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RESEARCH ARTICLE

The Analysis of Communication Strategy of Disabled Sports Information Based on Deep Learning and the Internet of Things

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ABSTRACT The ever-growing landscape of Internet of Things (IoT) technology and the evolution of deep learning algorithms have ushered in transformative changes in the communication strategy for disseminating information on disabled sports. This specialized information resource aims to provide relevant support and services related to sports activities for disabled individuals. This study investigates the communication strategy of disabled sports information driven by deep learning within the framework of the IoT and assesses the practical application performance of the proposed model. To achieve this objective, an appropriate deep learning model for the dissemination of sports information for the disabled is selected through a thorough literature review. Subsequently, an experimental framework is proposed for comprehensive performance verification, evaluating the model's performance in reasoning time and user satisfaction through comparative experiments. By constructing deep learning models, extensive data on disabled sports activities are analyzed, enabling the identification and prediction of key factors in information dissemination. The results indicate that the proposed sports information dissemination model outperforms similar models across various performance metrics, particularly in real-time performance and user experience. Comparative analysis with attention-based deep neural networks and traditional machine learning algorithms reveals that the proposed model achieves an accuracy rate as high as 0.85, significantly surpassing the 0.78 and 0.82 accuracies of these models, respectively. Moreover, the proposed model demonstrates the shortest inference time (15ms), surpassing both aforementioned models. This study validates the relative advantages of the proposed model through comparison with similar studies, offering a novel solution for the dissemination of sports information for the disabled.

INDEX TERMS Dissemination of sports information for the disabled, Internet of Things, deep learning, network security.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

In the contemporary digital era, the ubiquity and convenience of information dissemination have become integral aspects of societal interaction and entertainment, with sports occupying a prominent position on the global stage [1], [2], [3]. However, amidst the information deluge, it is imperative to recognize that disabled groups continue to encounter significant inequalities in accessing sports-related information [4], [5]. The conventional modes of sports information dissemination predominantly rely on visual and auditory channels, potentially resulting in incomplete and inadequate accessibility for individuals with visual and auditory impairments [6], [7].

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This disparity not only constrains the involvement of disabled individuals in sporting activities but also hampers their comprehension and assimilation of social sports culture [8], [9], [10]. While certain sports events offer auxiliary commentary services or subtitles, these provisions often fall short of catering to the diverse needs of disabled individuals, particularly those seeking real-time competition updates [11], [12].

The ongoing advancement in the Internet of Things (IoT) technology and deep learning presents a promising avenue to deliver intelligent, real-time, and personalized sports information dissemination services for individuals with disabilities by integrating these cutting-edge technologies [13], [14], [15]. IoT sensor technology facilitates the capture of intricate scene details, while deep learning models excel in comprehending and processing such complex data, thereby enhancing the overall sports viewing experience for individuals with disabilities [16], [17], [18].

This study outlines the design and implementation of a sports information dissemination model catering to individuals with disabilities, leveraging IoT and deep learning technologies. Our initiative not only fosters social participation and encourages a healthier lifestyle among individuals with disabilities but also addresses information access inequalities through technological interventions. Furthermore, the research endeavors align with the principles of sustainable development by promoting social inclusivity through the enhanced dissemination of sports information.

B. RESEARCH OBJECTIVES

The rapid evolution of IoT and deep learning technologies offers unprecedented opportunities to enhance the dissemination of sports information for individuals with disabilities through technological innovations. This study endeavors to design and implement an innovative sports information dissemination model tailored to individuals with disabilities, leveraging IoT and deep learning technologies. At the heart of this study lies the development of a novel sports information dissemination model, integrating Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and an attention mechanism. This amalgamation aims to augment the model's capacity to process sports information and enrich users' comprehension. CNN facilitates the extraction of spatial features from images, LSTM handles sequential data to capture temporal dependencies, while the attention mechanism directs the model's focus toward pivotal information within the dataset. Additionally, real-time monitoring using IoT technology furnishes abundant real-time data, thereby further enhancing the quality and diversity of input for the model.

A set of evaluation parameters has been established to comprehensively evaluate the efficacy of the proposed model. These parameters encompass: 1) Accuracy, which pertains to the precision of the model's prediction outcomes; 2) Efficiency, encompassing the speed of data processing and output generation by the model; 3) User satisfaction, determined through survey questionnaires to ascertain user' satisfaction with the effectiveness of information dissemination. These evaluation metrics not only facilitate the quantification of the model's performance but also offer guidance for future enhancements.

This study introduces several innovative contributions:

1) Technological Integration Innovation: This study pioneers the integration of IoT technology with deep learning models to disseminate sports information among individuals with disabilities. This integration enhances the real-time nature and accuracy of information dissemination while effectively improving the quality of personalized recommendations through deep learning model optimization.
2) Application of Attention Mechanism: The incorporation of an attention mechanism into the model enables more precise identification and response to users' points of interest. Consequently, it filters out the most relevant and engaging content from vast sports information databases, thereby enhancing the effectiveness of information dissemination and improving user experience and satisfaction.
3) Specific Optimization for the Disabled Community: In recognition of the unique challenges faced by individuals with disabilities in accessing and processing information, this study meticulously optimizes model design. Examples include interface design and interaction logic optimization to ensure barrier-free usage of the information dissemination platform, and the utilization of intelligent algorithms to tailor content presentation to meet the specific needs of diverse groups within the disabled community.

This study is structured into five main sections. The introductory section provides a comprehensive overview of the research background, objectives, and the study's significance. The second section conducts a review of related work, summarizing the dissemination of sports information for individuals with disabilities and exploring the applications of IoT and deep learning in analogous domains. The third section offers a detailed exposition of the proposed methods and model, elucidating the model architecture, algorithmic intricacies, and technological innovations. In the fourth section, the experimental design and performance evaluation are discussed, encompassing the experiment setup, the dataset utilized, and the specific methodologies employed to assess the model's performance. This section also presents results and analysis, comparing the performance of the proposed model with existing technologies and discussing the implications of the findings. The fifth section, the conclusion, and future work, succinctly summarizes the study's main findings, acknowledges its limitations, and proposes potential avenues for future research.

II. LITERATURE REVIEW

The intersection of sports information dissemination and disabled groups spans various domains, encompassing

TABLE 1. Comparison of the results of similar studies.

Authors	Research Focus	Method	Key Findings	Existing Issues
Cojo Caru et al. (2022)	Positive impact of technology in sports	Regression model	Technology positively impacts the sports domain	Data may lack universality
Gyamfi & Jurcut (2022)	Network intrusion detection based on edge computing	Machine learning	Comparison of different evaluation metrics	Lack of in-depth analysis on actual deployment effects
He & Tian (2022)	Dissemination of traditional national sports culture	Quantitative methods	Studied dissemination of martial arts, Go, and chess	May overlook the impact of modern digital dissemination platforms
Shao (2022)	Evaluation of sports information communication models	AHP	Constructed an evaluation index system and weights	Lacks empirical research to support the effectiveness of its model
Yüceba (2022)	World Cup data analysis	Multilayer artificial neural networks	Found diverse factors affecting player performance	Analysis may insufficiently consider external factors such as psychological states
Karakaya et al. (2022)	Sports systems under IoT infrastructure	Machine learning	Provided information on technical team and alarm systems	Lack of analysis on user acceptance and actual application effectiveness

information technology, accessibility, and social participation. Caru et al. [19] delved into a regression model, showcasing the positive impact of technology on the contemporary sports landscape. Their study, conducted on data collected from 260 students across two Romanian sports universities, demonstrated the transformative influence of technology in the sports domain. Gyamfi and Jurcut [20] explored a methodology utilizing multi-access edge computing platforms and machine learning technology. They meticulously analyzed publicly available datasets, evaluation indicators, and deployment strategies for designing a network intrusion detection system. Focusing on mature traditional national sports cultures such as Wushu, Weiqi, and China Chess, He and Tian [21] introduced a quantitative method for studying communication modes and effects based on sports events and network communication. Shao [22] employed an analytic hierarchy process (AHP) to construct an evaluation index system for the sports information communication model, considering network sports information content, audience experience, organization, and communication, as well as the network environment. Yüceba [23] utilized multi-layer artificial neural networks to analyze datasets from the 2010 and 2014 World Cups, revealing position-dependent factors influencing players' performance. Karakaya et al. [24] proposed a machine learning approach for an IoT-based sports system infrastructure, facilitating the provision of information and alerts to technical teams regarding goal occurrences. This literature review encapsulates diverse perspectives, methodologies, and findings at the intersection of sports information, technology, and accessibility, providing valuable insights for this study on sports information dissemination for individuals with disabilities. Further analysis of these related studies is detailed in Table 1:

Previous studies have highlighted the inadequacies of traditional sports information dissemination methods in meeting the needs of individuals with disabilities [25], [26], [27]. For instance, television broadcasts often fall short in accommodating individuals with visual and hearing impairments, resulting in incomplete information and comprehension challenges [28], [29], [30]. Moreover, the utilization of words and images may pose obstacles for individuals with language or cognitive disabilities. While the IoT offers more detailed information sources for individuals with disabilities, leveraging this data to cater to their individual needs remains an ongoing challenge [31], [32], [33]. Although some studies have explored the application of IoT and deep learning in sports information dissemination, the focus has predominantly been on the experiences of does not have a disability users, with limited attention given to the requirements of individuals with disabilities. Hence, there is a pressing need to investigate how to integrate these technologies to better serve individuals with disabilities, facilitating their comprehensive understanding and engagement with sports information, thus addressing the existing research gap.

III. RESEARCH MODEL

A. ESTABLISHMENT OF THE DEEP LEARNING MODEL

In selecting the deep learning model, CNN is employed to process image data from the game scene. Through convolution operations, CNN effectively extracts key features from the images, such as edges and textures, thereby furnishing the model with more precise and meaningful information (as depicted in Figure 1). The fundamental calculation process can be represented by the convolution operation equation:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n) \cdot K(i-m, j-n) \tag{1}$$

Here, I signifies the input image, K denotes the convolution kernel, and S refers to the output feature map. This convolution operation aids in capturing spatial features within the image, including object edges and textures.

Incorporating the LSTM network addresses the temporal dynamics inherent in sports competitions. LSTM's gating mechanism enables it to effectively capture the dynamic

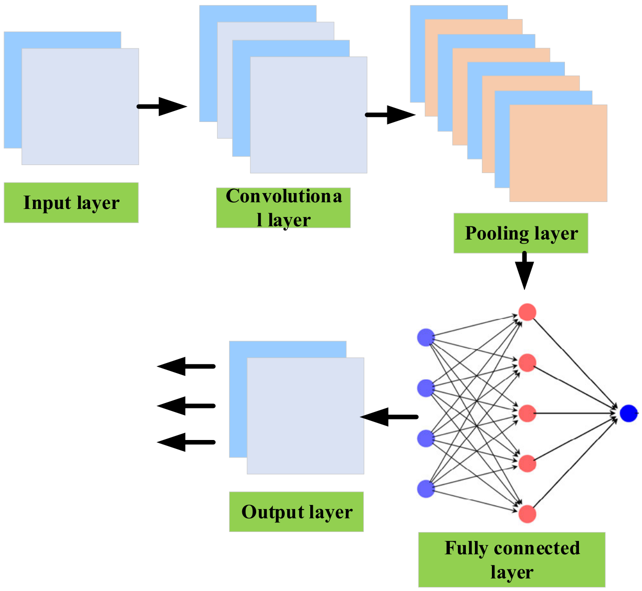

FIGURE 1. CNN structure.

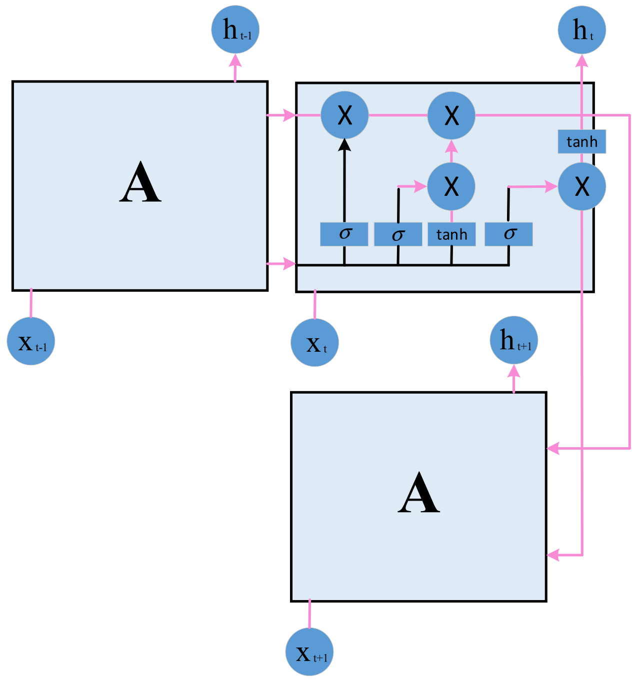

FIGURE 2. LSTM network structure.

changes during the competition process, thereby enhancing the model's comprehensive understanding [34], [35], [36]. In this study, LSTM is integrated to handle time series data in sports competitions, such as the evolution of the competition process (as illustrated in Figure 2). The fundamental calculation process of LSTM is expressed as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$
$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{5}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$
$$h_t = o_t \cdot tanh(C_t) \tag{7}$$

The variables f_t, i_t, $\tilde{C}_t$, C_t and o_t denote the forgetting gate, input gate, candidate value of the cell state, cell state, and output gate, respectively. W_f, W_i, W_C and W_o represent the weight matrices, while b_f, b_i, b_C and b_o denote the offset terms. The integration of these two models not only enhances the processing capability of static image information but also enables the model to better comprehend the dynamics of the game's evolution.

To enhance attention towards crucial information, an attention mechanism is introduced. This mechanism enables the model to concentrate on specific areas within the image, rather than processing the entire image uniformly. The calculation equation for attention weight is as follows:

$$\alpha_i = \frac{exp(e_i)}{\sum_{j=1}^{N} exp(e_j)} \tag{8}$$
$$e_i = AttentionScore(h_{t-1}, x_i) \tag{9}$$

Here, α_i signifies the attention weight of the i-th position; e_i represents the attention score; h_{t-1} denotes the hidden state of LSTM; x_i is the i-th position in the output feature map of CNN.

B. INTEGRATION OF IoT AND DEEP LEARNING

To achieve comprehensive monitoring of the game scene, full integration of IoT technology is implemented, utilizing sensor data for real-time monitoring. Sensor data not only offers static information about competition venues but also captures real-time dynamics of athletes during the competition [37], [38], [39]. This integration enables the deep learning model to access more detailed input information, enhancing its perception of changes in the game scene. Real-time monitoring of game scenes is facilitated by IoT technology through the fusion of sensor data. The specific process is illustrated in Figure 3.

In Figure 3, the sensor layer comprises various sensors, including cameras and motion sensors, each tasked with collecting specific data types such as images and motion states. Data from the sensor layer is transmitted to the data integration layer via IoT technology, where integrated data encompasses information from each sensor, forming comprehensive game scene data. The resultant integration reflects a holistic view of the competition scene, encompassing static elements like venue layout and dynamic elements such as athletes' positions and competition progress. This furnishes the deep learning model with more detailed input, enhancing its ability to perceive changes in the game scene.

The real-time capabilities of IoT technology enable real-time data processing [40], [41], [42]. The mechanism for real-time data processing and feedback is depicted in Figure 4.

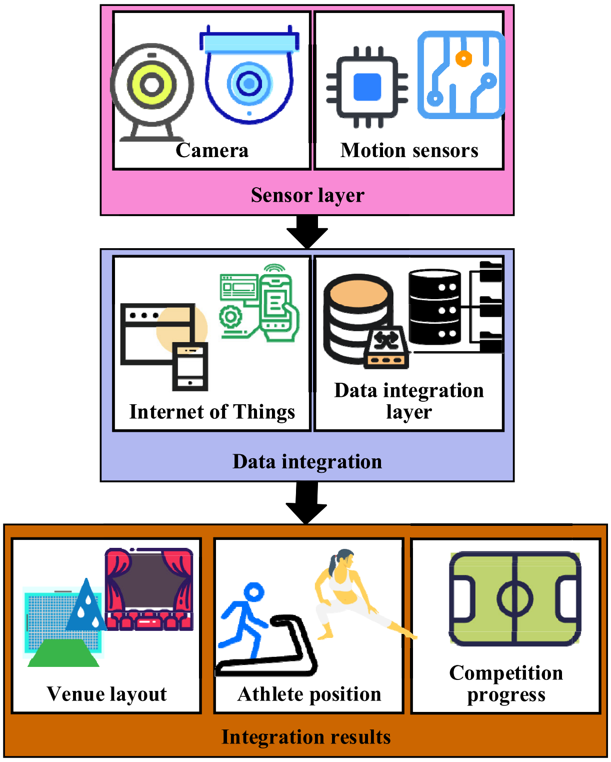

FIGURE 3. Fusion process of sensor data.

The data collected by various sensors in Figure 4 are transmitted to the data processing layer through IoT technology. This includes real-time images, motion states, and environmental data. The data processing layer is responsible for real-time processing of sensor data, encompassing tasks such as data cleaning and feature extraction. This ensures that the model can respond promptly based on the latest data. User feedback information is relayed to the system via IoT, prompting dynamic adjustments based on this feedback. This includes users' points of interest in the game scene and elements of concern. Ultimately, the system dynamically adjusts sports information to cater to individual user needs, enhancing user satisfaction. This process enables user feedback to directly influence the presentation format of sports information.

C. ALGORITHM IMPLEMENTATION DETAILS

To ensure the validity and feasibility of the model, meticulous attention is given to the implementation details of the algorithm [43], [44]. In network architecture design, the combination of CNN and LSTM networks is thoughtfully selected to enhance the processing of images and time series data while maintaining model complexity. Additionally, during the training process and hyperparameter adjustment, emphasis is placed on enhancing robustness and generalization to accommodate various competition scenes and user groups. The network architecture design serves as the cornerstone of the deep learning model, with the specific structure depicted in Figure 5.

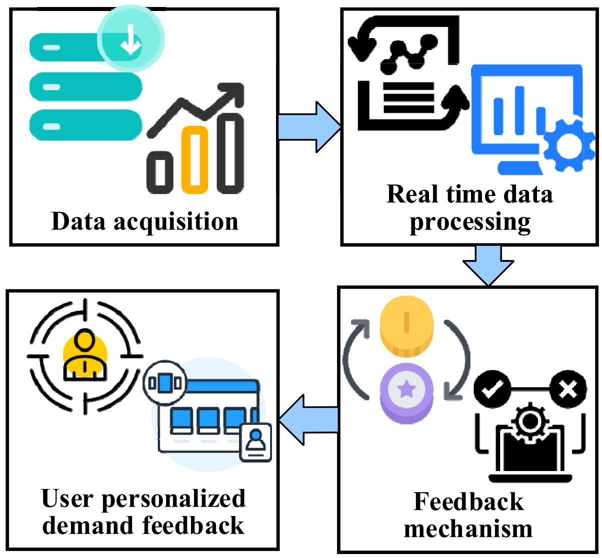

FIGURE 4. Real time data processing and feedback mechanism of IoT.

In Figure 5, CNN is employed to process image data and extract key features, while the LSTM network is utilized to handle time series data and capture the dynamic changes in the competition process. The attention mechanism enhances the model's perception of key information by dynamically adjusting attention to different regions of the image. The attention mechanism plays a pivotal role in the model, dynamically adjusting focus to different regions of the image. This allows the model to prioritize crucial information, such as athlete movements or specific game moments, thereby improving the accuracy of information extraction. The attention mechanism is equally vital for time series data. It enables the LSTM network to more effectively identify and weigh key moments during the game process, such as changes in actions like jumping or landing, thereby enhancing the model's capacity to capture dynamic changes.

In the fully connected layers of the model, information from different levels is integrated to generate the final prediction result. The introduction of the attention mechanism facilitates the automatic identification and integration of influential features, optimizing the decision-making process. During training, the cross-entropy loss function is utilized to optimize the model, ensuring effective learning to distinguish information from various categories. Incorporating the attention mechanism not only enhances the model's capability to handle complex data but also improves its performance and generalization ability when dealing with large-scale and high-dimensional data.

Through this design, the proposed model not only accurately handles and disseminates information about disability sports but also offers users a richer and more personalized sports information experience, highlighting the significant potential of attention mechanisms in enhancing the performance of deep learning models. In the training process, the adopted loss function is the cross-entropy, represented by

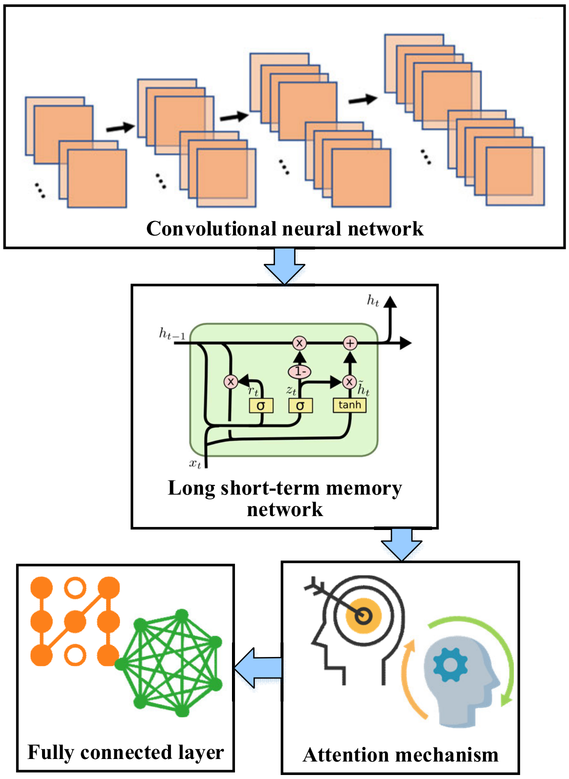

FIGURE 5. Composition of sports information dissemination model of deep learning.

Equation (10).

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} log(\hat{y}_{i,c}) \tag{10}$$

In Equation (10), N represents the number of samples; C denotes the number of categories; $y_{i,c}$ refers to the actual label; $\hat{y}_{i,c}$ signifies the prediction probability of the model. By minimizing the cross-entropy loss, the model can more accurately learn the probability distribution of target classifications. The optimization algorithm for model parameters employs the Adam optimization algorithm, with the following updating rules:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + \epsilon} \cdot m_t \tag{11}$$

In Equation (11), θ represents the model parameter; η is the learning rate; m_t denotes the estimation of gradient; v_t signifies the estimation of gradient square; ϵ indicates a smooth term. To prevent overfitting, a regularization term is added to the loss function to constrain the size of model parameters. The expression is as follows:

$$Loss = CrossEntropy + \lambda \sum_i |w_i|^2 \tag{12}$$

Through meticulous training processes and hyperparameter adjustment strategies, this study ensures that the deep learning model effectively learns features during the training stage and demonstrates high performance during testing.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

To validate the effectiveness of the proposed disability sports information dissemination model, this study meticulously selected two existing datasets for in-depth analysis and application: the ParaSport-Images dataset [45] and the ParaMotion dataset [46]. The ParaSport-Images dataset comprises high-quality images from the Paralympic Games and other disability sports competitions. It is segmented into a training set (70%), validation set (15%), and test set (15%), ensuring ample learning during training and effective validation during validation. Each image undergoes preprocessing, including size normalization, color standardization, and the application of data augmentation techniques such as rotation and flipping, to enhance the model's recognition capability under varied conditions. Conversely, the ParaMotion dataset includes time series data from disability sports competitions, capturing information such as athletes' positions and trajectories. These data are acquired through sensor technology, including accelerometers and gyroscopes, with a sampling frequency of ten times per second to ensure precise and continuous movement information capture. Before utilization, the data undergo denoising, interpolation, and normalization processes to enhance data quality and conform to the model's input requirements.

For the ParaSport-Images dataset, image enhancement techniques such as random rotation, scaling, and flipping during data preprocessing are employed to bolster the model's generalization capability. Concerning the ParaMotion dataset, data cleaning (removing outliers), smoothing (reducing noise influence), and data interpolation (ensuring the continuity of time series) are conducted. The selection of these two datasets aims to comprehensively understand and disseminate information about disability sports competitions by integrating static images and dynamic time series data. The ParaSport-Images dataset enables the model to deeply learn visual features, while the ParaMotion dataset trains the model to comprehend and predict athletes' dynamic behaviors. Integrating such multimodal data aims to achieve more comprehensive and in-depth dissemination of disability sports information, aligning with the study's goal to enhance the efficiency and quality of disseminating disability sports information through IoT and deep learning technologies.

B. EXPERIMENTAL ENVIRONMENT

This study adopts the experimental environment settings outlined in Table 2 to ensure the accuracy and repeatability of the experiment.

C. PARAMETERS SETTING

In the experiment, the model's hyperparameters are meticulously configured to ensure optimal performance during both training and evaluation stages. Table 3 presents the detailed setting of the model's hyperparameters.

TABLE 2. Experimental environment setting.

TYPE	TOOL	SETTING
Hardware equipment	GPU	NVIDIA Tesla V100 GPU (16GB VRAM)
	CPU	Intel Xeon Gold 6248 Processor (20 cores, 2.5GHz)
	Internal storage	256GB DDR4 RAM
	Memory	1TB SSD
Software framework	Deep learning framework	TensorFlow 2.5.0
	Python	3.8.10
	Operating system	Ubuntu 20.04
Data preprocessing tool	OpenCV	4.5.2
	NumPy	1.19.5
	Pandas	1.2.4

D. PERFORMANCE EVALUATION

The performance evaluation encompasses the following indicators: Accuracy measures the correctness of model classification. Precision evaluates the accuracy of the model in predicting positive cases. Recall assesses the model's ability to identify positive examples. F1 Score provides a comprehensive evaluation of the model's performance by combining accuracy and recall. User satisfaction survey evaluates the practical effectiveness of disseminating disability sports information, this study conducted a questionnaire survey to gather users' subjective feedback on their experience with sports information dissemination. The survey questionnaire was designed to encompass multiple indicators, including the availability, comprehensibility, and personalization level of information, to quantify user satisfaction and acceptance. The calculation equation for each index is as follows:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{13}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{14}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{15}$$

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{16}$$

To comprehensively evaluate the performance and advantages of the proposed sports information dissemination model, it is compared with three other similar models:

1) Model A: A deep neural network based on attention mechanism designed for sports information dissemination tasks [47].
2) Model B: A support vector machine model based on traditional machine learning algorithms, utilized for sports information dissemination tasks [48].

TABLE 3. Parameter setting.

Hyperparameter	Setting
Learning Rate	0.001
Optimizer	Adam
Batch Size	32
Architecture	CNN-LSTM with Attention
Regularization	L2 Regularization (0.001)

3) Model C: A model based on recurrent neural networks, applied for sports information dissemination tasks [49].

The comparison results are illustrated in Figure 6.

In Figure 6, the proposed sports information dissemination model outperforms other exemplary models in terms of accuracy, precision, recall, and F1 Score. Notably, the accuracy rate reaches 0.85, a significant improvement compared to the range of 0.78-0.82 achieved by other models. Particularly noteworthy is the recall score of 0.90 attained by the proposed model, indicating its robust capability in correctly identifying positive instances, i.e., important sports information for the disabled community. A high recall rate suggests that the model effectively captures and disseminates crucial information to the target user group, thereby enhancing the accessibility and usability of disability sports information. This underscores the model's superior ability to accurately classify sports information. Furthermore, the operational efficiency of different models is compared, as depicted in Figure 7.

In Figure 7, the proposed sports information dissemination model exhibits the shortest reasoning time (15ms), surpassing other exemplary models. Model A and Model C demonstrate better reasoning times, whereas Model B exhibits longer reasoning time. Regarding resource occupation, the proposed sports information dissemination model demonstrates the lowest performance, indicating its relatively low demand for computing resources. The model's power consumption is moderate compared to other models. Additionally, the proposed sports information dissemination model achieves the highest score in real-time performance, rendering it suitable for scenarios with stringent real-time requirements. Concerning user satisfaction, the comparison results of different models are illustrated in Figure 8.

In Figure 8, the proposed sports information dissemination model excels with the highest scores in interface friendliness and overall user experience. It demonstrates exceptional response speed, ensuring a smooth user experience. Moreover, the model achieves the highest score in information accuracy, guaranteeing precise information dissemination. In terms of personalized experience, the model also garners the highest score, catering to users' individualized needs. Overall, the proposed sports information dissemination model clearly outperforms other exemplary models in total score. However, Model A and Model C also exhibit

TABLE 4. Comparison of key aspects of different studies.

Author and Year	Application Area	Technological Innovation	Applicability
This study	Dissemination of sports information for the disabled	Integration of IoT and deep learning, introduction of attention mechanism	Broad, particularly suitable for disability sports information dissemination
Tang (2023) [50]	Sports marketing strategy	Application of IoT platform and blockchain technology	Mainly focused on sports marketing
Hohmuth et al. (2023) [51]	Sports measurement system	Development of a novel wireless rowing measurement system using electromyography technology	Applicable to rowing sports analysis
Seeberg et al. (2023) [52]	Sports performance analysis	Study of speed curves, stride strategies, etc., in international skiing competitions	Applicable to skiing sports analysis

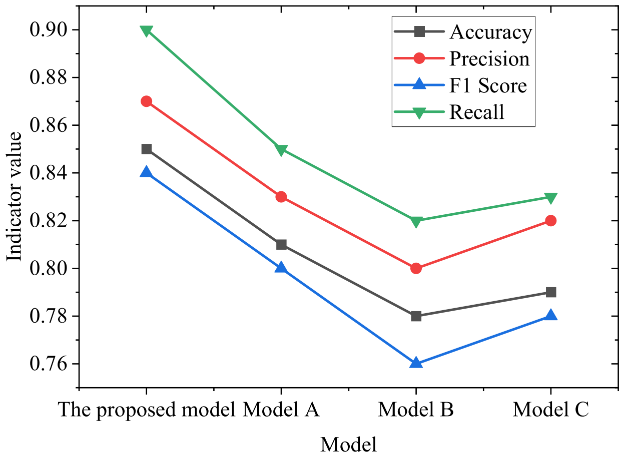

FIGURE 6. Performance comparison of different models.

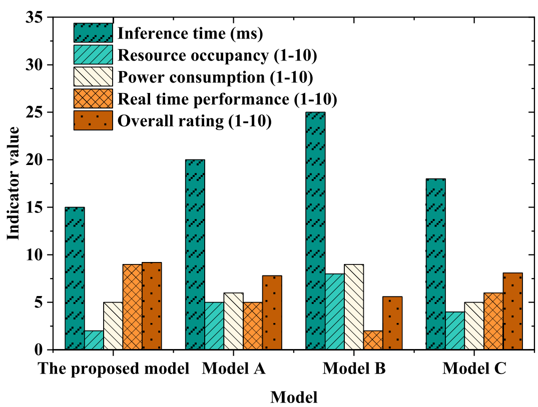

FIGURE 7. Comparison of operating efficiency of different models.

commendable performance in overall score, whereas Model B lags behind.

E. DISCUSSION

Through comprehensive comparison with existing similar models, the proposed sports information dissemination model demonstrates notable performance in operational efficiency and user satisfaction, attributed to the seamless integration of deep learning and IoT technology. This integration

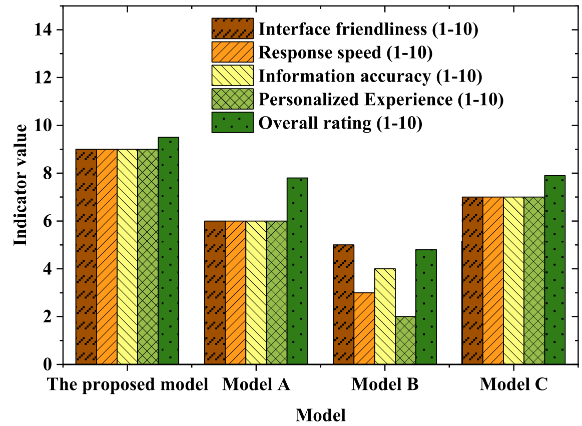

FIGURE 8. Comparison of user satisfaction of different models.

confers clear advantages in real-time processing, accuracy, and user experience. Literature review highlights related research endeavors, such as Tang's exploration of sports marketing strategy based on IoT platform and blockchain [50]. Hohmuth et al. [51] developed a novel wireless rowing measurement system utilizing electromyography to capture rowing movement and measure muscle activity. Seeberg et al. [52] investigated speed curve, pace strategy, group dynamics, and their significant impact on performance in cross-country skiing collective starting competitions. The proposed model selects a deep learning framework tailored for disseminating sports information to individuals with disabilities, surpassing existing models in performance. Comparative experimental results underscore the superiority of the proposed model in accuracy, user satisfaction, and operational efficiency, aligning with findings from related literature. This consistent validation affirms the efficacy of the proposed model. Through comparative analysis, it is evident that the proposed sports information dissemination model excels in real-time performance and user experience, rendering it highly applicable in disseminating sports information for individuals with disabilities. This also lays a robust foundation for extending the model's utility to other domains [53].

To facilitate a clear comparison between our study and existing research, Table 4 presents the following insights:

The comparison in Table 4 illustrates that our study, through the integration of IoT technology and deep learning models, particularly incorporating the attention mechanism, showcases technological innovation. Moreover, it offers a wide-ranging and effective application in disability sports information dissemination. In contrast to other research, our focus lies in enhancing real-time performance, accuracy, and user experience, all pivotal aspects in the realm of disability sports information dissemination. In conclusion, the proposed sports information communication model excels in the choice of deep learning model, consistency, and applicability of experimental outcomes, offering a valuable reference for research in the domain of sports information communication for the disabled. Future studies could enhance the model's performance, explore additional applications in practical contexts, and bolster its interpretability.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This study introduces a sports information dissemination model based on deep learning, leveraging IoT technology. This innovative integration offers a promising solution for enhancing sports information accessibility for the disabled. Comparative experiments demonstrate the model's superiority in reasoning time and user satisfaction compared to existing models, showcasing its practical potential and contribution to enhancing sports information dissemination systems for the disabled.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

Future research directions and limitations are as follows: Firstly, efforts can be directed towards enhancing the explanatory power of the proposed model to better elucidate its decision-making process and bolster its credibility in practical applications. Further studies can incorporate more considerations of user participation, including collecting users' actual feedback and opinions to comprehensively evaluate the user experience of the sports information dissemination system [54], [55]. To enhance the verification of the proposed model in practical scenarios, future research can collaborate with disabled sports information dissemination agencies or communities for extensive real-world validation. Additionally, further optimization of the algorithm is needed to improve the model's generalization performance across various datasets and scenarios. Moreover, when implementing the sports information dissemination system, considerations such as network security and user privacy protection should be addressed to ensure system reliability and user data security.

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