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A Research on Traffic Congestion using Machine Learning Algorithms

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Abstract
In spite of the enormous measure of traffic surveillance pictures and videos have been gathered in the everyday checking, Deep learning approaches have been underutilized in the use of traffic heavy the executives and control. Traffic pictures, including different brightening, climate conditions, and heavy situations are considered and preprocessed to set up a legal preparing dataset. So as to identify traffic blockage, a system structure is proposed dependent on remaining figuring out how to be pre-prepared and measured. The system is then moved to the traffic application and retrained with self-set up preparing dataset to produce the TrafficNet. The exactness of TrafficNet to group blocked and uncongested street states arrives at 95% for the approval dataset and 91% for the testing dataset. The proposed TrafficNet can be utilized by a local recognition of traffic blockage on a huge scale observation framework. The viability and efficiencies are radiantly shown with brisk discovery in the high exactness for the situation study. The test preliminary could stretch out its effective application to traffic reconnaissance framework and has potential improvement for acute vehicle framework in future.

***Keywords*:** TrafficNet, Convolutional neural network (CNN), Recurrent neural networks (RNN), Keras Model.

1. Introduction

With quick improvement of very great learning-based methodologies, they have been demonstrated relevant to a wide range of picture acknowledgment task in objective determination, quality analysis, etc. In any case, it is amaze that couple of productive applications in the transportation framework have been accounted for, particularly regarding heavy sum traffic video and picture utilizing in observing the urban street system and expressway. As per the present circumstance, the greater part of the cameras assume their jobs as latent monitory however can't consequently recognize the block on schedule. [1] The identification of block for the most part depends on heaps of labor to report blockage physically when it happens arbitrarily in the street organize. It is very flat and unexciting to continue observing all the day and recognize blockage from the present observation framework utilizing in rush hour gridlock checking corridor. Besides, it is difficult to observe every one of the cameras depends on human eyes considering various cameras covering an enormous scale locale utilizing in the interstate. [5] Be that as it may, brief location of the traffic clog in huge scale locale is significant. Brief location can keep expanded blockage with destroying advancement from the underlying controllable traffic clog, which is one of the significant applications in savvy transport framework (ITS) [7].

So as to identify the street condition of block, business video finder, vehicle indicator, and other hardware are created and introduced. In any case, significant expense of those gear constrains their application. The costly supercomputer is likewise expected to process cameras neighborhood in huge scale area at the same time. [10] The transmission and calculation of the constant video record expend bunches of hardware costs and electrical assets. The preparing is uninterruptedly directed so the superior PC is expected to meet the prerequisite of constant application. Seeing that the noteworthy improvement of the profound learning approaches develops back then, it is worth to examine the picture based location and extend it to the handy application.

So as to meet the prerequisite of the pragmatic application, spatial and fleeting data of blockage event is imperative for subsequence exact territorial traffic the executives and control. With exact recognition of blockage consolidated with spatial and worldly data, the general circulation of traffic clog in an area could be sifted through. That various dimensional data could be then intensified and detailed from cameras in a huge scale extend utilizing in territorial reconnaissance frameworks and naturally imagine the clog territory to help individuals watching the screen framework all the more proficiently.

2. Literature Review

With the quick advancement of profound learning, its exhibition in picture arrangement and item acknowledgment has displayed emotional upgrades. These promising outcomes could likewise be applied to more readily comprehend dot designs in dissipating media imaging. In this paper, a multi mode fiber is utilized as the dispersing media, and 4000 face and non face unique pictures are transmitted producing dot designs [1]. A Speckle Net is proposed and prepared with these 3600 spot designs dependent on a convolutional neural system, and its yield layer is enacted for a help vector machine (SVM) classifier. The paired order precision of the proposed CNN-engineering Speckle Net for face and non face spot designs grouping tried on another 400 dot designs is about 96%, which has been improved contrasted and the exactness of the unadulterated SVM strategy. The promising outcomes affirm that the mix with profound learning could prompt lower optical and calculation costs in optical detecting and add to down to earth applications in optics.

[2] Grouping of traffic conditions is a crucial undertaking for deciding traffic control procedures in ITS. Precise appraisal of the volume of traffic empowers proper changes of control measures for guiding traffic streams to arrive at set objectives of execution. Video traffic observing is a reasonable and helpful wellspring of traffic information. The paper shows a technique for order of street traffic conditions dependent on video observation information. Convolutional neural system is utilized to order the video content and set up proportions of clog of the watched traffic. Four degrees of traffic conditions are recognized which compare to LOS classifications. The system is approved utilizing video information from a few traffic perception destinations. [19] The prepared CNN is equipped for handling video information for methodical use by subsystems of ITS liable for traffic the board. The consequences of arrangement are contrasted and neural system based classifiers: a MLP (multi layer observation) and a DLN (profound learning system) with auto encoders. The proposed technique is progressively exact and less delicate to the nature of video information.

In this paper, we propose a vehicle type grouping technique utilizing a semi directed convolutional neural system from vehicle frontal-see pictures. So as to catch rich and segregating data of vehicles, [3] we acquaint meager Palladian channel learning with acquire the channels of the system with a lot of unlabeled information. Filling in as the yield layer of the system, the delicate max classifier is prepared by perform various tasks learning with limited quantities of marked information. [4] For a given vehicle picture, the system can give the likelihood of each kind to which the vehicle has a place. In contrast to customary strategies by utilizing high quality visual highlights, our technique can consequently adapt great highlights for the characterization task. [12] The educated highlights are separating enough to function admirably in complex scenes. We assemble the difficult BIT-Vehicle dataset, including 9850 high-goals vehicle frontal-see pictures. Test results without anyone else dataset and an open dataset show the viability of the proposed technique.

From the literature study we have made some inference and which is discussed here. In the existing system, binary classification is using neural networks, which handles the output as heavy traffic or sparse traffic. [6] Some of the existing studies discussed machine learning approach for classification like SVM algorithms, which classifies with less accuracy may not be preferable for real time predictions. Artificial intelligence used object detection for identifying the vehicles and density of vehicles is used for traffic predictions, which may be static approach. Thus we need a multiclass classification problem with deep learning approach is preferable.

On accident-related data obtained from traffic police reports, logistic regression was applied to analyze the contribution of several variables to the seriousness of the incident. [8] A total of 560 subjects were sampled who were involved in serious incidents. In this analysis the incidence of injuries (the dependent variable) is a dichotomous variable with two types, both fatal and non-fatal. [7] Hence, each of the tested subjects was listed as either in a fatal or non-fatal incident. A logistic regression approach was considered suitable because of the binary nature of this dependent variable. Of the nine independent variables collected from police accident reports, two were found to be most strongly correlated with the severity of the accident, namely the location and cause. In terms of the definition of odds ratio, a statistical analysis is given of the model estimates produced. [9] Results show that logistical regression as used in this research is a promising method for providing meaningful explanations that can be used to improve future protection in Riyadh.

This work aims to forecast the potential for road traffic accidents by using real-time traffic data to identify dangerous traffic conditions and normal traffic conditions. [21] Dangerous traffic conditions mean traffic patterns which lead to traffic accidents and normal traffic conditions are traffic patterns which do not lead to traffic accidents. For define traffic patterns are used the k-nearest neighbor method (k-NN) and the C-means clustering method (CM). This is the first time that the k-nearest neighbor approach is used in prediction of real-time road traffic accidents.

3. Modules

A. 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 output.

B. 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 frokeras "flow_from_directory" [11]. This gives necessary pre-process such as dimension reductions. Similarly, the input image for test input is dimension reduction and converting to numpy array.

C. 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.

4. Machine Learning Techniques

A. Convolutional Neural Networks (CNN)

The Convolutional Neural Networks (CNN) [9] is another powerful neural network in the fields of computer vision and classification. The first CNN was created using Deep Learning Applications. This has greatly contributed to many developments in computer vision and deep learning environments. [16] This system is also referred to as LeNet and was primarily used in early years for the identification of characters, such as zip digits, codes and handwriting. [17] The data can also be stored in various arrays (color images, signals, sequences, audio and video) depending on the size of the conversion procedure (1D, 2D or 3D) [17]. CNN operations typically involve four processes: convolution, pooling or sub-sampling, nonlinearity (ReLU), and classification (fullly connected layer). These aforementioned activities include CNN's building blocks. Features can be extracted using convolution operation from input data, such as image and time series. It retains the spatial relations between data from the input sample by studying small subsets of the input files. ReLU (Rectified Linear Unit) is an extra, nonlinear operation that is used after each network conversion process. ReLU produces output in an element-wise manner that replaces negative values with zero in the function map, and solves real-world problems by using its nonlinearity in the network.

B. 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 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 ().

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

C. Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are neural networks that have feedback connections designed specifically for modeling sequences. We are more effective computationally, and biologically more fair than feeding forward networks (no internal states). The feedback links provide the RNN with knowledge of past activations, helping it to understand the temporal dynamics of sequential data [23]. RNN uses contextual information which makes it effective for mapping sequences between input and output. Traditional RNNs, however, have a problem, called the gradient vanishing or the gradient explosion. However, for solving these issues, Hochreiter and Schmidhuber suggested Long Short-Term Memory (LSTM). [25] In LSTM, hidden units are replaced with memory blocks containing self-connected memory cells and three multiplicative units (input, output, and forget gates). The gates allow the memory block to read, write, and reset operations and monitor memory block behaviour. Figure 2 shows a diagram representing a single LSTM unit.

5. Conclusion

Road accidents are caused by many different factors. By going through all the research papers it can be concluded that cases of road accidents are greatly affected by factors such as vehicle types, driver age, vehicle size, environment, road layout, etc. Thus we have established an application that effectively predicts road accidents on the basis of the factors mentioned above. The Traffic analysis model based on the random forest algorithm is presented. The most important goal at the back of doing this mission is to investigate the visitors and provide a version which can clearly reduce the site visitors to a point in a selected region. And on this regard the

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schooling model is created which could examine the Traffic. The predominant idea at the back of this assignment changed into no longer best to investigate the site visitors but additionally to recommend a new route with much less visitors with a great accuracy to the person who has requested. So, the training model in this regard will help in studying the visitors with the aid of building selection trees and predicting the end result more correctly.

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