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TRAFFIC ANOMALY DETECTION IN VIDEO

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ABSTRACT

Nowadays technology becomes more powerful andadvanced. It also helps in human daily life routines andmakes tasks easier for humans. So here, we are going to survey about how to make traffic management easy and safe. There are too many technologies like computer vision, AI and their applications like anomalies detection. Due to its significance in intelligent transportation networks, anomaly detection in real-time traffic videos has recently gained interest in research areas. Because of different types of weather conditions, viewpoints angles. The video quality of traffic footage, lighting conditions, etc., continues to be a difficult issue. In this survey paper, we discuss how tosolve this type of problem what different techniques and algorithms used what their pros and cons. what types of challenges according to different popular research papers.

Keywords: Anomaly Detection, Computer Vision, ConvNet, LTSM.

I. INTRODUCTION

The traffic video detection of anomaly plays a major role in the traffic ensuring its safety and security. It also help the traffic police to investigate about the anomalies to catch the anomaly easily which break traffic rules such as not wearing helmets, not wearing a seat belt, wrong turns etc. Sometimes there are very bad or complex conditions to detect anomalies like bad weather and size of vehicles and Number plate not according to pattern/without-Number plate/Registration mark.

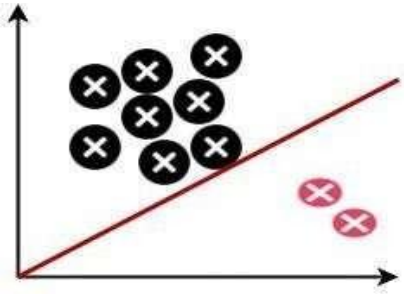

Figure 1

Anomalies that possible in traffic videos are over speeding, wrong turn, stalled vehicles, road accidents etc. Anomaly detection systems works bylearning patterns to build normal model.

The essence of input data, feasibility of supervised/unsupervised learning, types of anomalies, suitability of the techniques, outputs for anomaly detection and requirements for evaluation should be protected by the scope of the analysis.

Figure 2: Accidents detection using Motion Interaction Field (MIF) [1].

This survey presented from above perspectives. A common Traffic anomaly detection framework is shown in Fig. 3. [2]

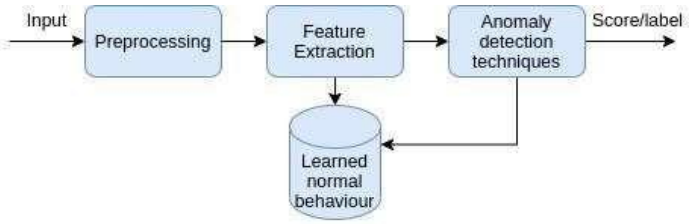

Figure 3: Anomaly Detection Framework.

In this framework first we extract feature/data from input this is called preprocessing as shown in Fig. 4.

In terms of laws, templates, or data repositories, natural behavior is represented. For the identification of anomalies using the anomaly scoring and marking mechanism, specific anomaly detection techniques are used.

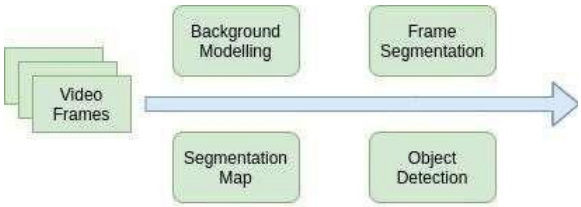

Figure 4: The Preprocessing Pipeline

II. LITERATURE SURVEY

Here we provide summery of recently published good research papers. What approaches they usedand their model performance. All these research arefrom AI City Challenge.

To study traffic anomaly detection, a context modeling module, a mask extraction module and a multi-granularity tracking algorithm consisting of box- level tracking and pixel-level tracking, they used the Multi-Granularity tracking method with modularized components in this paper. To make abnormal predictions. Moreover, a novel fusion and backtracking optimization to make model more efficient and improve its performance. This approach improve therobustness and accuracy of the results.

This study placed first in this competition in the Track 4 test set of the NVIDIA AI CITY 2020 CHALLENGE.

F1-Score	RMSE	Total Score
98.55	4.87	0.96

Traffic Anomaly Detection through a Spatial-temporal Information Matrix based Perspective Map[4].

In this paper they used ResNet [50] based Faster R- CNN model with feature pyramid network (FPN) and Deformable Convolutional Network (DCN) to vehicles detection and an anomaly discrimination based on spatial-temporal information matrix.

Benefits of this approach it overcome problem of heterogeneous scene like Shanghai and other real world situation where complex traffic situations.

The only cons of this model is not accurately ableto locate the anomaly start and stop time. Track 3 NVIDIA AI CITY 2019 CHALLENGE dataset, which put first in the competition.

F1-Score	RMSE
97.06	5.31

Anomaly Detection with GAN-based Future Frame Prediction in Traffic Surveillance Videos (2020) [5].. In this paper approach they used is semi-supervised method using Generative Adversarial Network (GAN), U-NET Generator for generate future frames, U-Net GAN model, and loss function they used is Scaled Intensity Loss Function, and metric is Weighted PSNR.

Benefits of this model is overcome the problem of background modeling detection stalled vehicles after certain time-span with the help of this model detect incident right when the event begins and high detection time and accuracy.

F1-Score	RMSE
94.12	4.81

In traffic images, quick unsupervised anomaly detection[6].

The approaches they in the paper is to detect anomalies and preprocessing, the nearest neighbor and k-mean clustering method consists of context modeling, road segmentation and object detection, candidate detection, selection and localization technique and find potential region of interest then apply anomaly detector.

F1-Score	RMSE	S4
59.26	8.24	0.5

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2.1 Learning Methods

Learning the normal behavior is very importance part of the anomaly detection process and helps model in Pattern analysis [17], classification [18], predictions [19], density estimation [20], and behavior analysis [21] and many more.

It is possible to define learning methods assupervised, unsupervised or semi-supervised. In monitored learning model learns from labeled data [22], [23], [24]. In unsupervised learn model learns from Unlabeled [25] dataset. Semi-supervised learning uses mostly unlabeled datasets and some tracking with limited quantities of labeled data. [26], [27].

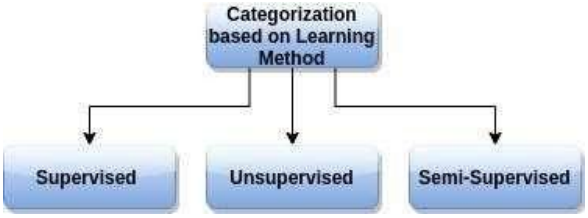

Figure 5: Types of Learning Method

2.2 Anomaly Methods for Identification

Approaches to anomaly detection can be listed as shown in fig.6.

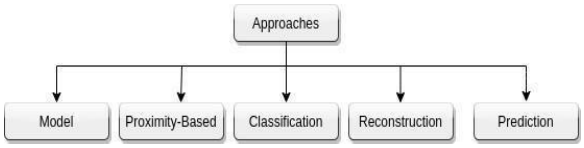

Figure 6: Anomaly Detection Approaches

2.2.1 Model-based approaches: Model-based approaches learn standard dataset behavior by representing the parameter set. To learn the parameters of the model, statistical methods are used as they try to fit data into the stochastic model. Parametric and non-parametric can be mathematical models. As shown in Fig. 7.

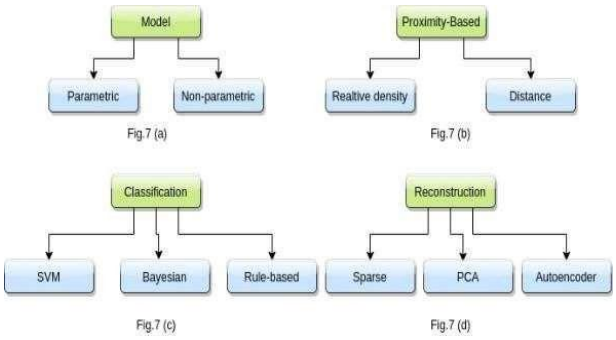

Figure 7: Approaches

2.2.2 *Proximity-Based:* By using proximity based approaches. We can identify anomalies whetherthey are close to neighbors or not. It can be classified into two categories Fig. 7(b). In The assumptions of distance-based, methods are that knowledge has dense neighborhoods. Comparison of density around a point in density-based approaches and its local neighbors it computed as an outlier score [107].

2.2.3 *Classification-based:* This method is work as a classifier between abnormal and normal event in anomaly detector. The technique of class-based anomaly detection is divided into two categories: single and multi-class. Multi-class-class assumesthat it contain labeled class whether it is normal or abnormal class. Single or one class means that it has only single labeled class [190] Rule-based methods learn the theory of the system's natural behavior [156].

2.2.4 *Reconstruction-based:* In this technique the premise is that ordinary data embedded in a lower dimension appears differently in regular and anomalies. Moreover, a measure of anomaly based on an error in data reconstruction. Sparse coding [172] [208], auto-encoder [59], concept component analysis (PCA) [40] are some examples of this technique.

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Table 1. Learning Methods Used in Anomaly Detection

Learning Method	Methods
Supervised	Hidden Markov Model(HMM) [28] Support Vector Machine(SVM)[29] Gaussian Regression(GR)[30] Convolutional Neural Network(CNN)[31] Multiple Instance Learning(MIL)[32] Long short-term memory(LTSM)[34] Fast Region-based-CNN(Fast R-CNN)[34]
Unsupervised	Latent Dirichlet Allocation(LDA [35] Probabilistic latent semantic analysis(PLSA)[36] Hierarchical Dirichlet Process(HDP) [37] Gaussian Mixture Model(GMM)[38] Fisher Kernel method[39] Principle component analysis(PCA)[40] Particle swan optimization[41] Generative adversarial network(GAN)[5]
Hybrid	HDP+HMM GAN+LTSM [42] CNN+LTSM

III. RELATED WORK

3.1 Algorithms Used

3.1.1 Auto- encoder Algorithm:

Algorithm 1. Auto-encoder based data clustering

Input: Dataset X, the number of clusters K hyper-parameter λ,the maximum number of iterations T.

Initialize sample assignment C^0 randomly.

Set t to 1

Repeat

Update the mapping network by minimizing Eqn**. (4)** with stochastic gradient descent for one epoch.

Update cluster center c^t via Eqn. (6).

Partition X into K clusters and update the sample assignment C^t via Eqn. (5).

t=t+1.

Until t>T.

Output: Final sample assignment C.

3.1.2 Sparse Combinations Testing:

Algorithm 2 Testing with Sparse Combinations

Input x, auxiliary matrices {**R1,….,Rk**} and

Threshold T.

for j=1 →K do

if ||**R**kX||^2 < T **then**

return normal event;

end if

end for

return abnormal event;

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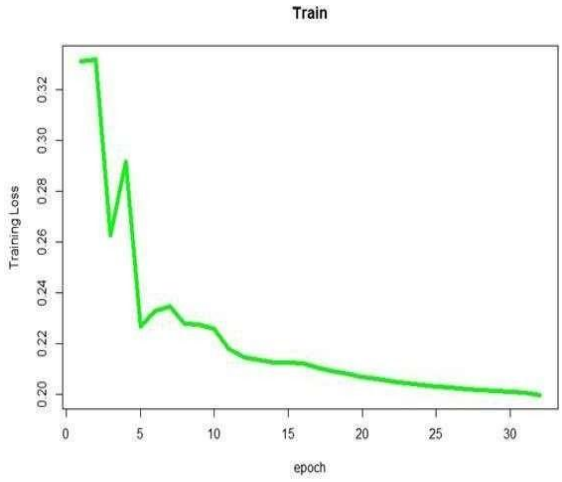
IV. RESULTS AND DISCUSSION

4.1 Training loss per epoch Graph



4.2 Analysis of Accuracy

Accuracy	Loss
78.05	0.213

4.3 Model

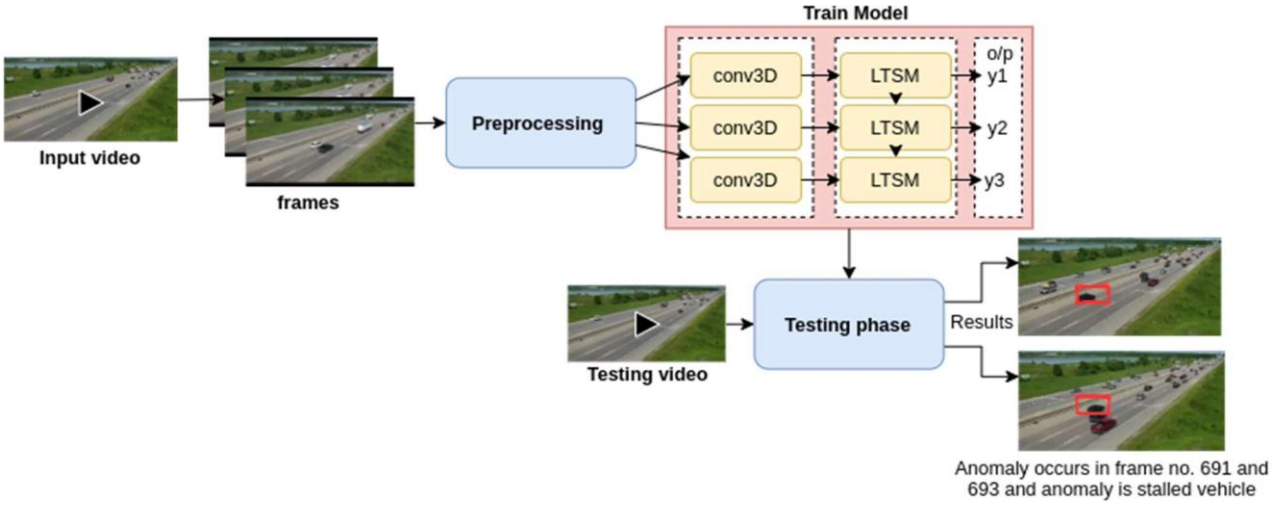


Figure 8: Overview and Work Flow Diagram

V. CONCLUSION

We have revisited important computer vision based survey papers. Then, we explored various anomaly detection techniques that can be applied for road traffic it also involves vehicles, people, and their interaction with the environment. We approach anomaly detection by treating data as the primary unit and describing the learning methodologies, features used in learning, anomaly detection algorithms, and application situations. We plan to chart a few potential directions by examining the gaps in present computer vision-based techniques and discussing potential options.

We have presented an anomaly detection method by using sparse combination learning. This approach directly learns sparse combinations, which increase the testing speed without losing its effectiveness. In a time where surveillance cameras are, being used everywhere, effectively checking it for any abnormal event. Thus, a fast and intelligent method to check these surveillance cameras is at most required. It helps to reduces cost of government and cutting down lot or work to be done by people struggling to monitor it and would help it taking faster actions during those situations by integrating these with alerts and other important actions like informing police or calling an ambulance.

Since it achieves a frame rate of 100fpm, frames can be analyzed at a decent rate and thus can be used in surveillance cameras to detect anomalies automatically. Based on the signal of this system, alarms and other actions can be controlled.

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