FAST PREDICTION FOR SUSPECT CANDIDATES FROM CRIMINAL NETWORKS

[1]Jothika.J, [2]Kowsalya.[3]Deepa.M,[4]Sridevi.V, [5]Mrs.Lurdhu Jayasree.S
[1,2,3,4]Student,[5]Assistant Professor
Department of Information Technology,
Loyola Institute of Technology andScience, Kanyakumari, Tamil Nadu, India.

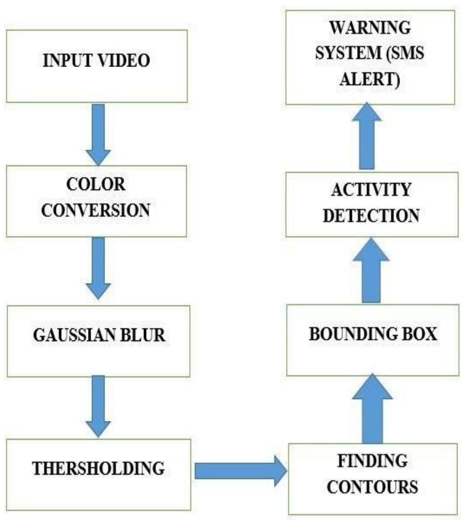
Abstract-This research explores the integration of YOLO (You Only Look Once) object detection framework with Dark net architecture to develop a cutting-edge Intelligent Video Image Processing and Monitoring Control System tailored for enhancing security in the banking sector. The system utilizes YOLO's real-time object detection capabilities, enabling efficient monitoring and surveillance across bank premises. Darknet, a neural network framework, serves as the foundation for implementingand optimizing YOLO, ensuring robustperformance real-time but alsointegrates seamlessly with monitoring and control mechanisms. The proposedsystem aims to enhance security measureswithin banking environments by providing instantaneous and accurate alerts for potential security threats or unusual activities.

Keywords — Fast Prediction Suspect Candidates, YOLO, Sensor-basedSystems, Dataset.

I. INTRODUCTION

This research introduces a pioneering approach to bolstering security in the banking sector by integrating YOLO (You Only Look Once) with the Darknet architecture, forming an advanced Intelligent Video Image Processing and Monitoring Control System. YOLO's real- time object detection capabilities are seamlessly incorporated with Darknet's robust neural network framework to create a sophisticated surveillance system. The primary objective is to enhance security measures by achieving instantaneous, accurate object detection and tracking within banking premises. The system is trained on a diverse dataset, ensuring adaptability to varying environmental conditions. This integration goes beyond traditional video surveillance, offering a comprehensive solution for real-time threat detection.

II. PROPOSED SYSTEM



Activity Recognition is divided into two categories: sensor-based activity recognition and vision-based activity recognition, depending on the system's components.

1. In order to extract some crucial information from the data acquired from numerous sensors, it may be processed and aggregated. They are also used to train the model utilizing various machine learning, deep learning, and data analytics methods.

2. Using a camera-based system, vision-based activity recognition may identify the activities present in an environment by processing and analysing video. These systems often employ digital image processing to draw out relevant data from video, which is regarded as a series of images. In this project, we used a vision- based system using Yolo v3 algorithm.

2.1 DIGITAL IMAGE PROCESSING

The identification of objects in animage and this process would probably start with image processing techniques such asnoise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures.

The clever bit is to interpret collections of these shapes as single objects,
e.g. cars on a road, boxes on a conveyor belt or cancerous cells on a microscope slide.One reason this is an AI problem is that an object can appear very different when viewed from different angles or under different lighting. Another problem is deciding what

features belong to what object and which are background or shadows etc. The human visual system performs these tasks mostly unconsciously but a computer requires skillful programming and lots of processing power to approach human performance. Manipulation of data in the form of an image through several possible techniques. An image is usually interpreted as a two- dimensional array of brightness values, and is most familiarly represented by such patterns as those of a photographic print, slide, television screen, or movie screen. An image can be processed optically or digitallywith a computer.

Segmentation:

Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually.

On the other hand, weak or erratic segmentation algorithms almost always guarantee eventual failure. In general, the more accurate the segmentation, the more likely recognition is to succeed.

Digital image is defined as a two dimensional function f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called intensity or grey level of the image at that point. The field of digital image processing refers to processing digital images by means of a digital computer. The digital image is composed of a finite number of elements, each of which has a particular location and value. The elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used.

2.2 Image Compression

Digital Image compression addresses the problem of reducing theamount of data required to represent a digital image. The underlying basis of the reduction process is removal of redundant data. From the mathematical viewpoint, this amounts to transforming a 2D pixel array into a statically uncorrelated data set. The data redundancy is not an abstract concept but a mathematically quantifiable entity.

2.1.1. Lossy Image compression:

Lossy compression provides higher levels of data reduction but result in a less than perfect reproduction of the original image. It provides high compression ratio. lossy image compression is useful in applications such as broadcast television, videoconferencing, and facsimile transmission, in which a certain amount of error is an acceptable trade-off for increased compression performance. Originally, PGF has been designed to quickly and progressively decode lossy compressed aerial images. A lossy compression mode has been preferred, because in an application like a terrain explorer texture data (e.g., aerial orthophotos) is usually mid-mapped filtered and therefore lossy mapped onto the terrain surface. In addition,decoding lossy compressed images is usually faster than decoding lossless compressed images.

In the next test series we evaluate the lossy compression efficiency of PGF. One of the best competitors in this area is for sure JPEG 2000. Since JPEG 2000 has two different filters, we used the one with the better trade-off between compression efficiency and runtime. On our machine the 5/3 filter set has a better trade-off than the other. However, JPEG 2000 has in both cases a remarkable good compression efficiency for very high compression ratios but also a very poor encoding and decoding speed. The other competitor is JPEG. JPEG is one of the most popular image file formats.

2.1.2. Lossless Image compression:

Lossless Image compression is the only acceptable amount of data reduction. It provides low compression ratio while compared to lossy. In Lossless Image compression techniques are composed of two relatively independent operations: (1)devising an alternative representation of the image in which its interpixel redundancies are reduced and (2) coding the representation to eliminate coding redundancies.

Lossless Image compression is useful in applications such as medical imaginary, business documents and satellite images. Table 2 summarizes the lossless compression efficiency and Table 3 the coding times of the PGF test set. For WinZip we only provide average runtime values, because of missing source code we have to use an interactive testing procedure with runtimes measured by hand. All other values are measured in batch mode.

2.3 Input:

The input module of the system serves as the gateway for gathering data relevant to suspect prediction from criminal networks. This may include various types of data such as textual information from police reports, social media data, surveillance footage, or communication records. The input module ensures the acquisition of diverse and comprehensive data sources to provide a holistic understanding of the criminal network under scrutiny. Data collected in this phase forms the foundation for subsequent analysis and prediction tasks.

2.4 Pre-processing:

Pre-processing is a crucial step where raw data undergoes cleaning, normalization, and transformation to make it suitable for analysis. In the context of suspect prediction from criminal networks, pre-processing involves tasks such as removing irrelevant information, handling missing data, standardizing formats, and anonymizing sensitive data to ensure compliance with privacy regulations. Effective pre- processing enhances the quality of input data, minimizing noise and inconsistencies that could adversely affect the accuracy of predictions.

2.5 Feature Extraction:

Feature extraction involves identifying and extracting relevant attributes or features from pre-processed data that are informative for predicting suspect candidates within criminal networks. This module employs techniques such as natural language processing (NLP), image processing, graph analysis, or signal processing, depending on the nature of the input data. For instance, features extracted from textual data may include keywords related to criminal activities, while features from surveillance footage may include facial recognition or object detection. Extracted features serve as input variables for subsequent predictive models.

2.6 Dataset:

The dataset module encompasses the organized collection of pre-processed and feature-extracted data used for training and testing predictive models. This dataset comprises labeled examples of known suspects, their associations, and criminal activities. It also includes negative examples to ensure balanced training data. Curating a representative and diverse dataset is critical for building robust predictive models that can effectively generalize to new, unseen data instances. Regular updates and augmentation of the dataset ensure its relevance and adaptability to evolving criminal trends.

2.7 YOLO (You Only Look Once):

YOLO, an object detection algorithm, plays a pivotal role in identifying and localizing objects or entities of interest within multimedia data, such as images or videos. In the context of suspect prediction from criminal networks, YOLO is employed to detect and recognize individuals, vehicles, or other relevant objects from surveillance footage or imagery. By efficiently processing input data in real-time with high accuracy, YOLO enhances the system's ability to detect and track potential suspects, facilitating timely intervention by law enforcement agencies.

III. RESULTS and DISCUSSION:

According to the implementation setup, the module presents the results of suspect prediction generated by the system based on the processed data and predictive models. This includes identifying individuals or groups flagged as potential suspects within the criminal network, along with supporting evidence or contextual information derived from feature extraction and analysis. The output may be presented in various formats, such as graphical visualizations, textual reports, or real-time alerts, to enable law enforcement authorities to take appropriate actions, such as initiating investigations or surveillance operations. Additionally, feedback mechanisms may be incorporated to iteratively improve the system's performance based on user input and outcomes.

CONCLUSION:

In conclusion, the integration of sensor- based and vision-based activity recognition systems provides a comprehensive approach to understanding and interpreting human activities in diverse environments. The utilization of machine learning, deep learning, and data analytics techniques in sensor-based systems allows for the extraction and processing of valuable information from various sensors. Meanwhile, the vision-based system, exemplified in our project through YOLOv3 with Darknet, proves effective in identifyingand analyzing activities within video data. The amalgamation of these approaches contributes to a more nuanced and robust understanding of human actions, paving the way for enhanced applications in surveillance, healthcare, and other domains where real-time activity recognition is crucial.

REFERENCE

[1] J. K. Aggarwal and M. S. Ryoo, “Humanactivity analysis: A review,” ACM Comput. Surv., vol. 43, no. 3, 2011, doi: 10.1145/1922649.1922653.

[2] A. G. D’Sa and B. G. Prasad, “A survey on vision based activity recognition, its applications and

challenges," 2019 2nd Int. Conf. Adv. Comput. Commun. Paradig. ICACCP 2019, pp. 1–8, 2019, doi: 10.1109/ICACCP.2019.8882896.

[3] G. Cheng, Y. Wan, A. N. Saudagar, K. Namuduri, and B. P. Buckles, "Advances in Human Action Recognition: A Survey," no. February, 2015, [Online]. Available: http://arxiv.org/abs/1501.05964.

[4] C. Dhiman and D. K. Vishwakarma, "A review of state-ofthe-art techniques for abnormal human activity recognition," Eng. Appl. Artif. Intell., vol. 77, no. August 2018,pp. 21–45, 2019, doi: 10.1016/j.engappai.2018.08.014.

[5] S. A. R. Abu-Bakar, "Advances in human action recognition: An updated survey," IET Image Process., vol. 13, no. 13,pp. 2381–2394, 2019, doi: 10.1049/ietipr.2019.0350.

[6] T. Huynh-The, B. V. Le, S. Lee, and Y. Yoon, "Interactive activity recognition using pose-based spatio–temporal relation features and four-level Pachinko Allocation Model," Inf. Sci. (Ny)., vol. 369, pp. 317–333, 2016, doi: 10.1016/j.ins.2016.06.016.

[7] S. Abdelhedi, A. Wali, and A. M. Alimi,"Fuzzy logic based human activity recognition in video surveillance applications," Adv. Intell. Syst. Comput., vol. 427, pp. 227–235, 2016, doi: 10.1007/978-3-319-29504-6_23.

[8] P. Guo, Z. Miao, Y. Shen, W. Xu, and D.Zhang, "Continuous human action recognition in real time," Multimed. Tools Appl., vol. 68, no. 3, pp. 827–844, 2014, doi:10.1007/s11042-012-1084-2.

[9] A. Jalal, M. Uddin, and T. S. Kim, "Depth video-based human activity recognition system using translation and scaling invariant features for life logging at smart home," IEEE Trans. Consum. Electron., vol. 58, no. 3, pp. 863– 871, 2012, doi: 10.1109/TCE.2012.6311329. [10] J. Hu and N. V. Boulgouris, "Fast human activity recognition based on structure and motion," Pattern Recognit. Lett., vol. 32, no. 14, pp. 1814–1821, 2011, doi: 10.1016/j.patrec. 2011.07.013.