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Application of the artificial intelligence system based on graphics and vision in ethnic tourism of subtropical grasslands

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ABSTRACT

This study aims to optimize the evaluation and decision-making of ethnic tourism resources through the utilization of deep learning algorithms and Internet of Things (IoT) technology. Specifically, emphasis is placed on the recognition and feature extraction of Mongolian decorative patterns, providing new insights for the deep application of cultural heritage and visual design. In this study, the existing DL algorithm is improved, integrating the feature extraction algorithm of ResNet + Canny + Local Binary Pattern (LBP), and utilizing an intelligent decision method to analyze the intelligent development of indigenous tourism resources. Simultaneously, the DL algorithm and IoT technology are combined with visual design and convolutional neural networks to perform feature extraction and technology recognition. Visual design offers an intuitive representation of tourism resources, while fuzzy decision-making provides a more accurate evaluation in the face of uncertainty. By implementing an intelligent decision-making system, this study achieves a multiplier effect. The integration of intelligent methods not only enhances the accuracy of tourism resource evaluation and decision-making but also elevates the quality and efficiency of the tourism experience. This multiplier effect is evident in the system's capacity to manage substantial datasets and deliver prompt, precise decision support, thus playing a pivotal role in tourism resource management and planning. The findings of this study demonstrate that optimizing intelligent development technology for rural tourism through IoT can enhance the efficacy of intelligent solutions. In terms of pattern recognition accuracy, AlexNet, VGGNet, and ResNet achieve accuracies of 90.8 %, 94.5 %, and 96.9 %, respectively, while the proposed fusion algorithm attains an accuracy of 98.8 %. These results offer practical insights for rural tourism brand strategy and underscore the utility of applying fuzzy decision systems in urban tourism and visual design. Moreover, the research outcomes hold significant practical implications for the advancement of Mongolian cultural tourism and provide valuable lessons for exploring novel paradigms in image analysis and pattern recognition. This study contributes beneficial insights for future research endeavors in related domains.

1. Introduction

As living standards improve, rural tourism has increasingly become the preferred option for many urban residents. Rural tourism plays a pivotal role in promoting rural societies, augmenting farmers' income, and advancing agricultural modernization [1–3]. However, after more than a decade of rapid development, several practical challenges have emerged. The New Dimension, a cultural

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tourism planning organization, suggests four key areas for enhancing rural tourism.

1) Environmental governance optimization and appropriate landscape expression.
2) Emphasizing rural characteristics and fostering the integration of culture and tourism.
3) Innovating industrial financing methods and diversifying comprehensive businesses.
4) Nurturing innovative talents and enhancing management proficiency.

From a tourism perspective, landscapes encompass both objective and subjective elements. Rural tourism development should prioritize the portrayal of rural scenery, distinct from the urban landscape experience [4]. Since the onset of the 21st century, China's tourism industry has witnessed rapid economic growth, largely attributed to increased tourism expenditure following rises in per capita income. Concurrently, with the surge in social activities and the rapid advancement of information technologies such as cloud computing, physical networking, and mobile communication, there is a growing interest in the informatization and intelligent management approaches within the tourism sector.

In the current landscape, the integration between the information industry and the tourism, cultural, and creative sectors is pronounced [5,6]. The advent of the Internet has catalyzed the onset of the big data era in the tourism industry, offering more convenient and superior tourism services. In the realm of modernization, the pursuit of intelligent rural tourism underscores the importance of researching the "feature extraction and application" of traditional patterns across various villages. This serves as an effective strategy to safeguard and promote traditional decorative patterns while fostering local tourism development. A pattern's feature comprises distinctive information, necessitating discernible properties from both low-level visual and high-level semantic perspectives [7,8]. In the domain of artificial intelligence (AI), the application of deep learning (DL) in image processing mitigates errors inherent in manually extracting image feature vectors. Monga et al. (2021) [9] conducted a comprehensive review of DL methods for signal and image processing, culminating in the development of an interpretable and efficient deep network capable of fully learning underlying mappings through end-to-end training, particularly effective in image classification and feature extraction. Similarly, Maier et al. (2019) [10] delved into the application of DL in medical image processing, elucidating its theoretical underpinnings and practical applications. Their findings underscored DL technology's significant impact on image detection, recognition, segmentation, and registration. Additionally, Udendhran et al. (2020) [11] investigated the image-processing architecture of embedded vision systems, proposing and analyzing a DL method to enhance said architecture. Their experiments demonstrated the effectiveness of implementing DL algorithms and testing them on embedded vision systems. Moreover, two recent papers featured in the journal "Mathematics" have introduced novel findings and methodologies pertinent to the research trajectory. Specifically, Li et al. (2022) [12] investigated AI-driven intelligent graphic design techniques, with a particular emphasis on optimization strategies for intelligent graphic design within traditional contexts, such as pottery carving patterns. Theoretical and empirical investigations demonstrate the significant impact of their image feature extraction model on traditional carving pattern analysis. Notably, brightness processing streamlines image feature extraction, while convolutional operations enhance accuracy. In a related study, Li et al. (2023) [13] introduced a feature graphic creation approach leveraging a channel attention module within DL algorithms. Experimental outcomes underscore the method's ability to accentuate geometric line features in images, streamlining image generation complexity, and enhancing efficiency. Building upon this method, they successfully generated images with enhanced line features from descriptive text and developed dynamic graphics for image presentation, showcasing potential applications in intelligent museum curation.

Presently, rural tourism destinations in Inner Mongolia are widespread, yet the level of intellectual development remains comparatively underdeveloped. Notably, deficiencies in tourism infrastructure construction and product design represent primary research challenges. The overarching aim and impetus of this study lie in leveraging the resource advantages of Inner Mongolia. The fundamental research objective entails advancing the comprehensive development of smart rural tourism through the establishment of a distinctive local rural smart tourism brand.

This study has made significant contributions and innovative strides in Mongolian decorative pattern recognition. Firstly, it successfully integrates the traditional texture feature extraction method, Local Binary Pattern (LBP) algorithm with modern DL technology, forming a highly effective feature fusion strategy. This approach not only enhances pattern recognition accuracy but also maximizes the strengths of diverse feature extraction methods, facilitating a comprehensive understanding of the intricate Mongolian decorative patterns. Secondly, the incorporation of the Canny operator for edge feature extraction enables the designed system to capture pattern outlines and structures more effectively. This edge feature introduction provides essential support for pattern shape analysis and enhances overall pattern recognition performance. Most notably, a novel feature fusion method is proposed, merging DL with traditional methods. This integration offers advantages in recognition accuracy and renders the designed system more adaptable to various styles and types of Mongolian decorative patterns. The multi-level and multi-angle feature integration represents the innovative cornerstone of this study, presenting a fresh approach for addressing similar problems in research. The integration of DL algorithms and IoT technologies provides robust technical support for the intelligent advancement of ethnic tourism. DL algorithms, trained on extensive ethnic pattern data, autonomously identify and categorize patterns. Meanwhile, IoT technology, employing sensors and network technology, monitors the tourism environment in real-time, providing live data support for tourism management and services. Additionally, fuzzy decision-making systems adeptly navigate ambiguity and uncertainty, introducing a novel decision-making approach for tourism planning and visual design. This method adapts to dynamic shifts in the tourism market and diverse tourist needs, thereby enhancing the quality and satisfaction of tourism products and services. Moreover, Convolutional Neural Network (CNN) automatically learns deep features of image data, crucial for pattern recognition, scene comprehension, and enriching tourism experiences. Leveraging CNN, ethnic patterns can be more precisely identified and classified, providing robust technical support for the development and promotion of tourism products. In summary, this study combines advanced DL algorithms, IoT technologies, and fuzzy decision-making systems to chart a new intelligent development trajectory for ethnic tourism in the subtropical grassland region. This holds significant importance in bolstering tourism competitiveness and fostering regional economic development.

The structure of this study comprises six parts, each delving into the application of AI systems in ethnic tourism within subtropical grassland areas. The introductory section underscores the pivotal role of rural tourism in enhancing farmers' income, fostering rural social development, and advancing agricultural modernization. It identifies prevalent challenges in rural tourism, such as inadequate infrastructure and a lack of personalized and innovative tourism experiences. Furthermore, it proposes a method to optimize the assessment and decision-making of ethnic tourism resources through DL algorithms and IoT technologies, emphasizing the importance of Mongolian decorative pattern recognition and feature extraction in cultural heritage preservation and visual design. The literature review section surveys pertinent studies on rural tourism development, AI and IoT technologies in tourism, as well as image processing and pattern recognition. Through this analysis, it establishes a theoretical framework and references to inform the research purpose and methodology. The section on intelligent development of rural tourism in Inner Mongolia provides a detailed overview of the region's tourism resources and analyzes the current state and intelligent trends of rural tourism. It also discusses leveraging cloud computing, big data, and other information technologies to enhance tourism services and management levels. The methodology section details the technical approaches employed in the study, including the feature extraction of Mongolian decorative patterns, CNNs based on DL, and the recognition and feature extraction of patterns. Additionally, it explores the integration of IoT technology for intelligent management and development of tourism resources. Next, the results and discussion section unveils the outcomes of texture feature extraction of Mongolian decorative patterns and compares the performance of different DL networks. Through case studies, it validates the efficacy of the proposed technology in practical tourism resource assessment and decision-making, while also exploring the significance and application prospects of the research findings. The conclusion section summarizes the main contributions of this study, including technological innovation, accuracy improvement of Mongolian decorative pattern recognition, promotion of fuzzy decision-making systems, impact analysis of actual tourism development, and cultural heritage protection. Additionally, it identifies study limitations and suggests future research directions. Overall, by integrating DL algorithms, IoT technology, and fuzzy decision-making systems, this paper presents a novel method and idea for the intelligent development of ethnic tourism in subtropical grassland areas. It holds significance in enhancing tourism competitiveness and promoting regional economic development.

2. Literature review

As urbanization progresses rapidly, rural tourism has emerged as a significant and supported alternative in the tourism sector. The expansive potential of rural tourism in China offers urban dwellers a tranquil and comfortable holiday destination while fostering local economic development and cultural preservation. However, challenges persist in the quality of experience and service standards within China's rural tourism sector, characterized by outdated infrastructure, traditional agricultural practices unable to meet consumer demands, and a dearth of personalized and innovative tourism experiences. Thus, leveraging DL and visual art design technologies for the feature extraction of Mongolian decorative patterns holds promise in providing robust support and ensuring the development of rural tourism in China.

AI and IoT technologies are increasingly permeating various industries, including agriculture and tourism. With growing emphasis on quality of life, rural tourism and smart agriculture have garnered significant attention. Consequently, the integration of cutting-edge technology with these industries has become an urgent imperative. This section introduces the latest research and development (R&D) trends in crop disease detection, smart tourism city construction, personalized recommendations for rural tourism, smart agriculture, and low-carbon slow tourism. Orchi et al. (2022) [14] examined the utilization of AI and IoT technology for crop disease detection, comprehensively analyzing existing techniques and methods while proposing future research directions. Sharma et al. (2022) [15] outlined the realization of smart agriculture through the implementation of AI and embedded sensing technology. They introduced a novel intelligent agricultural system capable of precise water, soil, and fertilizer management through embedded sensors, data acquisition, and processing to enhance agricultural efficiency and quality. Guo et al. (2022) [16] primarily focused on smart tourism city construction and digital marketing of cultural tourism. Given the competitive market environment, they advocate adopting online publicity strategies to enhance market awareness. Chen et al. (2022) [17] examined rural-urban mobility in China, focusing on China's rural tourism makers as a case study. Drawing on field trips to four rural tourism maker model bases and conducting 131 interviews and participant observations, they elucidated how mobility manifests "on the ground." Through case analysis and investigation, they proposed a smart tourism development plan, featuring intelligent, personalized, real-time, and ecological suggestions. Bi et al. (2022) [18] investigated personalized recommendations for rural tourism based on traffic classification and user data analysis, utilizing data from a mobile Internet application. By analyzing users' travel data to discern travel biases, they offered personalized recommendations to optimize tourist trips and enhance the tourist experience. However, the study's scope was limited to certain users, potentially constraining the generalizability of the results. Jiang et al. (2023) [19] primarily explored the utilization of geographic information visualization and AI technology in fostering sustainable development within low-carbon rural slow tourism. Through data analysis and modeling methods, they proposed strategies for integrating rural tourism, reducing carbon emissions, and preserving ecological environments. Findings suggested that AI vision technology could enhance tourists' travel experiences and contribute to rural tourism development. Nonetheless, the study's limited timeframe and constrained data sources and scale may impact the generalizability of the results. Li et al. (2022) [20] introduced a hybrid method combining CNN, a gated cycle unit, and an improved artificial bee colony (ABC) algorithm for predicting ship motion. Through learning, extracting, and capturing features in the data alongside an enhanced ABC algorithm, the model's performance was optimized. Experimental outcomes revealed that this hybrid approach exhibited superior prediction accuracy and practicality compared to traditional machine learning and intelligent optimization methods. This method holds significant practical implications for enhancing maritime safety and ship management.

Qin et al. (2023) [21] introduced GuideRender, a large-scale scene navigation method based on multi-modal view frustum movement prediction. Leveraging information from previous frames, user input, and object data, GuideRender spatially and temporally extracted frame, user input, and object features using a multi-modal extractor. Results demonstrated GuideRender's superior performance in navigating large scenarios compared to the baseline approach. Jiang et al. (2020) [22] presented a real-time simulation for producing high-fidelity hair animation, effectively capturing non-ductility, bending, and twisting chain mechanics, along with adhesion/repulsion and detailed real-time collision effects. Ertugrul et al. (2020) [23] introduced a novel method for embedding 3D models in offline physical environments using fast response codes, considering settings for 3D models that cannot be retrieved from remote servers. These methods exhibit high practicality in large-scale scene navigation. In contrast to ethnic tourism applications in subtropical grasslands, this study focuses on AI methods that integrate graphics and vision to offer tourists a smarter and more intuitive navigation experience. Moreover, these techniques offer instructive insights, particularly in simulating natural elements like vegetation in graphics and visual processing. A similar real-time simulation approach could enhance the immersion experience for visitors in subtropical grassland regions.

The continuous evolution of AI technology has led to its widespread integration into the tourism sector. Scholars have contributed theoretical frameworks and practical insights, examining AI's application in tourism recommendation systems, customer service, and resource management. For instance, Al Fararni et al. (2021) [24] investigated AI-driven tourism recommendation systems, offering personalized travel advice to tourists through analysis of their preferences and behavioral data, thereby significantly enhancing their travel experiences and satisfaction. DL has exhibited considerable potential in feature extraction. For example, Belhi et al. (2023) [25] employed DL algorithms to extract features from cultural heritage images, introducing novel technological avenues for the digital preservation and dissemination of cultural heritage. In the realm of ethnic tourism and scenic resource optimization, AI technology has inspired innovative approaches to tourism planning and management. Kang et al.'s study (2021) [26] utilized DL algorithms to analyze image data from ethnic tourism areas, extracting key features of tourist attractions. This data-driven methodology informs scientific planning and optimization strategies while exploring methods to enhance the allure and competitiveness of ethnic tourism through AI technology. Additionally, fuzzy decision-making systems, serving as a method for addressing uncertainty and ambiguity, have found wide application in tourism resource assessment and decision-making. Fuzzy decision systems, as a method for addressing uncertainty and fuzziness issues in decision-making, have been widely applied in tourism resource assessment and decision-making. Cepeda--Pacheco et al. (2022) [27] utilized fuzzy decision systems for evaluating tourism resources, constructing fuzzy evaluation models to integrate multiple evaluation indicators and expert opinions effectively. This provided decision support for the rational development and utilization of tourism resources. Visual design plays a crucial role in promoting and branding ethnic tourism. Zhou et al. (2024) [28] explored enhancing the brand image and market competitiveness of ethnic tourism by combining ethnic tourism elements with modern visual design. Their research indicated that innovative visual design techniques can better convey ethnic culture and tourism characteristics, attracting more tourists and promoting the development of ethnic tourism. In summary, the application of artificial intelligence technology in the tourism industry provides new possibilities for innovation and optimization of tourism operations. Especially in the optimization of ethnic tourism and scenic resources, the application of DL algorithms, Internet of Things (IoT) technology, and fuzzy decision systems provides powerful technical support for the sustainable development of the tourism industry. Meanwhile, the role of visual design in promoting ethnic tourism and branding cannot be ignored, as innovative visual expression methods enhance the dissemination power and influence of ethnic culture.

DL, a vital component of AI, is founded on the theoretical underpinnings of artificial neural networks and machine learning. By mimicking the neural network architecture of the human brain, DL models autonomously learn from vast datasets and extract features, enabling intricate pattern recognition and decision-making tasks. The essence of DL lies in its capacity to abstractly represent data at a sophisticated level through multi-layer nonlinear transformations. Milestones like Deep Belief Networks and the AlexNet model mark significant advancements in the history of DL. The successful applications of these models underscore the effectiveness and superiority of DL across domains such as image recognition, speech recognition, and natural language processing. The development of AI systems draws upon theoretical insights from diverse disciplines, including computer science, cognitive science, and psychology. Krenn et al. (2022) [29] systematically elucidate the fundamental principles and key technologies of AI, providing theoretical guidance for the design and implementation of AI systems. Moreover, the design of AI systems must address aspects such as user interaction, system performance, and ethical considerations. Visual recognition stands as a central challenge in image processing and computer vision, drawing from theoretical foundations in image processing, pattern recognition, and machine vision. With the advancement of DL technology, DL-based image recognition methods have emerged as the predominant research focus in visual recognition. Expanding upon existing theories, various studies have developed theoretical frameworks to inform practical applications. For instance, Suganyadevi et al. (2022) [30], in their study on the application of DL in medical image processing, proposed a theoretical framework that combines DL and traditional image processing techniques, effectively enhancing the recognition and analysis capabilities of medical images. This study extends existing theoretical foundations by integrating DL algorithms and IoT technology, proposing a novel method for evaluating and decision-making in ethnic tourism resources. This not only enhances the level of intelligence in tourism resource management but also provides new technological support for branding and promotion in ethnic tourism. Additionally, it innovates on the theoretical framework by introducing a fuzzy decision system, effectively addressing uncertainty and fuzziness issues in tourism resource assessment, thereby improving the accuracy and reliability of decision-making. Furthermore, the research explores the role of visual design in promoting ethnic tourism, offering new ideas and methods for branding and cultural dissemination in ethnic tourism.

In previous literature, the recognition of cultural heritage patterns predominantly relied on traditional texture feature extraction methods and DL-based image classification techniques. While traditional methods often faced limitations in feature selection and accuracy, DL technology has made significant strides in image recognition. However, the complexity and diversity of cultural heritage pattern data can pose challenges to DL approaches. Consequently, researchers have sought recognition methods for cultural heritage patterns that can effectively leverage both traditional and modern technologies while ensuring high accuracy and computational efficiency. In comparison to traditional feature extraction methods, this study introduces the Canny operator and Principal Component Analysis (PCA) dimensionality reduction technology, enabling more precise extraction of texture and edge features from cultural heritage patterns. Furthermore, the designed system incorporates DL technology, particularly emphasizing the feature fusion strategy, to leverage DL's advantages in image recognition fully. By integrating both traditional and DL features, this system enhances recognition accuracy while reducing computational complexity, making it suitable for large-scale cultural heritage pattern recognition. This study addresses gaps in existing literature, providing a comprehensive and efficient approach to cultural heritage pattern recognition. The proposed method demonstrates efficacy across various cultural heritage pattern types and excels in handling large-scale data. Through the integration of traditional and modern technologies, this study strongly supports cultural heritage preservation and digital legacy, offering novel ideas and methodologies for related research and practical applications.

3. Intelligent development of rural tourism in inner Mongolia

3.1. Regional overview and tourist landscape of inner Mongolia

The Inner Mongolia Autonomous Region spans 1.183 million square kilometers in the heart of the Eurasian continent, situated on China's northern frontier as an autonomous region of diverse ethnic groups. Among its 49 ethnic groups, prominent ones include Han, Mongolian, Manchu, Hui, Daur, and Ewenki. Inner Mongolia holds the distinction of being China's earliest-established ethnic minority autonomous region. Renowned for its abundant natural resources, Inner Mongolia is often dubbed "East Forests West Mines, South Agriculture, and North Animal Husbandry". It boasts China's largest grassland, forest, and per capita arable land area. Additionally, Inner Mongolia leads globally in rare earth metal reserves, with vast pastoral landscapes defining its character. Its capital, Hohhot, is endowed with rich natural beauty, encompassing forests, grasslands, wetlands, lakes, and rivers, forming China's most extensive and diverse ecosystem. Recognized as a premier tourist destination in China, Hohhot is the sole key development area for grassland tourism nationwide and a pioneering hub for tourism industry reform and innovation. Hulunbuir, within Inner Mongolia, holds a storied cultural heritage, serving as a historic cradle for hunting and nomadic cultures in northern China. It has been inhabited by various ethnic groups over the centuries, including the Xianbei, Khitan, and Jurchen.

The Hulun Buir Prairie, spanning 11.2667 million hectares, stands as China's most pristine grassland, earning the moniker "Kingdom of Pastures". Its peak tourist season, from June to September, particularly shines in July and August when lush pastures invite activities like horseback riding, inland fishing, or boating on the expansive Hulun Lake to the west. Xiangshawan, situated in Dalat Banner of Ordos, offers a distinctive desert landscape highlighted by the awe-inspiring Xiangsha spectacle. Here, one encounters sand lakes, oases, and Mongolian cultural traditions. Xiangshawan's hallmark is its curved sandy slope, rising nearly 100 m high with a 45-degree incline and spanning over 400 m in width. The Tengger Desert, China's fourth-largest desert, showcases a diverse terrain featuring dunes, salt marshes, grassy plains, and mountainous regions. Nestled within this expanse are ancient ecological marvels, including Moon Lake and Swan Lake, which have endured for millions of years, adding to the desert's allure.

3.2. Development status and intelligent trends in rural tourism

In Inner Mongolia, rural tourism has undergone extensive construction and standardized operation, primarily led by government participation models. By the end of 2019, the region had established 4584 rural tourism reception households, nine nationally recognized key rural tourism villages, and 78 demonstration sites for leisure agriculture and rural tourism, thereby steadily enhancing tourism service capacity. Inner Mongolia boasts abundant tourism resources, featuring over 350 A-level tourist attractions. Its tourism development predominantly revolves around resorts, ecological scenic spots, and religious landmarks. With a focus on sustainable cultural tourism resources deeply rooted in local heritage, Inner Mongolia emphasizes six key tourism elements: visitation, travel, accommodation, dining, shopping, and entertainment. Meticulously crafted rural resources are transformed into compelling tourism products, facilitating diverse forms of rural tourism, including cultural exploration, leisure and wellness, ecological sightseeing, and experiential living. This has established the foundation of the rural tourism model in Inner Mongolia, encompassing pastoral experiences, scenic drives, unique culinary offerings, and health-focused activities. Additionally, themed tours such as herdsman excursions showcasing local customs, city outskirts sightseeing and harvesting tours, and immersive experiences centered around rivers, forests, and farms, further contribute to cultivating a distinctive leisure and vacation brand characterized by regional uniqueness. Inner Mongolia also boasts 7570 km of the Great Wall across different periods, while the Yellow River traverses 743 km of its territory. The amalgamation of grassland and agricultural civilizations has given rise to renowned cultures like Hongshan, Dayao, and Hetao.

The advancement of smart rural tourism relies on the integration of cloud computing and big data technology. This combination enables the processing of smart tourism data, facilitating enhanced interaction between tourists and scenic spots while improving the overall tourism experience. By transmitting urban information encompassing politics, economy, culture, and consciousness to rural areas, tourists contribute to the adoption of modern customs and consciousness among rural residents, thereby elevating their quality of life. Smart rural tourism development aims to meet the modern information needs of tourists, enhance tourism convenience and operational efficiency, and achieve the intellectualization of tourism services, management, marketing, and experiences. This involves integrating online and offline tourism operations, which is facilitated by various subsystems within the smart rural tourism system.

These subsystems include the rural tourism smart management system, integrated flow analysis system for scenic spots, monitoring command center, electronic ticketing system, smart parking system, air and water environment monitoring system, smart tour guide system, and integrated marketing system. Through mutual integration and support, these subsystems collectively contribute to the establishment of a sustainable green rural tourism economy.

4. Methods

4.1. Development of characteristic rural tourism integrating Mongolian d decorative patterns

Mongolian patterns represent a crucial aspect of traditional national culture and constitute one of the most representative intangible cultural heritages within Mongolian culture. Evolved over thousands of years of cultural evolution, these patterns are crafted by Mongolians while on horseback, embodying a profound cultural heritage. Among the widely recognized Mongolian patterns are the fretwork pattern, swastika pattern, Panchang pattern, Fangsheng pattern, Ruyi pattern, cloud pattern, loong design, and scroll design, each rooted in geometric principles of “number” and “law”. These patterns, exemplified by the classic Mongolian pattern depicted in Fig. 1, transcend natural form, integrating subjective and objective aesthetic concepts to create captivating artistic images cherished by the masses. The stylized representations of loong design and scroll design strike a balance between figurative and abstract elements, displaying vivid yet elongated forms. In contrast, fretwork and swastika patterns exude a sense of neatness, dignity, and winding complexity. The Panchang pattern, characterized by its staggered and meandering appearance, conveys a sense of continuity. Rich in symbolism and connotation, these patterns articulate the Mongolian people’s aspirations for a better life and convey good wishes through analogies, homophones, and implicit meanings. The enduring legacy and evolution of Mongolian patterns are vividly reflected in the widespread availability of Mongolian tourism products. These products leverage Mongolian cultural themes in their decorative expressions, significantly enriching the cultural experiences of foreign tourists and expanding the influence of Mongolian decorative patterns.

The patterns depicted in Fig. 1 are characterized by prominent geometric designs, captivating forms, and profound connotations, expressing the Mongolian people’s aspirations for a better life and conveying good wishes through metaphors and symbolic meanings. Moreover, the widespread adoption and evolution of these patterns in popular Mongolian tourism products underscore their enduring cultural significance. By deepening the cultural impressions of foreign tourists and expanding the influence of Mongolian decorative patterns, these designs play a crucial role in promoting Mongolian characteristic culture on a global scale. Therefore, Fig. 1 serves as a representative showcase of Mongolian decorative patterns, showcasing the unique allure and rich cultural heritage of Mongolian culture. Mongolian decorative patterns constitute an integral aspect of Inner Mongolian culture, boasting deep historical roots and distinctive artistic significance. These patterns are not only evident in everyday items such as clothing, home furnishings, and handicrafts but also prominently featured in tourism souvenirs and cultural exhibitions. Typically characterized by intricate ethnic symbols like dragons, clouds, and lotus flowers, these designs embody concepts of auspiciousness, prosperity, and the beauty of nature. Beyond mere aesthetics, Mongolian decorative patterns serve as potent symbols of ethnic identity and cultural heritage within the local community. Consequently, efforts to preserve and advance these patterns enjoy widespread support from both local authorities and communities. Through educational initiatives, workshops, and cultural festivities, the craftsmanship associated with Mongolian decorative patterns is carefully nurtured and transmitted to future generations. Moreover, in the realm of tourism development, these patterns hold considerable allure. Tourists gain profound insights into Inner Mongolian culture by engaging with and acquiring these decorative items. Furthermore, integrating Mongolian decorative patterns into the design and offerings of tourism products not only enhances the tourism experience but also stimulates the market for local handicrafts, thereby catalyzing the growth of associated industries.

Fig. 1. Representative Mongolian decorative patterns.

4.2. CNN based on DL

CNN represents a DL algorithm tailored for image processing and visual recognition tasks. It emulates the workings of the human visual system to autonomously and efficiently extract features from images. At the heart of CNN lies the convolutional layer, comprising a sequence of trainable filters (convolution kernels) adept at capturing local image features such as edges, textures, and shapes. Notably, neurons within CNN are selectively linked to local input data regions, thereby curtailing network parameters and enhancing computational efficacy. The convolutional layer's filters share weights throughout the entire input image, ensuring consistent filter application across all image positions and fortifying the model's translational invariance. Additionally, pooling (subsampling) layers serve to condense feature map spatial dimensions, reducing computational complexity while retaining critical features. Nonlinear activation functions like Rectified Linear Unit (ReLU) introduce model nonlinearity, empowering it to discern increasingly intricate features. The disparity between CNNs and conventional neural networks lies in CNN's inclusion of a feature extractor comprising a convolutional layer and a subsampling layer. Within a CNN's convolutional layer, neurons connect exclusively to select adjacent neurons [31–33]. Typically, a convolutional layer encompasses multiple feature planes, with neurons organized in rectangular patterns, sharing weights (convolution kernels) within the same feature plane. The convolution kernel typically begins as a random decimal matrix during initialization, with its weights adjusted to reasonable values throughout the network's training process [34]. Weight sharing offers an immediate advantage by reducing connections between network layers, mitigating overfitting risks. Subsampling, also known as pooling, resembles a specialized convolution process, significantly simplifying the model's complexity and reducing parameters.

Equation (1) represents the convolution operation in CNN:

$$x_j^{\ell} = f\left(\sum_{i \in M_j} x_j^{\ell-1} \otimes W_{ij}^{\ell} + b_j^{\ell}\right) \tag{1}$$

In Equation (1), ℓ refers to the network level; M_j represents the set of characteristic graphs; x_j^{ℓ} signifies the input variables; b denotes the deviation value; W stands for the weights in the convolution kernel.

In the realm of image processing, Figs. 2 and 3 illustrate the fundamental functionality of convolution operations. The formation of the convolutional layer relies on applying the convolution kernel operation to the input layer, employing a sliding window approach. Typically, CNNs feature multiple convolution kernels, each representing a pattern within the image [35]. A high convolution value between an image block and a specific convolution kernel indicates a high similarity between them. Each neural node is linked to its corresponding region, with its weight associated with bias. The output of the convolutional layer is determined by a predefined function. Through the filtering operation of the convolutional kernel, the convolutional layer extracts local features from the image, akin to the feature extraction process of human vision. This method of feature extraction aligns with a crucial research direction in visual computing, which extensively addresses image generation and shape modeling, showcasing broad application prospects.

Fig. 2 illustrates the neuron operations during the convolution process, a crucial method in DL. By sliding a small convolution kernel over an image or other data, feature extraction and transformation of input data occur. Neurons multiply the data with the convolution kernel and add the results to output to the next layer of neurons, enabling the processing and analysis of input data. This visual representation in Fig. 2 aids in understanding convolutional operations in neural networks. Fig. 3 depicts an example of a 3x3 convolution operation on a 3x3 grayscale image. Blue and red denote the input image and the convolution kernel, respectively. The convolution operation slides the kernel across the input image, computing the result at each position, shown in yellow. Thus, the convolution operation effectively extracts features from the input image. In DL, the convolution operation serves as a vital feature extraction method, enabling the extraction of meaningful and representative features from images, videos, and other data. A typical CNN typically comprises three layers. Firstly, the convolutional layer computes multiple convolutions in parallel, generating a set of

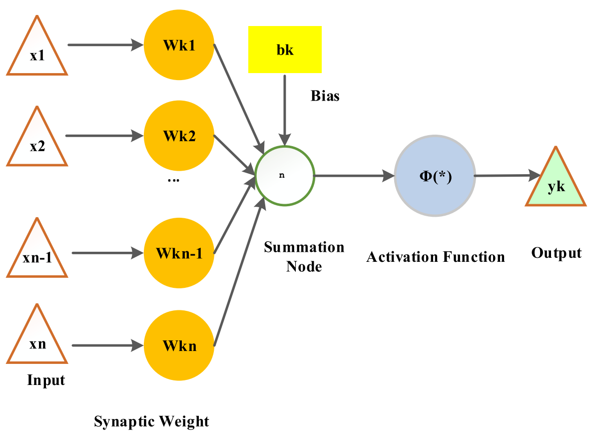

Fig. 2. Neuron operation in convolution processes.

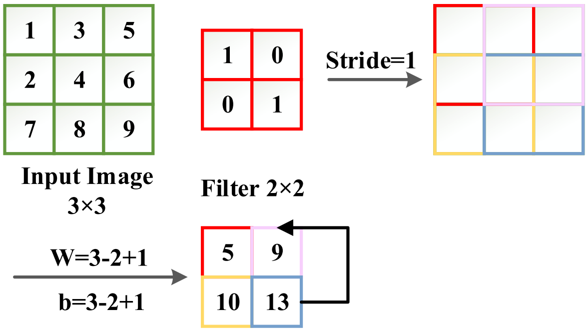

Fig. 3. Example of the convolution operation.

linear activation responses. Secondly, the activation function applies non-linear activation processing to each linear activation response. Thirdly, the pooling layer further adjusts the output of this layer. CNNs are constructed by stacking these layers through operations such as convolution, non-linear activation, and pooling. This stacking process extracts high-level semantic information layer by layer from the original data, known as the feedforward operation [36,37]. CNN formalizes the last layer as an objective function based on different target tasks, such as classification and regression. This is done by calculating the error or loss between the model's predicted value and the true label. The back-propagation algorithm then iteratively feeds back the error or loss layer by layer from the last layer. It computes the loss gradient to each layer's parameters and updates the corresponding parameters accordingly. After completing a round of parameter updates, the feedforward operation is performed again. This process of feedforward and feedback operations continues iteratively until the model converges, optimizing the model parameters. Fig. 4 illustrates the basic flow of CNN's feedforward and feedback operations.

Fig. 4 illustrates the fundamental flow of feedforward and feedback operations in CNN. Feedforward denotes the process from input data to output results, traversing multiple convolutional layers, pooling layers, and fully connected layers for feature extraction, mapping, and classification. Feedback the processprogresses from output results to input data. Employing the error backpropagation algorithm, network parameters adjust based on the disparity between output results and actual labels to facilitate model training and optimization. This schematic diagram in Fig. 4 succinctly depicts the CNN model's basic operational flow, aiding comprehension of its principles and applications. In Fig. 4, the convolutional layer directly interfaces with the pooling layer during the CNN's feedforward and feedback processes. The pooling layer transmits information to the activation layer, which achieves system objectives and functions through the fully connected layer. Specific operations required for system completion are implied. During the network's node output process, applying a logical function is necessary for binary classification, expressed as Equation (2).

$$Sigmoid(\mathrm{x}) = \frac{1}{1 + e^{-x}} \tag{2}$$

The derivative of the hyperbolic tangent function expressed as Equation (3):

$$Sigmoid'(\mathrm{x}) = \frac{e^{-x}}{(1 + e^{-x})^2} = Sigmoid(\mathrm{x})(1 - Sigmoid(\mathrm{x})) \tag{3}$$

However, in practical applications, the hyperbolic tangent function, as a non-linear function, performs better than the Sigmoid

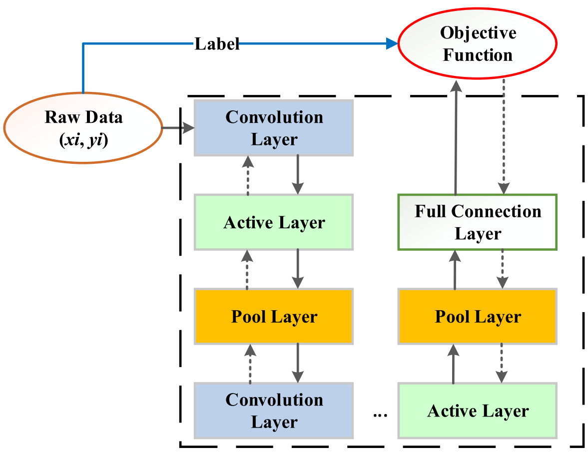

Fig. 4. Basic flow of feedforward and feedback operations in CNN.

function when dealing with significant differences in image features. The analytical equation of the hyperbolic tangent function is expressed as Equation (4):

$$TanH(\mathrm{x}) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{4}$$

In supervised learning, the objective is to minimize a loss function, typically represented as Equation (5):

$$w* = \underset{w}{\operatorname{argmin}} \sum_{i} L(y_i, \mathrm{f}(x_i; \mathrm{w})) + \lambda \Omega(\mathrm{w}) \tag{5}$$

In Equation (5), $L(y_i, \mathrm{f}(x_i; \mathrm{w}))$ evaluates the error between the predicted value $\mathrm{f}(x_i; \mathrm{w})$ of the model for the ith sample and the true label y_i.

In neural networks, cross-entropy is a commonly used loss function, expressed as Equations (6) and (7):

$$E(\mathrm{t}, \mathrm{y}) = -\sum_{j} t_j \log y_i \tag{6}$$

$$y_i = \frac{e^{zj}}{\sum_j e^{zj}} \tag{7}$$

Here, y_i means the *softmax* loss function; t and y refer to the target label and output of the neural network, respectively.

Weighted cross-entropy assigns weights to different categories, enabling the network to prioritize smaller sample sizes. Its expression is illustrated in Equation (8) and Equation (9):

$$loss = (1 - \mathrm{t}) \times \mathrm{y} + \mathrm{l} \times (\log(1 + \exp(-\mathrm{abs}(\mathrm{y})))) + \max(-\mathrm{y}, 0) \tag{8}$$

$$l = 1 + \left(\mathrm{pos\_weight} - 1\right) \times \mathrm{t} \tag{9}$$

Typically, the network outputs a predicted value when solving a regression problem. For image processing, the mean square error (MSE) represents the pixel-level error between the output image and the ideal image. Its function expression is shown in Equation (10):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - t_i)^2 \tag{10}$$

In Equation (10), y and t represent the predicted value and the target value, respectively.

In this study, CNN is employed to automatically extract features from Inner Mongolian decorative patterns. By training the CNN model, various patterns can be identified and classified, offering significant contributions to cultural heritage preservation and tourism promotion. CNN excels at extracting valuable features from images, enhancing processing efficiency and accuracy through end-to-end training, without the requirement for manual feature engineering.

4.3. Identification and feature extraction of Mongolian decorative patterns

In the domain of national culture, ethnic patterns represent invaluable heritage in cultural preservation, embodying unique artistic aesthetics [38,39]. However, these patterns often exhibit complex and diverse features, including texture, color, and shape, making them challenging to capture using traditional manual methods. To address this challenge, DL technology is introduced for automated feature extraction. DL leverages convolution operations to accurately capture underlying features such as edges and textures. Additionally, pooling facilitates the extraction of higher-level abstract features, such as shape and structure. This hierarchical feature extraction method enables a more comprehensive and accurate understanding and description of complex ethnic patterns. Furthermore, DL's end-to-end learning approach enables the system to automatically learn the most suitable feature representation for a specific task, eliminating the need for laborious manual feature engineering and thereby enhancing processing efficiency.

This study extends beyond pattern recognition and classification to delve into the profound application of patterns in visual art and cultural heritage. The DL-based pattern feature extraction method introduced herein presents a novel approach for researchers in image processing and a practical tool for professionals in culture and art. The insights gained from this study contribute valuable experience to the exploration of new paradigms in image analysis and pattern recognition, offering meaningful guidance for future research endeavors in this domain.

In this study, three prominent DL networks—AlexNet, VGGNet, and Residual Network (ResNet)—are examined for feature extraction from Inner Mongolian decorative patterns. AlexNet, an early DL network, demonstrates proficient performance in pattern recognition tasks, with rapid convergence and lower computational demands, making it suitable for initial image classification. However, due to the shallow structure of the network, AlexNet may overlook finer details in complex patterns, potentially leading to accuracy issues. VGGNet significantly improves the model's ability to capture details by using multiple small 3x3 convolution kernels instead of a large convolution kernel. In Mongolian decorative pattern recognition, VGGNet is capable of identifying more detailed features, thereby enhancing recognition accuracy. However, VGGNet incurs higher computational costs and requires more training time and computational resources. ResNet, by introducing residual connections, facilitates the training of deeper network structures and mitigates the problem of gradient vanishing in deep networks. Notably, ResNet exhibits remarkable performance in recognizing complex and diverse Mongolian decorative patterns. However, ResNet has a large number of model parameters, necessitating extensive data and computational resources for training. This study assesses the strengths and limitations of these three networks in feature extraction by comparing their performances on the Inner Mongolia Decorative Patterns dataset. Three DL networks, namely AlexNet [40], VGGNet [41], and ResNet [42], are utilized to extract features from the ethnic pattern dataset. The training and test sets consist of 1000 and 200 images, respectively. AlexNet, originally applied to ImageNet, has substantially enhanced accuracy compared to traditional methods. It employs the ReLU activation function in five convolutional layers followed by three fully connected layers, as expressed in Equation (11).

$$f(\mathrm{x}) = \max(0, \mathrm{x}) \tag{11}$$

AlexNet mitigates model overfitting by incorporating a Dropout layer after each fully connected layer. This layer randomly deactivates neuron activations in the current layer with a specified probability, as illustrated in Fig. 5(a)(b). Dropout proves effective in reducing overfitting by decreasing inter-neuron dependencies, thereby facilitating the extraction of independent and significant features.

Fig. 5 illustrates the schematic impact of the Dropout layer. In Fig. 5 (a), all neurons are activated and participate in feature learning. Fig. 5 (b) reduces the interdependence between neurons by randomly deactivating a portion of them, which helps to extract independent and important features and effectively reduces overfitting of the model. Dropout layer serves as a regularization technique, reducing model overfitting by randomly deactivating some neurons. VGGNet improves upon AlexNet by employing consecutive 3 × 3 convolution kernels instead of larger ones (11 × 11, 5 × 5). Stacked smaller convolution kernels are preferred for a given receptive field. This approach allows for increased network depth with multiple non-linear layers, enabling the learning of more complex patterns at a lower computational cost. In the VGG16 architecture, three consecutive convolutional layers perform Relu activation function-based non-linear corrections, significantly enhancing model accuracy.

As the network depth increases, so does its accuracy; however, the risk of overfitting also rises. Deeper networks face the challenge of vanishing gradients, where earlier layers stagnate in learning due to small gradients. Moreover, deeper networks entail a larger parameter space, exacerbating optimization difficulties and increasing training errors. ResNet addresses these issues with residual modules, enabling the training of exceptionally deep networks. Despite achieving impressive depth, such as the 152-layer ResNet, computational demands are higher than those of VGGNet. ResNetemploys shortcut connections to alleviate the vanishing gradient problem. Fig. 6 illustrates the concept of these connections.

Fig. 6 illustrates the shortcut connection diagram in ResNet. Shortcut connection involves directly skipping one or more input layers and connecting them with subsequent layers, alleviating the vanishing gradient problem in deep neural networks and enhancing model depth and accuracy. In ResNet, this design facilitates deeper networks that are easier to train, leading to improved performance and generalization. Alongside DL feature extraction, traditional methods can complement extracted features. Edge detection using the Canny operator and texture feature extraction using LBP are chosen to optimize ResNet. The initial step of the Canny edge detection algorithm involves noise reduction through Gaussian filtering. For a pixel at position (m, n), with gray value $\mathrm{f}(\mathrm{m}, \mathrm{n})$. Equation (12) reveals the gray value after Gaussian filtering:

$$(\mathrm{m}, \mathrm{n}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{m^2+n^2}{2\sigma^2}} \cdot f(\mathrm{m}, \mathrm{n}) \tag{12}$$

The second step involves computing the gradient value and direction. The gradient values $g_x(\mathrm{m}, \mathrm{n})$ and $g_y(\mathrm{m}, \mathrm{n})$ are obtained in various directions by applying a Sobel operator. Equations (13) and (14) determine the integrated gradient value and direction.

$$\mathrm{G}(\mathrm{m}, \mathrm{n}) = \sqrt{g_x(\mathrm{m}, \mathrm{n})^2 + g_y(\mathrm{m}, \mathrm{n})^2} \tag{13}$$

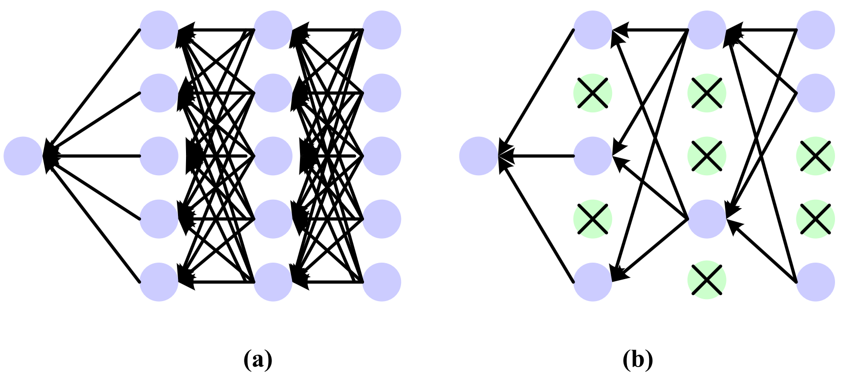

Fig. 5. Schematic representation of the Dropout layer's function (a. Full Connection; b. Dropout).

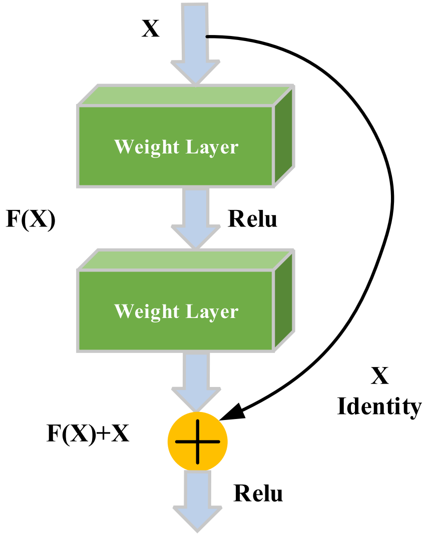

Fig. 6. Shortcut connection in ResNet.

$$\theta = \arctan\frac{g_y(\mathrm{m,n})}{g_x(\mathrm{m,n})} \tag{14}$$

The third step involves filtering non-maximum values. If a pixel is part of an edge, its gradient value in the gradient direction is maximal. Otherwise, if it is not an edge, its gray value is set to 0, expressed as Equation (15).

$$M_T(\mathrm{m,n}) = \begin{cases} M(\mathrm{m,n}), & \mathrm{if} M(\mathrm{m,n}) > \mathrm{T} \\ 0, & otherwise \end{cases} \tag{15}$$

The last step involves edge detection using upper and lower thresholds. Two thresholds, max *Val* and min *Val* are set. Pixels with values above max *Val* are identified as edges, while those below min *Val* are classified as non-edges. For pixels in between, if they are adjacent to an edge pixel, they are considered edges; otherwise, they are labeled as non-edges.

The information derived from LBP is robust to changes in grayscale and position within the image, enhancing stability. Combining texture features from LBP with those from ResNet further enhances image classification accuracy. Equations (16) and (17) calculate LBP:

$$\mathrm{LBP}(x_c, y_c) = \sum_{p=1}^{8} s(\mathrm{I(p)} - \mathrm{I(c)}) * 2^p \tag{16}$$

$$s(\mathrm{x}) = \begin{cases} 1, & ifx > 0 \\ 0, & otherwise \end{cases} \tag{17}$$

In Equations (16) and (17), p represents the $\mathrm{p}-\mathrm{th}$ pixel point in the 3×3 window excluding the center pixel point; $I(\mathrm{c})$ denotes the gray value of the center pixel point, and $\mathrm{I(p)}$ indicates the gray value of the p-th pixel point in the field.

After feature extraction from the training and test sets, the Euclidean distance function is employed to gauge the similarity between the test image and the training image. Its expression is as Equation (18):

$$d = \sqrt[2]{(a-b)^T(a-b)} \tag{18}$$

In Equation (18), a and b are two n-dimensional vectors.

Three feature extraction methods based on AlexNet, VGGNet, and ResNet are utilized to evaluate the effectiveness of the proposed optimization algorithm (ResNet + Canny + LBP). A sizable dataset of Mongolian decorative patterns is assembled for training the neural networks. The experimental setup comprises the Windows 7 operating system, Matlab R2016a, and an Intel i7 processor. The accuracy rate serves as the evaluation metric, expressed as Equation (19):

$$Accuracy = \frac{num_{right}}{sum_{test}} \times 100\% \tag{19}$$

In Equation (19), num_{right} represents the number of correctly classified test samples, while sum_{test} denotes the total number of test samples.

4.4. Application of Internet of Things (IoT) and intelligent development of rural tourism

In the application of intelligent rural tourism development, an IoT-based system has been designed, incorporating RFID technology, data storage and processing units, and a user-friendly frontend interface. This system facilitates real-time monitoring of key locations in the tourist area, such as entrances, outer lanes, and exits, and gathers information on tourists' positions, times, and trajectories. In the computer IoT system, the tourism navigation network serves as an event capture network for tourists, with monitoring nodes strategically placed at key locations such as scenic spot entrances, outer lanes, and exits. Users carry electronic labels as needed for the scene. The Radio Frequency Identification (RFID) reader and writer emit pulse waves to the electronic label via the frequency converter. When the label enters the antenna range of the reader and writer, the system is triggered, transmitting an RFID-encoded high-frequency pulse through the card's transmitter module. The receiver detects the high-frequency pulse radio waves, and the electronic identifier queries sensitive information, which is then relayed to the main device via the field bus. The control unit conveys position, time, track, and other data in real-time, with users accessing the database server through industrial Ethernet. The electronic ticket management and tourism development system based on IoT primarily consists of hardware and software. The hardware system includes user management, a communication module, and a user interface, facilitating the collection of rural tourism signals, ensuring fast and accurate communication within the network, and enabling automatic detection and entry management. The software system comprises front-end and back-end office programs and data collection programs for information collection, ticket identification, and data processing. Combining RFID and data storage technology optimizes the intelligent program of rural tourism within the computer IoT system. Moreover, the "Mongolian model" represents an integration of national characteristics with tourism development, achieved through visual design, the extraction, and aesthetic analysis of unique Mongolian decorative patterns. This approach effectively communicates cultural information, enhances the quality of tourism products and experiences, and boosts the competitiveness of local tourism in the market. The fuzziness of visual design, stemming from the complexity and diversity of decorative patterns, necessitates identification, classification, and aesthetic feature extraction through fuzzy mathematical methods to conduct decision analysis and evaluation effectively. In the implementation process, ResNet + Canny + LBP, a novel feature extraction algorithm, combined with fuzzy decision systems, efficiently evaluates and makes decisions about tourism resources. This research method, based on visual design and fuzzy algorithms, can be applied to the development of Mongolian cultural tourism and offer new ideas and approaches for developing tourism products and services in other regions.

4.5. Data collection and experimental preparation

In this study, a strict process of experimental design and execution is followed. Initially, the Curet Material Image dataset, containing about 10,000 images, is utilized. Each image category undergoes careful screening and manual labeling to ensure the quality and diversity of the training data. The dataset encompasses 10 image categories related to rural tourism in Inner Mongolia, with each category undergoing rigorous hand-screening and annotation. During the statistical analysis of the experimental data, the repeatability and stability of the dataset are analyzed. The dataset is divided into training and validation sets to adjust and optimize the model during training. In the experiment, particular emphasis is placed on evaluating the model's performance using metrics such as accuracy, recall, and F1 scores to assess its effectiveness in image recognition tasks. These metrics reflect the model's accuracy, stability, and robustness, ensuring the versatility of the proposed algorithm across various scenarios and datasets. Regarding system design, the Windows operating system serves as the foundational platform for intelligent development systems. Apache is employed as a Web server to ensure a stable service environment, while Oracle is chosen as the database to ensure both data security and efficiency. Additionally, PHP is utilized as the website development language to ensure the scalability and user-friendliness of the system. During the experiment, the hierarchical and scale parameters of the DL model are meticulously designed to optimize the algorithm's performance in image recognition tasks. The selection of these parameters is thoroughly analyzed and validated through experiments. Detailed information regarding the level and scale parameters of the model is presented in Table 1.

Table 1 illustrates the hierarchy and scale parameter values of the network model. It indicates that a 3x3 convolution kernel is employed, with a total of 10,000 training iterations. The learning rate is set to 0.001, the batch size is 50, and 80 training epochs are executed. These parameters are meticulously selected based on thorough analysis of the dataset's characteristics and experimental requirements. After numerous experiments and adjustments, it is ensured that these parameters facilitate rapid convergence of the designed model during training without overfitting. Their judicious selection enables the model to achieve outstanding performance in recognizing and classifying rural tourism images, demonstrating excellent generalization capability. The optimal parameter selection enhances the reliability of the experimental results and offers valuable insights for future research endeavors. This systematic experimental design and parameter selection contribute to the credibility and practicality of the study's findings.

Table 1
Hierarchy and scale parameter values of the network model.

Convolution Kernel	Iterations	Learning Rate	Batch Size	Epochs
3*3	10000	0.001	50	80

5. Results and discussion

5.1. Extraction results of Mongolian pattern texture features

The LBP algorithm effectively extracts pattern texture features and local texture information in this experiment. Fig. 7(a)(b) depicts a sample of the extracted pattern features, showcasing the regularity and repetition characteristics of texture in Mongolian decorative patterns. Fig. 7 (a) shows the original image, while Fig. 7 (b) shows the feature-extracted image, where the regularity and repeatability of texture features are significantly enhanced, providing a unique basis for image classification. This texture serves as a basis for image classification due to its distinctiveness. Compared to the original image, the LBP-processed image enhances the clarity of each typical area's texture while diminishing the features of smooth areas with little research value, thereby reducing feature dimensionality. Fig. 8 (a)(b) illustrates the edge features of Mongolian patterns extracted using the Canny operator. Fig. 8 (a) and 8 (b) respectively show the edge features of two different Mongolian patterns, where the edge points are highlighted in white and the other points are represented in black. By setting dual thresholds, edge images that are very close to the actual pattern edges can be obtained. Edge features from different patterns are extracted separately, with an extraction accuracy value of 0.001.

5.2. Analysis of the test results of the optimized DL algorithm

Fig. 9 indicates the performance comparison results of various feature extraction algorithms. It reveals that the accuracy of pattern feature extraction using AlexNet, VGGNet, and ResNet is 90.8 %, 94.5 %, and 96.9 %, respectively. In contrast, the accuracy achieved by the proposed fusion algorithm reaches 98.8 %. This suggests that by combining features extracted by DL with those from traditional methods using weighted fusion, the final pattern recognition accuracy surpasses that of any individual DL algorithm. The divergence in feature extraction perspectives among different algorithms allows their fusion to complement each other effectively, enhancing the overall classification accuracy. Regarding the algorithm's time overhead (TOH), the proposed fusion algorithm exhibits the lowest TOH of 0.667s, whereas ResNet incurs the highest time cost of 2.042s. TOH is directly correlated with feature length. The proposed algorithm addresses this by conducting PCA dimensionality reduction after fusing features from each method, thus notably reducing the TOH of pattern recognition.

The study demonstrates the superior performance of a fusion strategy involving multiple feature extraction algorithms in Mongolian decorative pattern recognition. Compared to traditional DL algorithms, the proposed fusion algorithm excels in both accuracy and TOH. Firstly, the LBP algorithm adeptly captures precise texture features from Mongolian decorative patterns, particularly effective with regular and repetitive designs. Its sensitivity to texture information enables the extraction of unique features crucial for pattern recognition. Secondly, the Canny operator extracts edge features, offering valuable insights into pattern outlines and shapes. The Canny operator effectively identifies the edge structure within the pattern, aiding in the accurate capture of its morphological features and enhancing recognition accuracy. Crucially, a fusion strategy combining DL algorithms (e.g., AlexNet, VGGNet, and ResNet) with traditional methods is employed. This fusion maximizes the strengths of different algorithms, leveraging features extracted from various perspectives to comprehensively understand Mongolian decorative patterns and enhance recognition accuracy. This comprehensive feature extraction approach renders the proposed algorithm adaptable to diverse types and styles of Mongolian decorative patterns, exhibiting strong versatility and robustness.

Additionally, the proposed algorithm exhibits notable advantages in processing speed. By integrating features ingeniously and employing PCA dimensionality reduction, the time required for pattern recognition is significantly reduced. This aspect holds crucial importance for swift responses in practical scenarios, particularly in large-scale pattern database searches and matches. In conclusion, this study presents an efficient, accurate, and rapid method for identifying Mongolian decorative patterns, which holds significance not only in academic research but also provides substantial support for practical applications such as cultural heritage preservation and tourism promotion. The proposed algorithm introduces a fresh approach to integrating DL with traditional image processing methods, offering valuable insights for future research on similar challenges.

Fig. 7. Results of ethnic pattern feature extraction by LBP algorithm(a. Original Image; b. Feature Extraction Image).

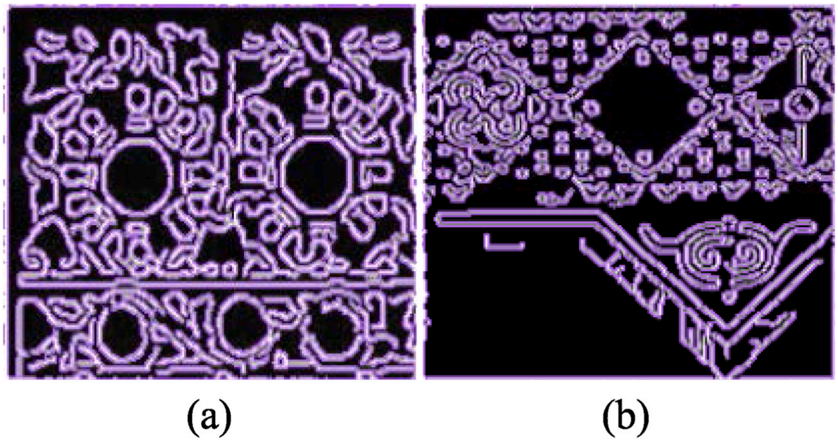

Fig. 8. Mongolian pattern edge features extracted by Canny operator(a. Edge Feature Pattern 1(The accuracy is 0.001); b. Edge Feature Pattern 2 (The accuracy is 0.001)).

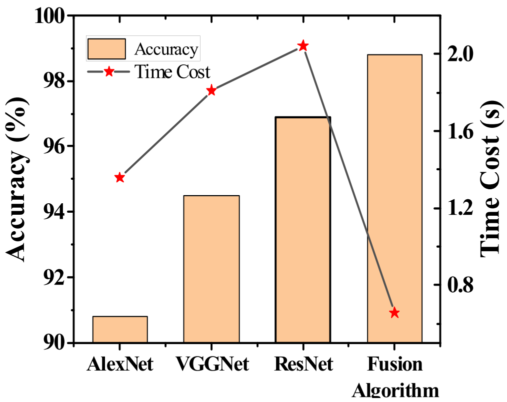

Fig. 9. Performance comparison results of different feature extraction algorithms.

5.3. *Case study*

To validate the effectiveness of the proposed DL algorithm and IoT technology in practical tourism resource assessment and decision-making, the following case study is conducted:

A renowned tourist attraction in Inner Mongolia, celebrated for its rich Mongolian culture and decorative patterns, is selected. By deploying IoT devices and employing DL algorithms, real-time monitoring and analysis of tourist flow, behavior, and decorative pattern popularity are conducted. The statistical results of this well-known tourist attraction in Inner Mongolia are presented in Table 2. These results demonstrate that the DL algorithm accurately identifies and classifies decorative patterns that are of significant interest to tourists, while IoT technology offers real-time data support, aiding managers in optimizing tourism routes and product displays.

In the field survey, local tourism practitioners and tourists are interviewed to gather their views and demands regarding Mongolian decorative patterns. The survey results are presented in Table 3.

In the field survey, local tourism practitioners and tourists were interviewed to gather their views and demands regarding Mongolian decorative patterns. The survey results highlight tourists' strong interest in decorative patterns reflecting Inner Mongolia's

Table 2
Statistical results of a well-known tourist attraction in Inner Mongolia.

Serial No.	Decorative Pattern	Tourist Attention (%)	DL Algorithm Recognition Accuracy (%)
1	Mongolian Classic Patterns	85	92
2	Mongolian Grassland Style	78	89
3	Mongolian Ethnic Dance	65	73
4	Mongolian Traditional Instruments	70	78
5	Mongolian Featured Architecture	80	87

Table 3
Survey results on mongolian decorative patterns.

Survey Question	Tourist Response Frequency (%)	Tourism Practitioner Response Frequency (%)
Are you interested in Mongolian decorative patterns?	95	80
Do you believe Mongolian decorative patterns can enhance the tourism experience?	90	85
Do you wish to see more Mongolian decorative elements in tourism products?	85	75
Do you wish to see tourism products utilizing modern technology to showcase Mongolian decorative patterns?	95	90
What role do you think the introduction of DL algorithms and IoT technology plays in enhancing the attractiveness of tourism products?	90	95
Do you believe DL algorithms and IoT technology can provide effective decision support for tourism practitioners?	85	90

characteristics, while tourism practitioners seek to enhance tourism products' attractiveness through more effective technological means. The introduction of DL algorithms and IoT technology can better cater to tourists' needs and provide decision support for tourism practitioners, thereby fostering the sustainable development of the tourism industry.

5.4. Application cases and comparative analysis of DL in other tourism fields

DL, a potent machine learning approach, has exhibited its distinct efficacy across various domains within the tourism industry. Here are some application cases of DL in urban tourism, coastal tourism, and cultural heritage tourism, along with a comparative analysis with the methods applied in this study. DL contributes to intelligent transportation systems, optimizing urban tourism route planning and traffic management by analyzing traffic flow and pedestrian behavior. For instance, DL models predict traffic congestion to offer optimal travel recommendations for tourists. In coastal tourism, DL technology aids in water quality monitoring and beach safety assessment. Through the analysis of water quality images and environmental data, DL models can timely predict and warn of potential pollution events to ensure tourist safety. In cultural heritage conservation and digital exhibition, DL plays a pivotal role. Utilizing image recognition and 3D reconstruction techniques, DL facilitates precise digital recording and virtual restoration of cultural heritage, providing tourists with immersive cultural experiences. The application cases and comparative analysis results of different DL methods in other tourism fields are presented in Table 4.

From Tables 4 and it is evident that DL has achieved significant effectiveness across various tourism fields. In urban tourism, DL models accurately predict traffic congestion, offering effective travel recommendations and enhancing the urban tourism experience. In coastal tourism, DL image analysis technology excels in water quality monitoring and safety assessment, ensuring tourist safety with high accuracy. In cultural heritage tourism, the application of DL 3D reconstruction technology enables more accurate digital recording and virtual restoration of cultural heritage, enriching tourists' cultural experiences. In comparison, the application of DL technology in ethnic tourism, particularly in Mongolian decorative pattern recognition, attains a high accuracy rate of 98.8 %. This result underscores the substantial application value of DL in ethnic tourism, effectively enhancing the accuracy of tourism resource assessment and decision-making while improving the quality and efficiency of tourism experiences. In conclusion, DL technology demonstrates its potent application potential and value across various sectors of the tourism industry, not only enhancing tourism experiences but also providing technical support for the industry's sustainable development.

6. Conclusion

(i) Research summary and key findings

This study explores the intelligent development of ethnic tourism in subtropical grassland areas, presenting an innovative approach for tourism resource assessment and decision-making through the integration of DL algorithms and IoT technology. The key findings are as follows: Integration of DL algorithms with traditional image processing techniques significantly improved the recognition accuracy of Mongolian decorative patterns to 98.8 %. The implementation of fuzzy decision-making systems effectively addressed

Table 4
Application cases and comparative analysis of different DL in other tourism fields.

Application Field	Application Case	Technical Method	Performance Metric	Result
Urban Tourism	Traffic Flow Analysis	CNN	Traffic Congestion Prediction Accuracy	85 %–90 %
Coastal Tourism	Water Quality Monitoring	DL Image Analysis	Pollution Event Prediction Accuracy	92 %–95 %
Cultural Heritage Tourism	Digitization Recording	DL 3D Reconstruction	Digital Accuracy	0.01 mm–0.05 mm Error
Ethnic Tourism (This Study)	Mongolian Decorative Pattern Recognition	ResNet + Canny + LBP	Pattern Recognition Accuracy	98.8 %

uncertainty issues in tourism resource management and planning. Visualization design emerged as a pivotal factor in promoting ethnic tourism and brand building. These findings not only pave new technological pathways for the intelligent advancement of ethnic tourism but also offer invaluable experiences and insights for related research domains.

(ii) Theoretical contribution

At the theoretical level, this study extends the application scope of DL in the tourism domain, particularly in ethnic tourism and cultural heritage conservation. By constructing a novel model that integrates traditional methods with modern technology, this research enriches the theoretical framework of tourism resource assessment and decision-making, offering a fresh perspective on addressing fuzziness and uncertainty issues in tourism data. Additionally, the study underscores the theoretical significance of visualization design in cultural dissemination and brand building, providing a foundational basis and reference for future research endeavors.

(iii) Practical contribution

From a practical perspective, the intelligent tourism resource assessment and decision-making method proposed in this study offer effective technical support for tourism management and services. Through real-time monitoring and data analysis, tourism managers can allocate and plan resources more accurately, thereby enhancing tourism efficiency and visitor experience. Additionally, the study presents fresh ideas for the development and promotion of ethnic tourism products, contributing to the enhancement of tourist destinations' attractiveness and competitiveness.

(iv) Research Limitations

While this study has achieved certain accomplishments, it also has several limitations. Firstly, the study primarily focuses on the recognition of Mongolian decorative patterns, necessitating further investigation into the recognition and preservation of other types of cultural heritage. Secondly, the study's application scenarios are limited to the Inner Mongolia region, and the applicability of tourism resource assessment and decision-making for other regions and types requires further validation. Additionally, with the rapid development of DL technology, there may be a need for further optimization and adjustment of models to accommodate new technological advancements and application demands in the future.

(v) Future research

Future research can expand in the following directions: Firstly, by broadening the scope of research to explore the application of DL in other cultural heritage and tourism resource assessments. Secondly, by developing and optimizing customized models for different regions and cultural backgrounds. Thirdly, by enhancing the performance and application effectiveness of models through the integration of the latest research achievements in DL. Fourthly, by exploring the integration of DL with other emerging technologies (such as big data, cloud computing, etc.) to promote the comprehensive intelligence and digital transformation of the tourism industry. Through these studies, more comprehensive and in-depth theoretical support and practical guidance can be provided for the sustainable development of the tourism industry.

Compliance with ethical standards

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Conflict of interest

Authors declare that they have no conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author, upon reasonable request.

CRediT authorship contribution statement

Hong Yu: Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Hong Yu reports financial support was provided by Department of Higher Education, Ministry of Education.

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