Undergraduate Conference on Intelligent Computing and Systems (UCICS 2025)
26-27 February, 2025; Varendra University, Rajshahi, Bangladesh

Enhancing Civic Mobility: The Synergy of IOT Road Data Monitoring and Artificial Intelligence in Smart Urban Infrastructure

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***Abstract*-- Smarter cities will benefit from real administration of the vehicular activity, which challenges a real and urgent situation demanding imaginative highlights to comprehend. The paper proposes an AI work overseeing street stream in real-time through the correlative study of IoT-based activity information. IoT edge sensors combined with machine learning calculations such as bolster vector machines, calculated relapse, k-nearest neighbors, and profound learning models such as long short-term memory empower more exact short-term and long-term determining of activity. The results outperform state-of-the-art methods and enable real-time monitoring for proactive decision-making and active activity management. The research shows how IoT and AI can be very much capable in the clearance of congestion, making stride urban mobility and constituting keen transportation framework in shrewd cities.**

Keywords: *Smart cities, IoT, Machine learning, Traffic prediction, Big data analytics, Deep learning, Real-time monitoring, Traffic management, LSTM, Optimization algorithms.*

I. INTRODUCTION

Savvy cities coordinated state-of-the-art advances to improve the quality of life for citizens and progress the conveyance of urban administrations [1], [2]. Among different savvy city activities, activity administration may be a basic zone of center. Quickened urbanization and innovative headways in cutting edge cities posture noteworthy challenges to proficient activity administration, basically due to urbanization and blockage emerging from these variables [3], [4]. Tending to this issue, developing innovations such as the Web of Things (IoT) [5]–[7] have earned noteworthy consideration. IoT encourages the collection of real-time information on activity designs, street conditions, and vehicle developments. This real-time information, frequently alluded to as huge information, holds gigantic potential for making exact and energetic activity forecast models [8], [9]. In any case, the volume, speed, and assortment of traffic-related information produced by IoT gadgets display both challenges and openings for activity forecast [10], [11].

Conventional activity modeling strategies have battled to oversee and analyze endless and differing datasets. Be that as it may, the coming of huge information analytics and machine learning calculations has presented modern bearings for extricating fast and prescient investigations of activity scenarios. Exact activity estimating and ideal activity administration essentially contribute to lightening clog, diminishing travel time, fuel utilization, and toxins, whereas improving security and operational proficiency.

The objective of this investigate is to improve traffic expectation techniques for savvy cities by leveraging the developing potential of IoT [13], [14], huge information analytics [15], and optimization calculations. This consider points to create a comprehensive and adaptable system for activity forecast and stream optimization. It'll evaluate the viability of different machine learning calculations in handling and analyzing large-scale activity information. The

challenges and openings related with activity estimating in savvy cities, especially including machine learning and profound learning coordinates with IoT-based information collection [16], have gathered considerable consideration in applications and investigate spaces.

II. LITERATURE REVIEW

Studies on innovative approaches to traffic prediction and management systems based on the Internet of Things have sought solutions to these challenges. For instance, Neelakandan et al. [17] set about doing a benchmarking study on an IoT-based traffic prediction and signal management system inside a smart city. Their proposal used an Intel 286 chip and engaged data collection and feature processing, segmentation, optimization, and management of traffic data enabled by IoT. An Elman neural network [18], which outperformed other tested methods, was employed for the classification of traffic data for congested areas.

Similarly, Lilhore et al. [19] proposed on adaptive traffic management scheme for smart cities with the aid of machine learning and IoT. The scenarios listed covered different aspects of the transport systems available in urban setups. At the heart of this system lay a clustering algorithm based on machine learning that detected anomalies and optimized the scheduling of traffic lights according to traffic flow and nearby signal intersections. The results of the simulation proved that this was performed significantly better than the previous methods in terms of median reduction in congestion times, vehicle idle times, and accidents [20].

The body of research focuses on the potential of combining IoT, machine learning, and big data analytics to build on the idea of a smart city traffic management system.

III. METHOD AND IMPLEMENTATION

The proposed design of the location-based information collection from IoT gadgets on the thruway has three central components: the highway-based IoT switch; the IoT stage; and the information center. The design in this respect and its components for gathering information from the IoT gadgets on the street are appeared in Figure 1. The IoT switch acts as a portal for interfacing and transmitting information from IoT gadgets to other frameworks. It is the IoT stage that permits for the administration and investigation of collected information, grasping information ingestion techniques and security conventions. The information center employments AI calculations for preparing the information and thus inferring experiences that offer assistance in overseeing activity effectively. This design serves as a conversion point of IoT street activity information and AI scaled up to make an productive activity change arrangement for urban versatility in savvy cities.

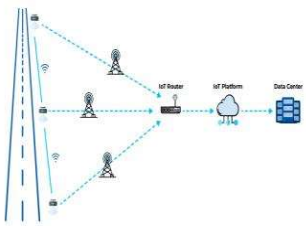

Figure 1. IOT architecture for SC traffic data collection

An amazing dataset around vehicle activity has been provided by the Shah Amanat Bridgein zone, Chattogram in Bangladesh for utilize in this paper. Datasets are compiled from fastidious perceptions of vehicle activity between any two points-the begin and conclusion of the street portion. In arrange to pick up exact and persistent information, sensors are found off the street sections from crossing points; in this manner, vehicles don't halt at ruddy lights at the sensors, subsequently not ruining such information collection. This course of action permits a appropriate examination of activity stream and patterns along the desired street portion, which gives important understanding into the elements of vehicle development.

Starting with exploratory data examination is for the most part a shrewd choice because it permits one to pick up understanding into critical characteristic highlights of the dataset in hand, like, its measurement, the estimate of the test, and sorts of information. In this case, the dataset comprises of a add up to of 12,037 information focuses over 8 properties. Figure 2 gives a measurable representation of a test of the information. The sensor network segment is most vital for setting up a arrange on Serene endpoints for the perusing from the sensors. Furthermore, whereas the information wrapper demonstrate semantically explains the information, we center primarily on the crude information alone without touching on semantic comments given by the wrapper show.

The information comprises two foremost sorts of records, which are the crude information records and the metadata records. Additionally, the dataset has metadata, which comprises of other critical relevant data, for case, the areas of the two sensors utilized for information collection, the separate between these sensors, and their inevitable scope and longitude. This data will give understanding into physical format and positions along the street section, improving the spatial setting and way better understanding of the dataset made.

	status	avgMeasured Time	avgSpeed	medianMeasured Time	TIMESTAMP	vehicleCount	_id	REPORT_ID
0	OK	66	46	66	2024-10-13T11:30:00	7	190000	158324
1	OK	69	37	69	2024-10-13T11:35:00	5	190449	158324
2	OK	69	32	69	2024-10-13T11:40:00	6	190898	158324
3	OK	70	41	70	2024-10-13T11:45:00	3	191347	158324
4	OK	64	38	64	2024-10-13T11:50:00	6	191796	158324
...	...	...		...	...	...	...	...
12033	OK	1798	28	1798	2024-11-13T10:20:00	0	32507360	210199
12034	OK	1798	37	1798	2024-11-13T10:30:00	0	32507801	210199
12035	OK	1798	31	1798	2024-11-13T10:35:00	0	32508244	210199
12036	OK	1798	46	1798	2024-11-13T10:40:00	0	32508648	210199
12037	OK	1798	40	1798	2024-11-13T10:45:00	0	32509519	210199

Figure 2. Sample data illustration and dataset overview

A. Feature engineering

In building a show, one must go through thorough information investigation to check that the dataset is able for demonstrate input. Within the current dataset, the datetime column is exceptionally wealthy in data, but its string nature needs preparation for an successful examination. Direct treatment of time may dispose of data related to the deviation of characteristic wonders, particularly when moving from 23:00 to 00:00. The cyclic nature of time must be accounted for because every day periodicity is evident. One effective and viable approach to handle periodicity may be a combination of sine and cosine changes, which abdicate significant highlights that signify "time of day" and "time of year." These transformations improve the representation of time-dependent designs, honing the capacity of the show to capture dynamism within the information over time.

Figure 3 outlines how time showed up in its purest frame, spoken to by the green plot, which is in hours from to 23. The other plots incorporate changes of sine and cosine of the time. It makes a difference to normal over 5 minutes' worth of information to create the forecast of activity design fitting over a more amplified period less demanding. Hence, 12 columns of information are amassed into a single push, with the unused dataset containing one push for each hour.

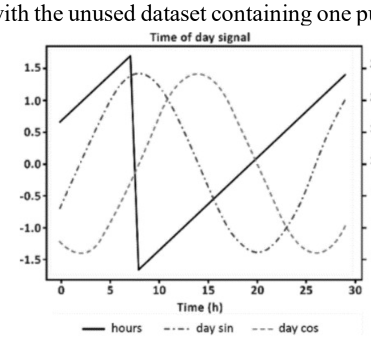

Figure 3. Transformation of time intervals for long-term traffic pattern prediction

B. Machine learning methods

Different models were utilized in this thing about to foresee activity designs based on the collected information, which included both classical factual strategies and progressed profound learning strategies. Such an assortment of models permitted a comprehensive ponder to be made of distinctive modeling approaches and their adequacy in capturing the complexity of activity designs.

C. Linear regression

Straight relapse may be a factual demonstrate utilized to analyze the direct relationship between a subordinate variable and one or a few free factors. It points to determine a straight condition that best fits the information and gives a strategy to foresee the esteem of the subordinate variable decided by the free factors [21], [22]. In activity expectation, direct relapse can analyze how changes in autonomous factors, such as time of day or climate conditions, influence activity conditions.

D. K-nearest neighbors

K-nearest neighbors speak to a common and well known machine-learning calculation for tackling classification and relapse issues. This calculation predicts primarily after doling out a course to the input by distinguishing the k-nearest neighbors of that information point and looking upon their essential qualities. For activity forecast, k-nearest neighbors can take advantage of the similitude with other designs and attempt the forecasts based on the execution set up by adjacent occurrences [23], [24].

E. Support vector regression

Back vector relapse could be a sort of back vector machine outlined for relapse issues [25]. They point to discover the work that maps input information onto yield values whereas minimizing forecast blunders. Bolster vector relapse finds the fundamental data patterns and makes expectations by recognizing within the high-dimensional highlight space a hyperplane containing a subset of preparing tests; these tests are characterized as back vectors.

F. Long short-term memory

LSTM may be an extraordinary kind of repetitive neural arrange (RNN) that was created to illuminate the specific vanishing angle problem of conventional RNNs. In this case, a really little slope utilized to upgrade weights leads to a moderate learning of long-term conditions. This issue has been unraveled by LSTM utilizing the memory cell and gating mechanisms, allowing to keep the stream of data in time for an awfully long period of time [26], [27]. LSTMs are regularly utilized totally different areas counting activity expectation due to their capacity to show and capture complex worldly connections.

The usage of these models was based on the well-known Tensor Flow and PyTorch profound learning systems that permit simple development and preparing of neural systems [28]. To this conclusion, this cross breed technique endeavored to combine the interpretability and space understanding of factual models with the prescient capacity and design capture of profound learning.

IV. RESULTS AND SIMULATION

Comes about of us ponder to improve urban versatility through the integration of IoT street activity information with counterfeit insights are empowering. We embraced a 70% preparing, 20% approval, and 10% test information part with no rearrange. In our to begin with errand of anticipating activity for the following three hours from the current values of all highlights, we executed directed machine learning calculations such as direct relapse, K-nearest neighbor, and bolster vector machines. The execution comes about for these models were direct relapse, 41; bolster vector relapse − 46; and K-nearest neighbor, 43. It was moreover commendable of noticing that these models would have moderately destitute execution when activity is anticipated for longer timesteps into end of the.

An LSTM layer of RNN has been applied, which works best for time arrangement information. RNNs handle time arrangement information within the shape of arrangements, keeping up a few inner state over time steps. Sometime recently preparing the LSTM show, the information was preprocessed by the strategy of information windowing. This approach permits for a rolling window of input for preparing and testing. The demonstrate employments windows of 24 hours as input, with yields for expectations taken with an 8-hour balanced. Figure 4 has appeared a graph comparing all execution comes about.

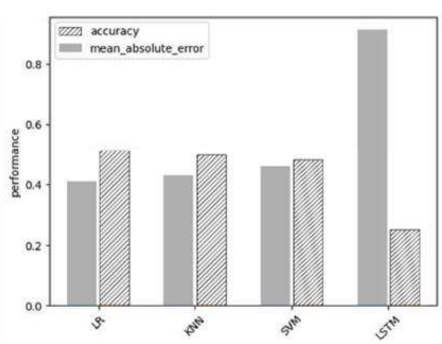

Figure 4. Performance comparison of predictive models for traffic forecasting

We come to an amazing precision rate of 91ter a few emphases and refinements on the show utilizing profound learning. Such an awesome advancement assist substantiates the viability of LSTM in anticipating vehicle checks and activity design estimates in close real-time. Known for utilizing transient flow and conditions as one of its preferences, the LSTM demonstrate acts extraordinarily towards bettering urban portability. On the other hand, all other machine learning models did not perform as well, illustrating their restrictions in capturing the or maybe complex nature of activity designs. The LSTM's predominance altogether illustrates the critical part that profound learning plays in strong, exact activity estimating.

Moreover, the benefits of IoT street activity information coordinates with AI in optimizing urban portability. Such expectation, with progressed data-driven modeling methods, permits for educated decision-making, course arranging, and upgrading street users' by and large transportation involvement in Keen City situations. We utilized two estimation criteria for both execution assessment and comparison of the calculations, such as the precision of relapse (R^2) and cruel outright blunder (MAE) [29], [30]. Each of these criteria are characterized as takes after:

$$MAE(y, \hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}|y_i - \hat{y}_i| \tag{1}$$

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n}(y_i - \bar{y})^2} \tag{2}$$

Figure 6: Performance comparison of predictive models for traffic forecasting

where: n: number of tests, y: watched activity stream, $\hat{y}$: anticipated activity stream, $\bar{y}$: cruel.

The cruel supreme mistake and R-squared are both commonly utilized parameters with which to evaluate machine learning models. The MAE fundamentally looks at the outright forecast mistake, showing how near the anticipated values are to the genuine ones. The lower the MAE, the way better the expectation execution. On the other hand, R-squared evaluates and summarizes the goodness-of-fit of the relapse demonstrate, with a scale from to 1:The more prominent R-squared is, the more grounded the relationship between subordinate and free variable(s) and, so, the more changeability within the information is captured by that demonstrate.

In Table 1, the results of reenactments done with these calculations are summarized, together with forecast exactness and blunders. These comes about more than enough illustrate that machine learning calculations are not reasonable and productive devices for exact forecast in activity. On that note, be that as it may, the profound learning demonstrate yielded ideal execution, being both greatly error-free and reasonable as activity forecasting/simulation calculation.

Table 1. Comparison of machine learning and deep learning models performance metrics

Model	Predict N hours in advance	R2	MAE
Linear regression	3	41%	0.595
K-nearest neighbor's	3	43%	0.577
Support vector machines	3	46%	0.570
LSTM	8	91%	0.285

Figure 7:Performance comparison of predictive models for traffic forecasting

In Figure 5, one seem see the result of three distinctive tests that considered proficiency and precision. Presently, those tests were executed exclusively to recognize a demonstrate that seem palatably display unwavering quality and precision in its expectations. The reason of this comprehensive assessment was to guarantee that the chosen LSTM demonstrate has viably reenacted real-world activity scenarios for making strides urban portability. It was utilized hand in hand with IoT street activity information and manufactured insights, combining those two innovations to offer experiences on. We utilized a reenactment made utilizing the pygame system [31], [32] to demonstrate our work and interface comes about to real-world circumstances. The foremost objective of recreation was to discover a real-time exact expectation of the number of vehicles right now on a chosen street fragment, with expectations concerning the taking after hour. Within the recreation, activity conditions were outwardly modeled based on color. The influenced vehicles were colored ruddy amid congested conditions (Figure 6), whereas those beneath superior conditions were colored green (Figure 7). This color visualization made it simple to get it and recognize a few set up activity conditions inside our reenacted environment, in this manner taking us closer to reality with valuable knowledge on moving forward urban portability for savvy city settings.

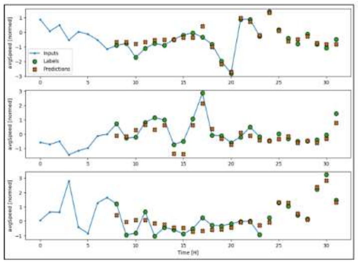

Figure 5. Comparative analysis of LSTM models for traffic prediction accuracy

V. CONCLUSION

All in all, it can be concluded that the integration of IoT street activity information with AI inside savvy city situations seem contribute a parcel toward urban portability. In this work, we have concocted a system that appears the viability of utilizing IoT sensors and profound learning calculations, most unmistakably, LSTM, to precisely anticipate activity stream. Whereas starting experimentation performed substantively well with machine learning calculations, they fizzled to attain the precision edge required for traffic predictions. This driven us to examine advance choices, inevitably settling on the plausibility of the LSTM demonstrate. The application of LSTM empowered critical upgrade in real-time vehicle number estimation and activity determining. With this estimate information, individuals can select the most astute way on the street, whether it is for their day by day commutes or long-term arranging.
has extraordinary capabilities in savvy cities. In each perspective of the headway of this innovation, we cultivate the plausibility for more productive administration of activity, less blockage, higher operational efficiencies, and hence way better urban portability. By utilizing the data-driven knowledge so gathered, we develop more dependable and bearable cities for the total society.

REFERENCES

[1] A. Atta, S. Abbas, M. A. Khan, G. Ahmed, U. Farooq, "An adaptive approach: A smart traffic congestion control system," Journal of King Saud University - Computer and Information Sciences 32, no. 9 (Nov. 2020): 1012–1019, doi:10.1016/j.jksuci.2018.10.011.

[2] Miz, V., and Hahanov, V. "Smart traffic light based on the cognitive road traffic management system (CTMS) using Internet of Things." In Proceedings of the IEEE EB-COM 2014, 2014: 1–5.

[3] H. F. Al-Selwi, A. B. A. Aziz, F. S. Abas, N. A. A. Hamzah, and A. B. Mahmud, "An impact of weather data on traffic flow prediction models," IAES International Journal of Artificial Intelligence 11 (2022): 1223–1231, doi:10.11591/ijai.v11.i4.pp1223-1231.

[4] Slimani, N., Yousfi, S., Amghar, M., and Sbiti, N."Towards a new intelligent traffic system based on deep learning and data integration- international journal of electrical and computer engineering(ijecce)." 13 (2023): pp.4649-4660, doi:10.11591/ijece.v13i4.pp4649-4660.

[5] E. Al Nuaimi, H. Al Neyadi, N. Mohamed, J. Al Jaroodi, "Application of big data to smart cities." Journal of Internet Services and Applications 6, no. 1 (Aug. 2015): 1–15, doi:10.1186/s13174-015-0041-5.

[6] Rathore, Mao Zongbin, Ph.D. RAV, And G Jeon."iot-based big data: from smart city to next-generation super city planning iv."International Journal on Semantic Web and Information Systems 13, no. 1 (Jan. 2017): 28–47, doi:10.4018/IJSWIS.2017010103.

[7] K. Ramesh, A. Lakshna, and P. N. Renjith. "Smart traffic congestion model in IoT: a review." In Proceeding of 4th ICECA- 2020, the 4th International Conference on Electronics, Communication and Aerospace Technology, 651-658, Nov. 2020, doi:10.1109/ICECA49313.2020.9297631.

[8] Otoshi, T., Y. Ohsita, M. Murata, Y. Takahashi, K. Ishibashi, and K. Shiomoto. "Traffic Prediction for Dynamic Traffic Engineering." Computer Networks 85 (Jul. 2015): 36-50, doi:10.1016/j.comnet.2015.05.001.

[9] Y. Wang, W. Y. Szeto, K. Han, and T. L. Friesz, "Dynamic Traffic Assignment: A Review of Methodological Advances for Environmentally Sustainable Road Transport Applications," Transportation Research Part B: Methodological, vol. 111, pp. 370-394, May 2018, doi: l0.1016/j.trb2018.03.011.

[10] I. Cvitić, D. Peraković, M. Periša, and M. D. Stojanović, "A New Classification of IoT Devices Based on Traffic Flow Features," Journal of Organizational and End User Computing, vol. 33, no. 6,i pp. 1-20, May 2021, doi: 10.4018/JOEUC.20211101.oa12.

[11] M. Shafiq, Z. Tian, A. K. Bashir, X. Du, and M. Guizani, "CorrAUC: A Malicious Bot-IoT Traffic Detection Method in IoT Networks Using Machine Learning Techniques," IEEE Internet of Things Journal, vol. 8, no. 5, pp. 32423254, Mar. 2021, doi: 10.1109/JIOT.2020.3002255.

[12] I. Moumen, J. Abouchabaka, and N. Rafalia, "Adaptive Traffic Lights Based on Traffic Flow Prediction Using Machine Learning Models," International Journal of Electrical and Computer Engineering (IJECE), vol. 13, no. 5, pp. 5813-5823, Oct. 2023.

[13] B. Yan, G. Wang, J. Yu, X. Jin, and S. Zhang, "Spatial-temporal Chebyshev graph neural network for traffic flow prediction in IoT-based intelligent transport systems," IEEE Internet of Things Journal, vol. 9, no. 12, pp. 9266-9279, Jun. 2022, doi: 10.1109/JIOT.2021.3105446.

[14] F. Wang et al., "Short-term forecasting for large-scale traffic flow in massive IoT under 6G using time-aware locality-sensitive hashing," IEEE Internet of Things Journal, vol. 8, no. 7, pp. 5321-5331, Apr. 2021, doi: 10.1109/JIOT.2020.3037669.

[15] Y. Zhang,Y. Zhou, H. Lu, and H. Fujita, "Spark cloud-based parallel computing for traffic network flow predictive control using non-analytical predictive models," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 7708-7720, July 2022, doi: 10.1109/TITS.2021.3071862.

[16] S. Kolozali, M. Bermudez-Edo, D. Puschmann, F. Ganz, and P. Barnaghi, “A knowledge-based approach for real-time IoT data stream annotation and processing,” in Proceedings - 2014 IEEE International Conference on Internet of Things, iThings 2014, 2014 IEEE International Conference on Green Computing and Communications, GreenCom 2014 and 2014 IEEE International Conference on Cyber-Physical-Social Computing, CPS 2014, Sep. 2014, pp. 215–222, doi: 10.1109/iThings.2014.39.

[17] S. Neelakandan, M. A. Berlin, S. Tripathi, V. B. Devi, I. Bhardwaj, and N. Arulkumar, “IoT-based traffic prediction and traffic signal control system for smart cities,” Soft Computing, vol. 25, no. 18, pp. 12241–12248, Sep. 2021, doi: 10.1007/s00500-021-05896-x.

[18] X. Wang, C. Zhang, and S. Zhang, “Modified Elman neural network and its application to network traffic prediction,” in Proceedings - 2012 IEEE 2nd International Conference on Cloud Computing and Intelligence Systems, IEEE CCIS 2012, Oct. 2013, vol. 2, pp. 629–633, doi: 10.1109/CCIS.2012.6664250.

[19] U. K. Lilhore et al., “Design and implementation of an ML and IoT-based adaptive traffic-management system for smart cities,” Sensors, vol. 22, no. 8, p. 2908, Apr. 2022, doi: 10.3390/s22082908.

[20] S. Gadal, R. Mokhtar, M. Abdelhaq, R. Alsaqour, E. S. Ali, and R. Saeed, “Machine learning-based anomaly detection using k-mean array and sequential minimal optimization,” Electronics (Switzerland), vol. 11, no. 14, p. 2158, Jul. 2022, doi: 10.3390/electronics11142158.

[21] A. Boukerche and J. Wang, “Machine learning-based traffic prediction models for intelligent transportation systems,” Computer Networks, vol. 181, p. 107530, Nov. 2020, doi: 10.1016/j.comnet.2020.107530.

[22] J. Artin, A. Valizadeh, M. Ahmadi, S. A. P. Kumar, and A. Sharifi, “Presentation of a novel method for prediction of traffic with climate condition based on ensemble learning of neural architecture search (NAS) and linear regression,” Complexity, vol. 2021, pp. 1–13, Aug. 2021, doi: