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Non-divergent traffic management scheme using classification learning for smart transportation systems

Manimurugan S *, Saad Almutairi

Industrial Innovation & Robotics Center, Faculty of Computers and Information Technology, University of Tabuk, Tabuk City, Saudi Arabia, 47512

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ABSTRACT

Smart transportation is an autonomous arrangement that embodies technologically enabled intelligent vehicles and traffic systems to assist diverse real-time roadside applications and navigation. Intelligent Pervasive computing techniques with a common shared platform, such as the cloud, are employed to ease operations. This article introduces a Non-Divergent Traffic Management Scheme (NDTMS) to improve roadside driving for users and vehicles. This scheme recognizes and classifies traffic, neighbors, and environmental navigation data. Combining two inputs into the ecological data, the Pervasive computing systems assist in non-deviating seamless application support. The input data gives information regarding the traffic on roads and traffic density. The extracted data from the neighbors help in matching the data with features and reduces traffic. The problem of data mishandling for traffic management is addressed by classifier learning links to the application-specific requirements. This Pervasive computing technique operates on combinational data for precise traffic management through navigation/ alerts/ communications.

1. Introduction

Road traffic management is a system that controls traffic based on established rules, functions, and conditions. Various measures and methods are used in road traffic management systems. Traveler information service, traffic incident management, and traffic signal management are some of the processes involved in road traffic management systems [1]. Pervasive computing is used in road traffic management systems for effective travel organization. The main aim of Pervasive computing is to create an ambient intelligence system for specific fields and applications. It also provides electronic services to users through internet connections [2]. Pervasive computing also necessitates possible wireless communication services to travelers that provide essential information regarding traffic and road conditions. The main advantage of Pervasive computing is to reduce service costs through smart devices [3]. Pervasive computing reduces time and cost-consuming levels in road traffic management systems. It identifies problems and causes of traffic; solves them by sending an alert message to relevant authorities via management systems. Pervasive computing utilizes traffic infrastructure information to direct traffic on the road [4] effectively.

A smart transportation system is an advanced technological approach in various applications and systems. When smart transportation is used in traffic management systems, it collects accurate information about roads, traffic, and accidents [5]. Smart transportation system reduces the latency ratio in identifying routes, destinations, road conditions, and traffic level for travelers. It

* Corresponding author.
E-mail addresses: mmurugan@ut.edu.sa (M. S), s.almutairi@ut.edu.sa (S. Almutairi).

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incorporates modern technologies such as cloud computing and wireless communication system that provide optimal services to users [6]. Smart transportation suggests alternative routes and understands the exact meaning of the user's request. Smart transportation systems maintain the reliability and efficiency of traffic management systems [7]. It controls vehicles through sensors and other electronic devices. Traffic-related data are sent through wireless communication that alerts drivers, reducing road accident ratio [8]. An Intelligent Transportation System (ITS) is an innovative technology that improves the mobility and safety measures of users. It is mainly used for vehicle communication and interaction [9].

Ubiquitous learning is an everyday environment that employs both mobiles and computers to provide wireless communication services. It is used in smart transportation traffic management systems [10]. Smart transportation traffic management system is mainly used to regulate traffic flow and signals based on certain conditions. Ubiquitous learning identifies patterns and features of traffic that provide necessary information for analysis and detection processes [11]. Important fundamental values and points related to the flow of traffic and signals are also identified through ubiquitous learning. Ubiquitous learning improves the Quality of Service (QoS) and performance levels in providing services to users [12]. Pedagogical patterns are detected that provide feasible information to smart transportation traffic management systems. Internet of Things (IoT) based ubiquitous learning technique is also used in traffic management systems [13, 14]. IoT connects every nearby vehicle to provide proper wireless communication to users. IoT reduces road accident levels, enhancing the effectiveness and robustness of traffic management systems [15].

The rest of the paper is organized as follows: Section 2 discusses the related works, Section 3 proposes the NDTMS scheme, Section 4 deliberates the results and discussion, and Section 5 concludes the research paper.

2. Related works

Zhang et al. [16] have developed a Decomposition-based Constrained Dominance Principle Genetic (DBCDP) algorithm for transportation scheduling in open-pit mine vehicles. Artificial intelligence (AI) is used to enhance efficiency in scheduling. Multi-objective and high-dimensional problems are solved by the DBCDP algorithm that reduces errors in transportation schedules. The proposed DBCDP algorithm maximizes the performance and feasibility of mine vehicles via Intelligent Transportation Systems.

Zheng et al. [17] have proposed a deep learning framework to solve Spatiotemporal disturbance (STD) problems, named DeepSTD, for traffic flow prediction. STD modeling method is used to identify region functions and effects. Deep Learning has eliminated unwanted problems and causes present in road traffic. Compared with other methods, the proposed framework improves accuracy in traffic flow prediction, thereby enhancing the systems' effectiveness level.

Zhu et al. [18] have introduced a new Multi-Sensor Neural Network model (MSCPT) based on a Cross-Place Transportation Mode Recognition algorithm for an Intelligent Transportation System. A recognition algorithm extracts unique and temporal details necessary for further scheduling and prediction processes. The proposed MSCPT model provides effective performance and services to users through transportation systems. The proposed model also improves the robustness and mobility of transportation systems.

Mushtaq et al. [19] have developed the Deep Reinforcement Learning (DRL) algorithm and Smart Rerouting (SR) technique-based traffic flow management for autonomous vehicles (AV). DRL is mainly used to optimize traffic flow at intersections and junctions of the roads. SR is employed to reroute paths for users to reduce their waiting period during traffic jams. The proposed system achieves high efficiency and effectiveness in balancing user traffic flow.

Ahmed et al. [20] have proposed a congestion-aware route suggestion protocol for Internet of Vehicles (IoV) traffic management systems. This system provides intelligent communication devices to get basic information about the destination. Congestion-aware routing provides relevant routes and paths to travelers to reduce the waiting time of vehicles in traffic. Compared with other methods, the proposed protocol improves performance by reducing the travel time of IoV.

Wang et al. [21] have developed a fused computational approach for congestion monitoring in Intelligent Transportation Systems. Anxiety, misunderstanding, delayed conveyances, and roads are the primary reasons for congestion traffic. The computation approach identifies the traffic's exact cause and provides users with alternate routes. The proposed approach achieves high accuracy in monitoring systems that improve the performance level of transportation. The proposed approach also increases the efficiency and reliability of congestion monitoring systems.

Farrag et al. [22] have designed a Smart Traffic Incident Management Framework (STIMF) for transportation systems. A fuzzy-logic inference system provides optimal data for STIMF, thereby reducing identification latency. STIMF detects traffic causes, scenarios, and conditions. Compared with other methods, the proposed STIMF improves accuracy in management, leading to enhanced transportation systems.

Ali et al. [23] have developed big data analytics and cloud computing (BCC) for smart transportation systems (STS). BCC gets feasible information through device-to-device communication. The main aim of STS-BCC is to improve the mobility and robustness of Intelligent Transportation Systems. BCC reduces the time and energy consumption ratio in classification. The proposed STS-BCC maximizes accuracy in traffic prediction, which improves the efficiency level of STS.

Mondal et al. [24] have proposed a priority-based adaptive traffic signal control system for smart cities. Traffic cameras are fixed in intersections, junctions, and main roads to capture traffic flow. Traffic parameters and patterns are calculated based on priorities. The proposed method improves the effectiveness and feasibility of transportation services in smart cities.

The traffic on the roads is the major problem that reduces the accuracy of flow prediction. Few special characters are not scheduled and predicted in the process. The proposed NDTMS improves traffic congestion and route path prediction. NDTMS manages the traffic and improves the moving vehicle's efficiency regardless of the density and user requirements.

3. Proposed scheme

NDTMS provides improved support for roadside driving among users. Vehicle support smart transportation is an autonomous arrangement that embodies technologically enabled intelligent vehicles and traffic systems to assist diverse real-time roadside applications. The data from traffic, neighbors, and navigation are collected in the small transportation system to deliver the demands of their application. This scheme independently recognizes and classifies the environmental data for traffic, neighbors, and navigation. The road information is given to the smart transportation process's traffic, neighbors, and navigation data. These data are entered into the application demanded to receive information about road traffic, signal, and density. The information about the traffic data, neighbors, navigation, road traffic, signals, and density of the traffic is mentioned in the application demands to extract the needed and matching data. This will help the traffic management systems with the reduction in traffic ratio. The management system eases time calculation on the roads. Hence, the system prevents the applicant's vehicles from waiting unnecessarily on the road, which causes traffic jams, and also avoids additional time delays, etc. The proposed scheme is portrayed in Fig. 1.

The traditional traffic signal cannot provide the features of smart transportation management. The traditional traffic signal system includes traffic control, fixed time, manual operation, traffic actuation, specific traffic, and pedestrian signals. The traditional traffic signals provide detailed information to create flexible smart transportation services. The implementation of smart transportation in NDTMS reduces traffic jams, time delays, and pollution. This is used to provide the incompetent traffic glide under traffic obstruction. The main disadvantage of traditional traffic management is that they cannot provide zestful and flexible services, but smart transportation management can offer them. The zestful and flexible services are nothing but the energy enthusiasm that traditional transportation systems cannot provide. It is supported only by smart transportation. Traffic management and traffic flow need to be maintained in smart transportation. It is necessary to improve the functionality of the old traffic management so that smart transportation can be introduced. It helps to reduce traffic jams, pollution, time delays for the applicants, etc. The coordination of smart vehicles and automated highways can reduce traffic congestion. The regimentation of the traffic flow can be accomplished by Pervasive computing in vehicles and the environment. This can also improve the safety of the road passenger with Pervasive computing vehicles. The applicants can use their interesting pathway through information from the smart transportation system. The road traffic, signals, and density information are assigned in the system. So that the passenger can choose their path according to the application's report that matches their desired needs. Smart management mainly helps in reducing roadside accidents and is also helpful during emergencies. This also helps in the improvement of urban planning.

The navigation data can vary depending on the traffic density in the environment. This smart transportation system reduces the delay of vehicles and also traffic congestion. Lowering the problem is to make the capacity of existing roadways high by the induction of many lanes. Effective transportation management can be done through detailed study and the duplication of traffic models. The traffic density depends on the number of vehicles, and the traffic congestion rate also depends on the capacity of existing roadways. Smart transportation reduces traffic density and congestion with the minimum number of lanes by reducing the power of roads.

The application's demands are used to register the information about the passenger and the roads (or) environment. The application demands in smart traffic management can be explained by the following equation given below:

$$S = \frac{(A+B)}{X_\alpha + X_\beta}$$

Such that,

$$S\left(X_\alpha + X_\beta\right) = (A+B) \tag{1}$$

Where$S$ denotes the Pervasive computing, $(X_\alpha + X_\beta)$is the information about the road signals and the applicants.$(A+B)$ denotes the demands of the application; equation (1) explains the application demands in smart traffic management. In this application, the neighbors can also update their information in the application demands to receive information about the traffic signals and density of the road.

In the process of smart traffic transportation systems, Pervasive computing is used. It is used to sense the situations of the

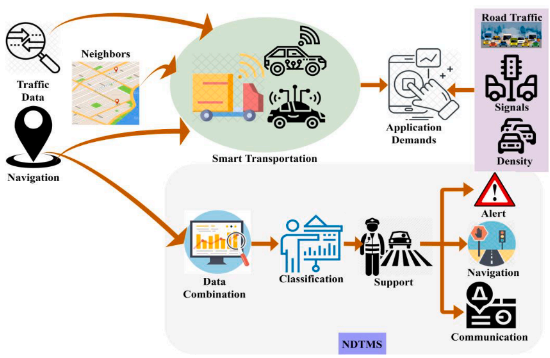

Fig. 1. Proposed Scheme

environment and predict the needs and enterprisingly act in necessary conditions to find the best solutions. In the traditional traffic model, there is a delay in observation of the fault; if there is congestion in the traffic. When Pervasive computing is introduced, it helps to find counterfeit in traffic management actions. The main advantage of Pervasive computing is that it can reconcile them to run time, to make things such as passenger maneuverability, navigation variability, changing traffic and passenger needs, and computing mistakes. Pervasive computing has a worldwide outlook and sharp-witted interconnection with the environment. Intelligence and invisibility are the primary connotations of Pervasive computing, which is used to sense the situation of the environment and the passengers. Detailed information about the neighbor's context is necessary to behave following the environmental change.

Pervasive computing plays an essential role in smart transportation and traffic management. It acts according to the application-specific requirements. So, the passengers can choose their roadways based on traffic density. The application demands help to produce the passenger's information and the environment to make Pervasive computing more intelligent by providing the best solutions for the users. Pervasive computing in this proposed system aims to reduce roadway accidents compared to the existing models. With the combination of two or three inputs, such as traffic data, neighbors data, and navigation data, the Pervasive computing systems assists in non-deviating seamless application support. It is an excellent source of facing problems in the traffic management system to avoid traffic collisions and traffic congestion. The application demands in smart transportation with Pervasive computing are to predict the needs. So, it gives the best option for processing the inputs. Traffic resource management and Pervasive computing are for better communication. They both prevent accidents, as given in the equation below. It requires proper communication between the vehicles and traffic to prevent accidents and manage the traffic. The process of the system can be elucidated in the equations given below:

$$\overline{X} = X_{\beta} - BS^{-1} \tag{2}$$

$$S = MQ^{-1} \tag{3}$$

Where $(\overline{X})$ is denoted as the sensor data of Pervasive computing, $(MQ^{-1})$is denoted as the outcome of Pervasive computing and (BS^{-1}) is the resources to manage the traffic. Equations (2) and (3) explain the process of Pervasive computing in smart transportation management. The application demands and navigation information are also registered for passengers' use. The navigation can be re-based on road traffic signals and traffic density. If the navigation system and the traffic system can communicate with each other, the traffic system can make decisions depending on the destination of the vehicles. In this navigation, the traffic signals and the traffic density can detect chances for the clearance of the blocked roads. In a smart transportation system, ambulances and government vehicles can be given higher precedence. Navigation will provide the shortest way for the passengers according to the lower traffic density in the environment. It also gives the waypoints and also the additional information about parking places and so on. Pervasive computing is used in providing smart and intelligent devices to deliver the positions of some services. By using the navigation system, there will be the production of better solutions with some connectivity to the internet in the time. It can also provide real-time information on the traffic by reducing the time delays of vehicles. The data augmentation using $\overline{X}$ and $(A + B)$ is portrayed in Fig. 2.

The $\overline{X}$ and BS^{-1} serve as the primary source of smart transportation assistance. The references are accumulated from the moving vehicle for X_{α} and X_{β} in varying$T$. Contrarily, theBS^{-1} is aggregated from/through the neighbors within the coverage region. In this accumulation $MQ^{-1} \in A$ and $(S \cup \overline{X}) \in B$ is harmonized for further navigation support. If this data is less promising, then the navigation output is required alongside$A$ and B for traffic management (Refer to Fig. 2). Navigation with Pervasive computing collects information because they provide unique services about the traffic jams in the environment. Navigation in the smart transportation system helps vehicles to be positively involved in traffic situations with the help of Pervasive computing. This navigation will have an independent sense which allows control of the present traffic system and helps to make the best solution. It has a central network where passengers and traffic systems can communicate. It can ensure comfort for passengers who use the navigation system. Navigation in this traffic management can solve the problems in the traffic as an exceptional service and can give solutions for problematic situations. The following expressions can elucidate the navigation in smart transportation and traffic management:

$$Q = \sum_{i=1}^{M} V_i \tag{4}$$

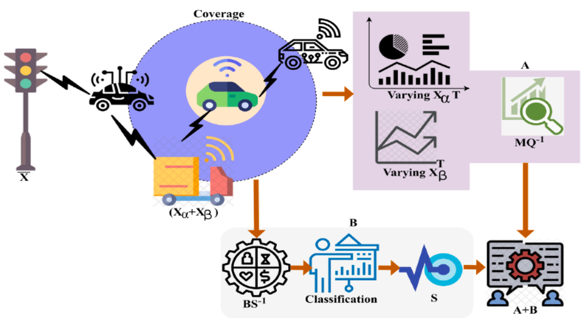

Fig. 2. Data augmentation using$\overline{X}$ and $(A + B)$

$$S = MQ^{-1} = M\left(\sum_i V_i\right)^{-1}$$

Such that,

$$S = \frac{1}{M}\left(\sum_i V_i\right)^{-1} = \overline{V} \tag{5}$$

Where (Q) is denoted as the navigation system output, $(\sum_i V_i)$ is denoted as the solutions by the navigation with Pervasive computing $(\overline{V})$ and it is indicated as the best way. Equations (4) and (5)explain the navigation processes used in the traffic management scheme. Now, the navigation combines the traffic, neighbors, and navigation data. The navigation can be included in the form of three input data for controlling and planning the traffic without affecting the routes of the roads. The traffic flow depends on the characteristics of the traffic data, neighbor data, and navigation data. The different data input is illustrated in Fig.3. The data combination and traffic procedures deliver the appropriate solution for traffic environment conditions. With the combination of two or three of the above inputs, the Pervasive computing systems assist in non-deviating seamless application support. Combining the data is necessary to improve traffic congestion in both the real-time traffic control and the planning perspective of traffic control. Collecting two or three pieces of data from the above inputs of the passenger is used in the escalation of the traffic control system. It also helps in the clear communication between the passenger data and the traffic controller about the actual road conditions without affecting the escalation. Firstly, this data combination understands the traffic pattern in the environment to deliver the appropriate solution. This combination of data includes the operation of sensors and the analysis of traffic using machine vision. This is used to determine the functions of roadways, the density of the traffic in the environment, and the best solution for problematic situations. The data combination is used in the accuracy of estimation and the prediction of traffic flows. The sensors are used to circumscribe information about the conditions of the traffic procedures, such as roads and bridges. The combination of data from the passenger inputs produces smooth application support. It majorly helps in the control of traffic congestion and accidents on the roadways. The data combination in the smart transport system is expressed by the equations below:

$$H_i = \frac{dx}{dt} = L(t_2 - t_1)$$

Such that,

$$L(t_2 - t_1) \rightarrow 0\frac{A_2 - A_1}{t_2 - t_1} \tag{6}$$

$$\frac{\overline{H_t}}{\sum_{i=1}^{M} H_i} = N^{-1} \tag{7}$$

Where (L) is the limit of the traffic, $(t_2 - t_1)$ is the data combinations and $(A_2 - A_1)$ is the output solution from the data combination in the smart transport system. Equations (6) and (7) elucidate the process of data combinations from the inputs of traffic data, neighbor data, and navigation data. The data combination is illustrated in Fig. 3.

The data combination handles variations in the vehicle's travel time. Therefore $(\overline{X} \cup \overline{V} \cup MQ^{-1})$ is the combinational data along$L$. L fluctuates and the $(A + B)$ is requirements and identification. Therefore, t_1,t_2 are distinguishable for$L$ and H_i is performed for it. The classification output(*i.e.*)$(A_2 - A_1)$ is observed across multiple H_i for whichMQ^{-1} based on$L$ is updated (Fig. 3). Now, the classification of the user requirements takes place. The problem of data mishandling for traffic management is addressed by using

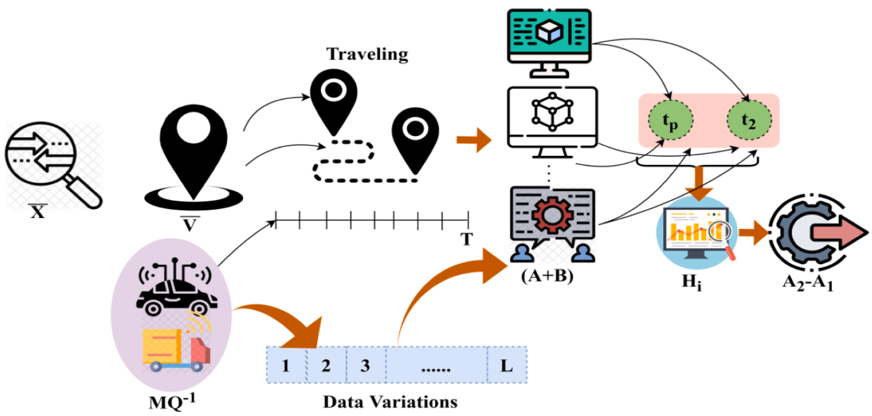

Fig. 3. Data Combination

classifier learning links to the application-specific requirements. The user requirements are identified and classified by learning to possess the required sensed data combination. The research article employs the Tree Classifier to distinguish the user requirements and provide support without counterfeiting data. This NDTMS improves the application and navigation of intelligent Pervasive computing techniques used in the classification process. Tree Classifier is precisely used for developing control applications of the traffic data by availing existent data of the urban regions. The Tree Classifier algorithm is used to classify the traffic into low, medium, and high traffic ranges. This classifier algorithm is also used to detect malformation in traffic and gives information about the malformation to the passenger through the Pervasive computing sensors. Among all the classification algorithms, the Tree Classifier is chosen to concentrate on traffic control and mishandling of data. The Tree Classifier is selected for the accurate classification of traffic data and to manage the mishandling of data for traffic management. The Tree Classifier algorithms find the best route path among the original routes with less time to reduce the traffic density.

The Tree Classifier algorithm helps users to find the best route to be admitted and allows them to choose the best low-time squandering path than their original route. It helps in classifying the user requirements based on the application demands. This gives a clear pathway for the users according to their needs based on the outputs from the traffic signals and the traffic density. The problem of data mishandling for traffic management is addressed by using classifier learning links to the application-specific requirements. This Tree Classifier is used to correct the mishandling of data with counterfeits information. The classification process uses the Tree Classifier algorithm to make the user choose the best solutions for difficult circumstances. The Tree Classifier in the process of classification is to classify the user requirements data that the below equations can express:

$$\overline{H_C} = P\left(N^{-1}\sum_i q_i\right)^{-1} \tag{8}$$

$$H_i T_i = P \tag{9}$$

Where(T) is the vehicle time, (P) is the output of the classification, and $\left(N^{-1}\sum_i q_i\right)$ is the low-time squandering path. Equations (8) and (9) explain the process of classification by using the Tree Classifier algorithm. The classification supports by providing alert messages, navigation routes, and appropriate communications. In particular, the data update with the navigation is required for improving the moving vehicle's efficiency regardless of the density and user requirements. The alert supports sending messages about the starting and the final destination to the user's number, which they have provided. And also, the user will be informed about the route they can choose to avoid the traffic. The navigation support chooses the correct best route with less traffic and low consumption of time, and also, Customers can view the alert message without internet access. Fig. 4 presents the classification of combinations and requirements.

Classification learning is initially taken for $\overline{H}_c$, $\overline{H}_S$, and $\overline{H}_t$ using H_i. Contrarily, the final learning relies on $(\overline{H}_C + H_i)$ Combination for P. $\forall P$, the θ^2 is the final output generating N^{-1} such that $\sum_i q_i$ is required for meeting $(A+B)$. The final classification surpasses A_1 and A_2 for which MQ^{-1} is the output in any$P$ Fig. 4). Navigation is used to identify the blocked roads and can change the route without traffic to the passenger. The support is provided as a source of communication for the users to interact with the Pervasive computation to identify the best ways. It also helps to communicate between the users and the sensors. It is useful to detect the best route for the passengers. Hence, these supports help in finding the problem of data mishandling for traffic management and correcting the user data according to the correct information delivered by the passenger. The support provides for the alert, navigation, and communication process in smart traffic management as expressed by the following equations (10) & ((11) given below:

$$\overline{H_C} = P\left(N^{-1}\sum_i q_i\right)^{-1} = P\left(N^{-1}\sum_i \frac{P}{H_i}\right)^{-1}$$

$$\overline{H_C} = 1\left(N^{-1}\sum_i \frac{1}{H_i}\right)^{-1} \tag{10}$$

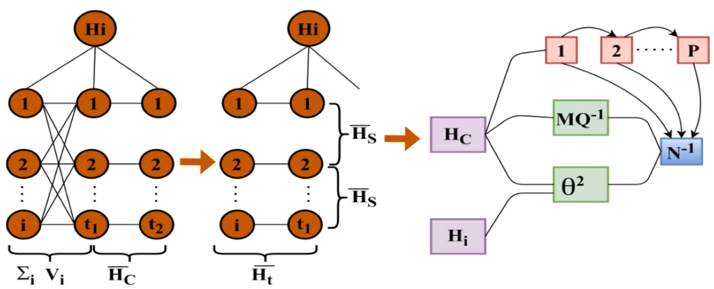

Fig. 4. Classification Illustration

Such that,

$$\overline{H_t} - \overline{H_S} = \theta^2 (\overline{H_S})^{-1} \tag{11}$$

Where (θ^2) is denoted as the final best route with low traffic $(N^{-1}\sum_i \frac{P}{H_i})$ is denoted as the support for alert, navigation, and communication. $(\overline{H_t} - \overline{H_S})$ is the classified solution of the Tree Classifier in the classification process. This proposed scheme is used in finding the best route for passengers with less traffic range. A Tree classifier is used to classify the user requirements in smart transportation and the traffic management scheme. Pervasive computing is used to detect the traffic road for the passengers, and it also improves the moving vehicle's efficiency regardless of their density and user requirements. In this proposed method, the best route with a low traffic range is found by using Pervasive computation. The accuracy of the traffic information provided for the users is high when compared to the other existing models.

4. Data and Analysis

The data from [25] is used for analysis with an open street map displayed in Fig. 5. This map contains interchanges, crossroads, and highways.

The starting point is marked in green, and the destination is marked in red; the possible observed data in this route, as present in the dataset, is given below:

Between Interchanges 6 and 11, the considered 20-km portion of the UK expressway is located. The considered portion of the UK is branched into six sections of divergent measures, each containing two interchanges. The sections of that portion are replicated separately in both directions, having six lanes. These six lanes are divided into two sets of three and apportioned by the concrete median of 12m street lamps and panorama. Light vehicles have a 120km/h speed limit, and heavy trucks have a 100km/h speed limit. For the smart transportation system, a small allotment of the traffic density, the inadequate amount of inputs of the passenger, and the control measures are considered. However, this proposed system is overpriced by increasing the capability and obtaining extra data. The navigation factors can be included for finding the best route path and the road type with a particular number of routes. The navigation factors are included in the data-impacting elements for controlling traffic congestion and travel time. The components of the navigation factors are road type, classification, width, and the number of routes. This case study is the confirmation of the concept. The considered data factors for sensing, assessment, and vehicles are:

- Variable X_α
- Variable X_β
- Variable limit
- V → V

upperRoman%1 Data Impacting Factors

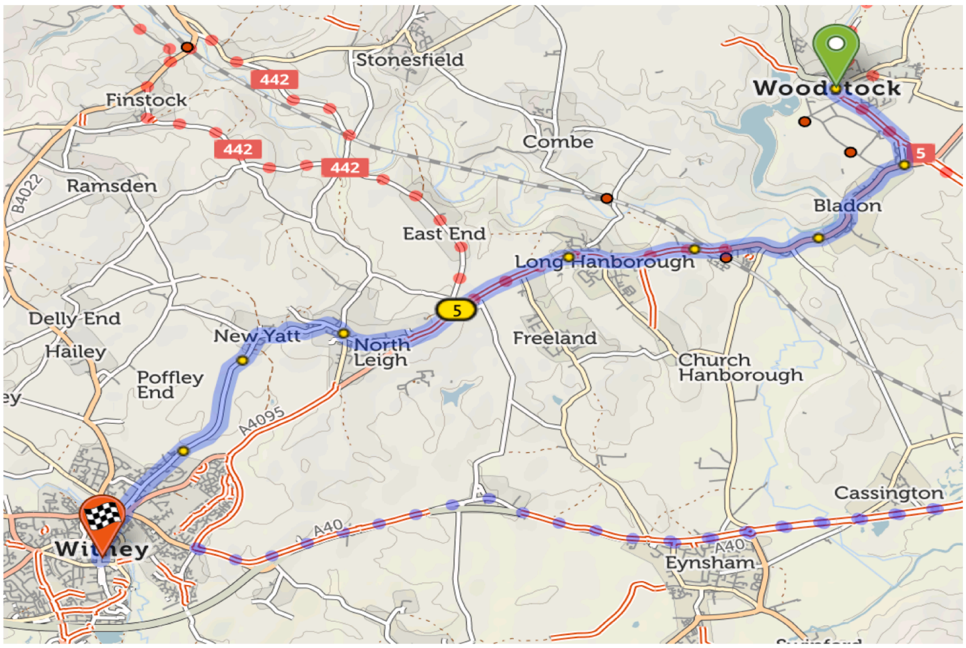

Fig. 5. Map Illustration

- Traffic factors are used to portray the prevailing traffic state, including the speed, traffic layout, traffic mass, and travel time.
- Navigation factors represent the sensor network conditions, where the route patterns are included mainly, such as road type, road classification, road width, and the number of routes.
- Neighbor data factors are used to identify the neighbor type, the number of neighbors, neighbor location, time and duration of the neighbor, and several blocked roadways.

upperRoman%1 Data Classification

- Motility: It is used as a predictor: of vehicle productivity, travel time, and the delay time of the vehicle.
- Traffic: Traffic is used as a predictor: of the number of halts.

Considering the data from Table 1, the following assessments are performed. First, the analysis of$S$ andH_i for the "miles" of the above vehicle, classification is made.

The analysis of S and H_i over the varying vehicles is presented in Fig. 6. The analysis for Fig. 6, considering the data in Table 1, is validated using the proposed NDTMS. The actual data provides $(X_\alpha + X_\beta)$ at two junctions (i.e.) start point and end point. In these two points, the $(A + B)$ is completely satisfied using $(X_\alpha + X_\beta)$,MQ^{-1}, and $\overline{V}$. If any information is missing, then the combination is varied from which $\sum_i V_i$ is extracted. Therefore, the data is high for $\overline{X}$ as it relies on neighbors within the coverage. Contrarily, the H_i increases with the available data from which multiple classifications $(\overline{H}_C,\ \overline{H}_t$ and $N^{-1})$are performed. The analysis for$P$ and N^{-1} is presented for varying H_i.

As the classification increases, P and N^{-1} increases with the available data (Fig. 7). In the traveling time$T$, the vehicle faces differential data for navigation, traffic information, and neighbors. This data is valid until a new $(A + B)$ is generated by the vehicle. On receiving a new $(A + B)$, the classification for $\overline{X}, \overline{V}$ and $(X_\alpha + X_\beta)$ is performed. The outputsMQ^{-1},S, and $P\forall BS^{-1}$are achieved from the above classifications. Therefore, for a struck input, $(A_2 - A_1)$ and $(t_2 - t_1)$ is the optimal learning end for improving further suggestions. Therefore, the P is high; however, this is confined to the actual N^{-1} outputs. Therefore, H_i and θ^2 outputs are revisited across multiple classification iterations. The analysis for T is presented in Fig. 8.

As the neighbors/ coverage vary, $(X_\alpha + X_\beta)$ shows variations where in BS^{-1} is limited to the occurrences. Therefore, $\overline{H}_C$ relies upon under varying $\overline{V}$ for precise$P$; then $(t_2 - t_1)$ is sufficient for the optimal analysis in determining$T$. This T is sustained until new information is available to satisfy $(A + B)$. Hence, the new classification is required to prevent a hike in T. This is confined through H_i across multiple combinational classifications (Fig. 8).

Table 1
Data Observed

Region	Road Category	Length in Miles	Vehicles
South West	TM	203.75	5269835019
South West	TA	464.47	4078835955
South West	PA	2643.87	9168884751
South West	M	28108.37	13091829040
East Midlands	TM	124.21	3834836014
East Midlands	TA	385.13	4924660817
East Midlands	PA	2066	7751253809
East Midlands	M	17280	9753046733
North West	TM	393.95	10451248396
North West	PM	14.11	312848648.9
North West	TA	187.16	1362229668
North West	PA	2354.5	9738314622
North West	M	20292.09	10631960796
South East	TM	403.58	11979757256
South East	PM	6.59	124064634.2
South East	TA	432.54	6272764628
South East	PA	2866.94	13697997882
South East	M	26538.42	14830576462
West Midlands	TM	274.15	7283469668
West Midlands	PM	2.36	59736112.48
West Midlands	TA	282.85	2648796269
West Midlands	PA	1967.88	8034868836
West Midlands	M	18260.4	10274107776
North East	TM	34.55	674947747.2
North East	PM	1.74	31015659.56
North East	TA	218.41	2491050142
North East	PA	904.72	3670429539
North East	M	9068.81	4347869668

TM-Trunk Motor, PM-Prime Motor, TA-Three Axels, PA-Principal Vehicles, M-Motor Vehicle

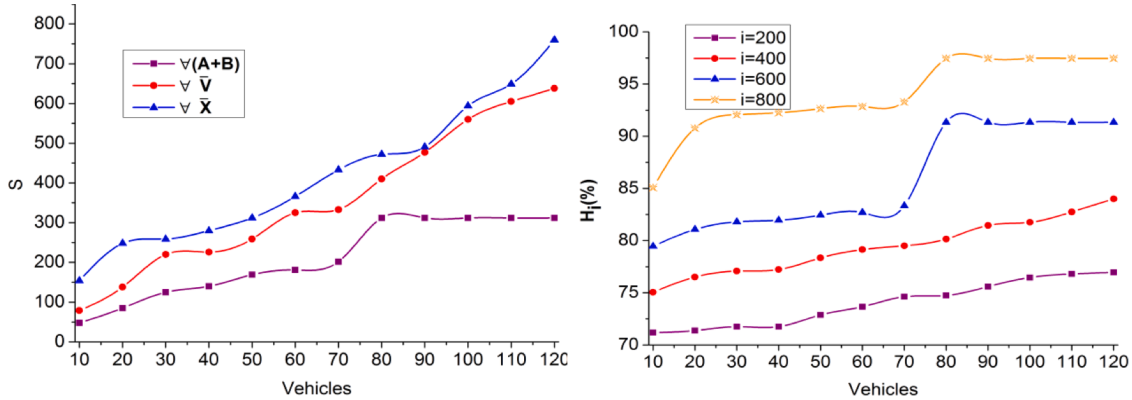

Fig. 6. *S* andH_i Analysis

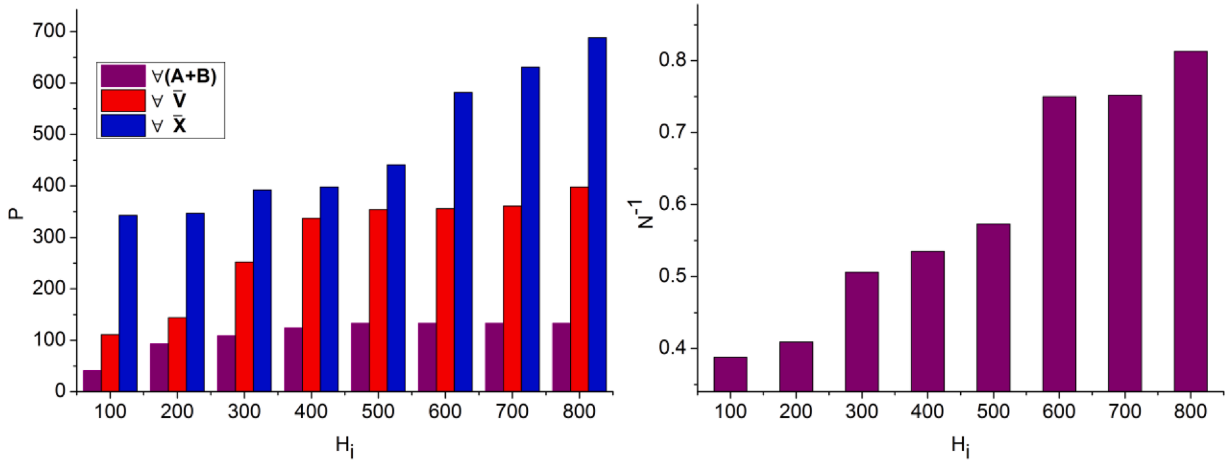

Fig. 7. **Analysis for*P* and*N*$^{-1}$**

4.1. Comparative analysis section

The comparative analysis section discusses the proposed scheme's performance using requirement identification, data combination ratio, data classifications, mishandling rate, and classification time. The variants are vehicles (10-120) and requirements (50-750). The parallel methods considered are ROSP [20], STIMF [22], and SR-DRL [19].

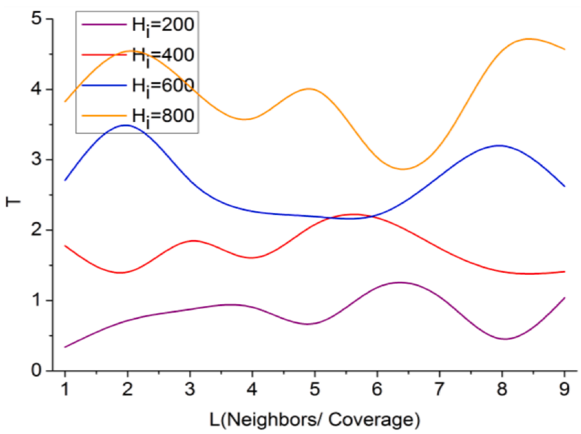

Fig. 8. *T* Analysis

4.1.1. Requirement identification

This proposed method's required identification efficiency is higher than the surviving models. The user requirements are identified and classified by learning to possess the required sensed data combination. Identifying the user requirements is quick by using the Tree Classifier technique. The user requirements help in identifying the efficiency of the sensed data. The sensed data combination helps in increasing the efficiency of classifying traffic data. The user requirements determine the number of vehicles required to detect traffic congestion. This will be helpful in the traffic management systems with the reduction in traffic ratio. This system is helpful for time management on the roads. This prevents the applicants with vehicles from waiting unnecessarily on a road which causes traffic jams, and also avoids the additional delay of time, etc., by knowing the user requirements; the solutions can be given according to NDTMS. Effective transportation management can be done by studying the passenger's requirements. Pervasive computing is used to sense the situations of the environment, predict the needs and enterprisingly act on the problems to find the best solutions according to the users' needs (Fig. 9).

4.1.2. Data combination ratio

The data combination ratio is high in this scheduled system compared to the existing models. Considering the combination of two or three data as inputs, including traffic, neighbor, and navigation, the Pervasive computing systems assist in non-deviating seamless application support. Combining the data is necessary to improve traffic congestion in real-time traffic control and the planning perspective of traffic control. Collecting two or three pieces of data from the above inputs of the passenger is used in the escalation traffic control system. This is used to determine the functions of roadways, the density of the traffic in the environment, and the best solution for problematic situations. The data combination produces an accurate estimation and prediction better than the other models. The data combination is used in the communication between passengers and the sensors of the Pervasive computation to find the best route according to the low traffic ratio. The learning identifies the user requirements by confining the required sensed data combination (Fig. 10).

4.1.3. Data classifications

The data classification efficiency is higher in this proposed method compared to the existing models. The problem of data mishandling for traffic management is addressed by using classifier learning links to the application-specific requirements. A Tree Classifier algorithm is used in the classification process. The Tree Classifier algorithm is used to classify the traffic into low, medium, and high traffic ranges. This classifier algorithm is also used to detect malformation in traffic. It also conveys the malformation to the passenger through the Pervasive computing sensors. The Tree Classifier algorithm helps users to find the best route to be admitted and allows them to choose the best low-time squandering path than their original route. It helps in classifying the user requirements based on the application demands. It directs the users according to their needs based on the outputs of traffic signals and the traffic density. Classifier learning links to the application-specific requirements and addresses the mishandling of data (Fig. 11). The accuracy of the proposed method is based on data classification. The Tree Classifier algorithm gives the best way for users with low time finding paths in the original route. The efficiency and accuracy mainly depend on classifying traffic into low, medium, and high traffic data.

4.1.4. Mishandling rate

The mishandling of data rate is less in this proposed method compared to the other traditional models. The problem of data mishandling for traffic management is addressed by using classifier learning links to the application-specific requirements. The alert, navigation, and communication support reduce the data mishandling ratio in this proposed method more than in the existing models. The Tree Classifier is used to classify and correct counterfeits data according to user requirements. Data combination is necessary to improve traffic congestion and also in the amelioration of the imposture data. The mishandled data contains the wrong information about the user and the traffic density in the traffic management systems using Pervasive computing techniques. The support delivered from the output of the classification process helps in finding the problem of data mishandling for traffic management and corrects the

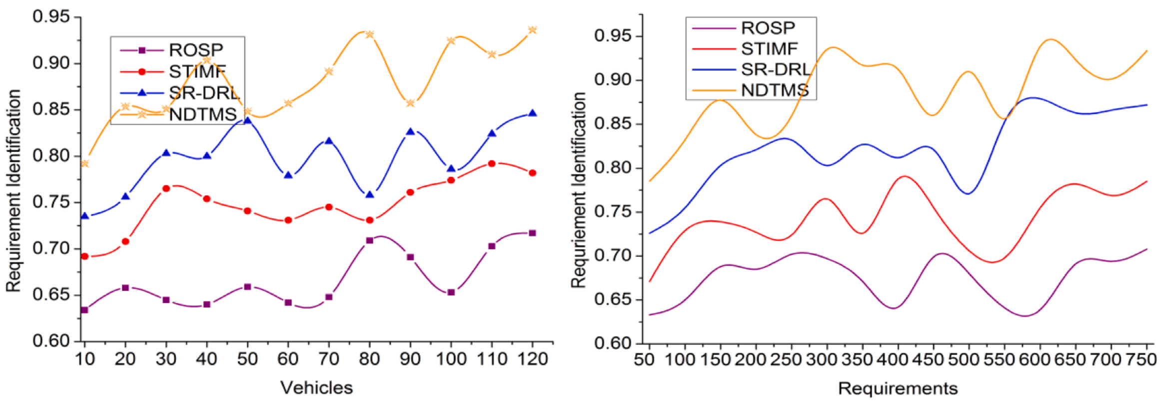

Fig. 9. Requirement Identification

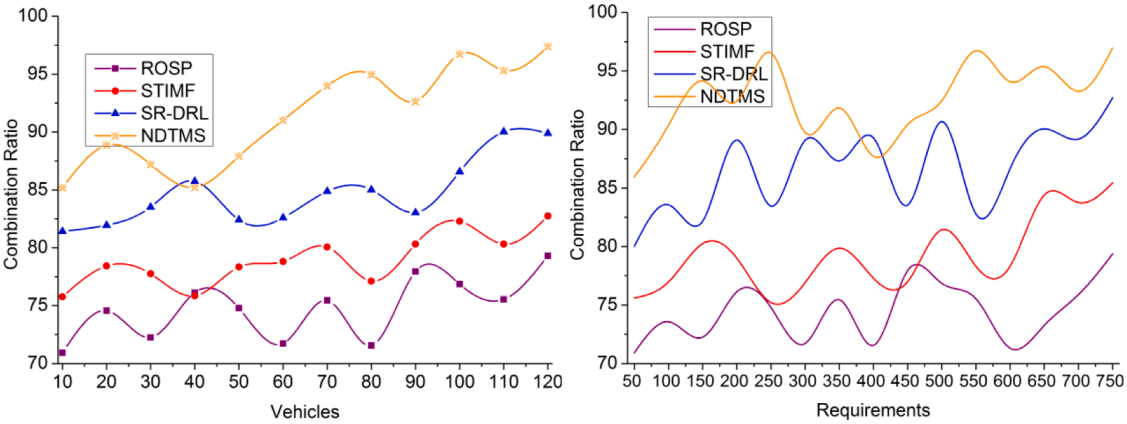

Fig. 10. Data Combination Ratio

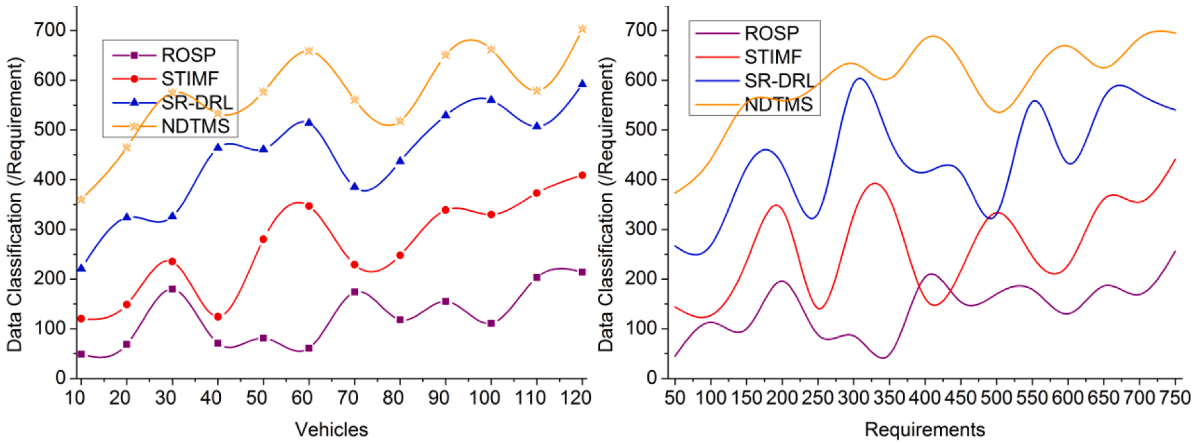

Fig. 11. Data Classifications

user data according to the right information provided by the passenger (Fig. 12).

4.1.5. Classification time

The time taken for the classification process is less in this proposed system compared to the surviving models. The Tree Classifier algorithm is used for the classification process to reduce the classification time. The classification process uses the Tree Classifier algorithm to make the user choose the best solutions for difficult circumstances within a shorter time. This Tree Classifier is used to correct the mishandling of data with counterfeits information. Then with the correct data about the user and the traffic density, the classification can be done quickly. This gives explicit knowledge for the users to choose the best route according to their needs from the outputs of traffic signals and the traffic density. The proposed scheme improves the application and navigation of intelligent Pervasive computing techniques used in the classification process. With all the correct inputs from the user and the pervasive computation of the traffic density, the classification process is done with less time in this proposed method (Fig. 13). Tables 2 and 3 present the comparative analysis results for vehicles and requirements.

5. Conclusion

The role of smart transportation in traffic management is predominant by acquiring distinguishable data throughout the travel time. Smart transportation in smart cities is reconsidering their methods of accessibility and urgent responses for traffic control, which are also helping to reduce traffic issues. The environment data, including traffic, neighbors, and navigation, will be promptly used for better application support. The data utilized for traffic, neighbors, and navigation is recognized and classified by Tree Classifier. The data mishandling is implemented for traffic management and control of specific applications. The user requirements help in handling the sensed data. Pervasive computing helps to control traffic and traffic management through navigation, alerts, and communication. The vehicle's efficiency is based on the user's requirements and the density of the moving vehicles. NDTMS introduces a Non-Divergent Traffic Management Scheme to augment traffic management in the smart transportation system. NDTMS classifies the data

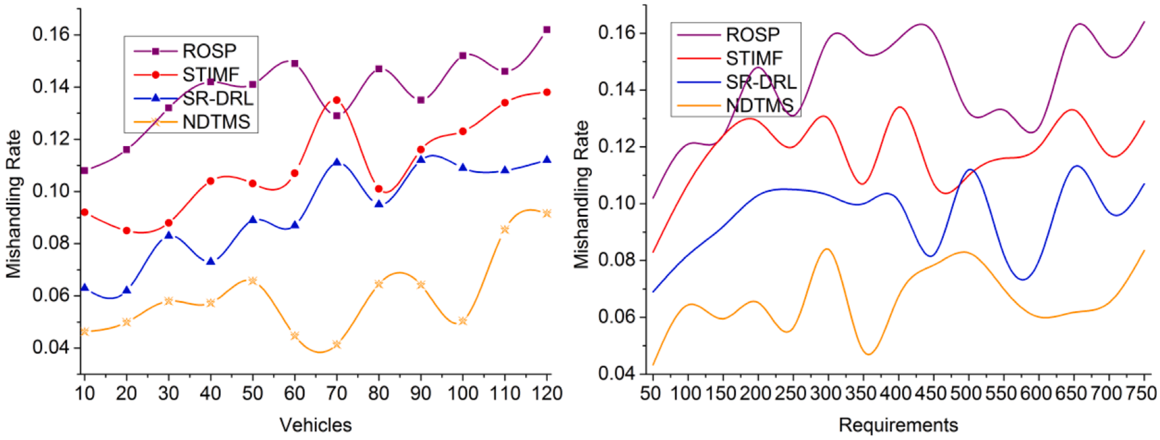

Fig. 12. Mishandling Rate

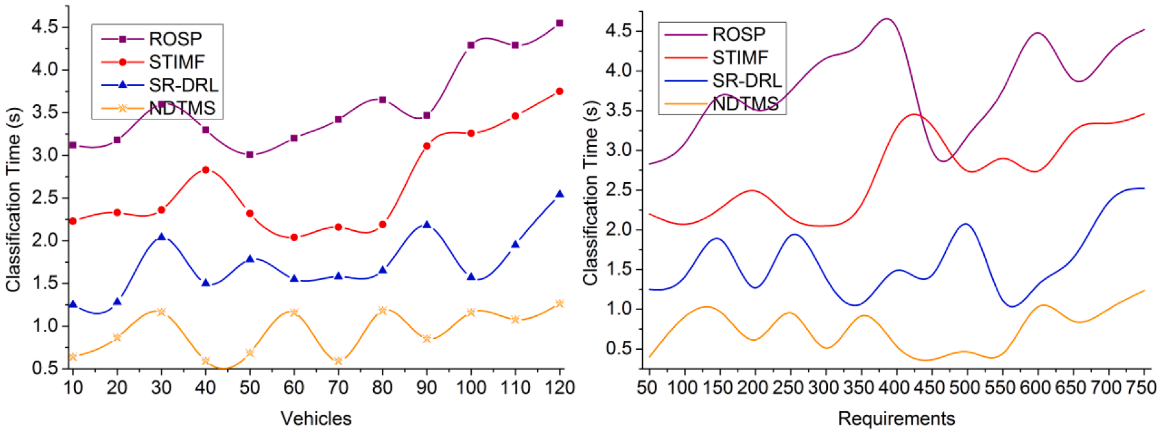

Fig. 13. Classification Time

Table 2
Comparative Analysis Results (Vehicles)

Metrics	ROSP	STIMF	SR-DRL	NDTMS	Findings
Requirement Identification	0.717	0.782	0.846	0.9362	15.45% High
Combination Ratio	79.31	82.74	89.88	97.378	13.4% High
Data Classification (/Requirement)	214	409	592	703	7.06% High
Mishandling Rate	0.162	0.138	0.112	0.0916	9.15% Less
Classification Time (ms)	4.55	3.75	2.54	1.265	10.84% Less

Table 3
Comparative Analysis Results (Requirements)

Metrics	ROSP	STIMF	SR-DRL	NDTMS	Findings
Requirement Identification	0.708	0.785	0.872	0.9337	14.54% High
Combination Ratio	75.89	83.76	89.18	93.269	10.33% High
Data Classification (/Requirement)	256	441	540	695	6.78% High
Mishandling Rate	0.164	0.129	0.107	0.0835	9.97% Less
Classification Time (ms)	4.52	3.46	2.52	1.234	9.27% Less

mishandling feature across various application requirements improving the classifications. The heterogeneous data are combined depending on the application demand with less time aiding a full navigation or traffic management assistance. The traffic, neighbor, and navigation data is utilized for identifying best-afford routes, alerts, and communication utilization through different road categories. The proposed scheme increases the resources through different outputs before and after classification for mitigating false data handling. Therefore, the proposed method leverages traffic management using smart transportation systems. The classification time is reduced by making use of Tree Classifier. Future work can be carried out by including more parameters like traffic congestion rate and the computational time for data combining. Through the experimental analysis, it is seen that the proposed scheme increases requirement identification by 14.54%, data combination ratio by 10.33%, classification requirement by 6.78%, reduces mishandling rate by 9.97%, and classification time by 9.27% as observed for the varying conditions.

Consent for publication

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Availability of data and materials

Not applicable.

Authors' contributions

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Data Availability

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MANIMURUGAN S is currently working as an Associate professor in the Faculty of Computers and Information Technology, University of Tabuk, Tabuk City, Kingdom of Saudi Arabia and Guest academic member in Department of Electrical and Computer Engineering, Oakland University, Rochester. 112345. USA. He has completed his Ph.D in Computer Science and Engineering from Anna University, India, Master's in Computer Science and Engineering from Karunya University, India, Bachelor's in Computer Science and Engineering in Anna University, India. His research interests are Artificial Intelligence, Security, Image processing and Internet of Things. He has published ample of papers in various conferences and journals. He is an associate editor in IET Image processing. He is also the life member of ISTE and senior member of IEEE.

SAAD M ALMUTAIRI received the Ph.D and MSc degrees from De Montfort University, U.K and the BSc from Al-Ahliyya Amman University, Jordon. He is currently working as Vice President for Post Graduate Studies and Scientific Research University of Tabuk, Saudi Arabia. His research interests are Artificial Intelligence, Software Engineering, Context Aware System, Cloud Computing, Cyber security, Steganography, etc., He has published plenty of papers in international refereed journals and conferences. He is a professional member in IEEE.