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Geographical Detection of Traffic Congestion Using Machine Learning Algorithms

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Abstract

It is extremely tedious and time-consuming to keep watching all the day and identify congestion from the current surveillance system using in traffic monitoring hall. Furthermore, it is impossible to watch all the cameras relies on human eyes considering numerous cameras covering a large-scale region using in the freeway. However, prompt detection of the traffic congestion in large-scale region is important. Prompt detection can prevent extended congestion with devastating evolution from the initial controllable traffic congestion, which is one of the important applications in intelligent transport system (ITS). Deep learning algorithms have the potential implementation meanings to be intensely used in many fields of the transportation system, from traffic flow prediction to traffic congestion recognition. Classification of traffic condition is one of the most important parts of an ITS, which can be widely utilized in traffic control strategies, traffic flow analysis and so on. Thus it is necessary to propose an intelligent transport system. So, as we use the convolutional neural network (CNN) to filter the traffic videos and images to form the better results to update in TrafficNet. Traffic feature is successfully extracted and interpreted for classification. In order to further improve the detection accuracy of deep learning approaches, residual learning is proposed and has successfully applied to various aspects. The residual network-based approaches make the deep network to get better performance. With the exploration of the state-of-art deep residual network, improvement technologies are investigated including typical milestone nets, data augmentation methods, transfer technology and supervised learning for higher detection accuracy. Consider the feature difference between traffic image and that in vision benchmarks, a systematic study should be conducted to push the congestion recognition accuracy to a new level for daily surveillance use. For this practical application, the generalized ability of the network for new input images and videos is significant to explore.

Keywords: *Convolutional neural network (CNN), intelligent transport system (ITS), Keras Model*

INTRODUCTION

Urban roads and highways have, nowadays, plenty of surveillance cameras initially installed for various security reasons. Traffic videos coming from these cameras can be used to estimate the traffic state, to automatically identify congestions, accidents, and infractions, and thus helping the transport management to face critical aspects of the mobility. At the same time, this information can also be used to plan the mid and long-term roads mobility strategy. This is a clear example of a smart city application having also a strong impact on citizens' security [1].

Identification of traffic clog is critical to forestall its all-inclusive blockage with destroying development from the underlying controllable traffic clog. Without quick recognition and activity after beginning clog, reasonable control methodology can't be anticipated. Temperamental acceleration of clog and comparing framework debasement may introduce [1]. Along these lines, loads of labor are included to recognize from current observation framework utilizing in rush hour gridlock the executives authority as appeared in fig. 1. Current discovery of traffic clog depends on human eye with their complete consideration influenced by different enlightenment, climate and different aggravations [2]. It is important to consider methodologies to ease human from the weight of distinguishing traffic clog physically.

With ongoing advancement of profound learning, the exactness of item acknowledgment and picture order have been significantly improved [3,4]. In 2012, AlexNet utilizing CNNarchitecture has seriously improved with profound learning calculation which has been effectively utilized in the well known picture rivalry ILSVRC [5,6]. Profound learning calculations dependent on blend multi-layers of the convolutional neural system (CNN) have examined from that point on. The discriminative ability of machine-based article acknowledgment is end up being higher than that of human eyes [7]. Promising advancement of the profound learning calculations are introduced, for example, VGGNet, GoogleNet, and ResNet with increasingly various CNN layers [8-10]. In spite of the fact that the precision is high, preparing of these profound ImageNet is avaricious from the gigantic measures of pictures, which is at some point hard to accomplish [11]. Specialists have proposed move figuring out how to keep a few layers of the effective net and added some new layers to get another design net [12]. This strategy can spare bunches of preparing time. As the reconnaissance framework utilized on turnpike has collected picture source database for a considerable length of time, it is normally to utilize present day calculation to consequently distinguish the traffic clog and report its definite fleeting/spatial data.

In order to meet the requirement of the practical application, spatial and temporal information of congestion occurrence is vital for subsequence precise regional traffic management and control. With accurate detection of congestion incorporated with spatial and temporal information, the overall distribution of traffic congestion in a region could be sorted out. That multiple dimensional information could be then compounded and reported from cameras in a large-scale range using in regional surveillance systems and automatically visualize the congestion area to assist people watching the monitor system more efficiently.

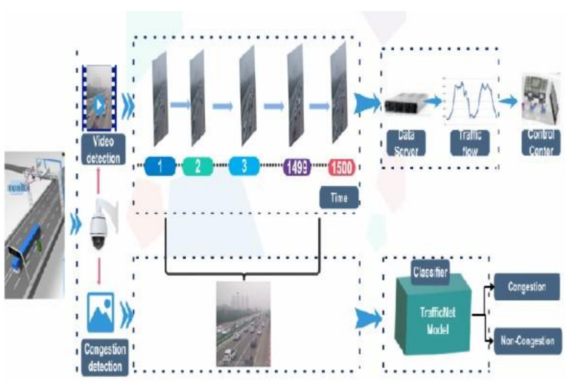

Fig1: Overall Traffic detection from Surveillance

In order to detect the road state of congestion, commercial video detector, vehicle detector, and other equipment are developed and installed. However, high-cost of those equipment limits their application. The expensive supercomputer is also needed to process cameras local in large-scale region simultaneously. The transmission and computation of the continuous video record consume lots of equipment costs and electrical resources. The processing is uninterruptedly conducted so the high- performance computer is needed to meet the requirement of real-time application. Seeing that the remarkable improvement of the deep learning approaches emerges in those days, it is worth to investigate the image-based detection and extend it to the practical application.

Among the different methods that can be adopted to provide traffic flow (congestion) estimation, surveillance cameras play a crucial role. These systems can be installed without interfering with road infrastructures. Moreover, a large plethora of retrofit solutions are available in many cases, or systems have been already installed for some initial different aim. In any case, surveillance cameras can supply real-time information. The estimation of the traffic can be provided to users and police patrols to help in departures planning and congestion avoiding. Road panels or integrated vehicular monitors can also be used to reach the aim [3].

I. LITERATURE REVIEW

Despite the huge amount of traffic surveillance videos and images have been accumulated in the daily monitoring, deep learning approaches have been underutilized in the application of traffic intelligent management and control. Traffic images, including various illumination, weather conditions, and vast scenarios are considered and preprocessed to set up a proper training dataset. In order to detect traffic congestion, a network structure is proposed based on residual learning to be pre-trained and fine-tuned. The network is then transferred to the traffic application and retrained with self-established training dataset to generate the TrafficNet. The accuracy of TrafficNet to classify congested and uncongested road states reaches 99% for the validation dataset and 95% for the testing dataset. The proposed TrafficNet can be used by a regional detection of traffic congestion on a large-scale surveillance system. The effectiveness and efficiencies are magnificently demonstrated with quick detection in the high accuracy in the case study. The experimental trial could extend its successful application to traffic surveillance system and has potential enhancement for intelligent transport system in future.

Automatic traffic flow classification is useful to reveal road congestions and accidents. Nowadays, roads and highways are equipped with a huge amount of surveillance cameras, which can be used for real- time vehicle identification, and thus providing traffic flow estimation. This research provides a comparative analysis of state-of-the-art object detectors, visual features, and classification models useful to implement traffic state estimations. More specifically, three different object detectors are compared to identify vehicles. Four machine learning techniques are successively employed to explore five visual features for classification aims. These classic machine learning approaches are compared with the deep learning techniques. This research demonstrates that, when methods and resources are properly implemented and tested, results are very encouraging for both methods, but the deep learning method is the most accurately performing one reaching an accuracy of 99.9% for binary traffic state classification and 98.6% for multiclass classification.

With the increasing number of vehicles running on the urban roads, the traffic jam becomes much more serious. Properly estimating the traffic jam level from traffic videos is essential for the department of transportation management and drivers. Currently, for estimating the traffic state on videos, most solutions are built on evaluating traffic flow by counting the running vehicles per time unit or detecting their moving speed. However, the main challenge of these solutions is on the vehicle tracking method, in which the vehicles are necessary to be effectively and integrally segmented from the scenes.

The solutions should tradeoff the accuracy of the estimation results and the efficiency of the method. In this paper, we propose a learning-based aesthetic model to estimate the traffic state on videos. The model uses multiple video-based perceptual features about traffic state to train the random forest classifier with the labeled data, and estimates traffic state by data classification. The evaluation experiments are conducted on a testing image set, and the results show that the traffic state estimation accuracy of the proposed model is higher than 98% and the efficiency performance is achieved in real-time.

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II. MODULES

In this paper they are three approaches are compared: The first one relies on visual features evaluated from traffic videos through computer vision algorithms using state-of-the-art object detectors and classifiers, the latter considers deep learning models able to automatically extract features from videos needed for the final classification.

The modules included in our implementation are as follows

- Dataset collection
- Video Datasets
- Image pre-processing
- Training using Convolutional 2D neural network
- Recognition

Dataset Collection:

Different classes of input traffic scene images are collected from web. The class value output of scenes are given along with dataset image collection. We have created four folders namely sparse_traffic, dense_traffic, fire, accident, every folder contains images of 900 for train and validation purposes. The folder name itself represent the class value for classification outpu

Layer Type	Layer operation	No of feature images	Feature map size	Validation steps	Total parameters
C1	Conv2D	900	150X150	300	900

Table 1: Sample Data Set

Video Datasets

Different datasets, used for different aims, were adopted in this research. The GRAM Road Traffic Monitoring (RTM) is generally used for vehicle detection and it was adopted here to evaluate and compare performance of object (vehicles) detectors . Traffic db contains annotations related to the state of the traffic and it is here used to compare classification techniques.

Image Pre-Processing

There is no much pre-processing required in this implementation. The training and test dataset is classified in different folder is given as input using a function fro keras " flow_from_directory". This gives necessary pre-process such as dimension reductions. Similarly, the input image for test input is dimension reduction and converting to numpy array.

Fig2: Traffic Congenstion Images

Fig3: Fire Accident Images

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Fig4: Accident Images

Hear we mentioned the three images that are fig1 should be traffic images,fig 2 should be fire accedient images and fig3 will be normal accident images. This three images should be the example of the traffic congenstion then it will be the used for the image preprocessing steps. Based on this images the traffic control system will be decide that the areas will be having this type of troubles like that. This is example main process also.

Training Using Convolutional 2d Neural Network

We used convolutional 2D neural network available in keras for traing and testing our model. The overall architecture of Conv2D is shown below.

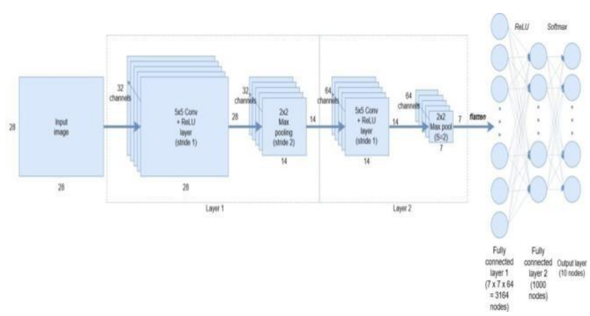

Fig5: Traffic Congestion preprocessing structure

Sequential Model

- Models in Keras can come in two forms – Sequential and via the Functional API. For most deep learning networks, the Sequential model is likely. It allows to easily stack sequential layers (and even recurrent layers) of the network in order from input to output.
- The first line declares the model type as Sequential().

Adding 2D Convolutional layer

- Add a 2D convolutional layer to process the 2D input images. The first argument passed to the Conv2D() layer function is the number of output channels – in this case we have 32 output channels. The next input is the kernel_size, which in this case we have chosen to be a 5×5 moving window, followed by the strides in the x and y directions (1, 1). Next, the activation function is a rectified linear unit and finally we have to supply the model with the size of the input to the layer. Declaring the input shape is only required of the first layer – Keras is good enough to work out the size of the tensors flowing through the model from there.

Adding 2D max pooling layer

- Add a 2D max pooling layer. We simply specify the size of the pooling in the x and y directions – (2, 2) in this case, and the strides.

Adding another convolutional + max pooling layer

- Next we add another convolutional + max pooling layer, with 64 output channels. The default strides argument in the Conv2D() function is (1, 1) in Keras, so we can leave it out. The default strides argument in Keras is to make it equal to the pool size.The input tensor for this layer is (batch_size, 28, 28, 32) – the 28 x 28 is the size of the image, and the 32 is the number of output channels from the previous layer.

Flatten and adding dense layer

- Next is to flatten the output from these to enter our fully connected layers. The next two lines declare our fully connected layers – using the Dense() layer in Keras, we specify the size – in line with our architecture, we specify 1000 nodes, each activated by a ReLU function. The second is our soft-max classification, or output layer, which is the size of the number of our classes.

Training neural network

- In the training model, we have to specify the loss function, or told the framework what type of optimiser to use (i.e. gradient descent, Adam optimiser etc.).
- Lass function of standard cross entropy for categorical class classification (keras.losses.categorical_crossentropy). We use the Adam optimizer (keras.optimizers.Adam). Finally, we can specify a metric that will be calculated when we run evaluate() on the model.
- We first pass in all of our training data – in this case x_train and y_train. The next argument is the batch size. In this case we are using a batch size of 32. Next we pass the number of training epochs (2 in this case). The verbose flag, set to 1 here, specifies if you want detailed information being printed in the console about the progress of the training.

RECOGNITION

- Finally, we pass the validation or test data to the fit function, the input image is convereted to numpy array and compared with trained model to get the classified output namely dense_traffic, sparse_traffic, fire or accident.

III. MACHINE LEARNING TECHNIQUES

A. Keras Model : Sequential Model

We used convolutional 2D neural network available in keras for traing and testing our model Models in Keras can come in two structures – Sequential and through the Functional API. For most significant

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learning frameworks, the Sequential model is likely. It licenses to viably stack progressive layers (and even dull layers) of the framework all together from commitment to output.The first line reports the model sort as Sequential().

At the last moment we are moving to validation or test data to the fit function, input image is convereted to numpy array and compared with trained model to get the classified output namely dense_traffic, sparse_traffic, fire or accident.

Image Data Input Parameters: number of images, image height, image width, number of channels, number of validations.

Image Preprocessing: Aspect Ratio: Square. Cropping, giving importance to the middle of the image.

Image Scaling: Use 150X150

B. Convolutional Neural Network(CNN)

Traffic condition has been classified based on convolutional neural network (CNN) are proposed recently. Traffic feature is successfully extracted and interpreted for classification. In order to further improve the detection accuracy of deep learning approaches, residual learning is proposed and has successfully applied to various aspects. The residual network-based approaches make the deep network to get better performance. With the exploration of the state-of-art deep residual network, improvement technologies are investigated including typical milestone nets, data augmentation methods, transfer technology and supervised learning for higher detection accuracy. Consider the feature difference between traffic image and that in vision benchmarks, a systematic study should be conducted to push the congestion recognition accuracy to a new level for daily surveillance use. For this practical application, the generalized ability of the network for new input images is significant to explore.

IV. RESULT AND DISCUSSION: IMPLEMENTATION:

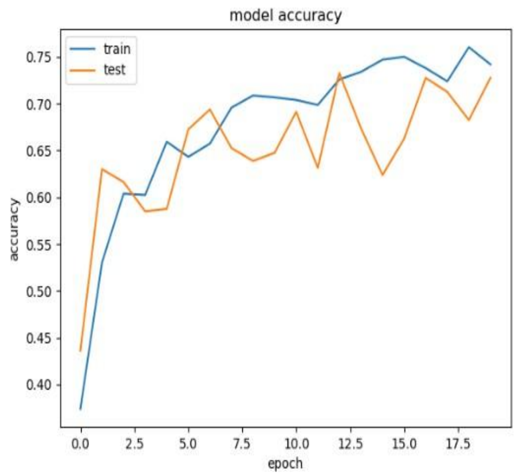

Fig6: Traffic Congestion Training and testing Model Accuracy Graph

In the model Accuracy Graph the Training set of the images and videos should be trained by the Keras and sequential Model. The Model Accuracy will be more increased then the other Algorithms. This is the best suitable algorithm to get the better results.

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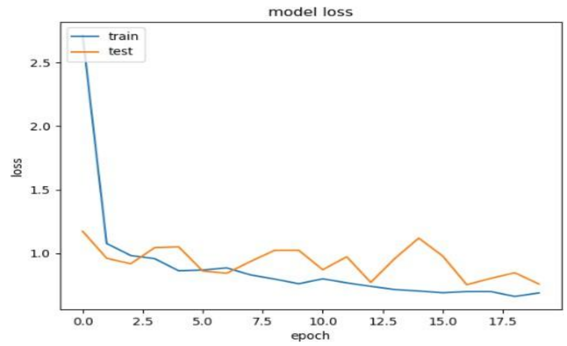

Fig7: Traffic Congestion of Training and Testing Model Loss

In the Model Loss graph the Train set will be decreased based on the usage of Recurrent neural network algorithm. This algorithm should be mainly focused on the time complexity of the model So its been failed in this condition Then while coming to the Testing set the model will be performed moderate level. So it will be slightly changed the graph based on the traffic conditions.

OUTPUT:

Fig8: Traffic Congestion has showed Low Traffic

Fig 9: Traffic Congestion has showed Heavy Traffic

This is the final outputs of the Traffic Congestion paper Hear we applied all the possible and usable algorithms to find the more accuracy. Then Finally we got the better results by doing the image preprocessing and machine Learning algorithm techniques applying, we get the got the better results on images and videos. Based on this requirements the Traffic will be heavy its showed Heavy Traffic and if the traffic will be low it will be showed Low Traffic.

Preprocessing Models	**Keras Model : Sequential Model**	**Conolutional Neural Network (CNN)**
Training RSS(Residual Sum of Squares)	95.52%	74.2%
Test(Residual Sum of Squares)	15.4%	9.99%

Table 1: **Comparison Table for Machine Learning Algorithm Model Accuracy**

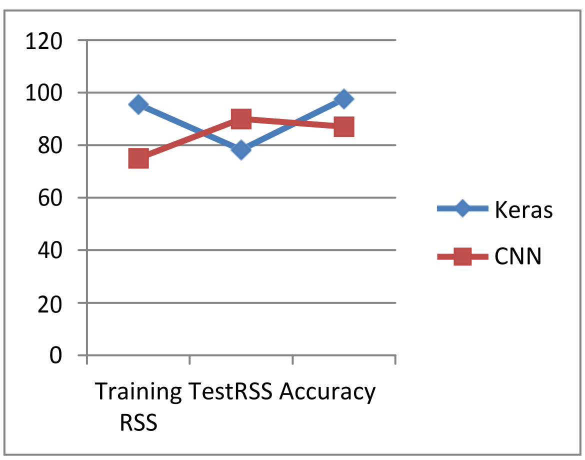

Fig 10: Accuracy Graph for Machine Learning Algorithm

V. CONCLUSION

In order to promote the application of the deep learning approaches into transportation application, the theoretical network is specialized to automatically detect road state of congestion. This is proposed to bridge the current advanced deep learning approaches and practical application. We proposed Conolutional Neural Network (CNN) for training and validation. We considered as multi class problem. However, the detection accuracy for the new input images is not as high as that of the validation set. Then we use the Keras Model to find the better results of the available traffic congestion information. It is filter the dataset which is downloaded in the traffic portal. As before based on the images it is finding the result of traffic Now by using this algorithm, we can get the results by using the images and videos. This algorithm is helps to form the better results at the end. In this paper we get the accuracy of the project is 97%. It helps to clear the traffic and helps to create the fastest routs for the destination.

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