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FIVE LEVELS OF TRAFFIC CONGESTION CLASSIFICATION USING IMAGES OF CLOSED-CIRCUIT TELEVISION AND TRAFFIC JAM NETWORK APPROACH

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Abstract- Reduced traffic congestion is the main objective of road management. Several approaches have been developed to address the problem using various types of data. One of which, is analyzing behaviors of drivers and pedestrians using their GPS data. However, this approach raises individual confidentiality problems. Instead, providing drivers with road status information might help to reduce traffic congestion. In this paper, to classify traffic congestion, we provide a new contribution called TraJamNet. The contribution is based on computer vision techniques. It classifies images recorded by closed-circuit television (CCTV) cameras with the consideration of external factors including sequentially of status, weather conditions, and period of the day. Further, we have established five classes of traffic congestion, the classes represent the degree of congestion on a specified road point. To evaluate the performance of the proposed TraJamNet contribution, it has been trained and tested on the UA-DETRAC dataset. Consequently, TraJamNet achieves good results according to accuracy, precision, recall, and f1-score metrics. The results are approved by the comparison with other models. Such a TraJamNet approach might be refined and placed in roadside cameras.

Keywords: Traffic Congestion, Traffic Jam, Traffic Congestion Levels, Image Classification, Deep Learning.

1. INTRODUCTION

Traffic congestion (TC) is a worldwide problem, it may have serious consequences for both people and the larger society. It negatively impacts productivity and the health of individuals, and increases the degree of pollution, it also has the potential to stifle national progress. It happens due to several reasons including the number of vehicles on roads, road conditions, weather conditions, and so on. Despite the many initiatives taken by governments and concerned authorities, the problem still exists and is increasing day by day. Various approaches have addressed TC in different domains. The state of the art is employing computer vision techniques, so that, deep learning (DL) algorithms have allowed building models to predict TC. These models could be injected into closed-circuit television (CCTV) cameras. The aim is to analyze the massive volume of data recorded by CCTV. With the help of DL, it becomes possible to forecast the status of roads. Furthermore, these forecasts are helpful to inform drivers about congested points to avoid, it is useful also in transportation systems or for road management authorities.

Besides, one of the challenges related to the topic is "how do we assess that we have TC? or in terms of machine learning (ML), how to classify road points?". Basically, TC could be classified into two levels: congestion, and non-congestion. It can be also classified into three or five or ten or other classes. Generally, it depends on density (i.e., the number of vehicles on the roadway regarding the number of lanes), travel time spent by drivers on a path, and the average speed of vehicles. it is important to consider the context and purpose of the classification task to determine the appropriate number of classes. The remainder of the paper is structured as follows: Section 2 is about related works; it illustrates some previous approaches to predict congestion on roads. section 3 is devoted to explaining and describing the method adopted to deal with the raised problem. Next, the method is followed by the experiment and results section, in which we evaluated and then we compared the built model with others. Finally, section 5 represents the conclusion.

2. RELATED WORK

There have been many studies addressing the topic of traffic congestion. The studies have employed different approaches and technics from different disciplines. Moreover, they have based on different types of data including Global Positioning System (GPS) data

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information of road users, social media data, historical data of regions or road points, as well as extracting patterns using records of CCTV cameras fixed on roads. Most of the time, the data used by these studies are either structured (i.e., table of values) or unstructured (i.e., dataset of images). First of all, structured data could be adopted in order to predict TC. In [1], the authors used the day, the time, and the weather conditions (temperature, humidity, etc.) to propose a model-based support vector regression with a radial basis kernel. The model was tested on four road points, and it resulted in an average Root Mean Square Error (RMSE) of 1.12. Zhenhua Wang, et al. [2] established a model to predict TC and solve other problems such as scientific transport infrastructure planning. To that aim, they employed various factors including vehicles, pedestrian and non-motor information on roads, road conditions, and other external data.

Otherwise, the researchers in several studies have adopted computer vision technics, they construct models to detect congestion in real-time using either traditional computing (e.g., detecting key points, implementing descriptors, establishing masks to determine mobile objects in a sequence of images) or modern computing (e.g. using ML and Deep Learning DL to build models). These technics improve the role of radars and CCTV cameras fixed on roads. the paper [3] proposes a system for TC monitoring, it provides the optimal paths for drivers by sorting trajectories ascendingly on the time dimension. Li Wei and Dai Hong-ying [4] based on texture analysis by extracting features of images to estimate density which achieves high accuracy. This estimation helps traffic managers classify roads by comparing the results with a predefined threshold. Dakshayani ljeri, et al. [5] combined Canny Edge detection, Gaussian Blur and Density calculation algorithms in order to control TC. Moreover, most researchers adopt ML algorithms to detect TC; mainly the entire image must be converted to a numerical vector using descriptors, and then the vector can be used as the input of various ML algorithms such as Decision Tree, k-Means, Naive Bayesian, and so on. In addition, the state of the art of modern artificial intelligent technics is DL, it has a reputation for being able to eliminate feature engineering entirely.

In [6], Researchers estimate the average speed of vehicles on a segment of roads. Furthermore, they provide coloured maps to represent the level of congestion on road segments. To that end, they used various technics including detecting changes between two successive frames. Umair Jilani, et al. [7] propose a binary classification model based on a 5-layer Convolutional Neural Network (CNN), the results of the model are approved based on an augmented dataset using the Generative Adversarial Network (GAN) technique.

Besides, DL enables us to go deeper, so that it can move from classifying the entire image as congestion or non-congestion to searching for the important object in an image, the approach is known as "object detection". Referring to the topic, DL allows the detection of pedestrians and vehicles on road points or in a segment of the road, then the calculation of the density which represents the number of mobile objects considering road conditions. To this, the following approaches, and architectures (R-CNN, Fast R-CNN, Faster RCNN, Mask-RCNN, YOLO) had demonstrated their performance. Chakraborty, et al. [8] have detected TC using You Only Look Once (YOLO) and Deep Convolution Neural Network (DCNN) algorithms, The benefit is that the models operate well in adverse situations, and they perform well in challenging conditions. As well as the authors of [9] combined a deep-SORT tracker with three object detectors which are CenterNet, Detectron2, and YOLOv4, to access the best density calculator framework.

3. METHODOLOGIES

Traffic Jam Network (TraJamNet) combines CNN and LSTM in one architecture. It uses as input a dataset of sequences of images from different locations. CNN is to deal with images, and it is useful for several tasks such as object detection, image segmentation [10], and so on, in this work CNN is used to help with classification, it takes as input an image and outputs a decimal number which represents the level of congestion in the current frame. While LSTM is adopted to deal with sequential data or time series, it has been used to update the level of congestion regarding the previous status in a determined location. In this section, we describe the proposed contribution to solving the raised problem, then we introduce the CNN architectures used and their involved operations and layers. Furthermore, we explain the LSTM cells and the logic operations behind them. At last, we expose the metrics used to evaluate models and their performance.

3.1. Proposed Contribution

As known, model-based DL must pass through three important steps: data preparation, model building, and testing. Firstly, the most important task for data preparation is data annotation, which means assigning a label to each image in the dataset, to this aim, we have established five levels of congestion using a metric named Ratio-Level of Congestion (RLC), this metric is a value related to the portion occupied by vehicles on road and then on the entire image. Secondly, the prepared train dataset has divided into 60 batches, the batch is determined by the number of images contained in a folder; or in ML terms before error calculation, each image is used as input for the embedded blocks. While the block takes an image and outputs the level of congestion y_i related to the frame i.

It is composed by AlexNet architecture to classify the input image into one of the defined levels of congestion. Furthermore, the last output is used as input for LSTM-cell. The goal of LSTM is to improve RLC calculation, it allows to predict congestion considering the previous road status. Finally, after training 80% of the dataset divided into 60 batches using TraJamNet, the model is built. Thus, the model must be tested. Therefore, we adopted accuracy and loss metrics through epochs to demonstrate the performance of the proposed TraJamNet Architecture. The suggested method's pipeline is depicted in Figure 1.

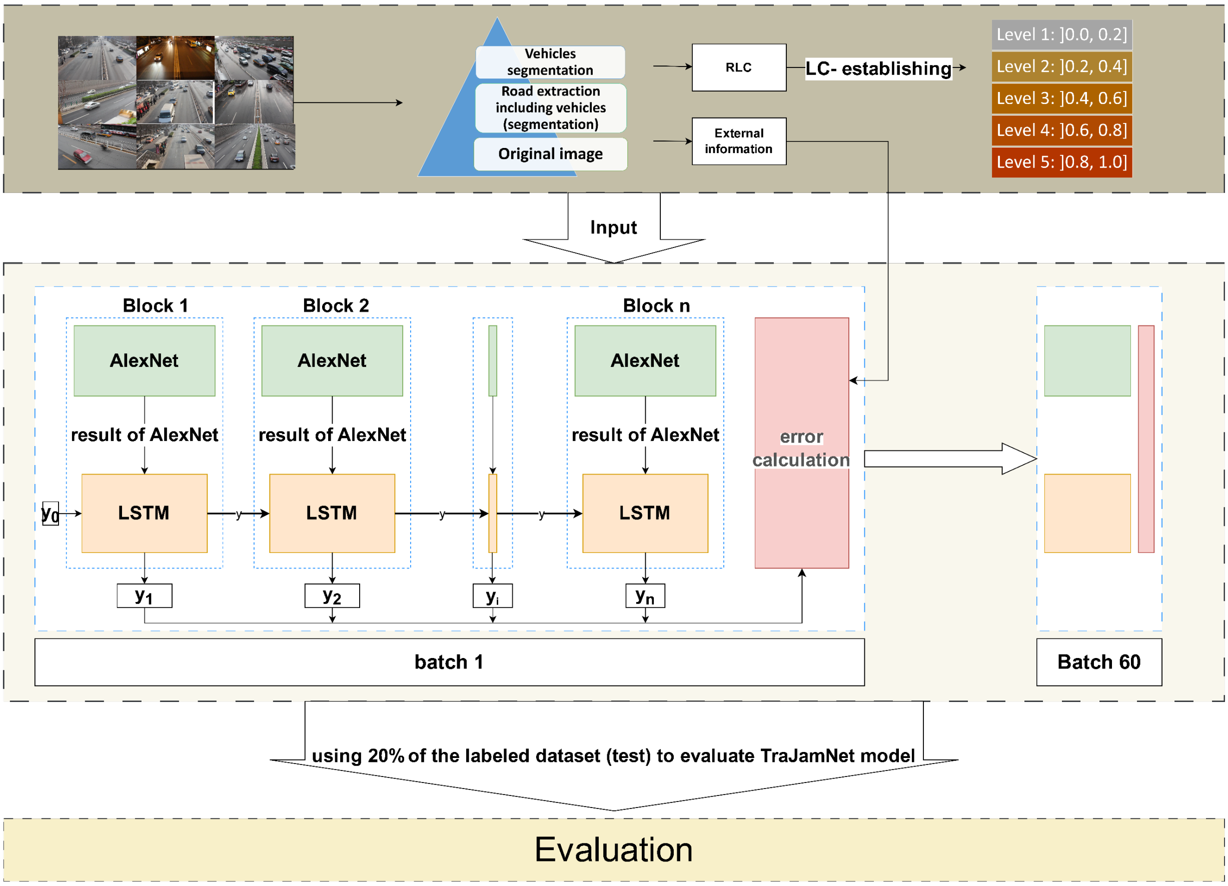


Figure 1. TraJamNet architecture for traffic congestion classification

3.2. Data Annotation for TraJamNet

It is obvious that the performance and the reliability of a DL model are related to the dataset used in training. In addition, it depends also on the type of labeling method chosen to assign classes to each image. Establishing classes to categorize the images is one of the benefits of this work. According to the literature, most studies relied on two methods: the first, is a binary classification which means that each image in the dataset is categorized into congestion or non-congestion, usually these labels are affected manually, while the second is using the density metric calculation [11]; the researchers detect vehicles and pedestrian, then they count the numbers of them in a frame, Next, to assign a label to an image, they compare the density with a pre-defined threshold.

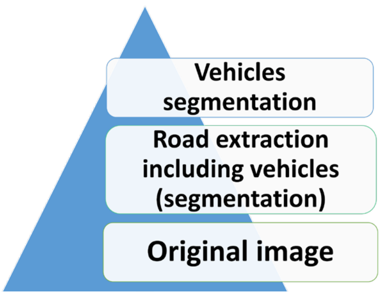


Figure 2. Segmentation pyramid to extract objects of interest

In order to annotate the dataset, we have considered the road and the vehicles, we used the image segmentation method to extract in two consecutive stages the vehicles and road regions from the entire image, and then the vehicles from the output of the first stage of extraction. the pyramid in Figure 2 illustrates the levels of extraction, at the beginning, extracting roads and vehicles means assigning the same label to pixels occupied by these two objects, thus, the result is a binary mask of the input image. Next, we extracted regions occupied by vehicles (i.e., assign another label to each pixel belonging to vehicles).

Besides, the RLC metric is established in Equation (1), it is a function related to three variables: vehicles, road, and the frame. Simply, RLC Equation (2) is the ratio of the traffic index g (v, r) on the area of the frame $W \times H$, where the W and H are respectively the width and the height of the image. As well, the g (v, r) Equation (3) index is defined by Equation (2), it represents the percentage of vehicles on roads, it is calculated by dividing the total of pixels occupied by vehicles by the total of the union of vehicles and road pixels, this last is determined based on a logical function lo (x, y) Equation (4) It returns 1 in the case if the location with (x, y) coordinates is occupied by o object, and 0 instead.

$$RLC = f(vehicles, road, image) \quad (1)$$

$$RLC = \frac{g(v,r)}{W \times H} \quad (2)$$

$$g(v,r) = \frac{\sum_{(x,y)} l_v(x,y)}{\sum_{(x,y)} l_v(x,y) + \sum_{(x,y)} l_r(x,y)} \quad (3)$$

$$l_o = \begin{cases} 1: (x,y) \text{ is occuped by the object } o \\ 0: (x,y) \text{ is not occuped by the object } o \end{cases} \quad (4)$$

3.3. Convolutional Neural Network Architecture to Predict Congestion in a Single Frame

CNN is a branch of DL that handles issues with datasets of images. Mainly, CNNs are a series of layers comprising convolutional layers and pooling layers (ConvNet), and fully connected layers (FCL) [12]. There are many types of CNN architectures, the most well-known are the following: LeNet, AlexNet, VGG, Inception, ResNet, and so on [13]. In order to extract information from a set of images, they process the images by preserving relationships between pixels. The proposed contribution is based on the AlexNet [14] architecture Figure 3, AlexNet architecture is made up of eight layers, the first five are convolutional layers followed by Max-pooling, and then the last three are FCLs. The developers of AlexNet made it special by adopting some features such as the Dropout technique, which allows for reducing overfitting through dropping out neurons with a specified probability.

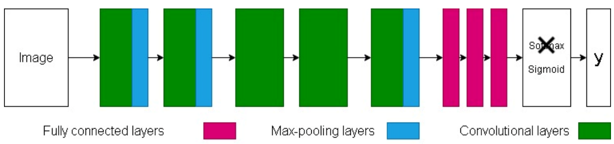


Figure 3. The modified AlexNet architecture using the sigmoid activation function [13]

As mentioned before, traffic congestion forecasting is related to several factors. so that, it can be impacted by the previous status of congestion. Thus, the aim of the AlexNet in this work is not to classify images into a category but only estimation of the level of congestion. Therefore, the SoftMax activation function is changed to a sigmoid function, this change delayed the classification process to the next stage.

3.4. Long Short-Term Memory Networks to Learn Dependencies Through a Sequence of Frames

LSTM stands for long short-term memory networks [15], adopted to address the sequential factor for traffic congestion forecasting. Technically, it is used to solve vanishing gradients problems. It is a kind of recurrent neural network (RNN) that is intended to return information in accordance with a context. LSTM stores and output data using a specific sort of memory cell. It is made up of a system of gates that control how information enters and leaves the cell. The gates give the network the ability to forget or choose data regarding the input values and the previous state of the cell in Figure 4 [16].

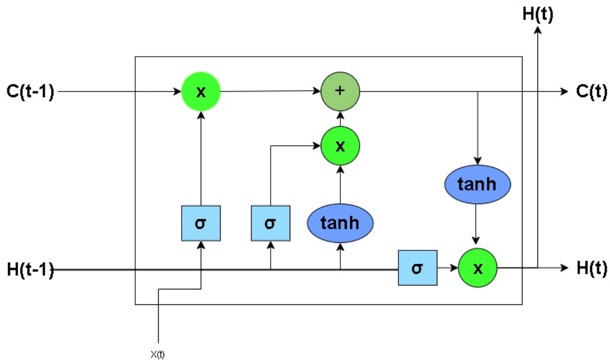


Figure 4. LSTM Cell and its operations; where (σ) represents the sigmoid layer, (tanh) tangent hyperbolic layer [15]

3.5. Metrics to Evaluate TraJemNet

Before deploying the TraJamNet model, it must be evaluated. This task process was carried out in two stages, we visualized the progress of the accuracy and loss of the training dataset, in this case, the model can be considered acceptable if the accuracy is increasing through the epochs and getting closer to 1, while the loss is decreasing to 0. Achieving good results in training allows us to pass the test stage [17]. So, the validation of the built model is confirmed based on precision, recall, and $f1$-score metrics Equations (5)-(7) applied to the testing dataset.

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

$$f1\text{-}score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (7)$$

4. EXPERIMENTS AND RESULTS

On a computer with the following configuration, the experiments were run.

- Operating system: Windows 11
- Installed RAM: 16.0 GB
- Processor: Intel(R) Core (TM) i7-8650U CPU @ 1.90GHz 2.11GHz
- System type: 64-bit

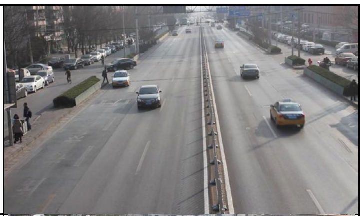
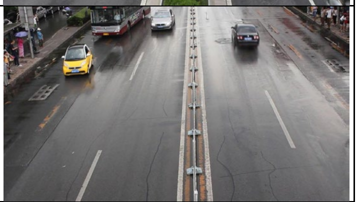
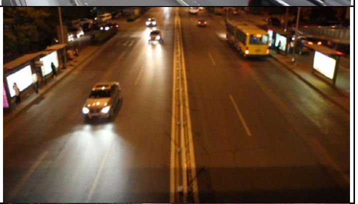
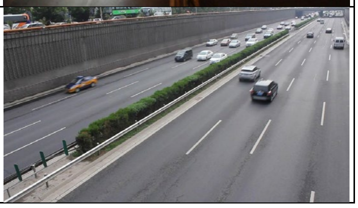
Python 3.11 and its libraries have been employed to build the TraJamNet model for five-level TC prediction.

4.1. Dataset Used to Demonstrate the Performance of the Proposed TraJamNet

To demonstrate the performance of the given contribution, we employed UA-DETRAC [18-20] dataset. Initially, it is a set of images extracted from 10 hours of captured CCTV cameras, the videos are recorded at 24 road points in two cities in China. In total, we have more than 140k images. The resolution of the images is not unified, it ranges from 352×288 to 1920×1080. Thus, according to the requirements of the use of AlexNet architecture, all these images are converted and resized to RGB images of size 227×227×3.

In addition to that, the dataset involves external features, such as weather conditions (i.e., rainy, cloudy, and sunny), and light conditions which represent the periods of the day, and so on. Table 1 shows samples of the dataset. After reforming and labelling the dataset, it remains only dividing it into two parts: training and testing. The proportions of these parts vary according to the resaid problem, it could be divided also into three parts including train, validation, and testing. Here, we have devoted 80% of dataset to training and 20% for test.

Table 1. Samples of the dataset with some external information

TC Level: 1 Weather conditions: Sunny Period of the day: Morning	
TC Level: 3 Weather conditions: Sunny Period of the day: Evening	
TC Level: 2 Weather conditions: Rainy Period of the day: Morning	
TC Level: 5 Weather conditions: Cloudy Period of the day: Morning	
TC Level: 1 Weather conditions: Cloudy Period of the day: Night	
TC Level: 2 Weather conditions: Sunny Period of the day: day	

4.2. Results and Discussion

As mentioned in the evaluation subsection, our model has been evaluated in two stages. the curves in Figure 5 and Figure 6 represent respectively the accuracy and loss progresses, the accuracy refers to the number of images predicted correctly over the entire data, while loss refers to the frequency of the values that indicate the difference from the desired class.

The curves show that the model returns good results, starting from the 10th epoch, in which the accuracy reached more than 90% and the loss is less than 20%. Despite this, that is not satisfactory to evaluate a model in the field of ML. Therefore, it is the turn of the testing dataset, it is used to predict TC level using the trained TraJamNet model, these predictions are compared with true labels in order to determine *TP*, *TN*, *FP*, and *FN* values [21]. Which allows the computing of the accuracy, precision, recall, and the *f*1-score. Table 2 provides the achieved results of TraJamNet. Additionally, it provides a comparison with other approaches to predict TC using the same dataset with different goals.

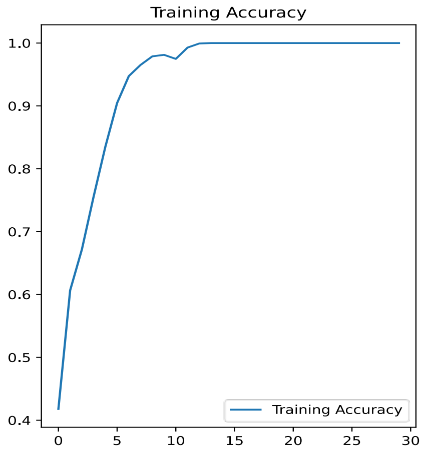


Figure 5. Training accuracy

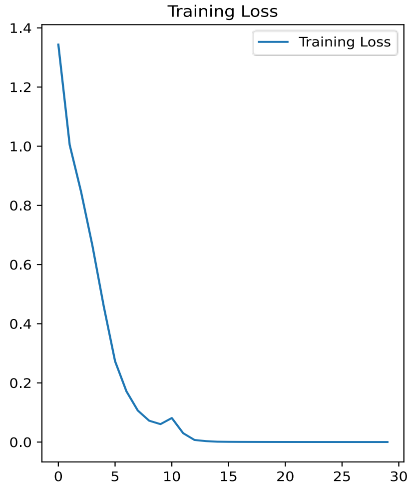


Figure 6. Training loss

As can be seen, TraJemNet reaches the best results in terms of accuracy compared with the other approaches. However, TrfficNet [22] could be considered as one of the performance approaches to classify road points, in which, it is capable to classify road statues into 10 levels of TC. Moreover, YOLO (You only look once) is a popular object detection, it is also a well-known for object segmentation technique that has transformed the area of computer vision. Despite, the good results of Our proposed model, it remains only a competitor and needs more improvements to make it more reliable.

Table 2. Results of the proposed TraJamNet model compared with other models

Method	Goal	Accuracy	Precision	Recall	$F1$-score
AlexNet	Binary traffic jam classification	85.37%	76.09%	70.26%	73.05%
ResNet	Binary traffic jam classification	68.76%	56.87%	69.90%	62.71%
Faster R-CNN	Road user detection and density calculation	73.84%	71.07%	58.08%	63.92
Traffic Net [18]	TC detection based on 10 levels of congestion	93.04%	NaN	NaN	NaN
TraJamNet	TC classification based on 5 levels of congestion	94.36%	83.28%	76.71%	79.86
YOLOv5	TC classification using the same proposed annotations	89.92%	79.56%	81.17%	80.35

5. CONCLUSIONS

This work introduces a new approach to predicting traffic congestion (TC) status; it is based on a metric named Ratio-Traffic-Congestion (RTC) which represents the percentage of occupied pixels on the road, next, to the entire image. Additionally, it considered also other factors such as the sequentially of TC status, and external information including weather conditions and period of the day. All of that is involved in the proposed TraJamNet contribution. Another benefit of this work is establishing a new five degrees of TC instead of two (i.e., congestion, non-congestion). Like all supervised deep learning-based projects, TraJemNet needs to be trained and evaluated on a specifically labeled dataset. Therefore, we adopted the image segmentation technique to mask in the two-stage road and vehicles and at the summit of the pyramid we mask vehicles. In the end, TraJamNet achieves reliable results while training, in which, after 10 epochs, it was able to reach more than 0.90 accuracy and less than 0.20 loss. Moreover, the model has been tested and compared with other approaches using the same dataset, although the aims were relatively similar and not the same.

NOMENCLATURES

1. Acronyms

CCTV	Closed-Circuit Television
CNN	Convolutional Neural Network
DL	Deep Learning
GPS	Global Positioning System
GNA	Generative Adversarial Network
LSTM	Long Short-Term Memory
ML	Machine Learning
RLC	Ratio Level of Congestion
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
TC	Traffic Congestion
YOLO	You Only Look Once

2. Symbols / Parameters

$f(.)$: function
TP: True positive
TN: True negative
FP: False positive
FN: False negative
$g\ (v, r)$: Function with parameters
(x, y): Couple of coordinate x and y
$l_o\ (x, y)$: Logical function indicates if the location (x, y) is occupied by the object o

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