Weighted Feature detection Mechanism for Internet of Vehicles over Heterogeneous Vehicular Network

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***Abstract*— The current feature detection method for big data in the Internet of Vehicles (IoV) does not consider the weight of the data attribute, resulting in its inefficiency and inability to provide satisfactory vehicle operation services. A hybrid attribute-feature detection method is proposed for IoV big data in a multi-source, heterogeneous environment to address this issue. This method utilizes an integrated model to combine data from various sources in the Internet of Vehicles, which is then standardized and reduces the number of attributes. The weighted principal component analysis method is used to extract attribute characteristics from the combined data, and the clustering method is employed for aspect clustering. This comprehensive approach completes the mixed attribute feature detection of big data in the Internet of Vehicles. Experiment results indicate that the proposed method outperforms existing methods in sensitivity evaluation index, requires less time, and is faster in completing the feature extraction task from the mix of attributes in big data in the Internet of Vehicles.**

Keywords— Feature detection, Heterogeneous Vehicular Network, Internet of Vehicles, big data, Hybrid attribute

I. INTRODUCTION

Over the years, the automotive industry has experienced significant growth as the number of cars continues to increase, meeting people's travel needs. As vehicle requirements evolve, there is a gradual shift towards intelligence and automation. The Internet of Vehicles has enabled the connection between cars and the internet, allowing for data exchange between people, cars, roads, and clouds. This has led to the realization of intelligent transportation and assistance for drivers. With the increasing intelligence of the Internet of Vehicles, the scale and type of associated big data are also expanding rapidly. This data, including traffic data, weather conditions, and driving trajectory, plays a crucial role in driving and is essential for the safety and stability of vehicle operation. However, the continuous influx of multi-source heterogeneous data has led to challenges in efficiently accessing and utilizing the data. To address this, it is vital to process the big data of the Internet of Vehicles in a multi-source heterogeneous environment to improve its utilization efficiency.

Furthermore, the mixture of multiple attributes is a salient feature of the big data of the Internet of Vehicles in a multi-source heterogeneous environment. This can confuse and make data characteristics less prominent, leading to incorrect guidance provided by the Internet of Vehicles to drivers, which can indirectly impact driving safety. Therefore, feature detection methods in multi-source heterogeneous environments have become crucial to solving complex problems in data utilization in the Internet of Vehicles.

II. RELATED WORKS

Relevant experts and scholars at home and abroad have researched the data processing of the Internet of Vehicles. To realize the Internet of Vehicles simulation research, literature [2] proposed the construction method of the IOV simulation platform integrating Vissim and Python. Based on the data, use Vissim and Python to build a car networking simulation platform. Vissim has dynamic traffic simulation technology, Python has an object library with a visualization function, which adds the advantage of deep data mining, and the algorithm is easy to implement. In this simulation platform, Python is used as the main control program to realize the acquisition of various traffic information in Vissim by communicating with the VissimCOM interface; on this basis, implement different traffic control algorithms and optimization models according to this information; finally, optimize The final result is fed back to Vissim through the VissimCOM interface, and then the control and optimization of the object can be realized in Vissim. The research results laid the foundation for the big data simulation experiment of the Internet of Vehicles in this paper. Literature [3] Combined with Hadoop, machine learning algorithms extract features from many unstructured complex data and extract data correlation and mutual information features., the method has high sensitivity and specificity, but the efficiency is not high. Literature [4] combined gray neural networks with residual learning methods and detected feature data from big chaotic data through continuous iteration of neural networks. , this method reduces the error rate of feature extraction, but the time complexity is high. Literature [5] proposed a plan based on stacked denoising autoencoders and batch normalization to extract deep new features for representative selection. The advantage of this method is its high efficiency, but it is easily affected by the parameters of the encoder, and the extraction accuracy has certain limitations. Literature. [6] proposed a feature detection method for mixed attributes of big network data combined with rough set theory to detect various features in big data. Through the construction of the quadruple model, any neighbourhood information of the quadruple model can be obtained to measure its length function; this function can be used to judge the knowledge of big data. Feature similarity; Introduce rough set theory to solve the neighbourhood entropy of similar information features to detect and classify duplicate data attributes; Introduce support vector machine classification idea, transform big data mixed attribute classification problem into a linearly separable problem, realize big network data mixed Detection and classification of attribute features.

Building upon existing research and addressing issues with current methods, a feature detection method is proposed for mixed attributes of big data in the Internet of Vehicles in a multi-source heterogeneous environment. This method aims to standardize hybrid attribute characteristics of multi-source heterogeneous data, ultimately improving the utilization rate of big data in the Internet of Vehicles.

III. Multisource Heterogeneous Big Data Mixed Attribute Feature Detection Method for Internet of Vehicles

The Internet of Vehicles data is essential for guiding drivers to complete driving tasks safely. Many driving suggestions given by the intelligent system are based on data from the Internet of Vehicles. The data of the Internet of Vehicles mainly comes from car perception data, driving behavior data and external surrounding environment data. These data come from different business systems and are multi-sourced and heterogeneous. The existence of multi-source heterogeneity will inevitably make data have multiple attributes, resulting in data confusion, which is not conducive to data utilization. Therefore, multi-source heterogeneous big data for mixed attribute feature detection has important practical significance. The research on feature detection methods of varied attributes of Internet of Vehicles big data in a multi-source heterogeneous environment mainly includes three parts: multi-source heterogeneous Internet of Vehicles data integration, multi-source heterogeneous data pre-processing and feature detection implementation.

A. Multisource heterogeneous data integration of Internet of Vehicles

In recent years, smart transportation and intelligent driving have gradually become mainstream. Against this background, the application of the Internet of Vehicles is indispensable. However, only when the Internet of Vehicles is associated with various business systems can the required data be obtained because these data come from different business systems, thus forming the multi-source heterogeneous data of the Internet of Vehicles [7]. To this end, the first link integrates multi-source heterogeneous data of the Internet of Vehicles.

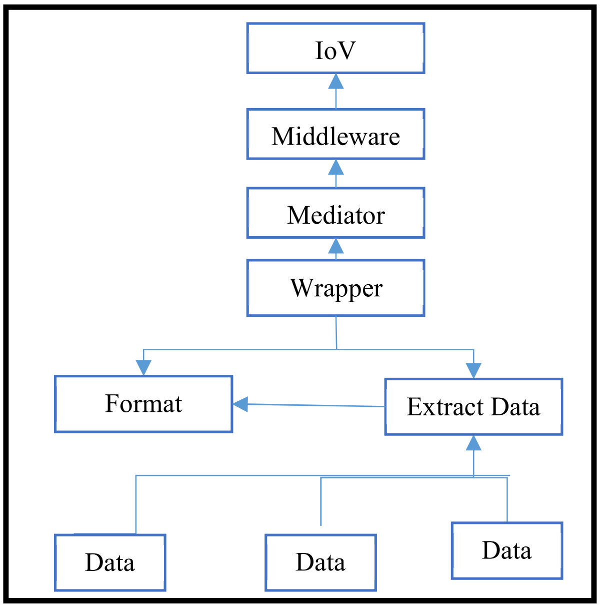

Figure 1: Multi-source heterogeneous data integration model of Internet of Vehicles based on middleware

This paper builds a heterogeneous data integration model through middleware, as shown in Figure 1.

Middleware is software that communicates between application software and system software. It mainly extracts data from the business system and then transmits it to the vehicle client for subsequent analysis [8].

In the middleware-based multi-source heterogeneous data integration model of the Internet of Vehicles, the wrapper and intermediary are the keys. Among them, the wrapper is a data access hub. Its primary function is to respond to the data integration request of the upper layer and then extract the source data and convert it to Transformation into a form acceptable to the Internet of Vehicles system [9]; the primary function of the intermediary is to transmit the upper-layer request, and then feed-back the result to the upper layer after the lower-layer wrapper completes the data extraction and conversion. This paper collects the data of the Internet of Vehicles through the integration model Multisource heterogeneous data for subsequent analysis.

B. Equations

Based on the integrated data, standard data cleaning and standardization techniques are used to convert it into a format suitable for the feature extraction model. The specific steps are as follows [10].

(1) Integrated data standardization

Data standardization processing aims to solve the problem of dimensional inconsistency in heterogeneous data of multi-source Internet of Vehicles so that all attributes have dimensional unity [11]. The specific process is as follows.

Step 1 Calculate the arithmetic mean value of the data; the calculation formula is as follows:

$$\bar{x} = \frac{x_1+x_2+\cdots+x_n}{n} \qquad (1)$$

Among them, $\bar{x}$ represents the arithmetic mean value; $x_1 + x_2 + \cdots + x_n$ represents the heterogeneous data of the Internet of Vehicles from multiple sources; n represents the number of data.

Step 2 Calculate the standard deviation of the data; the calculation formula is as follows:

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})}{n-1}} \qquad (2)$$

Among them, s represents the standard deviation of the data; x_i represents the i-th original multi-source heterogeneous data of the Internet of Vehicles.

Step 3: Standardize according to formula (3).

$$x_i' = \frac{x_i-\bar{x}}{s} \qquad (3)$$

Among them, xi' represents the standardized value.

Step 4 Swap the positive and negative signs before the inverse indicator.

(2) Attribute reduction Aiming at the defects of mixed attributes, attribute disturbance, and attribute reduction is carried out in this section to reduce the data confusion caused by composite details [12]. The process of attribute reduction is as follows.

Step 1: Give the decision table S=(U, A=C∪D, V,f), as listed in Table 1.

Table 1: Decision table

Scope	Condition Attribute 1	Condition Attribute 2	Condition Attribute 3	Condition Attribute 4	Decision Attribute
1	1	0	0	1	1
2	1	0	0	0	2
3	0	1	1	0	3
4	0	1	1	0	3
5	1	1	0	0	2
6	1	1	1	1	1
7	1	0	1	1	2
8	1	1	1	0	1
9	0	1	0	1	0
10	0	1	1	1	0

In S=(U, A=C∪D, V,f), U represents the domain of discourse; A represents the attribute set; C represents the conditional attribute; D denotes the decision attribute; V represents the set of attribute values; f represents the information function.

Step 2 Calculate the equivalent class cluster of the conditional attribute set C, denoted as $X = \{X_1, X_2, \cdots, X_r\}$.

Step 3 Find the equivalent cluster of the decision attribute set D, denoted as $Y = \{Y_1, Y_2, \cdots, Y_k\}$.

Step 4 Simplify the given decision table.

Step 5 Build the correlation matrix M.

Step 6: Determine whether a row of the matrix M has only one value and whether the value mi is 1; if so, consider the attribute of mi to be a nuclear attribute and add it to the reduced attribute set.

Step 7 Set the data in all rows corresponding to mi=1 to 0.

Step 8: Add the attribute ck with the most significant value of 1 in the conditional attribute set C column to the reduction.

Step 9: Determine whether ck is unique and if it is not, replace all the data of all rows corresponding to ck with a value of 1 to 0.

Step 10: Judge whether all the values in M are 0; output the minimum reduction value if they are all 0.

After the above reduction, the attribute characteristics of the data are more transparent and precise, which is convenient for subsequent feature detection [13].

C. Realization of mixed attribute feature detection of Internet of Vehicles Big Data

The mixed attribute feature detection is carried out based on the pre-processed multi-source heterogeneous data of the Internet of Vehicles. The detection process includes two parts: feature extraction and feature clustering. The features of the same type are aggregated through the components extracted by the former to achieve feature detection [14].

(1) Feature extraction

Feature extraction, that is, to extract representative features from all features. This paper uses the weighted principal component analysis method to perform feature extraction. The weighted primary component analysis method is optimized based on the original primary component analysis method. Different attribute types of data are given different weights to improve the representativeness of features [15]; the specific process is as follows.

Step 1 Assume that the extensive Internet of the Vehicles data sample is a sample of N attributes mixed, denoted as Z.

Step 2 Transpose Z to form a matrix form, which is described as follows:

$$\boldsymbol{Z} = \begin{bmatrix} z_{11}, & z_{12}, & \cdots, & z_{1n} \\ z_{21}, & z_{22}, & \cdots, & z_{2n} \\ & & \cdots & \\ z_{m1}, & z_{m2}, & \cdots, & z_{mn} \end{bmatrix} \quad (4)$$

Step 3 Perform normalization processing on the matrix, and the processing formula is as follows:

$$z'_{ij} = \frac{z_{ij} - min(z_{ij})}{max(z_{ij}) - min(z_{ij})} \quad (5)$$

Among them, z'_{ij} represents the normalized IOV data; z_{ij} is the original IOV big data; min(z_{ij}) and max(z_{ij}) represent the minimum and maximum values in the original IOV big data [16].

Step 4: Calculate the mean value of each column in the matrix M' after normalization processing, and perform mean value processing [17].

$$s_{ij} = \frac{z'_{ij}}{u} (i = 1,2,\cdots,m; j = 1,2,\cdots,n) \quad (6)$$

Among them, u represents the mean value.

Step 5: Calculate the weight of the significant data sample of the Internet of Vehicles; the calculation formula is as follows:

$$w_i = \frac{\left(\sum_{j=1}^{m} \frac{z'_{ij}}{\Sigma'_{z'_{ij}}}\right)}{n}, i = 1,2,\cdots,n \quad (7)$$

Among them, w_i represents the weight; z'_{ij} represents the normalized value of the element z_{ij} of the matrix Z; n represents the number of data [18].

Step 6 Multiply the result of step 4 with step 5 to construct a new data sample and form a new matrix H.

Step 7: Carry out principal component analysis on new data samples.

Step 8 Calculate the covariance of the matrix H and form the covariance matrix V.

Step 9 Calculate the eigenvalues and corresponding eigenvectors.

Step 10 Calculate the cumulative contribution rate, select the first k values through the cumulative contribution rate, and use it as the principal component [19].

Step 11: The selected first k principal components are used as data features.

(2) Feature clustering

Based on the mixed attribute characteristics of the Internet of Vehicles big data extracted above, this section clusters the features and gathers consistent features. The specific process is as follows.

Step 1: Randomly select a feature from the extracted feature set as the cluster center.

Step 2: Carry out fuzzy clustering according to the cluster center.

Step 3 Carry out feature consistency measurement, and the feature consistency measurement method is as follows:

$$\text{Sim}\ (x_1, x_2) = \sum_{i=1}^{c} \sum_{j=1}^{n} \|x_1 - x_2\| \quad (8)$$

Among them, Sim (x_1, x_2) represents the result of feature consistency measurement; x_1 and x_1 represent the extracted mixed attribute features of the Internet of Vehicles big data; c represents the clustering centre; n represents the number of features.

Step 4: Judging whether the features are redundant, that is, judging whether the value of the feature consistency measure Sim (x_1, x_2) is less than 0.5; if it is less than, it is considered that there is redundancy, and following steps are performed.

Step 4.1 sort the features from large to small;

Step 4.2 Determine the existence of redundant features;

Step 4.3 Delete redundant features.

If the value of feature consistency measure Sim (x_1, x_2) is more significant than 0.5, it is considered that there is no redundancy, and proceed to the next step.

Step 5 is to judge the completeness of clustering. When the clustering is incomplete, execute action 4.1-step 4.3; otherwise, output the clustering result.

Through the above two parts of feature extraction and feature clustering, this paper realizes the mixed attribute feature detection of the big data of the Internet of Vehicles, which provides great convenience for the big data of the Internet of Vehicles [20].

IV. Simulation Experiment Design

To confirm the efficacy of the proposed method for mixed attribute feature extraction of big data in the Internet of Vehicles in a multi-source heterogeneous environment, this paper employs the machine learning algorithm-based feature extraction method, the grey neural network and residual learning-based feature extraction method, and the stacked denoising autoencoder and batch normalization-based feature extraction method as a comparative approach. The simulation test is conducted using Matlab2017 programs.

A. Sample Data

The Internet of Vehicles' significant data types and attributes in a multi-source heterogeneous environment is diverse. However, they can be roughly divided into three categories: vehicle perception data, driving behavior data, and external peripheral environment data. These three categories include multiple attributes. To ensure the test simulation, this paper constructed the basic sample data to improve the accuracy of the results, which are listed in Table 2.

Table 2: Simulation Test Sample Data

Type	Content	Number of attributes	Number of samples
car perception data	Vehicle status	15	5566
	Driving position	5	3466
	Driving track	25	3220
	vehicle failure record	20	4544
driving behaviour data	Mileage	24	5444
	Fuel consumption	5	4556
	Travel time	8	5644
	Accident Violation Record	28	7548
surrounding environment data	Road type	25	6445
	Terrain conditions	21	5567
	Weather	15	4877
	Pedestrian situation	6	6445

B. *Sample data pre-Processing*

Pre-processing the big data from the Internet of Vehicles in a multi-source heterogeneous setting is described in Table 2 and is done in accordance with the processing procedure in Section 3.2. Figure 2 displays the processing findings.

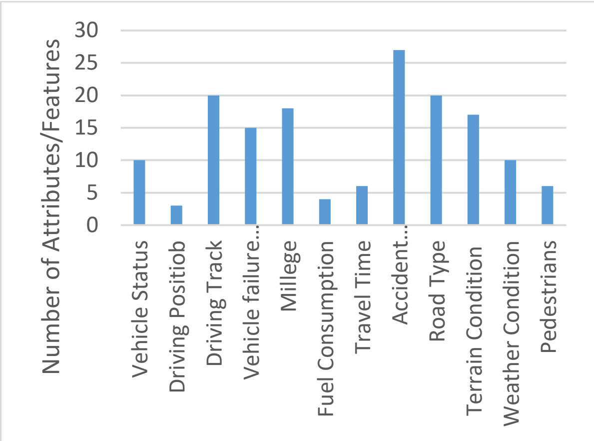

Figure 2: Processing result of attribute feature reduction of sample data

C. *Feature detection evaluation index*

Select two indicators to evaluate the feature extraction method, which is used to detect the accuracy and efficiency of the feature extraction method. The following two indicators are specifically analyzed.

(1) Sensitivity index

Sensitivity refers to the ratio between the square root of the balance between the number of samples, the total number of correctly detected features of the method and the balance of the number of false detections. The greater the sensitivity, the more sensitive the detection method is to the elements and the higher the accuracy.

$$\alpha = \sqrt{\frac{x}{X}}/y \qquad (9)$$

Among them, α is the sensitivity index; x is the number of samples with correctly detected features; X is the total number of pieces; y is the number of wrongly seen models.

(2) Time complexity

The computational workload needed to run the algorithm to find the mixed attribute features in the big data from the Internet of Vehicles is referred to as time complexity; the lower the time complexity, the more effective this technique is for finding features.

$$\beta = m^2 n + m^2 S^3 + \frac{x}{m+P+Nm-NP} \qquad (10)$$

Among them, β represents the time complexity; m represents the total number of attributes in the sample; n represents the number of pieces in the data set; S represents the running time of the method; P represents the number of attributes in the corresponding sample; N represents the maximum number of attribute values; x denotes the number of pieces with correctly detected features.

(3) Recall rate

The recall rate (Recall Ratio) refers to the ratio of relevant information retrieved from the database to the total amount. The absolute value of the recall rate is difficult to calculate and can only be estimated based on the content and quantity of the database. The higher the recall rate, the more ideal the comprehensiveness of big data mixed attribute feature detection and the higher the detection accuracy.

$$\text{Recall Ratio} = \frac{K}{L} \times 100\% \qquad (11)$$

Among them, K represents the detected and retrieved extensive data mixed attribute features, and L represents the total amount of diverse prominent data attributes.

D. *Result analysis*

Under the same test conditions, the method in this paper and the comparison method are used to judge the effectiveness of the detection method according to the statistical sensitivity index and time complexity of the detection results. The results are shown in Figure 3. (Note: From left to right, the method in this paper, the feature extraction method based on the machine learning algorithm, the feature extraction method based on gray neural network and residual learning, the feature extraction method based on stacked denoising autoencoder and batch normalization application result)

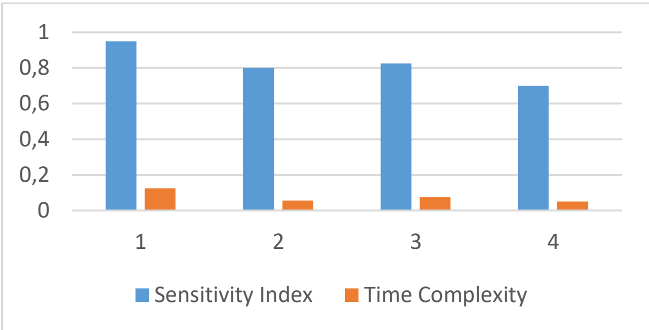

Figure 3: Sensitivity index and time complexity of the method in this paper and the comparison methods

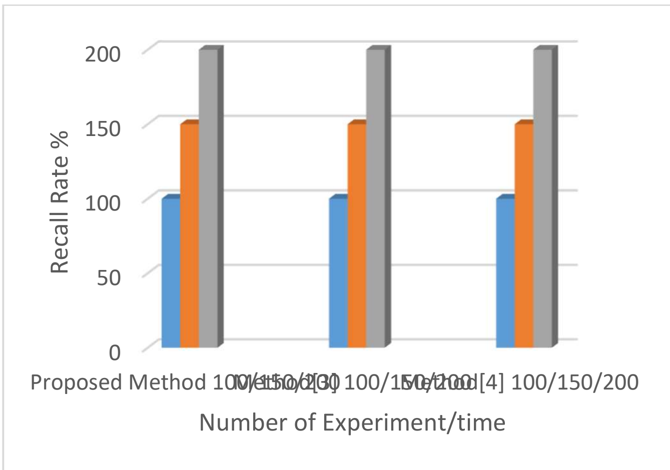

Figure 4: Comparison of recall rates of different methods

It can be seen from Figure 3 that the sensitivity index of this method is 0.9588. The time complexity is 0.1254, which is comparable to the feature extraction method based on the machine learning algorithm, the feature extraction method based on gray neural network and residual learning, and the method based on Compared with the application results of stacked denoising autoencoder and batch normalization feature extraction method, the way in this paper performs better.

Under the same test conditions, use the method in this paper, the feature extraction method based on the machine learning algorithm proposed in [3], and the feature extraction method based on gray neural network and residual learning proposed in [4] to perform feature detection recall test. , and the experimental results are shown in Fig.4

It can be seen from Figure 4 that the recall rate of the method in literature [3] and the way in literature [4] is 70%~80%, and the feature extraction method in this recall range realizes the essential feature extraction function. Still, It cannot meet the current application requirements of high-precision features. This paper verifies the effectiveness of this method through simulation experiments, and its recall rate is consistently above 95%.

IIV. Conclusion

This paper aims to propose a method for detecting multi-attribute features in a multi-source heterogeneous environment, specifically for the Internet of Vehicles, which is challenged by its large-scale data. This proposed method aims to process and extract mixed attributes of big data from the Internet of Vehicles, enabling standardized application of the data. Simulation tests have confirmed that this detection method can efficiently and accurately complete the feature extraction task of mixed attributes of big data in the Internet of Vehicles. However, there are still some limitations to the proposed method, including the use of small and ideal data in the simulation test and the need to improve the running speed of the technique for better practical applicability. Therefore, future research will focus on reducing mixed attribute characteristics of big network data and improving detection speed from the perspective of reduction speed improvement while ensuring detection accuracy to enhance detection efficiency further.

REFERENCES

1. H. Zhang, J. Bao, F. Ding and G. Mi, "Research on vehicle detection model based on attention mechanism," 2021 IEEE International Conference on Smart Internet of Things (SmartIoT), Jeju, Korea, Republic of, 2021, pp. 200-204.
2. C. Wu, Z. Huang and Y. Zou, "Delay constrained hybrid task offloading of internet of vehicle: a deep reinforcement learning method," in IEEE Access, vol. 10, 2022.
3. Y. Fang, H. Min, X. Wu, W. Wang, X. Zhao and G. Mao, "On-ramp merging strategies of connected and automated vehicles considering communication delay," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, 2022.
4. L. Bai, J. Liu, J. Wang, R. Han and J. Choi, "Data aggregation in uav-aided random access for internet of vehicles," in IEEE Internet of Things Journal, vol. 9, 2022.
5. S. Iranmanesh, F. S. Abkenar, A. Jamalipour and R. Raad, "A heuristic distributed scheme to detect falsification of mobility patterns in internet of vehicles," in IEEE Internet of Things Journal, vol. 9, no. 1, pp. 719-727, 1 Jan.1, 2022.
6. H. Chang, Y. Liu and Z. Sheng, "Blockchain-enabled online traffic congestion duration prediction in cognitive internet of vehicles," in IEEE Internet of Things Journal, vol. 9, 2022.
7. X. Xu, H. Li, W. Xu, Z. Liu, L. Yao and F. Dai, "Artificial intelligence for edge service optimization in internet of vehicles: a survey," in Tsinghua Science and Technology, vol. 27, no. 2, pp. 270-287, April 2022.
8. J. Qi, Y. Liu, Y. Ling, B. Xu, Z. Dong and Y. Sun, "Research on an intelligent computing offloading model for the internet of vehicles based on blockchain," in IEEE Transactions on Network and Service Management, vol. 19, 2022.
9. J. Cheng et al., "A dynamic evolution method for autonomous vehicle groups in a highway scene," in IEEE Internet of Things Journal, vol. 9, 2022.
10. S. Zhang and J. J. Q. Yu, "Electric vehicle dynamic wireless charging system: optimal placement and vehicle-to-grid scheduling," in IEEE Internet of Things Journal, vol. 9, no. 8, pp. 6047-6057, 15 April15, 2022.
11. W. Huang, T. Song and J. An, "QA2: qos-guaranteed access assistance for space–air–ground internet of vehicle networks," in IEEE Internet of Things Journal, vol. 9, no. 8, pp. 5684-5695, 15 April15, 2022, doi: 10.1109/JIOT.2021.3064322.
12. I. Ali, Y. Chen, C. Pan and A. Zhou, "ECCHSC: Computationally and bandwidth efficient ecc-based hybrid signcryption protocol for secure heterogeneous vehicle-to-infrastructure communications," in IEEE Internet of Things Journal, vol. 9, no. 6, pp. 4435-4450, 15 March15, 2022.
13. Y. Zhang, Y. Zhao and Y. Zhou, "User-centered cooperative-communication strategy for 5g internet of vehicles," in IEEE Internet of Things Journal, vol. 9, no. 15, pp. 13486-13497, 1 Aug.1, 2022, doi: 10.1109/JIOT.2022.3143124.
14. Y. Du, L. Du and L. Li, "An SAR target detector based on gradient harmonized mechanism and attention mechanism," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4017005, doi: 10.1109/LGRS.2021.3103378.
15. J. Yu, X. Cheng and Q. Li, "Surface defect detection of steel strips based on anchor-free network with channel attention and bidirectional feature fusion," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-10, 2022.
16. G. Zhang, H. Zhang, Y. Yao and Q. Shen, "Attention-guided feature extraction and multiscale feature fusion 3d resnet for automated pulmonary nodule detection," in IEEE Access, vol. 10, pp. 61530-61543, 2022.
17. Z. Jiang, J. Yu, J. Liu, Z. Chen, W. Gui and T. Cao, "A coke detection method based on reweighting a composite feature for mixed material recognition and quantification," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-12, 2022, Art no. 5024512, doi: 10.1109/TIM.2022.3216662.
18. H. Chen, Y. Du, Y. Fu, J. Zhu and H. Zeng, "DCAM-Net: A rapid detection network for strip steel surface defects based on deformable convolution and attention mechanism," in IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-12, 2023, Art no. 5005312, doi: 10.1109/TIM.2023.3238698.
19. W. Yu, H. Huang and G. Shen, "Deep spectral–spatial feature fusion-based multiscale adaptable attention network for hyperspectral feature extraction," in IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-13, 2023.
20. Z. Zhang, L. Zhang, Y. Wang, P. Feng and B. Sun, "Bidirectional parallel feature pyramid network for object detection," in IEEE Access, vol. 10, pp. 49422-49432, 2022.