Road Traffic Optimization and Energy Conservation Using Cost-Effective Approaches in Wireless Sensor Networks

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***Abstract*—Traffic congestion is a major issue in most large cities, resulting in a 20-minute delay for every 30-minute evening commute in Toronto for instance. These delays can impede Emergency Vehicle (EV) response, potentially resulting in fatalities. Furthermore, conserving energy from streetlights, which account for roughly half of some cities' energy bills, is critical. In this report, we discuss a low-cost, simple-to-implement solution that uses wireless sensors, smart decision-making traffic algorithms, Deep learning (DL), Computer Vision (CV), and Arduino to collect and process data to make traffic predictions, control a network of automated streetlights to save energy, and provide priority pass to EVs, allowing us to address the issues at their source.**

***Index Terms*—Computer Vision, Deep Learning, Emergency Vehicle, Internet of Things, Wireless Sensor Networks, Street Lights.**

I. INTRODUCTION

An amalgamation of fast and large-scale data collection by Wireless Sensor Networks (WSN) and Internet of Things (IoT) along with the development of various DL models (to process the data) is required to tackle the ever-increasing problem of traffic congestion which leads to long delays to public commuters as well as disrupts the schedule of logistic companies. It doesn't only contribute to time lost but also amounts to a hefty annual excess fuel consumption along with excess CO2 emission) (see Fig. 1) [1]. In addition to this, the continuous operations of streetlights lead to excess energy waste which contributes to depletion of energy resources and, as a result, causes harm to the environment. Thus, transitioning to an intelligent lighting system using the existing network is imperative.

One of the parameters that impact traffic congestion on the roads during peak hours is the unawareness of the current traffic volume and the lack of usage of tools to avoid congested routes and take alternate routes. Present research focuses on central solution considering every city traffic is the same, rather than building a specific model for the road or junction traffic of the city in scope. Traffic forecasting models are prevalent which work on both historical and real time trends and extrapolations. Currently machine learning and deep learning models like Convolutional neural nets, Recurrent neural nets, long short term memory algo and machine learning algorithms like K nearest neighbors and random forest are deployed to cluster data and predict traffic congestion [2]. We present distributed solution specific to cities/ junctions using Long short term memory algorithm which is designed to solve vanishing gradient problem and short-term memory problem of vanilla RNN.

Traffic management system (TMS) is also used to provide alternate paths and avoid time loss [3]. A cloud vision API paired with machine learning is used, along with the capability of the Intelligent Transportation System (ITS) [4]. Approaching vehicles (particularly EV) being stuck at a busy intersection with a traffic signal led to essential time being wasted. This time wastage can also lead to fatalities as it did in Ireland, where 700 fatalities were reported due to late Emergency response [5]. Present research in this domain focuses on Ad-Hoc networks / interconnected vehicles [6] but we are transforming it into a cost-effective solution based on isolated vehicles where the vehicles don't need to be connected via a network.

Unnecessary energy consumption by streetlights at times of no traffic, pedestrians or during daylight leads to a massive amount of energy being wasted [7]. It is observed that Street lighting accounts for about 5% of all the electricity use in America and the European Union. However, Street lights waste 2-3% of the monthly energy of the EU [8]. Besides, the energy wastage it also leads to the high maintenance cost that is to be adjusted in the municipality bill. Several research on streetlights have been conducted in order to improve energy efficiency; and reduce energy wastage one of these studies proposed a real-time adaptive lighting scheme that detects vehicles and pedestrians and dynamically adjusts their brightness to the optimal level [9]. It is simulated in an environment that models a road network, its users, and a networked communication system, as well as a real residential streetlight topology. The solution is effective but using complex algorithms. Our proposed cost-effective and less complex solution can achieve the same result of low maintenance cost and lower energy wastage. Money spent on wasted outdoor or streetlight in US for the year of 2012 can be observed in table 1.

Usage Breakdown	Breakdown	Breakdown ratio	Consumption totalKWh/Year	2012 Total $
Lighting	(19% of Total Elec.)[d]	0.190	700,592,657,276.26	$68,958,612,697
Outdoor Lighting	(16.857% of Lighting)[e]	0.16857	118,098,904,237.06	$11,624,353,342
Estimated Wasted Outdoor Lighting[f]	(30% of Outdoor Lighting)	0.300	**35,429,671,271.12**	**$3,487,306,003**

Table 1. Breakdown of money wasted on outdoor streetlights

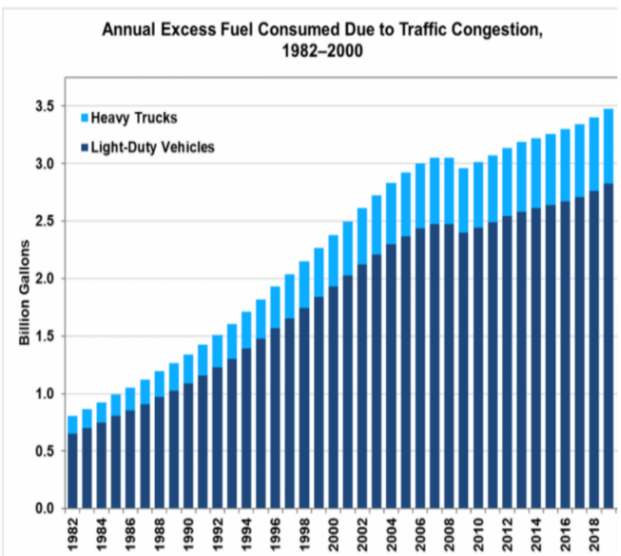


Fig. 2. Annual Excess Fuel Consumption in US.

In this project we extend an economical and feasible solution to tackle both energy conservation problem along with the traffic bottleneck by establishing a traffic prediction system and IoT paired with an astute decision-making algorithm which makes use of existing infrastructure, to partially resolve if not eliminate them completely.

A. Internet of things

The term Internet of Things, or IoT, is used to describe the interconnected network of billions of physical devices around the world via the internet, all accumulating and dispensing data (see Fig. 2). The arrival of super-cheap computer chips along with ubiquity of wireless networks, added to the digital intelligence of devices enabling them to communicate real-time data without the involvement of human beings [10].

We used IoT to connect our Arduino to firebase database for the traffic prediction to enable our smart street lighting system which works based on road usage and occupancy.

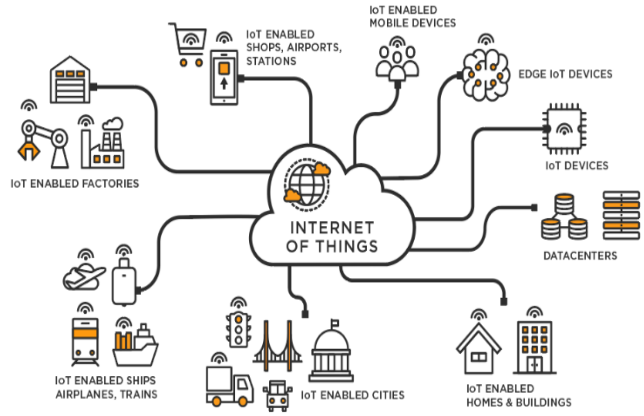
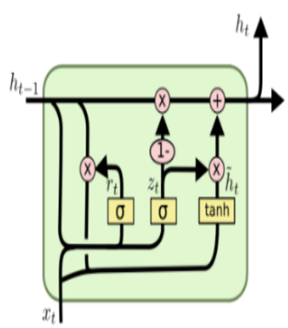


Fig. 2. Symbolic Representation of IoT.

B. Machine Learning and Deep learning models for Traffic Prediction

A large number of algorithms can be used in traffic flow prediction like Convolutional neural nets, K-nearest neighbors, Recurrent neural network, Random Forest, LSTM, Gated recurrent neural nets. [11] [12]

We chose to use only LSTM in our case. Long Short-Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997), and were refined and popularized by many people in following work [13]. They are designed to solve the long-term dependency or vanishing gradient problem of Vanilla RNN by using gates. They are composed of sigmoid activation function (to threshold how much information to let in) and a point wise operation (see Fig. 3).



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Fig. 3. LSTM Module

II. Proposed System Architecture

For smart streetlight we ran a simulation on TinkerCad using Arduino, LDR sensor and PIR sensor. Light or motion detection detected by a network of these sensors lead to switching of the streetlight via signal sent through the Arduino (see Fig. 4).

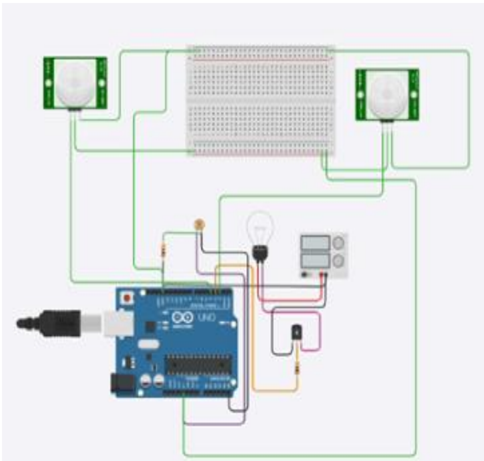


Fig. 4. Circuit Connections for Smart Streetlights

```
// C++ code
//

int ldr=5;
int ldr_value;
int light=3;
int pir1=2;
int pir2=4;
int database;

void setup()
{
  pinMode(light, OUTPUT);
  pinMode(ldr, INPUT);
  pinMode(pir1,INPUT);
  pinMode(pir2,INPUT);
}

void loop()
{
  ldr_value=analogRead(ldr);
  int value1=digitalRead(pir1);
  int value2=digitalRead(pir2);
  if (value1== HIGH && ldr_value>512)
    digitalWrite(light,HIGH);
  if (value2== HIGH && ldr_value>512)
    digitalWrite(light,HIGH);

}
```

Fig. 5. C++ code for Smart Streetlights

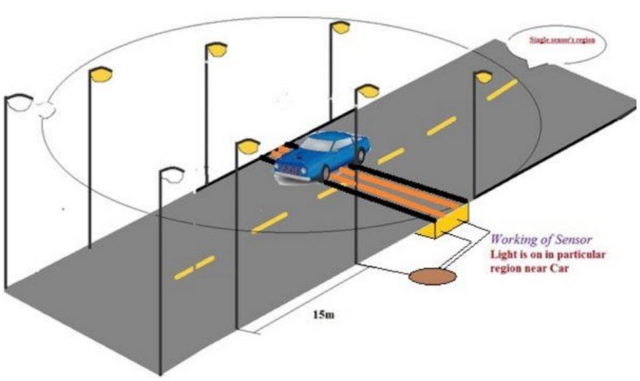


Fig. 6. Representation of smart streetlight implementation in real life

For Traffic Prediction we used a web cam, paired with Arduino and ESP8266 to protype the setting (see Fig. 5). Data acquired by using Yolo was stored in the cloud server and could be acquired in the form a CSV file which can then be processed through Deep learning algorithm like LSTM, which observe the trends, extract dependency, and make prediction on test data (see Fig. 8). Data prediction can also be made on annual/monthly or weekly basis.

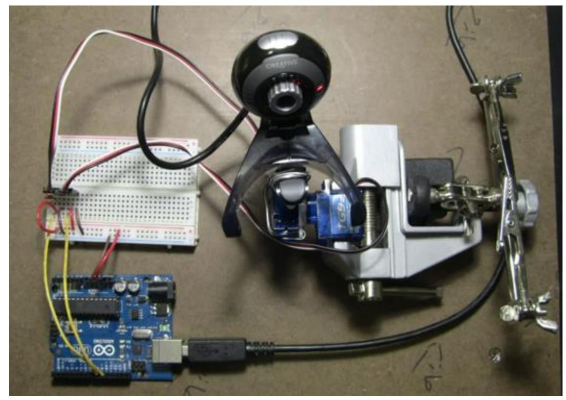


Fig. 7. Prototype

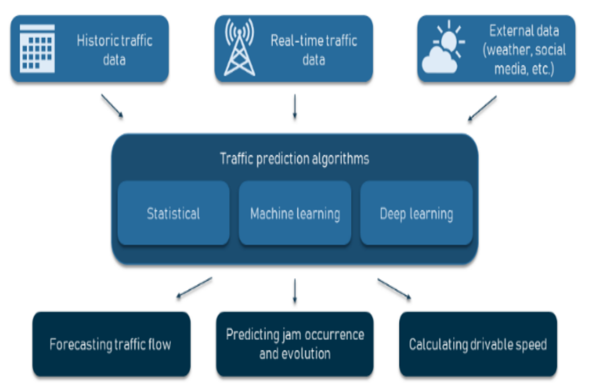


Fig. 8. Model for Traffic Prediction

A. YOLO (You Only Look Once Algorithm)

YOLO is based on CNN and does single forward propagation to predict real time class probabilities and bounding boxes simultaneously [14]. It works using the following three techniques (see Fig. 9):

Residual block: Dividing the input image into many SxS grids and each grid is responsible for detecting the objects which appear within them.

Bounding Box Regression: Each bounding box of dimensions Width (bw), Height (bh), Center (bx,by) and class represented by letter c is used to highlight an object in the input image.

Intersection over union (IOU): IOU is used by Yolo as description of how two bounding boxes overlap it is used to give confidence scores. It helps to eliminate bounding boxes which are not the real box by comparing them against the value "1".

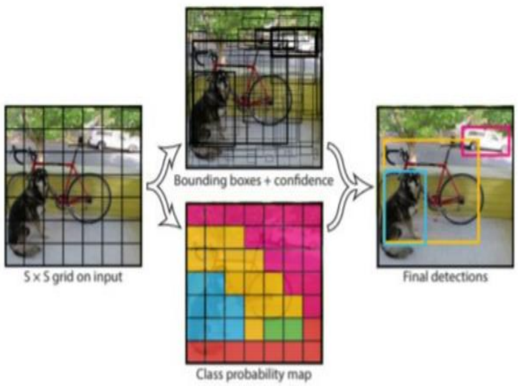


Fig. 10. Resultant representation of all three YOLO techniques

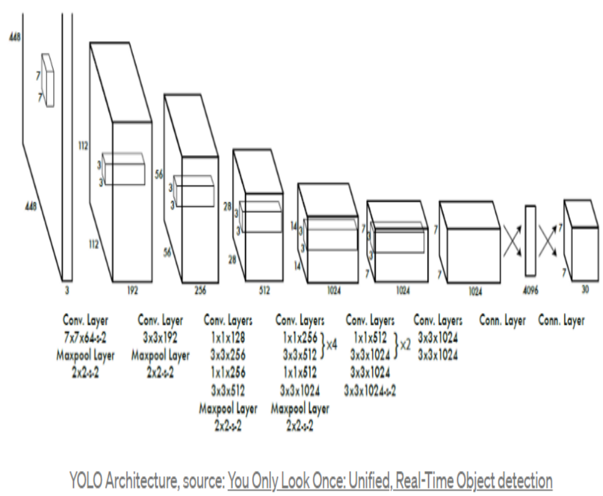


Fig. 11. Yolo Architecture

B. Webcam

A webcam paired with Arduino was used to stream traffic video sequences so that it can be processed by Yolo (see Fig. 12).

Fig. 12. Webcam

C. Firebase Database

The Firebase Realtime Database is a cloud-hosted NoSQL database that lets you store and sync data between your users in real-time [15] (see Fig. 13). Firebase is built to scale and provides user-based security for offline use. We used it to store our vehicle count detected by Yolo against the respective junctions.

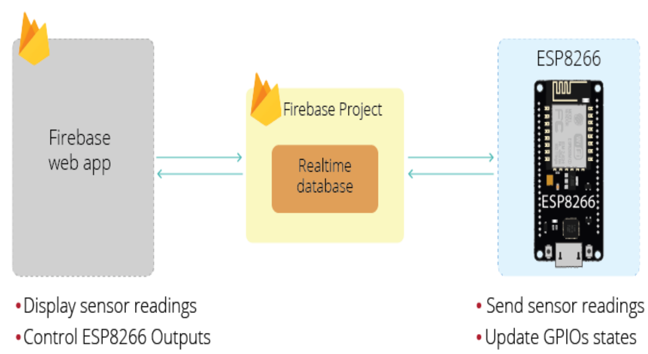


Fig. 13. Symbolic representation of firebase database and ESP8266 connection

D. Arduino Uno

Arduino UNO is an open-source Microcontroller board which is extensively used in embedded projects. With its easy-to-use hardware and software platforms it is easy to integrate different devices like Web cam, Host Yolo, and update data on the firebase database (see Fig. 14).

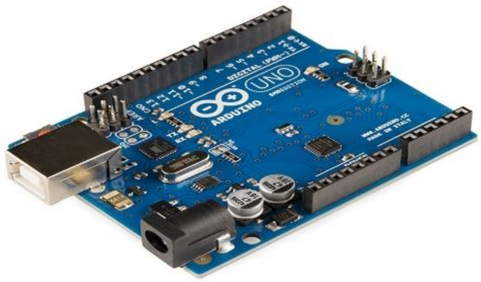


Fig. 14. Arduino Uno Micro Controller

E. ESP8266 Wi-Fi Module

The ESP8266 WiFi Module is a self-contained SOC with integrated TCP/IP protocol stack that allows a microcontroller, access to your WiFi network. It is capable of either hosting an application or offloading all Wi-Fi networking functions from another application processor [16]. We used it with our Arduino Uno to provide access to the Wifi using the serial port (see Fig. 15).

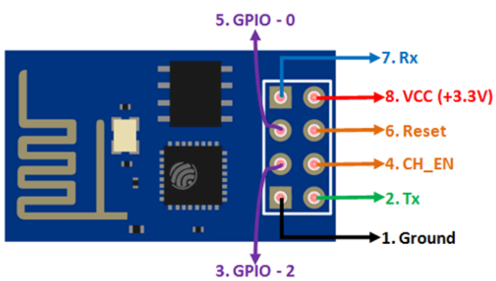


Fig. 15. ESP8266 Wifi Module Pin Configuration

F. LDR sensor (Photo Resistor)

LDR is a photo resistor which is used in light sensitive circuits. It is made up of a high resistance Semiconductor material called cadmium sulfide cell. Its resistance varies with light intensity (see Fig. 16). We used it to detect sunlight and turn off the streetlights by sending a signal via the Arduino to save energy wastage during daytime.

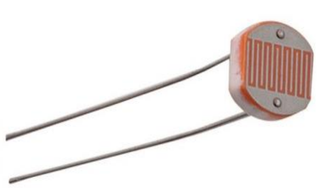


Fig. 16. LDR Sensor

G. Passive Infrared Sensors (PIR)

Passive infrared (PIR) sensors use two pyroelectric sensors to detect heat energy in the surrounding environment (see Fig. 15). They sit beside each other, and when the signal differential between them changes (if a person enters the room, for example), the sensor engages. We used a network of these sensors, paired with our Arduino to detect motion on the street to prevent energy wastage.

Fig. 15. PIR Sensor

H. Street Light simulation using Veins

The smart traffic light was implemented on StreetSim. StreetlightSim's primary building blocks were created using OMNeT++ modules and the road traffic simulator Simulation of Urban Mobility (SUMO).

The Vehicle in Network Simulation (Veins) framework, which offers a strong foundation for bidirectional interaction between OMNeT++ and SUMO, is the source of inspiration for StreetlightSim. Veins also makes it easier to model and simulate individual automobiles, enabling evaluation of the efficiency of street illumination from the viewpoint of each unique road user (see Fig. 16).

Additionally, OMNeT++ enables the simulation of communication networks, data processing and control algorithms, and supporting frameworks and models like MiXiM, INET, and INETMANET (see Fig. 17).

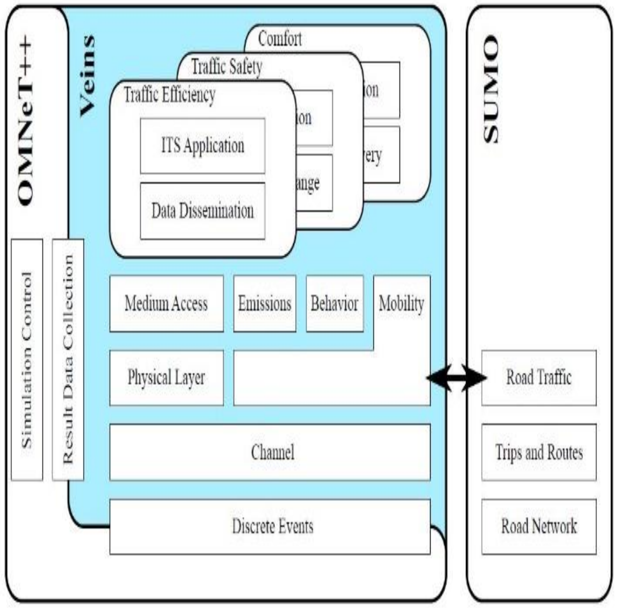


Fig. 17 Veins Architecture

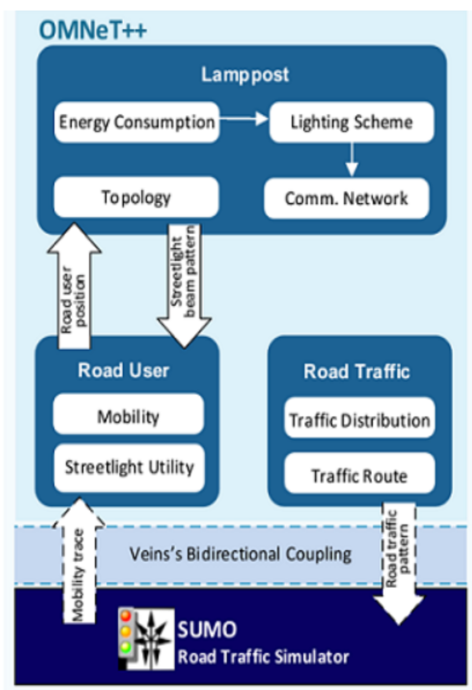


Fig. 18 Veins Integration with OMNeT++.

A client/server architecture-based interface for SUMO is called the Traffic Control Interface (TraCI). Through a Transmission Control Protocol (TCP) connection, this interface enables the real-time retrieval and manipulation of simulated objects including on-the-road drivers, traffic signals, and streetlights.Veins takes advantage of this interface by connecting to TraCI via a proxy TCP connection using a special OMNeT++ module. A TCP socket is used to link the simulators.

The Traffic Control Interface is the standard protocol for this communication (TraCI). This makes it possible to simulate network and road traffic in both directions.

In an OMNeT++ simulation, node movement corresponds to vehicle movement in the road traffic simulator. The ongoing road traffic simulation can then be interacted with by nodes, for example, to mimic how IVC affects traffic. Online simulations are run with a bi-directional coupling between the two simulators. In this approach, complicated relationships between the two domains may be looked at, and the impact of vehicular networks on road traffic can be studied as in Fig. 19.

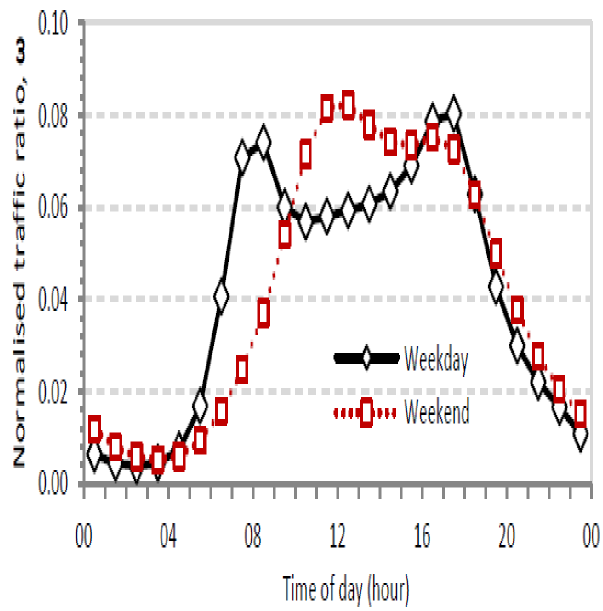


Fig. 19 Road Traffic Data.

This scenario includes traffic from other vehicles, which was calculated using readings from the precise location's induction loop. The sample includes weekday traffic for the entire day. For instance, a pre-emption program on the traffic signals is activated when an emergency vehicle approaches the intersection from the east.

In our design of Smart Traffic system with the help of Vein architecture [17] we have provided the node movement to come at a particular junction consisting of Smart decision-making traffic central station. The nodes (Interconnected Vehicles) accumulate at the junction and with the help of YOLO and Machine learning algorithms the central station makes smart decision based on the traffic at the junction. Thus, this makes the traffic flow to be smooth, more efficient, and robust.

III. Experimental Results

In recent years, both the use of bicycles and the incidence of motorcycle accidents have increased. A GPS-based car location, cameras, and an automatic vehicle recognition process were used to achieve this.

In our approach, the nodes (Vehicles) are gathered at a specific intersection, and the number of nodes is used to anticipate traffic. Once a decision has been made via the traffic control interface, the nodes are subsequently given the all-clear by the central station to proceed down the selected path (see Fig. 20).

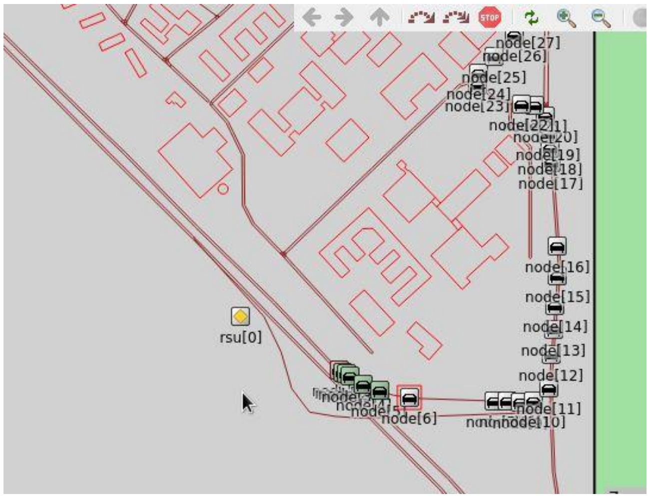


Fig. 20 Veins Traffic Simulation

Each traffic light opens for 20 seconds when it receives a message from the fog and it can open twice consecutively, but it will then be locked for 60 seconds to prevent starvation in the other 3 lanes.

The algorithm used by Fog is designed for intersections with four traffic lights. The fog determines the number of vehicles at each traffic light by video processing the video sent to it from the traffic light camera (see Fig. 21).

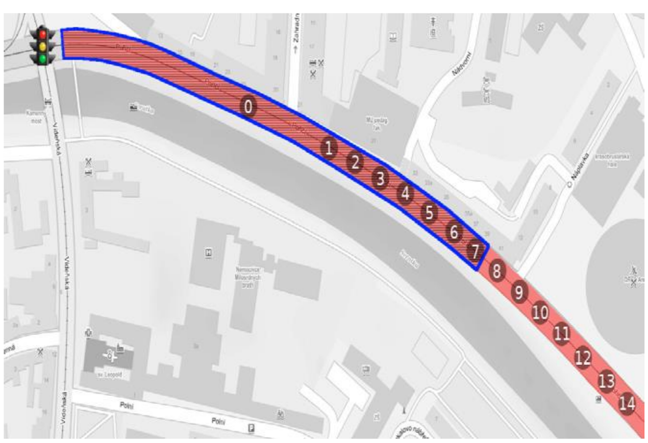


Fig. 21 Veins Traffic Simulation

Traffic Light: The traffic light is red by default and turns green when it receives a message from the fog to open. It stays open for 20 seconds before sending the fog a new reading detailing the number of automobiles waiting in its lane. The fog, which symbolizes the network's edge computing component, uses a particular algorithm to decide whether the next traffic light should be green (see Fig. 22).

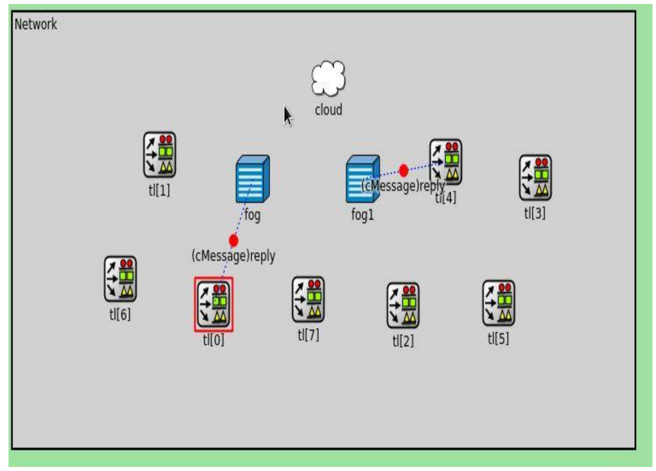


Fig. 22 Edge Computing for Traffic Signaling

For the traffic prediction we used Yolo to detect the vehicle count. The data was stored on firebase databased and later retrieved and processed to be trained and tested on LSTM. We used Root mean Squared error as the Loss function for LSTM to train again. Based on the calculated the Root Mean Squared Error for different junctions after training we found a Root Mean Squared Error of 0.24 for Junction 1 and 0.60 for Junction 3 (see Fig. 23 and 24).

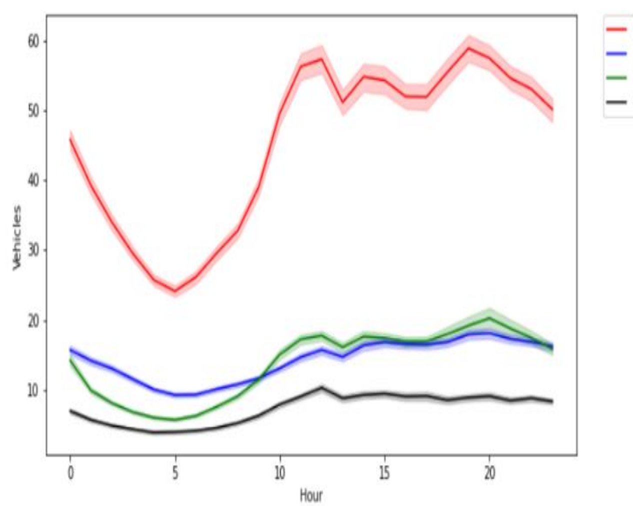


Fig. 23 LSTM Training Results on 4 junctions

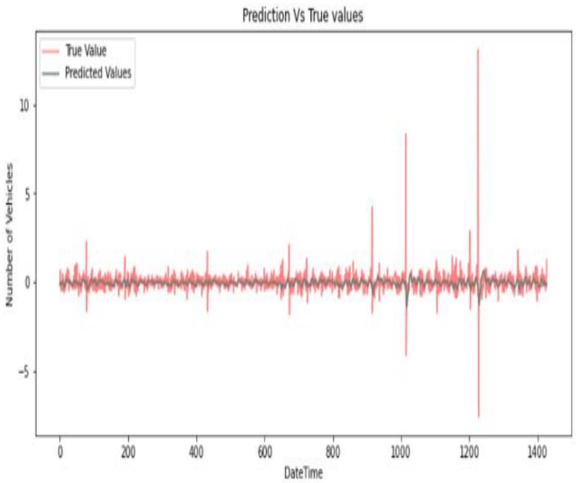


Fig. 24 LSTM Testing results on Test Data

IV. Recommendations

Besides capturing only, the vehicle count we can also use weather data for traffic prediction which will not only help in scheduling but also in maintenance planning. Also, we should use centralized computer system, adaptable communication network and compatible Traffic Signal controllers instead of implementing completely new and from the scratch solution which would cost significantly more while making a smart Traffic light.

The prediction accuracy can be increased by using spatiotemporal traffic flow prediction method combined with k-nearest neighbor (KNN) and long short-term memory network (LSTM), which can be called KNN-LSTM model. KNN can be used to pick associated or related neighboring junction with a test junction to capture spatial features of traffic flow. LSTM could then be utilized to mine temporal variability of traffic flow, paired with a two-layer LSTM network to predict traffic flow respectively in selected junctions. [18]

The coverage area of the smart street light system can be extended by using a web server to act as the central control unit and communicate with all the wireless sensors present in the coverage area.

Instead of scanning only for the traffic and detecting number of vehicles we can also use weather data, mapping data Data weather data to train our LSTM network for better traffic prediction (see fig 25)

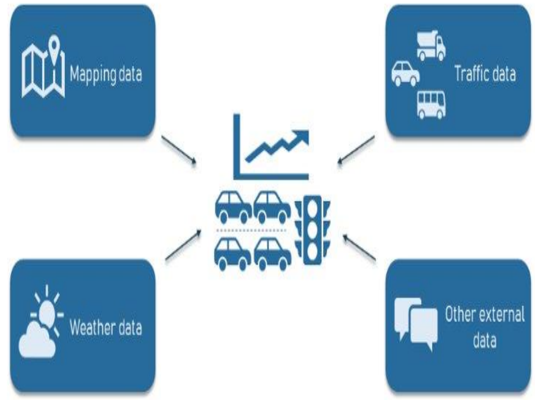


Fig. 25 Various sources of Data for LSTM

Lastly, we can integrate Wifi, camera and other sensors to monitor parking violations, enhance emergency response, support crime investigations, and do safety announcements [19] (see fig 26)

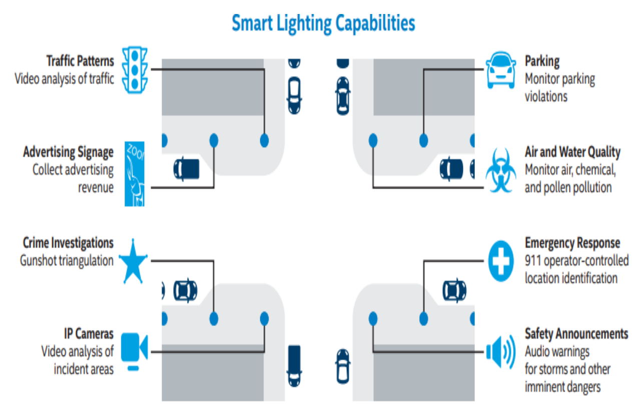


Figure 2. The benefits of smart street lights far exceed basic lighting; they can lead to improved safety, better services, and new revenue opportunities.

Fig. 26 Benefits proportional to proposed upgrades to streetlights

V. Conclusion

"We have not inherited the earth from our ancestors, instead we have borrowed it from our future generations." Therefore, it is obligatory that we scale and plan, with our future into consideration. Using the high influx of data generated by the traffic and by stationing a disposition of Wireless sensors we can curb the problem of Traffic congestion and extend the lifetime energy resources by preventing energy wastage which accounts for almost 50% of a typical city's energy bill [20]. Moreover, by enabling priority pass to EV's we can also save lifes. Thus our project supplements all the cause stipulated above.

REFERENCES

[1] "FOTW #1204, Sept 20, 2021: Fuel Wasted due to U.S. traffic congestion in 2020 cut in half from 2019 to 2020," *Energy.gov*. [Online]. Available: https://www.energy.gov/eere/vehicles/articles/fotw-1204-sept-20-2021-fuel-wasted-due-us-traffic-congestion-2020-cut-half#:~:text=The%20traffic%20decline%20associated%20with,3.5%20billion%20gallons%20in%202019. [Accessed: 01-Aug-2022].

[2] N. A. Razali, N. Shamsaimon, K. K. Ishak, S. Ramli, M. F. Amran, and S. Sukardi, "Gap, techniques and evaluation: Traffic flow prediction using machine learning and Deep Learning," *Journal of Big Data*, vol. 8, no. 1, 2021.

[3] N. Shamshad and D. Sarwr, "A review of Traffic Flow Prediction Based on Machine Learning approaches," *International Journal of Scientific & Engineering Research*, vol. 11, no. 3, Mar. 2020.

[4] R. Fu, Z. Zhang, and L. Li, "Using LSTM and GRU neural network methods for traffic flow prediction," *2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, 2016.

[5] D. Payne, "Poor ambulance response causes 700 deaths annually in Ireland," *BMJ : British Medical Journal*, 11-Nov-2000. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1173468/. [Accessed: 10-Aug-2022].

[6] C. Sommer, R. German, and F. Dressler, "Bidirectionally coupled network and road traffic simulation for improved IVC analysis," *IEEE Transactions on Mobile Computing*, vol. 10, no. 1, pp. 3–15, 2011.

[7] S. E. and UNEP, "Wastage of energy due to street lights on in daylight - ambassador report - our actions," *TUNZA Eco Generation*. [Online]. Available: https://tunza.eco-generation.org/ambassadorReportView.jsp?viewID=1905. [Accessed: 10-Aug-2022].

[8] E. A. Frimpong, "Assessment of Energy Wastage in Street Lighting," *Journal of Multidisciplinary Engineering Science Studies (JMESS)*, vol. 2, no. 7.

[9] Lau, Sei Ping & Merrett, Geoff & Weddell, Alex & White, Neil. (2014). StreetlightSim: A Simulation Environment to Evaluate Networked and Adaptive Street Lighting. Proceedings, APWiMob 2014: IEEE Asia Pacific Conference on Wireless and Mobile 2014. 10.1109/APWiMob.2014.6920267.

[10] "What is the IoT? everything you need to know about the internet of things right now," *ZDNet*. [Online]. Available: https://www.zdnet.com/article/what-is-the-internet-of-things-everything-you-need-to-know-about-the-iot-right-now/. [Accessed: 01-Aug-2022].

[11] Y. Liu and H. Wu, "Prediction of road traffic congestion based on Random Forest," *2017 10th International Symposium on Computational Intelligence and Design (ISCID)*, 2017.

[12] S. Du, T. Li, X. Gong, and S.-J. Horng, "A hybrid method for traffic flow forecasting using Multimodal Deep Learning," *International Journal of Computational Intelligence Systems*, vol. 13, no. 1, p. 85, 2020.

[13] "Understanding LSTM networks," *Understanding LSTM Networks -- colah's blog*. [Online]. Available: https://colah.github.io/posts/2015-08-Understanding-LSTMs/#fn1. [Accessed: 01-Aug-2022].

[14] "Introduction to yolo algorithm for object detection," *Section*. [Online]. Available: https://www.section.io/engineering-education/introduction-to-yolo-algorithm-for-object-detection/#:~:text=YOLO%20is%20an%20abbreviation%20for,probabilities%20of%20the%20detected%20images. [Accessed: 01-Aug-2022].

[15] "Firebase realtime database | store and SYNC data in Real time," *Google*. [Online]. Available: https://firebase.google.com/products/realtime-database#:~:text=The%20Firebase%20Realtime%20Database%20is,Learn%20more. [Accessed: 01-Aug-2022].

[16] Wia, "Espressif ESP8266," *Wia*. [Online]. Available: https://www.wia.io/things/espressif-esp8266#:~:text=Description,functions%20from%20another%20application%20processor. [Accessed: 01-Aug-2022].

[17] C. Sommer, D. Eckhoff, A. Brummer, D. S. Buse, F. Hagenauer, S. Joerer, and M. Segata, "Veins: The open-source vehicular network simulation framework," *Recent Advances in Network Simulation*, pp. 215–252, 2019.

[18] X. Luo, D. Li, Y. Yang, and S. Zhang, "Spatiotemporal Traffic Flow Prediction with KNN and LSTM," *Journal of Advanced Transportation*, vol. 2019, pp. 1–10, 2019.

[19] "Smart street lights for brighter savings - intel." [Online]. Available: https://www.intel.com/content/dam/www/public/us/en/documents/solution-briefs/smart-street-lights-for-brighter-savings-solutionbrief.pdf. [Accessed: 10-Aug-2022].

[20] "Everything you need to know about smart street lighting," *inteliLIGHT®*, 09-Mar-2021. [Online]. Available: https://intelilight.eu/smart-street-lighting/. [Accessed: 01-Aug-2022].

[21] “OMNeT++.” [Online]. Available: https://doc.omnetpp.org/omnetpp/SimulationManual.pdf. [Accessed: 10-Aug-2022].

[22] “A research of traffic prediction using Deep Learning Techniques,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 9S2, pp. 725–728, 2019.