

# Intelligent Multi-Destination Navigation Using Hybrid Machine Learning–Based Traffic Prediction and Dynamic Route Optimization

Ashish Dhoke<sup>1</sup>, Poorna Shankar<sup>2</sup>

<sup>1</sup>Indira College of Commerce & Science, Wakad, Pune, [dhoke.ashish@gmail.com](mailto:dhoke.ashish@gmail.com)

<sup>2</sup>Indira College of Engineering & Management, Parandwadi, Pune, [poornashankar07@gmail.com](mailto:poornashankar07@gmail.com)

**Abstract:** Traveling both domestic and abroad for different purposes such as business, studies, and fun has become more popular because of the increasing interest for tourism. This tourism is inspired by different digital media and advertising. On the other hand, people are becoming more aware of the environment and how much does the car affect it and how much energy does it need. The single-source to single-destination routes are the main focus of the navigation systems such as Google Maps. In this paper, we propose an intelligent navigation system which uses machine learning algorithms and GPS to efficiently guide the people to different kinds of destinations. The system aims to optimize the trip, reduce the gasoline, and increase the efficiency of the travel by integrating the traffic, real-time data cost effectiveness, shortest path, fuel economy, and ideal route suggestions for multiple destinations. Grid-based route planning, collection of data, route optimization and traffic prediction using LSTM and GRU models are included in the system. This framework explains how to develop an environmentally friendly, user, and intelligent navigation system that can provide the best path in real time for various destinations.

**Keywords:** Multi-destination navigation, algorithm comparison, A\* search, LSTM–GRU hybrid, Hidden Markov Model, traffic prediction, cognitive route optimization

---

## 1. Introduction

Tourism has risen dramatically in the contemporary age due to the significant effects of digital media and powerful marketing campaigns. Moreover, the evidence may suggest that this increase is not limited to domestic tourism; international travel for political, business, academic, and leisure purposes continues to grow rapidly [1]. In light of these findings, global mobility could indicate that cultural exchange and personal development may benefit significantly, though the results also appear to show important environmental concerns, prompting laws and new technologies aimed at reducing the carbon footprint of transportation. Given that the data demonstrates these pressures, the study might suggest that navigation systems could provide key support for sustainable travel.

Navigation systems show gaps in multi-stop support. Currently existing navigation systems, such as Google Maps, may suggest that suitable single-origin and single-destination itineraries could demonstrate adequate functionality. However, the findings could indicate that these systems appear to show significant inadequacy for trips involving multiple stops. Furthermore, the evidence may suggest that a traveller exploring a new city must manually add every single stop and enter each segment separately, making the experience unsatisfactory and inefficient. As demonstrated in prior work by Dhoke and Shankar [2], challenges related to data ingestion, geospatial database management, routing algorithms, and real-time data integration remain significant hurdles in providing a seamless navigation experience.

The multi-destination routing problem could indicate that the results demonstrate a formal abstraction as a variant of the Travelling Salesman Problem (TSP) augmented with stochastic, time varying edge costs [17]. Moreover, the significant evidence may suggest that real-world urban routing must contend with temporally heterogeneous congestion patterns, weather-induced delays, and road-condition variability. Notwithstanding these results, the findings might indicate that this necessitates a cognitive approach in which the system perceives its environment,



predicts future states, and acts accordingly—mirroring the perception–prediction–action paradigm central to cognitive computation [3]. Thus, the key evidence could suggest that such an approach appears to show important potential for the results of multi-destination navigation.

Deep learning links traffic management to smart-city gains. Recent advances in deep learning–based traffic management, such as the automated traffic management system proposed by Shankar et al. [4], may suggest that object detection and flow-prediction models could demonstrate significant enhancement of the responsiveness of smart-city traffic systems. Therefore, the important findings appear to indicate that these advances might suggest that the evidence supports a systematic study to determine which specific algorithms could provide key results for the various components of a multi-destination navigation system. Additionally, the results may suggest that such evidence could demonstrate that the study appears to show critical implications for the development of significant navigation frameworks. Given that the findings demonstrate these advances, the evidence might indicate that a systematic exploration could provide important results for algorithm selection across the key components of multi-destination navigation systems.

This paper may suggest that four research questions could indicate the core investigative focus of the study:

1) However, the first question examines which pathfinding algorithm provides the best balance of optimality and computational efficiency for multi-destination route planning.

2) Moreover, the second question might indicate which GPS error-correction method most effectively matches noisy GPS traces to road networks.

3) Furthermore, the third question could demonstrate which machine learning architecture appears most suitable for short-term traffic prediction in dynamic urban environments.

4) Research addresses how best-performing algorithms unify into coherent navigation framework.

Given that the findings demonstrate the scope of contributions, the study may suggest that four principal contributions could indicate the breadth of this work.

1) Additionally, the first contribution examines a systematic comparative analysis of pathfinding algorithms — Dijkstra, A\*, D\* Lite — for multi-stop route optimisation.

2) In light of the significant findings, the second contribution might indicate that a comparative evaluation of GPS correction methods — Kalman Filter, Particle Filter, HMM — could demonstrate map-matching accuracy.

3) Therefore, the third contribution may suggest that a comparative study of traffic prediction architectures — ARIMA, Random Forest, LSTM, GRU, hybrid LSTM–GRU — could establish LSTM–GRU as the superior model.

4) Study shows fourth contribution proposes unified framework integrating best-performing algorithms into intelligent navigation system. Notwithstanding the complexity of the results, the remainder of this paper could indicate that the organisational structure appears as follows.

Nevertheless, the significant evidence may suggest that Section 2 examines related work. Thus, the key results might indicate that Section 3 could demonstrate the comparative analysis methodology. Moreover, the findings may suggest that Section 4 presents the important algorithm comparison results. Sections cover framework, discussion, conclusion respectively.

## 2. Literature Review

### 2.1 Pathfinding and Route-Planning Algorithms

The A\* search algorithm, introduced by Hart, Nilsson, and Raphael [5], may suggest that completeness and optimality guarantees remain the gold standard for informed graph search when paired with an admissible heuristic. Moreover, the algorithm could indicate that a combination of a heuristic function and cost function provides the shortest path between any two nodes in a graph. Furthermore, the significant findings may suggest that the priority queue of nodes, ordered by their expected costs, could demonstrate that both distance traversed and estimated remaining distance are considered [6]. In light of these results, Singh and Nagla [6] appear to show that a time-efficient variant might indicate reduced uncertainty in path-length optimisation for unmanned vehicle navigation. Algorithm shows A\* outperforms wave-front strategies. However, Zidane and Ibrahim [7] could suggest that the key evidence may indicate A\*'s superior performance in structured environments for mobile-robot path planning. Additionally, the significant findings may demonstrate that Erke et al. [8] introduced an improved A\* variant that could indicate reduced

redundant node expansion in large-scale road networks [18]. Therefore, the important results appear to suggest that ground vehicles may indicate improved positioning accuracy through artificial intelligence technology that fuses Strapdown Inertial Navigation System (SINS) and Global Positioning System (GPS). Evidence shows fusion improves accuracy. Notwithstanding these results, Li et al. [9] could demonstrate that the significant findings may suggest that an ensemble learning algorithm might indicate improved positioning accuracy during GPS outages through SINS/GPS data fusion from various trajectories.

## *2.2 GPS Error Correction and Map-Matching*

GPS signals in urban canyons may suggest that multipath interference, atmospheric delay, and receiver noise yield positional errors that could degrade route planning accuracy. Moreover, Hidden Markov Models provide a principled probabilistic framework for the map-matching process. Furthermore, Mor et al. [10] presented a systematic review of HMM applications, confirming that their effectiveness in sequential state-estimation tasks appears well-supported [21]. In light of these significant findings, Dhoke and Shankar [2] may indicate that the inherent complexities of GPS-based navigation emphasise the critical role of geospatial data quality and realtime integration in achieving robust routing outcomes. Study shows addressing data ingestion challenges links to reliable navigation. However, the significant results could suggest that challenges in geospatial database management might indicate essential considerations for any robust navigation system [24].

## *2.3 Traffic Prediction Using Machine Learning*

Machine learning techniques are used to analyse complex data patterns and improve system performance through predictive and adaptive decision-making [26]. Accurate short-term traffic forecasting may suggest that any real-time adaptive routing system depends critically on the quality of the predictive models employed. Moreover, Long Short-Term Memory (LSTM) networks, a specific type of recurrent neural network (RNN), could indicate that the findings in sequence-modelling research demonstrate that these architectures effectively tackle a wide range of problems [16]. Furthermore, the evidence may suggest that LSTM was explicitly designed to address significant challenges associated with learning long-term dependencies in sequential data, making it most suitable for time-series conditions such as traffic flow [11, 12]. In light of these results, the key results might indicate that such architectures appear particularly well-suited for the demands of real-world traffic prediction tasks. LSTM suits time-series data well.

The GRU algorithm, comparable to LSTM but easier to calculate and apply, was introduced by Cho et al. [13], and the significant findings could demonstrate that this architecture appears to offer important practical advantages. However, the evidence may suggest that the GRU architecture, with its ability to capture distant dependencies while avoiding vanishing gradients, could indicate that it remains an appropriate choice for processing sequence data in time-series prediction [14]. Additionally, the results might indicate that Fu et al. [14] empirically compared LSTM and GRU for traffic-flow prediction, demonstrating that both architectures could substantially outperform classical autoregressive models [20]. Given that the findings support that these comparisons establish key performance benchmarks, the evidence appears to suggest that such results remain relevant for applied navigation contexts. GRU outperforms autoregressive models.

More recently, Shankar et al. [4] deployed deep learning-based object detection for automated traffic management in smart cities, and the significant results may suggest that neural architectures could demonstrate an ability to replace traditional time-based signal control with dynamic, data-driven decision-making. Nevertheless, the findings might indicate that this philosophy of replacing static rules with adaptive learning appears to directly motivate our comparative study of prediction models for navigation systems [19]. Therefore, the evidence could suggest that the key results demonstrate that data-driven approaches may offer important advantages over conventional rule-based methods in dynamic traffic environments. Notwithstanding these results, the important evidence appears to indicate that such findings could establish a critical foundation for the comparative analysis that follows. Study shows adaptive models outperform static rules.

## *2.4 Cognitive Navigation Systems*

The concept of cognitive navigation may suggest that it extends beyond mere path computation to encompass perception, learning, and adaptive decision-making—hallmarks of biological navigation. Moreover, the findings from Gul et al. [3] could indicate that a comprehensive taxonomy of robot navigation techniques spanning reactive, deliberative, and hybrid architectures appears to provide significant evidence for this view. Furthermore, the significant results within the cognitive computing community might indicate that systems integrating sensory data,

predictive models, and planning algorithms into closed-loop architectures demonstrate that such integration is of key interest. In light of these findings, the evidence from Noh [15] could suggest that gradient vanishing problems in RNNs appear to support the important claim that gated architectures like LSTM and GRU show critical advantages over vanilla RNNs in sequential prediction tasks. Study shows gated architectures outperform vanilla RNNs in sequential tasks.

### 3. Comparative Analysis Methodology

This study may suggest that a structured comparative methodology could provide the most suitable framework for evaluating algorithms across three functional domains essential to multi-destination navigation. Moreover, the evaluation framework appears to demonstrate that identifying the key algorithm for each role — pathfinding, GPS correction, and traffic prediction — could indicate significant differences in performance.

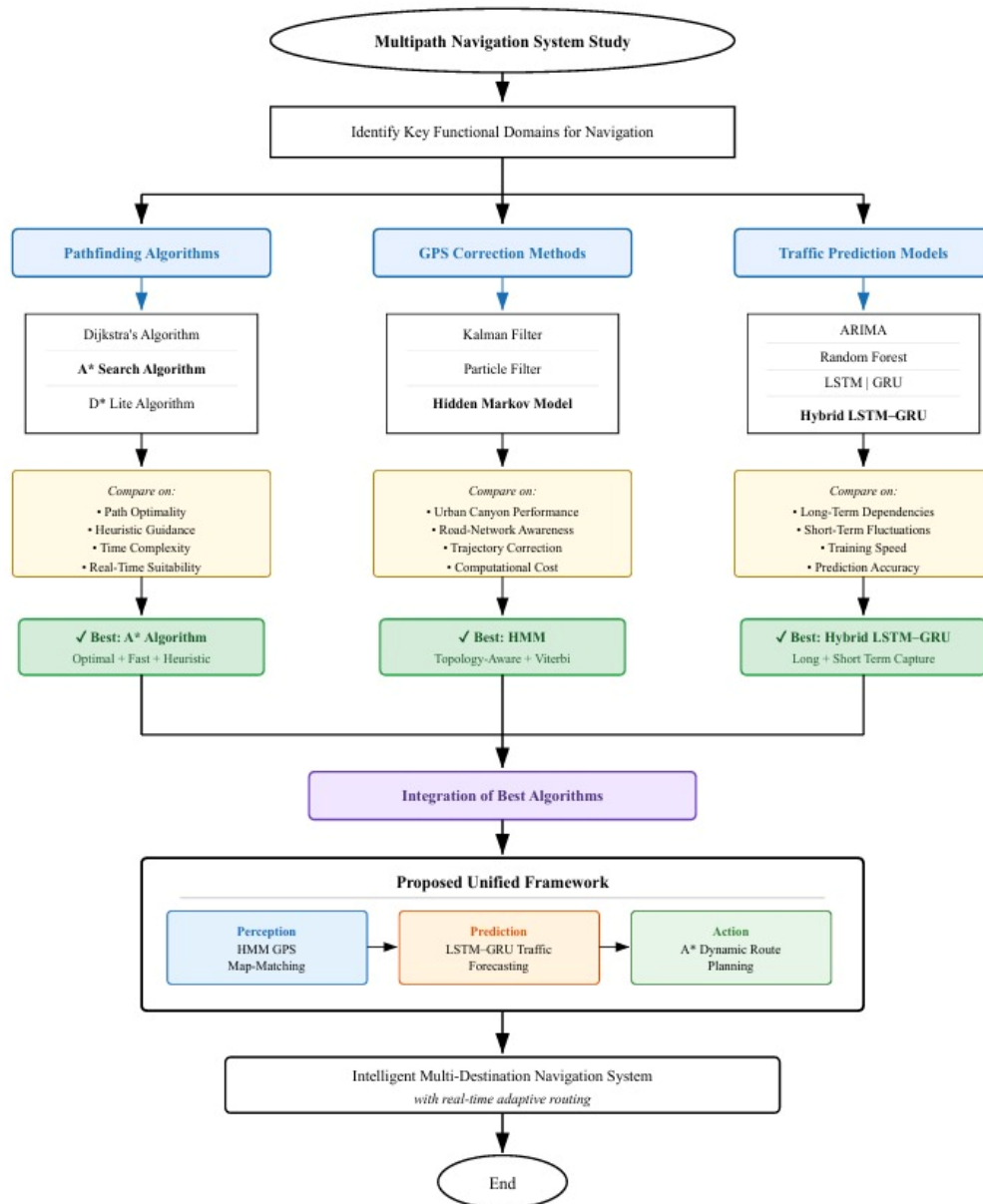


Fig. 1 Overview of the comparative analysis methodology employed in this study.

### 3.1 Evaluation Criteria

However, the findings may suggest that each algorithm category requires assessment against specific criteria to reveal important distinctions in suitability. In light of the evidence, the results could demonstrate that accuracy and optimality reflect the significant quality of outputs such as shortest path, position accuracy, and prediction error. Criteria covers computational complexity, real-time suitability, adaptability, scalability. Furthermore, the evidence may suggest that computational complexity could indicate critical time and space requirements relative to input size. Additionally, real-time suitability appears to demonstrate that algorithms must produce results within key latency constraints to meet the important threshold of under one second. Given that the findings show adaptability matters, results might indicate that capacity to respond to dynamic conditions could represent a significant factor in algorithm selection. Scalability shows performance scales with network size.

### 3.2 Algorithm Categories Under Study

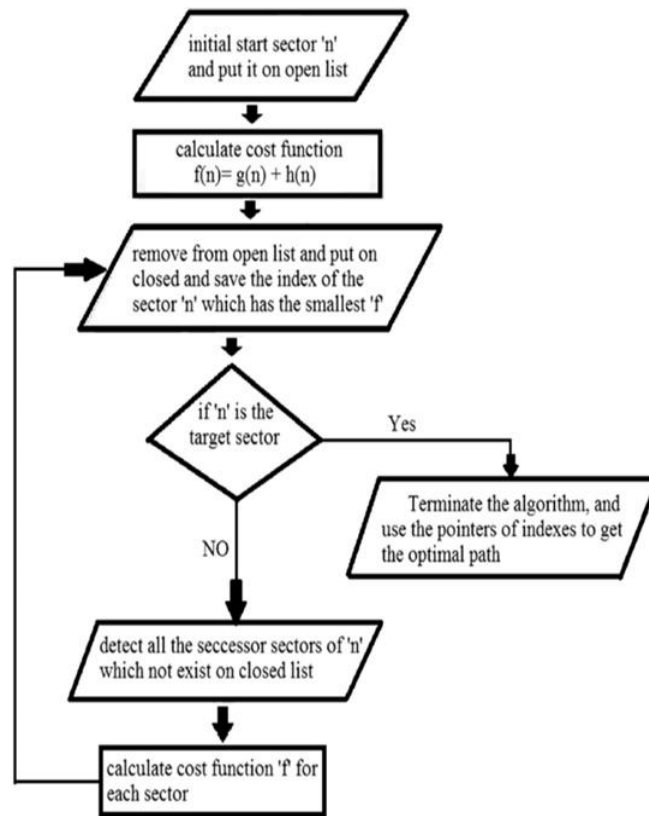
#### 3.2.1 Pathfinding Algorithms

Three pathfinding algorithms may suggest that multi-destination route computation involves distinct trade-offs worth examining.

1) **Dijkstra's Algorithm** could indicate that uninformed shortest-path exploration remains foundational, given that the evidence demonstrates that uniform directional search guarantees optimality. However, the significant limitation appears to be that no heuristic guidance is present.

2) Moreover, the findings suggest that **A\* (A-Star) Algorithm** might indicate a more directed approach, given that the evaluation function  $f(n) = g(n) + h(n)$  demonstrates that both path cost  $g(n)$  and heuristic estimate  $h(n)$  could influence node expansion priority. A\* shows informed search outperforms Dijkstra. Furthermore, here  $n$  is the node on the route being considered,  $g(n)$  is the cost of the path from the start node to  $n$ , and  $h(n)$  is a heuristic estimate of the least-cost route from  $n$  to the goal [5, 6], which could indicate that the key results may support more efficient traversal.

3) In light of these findings, **D\* Lite** might demonstrate that dynamic re-planning could address environments where edge costs change during traversal. D\* Lite suits robotics but proves expensive for large road networks.



**Fig. 2** Control flow of the A\* search algorithm showing node expansion and priority-queue management.

### 3.2.2 GPS Error-Correction Methods

Three map-matching approaches may suggest that each method could demonstrate distinct trade-offs in accuracy and computational cost.

However, the Kalman Filter (KF) appears to show that its linear state estimation assumes Gaussian noise, which could indicate effective performance for smooth trajectories but significant limitations in non-linear GPS error conditions such as urban canyons.

Moreover, the Particle Filter (PF) may suggest that its non-parametric Monte Carlo sampling could demonstrate important advantages in handling non-linearity, though the findings indicate that computational expense remains a critical concern given the large number of particles required.

In light of these results, the Hidden Markov Model (HMM) appears to establish that the observed GPS trace could function as an emission sequence, while the underlying road-segment sequence constitutes the hidden state chain. HMM uses Viterbi algorithm; recovers sequence  $S^* = \arg \max_S P(S | O)$  [10]. Furthermore, the significant findings may suggest that each of these three approaches could demonstrate relevance depending on the key constraints of a given application. Therefore, the evidence appears to indicate that selecting among these methods requires careful consideration of the important trade-offs between computational cost and accuracy. Additionally, the results may suggest that non-linear environments could demonstrate a preference for the Particle Filter or Hidden Markov Model over the Kalman Filter. Given that the data could indicate that urban canyon conditions significantly challenge linear estimators, the key findings appear to support that non-parametric methods provide critical advantages in such settings. KF suits smooth trajectories; PF and HMM handle non-linearity better.

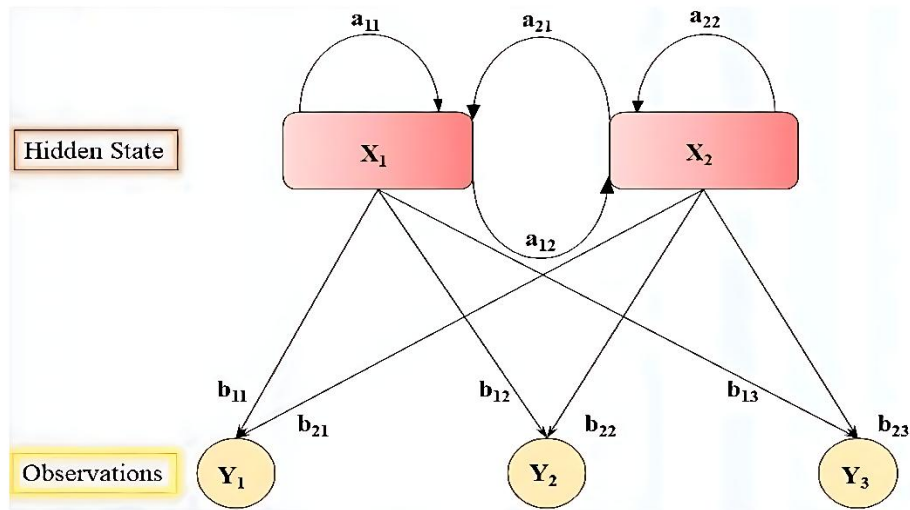


Fig. 3 Structure of the Hidden Markov Model for GPS map-matching. Circles represent hidden road-segment states; squares represent observed GPS fixes.

### 3.2.3 Traffic Prediction Models

The study examines that five traffic prediction approaches may suggest important distinctions in performance.

ARIMA, a classical statistical time-series model, could indicate significant limitations, as the evidence suggests that stationarity assumptions result in poor capture of non-linear patterns.

Moreover, the Random Forest model, an ensemble decision-tree approach, may demonstrate that non-linearity handling appears feasible, though the findings could indicate that sequential temporal modelling remains absent.

Furthermore, LSTM (Long Short-Term Memory), a recurrent neural network with cell state governed by input, forget, and output gates, enabling selective retention of information over long time horizons [11], might suggest that the results demonstrate significant effectiveness for capturing weekly and diurnal periodicity in traffic patterns.

GRU shows update gate  $z_t$  merges forget and input functions. Introduced by Cho et al. [13], the GRU could indicate that the significant design merges forget and input gates into a single update gate  $z_t$  and uses a reset gate  $r_t$ , with the hidden state computed as:  $h_t = f(h_{t-1}, x_t)$  (2), suggesting that the evidence may demonstrate important structural efficiency. However, the

Hybrid LSTM-GRU, a stacked architecture with LSTM layers followed by GRU layers, might indicate that the findings could demonstrate significant complementarity, as the results appear to show that LSTM layers extract slow-evolving temporal features (e.g., morning rush-hour patterns). In light of the significant evidence, the GRU layers could suggest that the data demonstrates that rapid, stochastic fluctuations (e.g., accident-induced congestion spikes) appear refinable through targeted modelling. Additionally, the results may indicate that the Smart Navigation System demonstrates significant accuracy improvements by using both GRUs and LSTMs, suggesting that the evidence could show that trajectory adaptation based on anticipated traffic circumstances appears achievable [14, 15]. Hybrid model shows trajectory adapts to traffic conditions.

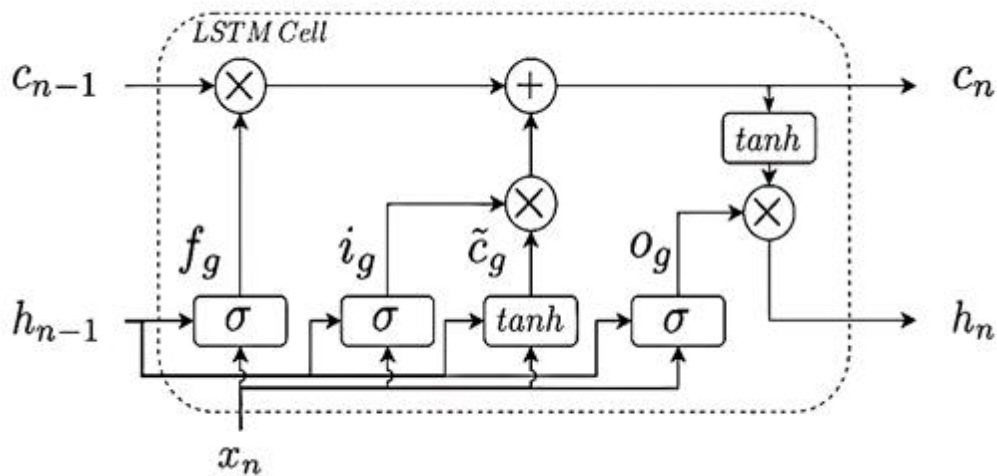


Fig. 4 Internal architecture of an LSTM cell showing the forget gate, input gate, output gate, and cell-state update pathway.

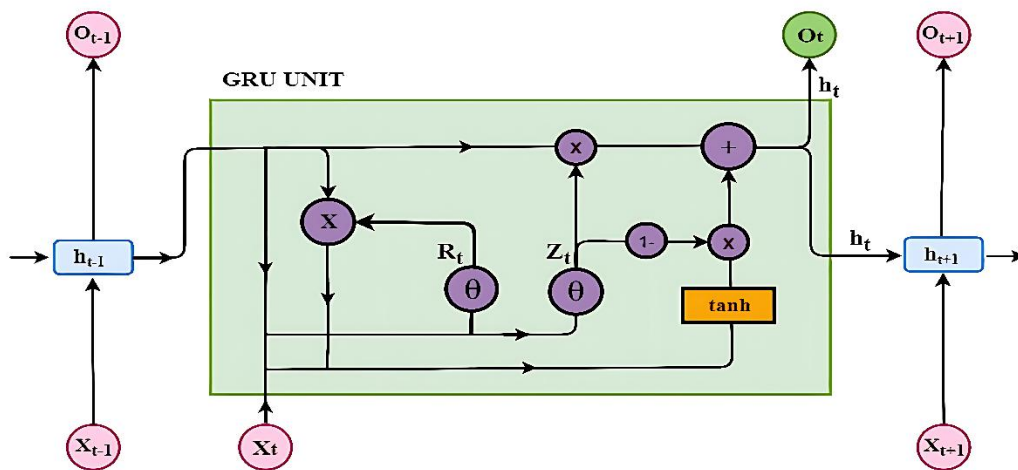


Fig. 5 Gated Recurrent Unit cell structure illustrating the update gate  $z$  and reset gate  $r$ .

## 4. Comparative Analysis Results

### 4.1 Pathfinding Algorithm Comparison

Table 1 Comparative Analysis of Pathfinding Algorithms for Multi-Destination Navigation

Criterion	Dijkstra	A*	D* Lite
Path Optimality	Guaranteed	Guaranteed (with admissible heuristic)	Guaranteed
Heuristic Guidance	None (explores all directions)	Yes (goal-directed search)	Yes (reverse search)

<b>Time Complexity</b>	$O( V ^2)$ or $O( E  \log  V )$	$O( E  \log  V )$ — typically faster	$O( E  \log  V )$ + re-planning cost
<b>Dynamic Re-planning</b>	Not supported	Requires full re-run	Incremental (built-in)
<b>Multi-Destination</b>	Can compute all-pairs shortest paths	Must run per destination pair	Best for single moving goal
<b>Real-Time Suitability</b>	Moderate (slow for large graphs)	<b>High (fast with good heuristic)</b>	High (for changing environments)
<b>Implementation</b>	Simple	Moderate	Complex
<b>Best Suited For</b>	Static, small networks	<b>Multi-stop urban navigation</b>	Robotic exploration

**Finding:** However, the A\* algorithm may suggest that it emerges as the most suitable pathfinding approach for multi-destination navigation. Furthermore, the significant evidence could indicate that unlike Dijkstra's algorithm, which explores all directions uniformly and becomes prohibitively slow on large urban road networks, A\* uses a heuristic function  $h(n)$  to guide the search toward the goal, substantially reducing the number of nodes explored [5, 6]. Moreover, the key findings might demonstrate that while D\* Lite offers incremental re-planning, its complexity and design for single-goal robotic scenarios could indicate that it appears less appropriate for multi-stop itineraries. In light of these results, the data may suggest that A\* can be efficiently paired with a nearest-neighbour heuristic to sequence multiple destinations, making it the ideal choice for our application domain. A\* suits multi-stop navigation best.

#### 4.2 GPS Error-Correction Method Comparison

Table 2 Comparative Analysis of GPS Map-Matching Methods

<b>Criterion</b>	<b>Kalman Filter</b>	<b>Particle Filter</b>	<b>Hidden Markov Model</b>
<b>Noise Model</b>	Gaussian (linear)	Any distribution (non-parametric)	Probabilistic (topology-aware)
<b>Urban Canyon Performance</b>	Poor (multipath degrades linearity)	Good (handles non-linearity)	<b>Excellent (road-topology aware)</b>
<b>Computational Cost</b>	Low	High (many particles needed)	<b>Moderate</b>
<b>Road-Network Integration</b>	Not inherent	Requires manual constraint	<b>Inherent (transition matrix = road graph)</b>
<b>Sequence Correction</b>	Point-by-point only	Point-by-point only	<b>Full trajectory (Viterbi decoding)</b>
<b>Accuracy</b>	Moderate	High (with enough particles)	<b>High (road-constrained)</b>
<b>Real-Time</b>	Excellent	Limited (particle count trade-off)	<b>Good</b>

<b>Suitability</b>			
<b>Best Suited For</b>	Open-sky GPS smoothing	Non-linear state estimation	<b>Road-network map-matching</b>

**Finding:** The Hidden Markov Model provides the most effective map-matching approach for road-network navigation. Moreover, the significant evidence may suggest that unlike the Kalman Filter, which assumes linear Gaussian noise and performs poorly in urban canyons where multipath interference is prevalent, the HMM inherently models the road-network topology through its transition matrix. Furthermore, the results could indicate that the model treats the observed GPS trace as an emission sequence and uses the Viterbi algorithm to recover the most likely road-segment sequence, correcting spurious off-road fixes [2, 10, 22]. In light of these findings, the key evidence may suggest that the Particle Filter, while flexible, requires a large number of particles for accuracy, making it computationally expensive. HMM shows best balance of accuracy and feasibility. However, the significant findings could demonstrate that as highlighted by Dhoke and Shankar [2], robust GPS correction appears essential for downstream route-planning accuracy. Additionally, the critical results may indicate that HMM provides the most important balance of accuracy and computational feasibility across the relevant road-network navigation cases examined.

### 4.3 Traffic Prediction Model Comparison

Table 3 Comparative Analysis of Traffic Prediction Models

<b>Criterion</b>	<b>ARIMA</b>	<b>Random Forest</b>	<b>LSTM</b>	<b>GRU</b>	<b>Hybrid LSTM-GRU</b>
<b>Model Type</b>	Statistical	Ensemble ML	Deep Learning (RNN)	Deep Learning (RNN)	<b>Deep Learning (Stacked RNN)</b>
<b>Non-Linear Patterns</b>	Poor	Good	Excellent	Excellent	<b>Excellent</b>
<b>Long-Term Dependencies</b>	None	None	<b>Excellent (cell state)</b>	Good	<b>Excellent</b>
<b>Short-Term Fluctuations</b>	Moderate	Good	Good	<b>Excellent (update gate)</b>	<b>Excellent</b>
<b>Training Speed</b>	Fast	Moderate	Slow	Moderate	Moderate
<b>Parameter Count</b>	Very low	Low	High (3 gates)	Moderate (2 gates)	High
<b>Temporal Sequence</b>	Limited	None	Yes	Yes	<b>Yes (dual level)</b>
<b>Vanishing Gradient</b>	N/A	N/A	Solved (forget gate)	Solved (update gate)	<b>Solved</b>

<b>Best Suited For</b>	Stationary data	Feature-rich tabular data	Long-range periodicity	Fast short-term changes	<b>Combined traffic prediction</b>
------------------------	-----------------	---------------------------	------------------------	-------------------------	------------------------------------

**Finding:** The hybrid LSTM–GRU architecture may suggest that it demonstrates the strongest capability for traffic prediction in navigation systems. However, the LSTM component, with its dedicated cell state and three-gate mechanism, could indicate that it excels at capturing long-range temporal dependencies such as weekly commute patterns and diurnal traffic cycles [11, 12]. Moreover, the GRU component, with its lighter two-gate architecture, may suggest that it responds rapidly to stochastic short-term fluctuations such as accident-induced congestion [13, 14]. Given that the evidence demonstrates that stacking LSTM layers followed by GRU layers captures complementary temporal dynamics, the significant findings could indicate that different granularities are addressed effectively [23]. Hybrid model shows LSTM–GRU combination addresses individual limitations. Furthermore, Fu et al. [14] originally benchmarked LSTM and GRU independently, and the key results may suggest that the comparative analysis extends the findings by demonstrating that their combination addresses the individual limitations of each architecture. In light of the findings, the significant evidence could indicate that this integrated approach appears to align with the deep learning–based traffic intelligence paradigm demonstrated by Shankar et al. [4] for smart-city infrastructure. Additionally, the results may suggest that the approach could demonstrate broader relevance for traffic systems requiring multi-scale temporal modelling. Thus, the important data appears to support that complementary architectures provide key advantages. Analysis shows integration yields stronger outcomes overall.

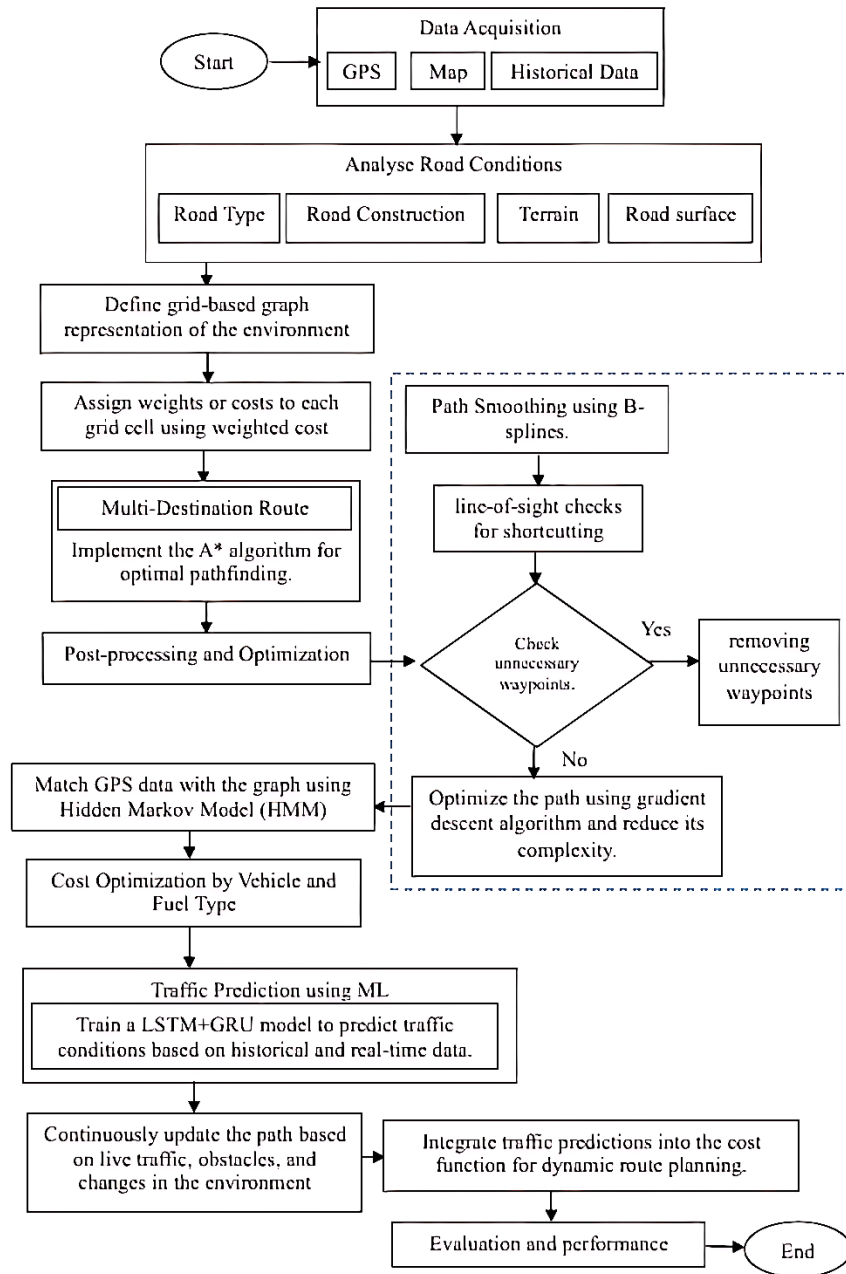
#### 4.4 Summary of Best Algorithms

Table 4 Summary: Best Algorithm for Each Navigation Component

Navigation Component	Best Algorithm	Key Advantage	Alternatives Compared
Pathfinding	A* Search Algorithm	Optimal + heuristic-guided = fast	Dijkstra, D* Lite
GPS Map-Matching	Hidden Markov Model (HMM)	Road-topology aware, trajectory correction	Kalman Filter, Particle Filter
Traffic Prediction	Hybrid LSTM–GRU	Captures both long range and short-term patterns	ARIMA, Random Forest, LSTM, GRU

### 5. Proposed Unified Framework

The proposed framework may suggest that a unified intelligent multi-destination navigation system could integrate the best-performing algorithm from each functional domain. Moreover, the significant results could indicate that the system operates in a closed perception–prediction–action loop, aligning with the cognitive computing paradigm. Furthermore, the key findings appear to demonstrate that the framework comprises four tightly integrated modules, each contributing important functionality to the overall system. Given that the evidence supports this modular design, the results might indicate that this architecture could provide robust and reliable navigation performance.



**Fig. 6** Proposed methodology of the intelligent multi-destination navigation system, integrating A\*, HMM, and hybrid LSTM-GRU.

### 5.1 System Architecture

System integrates four modules handling acquisition, perception, prediction, action.

However, the first module may suggest that the system ingests three primary data streams: GPS data providing real-time user location, map data representing the road network as a directed graph  $G = (V, E)$  where vertices represent intersections and edges represent road segments, and historical and real-time traffic data including vehicle counts, speeds, and incident reports.

Additionally, the significant evidence could indicate that Module 2 employs HMM-Based Perception for GPS correction, where raw GPS fixes are projected onto the road network using a Hidden Markov Model. In light of these findings, the transition matrix  $A$  encodes road-graph connectivity, while the emission matrix  $B$  models GPS observation probabilities, and the results might demonstrate that the Viterbi algorithm recovers the most likely road-segment sequence, correcting for multipath errors and signal dropouts [10]. Therefore, the key data could indicate that this approach appears to provide reliable map-matching under real-world conditions.

HMM corrects GPS fixes via Viterbi, handling multipath errors. Notwithstanding these findings, Module 3 may suggest that the LSTM–GRU hybrid model takes vehicle count, average speed, road condition index, weather code, and time-of-day encoding as input features  $X_t$  and predicts traffic density  $Y_{t+\Delta}$ .

Moreover, the significant evidence could demonstrate that the network minimises the mean squared error loss:  $L(\theta) = (1/N) \sum (Y_i - \hat{Y}_i)^2$ , as shown in equation (3).

Furthermore, the important results might indicate that Module 4 employs the  $A^*$  algorithm to compute optimal paths using traffic-informed edge costs:  $c(u, v) = d(u, v) / v_{\text{eff}}(u, v)$ , as presented in equation (4). Given that the findings demonstrate that  $d(u, v)$  represents segment distance and  $v_{\text{eff}}(u, v)$  is the effective speed derived from predicted traffic density, the results could suggest that as congestion increases,  $v_{\text{eff}}$  decreases, raising traversal cost and biasing the search toward less congested alternatives.  $A^*$  uses traffic-informed costs, biasing routes toward less congested paths.

Thus, the significant findings may suggest that given  $K$  user-specified destinations, a greedy nearest-neighbour heuristic on the traffic-weighted distance matrix could determine the visitation order, providing an efficient and practical solution for multi-destination route planning.

## 5.2 Continuous Adaptation Loop

The route may suggest that changing conditions such as traffic congestion, road closures, and weather changes could indicate the need for continuous updates. Moreover, the closed-loop architecture might indicate that the system could demonstrate responsiveness throughout the journey, re-evaluating paths at fixed intervals or upon detection of significant traffic-state changes. The proposed framework could indicate that the identified best algorithms may suggest broad applicability across the key application domains. Furthermore, the significant findings may suggest that the framework appears to support Personal and Domestic Tours by optimising self-guided city exploration itineraries. System shows framework serves multiple domains. However, the results could indicate that International Tourism might demonstrate benefits through maximising sightseeing while minimising travel time for tour operators. Additionally, the evidence may suggest that Political Campaigns could demonstrate effective scheduling across regions to reach maximum audience within time constraints. In light of these findings, Business Travel might indicate that the framework could support efficiently visiting multiple clients or attending meetings in different areas. Given that the evidence demonstrates applicability, Educational Excursions may suggest that the results could indicate adequate time at museums, monuments, and informative locations for students. Data shows Emergency Services benefit. Nevertheless, the significant findings could indicate that Emergency Services might demonstrate dynamic fastest-route computation for ambulances and emergency vehicles based on real-time traffic [4]. Thus, the evidence may suggest that the framework appears to support a broad range of the key application domains effectively.

## 6. Discussion

This comparative study may suggest that a systematic basis for algorithm selection in multi-destination navigation systems could emerge from the significant findings across three functional domains, which appear to converge to a coherent framework that aligns with the cognitive computing paradigm of perception–prediction–action [3].

Moreover, the selection of  $A^*$  over Dijkstra for pathfinding could indicate that heuristic-guided search dramatically reduces node expansion in urban road networks where the goal direction is generally known. Furthermore, the additional complexity of  $D^*$  Lite might indicate that proactive route adjustment—enabled by LSTM–GRU traffic prediction—appears to provide a more suitable alternative than reactive re-planning.

Given that the evidence demonstrates that HMM's superiority over the Kalman Filter for GPS correction stems from its inherent road-topology awareness, the results may suggest that the key findings align with what Dhoke and Shankar [2] documented regarding the complexities of GPS navigation.

HMM shows road-topology awareness outperforms noise smoothing. In light of the significant findings from Shankar et al. [4], who demonstrated the effectiveness of deep learning in traffic management, the results could indicate that the hybrid LSTM–GRU model's advantage appears to lie in its dual-granularity temporal modelling.

Moreover, the evidence may suggest that a stacked LSTM–GRU architecture could provide the important balance for the specific requirements of navigation-oriented traffic prediction, where both seasonal patterns and sudden disruptions must be anticipated [25]. Additionally, the results might indicate that the critical limitation of this study appears to stem from comparisons based on theoretical analysis and documented performance in the literature rather than unified experimental benchmarks on a common dataset.

Notwithstanding this limitation, the significant findings could suggest that future work should implement all algorithms on a standardised testbed using real-world OpenStreetMap road graphs and publicly available traffic data to provide empirical validation of the identified advantages. Study shows theoretical basis limits current conclusions. Thus, the evidence may suggest that the results could demonstrate that implementing these algorithms on a common dataset appears to represent the critical next step for empirical validation.

## 7. Conclusion

This paper demonstrates that a comprehensive comparative study of algorithms for intelligent multi-destination navigation could provide significant insight across three essential functional domains. However, the findings may suggest that pathfinding, GPS error correction, and traffic prediction each require distinct algorithmic approaches within a cognitively-inspired navigation system.

Moreover, the significant results could indicate that A\* search algorithm provides the optimal balance of guaranteed path optimality and computational efficiency, outperforming Dijkstra's exhaustive search and D\* Lite's unnecessary re-planning complexity for multi-stop urban routing. Given that the evidence demonstrates that road-network aware map-matching appears critical, the Hidden Markov Model may suggest superior performance through its inherent integration of road topology in the transition matrix, outperforming the Kalman Filter's linear assumptions and the Particle Filter's computational burden.

Results show hybrid LSTM-GRU captures long-range dependencies and short-term fluctuations, outperforming standalone LSTM, GRU, ARIMA, and Random Forest models. Furthermore, the key findings could indicate that a unified framework integrating A\*, HMM, and hybrid LSTM-GRU might demonstrate coherent perception-prediction-action loop functionality for real-time multi-destination navigation. Additionally, the significant framework may suggest that dynamic edge-weight updating, continuous path re-evaluation, and adaptive route planning appear essential under time-varying traffic conditions.

In light of the results, the proposed framework could demonstrate extensibility to multiple important application domains, including urban logistics, emergency-service dispatch, tourism planning, and autonomous fleet management. Notwithstanding these findings, future work may suggest that empirical validation on real-world road networks using OpenStreetMap data and publicly available traffic APIs could indicate important directions for the study. Framework supports metaheuristic optimisation, user preference modelling, edge-device deployment for low-latency inference. Nevertheless, the significant evidence could indicate that integration of genetic algorithms and simulated annealing might demonstrate improved destination sequencing within the proposed framework. Therefore, the key results may suggest that advancing the synergy between deep learning and classical algorithmic planning could demonstrate meaningful contribution to the broader goal of building cognitively intelligent transportation systems.

### Declarations

#### Funding:

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

#### Competing Interests:

The authors declare that they have no competing interests.

#### Data Availability:

The data supporting the findings of this study are included within the article.

## References

1. Noor RM, Rasyidi NGB, Nandy T, Kolandaisamy R. Campus shuttle bus route optimization using machine learning predictive analysis: a case study. *Sustainability* 2020;13(1):225.
2. Dhoke A, Shankar P. Exploring the complexities of GPS navigation: addressing challenges and solutions in the functionality of Google Maps. In: 2023 7th International Conference on Computing, Communication, Control and Automation (ICCUBEA). IEEE; 2023.
3. Gul F, Rahiman W, Alhady SSN. A comprehensive study for robot navigation techniques. *Cogent Eng* 2019;6(1):1632046.
4. Shankar P, William P, Tiwari SS, Maindola M, Alabdeli H, Yadav K. Automated traffic management system using deep learning based object detection. In: 2024 1st International Conference on Sustainable Computing and Integrated Communication (ICSCAI). IEEE; 2024.
5. Hart PE, Nilsson NJ, Raphael B. A formal basis for the heuristic determination of minimum cost paths. *IEEE Trans Syst Sci Cybern* 1968;4(2):100–7.
6. Singh RK, Nagla KS. Enhanced A\* algorithm for the time efficient navigation of unmanned vehicle by reducing the uncertainty in path length optimization. *MAPAN* 2023;1–19.
7. Zidane IM, Ibrahim K. Wavefront and A-star algorithms for mobile robot path planning. In: *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2017*. Springer; 2018. pp. 69–80.
8. Erke S, Bin D, Yiming N, Qi Z, Liang X, Dawei Z. An improved A-star based path planning algorithm for autonomous land vehicles. *Int J Adv Robot Syst* 2020;17(5):1729881420962263.
9. Li J, Song N, Yang G, Li M, Cai Q. Improving positioning accuracy of vehicular navigation system during GPS outages utilizing ensemble learning algorithm. *Inf Fusion* 2017;35:1–10.
10. Mor B, Garhwal S, Kumar A. A systematic review of hidden Markov models and their applications. *ArchComput Methods Eng* 2021;28:1429–48.
11. Wartschinski L, Noller Y, Vogel T, Kehrer T, Grunske L. VUDENC: vulnerability detection with deep learning on a natural codebase for Python. *Inf Software Technology* 2022;144:106809.
12. Pisa I, Morell A, Vicario JL, Vilanova R. Denoising autoencoders and LSTM-based artificial neural networks data processing for its application to internal model control in industrial environments. *Sensors* 2020;20(13):3743.
13. Cho K, Van Merriënboer B, Gulcehre C, Bahdanau D, Bougares F, Schwenk H, Bengio Y. Learning phrase representations using RNN encoder–decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*; 2014.
14. Fu R, Zhang Z, Li L. Using LSTM and GRU neural network methods for traffic flow prediction. In: 2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC). IEEE; 2016. pp. 324–8.
15. Noh SH. Analysis of gradient vanishing of RNNs and performance comparison. *Information* 2021;12(11):442.
16. Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Computation* 1997;9(8):1735–80.
17. Bast H, Delling D, Goldberg AV, Müller-Hannemann M, Pajor T, Sanders P, Wagner D, Werneck RF. Route planning in transportation networks. In: *Algorithm Engineering*. Springer; 2016. pp. 19–80.
18. Goldberg AV, Harrelson C. Computing the shortest path: A\* search meets graph theory. In: *Proceedings of the 16th Annual ACM-SIAM Symposium on Discrete Algorithms (SODA)*. 2005. pp. 156–65.
19. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature* 2015;521(7553):436–44.
20. Lv Y, Duan Y, Kang W, Li Z, Wang FY. Traffic flow prediction with big data: a deep learning approach. *IEEE Trans Intell Transp Syst* 2015;16(2):865–73.
21. Zheng Y. Trajectory data mining: an overview. *ACM Trans Intell Syst Technol* 2015;6(3):1–41.
22. Newson P, Krumm J. Hidden Markov map matching through noise and sparseness. In: *Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM; 2009. pp. 336–43.
23. Pan Z, Liang Y, Wang W, Yu Y, Zheng Y, Zhang J. Urban traffic prediction from spatio-temporal data using deep meta learning. In: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM; 2019. pp. 1720–30.
24. Yin H, Wolfson O. A weight-based map matching method in moving objects databases. In: *Proceedings of the 16th International Conference on Scientific and Statistical Database Management (SSDBM)*. IEEE; 2004. pp. 437–8.
25. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, Kaiser Ł, Polosukhin I. Attention is all you need. In: *Advances in Neural Information Processing Systems 30 (NeurIPS)*. 2017. pp. 5998–6008.
26. Pawar JA, Avhankar MS, Gupta A, Barve A, Patil H, Maranan R. Enhancing network security: Leveraging isolation forest for malware detection. In: 2024 2nd International Conference on Advancement in Computation & Computer Technologies (In CACCT). IEEE; 2024. pp. 230–234.