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# A Novel Optimized LSTM Networks for Traffic Prediction in VANET

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**Abstract.** A network of vehicular cyber-physical systems uses wireless communications or Internet for efficient data transfer, which includes, safety, transportation details, mobility and sustainability. With the advent of vehicular IoT, smart transportation systems play a vital role in today's life for the prediction of traffic flows and efficient data transfer. With the advent of machine learning algorithms, prediction of traffic flow has reached its new dimension but still usage of single model machine learning algorithms needs improvisation in terms of prediction accuracy. Hence this paper proposes the new model of predicting the traffic flows based on the hybrid optimized learning algorithm, which integrates the BAT optimized and LSTM algorithm (BAT-LSTM). First, BAT Algorithm is applied to obtain the hyper parameters of each LSTM predictor. Again, LSTM prediction is trained using the training samples obtained by the optimized BAT algorithm. More than 100 hours of real-time traffic datasets were analysed and used for evaluating the proposed hybrid algorithms, which was then experimented on SUMO with OMNET++ platforms. The empirical study demonstrates that the proposed approach outperformed other existing approaches in regards of accuracy, sensitivity, and selectivity. It infers that the proposed approach is extraordinary performance for traffic prediction and management systems.

**Keywords:** Smart Transportation System; Vehicular IoT; SUMO; OMNET++; Traffic Congestions; Optimized learning algorithms.

# 1. Introduction

Due to modernization and urbanization, there is inclination in the population over the globe. The competence of transport systems has not emerged in a way with the abundant growth of the population. INRIX reveals a report that the global economic loss is estimated as $121 billion in 2011 expected to increase in 2021 to $199 billion due to traffic congestion (D. Schrank, et al, 2012). People have urged the brilliant transportation system with safety assured property, a coherent, systematic mechanism in dealing with congestion problems, and a resolution of an environmentally friendly system. The researchers are eager to attain the system level brilliant transportation system, as it is not much easy to reinstate the vehicle with the smart vehicle on road, not only solves the issue. The unique key attribute of an intelligent transportation system is communication propensity among the participants, which authorizes the information commutating among them. As a fruit of people's demand, Vehicular Ad hoc Network is a promising technology that acts as a part of an Intelligent transportation system. It facilitates communication between the intelligent vehicles on road.

The exchange of information between a vehicle and another vehicle or non-vehicle agent is termed as V2X, inclusively Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), and Vehicle-to Cloud (V2C) (S. Biswas, et al, 2006). VANET affords a platform for resolving disparate techniques for enhancing road safety by Stephan and Michele (Olariu, S., et al, 2009) as well as Brian (M. Danya Priyadharshini, et al, 2015) use V2V and V2X communication is contemplated as an important part of future ITS. IVC concepts are also practiced in crash mitigation, avoidance, and Intersection Collision Warning Systems.

VANET comprises of (i) On-Board Units (OBUs), (ii) Road Side Units (RSUs) (Taherkhani and Pierre, 2016). The Vehicular Communication Module (VCM), receives the various unit network traffic. It connects with the other devices in the vehicles for achieving the competent monitoring and managing of vehicles on road. Figure. 1 shows an exemplar of VANET, where OBUs are hook-up with RSUs.

VANET being commit towards to saving time and lives, Qian et al. (Z. Qian, et al, 2017) discuss the design and classification of VANET as a technically and economically confrontation. Since, the traffic procreates massive amounts of data that are congregated from heterogeneous devices, such as intelligent cameras and sensors. The challenging obstacle is how to store, process, interpret and manage the massive traffic data. The traffic data is constantly varying spatial-temporal data has dynamic dependencies. The spatial-temporal traffic data is affected by external attributes like road factors, weather conditions. Since, the traffic prediction is challenging task due to this factor and dynamic spatial – temporal dependencies.

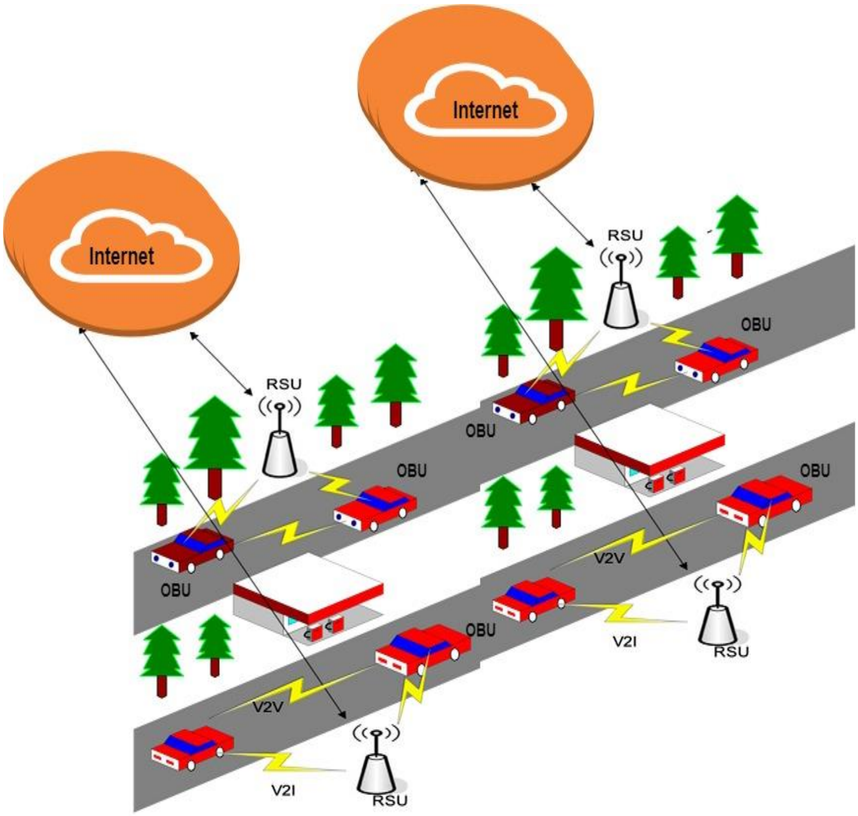


Fig. 1: VANET architecture

To resolve these issues, scientists have experimented with scholastic traffic flow prediction schemes tested on traditional model and machine learning approaches. The most effective algorithms such as Historical Average (HA), Auto-Regressive Integrated Moving Average (ARIMA) (B. M. Williams, et al, 2003) based on machine learning failed to satisfy the predictions, as it is working effectively on the small datasets. The existing technology is not gratified due to complexity in reflecting the traffic flow data characteristics. The recent emerging deep learning methods with complex architecture models can predict the accurate traffic flow (Xueyan Yin, et al, 2021). The accurate traffic prediction helps minimize road accidents and enhance traffic management.

The main objective of this paper is to increase the performance of LSTM by the integration of the BAT optimization algorithm. The proposed work main contributions are listed below

Our contribution is bifold. The two main phases are considered as the first work. The first part deals with the analyzes of different features collected from 100 Hrs. Real-time traffic data of Dehradun India.

Secondly development of a new hybrid BAT-LSTM learning algorithm that ensembles the BAT optimization algorithm with the LSTM network system was proposed and compared with other optimized algorithms to prove the proposed architecture finds its more suitability for the traffic flow prediction mechanism.

The paper organization is listed as: related works are described in section 2, s three phases working architecture of proposed method is appeared in section 3, Section 4 presents evaluation results and finally section 5 concludes the entire work with future enhancement.

## 2. Literature Survey

The advent of deep learning automatically observed the features from the large-scale dataset uses multilayer to detect the hidden information. To manage the traffic and forecast the crowds in the town region of Beijing and New York City. The author (B. M. Williams, et al, 2003) suggested the ST-ResNet – a deep learning strategy is employed as the crowds are moved instantly. The residual network framework is employed to temporal data, period of movement, properties of a crowd. The output of each branch on ST-ResNet is then aggregated with external factors such as weather and day to predict the inflow and outflow of the city. The experimentation results of the proposed ST-ResNet have significantly from 14.8% up to 37.1% lower RMSE was compared with the baselines of the existing ARIMA, SARIMA, VAR, and 4 DeepST variants, reveals that our propounded model has better generalization performance on existing traffic flow prediction tasks.

(Yuhan jia, et al, 2016) was inspired by the complex architecture of LSTM urban environment traffic prediction with the consideration of rainfall as an add-on factor. The traffic data on rainfall conditions of Beijing and china was learned for training and testing the LSTM in addition to temporal and spatial characteristics. The dataset is inclusive of July 8 to 14 rainy days with ten- and thirty-min predictions. The performance of LSTM is better than DBN in handling the multisource data with external rain factor uses only one hidden layer for LSTM but DBN uses three layers to handle the multisource data. The experimentation reveals that the deep learning methods outperform the traditional method.

(Kothai et al., 2021) propounded a new hybrid BLSTME (“boosted long short-term memory ensemble”) and CNN model for the traffic flow prediction. This framework obtains features form traffic images on the congested traffic roads. SUMO and OMNeT++. Tool was utilized to test the real traffic environment. The performance evaluation shows accuracy of 98%, recall of 94% and precision of 96%. It infers that this framework enhances performance of 10% higher than other models in regards of stability.

(Song et al., 2017) utilized CNN architecture to predict traffic. The Complex CNN efficiently handles the traffic data multiple source. This scheme totally have 5 layer and the 1st layer easily covers temporal data and other utilized for speed links. This propounded algorithm delivers to achieve the local dependencies and is a very low impact on noises in data. Thus, the CNN outperforms on adding multiple sub-models than subsisting models.

(Wei et al., 2019) proposed the AE-LSTM approach to predict the accurate .This predicts the traffic flow by choosing the specific historical and behavior data in the stream of traffic data. The complex multi-layer LSTM disassembles the received characteristics and historical traffic information for the prediction of traffic. The AE-LSTM approach exhibits elevated performance in anticipating the traffic flow in-stream data based on time and simple spatial attributes.

(Herbert et al., 2019) developed a high resolution in the prediction of accident model for portending the circumstances of the accident within some hours through big data analytics. With the big analytics approach, the author interferes the specific data from the large-scale heterogeneous data. The random forest (RF) is employed to sample the unbalancing data. By inheriting the features and attributes such as weather factors, arterial segments, date, time, circumstances of the accident are successfully portending. To improve the performance further, inclination angle of road, population of the region can be included to the dataset.

(Shengdong et al., 2020) worked on the HMDLF – The hybrid multimodal deep learning framework to forecast the traffic. The 1D CNN and GRU ("Gated recurrent units") are incorporated for the traffic prediction framework. England highway roads were chosen for experimentation. The hybrid CNN -GRU block heads the flow of traffic by confirms the long temporal dependencies for predicting the correlation among the journey speed in multimodal traffic flow of data. Thus, HMDLF encompass the time series expedite, error tolerance, multimodality input spatial and temporal data are attained to predict the traffic. However, the data collected for the dataset of England traffic consumes short period of time only.

(Kothai et al., 2020) did the examination of execution of Stationary model and Deterministic Portability models are finished utilizing AODV responsive directing convention. The recreation is completed in OMNET++ Simulator and the outcomes are introduced. After the examination, we saw that consolidating Stationary and Deterministic model gives 20% higher execution when contrasted with different models as far as number of occasions and time for more than one hub closure. By consolidating two Deterministic Models gives 10% better when contrasted with different models as far as number of occasions and time for one hub closure.

(Najada et al., 2018) made a VANET traffic dataset by utilizing real time traffic information. This information is applied for VANET human conduct model. Experimentation is done on the dataset by focusing on traffic congestion prediction. Traffic congestion can be controlled by traffic thickness and normal speed at some random point. Profoundly thick models are the essential meaning of clog bringing about lower rates of moving vehicles. Three time-arrangement models ARIMA, BATS, TBATS, and a neural organization model are created and applied them in to made VANET information to examine and anticipate the all-out number of hubs in a group (thickness) and the normal speed of the hubs. Time series prediction models are approved by contrasting the four created models as far as MSE, MAE, MAPE, and MASE. Principle benefit of this work is, the made dataset and created models can help with anticipating cluster density and normal hub speed to identify clog, which will improve course route. Primary impediment of this system is, Enormous information prompts significant expense of calculation and preparing.

(Taherkhani and Pierre, 2016) proposed a "Machine Learning Congestion Control" ("ML-CC") technique to address the congestion that may happen at crossing points, because of the huge measure of correspondences between vehicles halted before red traffic signals. This methodology was additionally a unified and limited technique in light of the fact that each RSU set at every convergence is liable for controlling the clog happening at that crossing point. ML-CC technique comprised of three units including blockage discovery, information control and congestion control units. Communication parameters determined by ML-CC methodology are sent by RSU to the vehicles halted before red traffic signals to diminish the impact in channels and control the clog. Also, ML-CC system expanded the normal throughput and PDR extensively. From the outcomes the proposed system is an adaptable in light of the fact that the exhibition measurements don't change essentially by expanding the quantity of vehicles in the organization. Be that as it may, for Real vehicular organizations, a RSU should be set at every crossing point. Additionally, since congestion control is a constant cycle, RSUs may should be outfitted with Graphic Processing Units (GPUs) for rapidly executing AI calculations. Note that the AI calculations lead countless estimations and activities that takes a ton of time.

(Najada and Mahgoub, 2016) utilized H2O and WEKA mining instruments to assess five classifiers on two major workbench datasets. The pre-owned classifiers are: Naive Bayes, C4.5, Random Forest, AdaboostM1 (with the base classifier C4.5), and Bagging (with the base classifier C4.5). Highlight choice is applied and tackle the class unevenness issue also. From our analyses Naive Bayes gave the ideal outcomes, with the most reduced calculation time. The general examination and the extricated designs too as discoveries can help chiefs and professionals to improve the transportation framework cleverly and grow new principles. Results uncovered that driver's credits, for example, age and sex could be anticipated effectively up to 70% by giving different ascribes to a mishap or loss. Just limit is, it need Consideration for the area of people, since area is a vital marker of human versatility.

(Najada and Mahgoub, 2017) Developed a reliable real-time prediction models for occurrence clearance time. Three forecast models DL (Deep Leaning), DRF (Distributed Random Forests), and GLM ("Generalized Linear Model") are created and looked at their exhibition brings about terms of MAE, RMSE, and MSE. The investigation uncovers that spatial and fleeting highlights are the main highlights that impact the forecast exactness. The injury seriousness immensely affects the freedom time. Terms of each kind of occurrences are plainly unique. In this way, each type needs various sorts of reactions and distinctive number of crisis vehicles to clear them. A curiously, the outcomes show no importance for the climate conditions in impacting the leeway time. This investigation showed that DL is a promising model to foresee episode term progressively. Fundamental downside this system is, there is a trouble to sum up the created models to various districts, were these models area explicit models.

(Yi et al., 2017) analysed transportation large information gathered from 0.5 million test vehicles with OBD (vehicle route), by Pandas. A DNN model with supervised learning was utilized to assess connect based traffic stream conditions utilizing genuine traffic information. The DNN model was fabricated utilizing Tensor Flow from Google Inc., and coded utilizing TFLearn. It ought to be noticed that it is vital to mark the info information when utilizing directed profound learning DNN. TPI was utilized to recognize clogged traffic conditions from no blocked traffic conditions, and results show that the proposed 3 layer model could appraise blockage with 99% exactness. This examination shows the potential for Tensor Flow profound learning models for the exact investigation of ongoing traffic information, and exact assessment of traffic stream conditions. There are, notwithstanding, a few impediments in this exploration; because of memory limit limits for instance, just 1% of traffic information for a given day could be utilized. To expand exactness of assessment and improve the DNN design, it is presently important to reclassify the TPI as indicated by transportation designing information.

(Lu et al., 2015) set up the local traffic stream connection model is for constant traffic stream forecast. It Uses speed and inhabitance to assemble the traffic stream state grouping model. To improve the plausibility of traffic stream state bunching, simulated annealing genetic algorithm based fuzzy *c*-means (SAGA-FCM) is used .Case study shows that the estimation of target work determined dependent on SAGA-FCM is better. Precision of proposed model is generally high.

(Koesdwiady et al., 2016) extremed target is to guarantee super-effective route and more secure travel venture. Creators proposed an extensive expectation engineering that consolidates DBNs and information combination to infer more exact traffic stream forecast in San Francisco, Bay Area utilizing traffic stream history and climate information. We have separated a few situations to feature the value of utilizing information combination at choice level in our proposed engineering. Analysis results show that our information driven metropolitan traffic framework forecast outflanks the state of the art methods. This higher traffic expectation exactness guarantees better activity and the board traffic methodologies. Besides, the execution of the proposed model requires altogether less assets. The principle detriment of this structure is memory prerequisite for the pre-preparing and managed preparing measures significantly bigger.

(Goves et al., 2016) introduced the aftereffects of applying AI, explicitly ANNs, to appraise traffic conditions a 15 minutes into the future given current/memorable traffic data. For this examination, information from Highways England's Motorway Incident Detection and Automatic Signaling (MIDAS) framework for around 20km of the M60, M62 and M602 motorway close to Manchester, UK was utilized to fabricate a transient expectation model. To decrease the intricacy of the issue, the quantity of info measurements to the model was effectively diminished utilizing an auto encoder. The last model shows excellent prescient force with 90% of all expectations inside 2.6 veh/km/path of noticed qualities. The methodology received in this examination is one that can be moved to different pieces of the UK motorway network where MIDAS is introduced, and once prepared, the utilization of an ANN is direct. A calculation, for example, the one inferred has various applications including: refining forecasts inside shrewd vehicle frameworks (ITS) and/or empowering traffic regulators to take proactive choices to relieve the effects of anticipated clog. It could likewise be the motor behind a "traffic-cast" framework which could give the public a figure of expected traffic conditions. This could bring about diminished clog on the vehicle framework as openness to more precise data could support gainful social changes in clients.

(Abadi et al., 2015) have assessed traffic streams on the whole connections in a rush hour traffic network where traffic information are inaccessible and utilized the data to foresee momentary traffic stream for the whole transportation organization. An enormous organization in the San Francisco zone was utilized to exhibit the proficiency and precision of the strategy. Monte Carlo recreations were utilized to represent irregular impacts and vulnerabilities. The outcomes exhibit exact expectations of traffic stream rates up to 30 min early under ordinary activities. On account of occasions, the expectation calculation adjusts to the progressions and alters its prediction yields with great precision. One of the constraints of this paper is the absence of sufficient number of information during ordinary and incident traffic conditions to play out extra tests.

(Lv et al., 2015) proposed a novel profound learning-based traffic stream expectation strategy, which considers the spatial and worldly relationships intrinsically. A stacked auto encoder model is utilized to learn conventional traffic stream highlights, and it is prepared in an eager layer savvy design. To the most awesome aspect our insight, this is the first occasion when that a profound design model is applied utilizing auto encoders as building squares to address traffic stream highlights for prediction. In addition, tests exhibit that the proposed strategy for traffic stream prediction has prevalent execution. Be that as it may, the proposed model doesn't perform well in low rush hour traffic stream conditions, which is equivalent to existing traffic stream expectation techniques.

(Rivoirard et al., 2016) introduced a short survey of various versatility models utilized for assessing execution of steering conventions and applications intended for vehicular impromptu organizations. Especially, it depicts how exact versatility follows can be worked from a true vehicle traffic dataset that installs the principle attributes influencing vehicle-to-vehicle correspondences. A successful utilization of the proposed portability models is represented in different street traffic conditions including imparting vehicles outfitted with 802.11p. This investigation shows that such dataset really contains extra data that can't totally be acquired with other scientific or recreated portability models, while affecting the aftereffects of execution assessment in vehicular specially appointed organizations. The distinction in the speed profiles affects the outcomes got through reproduction for a few exhibition measurements like the heap, the throughput and fundamentally the postponement. The below Table 1 gives the literature survey on traffic flow prediction using machine learning algorithms.

Table 1: Survey on traffic flow prediction using machine learning algorithms

| Author & Year | Methods | Objective | Limitation |
|---|---|---|---|
| Yuhan Jia [2016] | LSTM | To predict the traffic flow in urban accurately | During a long prediction of 30 mins, an error occurs. |
| Kothai et al. [2021] | BLSTME-CNN | To Predict traffic flow in Smart cities | Concentration needed to explore different combinations of speed and occupancy and to handle larger datasets |
| Song et al. [2017] | CNN | To predict the traffic flow and To anticipate the traffic speed | The multiple sub -models are persistent |
| Wei et al. [2019] | AELSTM | To predict the accurate traffic flow | spatial and time patterns are very simple and this leads premeditated in this framework |
| Herbert et al. [2019] | (i) XG boost algorithm (ii)Balanced RF algorithm | To predict the traffic flow and introduce, prognosticate model using big data analytics | It needs more properties in a dataset with populace density are tenacious for sensitive execution |
| Shengdong et al. [2020] | HMDLF | To predict traffic flow in short time | weather conditions are considered while collecting the data in short time period |

## 3. Proposed Methodology

Figure 2 shows the proposed architecture for the prediction of traffic flows. There are totally 3 phases in the proposed architecture namely Data collection unit, feature Extractor, and Predictor using proposed BAT -LSTM methods. The detailed working mechanism of this 3 phased are described in following sub sections.

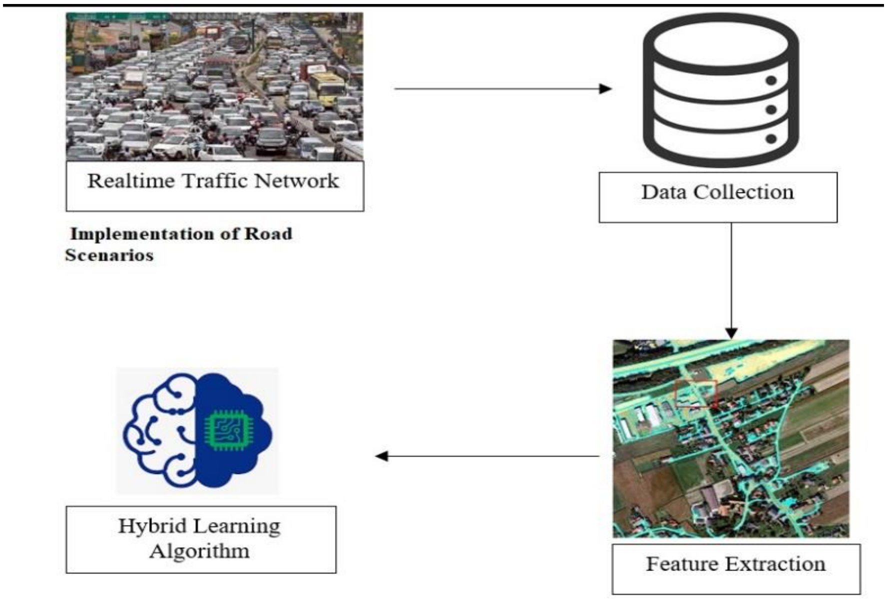


Fig. 2: Block diagram for the proposed architecture.

## 3.1. Data Collection Unit

The SUMO simulation software is utilized to generate real time traffic scenario. All vehicles positions on the road were computed by a microscopic traffic simulator at time t based on vehicles and road characteristics. These are mainly utilized for vehicle demonstration on a graphical user interface (GUI). The Figure 3 and Figure 4 displays the different real-time scenarios for the vehicular traffic systems. Nearly 100 hours of traffic data were collected for 30 days and used as the training samples for the proposed networks.

## 3.2. Feature Extraction

Once the real time traffic scenario is generated in SUMO-OMNET, different features such as latency, Speed of the vehicles, Signal Strength, Direction, distance, vehicle, throughput, throughput(T), No of data transmission(NRSU ), were calculated manually. After calculating the features from the real-time traffic scenarios, the calculated features are used for the prediction of traffic flows.

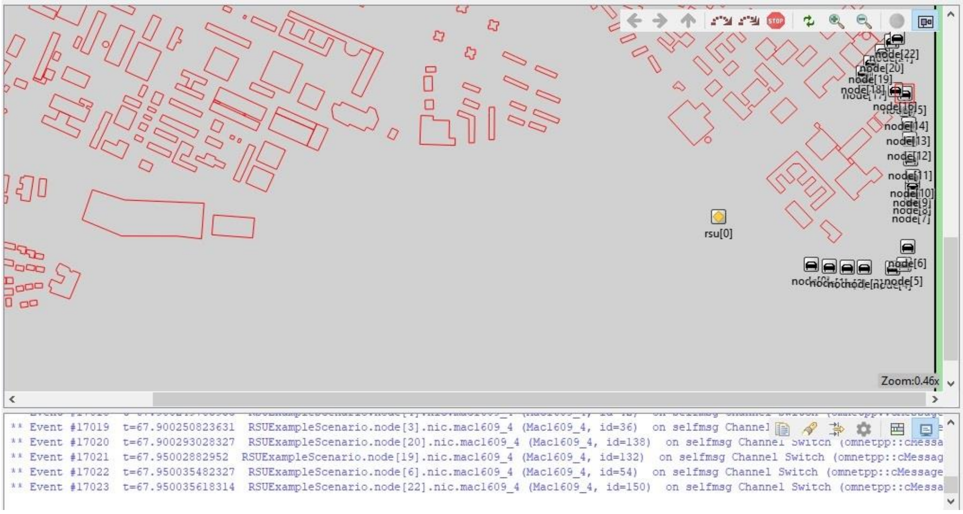

Fig. 3: Real-Time traffic environment generated by SUMO-OMNET.

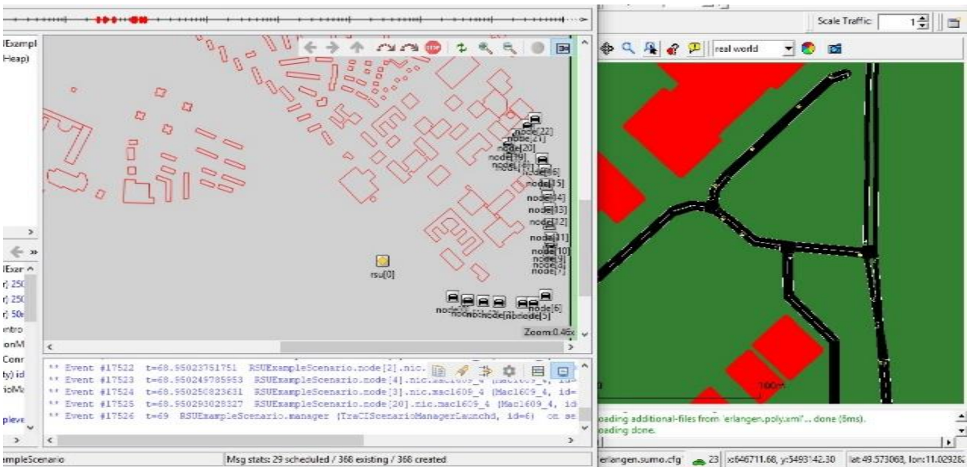

Fig. 4: Real-Time traffic environment generated by SUMO-OMNET.

## 3.3. Proposed Learning Algorithm

### 3.3.1. Long Short Term Memory (LSTM)

A LSTM is a upgraded version of RNN. This architecture comprises of 4 units namely cell, IG-("Input gate"), OG-("Output Gate"), FG-("Forget Gate"). This structure has capability to remember the values over time intervals. The gate input vector values are 0 and 1. If the vector values is 1 means the gate passes the data or it does not allow the data.

If the current input vector $Q = (Q_1, Q_2, \cdots, Q_{t-1}, Q_t)$ & the output vector $\mathbf{O} = (O_1, O_2, \cdots, O_{t-1}, O_t)$ then gate calculation is given in equations (1) and (2) as follows:

$$Z(q) = \sigma(\boldsymbol{Kq} + \boldsymbol{b}) \quad (1)$$

$$\sigma(\boldsymbol{Q}) = 1/(1 + e - Q) \quad (2)$$

$\boldsymbol{b}$ → indicates the BVb(“Bias Vector).

$\boldsymbol{K}$ → indicates the WM (Weight Matrix)

Cell state is given in equation (3) as follows

$$C_t = f_t C_{t-1} + i_t tanh(Z_c[Q_{t-1} Q_t + b_c ] \quad (3)$$

Where $Z_c$ → indicated cell state’s WM

$b_c$→ Indicated cell state’s BV.

$i_t$→ → Indicates IG

$f_t$ → indicated FG

The calculation of the IG & FG can be respectively expressed as equations (4) and (5):

$$i_t = \sigma(Z_i \cdot [Q_{t-1}, Q_t] + b_i) \quad (4)$$

$$f_t = \sigma(Z_f \cdot [Q_{t-1}, Q_t ] + b_f) \quad (5)$$

Where

$Z_i$ → indicates WM of IG

$Z_f$ → indicates WM of FG

$b_i$ → indicates BV of IG

$b_f$ → indicates BV of FG

The output $D_t$ can be represented as equation (6):

$$D_t = \sigma(Z_o \cdot [Q_{t-1}, Q_t] + b_o) \quad (6)$$

Where $Z_o$ → indicates the WM of OG

$b_o$ → indicates the BV of OG

The final LSTM output with its activation function is expressed in the mathematical expression by equation (7).

$$O_t = D_t \cdot tanh(c_t) \quad (7)$$

Since LSTM tends for decreasing the performance for the larger datasets, the Optimization algorithm s used to tune hyper parameters for the proposed architecture to achieve better accuracy.

### 3.3.2. Bat Optimized LSTM Networks

The bat calculation relies on the echolocation of microbats. The BAT algorithm working mechanism is as follows

1. Echolocation can be utilized by all bat to find the prey with its distance
2. Bats fly arbitrarily with "speed $v_i$ at position $x_i$ with a recurrence $f_{min}$, fluctuating wavelength and loudness $A_0$" to look for prey. The bats frequently changes its attributes according to prey distance.
3. The loudness can fluctuate from extensive (positive) $A_0$ to a minimum constant value Amin.

The best bat is chosen among all bats based on above mentioned conditions. The bat frequency is calculated by using equation (8). The updated initial distance $x_i^t$ and velocity $v_i^t$ using the 3 rules are given below in equation (9):

$$f_i = f_{min} + (f_{max} - f_{min})\ \beta \tag{8}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{9}$$

Where

$\beta$ € (0,1),

$f_{min}$ Indicates the minimum frequency = 0,

$f_{max}$ Indicates the maximum frequency.

Every bat has assigned with $f_{min}$ and $f_{max}$. generally bat algorithms is known as frequency tuning algorithm to present better investigation and exploitation. The loudness and emission presents a perfect mechanism with promising solutions.

Different loudness and the pulse emission are considered for the better solution. Since the loudness normally diminishes when prey is discovered by bat and pulse emission rate expands, the loudness can be picked as any estimation of accommodation, among $A_{min}$ and $A_{max}$ accepting $A_{min} = 0$ implies that a bat has quite recently discovered the prey and briefly quit transmitting any stable.

As discussed in Section 3.4.1, a decrease in performance is noticed in LSTM for handling the larger datasets. To encounter the above mentioned issue, the proposed BIL network combined the BAT algorithm with the LSTM network for the hyper parameters optimization such as input bias weights and hidden layers. The working mechanism of the proposed BIL network is presented in Algorithm-1. Table 2 presents the BAT optimized parameters used for tuning the network.

Table 2: BAT parameters incorporated for LSTM optimization

| SL.NO | Incorporated Bat parameters | Description |
|---|---|---|
| 01 | BATS count | 20(Initial) |
| 02 | Initial Velocity | 10% |
| 03 | Iterations count | 75 |

| | | |
|---|---|---|
| 04 | Loudness at initial condition | 1 |
| 05 | Pulse rate at initial condition | 0 |
| 06 | fmin | 0 KHZ |
| 07 | Active threshold | 99% Accuracy in Prediction/Classification |

**Algorithm 1 BAT optimized LSTM Training network(BILS)**

**Input**: Hyper parameters : no of epochs, bias weights, hidden layers
**Output**: Maximum Classification
Initialize the position of bats randomly
For every iteration
Find the best position of bat using Equation(9)
**while** stopping criteria not meet to do
    Select hyper parameters by using Equations (7),(8)
    Update the position of each bat by using the Equation (9)
    Calculate fitness function by using equation F = Maximum accuracy
    Update the hyper parameters of LSTM
**end while**

# 4. Result and Discussion

For the evaluation of performance, the features are extracted from different traffic datasets for testing phase and training phase. Among over all data, 70% adopted for training phase, remaining is for testing phase. The following equations (10-12), are the evaluation parameters to test the proposed framework.

$$Accuracy = \frac{DR}{TNI}\ x100 \tag{10}$$

$$Sensitivity = \frac{TP}{TP+TN} x100 \tag{11}$$

$$Specificity = \frac{TN}{TP+TN}\ x100 \tag{12}$$

Where, DR and TNI indicates the No. of Detected Results & Total No. of Iterations respectively. TP and TN indicates True Positive and True Negative values respectively and for the different cases the performance evaluation done for the proposed BAT -LSTM algorithms and which are presented as follows.

For the prediction accuracy evaluation, there are totally 100 trials are executed for the vehicular transportation networks. The predicted accuracy is compared with the LSTM (Without Optimization) which are given as follows.

Figures 5-7 show the analysis accuracy, sensitivity, and specificity for the different existing learning models and proposed architecture. The results graphs clearly infers that the proposed BAT-LSTM has maintained a constant accuracy of 99% whereas the other algorithms produced lesser accuracies, which varies from 91% to 96%. Meanwhile, the sensitivity and specificity are high for the proposed algorithm (99%), whereas the other existing models exhibit 90% to 95% respectively. Hence it is proved that proposed LSTM finds its strong suitability for the prediction of traffic flows. In summary, some fascinating findings can be summarized which are as follows as

1. The proposed BAT-LSTM has outperformed all other existing algorithms in regards of sensitivity, selectivity, and accuracy of prediction, which implies that the proposed BAT-LSTM is considered to be the more powerful algorithm for traffic flow prediction.
2. The above Figures 5, 6 and 7 clearly show that the proposed hybrid algorithm is much better than the other learning algorithm without the optimization and other optimization in terms of its performance, such as accuracy of prediction and sensitivity.

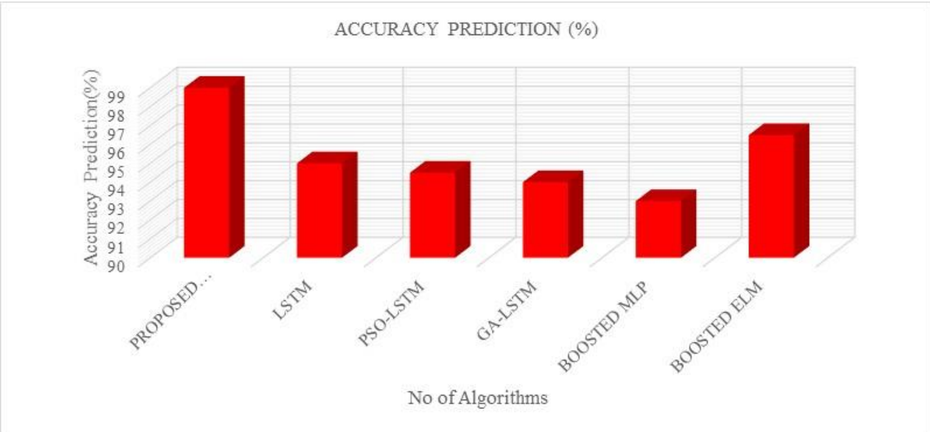


Fig. 5: Comparative Analysis of Accuracy between the Different Learning Algorithms.

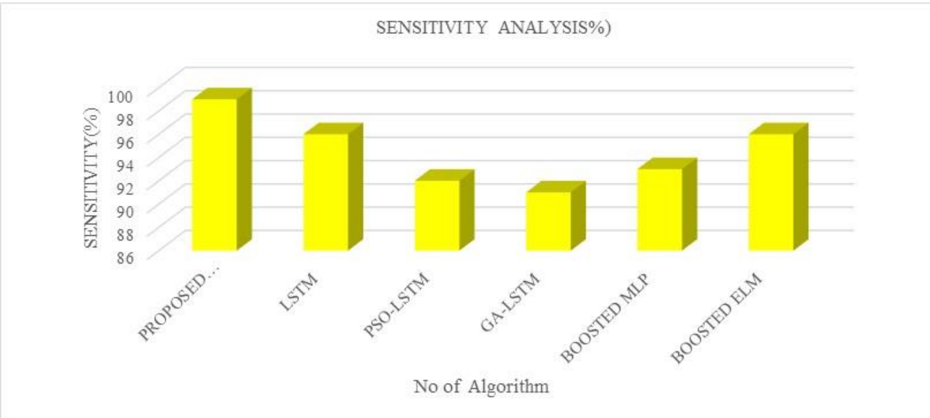


Fig. 6: Sensitivity Analysis: Proposed Algorithm Vs other existing Learning Algorithms.

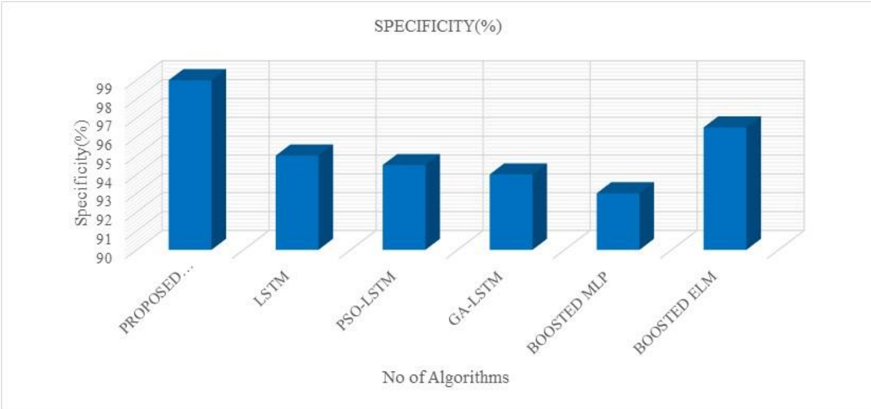


Fig. 7: Specificity Analysis: Proposed Algorithm Vs other existing Learning Algorithms.

The proposed BAT-LSTM infers that integration of the ensemble technique significantly improves the singles models hence the of proposed BAT -LSTM approaches highly suitable for traffic flow forecasting.

## 5. Conclusion

In this paper a BAT-LSTM learning approach that introduced which incorporates the BAT Optimization algorithm for fine-tuning the LSTM classifiers hyper parameters. Then, the proposed BAT-LSTM learning approach is applied to predict the traffic flows from real-time road scenarios. For performance evaluation, real-time traffic scenarios were collected from Dehradun City, India, and different features were extracted for the input to the proposed learning approaches. The final outcome strongly proves that the proposed BAT-LSTM approach achieves efficient performance in the traffic flow prediction and outperformed other single machine learning models and optimized learning techniques in regards of accuracy, selectivity, and specificity. In addition, the proposed approach can also be employed in each vehicle for accurate traffic flow prediction, which in turn finds its place of implementation in smart cities.

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