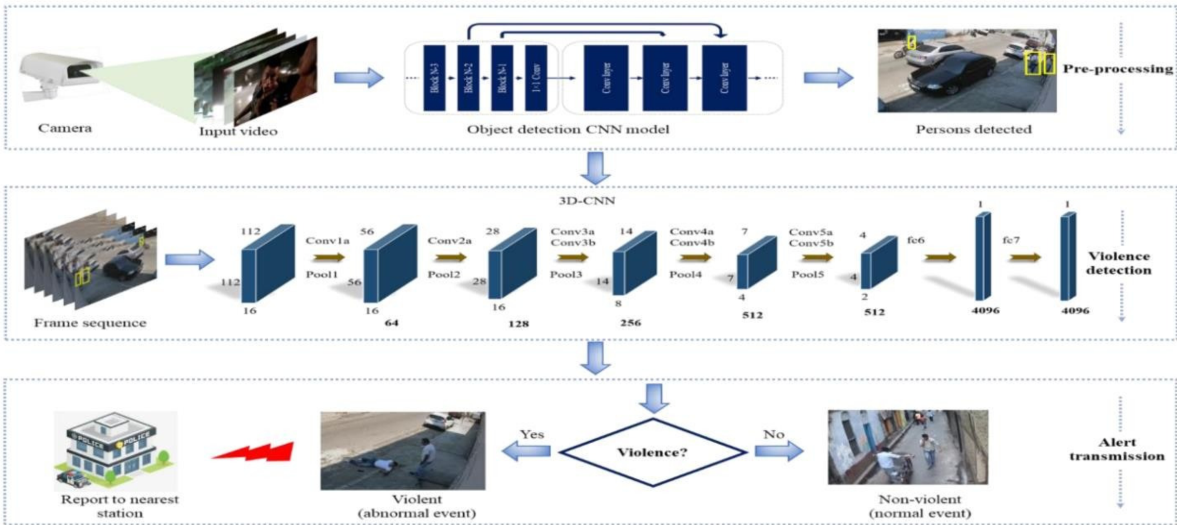


Fig 5. CNN process

## VI. FLOW OF WORK:

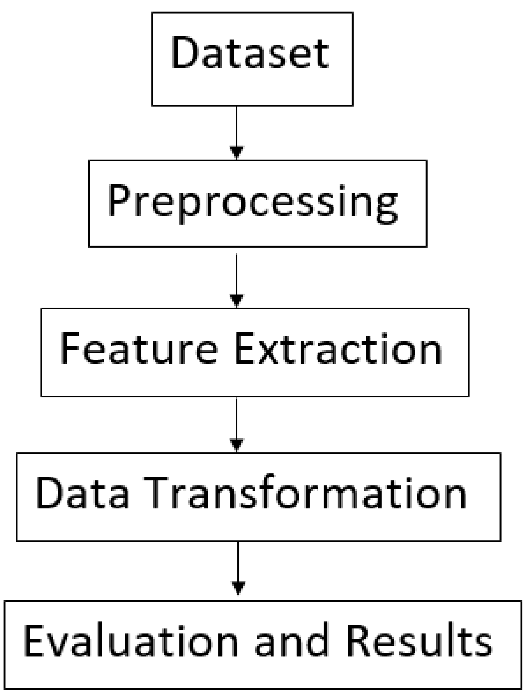


Fig 6. Flow of process [11]

DATASETS- A dataset is a collection of data that is organized and stored in a structured format for analysis and processing. Datasets can come in various forms, such as tables, spreadsheets, images, videos, audio files, or text documents. We train the model by giving some training datasets. The model will extract the data from the images and videos and store them.

PREPROCESSING- Preparing the given data for use is the process of data preparation and raw data to analyze and model further. It involves cleaning, transforming, and reorganizing data to make sure it's a match and suitable for machine learning algorithms or other data analysis techniques The stored data is then filtered and only the relevant information is passed on. That data is then fragmented into parts for easier access.

FEATURE EXTRACTION- It is the process of deciding which features from the data are most useful, pertinent, and instructive to utilize in machine learning models or other data analysis methods. Then, while still retaining the information in the original data, the raw data is transformed into numerical characteristics. It goes through multiple iterations as one feature is extracted at a time.

DATA TRANSFORMATION- The process of transforming data from one form or structure to another is known as data transformation. It is a critical step in data processing and analysis that makes it easier to clean, normalize, and prepare data for further analysis.

EVALUATION AND RESULT- Finally we give a few testing datasets to test the model. It will compare them with the classified information and perform analysis based on accuracy, AUC, MAP etc. Then the model will give the output whether the given situation is violent or not.

A camera will be installed to monitor or a specific place and detect incidents of violence. If a fight breaks out or illegal weapons are detected, the camera will identify the incident and send an alert to the police. This is accomplished through a process of recording video, extracting features, and classifying the footage as either violent or nonviolent.

## VII. OBJECTIVE

Creating a machine learning model that can identify criminal activity in real time is the goal of this project. We collect and preprocess a large dataset of images and videos related to crime and violence. We aim to improve the efficiency of criminal investigations by integrating the machine learning model into a real-world application such as a surveillance system.

1. To detect criminal activity and identify potential crime hotspots or high-risk areas.
2. We aim to improve the accuracy and efficiency of criminal investigations by providing police with better tools and technologies for collecting and analyzing evidence.
3. To enhance investigative capabilities by analyzing huge amounts of data and identifying patterns or trends related to criminal activity.

## VIII. CONCLUSION

As a result, Monitoring human behavior using surveillance cameras has become more widespread., and the demand for systems that can automatically recognize violent events has grown as well. The methods utilized for object recognition, along with feature extraction and classification, the datasets being used are as important, all affect how accurate violence detection systems are. The approaches for detecting violence are covered in this review, including SVM, CNN, YOLOv3, and other conventional machine learning classification-based methods. A number of improvements to the violence detection system are suggested, including the use of new and more effective object detectors and pose estimators, a better tracking algorithm, and an upgraded database, as well as illustrating the various approaches and procedures utilized for detecting violent activity from various datasets and surveillance footage. These upgrades could potentially lead to improved accuracy and more robust violence detection. This could potentially contribute to the development of more effective violence detection systems.

TABLE 5. ACRONYM TABLE

| | |
|---|---|
| Machine learning | ML |
| deep neural network | DNN |
| computer vision | CV |
| Random Forest | RF |
| Support Vector Machine | SVM |
| Artificial Neural Network | ANN |
| crime prediction and prevention | CPP |
| Deep Learning | DL |
| K-Nearest Neighbors | KNN |
| Convolutional Neural Network | CNN |
| Temporal Convolutional Network | TCN |
| empirical analysis of machine learning algorithms | EAMLA |
| cloud service providers | CSPs |
| Support Vector Machine | SVM |
| kernel extreme learning machine | KELM |
| and three-dimensional histograms of gradient orientation | 3DHOG |
| Automated Video Surveillance | AVS |
| universal serial bus | USB |
| Binary Support Vector Machine | BSVM |
| structural risk minimization | SRM |

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