Survey Paper on Abnormal Event Detection on Pathway

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Abstract- In the fast-paced environment,where road congestion and pathway related things are still a challenging issue,the installation of surveillance system proves only to monitor the incidents but fails to take an immediate action and leverage any issue spontaneously that can lead to fatal situations.This project uses a surveillance system to immediately identify unusual behaviors in public spaces, specifically using the YOLO (You Only Look Once) deep learning model to detect spirits with diverse states of being as indirect attacks, pilgrims and violence.Using advanced anomaly detection techniques, the system provides accurate information to rapidly address potential threats, thus Improving Security.Particularly specify the YOLOv8 model(which is the extension of YOLO family) which has a faster and accurate object detection capabilities,this model will be trained on a dataset of images featuring the events which are termed to be normal to set the baseline.This trained model is fed with the real-time videos ,by doing so, the applied model detects people and vehicles,track trajectories and identify deviation events which can be termed as abnormal.The Project also prioritizes ethical considerations, recognizes privacy, and uses responsible technology to meet the appropriate needs.

Keywords - Abnormal behavior detection, Deep learning model, Ethical considerations, Privacy, Real-time detection, Safety and Security, Surveillance systems, Unusual behavior, YOLO (You Only Look Once).

I. INTRODUCTION

One of the issues which is going around globally is the exponential increase in road congestion and traffic, which makes it a crucial responsibility for us to address the issue. With the use of a cutting-edge approach to road safety by leveraging advanced computer vision technology, specifically the You Only Look Once (YOLO) models, in conjunction with CCTV cameras.A smart system that is capable of automatically identifying and responding to various events, such as accidents, illegal U-turns, wrong-way driving, traffic anomalies, and speeding vehicles, in real-time across diverse road locations is established.

The system's ability to swiftly recognise & respond to events lies in its core system. Real-time alerts are triggered by the system when an event is detected which is a critical component of the response strategy. The alerts mentioned enable prompt intervention which reduces risks and enhances the safety on the roads.

The event detection which is automated is integrated with CCTV cameras which represents an innovative stride toward improving monitoring and responses, contributing to the development of a safer and efficient system. Technical intricacies are explored, it also details the architecture, it capabilities, and real-world implications of YOLO based computer vision system for road safety

II. LITERATURE SURVEY

Riddhi Sonkar, Sadhana Rathod and Deepali Patil. [1] This new approach includes the use of security cameras, data collection, advanced preprocessing and deep learning to detect anomalies and alert security personnel early.With real-time analysis and dynamic threshold adjustment use a, continuous improvement. The results were extensively analyzed by the author using machine learning algorithms. Connecting security systems with security systems using crowdsourcing can enhance public safety by ensuring continuous surveillance and protection of privacy.

Megha Chhirolya [2] developed a new framework for identifying and categorizing abnormal human behavior in public spaces. Combining algorithms with optical flow properties, this approach addresses the limitations of traditional density-based models.Average kinetic energy, direction entropy, and tell potential energy are among the key properties recovered, and results in higher accuracy compared to KNN and similar traditional methods of complex life the cognitive functions of systems greatly contribute to our knowledge and conclusions for measuring results carefully.Security by assuring regular monitoring of the algorithm and protection of privacy

Mahdyar Ravanbakhsh, Moin Nabi, Enver Sangineto, Lucio Marcenaro, Carlo Regazzoni, Nicu Sebe. [3]This paper focuses on anomalous event detection in crowded video using [22]generative adversarial networks (GANs). The proposed method trains GANs with a normal frame so that typical patterns of crowd behavior can be detected During the experiment GANs cannot receive anomalous information, which identifies abnormal areas by comparing real data with synthetic positions Procedure for system-level pixel-level anomaly detection. The task outperforms existing methods, addressing challenges such as limited abnormal samples and subjective explanation of abnormal behavior in crowd situations

Lili Cui, Kehuang Li, Jiapin Chen, Zhenbo Li. [4] The introduced a method for detecting anomalies in vehicular traffic video monitoring using local features. Through foreground detection and morphology functions, the system extracts basic features such as area, shape, and velocity vectors. Three classifiers are used to detect pedestrian objects, vehicles, and noise, find them in areas where vehicles are operating, and measure their speed distribution. This method tested on a traffic monitoring dataset reduces the computational complexity and proves effective in early detection and ranking of subnormal behavior, showing potential for real-world application in complex cases.

Waqas Sultani, Chen Chen, Mubarak Shah. [5] The paper introduces an algorithm for real-world anomaly detection in surveillance videos that employs a [23]Multiple Instance Learning (MIL) framework with weakly labeled training data. In this approach, normal and abnormal videos are assumed as bags,video segments act as instances, framing the anomaly detection problem as a regression task within the MIL ranking model. To improve anomaly localization, the algorithm integrates sparsity and temporal constraints as loss function. This methodology is demonstrated and evaluated on a comprehensive dataset of 1900 real-world surveillance videos, illustrating its superior performance over state-of-the-art anomaly detection methods.

Louis Kratz, Ko Nishino. [6] The paper focuses on detecting abnormal motion patterns in highly congested video scenes using [24]Local Spatio-Temporal Motion Patterns. This involves capturing local motion patterns, employing Distribution-Based Motion Pattern Modeling, and incorporating Temporal and Spatial Modeling. The study utilizes a coupled Hidden Markov Model (HMM) to represent spatial relationships between local spatio-temporal motion patterns. Confidence Measures are integrated to enhance the reliability of the detection process. The research is particularly applied to extremely crowded scenes in video surveillance, emphasizing the identification of deviations from normal activities. The methodology involves factors such as Cuboids, Spatio-temporal gradients, and training data. Evaluation is conducted through Receiver Operator Characteristic (ROC) curves, assessing the efficacy of Distribution-based Hidden Markov Models and considering temporal statistics and spatial relationships in capturing unusual events within crowded video environments.

Dong-Gyu Lee, Heung-Il Suk, Sung-Kee Park. [7] Seong-Whan Lee, Detection and localization of unusual human activities in crowded video.The solution combines motion impact maps, [24]spatio-temporal feature extraction, and k-means clustering. Key features include the generation of motion impact maps from motion vectors, frame classification for spatio-temporal feature extraction, and the use of k-means clustering for maximum likelihood This method shows effectiveness in different tasks identifying and transmitting services to public data sets locally.A notable contribution was the development of an integrated algorithm using motion effect maps to capture spatiotemporal features efficiently The method collects similar motion patterns efficiently, pixel-level localization of unusual activities in surveillance video frames in output detecting strong divergence in scale, pose, a technique for adaptation in crowded environments is included, and demonstrates the potential of the technique for real-world applications

Kothapalli Vignesh; Gaurav Yadav; Amit Sethi. [8] The model uses [25]long-term memory (LSTM) networks and [28]linear support vector machines (SVM) to detect anomalies in surveillance videos to capture human group activities, affect observational learning processes so together and applied (MoG) after removal Some features are extracted using [21]Convolutional Neural Networks (CNN).The time evolution is modeled using LSTM, which performs well in sequential data processing, followed by SVM processing classification for two forward classifiers Averaging time is used to facilitate prediction energy increases. The combination of CNN, LSTM, SVM, and temporal averaging results in an efficient video analysis algorithm, which is particularly valuable in data-limited situations, and ultimately provides security and automation of consumption the role is helpfully effective

Weixin Li; Vijay Mahadevan; Nuno Vasconcelos.[9] The solution uses a hierarchical motion distribution transform (MDT) coupled with a conditional random field (CRF) for robust anomaly detection in crowded video scenes Leveraging a multi-dimensional texture model, it deftly captures complex spatiotemporal patterns, time with Gaussian filters to enhance detection capabilities for various anomalies. Coupled with spatial-scale anomaly detection, it ensures noise reduction and preservation of system details and contributes to better image processing The subsequent use of CRF statistics resolves anomaly localization by spatial, temporal, and scale contexts considered for accurate detection and detection of anomalies in crowded areas, video surveillance and improved public safety but noted that the solution may require computerization more features for real-world applications.

Borislav Antich, Bjorn Ommer.[10] This groundbreaking study introduces a probabilistic scene parsing approach for anomaly detection in roadside videos, providing state-of-the-art performance on the Ped1 and Ped2 datasets of statistical inference With f, the model achieves robust stability found by jointly defining optical anomalies and estimating metrics compared to ground truth, the method outperforms existing methods the old one shows good operating profitability. Probabilistic calculation improves the Area Under the Curve (AUC) metric significantly compared to the benchmark, making it a powerful tool for various conditions This work not only supports benchmark enhancement but also provides a new indirect malformation detection method by visual parsing so comes.

Bokun Wang, Caiqian Yanga, and Yaojing Che. [11] The paper surveys existing deep learning methods for video anomaly detection, highlighting their limitations (e.g., separate feature extraction and anomaly modeling). With the DSVDD approach the deep feature learning and SVMs have been combined giving the best results on public datasets. DSVDD is great at combining learning features and anomaly models, handling both appearance and motion anomalies. Thus, large datasets are required and also focus on frame-level detection, which leaves room for exploring long-term events.

Manjula Pattnaik.. [12] In this research an approach for detecting abnormal events in pedestrian pathways utilizing a combination of GARCH (Generalized Autoregressive Conditional Heteroscedasticity) modeling and a Multilayer Perceptron (MLP) classifier has gotten into existence. Works in video anomaly detection often relied on background subtraction and feature extraction, but this method differs by modeling the behavior of events dynamically using GARCH.In this, the framework first pre-processes video data to identify moving objects and then employs GARCH to capture the temporal dependencies and volatility of pedestrian flow.Then an , MLP classifier is used to classify the GARCH model parameters, distinguishing between normal and anomalous events. Hence, this approach is used to give the best possible results in automated surveillance systems in public places.

Kyung Joo Cheoi. [13] A method for figuring out the suspicious activities in the CCTV footage has been proposed in this paper. Inspired by human attention, it analyzes motion patterns using 'temporal saliency maps' built from optical flow features. According to the research, the maps capture the dynamics of motion, by highlighting abrupt changes, collisions, falls, and other deviations from typical movement patterns. With above 93% accuracy which the paper has produced by detecting six types of suspicious behavior, including running, fighting, and slipping. These existential methods give us the best accuracy possible.

Ali Atghaei, Soroush Ziaeinejad, Hamid Reza Alizadeh. [14] The paper tackles the hard assignment of unusual occasion detection (AED) in city surveillance movies the usage of a unique aggregate of [29]Generative Adversarial Networks (GANs) and the transfer gaining knowledge of from pre-educated Convolutional Neural Networks (CNNs). This technique addresses the complex nature of AED, which is based now not simply on body content but additionally on object appearance and motion patterns inside the scene. Transferring to know from pre-trained CNNs similarly boosts efficiency by leveraging existing feature extraction competencies. Optical waft information is integrated to enhance spatiotemporal facts handling, mainly to progress detection and localization of abnormal events in crowded scenes. On experimenting with datasets it showed the effectiveness of this method, in accuracy and efficiency.

Cem Direckoglu. [15] Detecting typical activities in crowded scenes, specifically panic and escape behaviors is approached in this paper. It introduces Motion Information Images (MIIs), a brand new visual illustration shooting crowd movement dynamics by means of studying optical flow vectors. These MIIs are then fed right into a CNN, allowing the community to analyze and distinguish among regular and bizarre crowd behaviors. Using benchmark datasets like UMN and PETS2009 it showed promising results outperforming others, suggesting its capacity for actual-international programs in crowd protection and surveillance.

Yuxing Yang, Zeyu Fu, Syed Mohsen Naqvi. [16] This work addresses the abnormal event detection in intelligent surveillance, which addresses the limitations of previous approaches caused by a lack of labeled data. Object, posture, and optical flow information are effectively utilized by a unique two-stream fusion technique. Object and pose information combined early removes obstructed pose graphs. A Spatio-Temporal Graph Convolutional Network (ST-GCN) is trained with trusted pose graphs to identify various aberrant behaviors. To detect anomalous frames, a video prediction framework compares the differences between ground truth and forecast frames. Results are improved when classification and prediction streams are fused at the decision level. The effectiveness of the suggested approach is validated through the evaluation of the PED1, PED2, and ShanghaiTech datasets from UCSD.

Bo Yan, Cheng Yang, Chuan Shi, Jiawei Liu, Xiaochen Wang. [17] The complexity of abnormal event detection in Attributed Heterogeneous Information Networks (AHIN) is discussed in this research, with a focus on the importance of taking complicated relationships and multi-typed attributed entities into account. This paper concentrates on unsupervised abnormal event identification in AHIN and introduces a unique hypergraph contrastive learning method called AEHCL. Pairwise and multivariate interaction anomalies within events and contextual anomalies among events are captured by AEHCL using intra-event and inter-event contrastive modules. Extensive studies on three datasets indicate that collaborative enhancement between these modules enhances detection outcomes, demonstrating up to a 12.0% gain in Average Precision (AP) and a 4.6% improvement in Area Under Curve (AUC) compared to state-of-the-art baselines.

Cewu Lu, Wei-Ming Wang, Jiaya Jia. [18] The requirement for quick abnormal event identification in surveillance footage is discussed in this study. The suggested [30]sparse combination learning approach makes use of both batch and online solvers, leveraging the redundancy present in video structures to provide efficient processing without compromising result quality. Using MATLAB, the approach achieves amazing speeds of 1000-1200 frames per second on an average desktop PC with a single core. It also obtains high detection rates on benchmark datasets. This effectiveness is ascribed to the efficient conversion of the initial complicated issue into a sequence of small-scale least square optimizations, which facilitates quick execution.

Hoang Duy Trinh, Lorenza Giupponi, Paolo Dini. [19] The study is an anomaly detection system based on Long Short Term Memory (LSTM) neural networks, which are made to handle sequential and recurrent inputs, to accomplish this problem. It is shown that the stacked LSTM architecture may efficiently detect traffic abnormalities caused by an abrupt spike in the number of users during crowded events close to the monitored location. The algorithm's higher performance is demonstrated by numerical results, where it performs other state of the art benchmarks with an F-score over by utilizing cutting edge neural network architectures and mobile network data for inventive and effective urban anomaly detection, this research advances public safety.

Dimitriou N, Lalas A, Dasygenis M. [20] This paper discusses the implementation and evaluation of a system for the detection of abnormal events, specifically focused on petty crimes, in a transportation setting. The system utilizes various techniques, including pose classification and deep learning, to accurately and timely detect abnormal behavior. The document provides details on the experimental setup, performance analysis, and classification metrics. It also compares different methods and discusses the challenges and limitations of the proposed solution.

III. COMPARISON TABLE

AUTHOR	YEAR	APPROACH	DESCRIPTION
Louis Kratz, Ko Nishino	2009	Detecting abnormal motion in crowded videos: Local Spatio-Temporal Motion Patterns, Distribution-Based Modeling, coupled HMM for spatial relationships, and Confidence Measures.	Detects abnormal motion in crowded scenes using local spatiotemporal patterns, distribution-based models, HMMs, and confidence measures
Lili Cui, and Kehuang Li	2011	use local characteristics for anomalous event identification, such as foreground detection.	They proposed a system that extracts features for accurate early alarms in traffic video, demonstrating effectiveness on surveillance datasets.
Borislav Antić; Björn Ommer	2012	Revolutionary probabilistic scene parsing detects abnormalities in pedestrian walkway videos, outperforming state-of-the-art methods, enhancing benchmark performance, and enabling real-world applications.	Novel probabilistic scene parsing elevates abnormality detection, outperforming benchmarks in pedestrian walkway videos for enhanced safety.
Megha Chhirolya	2013	Optical Flow and combining image processing with sociology	proposed a method using Optical Flow features for detecting and classifying abnormal behaviors in crowded environments, enhancing crowd analysis.
Weixin Li; Vijay Mahadevan; Nuno Vasconcelos	2013	Hierarchical MDT, CRF, and multi-dimensional textures enable robust crowd anomaly detection in complex video scenes.	Hierarchical MDT-CRF fusion for robust crowd anomaly detection, integrating texture models, Gaussian filters, and comprehensive inference.
Dong-Gyu Lee, Heung-Il Suk, Sung-Kee Park, Seong-Whan Lee	2015	The unified method integrates motion influence maps, feature extraction, and k-means clustering for robust unusual activity detection in crowds.	In crowded scenes, the method combines motion maps, feature extraction, and clustering for effective unusual activity detection.
Kothapalli Vignesh, Gaurav Yadav, Amit Sethi	2017	Integrate CNN, LSTM, and SVM with temporal averaging for accurate abnormal event detection in surveillance videos.	Unified CNN, LSTM, SVM, and temporal averaging model for robust abnormal event detection in limited-data surveillance videos.
Mahdyar Ravanbakhs, Lucio Marcenaro	2018	Generative Adversarial Networks learn normal crowd behavior for abnormality detection in crowded scenes.	GANs trained with normal data detect abnormal areas by comparing real and generated representations.
Waqas Sultani	2018	A framework for multiple instance learning, data with poor labeling, sparsity, and temporal smoothness constraints for real-world anomaly detection.	They proposed a system that treats segments as samples and videos as bags, excelling in real-world surveillance anomaly detection.
Cewu Lu Wei-Ming Wang Jiaya Jia	2019	Current Solution: Maximum Commonness Representation Strategy (MCRS)	Dividing the training data into passes allows for the creation of combinations that represent the remaining data, reducing the number of combinations needed.
Hoang Duy Trinh Lorenza Giupponi Paolo Dini	2019	Long Short-Term Memory (LSTM) neural networks.	This work provides valuable insights into the potential of utilizing mobile network data for anomaly detection and emphasizes the advantages of a supervised learning

			approach when a labeled dataset is available.
Manjula Pattnaik	2019	The GARCH model captures the variability of pedestrian flow, using statistical parameters to represent "normal" behavior.	Analyzes historical data (e.g., pedestrian counts) to predict future flow patterns and identify deviations as anomalies.
Riddhi Sonkar and Renuka Jadhav	2020	employed CNN and KNN for real-time crowd behavior detection, enhancing security in public spaces.	They proposed utilizing deep learning to analyze crowd motion, enabling their system to promptly detect and alarm abnormal behavior.
Dimitriou N Lalas A Dasygenis M	2020	Stacked Bidirectional LSTM Classifier	The goal is to develop a solution that can address the complexities of detecting abnormal events using modern technologies and deep learning techniques.
Kyung Joo Cheoi	2020	The paper analyzes CCTV footage using "temporal saliency maps" built from optical flow features. These maps capture the dynamics of motion, highlighting unusual changes, collisions, and falls.	Inspired by human attention, the system detects abnormal motion patterns like sudden running, fighting, or slipping, potentially leading to more efficient surveillance.
Ali Atghaei Soroush Ziaeinejad Hamid Reza Alizadeh	2020	The research leverages Generative Adversarial Networks (GANs) to learn the "normal" behavior of a scene in urban surveillance videos. Imagine two players: a generator that creates video samples mimicking real footage, and a discriminator that tries to distinguish real from generated	The research employs transfer learning, where a pre-trained Convolutional Neural Network (CNN) is fine-tuned for the specific task of AED. This CNN, already trained on a massive dataset of images, possesses valuable feature extraction skills. By "fine-tuning" this pre-trained model for AED, the researchers leverage its existing capabilities while adapting it to the nuances of video analysis.
Cem Direckoglu	2017	The research paper proposes a novel way to analyze this dynamic scene by capturing the flow of the crowd in a single image. This image called a Motion Information Image (MII), is like a snapshot of the crowd's movement, where each pixel encodes the speed and direction of people at that point.	The CNN acts like a detective, meticulously examining the MIIs to learn the patterns of normal crowd behavior. It analyzes the variations in brightness and color, searching for anomalies that might signal something unusual happening. Over time, CNN becomes adept at recognizing the "language" of crowd movement, able to differentiate between the ebb and flow of daily life and the sudden shifts that could indicate danger.
Bokun Wang Caiqian Yanga Yaojing Chen	2022	DSVDD trains a network on normal video frames, then builds a hypersphere in a high-dimensional space that tightly encloses them. Any frame outside this "normal zone" is flagged as anomalous.	DSVDD combines feature learning and anomaly detection, handling both appearance and motion anomalies through RGB and optical flow data. It achieves state-of-the-art results but requires large training datasets.
Yuxing Yang Zeyu Fu Syed Mohsen Naqvi	2023	Enhanced Fusion Framework with Classification and Prediction Streams	The system is designed to recognize anomalous items or unusual behavior in footage clips. The main objective is to enhance the detection of various abnormal events by using subjects.

IV. PROBLEM FORMULATION

Detecting abnormalities on paths is vital in creating safer, more efficient, and enjoyable spaces for everyone.Hence paving the way for the future by creating a better user experience.

The following objectives are to detect the anomalies on the pathway:

1. Specify how the data will be represented for the deep learning model (e.g., frames, time series, spatial grids).
2. Identifying the presence and location of any abnormal event within a frame.
3. Classify the detected anomalies into predefined categories (e.g., running, stopping, falling, vehicle presence).
4. Selection of model(YOLOv8) and training the model based on the annotated and augmented data.

5. Deployment of the system for the use of real-time application with variable accuracy.
6. Achieving X% accuracy for both detection and classification tasks, while being robust to variations in lighting, camera angle, and background noise.

V. SOLUTION FOR THE PROBLEM

From a collective standpoint, the problem of detecting abnormal events on pathways encompasses a wide range of approaches and techniques, depending on the specific details of data, requirements, and desired levels of complexity. The developed system feeds on the real-time video footage which has the capability of detecting the abnormalities(accidents,theft,etc..) and instantaneously alerting the concerned authorities so that immediate or proper action can be taken.

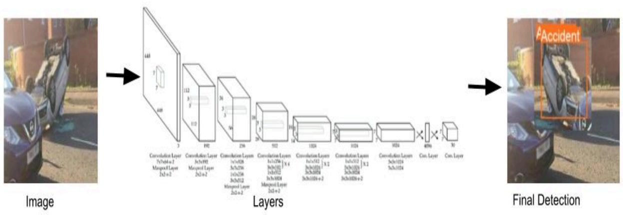

Fig 1. Detecting the Objects using YOLOv8 Algorithm

Working of the model from input to the output stage:
Fig 1 demonstrates how a custom dataset is created with labeled images and videos representing the realistic scenarios.All the parameters have been applied on the dataset to ensure the balance across categories and augment the data on which the YOLOv8 model can be trained, the model refines its performance by regularly updating the model with new data and hyperparameter tuning to address the data imbalances .Data acquisition[Cameras with high resolutions]-In the real-time implementation the surveillance system keeps monitoring the pathways and this live feed is transmitted to the system which keeps on tracking the objects associated on the pathway to frame it as either a normal or abnormal situation.Moreover,the captured footages will be not precise for the model to detect, hence it is preprocessed[noise reduction]. After a particular frame has been termed as abnormal,the alerting mechanism has been alerted to the concerned authority so as to take an immediate action. Additionally, there are cases wherein the situations could be misunderstood and are termed as abnormal, hence to prevent such circumstances a proper confidence threshold detection has been set 'false positives' (eg: misidentifying harmless interactions as fights) and corporating temporal reasoning or multi-frame analysis to reduce false negatives (e.g., missing subtle chain snatching attempts).The performance is determined on the models ability to adapt to different camera angles,lighting conditions and varied pathways.The metrics evaluation keeps improving with the time being as the learning rate improves and the accuracy gets higher.

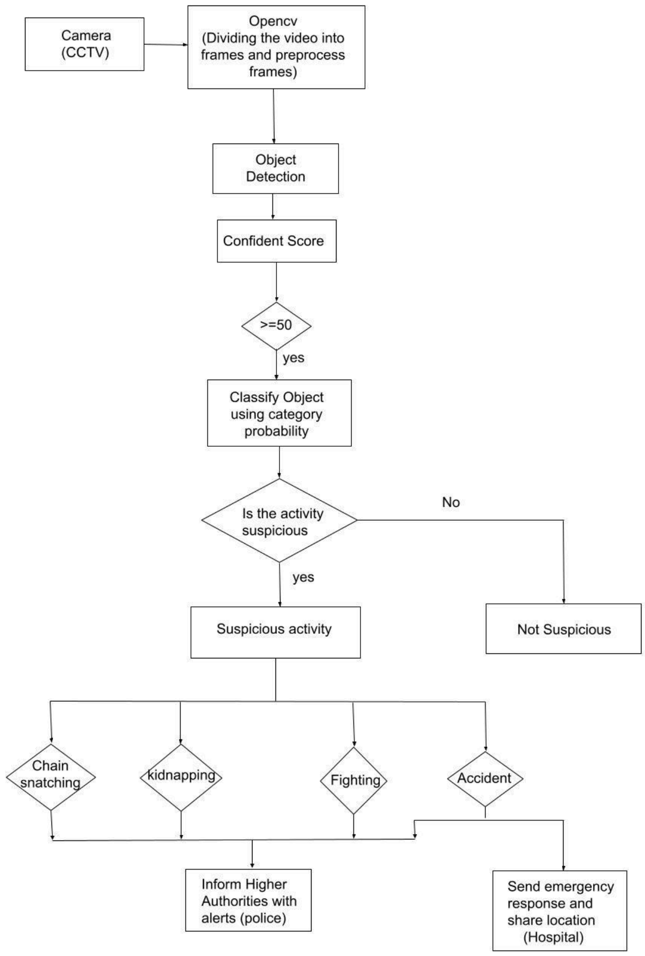

Fig 2.Flowchart representing the implementation of YOLOv8 Algorithm for abnormal event detection

VI. PREDICTED OUTPUT

- Abnormal event detection output:

Fig 3. Abnormal event detection

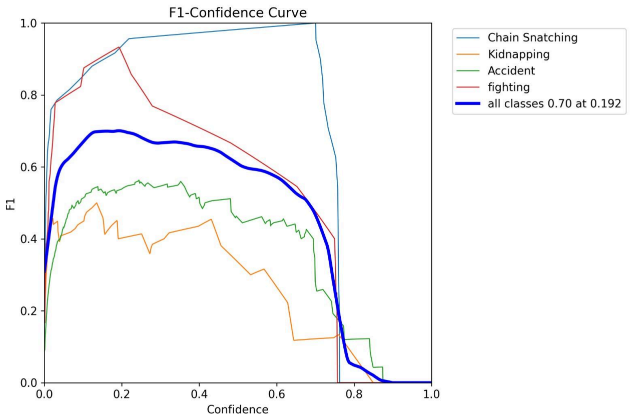

Fig 4. F1-confidence Curve

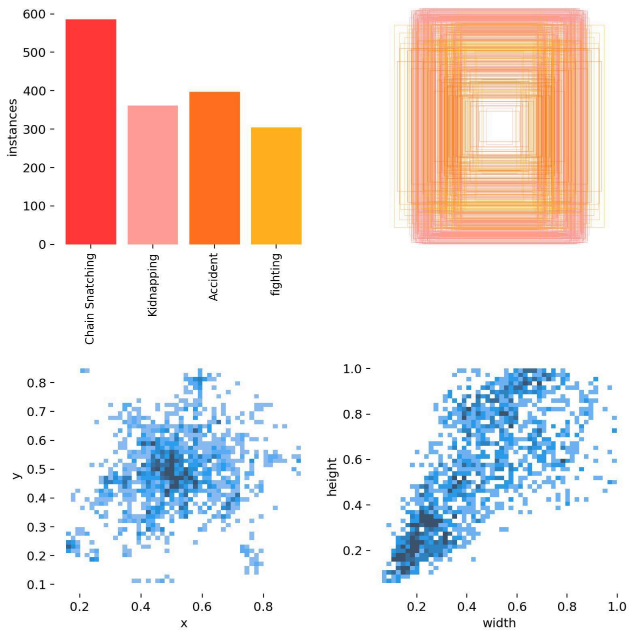

Fig 5. Performance Evaluation of CCTV Activity Classification Model

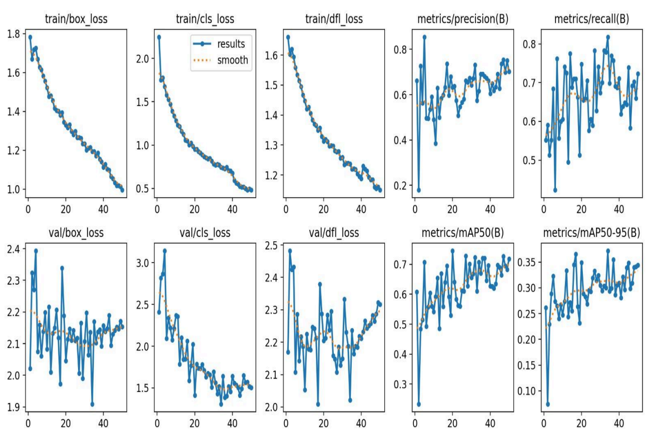

Fig 6. Multi-Class Object Detection Performance Metrics

VII. CONCLUSION

To detect aberrant occurrences in the setting of small-time crimes in a quick, accurate, robust, and automatic manner, a variety of strategies were used in this study. The suggested method can improve passenger security by detecting minor offenses like hostility and bag stealing, as well as aberrant passenger behavior like damage and accidents. Excellent outcomes are obtained by the solution in a variety of use cases and environmental settings. Deep learning algorithms provide their foundation, and they accommodate various camera types, positions, and angles. The system runs in an embedded configuration that uses little power.The final outcome is an optimized model that delivers accurate,fast detection of defined abnormal events along pathways.Hence,this project establishes a critical automated capability for real-world pathway in monitoring transportation hubs, industrial areas, commercial zones and urban environments to enhance public safety and operations.

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