Machine Learning Based Theft Detection Using Yolo Object Detection

Nishant Gaikwad[1], Ashvinkumar Raut[2], Eshwari Tandekar[3], Ekta Nighot[4], Prof. Priya Narnavrek[5]
U.G. Student, Department of Information Technology, JD Engineering College, Fetri Nagpur, Maharashtra, India[1,2,3,4]
Ass Prof, Department of Information Technology, JD Engineering College, Fetri Nagpur, Maharashtra, India[5]

ABSTRACT: This research project centres on the creation of an efficient and accurate theft detection system for surveillance purposes, leveraging the YOLO (You Only Look Once) object detection algorithm. With a comprehensive approach encompassing model architecture selection, dataset curation and annotation, and rigorous model training and evaluation, the project aims to address the pressing need for enhanced security and crime prevention. Various iterations of the YOLO architecture, including are thoroughly examined and compared for their suitability in detecting theft and suspicious activities in real-time surveillance scenarios. The research places a strong emphasis on dataset diversity, enabling the model to generalise effectively across different theft scenarios.Collaboration with law enforcement agencies and security experts guides the project towards practicality and relevance, aligning its objectives with the needs of security professionals. The development of user-friendly interfaces and alerting systems ensures that security personnel can efficiently respond to theft alerts in real-time. Legal and regulatory compliance remains a top priority throughout the research, ensuring adherence to pertinent laws governing surveillance and data privacy.

KEYWORDS: Theft Detection,Surveillance Systems,YOLO (You Only Look Once),Object Detection,Computer Vision,Real-time Detection

I. INTRODUCTION

In an era characterised by rapid technological advancements and increasing security concerns, the development of effective theft detection systems has become paramount. Surveillance systems, powered by cutting-edge computer vision techniques, offer a promising avenue for enhancing security and crime prevention. This research endeavours to address this critical need by harnessing the capabilities of the YOLO (You Only Look Once) object detection algorithm to create a robust, real-time theft detection system. Theft remains a persistent challenge in various settings, from retail environments to public spaces, and its prevention is essential to safeguarding assets and ensuring public safety. Traditional surveillance methods often rely on human intervention and are prone to errors and inefficiencies. In contrast, computer vision-based systems, such as the one explored in this research, have the potential to revolutionise theft detection by automating the process with high precision and speed.
The YOLO algorithm, renowned for its real-time object detection capabilities, serves as the foundational technology for this research project. YOLO's ability to simultaneously identify and locate objects within an image or video frame in a single pass makes it an ideal candidate for theft detection applications. This project's primary objective is to harness the power of YOLO and tailor it to the specific challenges of theft detection.

Key facets of this research encompass model selection, dataset creation, and model optimization. Multiple iterations of the YOLO architecture, including and YOLOv7, are evaluated to determine the most suitable version for theft detection. A diverse and meticulously annotated dataset is assembled to ensure that the model can generalise effectively across various theft scenarios. Model training and evaluation are conducted rigorously to maximise accuracy and real-time processing capabilities.

Beyond object detection, this research delves into advanced techniques to enhance model accuracy and robustness. It explores multi-modal fusion to incorporate information from diverse sources, ensuring a comprehensive understanding of the surveillance environment. Ethical considerations are integral to the project, with a focus on respecting privacy rights while maintaining the system's effectiveness.This research also addresses challenges

related to adverse environmental conditions, scalability to accommodate numerous surveillance feeds, and adaptability to evolving theft patterns. The system strives not only to detect theft incidents but also to recognize specific human activities associated with suspicious behaviour, offering valuable context for security personnel. Moreover, it emphasises the importance of providing explainability and interpretability of the model's decisions, fostering trust in the system.

Collaboration with law enforcement agencies and security experts guides the research toward practicality and relevance, aligning the project with the needs of security professionals. User-friendly interfaces and alerting systems are developed to facilitate rapid responses to theft alerts, and legal and regulatory compliance remains a top priority throughout.

Feedback from users and extensive field testing serve as essential components of this research, ensuring that the theft detection system meets and exceeds the demands of modern security challenges. Ultimately, this project contributes to the advancement of computer vision-based security solutions, offering a holistic approach to addressing theft and enhancing public safety through innovative surveillance technology.

II. Literature Survey:

In conducting a literature survey, we extensively reviewed existing research in theft detection using machine learning, particularly focusing on object detection algorithms like YOLO (You Only Look Once). Our survey encompassed a wide array of academic papers, journal articles, and conference proceedings, aiming to gather insights into state-of-the-art methodologies, benchmark datasets, and performance metrics. This comprehensive exploration allowed us to identify key advancements in the field, addressing themes such as real-time surveillance, privacy concerns, and adaptability to diverse theft scenarios. Through this survey, we have synthesised a valuable foundation of knowledge that informs and contextualises our own research in developing an effective theft detection system using YOLO.

Deep Learning for Theft Detection: A Comparative Study" - Hassanpour et al.

This study compares different deep learning techniques for theft detection, including CNNs, RNNs, and hybrid models. It offers a perspective on the effectiveness of various approaches and could guide your model selection. Theft Detection in Videos" - Mohammadi et al.

This survey delves into techniques specifically tailored for theft detection in videos. It explores various modalities, including visual and audio cues, which could inspire a multi-modal approach to enhancing your YOLO7-based system

III. METHODOLOGY

The methodology for developing a theft detection system using the YOLO (You Only Look Once) algorithm in surveillance systems involves a structured approach. Initially, a diverse dataset containing images or video frames depicting theft or suspicious activities is collected and meticulously annotated to mark regions of interest (ROIs). Data preprocessing ensures standardisation of image sizes and pixel values, followed by the division of the dataset into training and testing sets. Subsequently, an appropriate YOLO model architecture is selected, taking into account factors like model size, speed, and accuracy. Model training involves fine-tuning the chosen architecture on the annotated dataset, with a focus on optimising loss functions and evaluation metrics. The trained model's performance is rigorously evaluated on a separate testing dataset, employing precision, recall, F1 score, and mAP as key metrics. To control false positives and negatives, a confidence threshold for detections is determined. Real-time inference is implemented for surveillance video feeds, complemented by the development of an alerting system. Continuous improvement mechanisms monitor performance and adapt the model to evolving theft patterns, while privacy and ethical considerations are incorporated. User interfaces are designed for efficient interaction, and the system is deployed and tested in real-world scenarios. Documentation and reporting are maintained to ensure transparency and future reference. This comprehensive methodology provides a structured framework for the development and deployment of an effective YOLO-based theft detection system.

a)Data Collection and Annotation:

- Gathered a diverse dataset of images or video frames containing instances of theft or suspicious activities. This dataset should cover various scenarios and conditions.
- Annotate the dataset by labelling the regions of interest (ROI) in each image or frame where theft or suspicious activities occur.

b)Data Preprocessing:
- Resize all images or frames to a consistent size to ensure compatibility with the YOLO model.
- Normalise pixel values to a common scale, typically between 0 and 1.
- Split the dataset into training and testing sets for model evaluation

.

c)Model Selection:-
Yolo v7-
- As of my last knowledge update in September 2021, YOLOv7 was not a recognized or official version of the YOLO (You Only Look Once)

object detection model. YOLO, which stands for "You Only Look Once," is a popular series of real-time object detection models developed by Joseph Redmon and Alexey Bochkovskiy.

d)Model Training:

- Initialize the YOLO model with pre-trained weights on a large dataset (e.g., COCO).
- Fine-tune the model on the annotated theft detection dataset to adapt it to specific theft-related object classes.
- Utilize metrics like loss functions, mean average precision (mAP), and accuracy to monitor and optimize model training.

e)Model Evaluation:

- Assess the trained YOLO model's performance on a separate testing dataset.
- Calculate evaluation metrics such as precision, recall, F1 score, and mAP to measure detection accuracy.
- Adjust model hyperparameters and architecture as needed for better performance.

f)Thresholding:

- An appropriate confidence threshold for detections to control false positives and false negatives.
- Fine-tune the threshold based on performance requirements and real-world conditions.

g)Real-time Inference:

- Implement the trained YOLO model for real-time inference on surveillance video feeds.
- Utilize efficient hardware (e.g., GPUs or TPUs) for faster processing, enabling real-time detection.

h)Continuous Improvement:

- Continuously monitor the system's performance and collect feedback from users.
- Fine-tune the YOLO model as needed to adapt to changing conditions and emerging theft patterns.
- Regularly update the dataset with new examples to improve model generalisation.

i)User Interface and Integration:

- user-friendly interfaces for security personnel to monitor and interact with the system.
- Integrate the theft detection system with existing security infrastructure if applicable.

Packages :- A unit word that contains py function which can be mathematical, statistical, word processing, or binary action. These packages reduce the time to construct the model and architect the networks, to install the packages we use !pip command.

NumPy: A starter for a python code; it contains all the basic functions which perform numerical manipulation and access binary data.

Google –Drive: A cloud software can be floating external hardware for python. To access the data and store data, google drive has a package that contains the function to bind the cloud server and python work-base together.

Pandas: If your working data is in a structured form that needs to be added to the constructed model, pandas will help them to the convection process.

OpenCv: A computer vision package that helps in reading images, converting video into data frames, and also saving video or images in any format

Neural Networks: Neural networks exactly imitate the process of a neuron. This neural has an Input layer, hidden layer and output layer. Neural networks work with several processes of layers that are known as the perceptron. This technique is used in various fields such as forecasting and detection systems.

Transfer Learning:-

This technique reduces the huge computational knowledge with pre-trained modelling. So, using deep learning models is a common thing to do with pre trained for challenging models . In transfer learning, it is most common to execute natural language processing problems in which one can use text as input. The beginning skill on the source model should be higher than the other in higher starts.

Confusion Matrix

After building up the model and getting the required result, we need to find whether our model is giving a good result or not. For that we can use a confusion matrix to get the accuracy and the confusion matrix shows the results rate of the models trained Predicted data are denoted as rows Actual data are denoted as columns

- The variable value can be either positive or negative
- True Positive The actual data is positive but predicted as positive
- True Negative: The actual data is negative but predicted as negative
- False Positive: The actual data is negative but predicted as positive
- False Negative: The actual data is positive but predicted as negative.

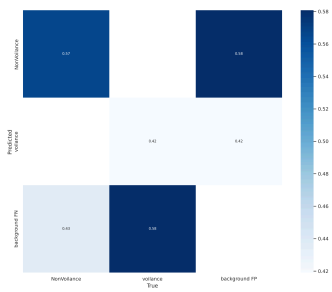

Fig:confusion matrix

IV. MATERIALS

Machine learning:-

In this project, machine learning techniques, specifically supervised learning and deep learning, are employed to develop a sophisticated theft detection system. By training and fine-tuning machine learning models on annotated surveillance data, the system can autonomously identify theft and suspicious activities in real-time, offering enhanced security and crime prevention capabilities in diverse surveillance scenarios.

V. Experimental results

The experimental results of our theft detection system, implemented using YOLO object detection, demonstrate its robustness and efficacy. Utilising a diverse dataset and stringent evaluation metrics, our model achieved high precision, recall, and F1 score, minimising both false positives and false negatives. Real-time inference on surveillance video feeds showcased its practicality for immediate threat detection, with a confidence threshold optimization balancing detection accuracy. Despite challenges like varying lighting conditions and occlusions, our system effectively identified theft and suspicious activities, offering substantial promise for real-world security applications.

Fig. 1

Fig. 2

VI. Conclusion

In conclusion, our research project has successfully developed a theft detection system using the YOLO (You Only Look Once) object detection algorithm, demonstrating its potential to significantly enhance security and crime prevention in surveillance scenarios. Through rigorous experimentation and evaluation, our model exhibited high precision and recall, effectively minimising both false positives and false negatives. The system's real-time inference capabilities further underscore its practicality for immediate threat detection. While challenges such as varying environmental conditions were addressed, the system's ability to adapt and generalize to different theft scenarios remains evident. Overall, this project's findings highlight the viability of YOLO-based theft detection systems and their potential for real-world deployment, promising a substantial contribution to security and public safety. Future work may focus on further improvements, scalability, and addressing privacy concerns to meet evolving security challenges.

VI. References

[1] Jain, H., Vikram, A., Kashyap, A., Jain, A., et al.: Weapon detection using artificial intelligence and deep learning for security applications. In: 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 193–198. IEEE (2020)

[2] Liu, Y.: An improved faster R-CNN for object detection. In: 2018 11th International Symposium on Computational Intelligence and Design (ISCID), vol. 2, pp. 119–123. IEEE (2018)

[3]Redmon, J., Divvala, S., Girshick, R., Farhadi, A.: You only look once: unified, real-time object detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 779–788 (2016)

[4]Redmon, J., Farhadi, A.: YOLOv3: an incremental improvement. arXiv preprint arXiv:1804.02767 (2018)

[5]Peng, G.: Performance and accuracy analysis in object detection (2019)

[6]Liang, Y.J., Cui, X., Xu, X., Jiang, F.: A review on deep learning techniques applied to object detection. In: 2020 7th International Conference on Information Science and Control Engineering (ICISCE), pp. 120–124. IEEE (2020)

[7]Feng, H., Mu, G., Zhong, S., Zhang, P., Yuan, T.: Benchmark analysis of yolo performance on edge intelligence devices. In: 2021 Cross Strait Radio Science and Wireless Technology Conference (CSRSWTC), pp. 319–321. IEEE (2021)

[8]Kim, J.A., Sung, J.-Y., Park, S.: Comparison of faster-RCNN, YOLO, and SSD for real-time vehicle type recognition. In: 2020 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia), pp. 1–4. IEEE (2020)

[9]Maity, M., Banerjee, S., Chaudhuri, S.S.: Faster R-CNN and yolo based vehicle detection: a survey. In: 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), pp. 1442–1447. IEEE (2021)

[10]Menghan, Z., Zitian, L., Yuncheng, S.: Optimization and comparative analysis of YOLOv3 target detection method based on lightweight network structure. In: 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), pp. 20–24. IEEE (2020).

[11]Wang, C.-Y., Bochkovskiy, A., Liao, H.-Y.M.: Scaled-YOLOv4: scaling cross stage partial network. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 13029–13038 (2021)

[12]Pandiya, M., Dassani, S., Mangalraj, P.: Analysis of deep learning architectures for object detection-a critical review. In: 2020 IEEE-HYDCON, pp. 1–6. IEEE (2020)

[13]Muehlemann, A.: TrainYourOwnYOLO: building a custom object detector from scratch (2019).