Advancements in Integrated Driver Behavior Analysis and Smart Routing Optimization for Enhanced Urban Mobility

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ABSTRACT
The integration of various methodologies to analyze driver behavior and smart routing algorithms represents a significant advancement in enhancing transportation safety and efficiency. These approaches leverage data-driven insights and sophisticated algorithms to tailor driving assistance systems and navigation experiences to individual users' needs. By utilizing techniques such as LSTM neural networks for driver behavior analysis and intelligent algorithms for smart routing, these advancements contribute to the development of more advanced driver-assistance technologies and dynamic navigation systems.

Driver behavior analysis, which aims to understand and predict driving actions, is crucial for enhancing safety through smarter assistance systems. By matching driving patterns with suitable analytical methods, advancements like LSTM neural networks decode intricate driving actions, contributing to the development of advanced driver-assistance technologies for safer driving experiences.

Similarly, smart routing employs intelligent algorithms to compute optimal routes in real-time, prioritizing efficiency and precision in navigating diverse urban landscapes. Leveraging sophisticated algorithms and graph theory, smart routing aims to craft dynamic navigation systems that adapt routes in real-time, optimizing efficiency and user-friendliness within specific road networks. This approach offers customized navigation experiences tailored to individual user needs, further enhancing the overall efficiency and safety of urban transportation systems.

General Terms
Driver Behavior, Smart Routing.

Keywords
Internet of Things, Long Short Term Memory, Recurrent Neural Network, Global Positioning System, Radio Frequency Identification, Application Program Interface.

1. INTRODUCTION
The field of transportation efficiency and safety includes a range of technological developments that are intended to improve our ability to drive and navigate. Fundamentally, this subject uses state-of-the-art methods like machine learning and neural networks to analyse complex patterns in order to comprehend driver behaviour. Understanding how drivers accelerate, change lanes, and make turns can help create intelligent systems that can anticipate and comprehend driver behaviour in real time, making driving safer overall. Simultaneously, advancements in smart routing modules transform urban navigation by utilising advanced algorithms and graph theory to dynamically modify routes, hence reducing inefficiencies and providing customised, context-sensitive solutions. When taken as a whole, these developments aim to transform how people move through busy city streets, encouraging efficiency as well as safety when exploring new places. Through the use of state-of-the-art machine learning techniques to explore complex patterns of driver behavior, this research paper advances the field and advances urban navigation through its Smart Routing module, which dynamically adjusts routes to minimize inefficiencies and provides customized, context-aware solutions for safer and more efficient city exploration.

2. RELATED WORK
This section presents an overview of existing research and contributions in the fields of Driver Behaviour Analysis and Smart Routing within transportation systems. The following summaries encapsulate the diverse range of studies and innovations dedicated to understanding driver behaviour intricacies and optimizing routing strategies.

2.1 Driver Behavior
In the realm of Driver Behaviour Analysis, studies delve into the intricate correlations between physiological responses, external stimuli, and driving maneuvers. They aim to understand fatigue detection, driver modelling using deep learning, and the feasibility of integrating cognitive architectures into autonomous vehicle systems. Each study highlights nuances in behaviour, underscoring the need for larger datasets and refined methodologies to bolster accuracy and reliability.

Othman, W.; Hamoud, B.; Kashevnik, A.; Shilov, N.; Ali et.al,[1] have proposed a sophisticated system to delve into the intricate correlation between driver states (such as vital signs, eye state, and head pose) and both internal (vehicle maneuver actions) and external events (proximity to other vehicles) using synchronized in-cabin/out-cabin videos. The study ingeniously employed hybrid deep learning techniques like CNN and BiLSTM for video analysis and decision tree classifiers for maneuver detection utilizing accelerometer and gyroscope sensor data. The outcomes revealed a nuanced relationship between driver physiological responses and driving scenarios, pointing out weak positive correlations between heart rate and specific maneuvers. However, the study's reliance on a relatively small dataset and potential error margins from model estimations emphasized the need for further research with larger and diverse datasets to bolster accuracy and reliability.

Li, J., Guo, F., Li, W., Tian, B., Chen, Z., Qu, S. et.al,[2] delved into the significant disparities in driving behavior between younger and older drivers, meticulously examining the change process of their behaviors across various scenarios. By recruiting participants from both age groups for a driving simulation experiment, the study highlighted substantial differences in driving behaviors, particularly in the timing of eye movement and operational nodes across conflict scenarios. It successfully established thresholds for different driving behavior nodes and developed comprehensive driving behavior graphs. The study, while limited to simulation-based data, served as a valuable reference for analyzing driving behaviors and offered essential insights for enhancing driving safety measures specifically tailored for older individuals.

Tin Lai Lai Mon et.al,[3] focused on enhancing driver behaviour detection by tackling the challenge of inaccurate and missing GPS points in trajectory mapping. The methodology involved the removal of erroneous GPS points from datasets followed by employing seven different interpolation methods to estimate missing points between consecutive GPS coordinates. Despite none of the interpolation methods precisely identifying missing points, all errors were within acceptable limits. The study's comparison of methods highlighted higher errors in certain interpolations, suggesting the potential for significantly enhancing system compatibility and accuracy by employing alternative methods.

Zhang, H., Ni, D., Ding, N., Sun, Y., Zhang, Q., Li, X. et.al,[4] conducted a comprehensive review and analysis to understand the relationship between fatigue detection methods and the underlying causes or prevention of fatigue in driving contexts. Through a systematic review of literature focusing on fatigue influential factors, identification, measurement, and prediction within the driving behavior domain, the study revealed significant correlations between time-related indicators, driving environment, vehicle performance, and driver fatigue. Elastic control of driving and rest times emerged as an effective preventive measure. The study's structured and comparative description of fatigue behavior research components offered valuable insights, although individual differences in fatigue behavior across driver populations underscored the need for more tailored research approaches.

Wei, H., Li, L., Xu, Y., Lei, S., Wang, Y. et.al,[5] aimed to develop a comprehensive dynamic shimmy model for the driver-vehicle-road system, focusing on understanding stability and bifurcation characteristics. The methodology involved deriving a constraint equation considering dynamic coupling, determining eigenvalues for zero equilibrium points, and applying centre manifold theory to reduce the dynamic system. The study's complexification-averaging (CA) method revealed critical vehicle speeds, stability regions, and mathematical expressions for periodic solutions. While offering insights into dynamic interactions and stability regions, potential complexities in real-world implementation and the need for detailed parameter calibration were noted for accurate predictions.

Mehdi Cina, Ahmad B. Rad et.al,[6] explored the feasibility of employing the Adaptive Control of Thought—Rational (ACT-R) cognitive architecture as a unifying platform for modeling human driving behavior and configuring an autonomous driving system. By scrutinizing multiple resources and driving simulation experiments, the research extensively discussed the potential integration of ACT-R into autonomous vehicle architecture, emphasizing its role in decision-making processes, ADAS establishment, and lower-level control algorithm design. The study highlighted the multifaceted nature of autonomous vehicle development, emphasizing the necessity of sophisticated simulation systems due to the challenges and costliness of real-world field tests. While highlighting advantages in providing a comprehensive framework for handling complex human-machine collaborative efforts, the implementation of ACT-R requires further exploration and refinement, particularly in addressing the intricate mechanisms of human-car interaction and designing perception and situation assessment within the architecture.

Heddar Yamina , Djebabra Mébarek , Belkhiri Mohammed , Saaddi Saadia et.al,[7] introduced the MASOCU-DBD method to analyze Driver Behavioral Drift (DBD) on congested road sections, focusing on assessing its occurrence and usefulness. Employing the BM-NSA model and Cost-Benefit Analysis (CBA) weighted by the Analytic Hierarchy Process (AHP), the study provided insights into professional drivers' behavioral deviations and suggested strategies for road managers. While offering comprehensive analysis and behavioral adjustments based on relevant data, the study highlighted the need for refined stress assessment via self-reported questionnaires for drivers and further sociological studies to explore drivers' perceptions and choices regarding DBD more deeply.

Tarek Ghoul, Tarek Sayed, Chuanyun Fu et.al,[8] developed a real-time safest route algorithm leveraging Bayesian hierarchal extreme value theory (EVT) modeling applied to drone trajectory data from Athens, Greece. By utilizing traffic conflict data to estimate dynamic crash risk along various routes in an urban network, the study identified the safest route between origindestination pairs. The study's reliance on weighted preferences for safety versus speed posed challenges in decision-making for users and agencies. Additionally, its dependency on data quality and continuous model updating highlighted potential drawbacks that need addressing for real-world scalability.

Yi He, Changxin Sun, Fangrong Chang et.al,[9] sought to uncover the underlying factors influencing delivery vehicle crash risks in three developed regions of China. Through a cross-sectional structured questionnaire survey involving couriers, the study revealed critical insights: specific urban agglomerations exhibited higher crash frequencies and risk levels, with prevalent risky behaviors such as distracted driving and wrong-lane-use. While providing comprehensive insights into the intersecting impact of workload, emotions, and risky behaviors on crash risks, the focus on macroscopic factors and reliance on self-reported data posed limitations, potentially neglecting crucial microscopic elements like fatigue and social-psychological aspects.

Mozhgan Nasr Azadani and Azzedine Boukerche et.al,[10] developed an efficient driver identification and impostor detection system leveraging deep learning and steering behavior analysis. The system employed a deep learningbased architecture to capture distinct steering behavior characteristics, subsequently using Siamese networks to verify drivers and detect impostors based on encoded representations.

The proposed system showcased superior accuracy rates compared to established benchmarks, although its reliance on labeled data for training raised considerations regarding the availability of substantial labeled datasets for optimal performance.

Arya R Anil and Anudev J et.al,[11] explored driver behaviour using smartphone sensor data through unsupervised clustering algorithms, primarily employing the K-means algorithm. By collecting accelerometer readings from smartphone sensors, the study effectively identified distinct driving events and characterized driving behavior. The study's advantage lay in its potential to model driver behavior accurately and optimize energy utilization in electric vehicles. However, challenges in interpreting clustering results and the dependence on the choice of clustering algorithms highlighted limitations in precisely capturing diverse driving behaviors.

Prasanna Kumar K R and Sindhuja A M et.al,[12] aimed to develop a reliable system using deep learning to detect and prevent accidents caused by driver fatigue or distraction. The methodology involved monitoring eye and mouth movements through a small security camera focused on the driver's face. The study's outcome showed promising results in identifying indicators of potential accidents, thereby providing an opportunity for timely intervention through an authentication SMS to authorized individuals. While the system exhibited potential in preemptively preventing accidents, its reliance on facial cues alone and potential variations in effectiveness across environmental conditions or individual behaviors posed challenges to its universal applicability.

2.2 Smart Routing

The Smart Routing front, the emphasis lies in optimizing route planning and navigation through a fusion of algorithms and real-time data. These studies aim to combat congestion, enhance user experience, and balance multiple objectives such as travel time, safety, and efficiency. Innovations range from personalized route recommendation systems to multi-objective optimization approaches using Genetic Algorithms and predictive models. While showcasing promising advancements in route planning, these studies transparently acknowledge limitations related to data availability, scalability, and real-time adaptability.

Smita Jangale, Rutuja Rajhans, Anuja Shetye, Ritik Wadhwani et.al,[13] innovatively introduce the "Location Tracking and Smooth Path Providing System," a pioneering solution combatting the limitations of GPS signals through a fusion of Machine Learning and Data Science Algorithms. By meticulously studying literature from renowned sources like IEEE, Springer, and ScienceDirect, the system strategically selects algorithms such as Dijkstra’s Algorithm and Kalman filter. These choices empower the system to not only determine the shortest routes but also ensure smooth tracking, enhancing accuracy in real-time location coordinates and travel route prediction. The system's impact is notable, positively influencing traffic management and offering users precise paths, effectively minimizing unnecessary travel distances. However, the paper astutely acknowledges potential limitations in areas with poor network connectivity or insufficient data, signaling the need for further advancements in these domains.

Lesch, Veronika & König, Maximilian & Kounev, Samuel & Stein, Anthony & Krupitzer, Christian et.al,[14] dive deep into the complexities of vehicle routing problems, specifically the multiobjective capacitated VRP with pickup and delivery stops and time windows. By devising a two-staged strategy and employing Genetic Algorithm (GA) and Ant Colony Optimization (ACO), this paper significantly advances existing algorithms, reducing computation time while ensuring efficient optimization. The study's future plans to explore additional optimization algorithms and incorporate uncertainty measures display a forward-thinking approach, aiming to further enhance adaptability and efficiency in routing solutions.

Josif Tomić, Nemanja Gazivoda, Miodrag Kušljević, Platon Sovilj and Milan Šaš et.al,[15] focus on the development of an advanced travel route planning system tailored for congested urban areas. Leveraging SCADA infrastructure and numerical algorithms, this system pioneers real-time data utilization to update traffic information. The paper underscores the system's accuracy in estimating travel times compared to standard auto routers, showcasing its potential in offering users precise estimations in dynamic urban environments. However, the study also pragmatically acknowledges limitations due to the system's reliance on human decision-making, inhibiting full automation potential and scalability.

Sophie Hayes, Shen Wang, Soufiene Djahel et.al,[16] introduce a personalized routing application designed to empower users with route preferences based on various factors like travel distance, estimated time, and safety levels. With real data from Manchester, England, this application showcases adaptability by providing drivers with route flexibility tailored to their preferences, potentially mitigating congestion caused by unforeseen incidents. The paper, while highlighting advantages in adaptability, pragmatically identifies limitations in incorporating additional criteria like fuel consumption, hinting at necessary refinements for broader applicability.

Pradhan, R., Agarwal, A. & De et.al,[17] focus on addressing the complexities of multi-criteria route selection in vehicular networks by formulating it as a multi-objective optimization problem. Through the employment of a Genetic Algorithm (GA) heuristic, this paper excels in concurrently finding multiple alternate routes based on various criteria, ultimately deriving a balanced optimal route that considers driver preferences. The study's experimental evaluation across diverse network sizes underscores the effectiveness of the proposed method in route optimization. However, the paper transparently highlights potential limitations in dynamically changing environments, suggesting avenues for future development using Vehicular Adhoc Networks (VANETs) for real-time traffic data incorporation and considering additional criteria like live traffic density for further adaptability.

Ning Sun, Huizhu Shi, Guangie Han, Bin wang and Lei Shu et.al,[18]present groundbreaking traffic path planning algorithms, TPPDP and TPPDP-LB, aimed at mitigating congestion in urban areas. By leveraging predictive models based on historical and real-time traffic data, these algorithms effectively forecast future road conditions, enabling the determination of the shortest travel time paths. Moreover, TPPDP-LB integrates predictive information with concurrent road segment recommendations to balance load and optimize travel time paths. While these algorithms showcase superior performance in avoiding congestion-prone sections and maintaining overall system efficiency, the paper candidly acknowledges potential complexities in implementing and maintaining the predictive models and distributed computing framework required for optimal functioning.

Dimitris Bertsimas, Patrick Jaillet and S´ebastien Martin et.al,[19] pioneer an optimization framework geared towards enabling real-time dispatching of taxis in the context of ride-sharing companies. Through historical simulations using New York City routing network and yellow cabs data, this framework showcases significantly improved efficiency and routing precision compared to existing heuristic-based systems. However, the paper critically evaluates assumptions about full vehicle control and proposes potential adaptations for evolving vehicle control paradigms, hinting at the need for a recommendationbased system for customer-driver matching. The framework's adaptability beyond taxi routing highlights its potential in various real-time vehicle routing contexts, emphasizing its versatility and scalability.

Jian Dai, Bin Yang , Chenjuan Guo and Zhiming Ding et.al,[20] introduce personalized route recommendation techniques by leveraging extensive trajectory data. With a focus on modeling and updating individual drivers' preferences based on their trajectories, this paper demonstrates the efficacy and efficiency of the proposed techniques. However, the study astutely notes a potential limitation in primarily focusing on travel costs without integrating richer semantic resources like points-of-interest. Future work aims to address this limitation, emphasizing the paper's forward-looking approach towards enhancing route recommendations.

Yu, Qian & Wang, Yuanguo & Jiang, Xiaogang & Zhao, Bailu & Zhang, Xiuling & Wang, Xiaobei & Liu, Qingqing et.al,[21] take on the challenge of enhancing vehicle path optimization in logistics using IoT technology and an improved Genetic Algorithm (GA). By optimizing the traditional GA and leveraging IoT enhancements, this study effectively creates a vehicle route optimization model that significantly reduces distribution costs while increasing customer satisfaction. However, the paper openly acknowledges limitations regarding assumptions about uniform vehicle speed, recognizing the need for future research to address real-time traffic constraints for broader applicability and improved model accuracy.

H. Raeesi and A. Hosseinpour et.al,[22] tackle the challenge of routing mobile robots in unknown dynamic environments using evolutionary algorithms. This study's methodology emphasizes off-line simulation and extensive evaluation of various evolutionary algorithms in guiding the robot optimally. The paper underscores the effectiveness of evolutionary algorithms in navigating through unknown environments but acknowledges limitations in complex settings. Additionally, it proposes adaptations for intricate vehicle routing scenarios, showcasing a forward-thinking approach toward enhancing robot navigation.

S. Jiang, M. Jafari, M. Kharbeche, M. Jalayer and K. N. Al-Khalifa et.al,[23] introduce the innovative Safe Route Mapping (SRM) methodology, integrating crash-based estimations and dynamic conflict risks for roadway safety evaluation. Through an advanced Safety Performance Function (SPF) and neural network (NN) model, this approach generates safety risk heat maps for roadways, enabling better safety planning and driver awareness. Yet, limitations concerning reliance on simulated driver-based data for real-time applicability are noted, presenting an area for future extension to include more factors for accurate realtime conflict predictions.

3. BACKGROUND

The study report uses a variety of strategies to achieve its goals of improving travel efficiency and safety. The Driver Behaviour module employs state-of-the-art machine learning techniques, specifically Long Short-Term Memory (LSTM) neural networks, to analyse complex patterns of human behaviour while driving. In order for these neural networks to interpret complex driving behaviours like lane changes, turns, and accelerations, they are trained on an extensive dataset that includes timestamps, spatial coordinates, and vehicle movement data. The module seeks to promote the development of intelligent systems for advanced driver assistance by utilising LSTM networks to anticipate and comprehend driver behaviours in real-time. Simultaneously, the Smart Routing module dynamically modifies navigation routes based on current traffic circumstances and road statuses by utilising complex algorithms, including a homemade version of the A* algorithm. This module offers effective and direct navigation methods by minimising needless turns and route redundancies through the application of graph theory principles. It also incorporates features like priority nodes, next-best-route, and loop avoidance that aren't seen in popular navigation apps like Google Maps, giving users an intelligent and flexible tool for effective urban exploration. The research article intends to revolutionise the transportation domain by improving both driver behaviour analysis and urban navigation skills through the synergistic operation of these modules.

4. METHODOLOGY

In this section, the methodology is focused on integrating advanced technologies. Initially, raw driving data undergoes meticulous preprocessing to extract key features. Then, sophisticated machine learning, including LSTM neural networks, analyzes driving patterns and forecasts future actions. Concurrently, the project employs graph theory and optimization techniques to optimize navigation routes in urban areas. Rigorous validation ensures the reliability and adaptability of both the driver behavior and smart routing modules across diverse driving scenarios.

4.1 System Architecture

The system architecture diagram depicted in Fig.1 illustrates a web application featuring a user interface with dedicated tools for passengers and drivers, facilitating ride requests management, real-time tracking, and alarm displays. IoT devices, including panic buttons and various sensors like accelerometers and GPS, are integrated into vehicles for emergency signals, hazard detection, and monitoring driver behavior and routes. A dynamic communication interface ensures seamless device connectivity via mobile networks and IoT protocols to a central server, which serves as an IoT gateway processing sensor data, analyzing driver behavior with a deep learning module, and storing relevant information in a database. The safety response system connects with emergency services, generates real-time alerts, notifications, and provides data on driver performance metrics. Real-time tracking, mapping services, and intelligent mapping contribute to rapid security measures. The architecture includes user feedback and reporting systems for continuous improvement, integrating smart routes into city taxi services, optimizing routes in real time for efficiency and safety, reducing travel time, enhancing fuel efficiency, and fostering economic stability, while instilling passenger confidence and aiding drivers in navigating urban areas efficiently.

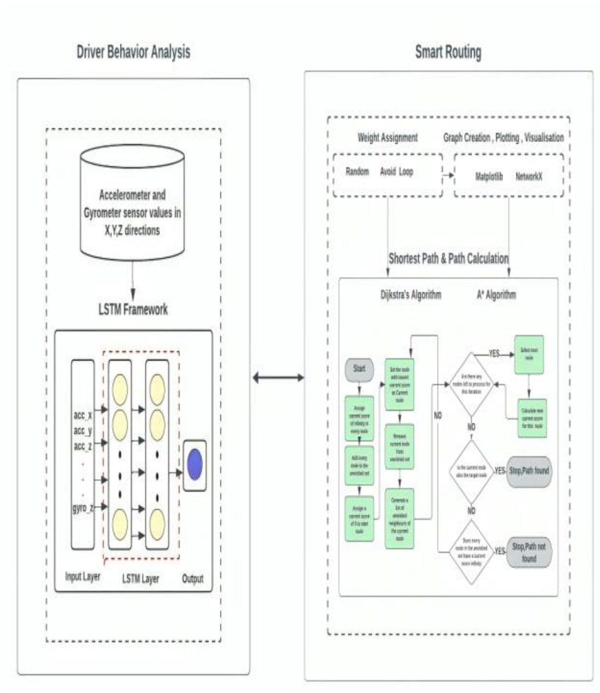

Fig.1 System Architecture of safe cab application

4.2 Development and Implementation of Driver Behaviour

The Driver Behaviour module uses cutting-edge techniques based in machine learning to decipher the subtleties of driving behaviour. The module begins by preprocessing and cleaning raw driving data in order to extract pertinent elements including lane changes, steering angles, accelerations, and decelerations. Following that, these properties are input into recurrent neural networks (RNNs) called Long Short-Term Memory (LSTM) neural networks, which are distinguished by their capacity to recognise temporal dependencies in sequential data. The input, output, and forget gates that are part of the memory cells in the LSTM network architecture allow the network to selectively propagate and store information over time. The LSTM model gains the ability to forecast future driver actions based on previous behaviour sequences by means of comprehensive training on a huge dataset of driving behaviours.

Input: Sensor data from Accelerometer, Accumulated Accelerometer and Gyroscope

Process: LSTM predicts the event label for each timeframe in the time series using the obtained sensor values

Output :List of the events occurring in each timeframe.

```
For each time step t from 1 to T do
1.Calculate gate activations:
    1.1 f_t = σ(Wf · x_t + Uf · h_{t-1} + bf) (forget gate)
    1.2 i_t = σ(Wi · x_t + Ui · h_{t-1} + bi) (input gate)
    1.3 o_t = σ(Wo · x_t + Uo · h_{t-1} + bo) (output gate)
    1.4 g_t = tanh(Wc · x_t + Uc · h_{t-1} + bc) (cell state update)
2.Update cell state:
    2.1 c_t = f_t ⊙ c_{t-1} + i_t ⊙ g_t (element-wise multiplication)
3.Calculate hidden state:
    3.1 h_t = o_t ⊙ tanh(c_t)
4.Calculate output:
    4.1 y_t = softmax(W_y · h_t + b_y) (optional for classification tasks)
End for
Return y, h_T, c_T
```

Fig.2 Algorithm for Driver Behavior

4.3 Development and Implementation of Smart Routing

Graph theory and optimisation approaches serve as the foundation for the complex computational approach used by the Smart Routing module. The road network is first represented by a graph created by the module, with nodes standing in for intersections or important locations and edges for the road segments that link these sites. The module uses an abridged version of the A* algorithm, a popular pathfinding technique in graph theory and artificial intelligence, by taking advantage of the graph structure. Improved features such priority node handling, loop avoidance, and next-best-route selection are included in this version, which is designed to meet the unique requirements of urban navigation. Iteratively exploring the graph, the algorithm modifies route selections in real time according to user preferences, road statuses, and traffic circumstances. The module computes optimal navigation paths that minimise redundant routes and needless turns through iterative refinement and optimisation, guaranteeing streamlined and efficient urban travel experiences.

Input: Start points, End points, Intermediate points and blockages

Process: The improvised A* algorithm takes the heuristic approach to find the nodes that form the optimal path and prevents looping by increasing the weights of each considered edge after considering.

Output: The optimal path from the start point and the end point

1. Initialize:
    1.1 Open list: Set of vertices to be explored, initially containing only s
    1.2 Closed list: Set of explored vertices, initially empty
    1.3 g(s) = 0 (cost from start to s)
    1.4 f(s) = h(s) (estimated total cost from start to goal through s)
2. While the open list is not empty do
    2.1 Remove the vertex v with the lowest f(v) value from the open list
    2.2 Add v to the closed list
    2.3 If v is the goal vertex g then
        2.3.1 Reconstruct the path from s to g using the parent pointers
        2.3.2 Return the path
    2.4 For each neighbor u of v do
        2.4.1 If u is not in the closed list, then
            2.4.1.1 tentative_g= g(v) + c(v, u)
            2.4.1.2 If u is not in the open list or tentative_g<g(u) then
                2.4.1.2.1 g(u) = tentative_g
                2.4.1.2.2 f(u) = g(u) + h(u)
                2.4.1.2.3 Set the parent of u to v
                2.4.1.2.4 Add u to the open list
                2.4.1.2.5 Set edge v-u weight to 10000
3. If the open list is empty then
    3.1 Return no path found

Figure.3 Algorithm for Smart Routing

5. DATASET

For the driver behaviour analysis module, the dataset was collected from a trusted Github repository on which multiple papers were published already. The dataset consisted of sensor data collected from 4 trips lasting 15 minutes each in different cars. The sensors used are : accumulated accelerometer , accelerometer and gyroscope. All in all, it had 65530 entries of data spanning across 11 columns which were the timestamp and time recorded in nanoseconds and the sensor values in the X,Y and Z plane.

For the Smart routing module, the data obtained was from a Python library called osmnx which helped us use an accurate map for implementing the logic proposed.

6. RESULTS AND INTERPRETATION

In this section the results of Driver Behavior and Smart Routing will be presented with in-depth analysis using various metrices and techniques

6.1 Driver Behaviour Analysis Results

The efforts made in this particular module can be categorised into three facets namely the analysis and inference taken from the dataset, the results obtained from running the model trained on the dataset and the results obtained from multi-class approach.

6.1.1 Dataset Analysis

#	Column	Non-Null Count	Dtype
0	Event	12130 non-null	object
1	Row	12130 non-null	int64
2	timestamp	12130 non-null	object
3	uptimeNanos	12130 non-null	float64
4	x	12130 non-null	float64
5	y	12130 non-null	float64
6	z	12130 non-null	float64
7	accl_x	12130 non-null	float64
8	accl_y	12130 non-null	float64
9	accl_z	12130 non-null	float64
10	accm_x	12130 non-null	float64
11	accm_y	12130 non-null	float64
12	accm_z	12130 non-null	float64
13	gyro_x	12130 non-null	float64
14	gyro_y	12130 non-null	float64
15	gyro_z	12130 non-null	float64
16	Seconds	12130 non-null	int64

Fig.4 Information about the dataset

	accl_x	accl_y	accl_z	accm_x	accm_y	accm_z	gyro_x	gyro_y	gyro_z
count	12130.000000	12130.000000	12130.000000	12130.000000	12130.000000	12130.000000	12130.000000	12130.000000	12130.000000
mean	0.062804	-0.073303	0.208888	0.062804	-0.073303	10.015538	0.023861	-0.004990	-0.011571
std	1.916139	1.711180	1.319404	1.916139	1.711180	1.319404	0.173733	0.153383	0.311217
min	-14.466542	-7.716832	-6.789372	-14.466541	-7.716832	3.017277	-1.282182	-1.203594	-2.014732
25%	-0.904577	-1.009884	-0.477733	-0.904577	-1.009884	9.328918	-0.051187	-0.066691	-0.099925
50%	0.066263	-0.053365	0.041600	0.066263	-0.053366	9.848251	0.004668	-0.001685	-0.003274
75%	1.008832	0.864607	0.752686	1.008832	0.864607	10.559336	0.074921	0.056186	0.070120
max	9.259089	15.537562	11.560664	9.259089	15.537562	21.367315	1.765886	1.476640	1.321046

Fig.5 Description of the dataset

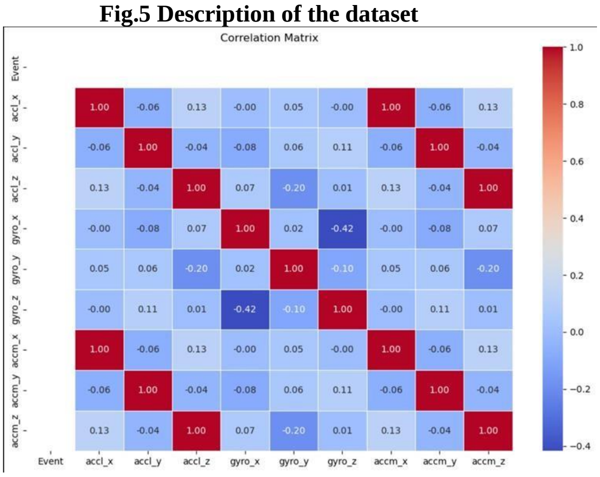

Fig.6 Correlation Matrix of the dataset

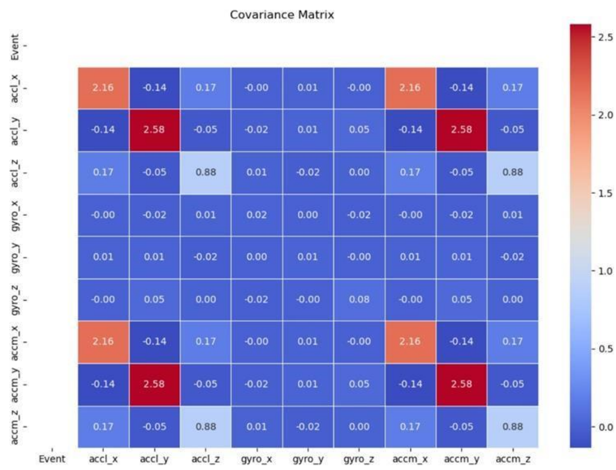

Fig.7 Covariance Matrix of the dataset

From the above findings it can be inferred that the two acceleration-based sensor values are somewhat correlated but not to the point that warrants action. With the values provided by the description and information data, decision making regarding the approach to the project becomes easier.

6.2.2 Results of Classification using LSTM and RNN

Table.1 Evaluation metrics of LSTM

Model	Accuracy	Loss
RNN(training)	0.699	0.875
RNN(testing)	0.689	0.887
LSTM(training)	0.965	0.118
LSTM(testing)	0.953	0.133

From the above findings, it can be inferred that the RNN model heavily suffers from the vanishing gradient problem in our case and would not be ideal, however intuitive it might be to use it. Thus, upon attempting to fit LSTM model, whose memory feature can be exploited for the algorithm to consider the previous 5 seconds of data. Thus, any loss of data is avoided and high accuracy can be obtained in all splits of data.

6.2.3 Results from the Multiclass Approach

Table.2 Evaluation metrics of LSTM in Multiclass Approach

Binary Classification	Accuracy (in %)	Loss (in %)
Aggressive vs Non-Aggressive	94.66	12.04
Lane Shift vs Non-Lane Shift	93.55	30.61
Aggressive Acceleration vs Aggressive Breaking	93.72	20.43
Aggressive Left Lane Shift vs Aggressive Right Lane Shift	99.70	1.22
Aggressive Right Turn vs Aggressive Left Turn	97.28	3.41

From the above data, it can be concluded that the model is consistent throughout multiple class splits and thus does not suffer from the problem of catering towards a particular event type due to imbalance in the dataset. This also gives us new insights such as the model is particularly good at predicting the directional differences than acceleration based factors.

6.3 Smart Routing Scenarios

The smart routing module is tested in two very different scenarios to confirm the integrity of the module. The scenario is based on the metropolitan area of the city Chennai.

6.3.1 Smart Routing in Chennai

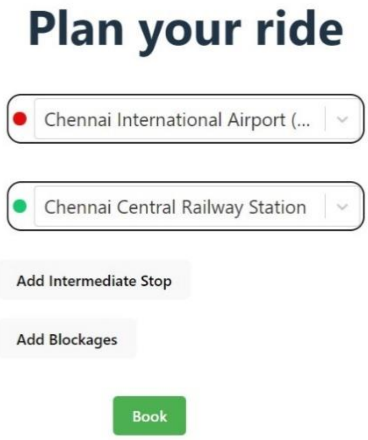

Fig.8 Plan your Ride Page

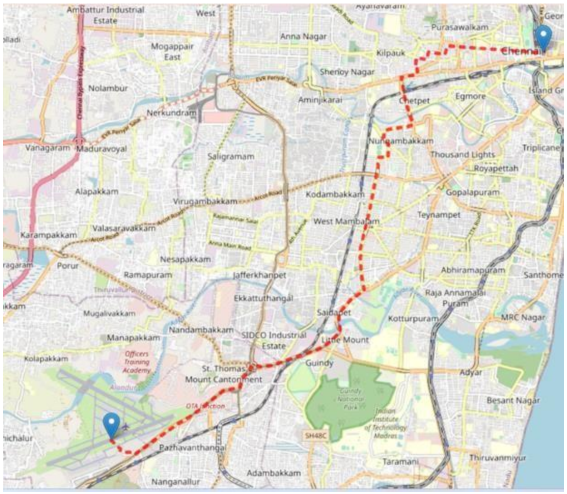

Fig.9 Optimal Path identified with proposed methodology

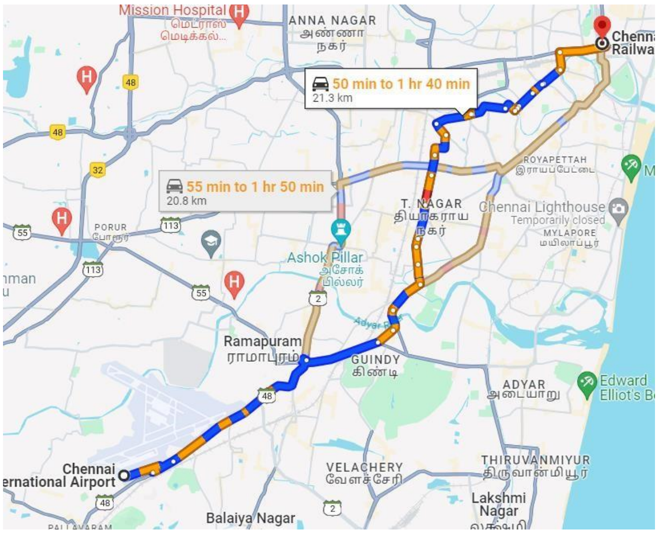

Fig.10 Comparison with ground truth using Google Maps

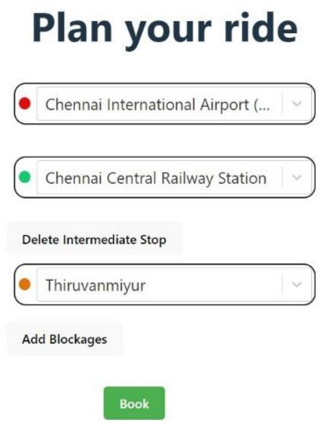

Fig.11 Intermediate stop added

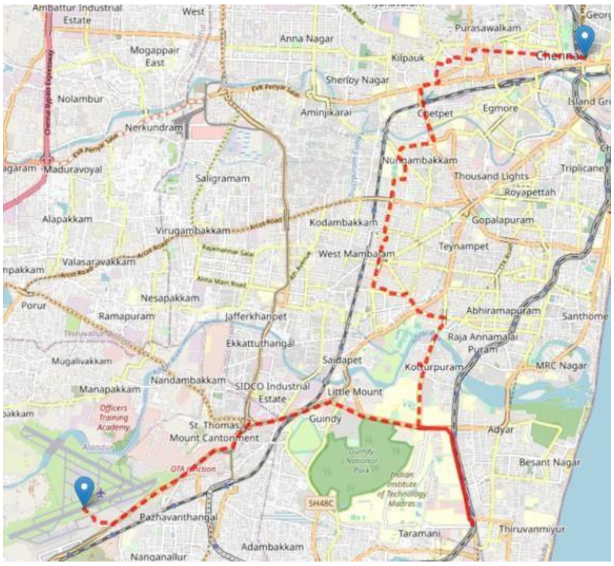

Fig.12 Optimal Path with intermediate stop using proposed methodology

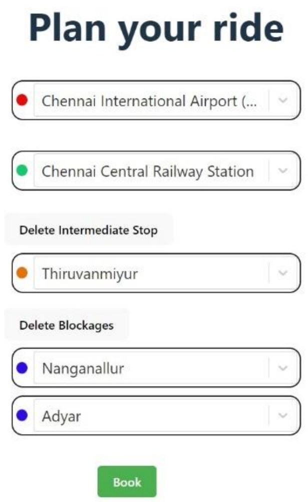

Fig.12 Comparing the intermediate stop logic with Google Maps

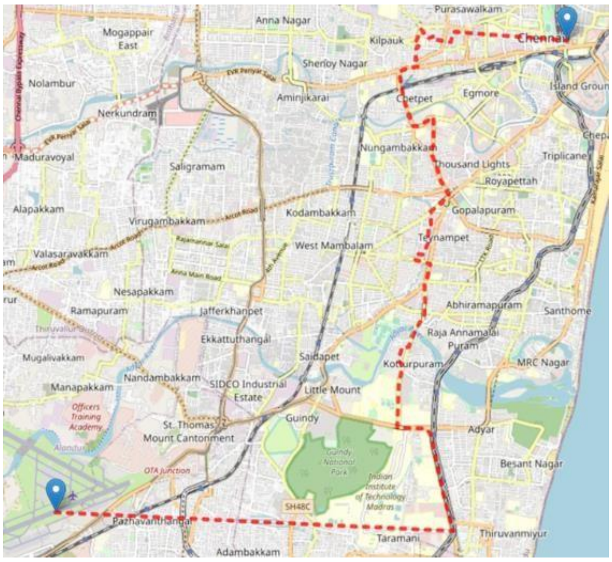

Fig.13 Blockages added for consideration

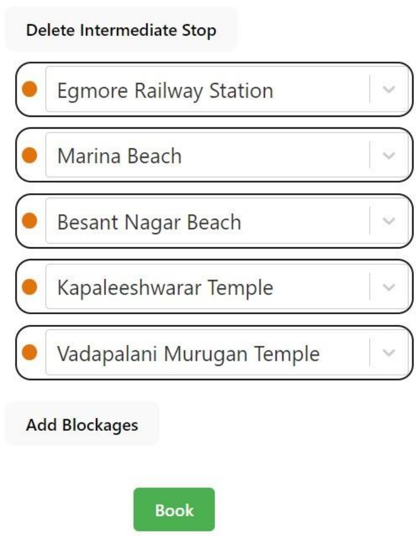

Fig.14 Optimized path with blockages and intermediate stop using proposed algorithm

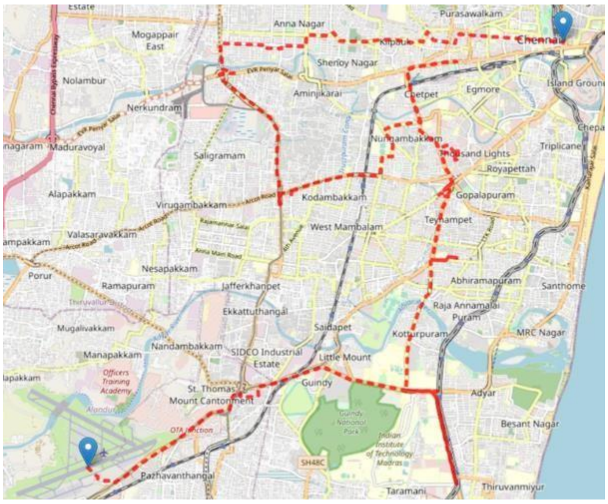

Fig.15 Optimal Path with multiple intermediate stop

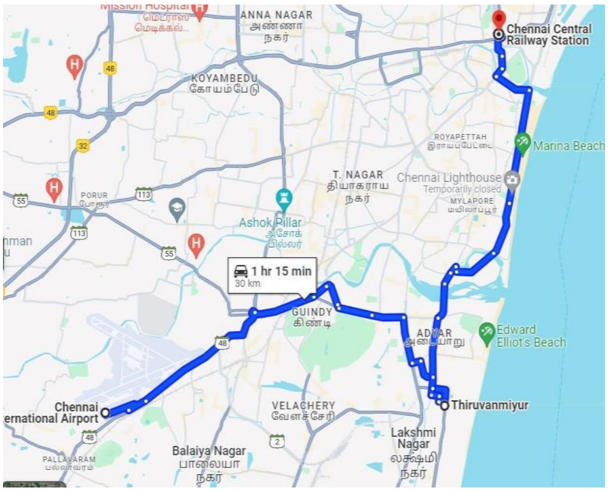

Fig.16 Optimized path with blockages and intermediate stop using proposed methodology

In this system, routing from Chennai Airport to Chennai Central with multiple stops, produced an optimized path spanning 53.186 km. In contrast, Google Maps indicated a distance of 56.9 km for the same route.

The screenshots comparing the system's optimized paths to Google Maps reveal a notable difference in distances. This algorithm showcased a shorter route, demonstrating the potential for improved fuel efficiency and reduced travel time. These findings underscore the effectiveness of our routing techniques, utilizing advanced algorithms for safe and efficient urban commuting.

7. CONCLUSION

In conclusion, this urban transportation system, designed with a client-server architecture and employing technologies like React, Python Flask, and Firebase, aims to provide an enhanced and efficient commuting experience. The integration of the Driver Behavior Analysis module, utilizing advanced techniques like LSTM, yielded insightful results from dataset analysis, classification efforts, and multiclass approaches. The findings indicate that LSTM outperforms RNN, offering consistent results across various class splits and showcasing its proficiency in predicting directional differences.

The improvised A* algorithm used in the Smart Routing module, tested in diverse scenarios like the Madras Institute of Technology campus and the broader Chennai metropolitan area, demonstrated its adaptability and effectiveness. In MIT, it successfully identified optimal paths, even when faced with blockages, showcasing its versatility. In Chennai, this system's optimized paths, compared to Google Maps, revealed shorter distances, emphasizing the potential for improved fuel efficiency and reduced travel time. These outcomes underscore the success of this project's routing techniques in utilizing advanced algorithms for safe and efficient urban commuting. Features such as loop avoidance, priority nodes, and next best route also enhance the user's experience.

Overall, the implemented modules contribute to an intelligent and user-centric transportation system, addressing key challenges in driver behavior analysis and urban route planning. The success of LSTM in deciphering driving patterns and the efficiency of this project's routing algorithms underscore the potential for safer, more efficient, and technologically advanced urban transportation systems in the future.

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