

Deep Traffic learning: An automatic vehicle speed assisting tool based on the varying traffic conditions to ensure a safe driving

N.V.S.Pavan Kumar, Feroz khan, Madhumitha kuppachi

Abstract: In a day to day life most of the accidents are increased due to lack of vehicle speed management by the driver in different traffic conditions. In some cases, it is hard to track speed limit board by the driver due to some several reasons like obstruction from large vehicles, trees and due to speed driving, etc. To decreasing accidents on-road we are extending the framework for vehicle speed assisting tool by continuous monitoring of traffic while driving. For this experiment, we are using popular deep learning technique named Convolutional Neural network (CNN) which consists of eight convolutional layers. To input a CNN, we have created our own data namely KL-Traffic Data comprising of nine traffic condition classes which consisting of on-road traffic images and we have set the speed limits for these nine-traffic conditions. The CNN model was trained by the KL-Traffic Data and the output will be Traffic condition class. Based on the traffic condition class our model sets the speed limit which driver must follow for a safe driving.

Index Terms: Convolutional neural network, on-road Traffic, Vehicle speed management.

I. INTRODUCTION

On-road Traffic is main problem for transportation. Traffic is gradually increasing due urban development and be- return a lot of engorged round the world and cause several issues. Traffic create tremendous problem of wasting travelers time and public resources, however, conjointly produce a lot of on-road and off-road accidents along with pollutions like Sound, Air, etc. Traffic over-crowding tends to extra gasoline emission which is harmful for the people and also creates a lot of problem in transportation maintenance, and it drains a mortal' time a lot and an extent fuel waste. Diagnosing traffic congestion [1] leads a major problem and due to these traffic congestions motorists takes different routes by violating the traffic rules and leads to accidents.

From last few decades ideas of traffic bottle necking and congestion maintenance are thought in several study-based research. This research is mainly conducted by researchers from urban transportation and engineering streams. Hence these study leads to computer complicated algorithms, traffic management systems and designing a knowledge-based system for predicting traffic flow [12].

Transportation system face lot of problems like overcrowding, signal jumps etc., the main issue throughout the world is "traffic accidents". Traffic accidents results in

Revised Manuscript Received on June 05, 2019

N.V.S.Pavan Kumar, Assistant professor, Computer science engineering, KLEF deemed to be University, Vaddeswaram, India.

Feroz Khan, Under Graduate Student, Computer science engineering, KLEF deemed to be University, Vaddeswaram, India.

Madhumitha Kuppachi, Under Graduate Student, Computer science engineering, KLEF deemed to be University, Vaddeswaram, India.

damaging the government property, severe traveler injuries and on-road fatalities. Since 1988, around 5,000,000 automobile crashes occurred based on the reports published by the national road traffic safety administration (NHTSA), most of the reports end with traveler injuries and on-road fatalities. NHTSA 2015 reports say that accidents have been decreased through effective traffic maintenance with several detection strategies and their corresponding responses. Transportation management can only be possible by detecting traffic accidents and congestions.

There are 3 common devices [13] which may be utilized to discover traffic congestion levels. First one is the Loop Detector which varies in several detection environments and is very sophisticated to install. The second is GPS based smart phones and vehicles, this leads to vary wide detection however the system results in lower detection. Last one is the camera-based systems in which capturing area is high so the detection is high and précised.

Deep learning [16] algorithms, became widely used in computer vision applications to overcome limitation of computer vision area and shows better performance. Deep learning techniques have been increasing their growth in several areas and helps in solving complex real-world problems and industry-based problems. Deep learning is datacentric and requires more computational power and less hand held engineering works. Due to increase in storage space and increase in computational capability deep learning have been succeeded in supervised learning schemes. State - of - the - art deep learning models for computer vision tasks mainly requires large amount of training datasets in order to make the model capable in performance. For example, the ILSRVC data set got better results which comprises of 1.2 million images over 1000 class labels.

All above mentioned plays a major role for detecting a traffic, amount of traffic flow, and detecting traffic congested places through deep learning algorithms. But these models have not centered on motorists and their safety measures. So, we concentrated on motorists and their safety with deep learning-based traffic classification with self-assisted speed limit alert.

II. LITERATURE REVIEW

Traffic related research is the newly emerging technique which is useful for human kind safety on-road. In traffic related research most of the researchers mainly concentrated on traffic flow prediction, traffic forecasting, vehicle detection, road lane detection, traffic accident detection, traffic speed



prediction and traffic signal detection.

A. Traffic flow prediction and Traffic forecasting:

Traffic flow prediction mainly focus on how fast the traffic flow is increasing on roads. Traffic forecasting gives the information on time to time traffic updates. Due to this prediction it is useful to avoid congestion in traffic in peak hours by managing and maintain the traffic by directing to appropriate detours. Fouladgar, M et al. [1] has used Caltrans Performance activity System (PeMS) dataset evaluated by CNN for classifying traffic flow supported this organization ready to predict the traffic flow with within the vary of 20kms by victimization of long short term memory (LSTM). Yu, B et al. [2] planned a completely unique deep learning framework, Spatio-Temporal Graph Convolutional Networks (STGCN), to tackle the statistic prediction downside in traffic domain evaluated on 2 real-world traffic datasets, BJER4 and PeMSD7 and is prosperous because of is speed and accuracy. Wu, Y et al. [3] has projected a unique deep design combined CNN and LSTM for prognostication future traffic flow (CLTFP). A 1-dimension CNN is exploited to capture spatial options of traffic flow, and 2 LSTMs area unit used to mine the short variability and periodicities of traffic flow and achieved short traffic flow prognostication.

B. vehicle detection and road lane detection:

Vehicle detection and road lane detection are one of the main problems in traffic monitoring system for driving automation to ensure safe drive. Li, J et al. [4] have developed a multitask deep convolutional network, that at the same time detects the presence of the target and the geometric attributes (location and orientation) of the target with relation to the region of interest. Second, a Recurrent CNN layer is adopted for structured visual detection. Huval, B et al. [5] have shown existing convolutional neural networks (CNNs) is accustomed perform lane and vehicle detection whereas running at frame rates needed for a time period system. Our results lend credence to the hypothesis that deep learning holds promise for autonomous driving.

C. Traffic accident detection:

Traffic accident detection is useful for automatic traffic systems for alerting ambulance team for better and early medication for people who met with accidents. Zhang, Z et al. [6] Show that paired tokens capture the alliance rules underlying in accident-related tweets and boosts in accuracy of accident detection. Secondly, two deep learning methods: Deep Belief Network (DBN) and Long short-term memory (LSTM) are unitedly investigated and enforced in extracted tokens. Chen, Q et al. [7] has collected massive and heterogeneous knowledge (7 months traffic accident knowledge and one.6 million users GPS records) to know however human quality can have an effect on traffic accident risk then this knowledge is inputted to a deep model of Stack denoise.

D. traffic speed prediction and traffic signal detection:

Traffic speed detection and traffic signal detection plays most important role in advanced traffic systems for assisted driving experience Jia, Y et al. [8] proposes a deep learning method for continuous traffic speed prediction with error feedback Recurrent Convolutionary Neural Network (eRCNN). Ma, X

et al. [9] . projected a convolutional neural network (CNN) based technique that learns traffic as images and predicts high-precision, large-scale, network-wide traffic speeds. Spatio-temporal traffic dynamics converted to images that describe traffic flow time and household relationships through a two-dimensional time-space matrix.

These predictions are only helpful for building a intelligent traffic systems which is only used for traffic maintenance and taking care of speed ambulance availability for the motorists met with accidents. In this work we modelled a frame work which is very useful for the motorists for their safe riding. Here we implemented and achieved a best result in model a CNN based traffic speed limit assistant tool and our model will mainly solves these problems:

1. The proposed CNN architecture can classify the traffic density.
2. Based on the classification our frame work can alert a motorist by alert message.
3. Our model is aimed for the motorist safety by continuous alerting of speed limit if motorist exceeded the limit.

III. METHODOLOGY

In this section we described about the creation of our KL-Traffic Data. Secondly, we evaluate with the proposed CNN model and the performance analysis to claim our novelty.

A. Dataset

KL-Traffic Data is a self-created dataset comprises of nine traffic classes taken with normal RGB camera which is available with us. Each class is divided with the different traffic classes based on the traffic congestion density based on the traffic classes we annotated the speeds which will be useful for the motorist's safety. This whole dataset is collected in Vijayawada, Krishna district, India.

In this data each class is having 250 images with 9 classes taken in morning, afternoon, evening and night condition to ensure better classification and it has total of $250 \times 9 = 2250$ images and these images are input to a CNN [10] for classification.

Fig 1 shows the sample data of KL-Traffic dataset which we have collected, and this dataset is labeled with the traffic congestion levels at different day times and also night times.

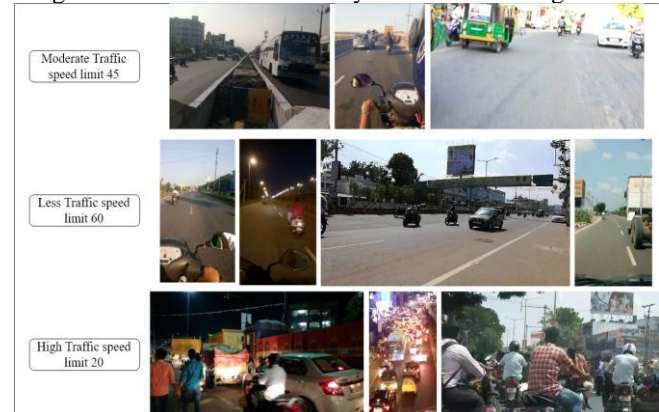


Fig 1. KL-Traffic dataset Sample data with varying traffic levels

B. Convolution neural network:

Our proposed is shown in Fig.2 and is inspired by traditional CNN architecture. Our VNN consists of six convolution layers followed by the Rectified Linear Unit (ReLU) as activation function and pooling layers. Finally, these features are given to two Dense layers among them first dense layer is followed by ReLU and other with Softmax activation layer which gives the output probability. No drop out is initiated in the network. We validate our model against the recent CNN architectures [11][13][15][16] to claim the novelty.

The weights and bias parameters of the networks are set arbitrarily using a zero-mean Gaussian distribution function with a variation of 0.01 on all sets of data at the beginning of each training stage. The system learns about bias by updating weights and using the gradient descend algorithm for backpropagation. Hyperparameter activations are connected to ReLU in convolutional layers and SoftMax in dense layers

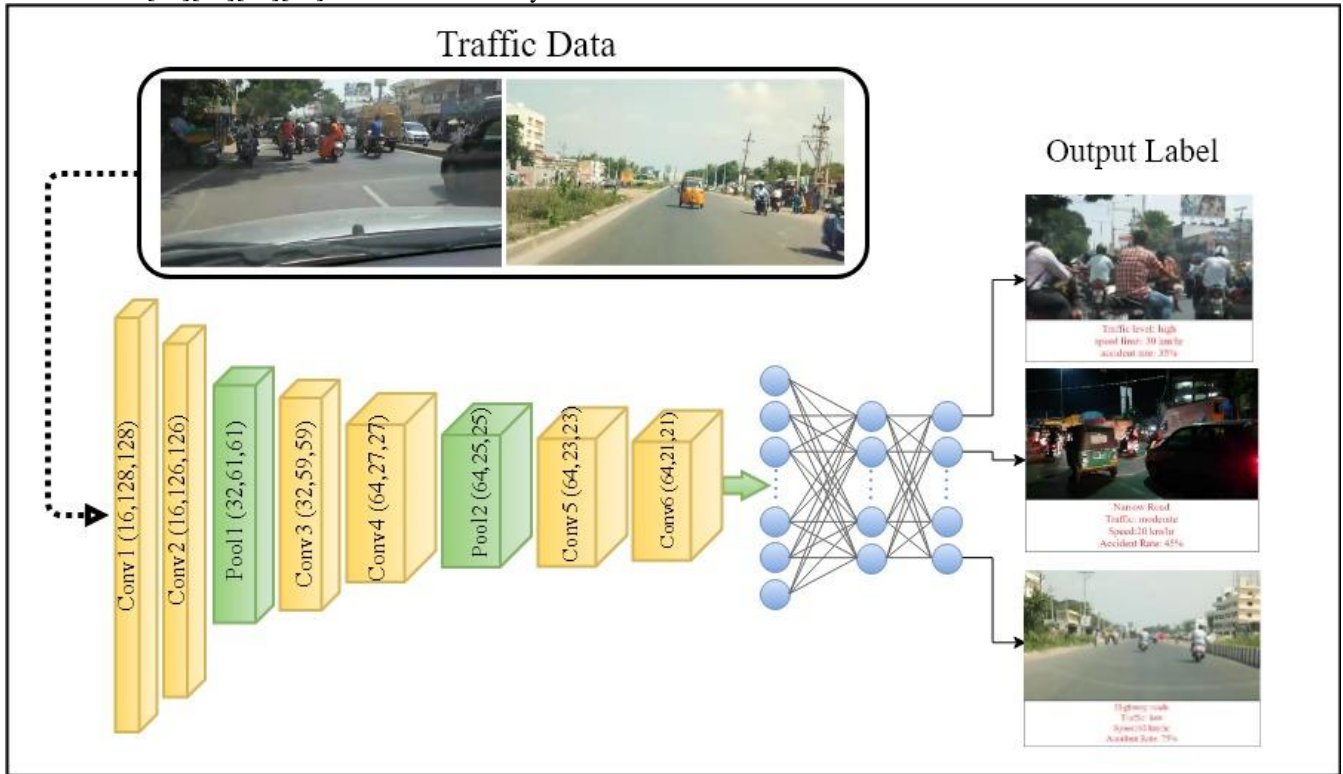


Fig 2. Proposed framework for the traffic-based speed limiting tool

C. Learning

Our Proposed CNN trains on KL-Traffic dataset and performance is evaluated using the learning scheme. we set the learning rate to 0.01 initially and then decreased by 0.1 for every 31k iterations for proposed CNN. The whole program has done in Python 3.7 by using libraries Keras and Tensorflow on a HPC (High Performance Computer) available in our university. HPC consists of two NVIDIA Tesla K20 graphics card with 6 nodes and Training takes almost 28 hours. We used stochastic gradient descendant (SGD) as optimizer and its expression is described in eqn.1 and categorical cross entropy (CCE) is a loss function in SGD the expression is shown in eqn.2.

$$CCE = -\frac{1}{N} \sum_{j=0}^M (y_j \cdot \log(y_j) + (1 - y_j) \cdot \log(1 - y_j)) \tag{2}$$

Where y_j is the predicted label and Y_j is the Actual label and CCE finds the loss based on these two weight functions.

$$\alpha_{sgd} = \alpha_{sgd} - \eta \cdot \nabla_{\theta} J(\alpha_{sgd}, x, y) \tag{1}$$

Where α_{sgd} is the parameter of model vector, η is the learning rate and $\nabla_{\theta} J(\alpha_{sgd}, x_i, y_i)$ is the gradient parameter of X input data to Y output class.



Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 32, 126, 126)	896
activation_5 (Activation)	(None, 32, 126, 126)	0
conv2d_10 (Conv2D)	(None, 32, 124, 124)	9248
activation_6 (Activation)	(None, 32, 124, 124)	0
max_pooling2d_4 (MaxPooling2)	(None, 32, 62, 62)	0
conv2d_11 (Conv2D)	(None, 64, 60, 60)	18496
activation_7 (Activation)	(None, 64, 60, 60)	0
conv2d_12 (Conv2D)	(None, 64, 58, 58)	36928
activation_8 (Activation)	(None, 64, 58, 58)	0
max_pooling2d_5 (MaxPooling2)	(None, 64, 29, 29)	0
conv2d_13 (Conv2D)	(None, 128, 27, 27)	73856
conv2d_14 (Conv2D)	(None, 128, 25, 25)	147584
max_pooling2d_6 (MaxPooling2)	(None, 128, 12, 12)	0
flatten_2 (Flatten)	(None, 18432)	0
dropout_3 (Dropout)	(None, 18432)	0
dense_3 (Dense)	(None, 1024)	18875392
dropout_4 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 9)	9225
Total params: 19,171,625		
Trainable params: 19,171,625		
Non-trainable params: 0		

Fig 3. Details of Architecture including parameters

This fig 3 shows the details of architectural implementation in a CNN and its parameter visualization. The above figure also gives the step by step implementation of the proposed CNN.

IV. RESULTS AND DISCUSSION

In this section we evaluate the proposed CNN with the KL Traffic data and proof of investigation. We also discuss about the developed framework. We divided the KL traffic data in to two parts one for training and another for testing i.e., 70 % of the data undergo training and remaining 30 % data undergo testing. After successful training of our CNN we are testing our CNN with the different Videos we only created for the testing the model.

Fig 4,5,6,7 gives the results of proposed CNN, we can clearly observe that our CNN is capable of Classifying the traffic scenes and based on the scenes we are getting a output as speed limitation and accident rate details and is displayed right below the image of the traffic scene. The images in Figure 4,5,6,7 are not from training data neither from the validation data



Fig 4. Result showing for High traffic index

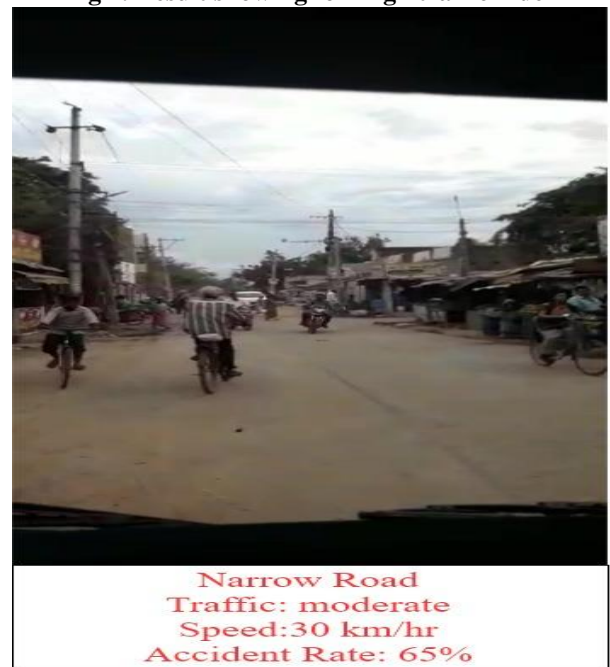


Fig 5. Result showing for moderate traffic index

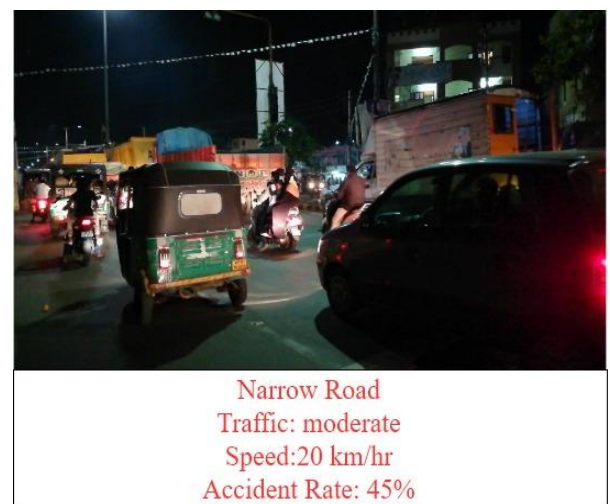


Fig 6. Result showing for moderate traffic index at nights



Fig 7. Result showing for low traffic index at highway

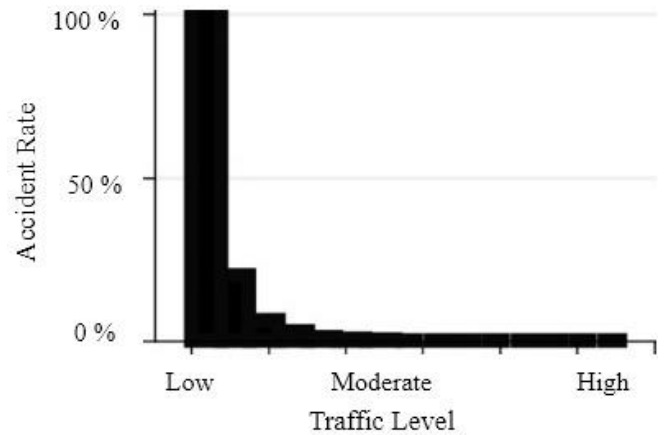


Fig 8. Plot of Accident rate V/s Traffic level

Figure 8 shows the plot of the Accident rate versus Traffic level on-road. When the road is free of traffic the motorists will cross the speed without even notifying by himself if any obstacle suddenly comes in between it will give high risk of accident. In the same way if traffic level is high, we don't have a chance of increasing speed even 10km/hr so there will be no risk of accident it has been shown clearly as follows.

Figure 9 shows the accuracy and loss plots of CNN, these plots are calculated by the stochastic gradient optimizer which calculates the error and accuracy for every epoch. These plots give the clear view of how CNN has minimized the losses in the model in both training and validation cases. Simultaneously, accuracy of the CNN model has increased in both training and valid

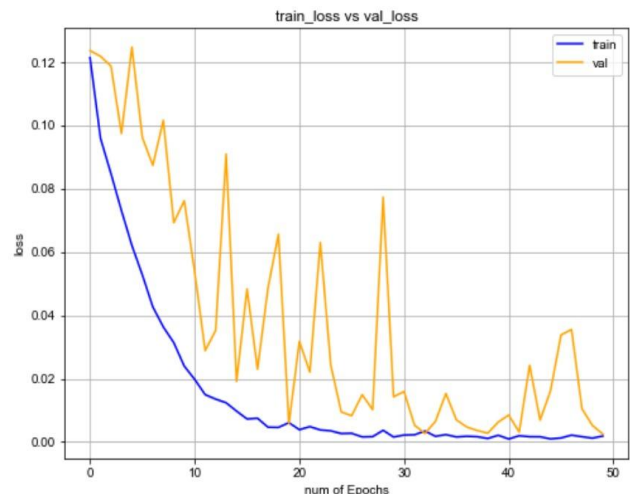
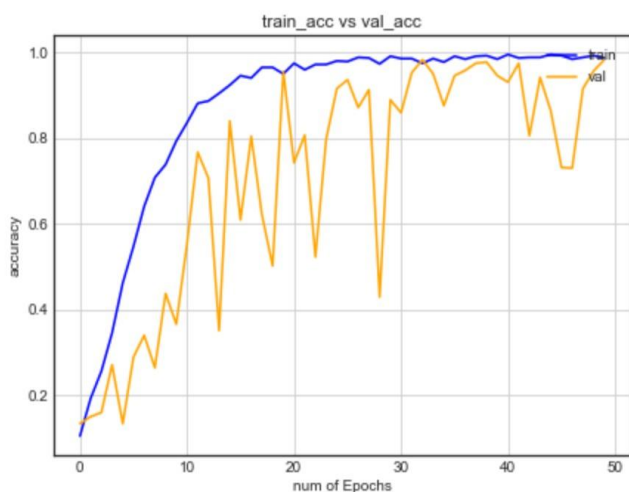


Fig 9. Accuracy and loss plots of CNN

V. CONCLUSION

In this study we have developed a convolutional neural network based on-road traffic classification with vehicle speed limit alert. This framework helps the vehicle's driver to alert for safety assisting drive with continuous traffic monitoring. To decrease the accident rate and to increase the safety measures for the driver and for co-drivers. This framework includes the study of how the convolution neural network architecture plays a major role in on-road traffic condition and its importance in day to day life.

REFERENCES

1. Fouladgar, M., Parchami, M., Elmasri, R. and Ghaderi, A., 2017, May. Scalable deep traffic flow neural networks for urban traffic congestion prediction. In 2017 International Joint Conference on Neural Networks (IJCNN) (pp. 2251-2258). IEEE.

2. Yu, B., Yin, H. and Zhu, Z., 2017. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. arXiv preprint arXiv:1709.04875.
3. Wu, Y. and Tan, H., 2016. Short-term traffic flow forecasting with spatial-temporal correlation in a hybrid deep learning framework. arXiv preprint arXiv:1612.01022.
4. Li, J., Mei, X., Prokhorov, D. and Tao, D., 2017. Deep neural network for structural prediction and lane detection in traffic scene. IEEE transactions on neural networks and learning systems, 28(3), pp.690-703.
5. Huval, B., Wang, T., Tandon, S., Kiske, J., Song, W., Pazhayampallil, J., Andriluka, M., Rajpurkar, P., Migimatsu, T., Cheng-Yue, R. and Mujica, F., 2015. An empirical evaluation of deep learning on highway driving. arXiv preprint arXiv:1504.01716.
6. Zhang, Z., He, Q., Gao, J. and Ni, M., 2018. A deep learning approach for detecting traffic accidents from social media data. Transportation research part C: emerging technologies, 86, pp.580-596.

7. Chen, Q., Song, X., Yamada, H. and Shibasaki, R., 2016, February. Learning deep representation from big and heterogeneous data for traffic accident inference. In Thirtieth AAAI Conference on Artificial Intelligence.
8. Jia, Y., Wu, J. and Du, Y., 2016, November. Traffic speed prediction using deep learning method. In 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) (pp. 1217-1222). IEEE.
9. Ma, X., Dai, Z., He, Z., Ma, J., Wang, Y. and Wang, Y., 2017. Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction. *Sensors*, 17(4), p.818.
10. Maddala, T.K.K. et al., 2019. YogaNet: 3D Yoga Asana Recognition Using Joint Angular Displacement Maps with ConvNets. *IEEE Transactions on Multimedia*, pp.1-1.
11. Chung, J. and Sohn, K., 2018. Image-based learning to measure traffic density using a deep convolutional neural network. *IEEE Transactions on Intelligent Transportation Systems*, 19(5), pp.1670-1675.
12. Wang, Q., Wan, J. and Yuan, Y., 2018. Locality constraint distance metric learning for traffic congestion detection. *Pattern Recognition*, 75, pp.272-281.
13. Chung, J. and Sohn, K., 2018. Image-based learning to measure traffic density using a deep convolutional neural network. *IEEE Transactions on Intelligent Transportation Systems*, 19(5), pp.1670-1675.
14. Erman, J., Mahanti, A., Arlitt, M., Cohen, I. and Williamson, C., 2007. Offline/realtime traffic classification using semi-supervised learning. *Performance Evaluation*, 64(9-12), pp.1194-1213.
15. Jang, H., Yang, H.J., Jeong, D.S. and Lee, H., 2015, January. Object classification using CNN for video traffic detection system. In 2015 21st Korea-Japan Joint Workshop on Frontiers of Computer Vision (FCV) (pp. 1-4). IEEE.
16. Wu, Y., Tan, H., Qin, L., Ran, B. and Jiang, Z., 2018. A hybrid deep learning based traffic flow prediction method and its understanding. *Transportation Research Part C: Emerging Technologies*, 90, pp.166-180.