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RESEARCH ARTICLE

The Analysis of Tourist Satisfaction Integrating the Artistic Intelligence Convolutional Neural Network and Internet of Things Technology

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ABSTRACT Aiming at the limitations of existing fire detection technology and the multi-dimensional challenge of tourist satisfaction analysis, this study proposes a series of innovative methods and models. Regarding fire detection, Depth Separable Convolution (DSC) and multi-scale detection structure are introduced to improve the You Only Look Once version 3 (YOLOv3) model. Moreover, the DSC-Anchor-Isoft-Non Maximum Suppression-YOLO (DAI-YOLO) model is implemented for the fire detection of scenic spots. The experimental results show that the precision, recall, and average precision of the DAI-YOLO model are 92.1%, 84.2%, and 84.6%, respectively, compared with other models, a minimum increase of 4.1%, 8.8%, and 6.0%, with higher detection accuracy and performance. Based on the analysis of tourist satisfaction, a comprehensive index system is constructed using the grounded theory of text mining, and emotion analysis is integrated into the satisfaction evaluation to reveal tourists' evaluation of scenic spots more comprehensively. According to the analysis, the environmental factor receives the highest satisfaction rating, reaching a positive rate of 98.78%. However, the satisfaction evaluation of scenic spot management is relatively low, accounting for 6.06% of the negative evaluation. The importance-satisfaction analysis reveals that the key factors affecting tourist satisfaction are traffic level, scenic spot tickets, and service. The results of this study provide valuable reference for the managers and researchers of scenic spots and are expected to contribute to the construction of a safer and more satisfying tourism experience.

INDEX TERMS Tourist satisfaction, fire detection, grounded theory, YOLOv3 model, depth separable convolution.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

In the vigorous development of tourism, the safety of scenic spots and tourist satisfaction have become the two core concerns to ensure the healthy development of the industry [1], [2], [3]. However, fire and other safety accidents occur from time to time, which seriously threaten the life and safety of tourists and also have a negative impact on the reputation of the scenic spot [4], [5], [6]. At the same time, with the continuous improvement of tourists' requirements for travel experience, the improvement of tourists' satisfaction has also become an important factor in the competitiveness of tourist attractions [7], [8], [9]. However, it is difficult for traditional satisfaction evaluation methods to capture the real feelings of tourists comprehensively and objectively, so more advanced technical means are needed for analysis.

In this context, this study aims to integrate the Artificial Intelligence (AI) Convolutional Neural Network (CNN), and Internet of Things (IoT) technology. It is applied to the fire detection of scenic spots to analyze tourist satisfaction. Introducing fire detection technology can strengthen the safety of scenic spots, timely warning of fire risks, and ensure the safety of tourists and property. Meanwhile, the integration of AI and IoT technology to achieve the collection and analysis of tourist satisfaction data will help a more comprehensive

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understanding of tourist needs, behaviors, and evaluations, thus providing accurate service optimization directions for scenic spots. Integrating fire detection and tourist satisfaction analysis can improve the scenic spot's overall safety and service level and offer more in-depth data support for scenic spot managers to make decisions and provide a basis for improvement measures. To sum up, this study aims to explore an innovative method of integrating technology under the dual challenges of scenic spot management and tourism experience, thereby contributing to the sustainable development of the tourism industry.

B. RESEARCH OBJECTIVES

This study's objective is to integrate CNN and IoT technologies, and improve the You Only Look Once version 3 (YOLOv3) model by introducing Depth Separable Convolution (DSC) and multi-scale detection structure. A scenic spot fire detection method based on the DSC-Anchor-Isoft-Non Maximum Suppression-YOLO (DAI-YOLO) model is constructed and combined with the analysis of tourist satisfaction, to promote the safety of scenic spots and the quality of tourist experience. Specifically, the main goals include: developing fire detection methods based on the DAI-YOLO model, and improving the accuracy and efficiency of fire detection models by introducing strategies such as DSC and multi-scale detection. A comprehensive tourist satisfaction index system for scenic spots is constructed. Based on the grounded theory, the multiple dimensions of tourist evaluation are quantitatively analyzed to understand the intrinsic relationship of tourist satisfaction deeply. According to text mining and sentiment analysis technology, the emotional tendency analysis of tourist review data is carried out, and the key factors of tourist satisfaction and their influence mechanism are further explored.

This study has vital practical application and theoretical value in scenic spot safety and tourist satisfaction. It has positively contributed to improving the management level of tourist attractions, enhancing tourist satisfaction, and promoting the development of related fields.

II. LITERATURE REVIEW

In recent years, video analysis technology based on machine learning (ML) and AI has gradually emerged in the field of fire detection. Avazov et al. improved YOLOv4 using emerging technologies such as digital cameras, computer vision, AI, and deep learning. They developed a fire detector that can accurately detect and issue alarms when a fire breaks out, thus replacing traditional fire detection methods [10]. Wahyono et al. proposed a new framework combining color-motion-shape features and ML technology for the early warning system of forest fire detection. The framework realized fast and accurate fire detection by analyzing the color, shape, and motion features of fires, to support the rapid response of relevant authorities [11]. Khan and Khan introduced a visual-based forest fire detection method through AI. They used the convolutional basis of the pre-trained MobileNetV2 model and solved the problem of forest fire identification by adding a fully connected layer, aiming to be applied in smart city applications to prevent disasters [12].

Tourist satisfaction analysis was an important research direction in the field of tourism management. Genc et al. explored the impact of authenticity on satisfaction in cultural heritage sites and focused on the moderating role of aesthetic experience in this relationship through quantitative data analysis and structural equation model (SEM). The study found that tourists' perception of existential authenticity impacted satisfaction, while objective and constructive authenticity did not directly influence satisfaction [13]. Rehman et al. surveyed international tourists in Khel, Saudi Arabia, and the results showed that enjoyment, destination loyalty, and destination image significantly and positively impacted tourists' satisfaction [14]. Jebbouri et al. focused on tourist destinations with cultural heritage and discussed the relationship among destination image building, tourist satisfaction, and tourist trust. The research results emphasized the positive impact of destination image and satisfaction on tourist trust [15].

To sum up, although previous studies achieved certain results in fire detection technology and tourist satisfaction analysis, there were still challenges and opportunities in detecting scenic fire areas and comprehensive analysis of scenic satisfaction. This study aimed to optimize the YOLOv3 model, implement a DAI-YOLO-based new fire detection model, and establish a tourist satisfaction index system through grounded theory and text mining technology, to make more comprehensive research and application in the safety of tourist attractions and tourist satisfaction.

III. RESEARCH METHODOLOGY

A. OVERVIEW OF FIRE DETECTION TECHNIQUES AND GROUNDED THEORY

Fire detection technology aims at early identification and response to fire risks to ensure people's and property's safety [16], [17]. Currently, common fire detection technologies involve smoke and flame sensors, thermal imaging cameras, gas sensors, wireless sensor networks, video analysis technologies based on ML and AI, etc. [18], [19], [20]. Smoke and flame sensors use optical, infrared, or ultraviolet sensing technology to detect smoke or flame in the air. Thermal imaging cameras utilize infrared thermal radiation to capture real-time temperature changes in a scene. Gas sensors detect fires by detecting changes in the concentration of specific gases in the air, such as carbon dioxide and carbon monoxide. Under the framework of IoT, various sensors can be networked and share data in real-time [21], [22]. For example, by working together, multiple sensor nodes can form a network to monitor fire risk. Using ML and AI technology, fire and non-fire data can be learned and models implemented. Employing computer vision and image analysis, the fire detection system can analyze video streams from surveillance cameras, identify features such as flame and smoke, and then issue alarms [23], [24], [25].

Grounded theory is a qualitative research method that aims to generate theories from actual data through systematic collection, coding, and analysis of data, and is mainly utilized to explore the intrinsic meaning and pattern of social phenomena, behaviors, and experiences [26], [27], [28]. The core idea of grounded theory is to develop a new theory from data gradually, rather than applying an existing theory to data. It emphasizes in-depth data analysis to discover patterns, relationships, and themes to build a theoretical framework with practical significance [29], [30], [31]. The practical application of grounded theory usually consists of five key steps. First, the concept is gradually formed based on the collected data, recorded step by step. Second, the theoretical problems extracted from the concepts are systematically explored by repeatedly comparing concepts and data. Third, it further expands the theoretical concepts and establishes their internal relations. Fourth, it ensures that the sampling process and data coding are systematic to guarantee the accuracy and consistency of data. Lastly, a theoretical framework is systematically constructed based on concepts' variation, density, and integration [32], [33], [34].

B. FIRE DETECTION MODEL BASED ON DAI-YOLO

YOLOv3 model is a real-time target detection algorithm based on CNN, which has high speed and good precision [35], [36]. Nevertheless, in the specific field of fire detection, some fire areas are small and need to be detected in time, and YOLOv3 needs to be improved to ensure the accuracy and speed of fire detection. Thus, YOLOv3 is improved and optimized, and a DAI-YLOL-based fire detection model is proposed.

Firstly, DSC replaces the traditional convolution in YOLOv3, and the residual structure design is displayed in Figure 1 [37], [38], [39].

In Figure 1, the designed residual structure uses 3*3 DSC, retains the original 1*1 convolution, and then adds 1*1 convolution to complete the dimensionality of the convolution after the increase, so that the output can be added with the shortcut connection. The amount of ordinary convolution calculation Q_1 is shown in equation (1).

$$Q_1 = D_L * D_L * m * n * D_T * D_T \tag{1}$$

D_L*D_L refers to the size of the convolution kernel; m indicates the number of input channels before convolution; n represents the number of output channels after convolution; D_T*D_T means the size of the feature map after convolution. The DSC is calculated, as expressed in equation (2).

$$Q_2 = D_L * D_L * m * D_T * D_T + m * n * D_T * D_T \tag{2}$$

The ordinary convolution and DSC calculation ratio can be written as equation (3).

$$\frac{Q_2}{Q_1} = \frac{D_L * D_L * m * D_T * D_T + m * n * D_T * D_T}{D_L * D_L * m * n * D_T * D_T} = \frac{1}{n} + \frac{2}{D_L^2} \tag{3}$$

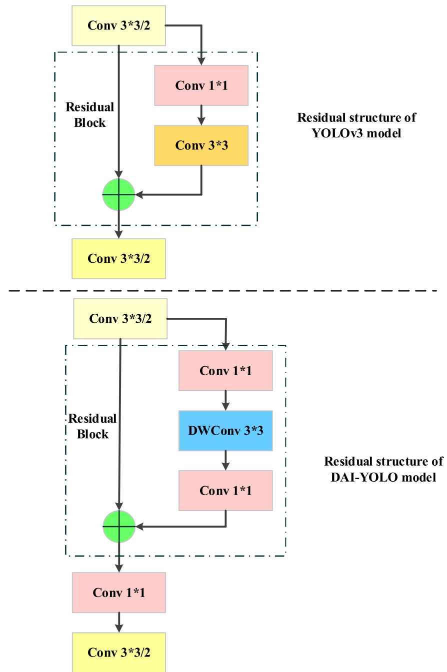

FIGURE 1. Comparison of feature extraction structures.

Secondly, the multi-scale detection is improved, and the improved multi-scale detection structure is presented in Figure 2 [40], [41], [42].

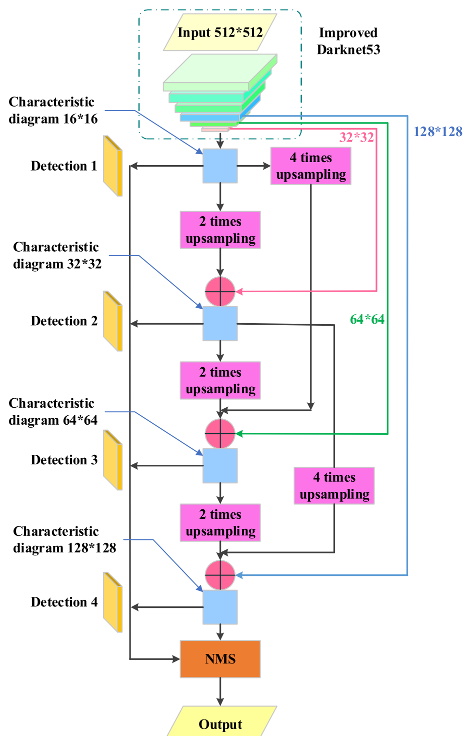

FIGURE 2. Improved multi-scale detection structure.

Figure 2 signifies that the input image size of the network model is first adjusted from 416*416 to 512*512. This adjustment effectively reduces the loss of small fire area target information caused by CNN downsampling by increasing the size of the input image. Second, to further improve the detection effect, the detection of 4 scales is adopted. A 4-fold up-sampling method is also introduced to fully integrate the information in the shallow and deep feature maps. Since the input image size is 512*512 for the DAI-YOLO model, the increased detection scale is 128*128.

In addition, in some cases, the Non-Maximum Suppression (NMS) algorithm results in a low recall of the model. Therefore, the ISoft-NMS algorithm is employed to optimize the NMS. The ISoft-NMS algorithm adds a threshold N_i, $N_t < N_i$ based on the Soft-NMS. If the intersection of union (IoU) of candidate region c_i and candidate region W with the highest score is $IoU\,(W, c_i) > N_i$, it is directly suppressed. If $N_t \leq IoU(W, c_i) \leq N_i$, c_i needs to be given weight with the $IoU\,(W, c_i)$ penalty ratio as a penalty factor combined with the original score; If $IoU\,(W, c_i) < N_t$, it is shown that the region where the c_i overlaps W is small enough to require no inhibition, preserving the original fraction:

$$score_f \begin{cases} score_i, & IoU\,(W, c_i) < N_t \\ score_i * (1 - IoU(W, c_i)), & N_t \leq IoU(W, c_i) \leq N_i \\ 0, & IoU\,(W, c_i) > N_i, \end{cases} \tag{4}$$

This double-threshold approach can reduce the probability of missed and false detection of target objects in the candidate area where $IoU\,(W, c_i)$ is less than N_i [43], [44], [45].

C. CONSTRUCTION OF A TOURIST SATISFACTION INDEX SYSTEM

This study takes X province as the research object. X province has complex terrain, historical sites everywhere, and is inhabited by many ethnic groups with different folk customs. It has rich tourism resources. Text mining from travel websites is utilized to get tourist reviews about scenic spots in X province. Data for the time period October 2018 to October 2022 was chosen. Web crawlers are used to crawl raw comments, use Python software for word frequency analysis, and get high-frequency words. Besides, according to the grounded theory, the tourist satisfaction index system is constructed, and the satisfaction model is established to measure tourist satisfaction. According to the obtained data and grounded theory, the tourist satisfaction index system of scenic spots is plotted in Figure 3 [46], [47], [48].

Figure 3 presents that tourist satisfaction with scenic spots in X province is evaluated from four aspects: scenic spot management, public service level, environmental factors, and tourist perception. Specifically, it is reflected in the scenic spot tickets, facilities, services, food, transportation, accommodation level, natural, cultural, and safety factors, the overall evaluation of tourists, and the willingness to visit again. Through this multidimensional evaluation system, it is possible to gain a more comprehensive understanding of tourist satisfaction with scenic spots, thereby providing valuable information for further improvement and enhancement.

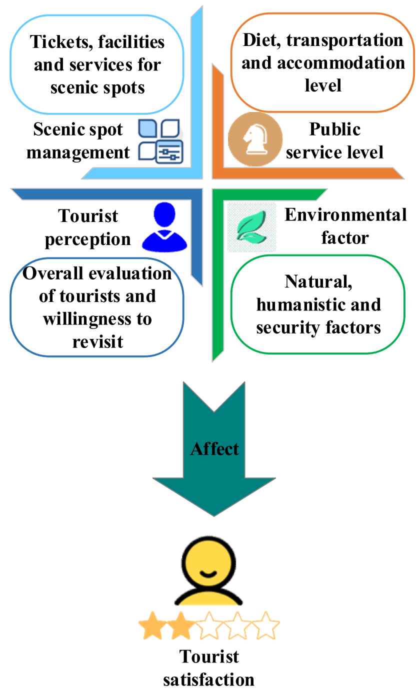

FIGURE 3. The tourist satisfaction index system of scenic spots.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. EXPERIMENTAL MATERIALS

The performance of the DAI-YOLO model is verified by comparative experiments. The training of the fire detection model requires massive data, so 6,000 fire images are collected from small public fire image/video databases, large public image/video datasets, and the Internet, which are divided into training sets, test sets, and validation sets according to the ratio of 8:1:1. And the fire image is rotated, flipped and other operations to achieve the purpose of data enhancement. DAI-YOLO is compared to Faster Region Convolutional Neural Network (R-CNN), Single Shot MultiBox Detector (SSD), YOLOv2, and YOLOv3. Model performance is measured using Precision (P), Recall (R), and Average Precision (AP) [49], [50], [51].

In the evaluation experiment of tourist satisfaction, the Snow Nlp package in Python is used to calculate the sentiment value of each comment crawled, and the emotional tendency of each comment is judged by this sentiment value. The calculated sentiment value ranges from [0, 1], where 0-0.2 refers to very dissatisfied, 0.2-0.4 is dissatisfied, 0.4-0.6 means fair, 0.6-0.8 represents satisfactory, and 0.8-1 indicates very satisfied.

B. EXPERIMENTAL ENVIRONMENT AND PARAMETERS SETTING

The experimental environment and validation parameter settings for the DAI-YOLO model are exhibited in Table 1.

TABLE 1. The experimental environment and parameter settings for the DAI-YOLO model.

Parameter name	Specification/Size
Operating system	Windows 10
Central Processing Unit	Intel Core i7-9700K
Graphics Processing Unit	NVIDIA RTX2080-8G
Memory	16GB
Deep learning framework	PyTorch 1.2.0
Momentum	0.9
Attenuation factor	0.005
Batch size	32
Initial learning rate	0.001
Epochs	300
Input size	512*512

C. PERFORMANCE EVALUATION

1) PERFORMANCE TEST OF DAI-YOLO FIRE DETECTION MODEL

The detection results of five models, DAI-YOLO, Faster R-CNN, SSD, YOLOv2, and YOLOv3, on the same data set are suggested in Figure 4.

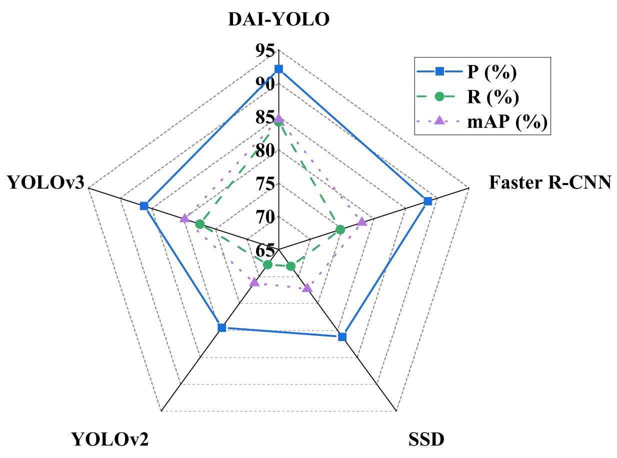

FIGURE 4. Comparison of detection results of different algorithms.

Figure 4 denotes that the DAI-YOLO model's precision, recall, and average precision are 92.1%, 84.2%, and 84.6%, respectively. Compared with other models, the highest increase is 15.8%, 24.2%, 18.8%, and the lowest is 4.1%, 8.8%, 6.0%. This indicates that the detection accuracy of the DAI-YOLO model is higher. Furthermore, the size and detection speed of the five models are compared, as revealed in Figure 5.

Figure 5 demonstrates that the size of the DAI-YOLO model is 215MB, and the detection speed is 35 frames /s. The SSD model has the smallest (96MB) and the fastest

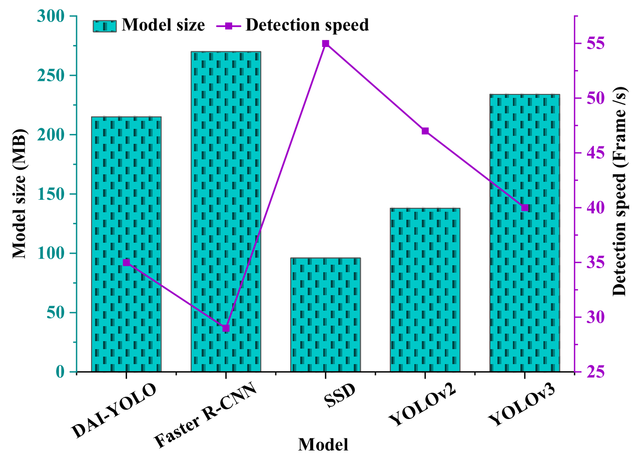

FIGURE 5. Comparison of the size and detection speed of various algorithms.

detection speed (55 frames/s), but its detection accuracy is not high, only 81.2%. Compared to the YOLO series models, the DAI-YOLO model has a reduced detection speed but is superior in precision.

To verify the feasibility of the DAI-YOLO model, the proposed model is compared with the pre-optimized model, including YOLOv3, improvement of the backbone feature extraction network, and YOLOv3-Net for multi-scale detection. The results of YOLv3-ISoft-NMS using the ISoft-NMS algorithm are depicted in Figure 6.

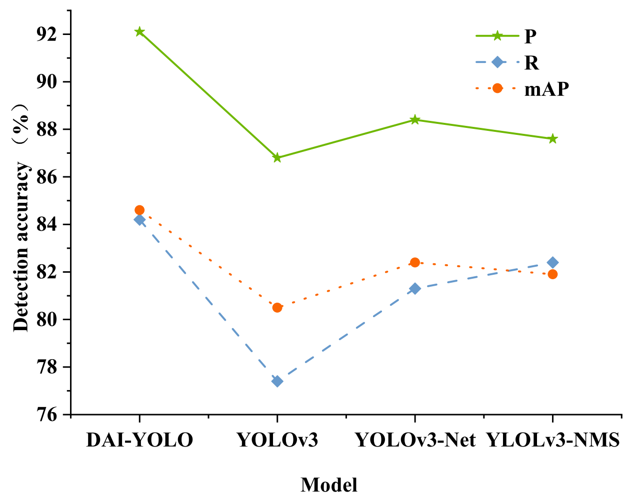

FIGURE 6. Comparison of improvement effects of different strategies.

In Figure 6, the detection accuracy of the DAI-YOLO model is 6.1%, 4.2%, and 5.1% higher than that of YOLOv3, YOLOv3-NET, and YLOLv3-NMS, respectively, and the recall is 8.8%, 3.6%, and 2.2% higher. The results illustrate that improving DSC, multi-scale detection structure, and ISoft-NMS for the YOLOv3 model helps enhance the model's accuracy.

2) TOURIST SATISFACTION ANALYSIS

The overall and dimensional satisfaction scores of tourists for scenic spots in X province are portrayed in Figure 7.

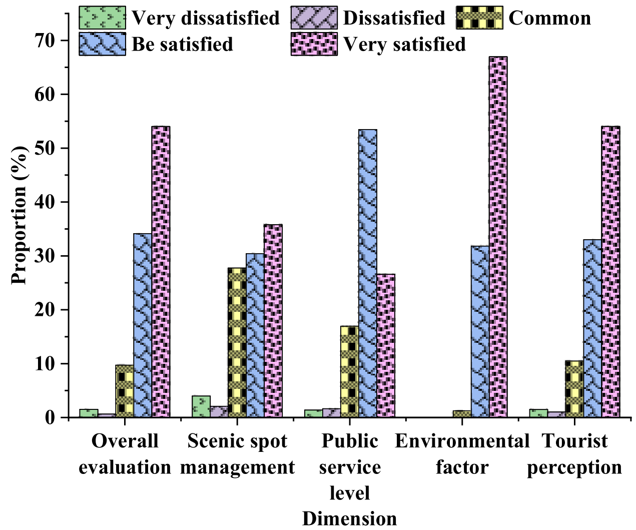

FIGURE 7. Emotional analysis of tourist satisfaction.

Figure 7 details that overall, 88.14% of tourists are satisfied with the scenic spots in X province, 9.72% have neutral comments, and 2.14% of tourists are dissatisfied. From various dimensions, environmental factors have the highest satisfaction, with positive reviews accounting for 98.78%; The most unsatisfactory aspect is the scenic spot management, with negative comments accounting for 6.06%. These data indicate that scenic spots in X province have a good reputation in the minds of most tourists, but it is still necessary to pay attention to and improve the management of scenic spots to improve overall tourist satisfaction.

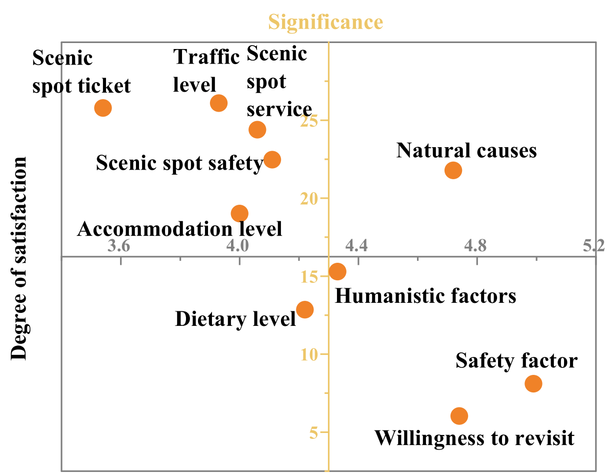

FIGURE 8. Importance - satisfaction analysis.

Subsequently, the Interpretative Phenomenological Analysis (IPA) is utilized to analyze the factors of tourist satisfaction, and the importance-satisfaction quadrant, as illustrated in Figure 8, is obtained.

Figure 8 describes that only natural factors are located in the first quadrant, indicating the higher importance and satisfaction of these factors. The indicators in the second quadrant include scenic spot tickets, services, transportation, and accommodation levels, which have high importance but low satisfaction. Dietary levels are low in importance and satisfaction, and humanities, safety factors, and willingness to revisit are low in importance but high in satisfaction. It can be found that the first three important factors affecting tourist satisfaction are service, scenic spot tickets, and traffic level. In addition, the scenic spots of X province need to improve the services, scenic spot tickets, transportation, and accommodation, and strengthen the publicity of food culture and safety factors.

D. DISCUSSION

In summary, the level of public service and scenic spot management are the biggest factors affecting tourist satisfaction. In addition, Zulvianti et al. investigated the impact of environmental and non-environmental factors on tourist satisfaction in halal tourism destinations in western Sumatra. The findings showed that perceived environmental value, halal-friendly destination performance, sustainable tourism development, and halal destination image all impacted tourist satisfaction [52]. Papadopoulou et al. developed and tested a comprehensive destination loyalty model for tourist hotspots. They found that the assessed congestion negatively affected tourist satisfaction, willingness to revisit and recommend destinations, as well as positively impacted revisiting and recommending destination aversion [53]. Monoarfa et al. explored the influence of Islamic characteristics and attraction motivation on the satisfaction of Muslim tourists visiting Indonesia using the SEM-partial least squares method. The results denoted that attraction motivation had a greater impact on tourist satisfaction, and Islamic characteristics and attraction motivation affected tourist satisfaction simultaneously [54]. In short, tourist satisfaction is affected by many aspects, and strengthening the management and service level of scenic spots can improve tourist satisfaction.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

To study the fire detection and tourist satisfaction of scenic spots, a new method based on the DAI-YOLO model is proposed, and a grounded theory is introduced in the analysis of tourist satisfaction, which offers a new perspective and strategy for the safety management and service improvement of tourist attractions. Through experiments, the following conclusions are obtained:

1) Compared to other models, the DAI-YOLO model has the lowest precision, recall, and average precision increase by 4.1%, 8.8%, and 6.0%, respectively. This indicates that the DAI-YOLO model has higher detection accuracy and better performance.
2) Overall, 88.14% of tourists are satisfied with the scenic spots in X province, and 2.14% are dissatisfied. Among

them, the highest satisfaction is the environmental factor, with 98.78%; The most dissatisfied aspect is the scenic spot management, with negative comments accounting for 6.06%.

3) The top three factors affecting tourist satisfaction are traffic levels, scenic spot tickets, and service. The scenic spots in X province must improve transportation, services, scenic spot tickets, and accommodation levels, and strengthen the promotion of safety factors and food culture to improve tourist satisfaction.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

First, the detection speed of the constructed DAI-YOLO model is not dominant. In the future, further exploration can be made to improve the model speed to promote the model performance. Second, a comprehensive system of tourist satisfaction indicators has been constructed. However, under different cultures, backgrounds, and regions, there may be differences in the evaluation criteria of tourists, and further consideration needs to be given to how to adjust the index system in a targeted manner. For different cultures and regions, more in-depth research can be carried out to explore the impact of diverse cultural factors on tourist satisfaction and provide personalized suggestions for managing scenic spots in various regions.

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