Advanced AI Surveillance for Human Trafficking and Accident Prevention

Shanthi Makka(✉), A. Sowmya, Sanagala Vishwanath, Kattekola Snigdha, and Vankadaru Charan

Vardhaman College of Engineering, Kacharam, Shamshabad, Hyderabad, Telangana 501218, India

dr.shanthimakka@gmail.com

Abstract. The population has grown, there have been significant urban developments, and there have also been upsetting social situations. Today, technology is improving human life. The use of AI-detector surveillance systems to identify people trafficking, accidents, and emergency situations and notify neighboring police stations, hospitals, and concerned departments is explored in this research article. Since there is a communication gap in the majority of these situations, particularly at night, fatalities and unsolved cases are the result. This technology functions as a communication channel, sending information about these incidents to the control center, prevent this gap in communication. The Artificial Intelligence Surveillance System promises to accelerate emergency response times by utilizing sophisticated computer vision algorithms and clever communication protocols. This paper offers a thorough methodology, explains the findings, and emphasizes the system's ramifications.

Keywords: Surveillance · Convolutional Neural Network · Video Processing · Human Trafficking · Control Room

1 Introduction

The population has grown, there have been significant urban developments, and there have also been upsetting social situations. Today, technology is improving human life. The use of AI-detector surveillance systems to identify people trafficking, accidents, and emergency situations and notify neighboring police stations, hospitals, and concerned departments is explored in this research article [1]. Since there is a communication gap in the majority of these situations, particularly at night, fatalities and unsolved cases are the result. This technology functions as a communication channel, sending information about these incidents to the control center, prevent this gap in communication. This technology promises to accelerate emergency response times by utilizing sophisticated computer vision algorithms and clever communication protocols. This paper offers a thorough methodology, explains the findings, and emphasizes methodology of the model [6].

X. Cheng (Ed): BROADNETS 2024, LNICST 602, pp. 124–134, 2025.
https://doi.org/10.1007/978-3-031-81171-5_13

Deep learning is a subfield of machine learning that uses artificial neural networks with hidden layers to handle complex tasks. Inspired by the human brain, it has been successful in computer vision, natural language processing, and speech recognition [10]. Convolutional Neural Networks (CNNs) are used for image analysis, while Recurrent Neural Networks (RNNs) are used for sequence data. Deep learning has revolutionized image classification, object detection, machine translation, autonomous driving, and healthcare. Challenges include interpretability, over fitting, and large datasets [9].

Regression-based detection models are computer vision algorithms used for detecting and localizing objects within images or video frames. They predict the coordinates of bounding boxes, which tightly enclose objects of interest. These models consist of two main components: object localization and object classification. They can be implemented using various architectures, such as Faster R-CNN, Single Shot Multi Box Detector (SSD), or You Only Look Once (YOLO) [1]. These models are trained on labeled datasets, where each image is annotated with bounding boxes and object classes. They offer a good trade-off between accuracy and speed, making them suitable for various applications. Regression-based detection models continue to evolve with improvements in model architectures and training techniques [4].

R-CNN, or Region-based Convolutional Neural Network, is a crucial method in computer vision for object detection. Introduced in 2014, it proposes potential object regions and uses convolutional neural networks to extract features [6]. The process involves selective search, CNN processing, and SVMs for object classification. R-CNN achieves high accuracy but is computationally expensive. Improvements like Fast R-CNN and Faster R-CNN have streamlined the process and enhanced efficiency. Despite advancements, R-CNN remains a pivotal concept in object detection algorithms [7].

2 Literature Survey

The authors [5] discussed about how current vision-based detection and tracking algorithms function in thermal imagery-based video surveillance is the primary goal. Although color-based surveillance has been extensively researched, its applicability is limited because these techniques cannot be used in low light, at night, or when there are changes in lighting and [27] shadows. The creation of a new color thermal dataset, a thorough performance comparison of various color-based detection [11] and tracking algorithms on thermal data, and the suggestion of an adaptive neural network for false positive detection rejection [12] are the three main contributions. In survey, we explored object detection and tracking in video surveillance systems using artificial intelligence, computer vision, and digital image processing. Object detection techniques [9] include background subtraction, statistical methods, and temporal [13] frame differentiation. Tracking methods include point tracking, silhouette tracking, and kernel tracking. Surveillance systems have evolved from tube cameras to modern technologies (Table 1).

3 Methodology

Data Collection: Different types of diverse datasets will be collected which includes human trafficking, accidents [10] and other many anomalies, patterns, images, videos

Table 1. Literature Survey

Ref. No.	Authors	Year of publication	Title	Name of the journal	Findings
1	Ms K.Suitha et., al	2021	Human& Object Detection Using Surveillance System	Journal Of Engineering Science	The Author Talked About Issues With Object Identification, Object Tracking, And Picture Detection Using Surveillance [1] Cameras. Additionally, They Talked About How Current Tracking Algorithms Don't Work With Object Identification Technologies, How Computer Vision May Be Utilized To Construct Surveillance Tracking Systems
2	Shilpa Jahagirdar, Sanjay Koli	2019	Automatic Accident Detection Techniques using CCTV Surveillance Videos: Methods,Data sets and Learning Strategies	International Journal of Engineering and Advanced Technology	Author discussed about issues [2] regarding the count of vehicles had increased which is resulting in numerous difficulties for Street Traffic Management authorities which is leading to many accidents they also discusses several accident detection technique which are detected using surveillance videos and discussed about the importance of computer vision and open cvv module

(*continued*)

Table 1. (*continued*)

Ref. No.	Authors	Year of publication	Title	Name of the journal	Findings
3	Ashok Kumar J M, Arun Kumar C, Abishek B R, Thirumagal E	2019	Crime Detection in Surveillance	International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249–8958 (Online), Volume-8 Issue-5S, May 2019	The author talks about how surveillance cameras have been installed everywhere and how looking through [3] the data has helped solve a number of issues, but we can abuse ongoing PC vision computations to replace human labor. The author also talks about different approaches that are used to learn inconsistencies and also forbid data manipulation
4	Aswin C.sankarnarayana	2008	Object Detection, Tracking and recognition for multiple smart cameras	Proceedings of IEEE	The writers talked about using [4] more than one smart camera in order to avoid a lot of difficulties. This system's goal is to make sure that items are detected and that quick action is taken to save many lives
6	Ms.K.suitha	2021	Human and object Detection using surveillance system	Journal of engineering science	Authors have discussed how Large-scale camera networks have recently [6] gained momentum due to technological advancements and falling camera costs. More cameras could lead to the creation of innovative signal processing applications that leverage several sensors for a variety of uses. Using a camera, object tracking is a novel way to identify moving objects in real time

(*continued*)

Table 1. (*continued*)

Ref. No.	Authors	Year of publication	Title	Name of the journal	Findings
7	Sreyan Ghosh Sherwin Joseph Sunny Rohan Roney	2019	Accident Detection Using Convolutional Neural Networks	International Conference on Data Science and Communication (IconDSC)	The author addresses that India is face a significant death toll from [7] accidents, with over 80% occurring due to lack of timely assistance. A system is being developed to detect accidents using live video feeds from CCTV cameras. The system uses a deep learning convolution neural network model to classify frames into accident or non-accident, with an accuracy of over 95% for smaller datasets
8	Dr. Narina Thakur Preeti Nagrath Rachna Jain Dharmender Saini Nitika Sharma Jude Hemanth	2021	Object Detection in Deep Surveillance	RESEARCH GATE - This is a preprint; it has not been peer reviewed by a journal	This paper evaluates deep neural network [8] models for object detection in computer visions and surveillance applications. Object detection is crucial for computer visions and surveillance applications, particularly pedestrian detection. Advances in deep neural network models have improved accuracy and granularity. The Yolov5 model outperforms all other models with 61% precision and 44% of F measure value. Object detection is used in various fields, including Human-Computer Interaction, consumer electronics, robotics, transportation, and surveillance

(*continued*)

Table 1. (*continued*)

Ref. No.	Authors	Year of publication	Title	Name of the journal	Findings
10	Hadi Ghahremannezhad Hang Shi Chengjun Liu	2022	Real-Time Accident Detection in Traffic Surveillance Using Deep Learning	IEEE International Conference on Imaging Systems and Techniques (IST)	This paper presents a new framework for automatic traffic accident detection [10] at intersections using computer vision techniques. The framework consists of three steps: object detection using the YOLOv4 method, object tracking using Kalman filter and the Hungarian algorithm for association, and accident detection by trajectory conflict analysis

[18]. The dataset also contains Surveillance feeds, anomaly examples, diverse conditions, normal behavior data, data annotations, data augmentation, and logical and ethical compliance.

Training and Validation: Data preprocessing involves standardizing your data, reshaping photos to fit their original dimensions, and using any necessary data augmentation methods to boost diversity. Convolutional neural networks (CNNs) and other machine learning models, including them, must be trained and evaluated using data partitioning [25]. The available dataset is divided into subsets for testing, validation, and training [26].

A CNN (Convolutional Neural Network)'s model parameters [15] can be optimized using a variety of methods and approaches to improve the network's functionality, boost accuracy, and avoid over fitting [17]. Techniques such as Regularization technique, batch normalization, hyper parameter tuning, and initialization of weights are used. In order to guarantee the efficacy and dependability of convolutional neural networks (CNNs), rigorous evaluation methods are essential for gauging their performance. Techniques like Cross-validation technique, confusion matrix, precision, recall and F1 score technique, assembling, [14] stratified sampling, model inter printability are used.

Integration with Communication Systems: Sensors will be used to raise alarm whenever detection is found [18] and immediately a notification will be sending to the control location of exact location and what kind of anomaly has been deducted (Fig. 1).

A variety of datasets, including those pertaining to accidents, kidnappings, human trafficking [16], and any kind of anomaly, will be collected. The dataset will be used to train the CNN [6] model and includes a variety of images, videos, details, and patterns about various anomalies. These datasets, a sensor alarm will be raised and a prompt notification will be sent to the control room if any anomalies are found and compared

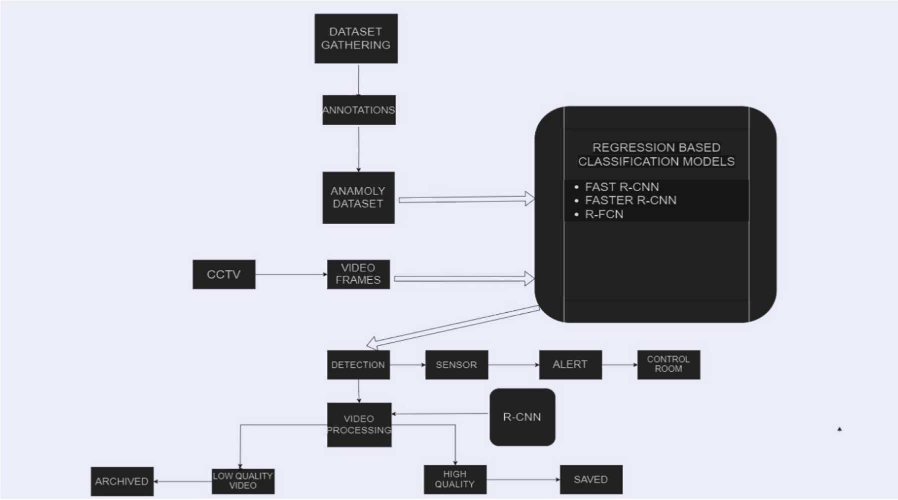

Fig. 1. Flowchart of the process

with the patterns in the datasets using various regression models, such as R-CNN and R-FCN. The video frames that contain the anatomic details will be compressed into high resolution and saved, while the remaining frames will be converted to low resolution and archived.

4 Proposed Architecture

We can automate the process of identifying unusual events [19] from surveillance camera feeds by using our system. Anomalies can be found both supervised and unsupervised using CNN and LSTM [6] technologies. Authorities can receive alert messages upon event detection. High-quality video clips of anomalous events can be preserved in their original quality, while recordings of normal events in lower quality [24] are kept apart. By putting this system into place, we can decrease the amount of time and labor required from humans to find anomalies, and the system also becomes more storage-efficient. This system's architecture is made up of a number of modules or components that must work together to complete the system (Fig. 2).

In image and video analysis, deep learning models particularly CNNs [20] have shown remarkable performance, opening up a range of applications in security, surveillance, object recognition, and anomaly detection in CCTV feeds [21]. An image is analyzed using a particular kind of deep learning model. CNNs are capable of analyzing video frames from CCTV cameras in order to identify objects, patterns, or anomalies [2]. The CNN model has to be trained first. In order for it to learn and extract features, a dataset must be fed into it during training. The CNN can process incoming video frames in real-time after it has been trained. It uses the patterns it has discovered to identify things or occasions [22].

Fig. 2. Proposed Architecture

CNN bases its predictions on its analysis of the video frames. It initiates an action or alert if, according to it's training, it recognizes an object or event. Then alerts [4] and notifications will be sent to the control room right away. The remaining video frames are archived and saved in low resolution, while the anomaly video is saved in high resolution. Using the sliding window method, divide the training video frames into temporal sequences of size 4.2. To guarantee that [23] all input images have the same resolution, resize each frame to 256 $\times$ 256.3. Divide each pixel by 256 to scale the values between 0 and 1.This model has an enormous number of parameters, so a lot of training data is needed. Thus enhance the data in the temporal dimension. In order to produce additional training sequences [2] and combine frames with different skipping strides. For instance, the frames in the first stride-1 sequence are 1, 2, 3, and 4, while the frames in the first stride-2 sequence are 1, 3, 5, and 7. We are expanding our training data in two steps. The out-of-strides are (1, 6, 11, 16) and (1, 11, 21, 31) since we are only using the fifth alternating frame. In addition to the aforementioned processing, every frame's resolution and quality are decreased before they are saved as video. This is the low-resolution video that has been saved for future use. As they don't have any anomalies, they are typically not brought up again in the future.

5 Results

The accuracy of this system in identifying objects, patterns, and anomalies in CCTV feeds would depend on the quality of the training data, the effectiveness of the CNN model, and the complexity of real-world scenarios. The training dataset consisted of 40 videos of accidents, human trafficking, no anomaly and no accidents (usual traffic). A series of 40 tests was conducted for the validation of the trained model. Every test had a single video for predicting its label. The training dataset consisted of 30 videos of accidents and no accidents (usual traffic). A series of 30 tests was conducted for the validation of the trained model. Every test had a single video for predicting its label (Fig. 3 and Table 2).

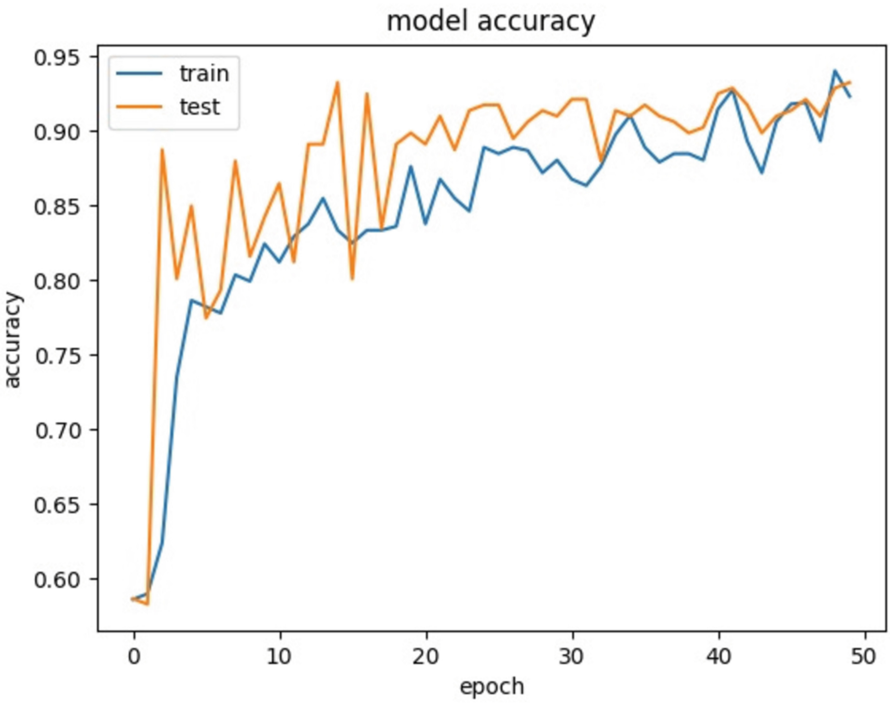

Fig. 3. Accuracy Measurement

Table 2. Accuracy and Precision values for various Models

Model	Accuracy	Precision		Recall		F1	
		NO_SEG	SEG	NO_SEG	SEG	NO_SEG	SEG
CNN-2 [3]	-	-	0.836	-	0.723	-	0.775
CNN-2A [3]	-	-	0.776	-	**0.799**	-	0.788
CNN-A_u	0.909	0.909	0	1	0	0.952	0
CNN-A	0.963	0.972	**0.853**	**0.988**	0.718	0.980	0.778
CNN-B	**0.965**	**0.975**	0.845	0.986	0.754	**0.981**	**0.795**
CNN-C	0.963	0.974	0.832	0.985	0.75	0.980	0.787

6 Conclusion

The project Accidence has developed an IOT-based product to detect and send a quick alarm to nearby police stations and hospitals. It will also focus on future research directions and recommend strategies to optimize and implement the system in real-world scenarios. People facing problems from years of road accidents, women trafficking, and kidnaps are the focus of this new solution. We worked and trained on various algorithms for quick responses and for high accuracy.

References

1. Suitha, K., Bramha Naidu, V., Gowri Shankar, P., Hemanth Kumar, P.: Human & object detection using surveillance system. Proceedings of IEEE (2008)
2. Jahagirdar, S., Koli, S.: Automatic accident detection techniques using CCTV surveillance videos: methods. Data sets and Learning Strategies international Journal of Engineering and Advanced Technology (IJEAT) **9**(3) (2020). ISSN: 2249-8958
3. Ashok Kumar, J.M., Arun Kumar, C., Abishek, B.R., Thirumagal, E.: Crime Detection in Surveillance. Int. J. Eng. Adv. Technol. (IJEAT) **8**(5S) (2019). ISSN: 2249-8958
4. Sankarnarayana, A.C.: Object Detection, Tracking and recognition for multiple smart cameras. Proceedings of IEEE (2008)
5. Bhusal, S.: Object Detection and Tracking in wide Area surveillance using thermal imagery. The University of Nevada Las Vegas (2015)
6. Ghosh, S., Joseph, S., Sunny, R.R.: Accident Detection Using Convolutional Neural Networks. International Conference on Data Science and Communication (IconDSC) (2019)
7. Thakur, N., et al.: Object Detection in Deep Surveillance. RESEARCH GATE - This is a preprint; it has not been peer reviewed by a journal (2021)
8. Mishra, P.K., Saroha, G.P.: A study on video surveillance system for object detection and tracking. 2016 3rd International Conference on "Computing for Sustainable Global Development (2016)
9. Hashmi, S.A.: Face Detection in Extreme Conditions: A Machine-learning Approach. Published in arXiv.org (2022)
10. Ghahremannezhad, H., Shi, H., Liu, C.: Real-Time Accident Detection in Traffic Surveillance Using Deep Learning. IEEE International Conference on Imaging Systems and Techniques (IST) (2022)
11. Gomathy, C.K., Geetha, V., Madhumitha, S., Sangeetha, S., Vishnupriya, R.: A secure with efficient data transaction in cloud service. Published by International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) **5**(4) (2016). ISSN: 2278-1323
12. Moreira, D., et al.: Temporal robust features for violence detection. IEEE Winter Conference on Applications of Computer Vision (WACV) 8 (2017)
13. Kamijo, S., Matsushita, Y., Ikeuchi, K., Sakauchi, M.: Traffic monitoring and accident detection at intersections. IEEE Transactions on Intelligent Transportation Systems **1**(2), 108–118 (2000)
14. Huang, X., He, P., Rangarajan, A., Ranka, S.: Intelligent intersection: two-stream convolutional networks for real-time near accident detection in traffic video. ACM Transactions on Spatial Algorithms and Systems (TSAS) (2019)
15. Yao, Y., Xu, M., Wang, Y., Crandall, D.J., Atkins, E.M.: Unsupervised Traffic Accident Detection in First-Person Videos. arXiv preprint arXiv:1903.00618 (2019)
16. Radford, A., Metz, L., Chintala, S.: UnsupervisedRepresentation Learning with Deep Convolutional GenerativeAdversarial Networks, arXiv preprint arXiv:1511.06434 (2016)
17. Johnson, R., Zhang, T.: Semi-supervised Convolutional Neural Networks for Text Categorization via Region Embedding. Advances in Neural Information Processing Systems 28 (NIPS 2015)
18. Sultani, W., Chen, C., Shah, M.: Real-world Anomaly Detection in Surveillance Videos. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2018)
19. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. IEEE Conference, Computer Vision and Pattern Recognition (CVPR) (2015)
20. Ashby, P.J.: The value of cctv surveillance cameras as aninvestigative tool: an empirical analysis. European J. Crimi. Policy and Res. **23**(3), 441–459 (2017)

21. Cosar, S., Donatiello, G., Bogorny, V., Garate, C., Alvares, L.O., Bremond, F.: Toward abnormal trajectory and eventdetection in video surveillance. IEEE Trans. Circuitsand Sys. Video Technol. **27**(3), 683–695 (2017)
22. Park, J., Kim, D.H., Shin, Y.S., Lee, S.-h.: A comparison of convolutional object detectors for real-time drone tracking using a ptz camera. In: Proceedings of the 2017 17th Inter-national Conference on Control, Automation and Systems(ICCAS), pp. 696–699. IEEE, Jeju, Korea (South) (2017)
23. Mehtre, K., Mehtre, B.M.: Automated camera sabot age detection for enhancing video surveillance systems. Multi-media Tools and Applications **78**(5), 5819–5841 (2019)
24. Mathur, G., Bundele, M.: Research on intelligent video surveillance techniques for suspicious activity detection critical review. In: Proceedings of the 2016 International Conference on Recent Advances and Innovations in Engineering (ICRAIE), pp. 1–8. IEEE, Jaipur, India (2016)
25. Zhao, Z.-Q., Zheng, P., Xu, S.-T., Wu, X.: Object detectionwith deep learning: a review. IEEE Trans. Neural Netw. Learn. Sys. **30**(11), 3212–3232 (2019)
26. Makka, S., Arora, G., Mopuru, B.: IoT based health monitoring and record management using distributed ledger. In Journal of Physics: Conference Series, Vol. 2089, No. 1, p. 012030. IOP Publishing (2021)
27. Makka, S., et al.: Application of Blockchain and Internet of Things (IoT) for Ensuring Privacy and Security of Health Records and Medical Services. 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), pp. 84–88. Uttar Pradesh, India (2022). https://doi.org/10.1109/IC3I56241.2022.10072427