A Short-Term Traffic Flow Prediction to Control Traffics in Large Scale Transportation using Internet of Things

S. Saravanan, K. Venkatachalapathy

Abstract*: *Traffic congestion is the key problem that occurs across urban metropolises around the world. Due to the increase in transportation vehicles the fixed light time on traffic signals not able to solve the traffic congestion problem. In this paper, First, we develop an IoT based system which is capable of streaming the traffic surveillance footages to cloud storage, then the vehicle count is recorded every 30 sec interval and updated in the traffic flow dataset. Second the traffic flow is predicted using our CNN-LSTM residual learning model. Finally, the predicted value is classified and traffic density at each road section is identified, thereby passing this density value to green light time calculation to set an optimal green time to reduce the traffic congestion. The traffic flow dataset, China is used for training and testing to forecast the short time traffic flow across the road section. Experiment results shows that our model has best accuracy by lowering the RMSE value.

Keywords* : *CNN, LSTM, Prediction, Traffic flow.

I. INTRODUCTION

A smart city is an unpredictable framework which comprises of numerous related computing subsystems where traffic controlling framework is one of its significant systems. An investigation on this subsystem reports that intelligent traffic control system is the foundation of the world's economy [1]. In addition, it is likewise announced as one of the significant elements of the smart city [2]. With the fast development of the number of inhabitants on the universe, the quantity of vehicles on roadways is expanding subsequently, the space of car influxes is additionally expanding in a comparable way [3] [4]. Automobile overloads such as traffic jams it may cause that crimes like versatile grabbing at traffic flag likewise occur in metropolitan urban communities [5]. Then again, it isn't just influencing environment seriously [6] yet the productivity of ventures is additionally being influenced [7]. It is, hence, recognized that dynamic traffic controller management is in a need. In major countries, traffic is overseen through fixed time signals while, in enormous urban areas of some countries, traffic is overseen through midway controlled frameworks. The worldview of the Internet of Thing (IoT) has been presented intelligent traffic management frameworks [8].

As far as possibly know, it is distinguished that till date the present traffic control system frameworks are centralized. If there arise an occurrence of system issue frameworks may crash. In addition, there is less spotlight on variances in traffic flow stream. In this manner, the proposed framework deals with the traffic on nearby and incorporated servers by using the ideas of IoT and Artificial Intelligence together. The portrayal of traffic information in factual structure can likewise be useful to experts for constant controlling and overseeing traffic. Additionally, it might likewise be useful for future arranging. With the nonstop extension of urban size, the size of urban traffic system is developing, and the quantity of vehicles is likewise expanding. Accordingly, traffic blockage has bit by bit advanced into an unavoidable issue. It is important to view the momentary traffic stream of the traffic organize absolutely and manage the traffic dependent on the forecast outcomes, to improve individuals' movement of vehicle, lighten the traffic issue, and give a decent choice help to the government to do the arranging and development of open traffic framework.

At present, analysts have proposed many traffic management models, which are for the most part separated into the accompanying two classifications. One is the kind of models dependent on mathematical and physical strategies, the other is the sort of models dependent on simulation innovation, neural system, fuzzy control, and other logical and mechanical techniques. The essential former methods incorporate historical average method, parametric regression model, Auto Regressive Integrated Moving Average (ARIMA) model, Kalman filtering model, exponential smoothing model. The last methods basically incorporate non-parametric regression model, spectral analysis method, wavelet neural network, complex prediction models combined with various intelligent algorithms, etc., and so forth. In addition, there are numerous other forecast models, for example, the Markov model, Deep Belief System (DBN), and so on.

In order to get reliant relationship among grouping information, Boon-Hee Soong et al. [9] proposed utilizing a Long Short–Term Memory (LSTM) model to predict traffic stream.

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* Correspondence Author
S. Saravanan*, Assistant Professor/Programmer, Department of Computer and Information Science, Annamalai University, Chidambaram, India, aucissaran@gmail.com,
K. Venkatachalapathy, Professor, Department of Computer and Information Science, Annamalai University, Chidambaram, India, omsumeetha@rediffmail.com

The above model neglect to give exact expectation results and consider the effect of various traffic conditions on the forecast outcomes in the real traffic network.

II. RELATED WORKS

In progress of forecast models dependent on scientific and physical strategies, Okutani et al. [10] proposed two models utilizing Kalman sifting hypothesis for anticipating momentary traffic stream. In the two models, expectation parameters are improved utilizing the latest forecast mistake and better volume forecast on a connection, which is accomplished by considering information from various connections. Perera et al. [11] proposed an all-inclusive Kalman channel as a versatile channel calculation for the estimation of position, speed and increasing speed that are utilized for forecast of moving sea vessel direction. Chen et al. [12] suggested a novel Autoregressive Integrated Moving Average with Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GARCH) model for traffic stream forecast. The model joins straight ARIMA with nonlinear GARCH, so it can catch both the restrictive mean and contingent heteroscedasticity of traffic stream arrangement. Shen et al. [13] proposed a blend forecast model including Kalman channel and outspread premise work neural system, and acquainted latency factor with guarantee the soundness of the crossover model. Zhu et al. [14] set forward a model that joins Kalman channel with Support Vector Machine (SVM). The model receives suitable figure technique wisely in every forecast period by the most extreme guidelines of blunder whole of squares and vector cosine of the edge, uses the steadiness of SVM and the continuous idea of Kalman channel, and takes individual favourable circumstances of the two models. Yang et al. [15] joined ARIMA model with Kalman channel through the mistake extent of prescient outcomes to anticipate the traffic stream in a street.

In form of prediction models dependent on present, logical and scientific techniques, for example, simulation innovation, neural network and fuzzy control, Li et al. [16] proposed a prediction strategy for improved Back Propagation (BP) neural system dependent on an altered Particle Swarm Optimization (PSO) calculation. By acquainting versatile transformation administrator with change places of the particles with dove in the neighborhood ideal, the adjusted PSO was utilized to enhance the weight and limits of BP neural system, and afterward the upgraded BP neural system was prepared to look for the ideal arrangement. Liu [17] proposed a model dependent on the mix of stage recreation and Support Vector Regression (SVR). The parameters of stage reproduction and SVR are upgraded by PSO in this model. Gao [18] proposed a model dependent on cuckoo search calculation and BP neural system. The time arrangement of transient traffic stream is reproduced to frame a multidimensional time arrangement dependent on clamorous hypothesis, and afterward the time arrangement are contribution to BP neural system to locate the ideal parameters of BP neural system dependent on the cuckoo search calculation.

In light of K-implies grouping, Zang et al. [19] incorporated Elman Neural Network (Elman-NN) with wavelet deterioration strategy to portray the presentation examination of traffic stream expectation. Minal et al. [20] recommended the use of a neural-fluffy half and half technique which united the corresponding abilities of both neural systems and fluffy rationale, and included the mix of the least square estimation and back proliferation. Kumar [21] utilized a counterfeit neural system model with numerous info parameters and built up an assortment of models as indicated by various blends of information parameters. Yu et al. [22] utilized the foremost part examination calculation to diminish the elements of information, and talked about the foundation and improvement of BP neural system as indicated by the issue of information hubs, beginning association loads and excitation capacities. Zhang et al. [23] set up an Elitist Adaptive Genetic Algorithm (EAGA) by joining Elitist Adaptive Genetic Algorithm (EGA) with Adaptive Genetic Algorithm (AGA), and afterward utilized the EAGA to upgrade BP neural system. Yin et al. [24] broke down the connection between the implanting measurement of stage space reproduction of traffic stream confused time arrangement and Volterra discrete model, and proposed a strategy to decide the truncation request and things of Volterra arrangement. At that point, a Volterra neural system traffic stream (VNNTF) time arrangement model was additionally proposed, and multi-step forecast trials dependent on Volterra expectation channel and BP system were performed.

As far as other prediction models, Emilian [25] utilized a mixture approach dependent on factor request Markov model to predict traffic stream, and included the normal speed of all vehicles going through every street area. Surya et al. [26] recommended anticipating traffic jam dependent on continuous traffic information of each segment, and controlling traffic lights at street convergences. As per the ideal activity determination methodology joined with Markov Decision Process (MDP), the ideal term of each traffic light was acquired by ascertaining the traffic jam factor at each sign change. Luo et al. [27] proposed an expectation model which joined DBN with SVR classifier. The expectation model utilized DBN model to concentrate traffic stream attributes, and afterward conveyed traffic stream forecast with SVR in the top degree of the DBN. Zhang [28] utilized the blemish information gathered by the finders installed at the street crossing points to acquire grouping examples dependent on Fuzzy C-Means (FCM) bunching examination, and utilized the traffic stream at the street convergence of a similar example to anticipate the traffic stream at another street convergence. Extraordinary Learning Machine (ELM). The calculation isolated the traffic stream into various examples along a period measurement by K-means, and afterward demonstrated and anticipated for each example by ELM. Pascale et al. [29] researched a factual strategy dependent on the graphical displaying of traffic spatial-worldly development, and afterward proposed a versatile Bayesian system where the system topology is changed after by the non-stationary qualities of traffic. Shao et al. [30] utilized a LSTM model to anticipate transient traffic stream, where the reliance connections of arrangement information are completely considered, yet the last test results show that the Root Mean Square Error (RMSE) estimation of forecast is 40.34.

A smart traffic management framework that is mostly in Cambridge city where line finders are covered in the streets that recognize the traffic line and advice the focal control unit which takes choice as needs be. Since the framework is brought together that can back off due to systems administration issues [31]. The scientist utilized reconnaissance cameras to distinguish traffic and OCR to recognize the vehicles through number plate acknowledgment which is a basic identification strategy however the framework will bomb in Pakistan as there are various types of traffic including cycles, jackass trucks which have no number plate [32].

Osman et al. proposed a framework in which they have utilized observation cameras to recognize traffic thickness utilizing MATLAB, a traffic controller and a remote transmitter used to send pictures to the server after that server determined traffic thickness by utilizing those pictures of each area. This framework utilized fixed (predefined) limits that rely upon various vehicles on street. A calculation was utilized to set a period length of red light for a specific path of the crossing point, which is dictated by traffic thickness on street and sent to the microcontroller and afterward server [33].

Jadhav et al. utilized observation cameras, MATLAB and KEIL (Microcontroller coding) to control traffic clog. This paper additionally talks about the need based traffic leeway and red sign intermediary (Number plate location). Because of utilizing substantial equipment, it is hard to oversee and turn out to be expensive [8].

Bui et al. Dissected an ongoing procedure synchronization based framework to deal with the traffic stream progressively. Sensors were utilized to recognize the traffic, where vehicle to vehicle and vehicle to foundation correspondence was finished by utilizing remote specialized gadgets. Controller put at the focal point of the crossing point got vehicles' and walkers' data and demands and procedure utilizing first start things out serve strategy [34].

Swathi et al. proposed savvy traffic directing framework that picks the briefest course having the least clog. Sensors are utilized to collect data about traffic thickness, these sensors utilize sun based vitality and battery. Sensors continued transmitting infrared light and when an item drew close, they identify traffic thickness by checking the reflected light from the vehicle. In any case, readings may change with the adjustment in temperature and stickiness [35].

III. PROPOSED METHODOLOGY

The proposed methodology is designed to control traffic signals at road intersections through the traffic surveillance video footages Figure 1. The video footages are streamed live to a cloud server where the number of vehicle passing through a traffic signals are counted and updated every 30 seconds to maintain a traffic flow data. The traffic density for short term flow is estimated through a deeper CNN-LSTM model with residual learning approach at each lane with the help of traffic flow data. The predicted traffic density is sent to calculate the effective green time allocation in each road interaction traffic light trough an IoT device. For experimental purpose we utilize the public Traffic Flow Dataset, Guizhou, and China. The traffic flow data is really helpful in predicting the traffic congestion earlier and also it reduces the journey time of the people.

In the following sub-sections, first we predict a short-term traffic flow in each lane, second, we apply the optimal green light calculation algorithm to reduce the congestion.

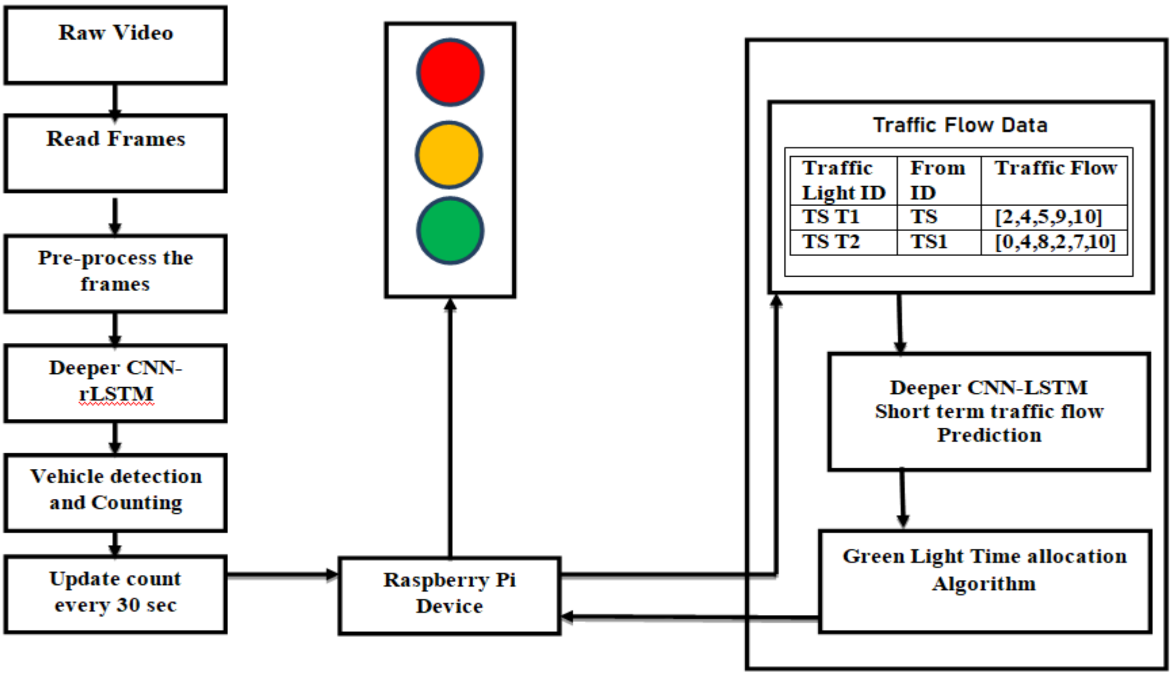

Figure 1. Proposed Architecture

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A. Short-term traffic flow prediction and classification

The proposed framework for traffic flow prediction is the joint model based on CNN and LSTM methods. The both the model has their own advantages the CNN and LSTM model captures both spatial and temporal information efficiently. The Convolution Neural Network extracts and learns the useful information which are then passed on to the LSTM layers to predict the traffic flow.

1) Convolution Neural Network with residual learning

The Convolution Neural Network performance can be increased by increasing the number of convolution layers in the network. However, increasing the number of layers leads to vanishing gradient problem (degradation). To prevent this problem of degradation and overfitting and also to maintain the deeper layers a residual learning approach is applied [CSR-Net]. The Convolution Neural network captures rich spatial information from a data exist in a grid like topology. The Convolution layer has some basic components.

Convolution Layer: A K size of filter is applied across the input to get an output.

Pooling Layer: The pooling layer reduces the spatial size of the input by taking either max or average pooling layer. So that to preserve important features are taken as data inputs.

Fully Connected layer: The Fully connected layer are the neurons that are fully connected with all activation function in the previous layer. Usually it is placed at the end of the neural network to generate the output.

Dilation Convolution layer: The dilation convolution layer applied successfully in many segmentation tasks [10, 11, 40]. The pooling layer in the convolution network reduces the spatial information so to maintain the important information dilation convolution is applied. The time series data has long term correlations. So to learn the long term sequence the dilated convolution applied in the CNN.

Residual layer: The residual connection is added after each dilated convolution layer from input to output. The same no of channels is maintained for residual connection and dilated convolution layer output. Thus is allows multiple layer by retaining the network complexity and to learn the information in the initial layer itself.

2) Long Short term Memory

Long short term memory is the improved form of recurrent neural network (RNN). The RNN is good at learning the patterns in the time series data. But the RNN has vanishing gradient problem which occurs when the number network gets deeper. The LSTM solves the vanishing gradient problem by using a memory block. This memory block has three gates and cell state. The forget state, input state and output state. Forget state improves the performance of the network by removing information that are no longer needed. It means that the sigmoid value always lies between zero and one. The zero values are discarded. Input gate adds new information to the cell state using tanh function. Output gate chooses and sends only important information as output. So with this memory block all information are stored for sequence prediction.

3) CNN-LSTM

The short term traffic flow prediction is deployed using CNN and LSTM methods combined. In convolution Neural Network (CNN) the VGG-16 network architecture is used for training. The first ten layers are taken from the VGG-16 network along with the dilation convolution layer is applied and produces a output on 1 X 1 X 1 convolution layer Figure 2. The output from the CNN is given as input to the LSTM layer. The residual learning is each convolution layer is processed, finally the short term traffic flow is predicted for 5 min and the result is classified as medium density or high density.

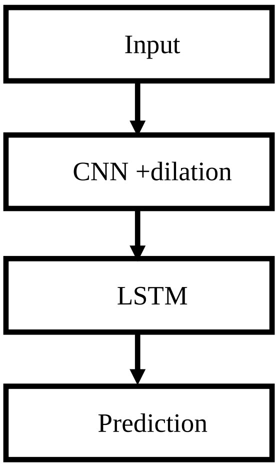

Figure 2. Proposed CNN –LSTM Method

The general configuration setting is given for the proposed model

Batch size = 50
Epochs = 8
Validation split = 0.3
Optimizer = SGD
Dropout rate = 0.5
Loss function = mean_square_error
Metrics = mean_absolute_error
Convolutional Layers parameter setting
Units of Dense = [128, 32, 1] in respective Dense Layers
No. of filters = [24, 48] in respective Conv1D Layers
Pool size = 2
Kernel size = 1
Activation Function: PReLU
LSTM parameter setting
No. of cells in LSTM layers = [40, 32] respectively
Activation Function: Softplus

B. Green Light time calculation

The dynamic green light time calculation proposed by Collotta et al [14] implemented here after the traffic density process is completed Figure 3. The algorithm has two steps, first the traffic density at different road intersections is given as input, and it assigns priority to each density and makes a queue process. Second, it determines the density in descending order and sets priority, then green light optimization is done. To calculate the green light time at each lane the CGT is given by

$$CGT = Traffic\ density + R - Y$$

Where r is the lost time during start-up of lights and Y is the yellow light duration time.

Remaining green time for each traffic light under a lane is calculated by

$$RGT = Traffic\ density - CGT$$

For the second lane green light calculation

$$REGT = RGT \frac{Current\ \ green\ light\ time}{Remaining\ green\ light\ time - previous\ green\ light\ time}$$

This process is repeated for different traffic light under different lane so that the congestion is avoided in all the traffic signals and reduce the waiting time of people.

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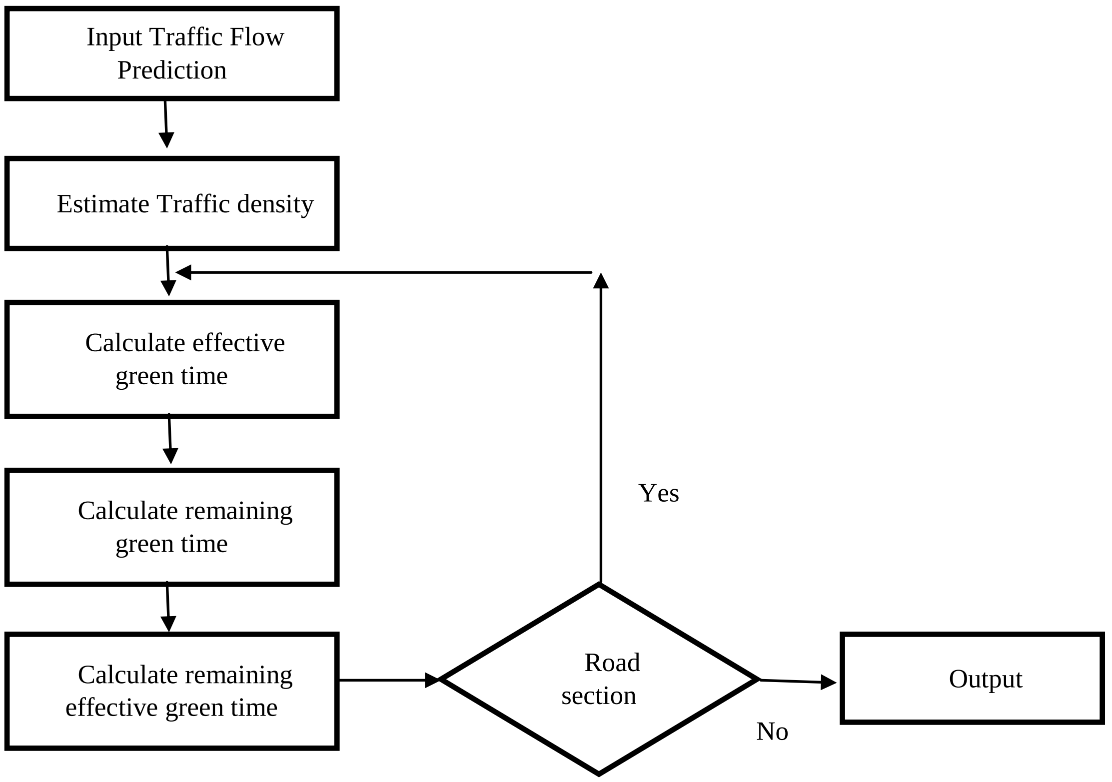

Figure 3. Green light time calculation

C. Hardware and Cloud Server

The proposed method uses a Raspberry Pi that is connected to 12 pcs LED for traffic light. The surveillance camera and traffic lights are controlled using this device. The video streamed to a cloud server where the count of vehicles is recorded every 30 sec and stores in a traffic flow table. This traffic flow data has three fields that source id, from id and traffic flow data [dataset]. In cloud server the short term flow of traffic is predicted and traffic density at different lanes is classified. This classified traffic density is passed to the green light time calculation to control the traffic light using raspberry Pi device. All the information are passed using JSON format. The Blynk IoT platform is used to store, visualize and send data through the cloud.

IV. EXPERIMENT

A. Evaluation metrics

In this proposed method, the performance is evaluated using RMSE. Since the traffic result is same as the predicted data this method can decrease the error. The RMSE is given as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2} \qquad 1$$

where y_i, and yˆ_i are the true values and the predicted values and n is the samples used for training.

B. Dataset Tuning Process

The traffic flow dataset of Yunyan District, Guizhou Province, China is used as the experimental dataset. This dataset has 230,000 vehicle count record which is updated every 30 sec. The dataset has three fields Traffic_LightID, From_ID and Traffic_Flow , as shown in the Table 1.

Table 1. Traffic flow dataset sample

Traffic_LightID	From_ID	Traffic_Flow
tl8	tl9	[10,6,5,1,0,23,13,,,,,,10]
tl11	t10	[1,0,0,3,3,5,6,7,8,…….5]

The Traffic_LightID is the traffic light identifier of the vehicle currently, the From_ID is the traffic light identifier of vehicles at the last previous lane. The data in the dataset are recorded during the hours 6:00 am to 8::00 pm, so the traffic flow data is a matrix dimensions of 1680. The local road structure involved in the experiment is shown in Figure 4, where the intersections are represented in hollow circles where unique ID's are given to each traffic lights and the solid line represents the road.

Generally, the traffic flow prediction is done for 5, 10, 15 minutes [38]. To get the accuracy the prediction is done for 5 minutes in this paper. A new dataset is created by taking every ten-traffic data. So new dataset contains 168 matrix dimensions with same respective fields. A statistical breakdown is done to generate road section with large and small traffic flow. The traffic flow ranges 10 to 100 and 120 to 180 is considered as small and large traffic flow. Traffic flow dataset is divided into training set 70% and test set 30%. The model will predict 50 values and finally use RMSE to evaluate the accuracy. The data tl8 to tl9 is selected for large traffic flow which is tested in the experimental process.

The CNN and LSTM configuration parameters are applied as mention above, to train and test the traffic flow.

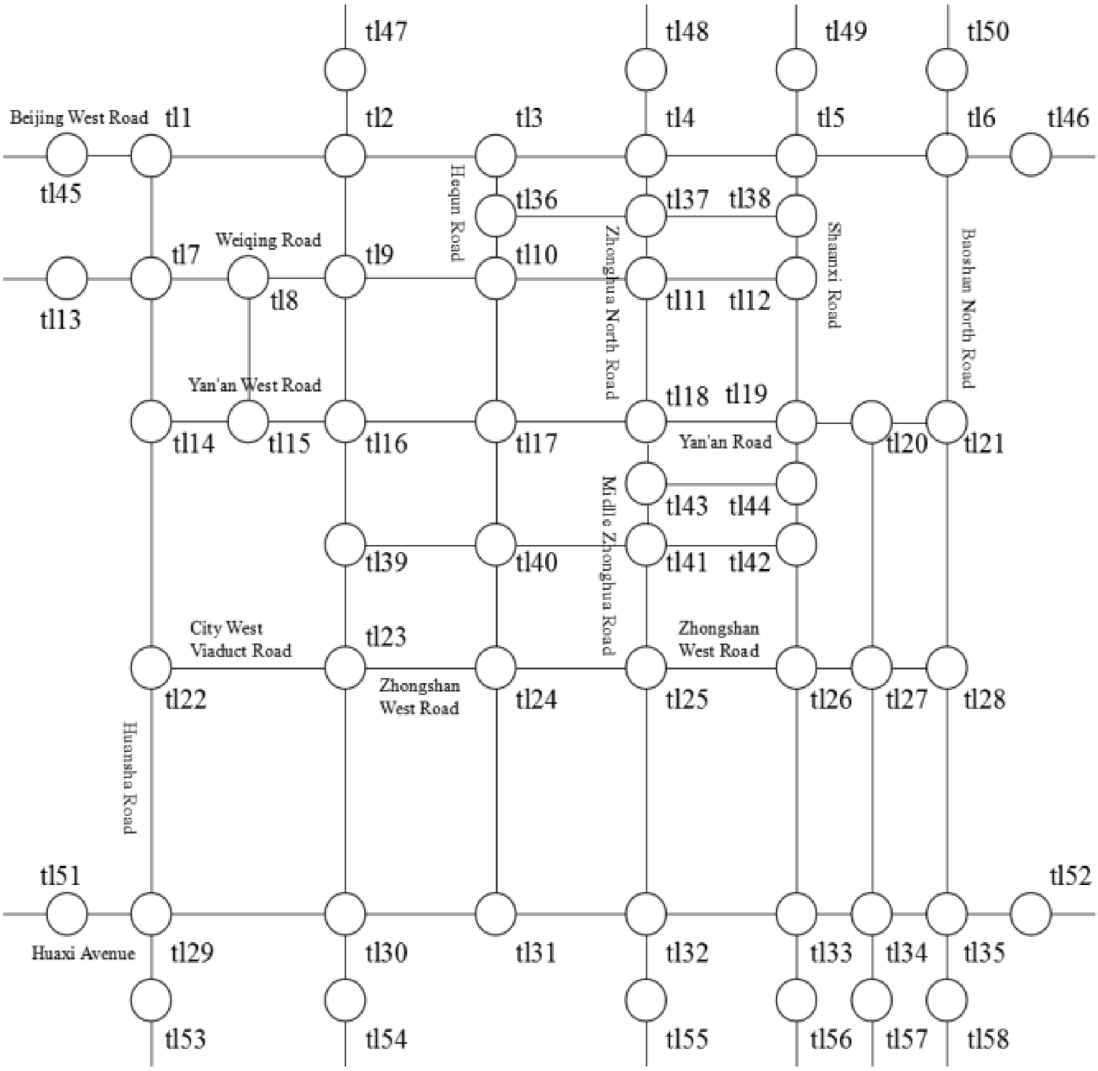

Figure 4. Local road structure diagram

C. Result Comparison

The proposed method compared with other methods as shown in table 2.

Table 2. Different prediction methods RMSE value

Prediction Model	RMSE For Large traffic flow	RMSE for Small traffic flow
FCM [25]	27.38	4.06
Kalman filter [6]	29.40	4.06
SVR [9]	15.04	1.23
LSTM [30]	31.57	2.38
CNN-LSTM	0.53	0.22

V. CONCLUSION

We propose a CNN-LSTM residual model for short-term traffic flow prediction. It is perceived that CNN and LSTM captures both spatial and temporal information efficiently. We trained the model using traffic flow dataset, China and was able to predict the traffic flow in each road sections. The results show that, the proposed model has a best prediction accuracy the RMSE error in the training rate is very less and suitable for different traffic situations and can be implemented in the actual traffic network. The predicted value considered to be the traffic density in particular road sections, thereby calculating the green light time to control the signal dynamically. This system completely replaces the existing manual and fixed time light operation to dynamic light cycle operations. The IoT device are capable of controlling the traffic light through a cloud server at each road section. With this system the traffic congestion can be controlled and overall journey time of people can be reduced. In future, the traffic trajectory data should be analysed and researched.

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