Automatic Generation System of Regional Cultural Symbols Based on Deep Learning

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Abstract. This paper presents a comprehensive study on the design and development of an automatic generation system for regional cultural symbols utilizing deep learning techniques. With the rapid advancements in artificial intelligence and particularly in deep learning, there is a growing need to digitize and automate the creation of cultural symbols that reflect the unique identity of various regions. The proposed system aims to streamline the process of symbol generation, ensuring that these symbols not only embody the essence of local cultures but also cater to the demands of modern digital platforms. Through extensive data collection, analysis, and model training, our system demonstrates the potential to generate visually appealing and culturally relevant symbols that can be widely adopted in various applications, including tourism promotion, urban planning, and digital communication.

Keywords: Deep learning, regional cultural symbols, automatic generation, data analysis, symbol design

1 Introduction

Cultural symbols embody a region's identity, encapsulating history, traditions, and societal values. In the digital age, their demand for online communication, advertising, and tourism has surged. Traditional manual creation methods are time-consuming, labor-intensive, and subjective, leading to inconsistencies. This research explores deep learning for automatic generation of regional cultural symbols. Our system uses deep neural networks to analyze cultural data, identifying region-specific patterns. These patterns are then used to generate visually appealing and culturally authentic symbols. The paper covers system design, data collection, processing, model training, and evaluation. Challenges faced and strategies to overcome them are discussed. Evaluation results show the feasibility and effectiveness of deep learning for cultural symbol generation, revolutionizing their creation and use in the digital age. This research contributes to cultural preservation and promotion, offering an efficient, cost-effective

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method to generate culturally rich symbols, fostering a sense of belonging and attracting visitors worldwide.

2 Literature Review

Previous studies emphasize the importance of cultural authenticity and relevance in symbol design, impacting societal perceptions[1]. Cultural context shapes symbol meaning and effectiveness[2], fostering regional identity[3]. Advances in computer graphics and AI explore algorithm use in generating visually appealing designs[4], with machine learning automating creative processes[5]. However, the intersection of visual communication and AI, particularly deep learning in generating regional cultural symbols, is understudied[6]. Deep learning, especially GANs, has shown progress in tasks like image recognition and generative modeling[7]. GANs' adversarial training enables realistic image generation, demonstrated in image-to-image translation[8]. This research adapts GANs for generating regional cultural symbols, capturing cultural nuances and creating visually compelling designs[9]. By bridging visual communication and AI, the study contributes a novel, efficient approach to cultural symbol design[10].

3 System Design

The proposed automatic generation system for regional cultural symbols is a sophisticated framework that integrates multiple advanced components to ensure high-quality and culturally accurate outputs. This section delves deeper into each component, providing a more detailed and data-driven approach.

3.1 Data Collection

Table 1. Comprehensive Multi-Strategy Approach for Data Collection

Data Collection Strategy	Description	Key Actions	Target Output
Expert Curation	Collaborate with cultural experts, historians, and art curators to identify key regional symbols.	Hold workshops and consultations to pinpoint symbols embodying distinct history, traditions, and artistic styles, and gather high-quality symbols.	At least 500 symbols per region
Crowdsourcing	Utilize online platforms to launch a crowdsourcing campaign for symbols.	Initiate a campaign on cultural heritage sites and social media, urging locals, enthusiasts, and amateur historians to submit contributions, and establish a verification system involving moderators and experts.	Verified and authentic symbols with metadata
Public Domain Resources	Leverage open-access repositories and databases for cultural artifacts and symbols.	Use advanced filtering and criteria to select symbols with distinct regional and cultural features, and integrate them into the current datasets.	At least 10,000 symbols

Data collection for regional cultural symbols involves multi-strategy approaches: expert curation with cultural experts to identify key symbols, crowdsourcing from online platforms to gather diverse contributions, and leveraging public domain resources for additional symbols. Aiming for a broad and representative sample, the study targets at least 500 symbols per region from experts, with crowdsourced and public domain contributions aiming to reach 10,000 symbols in total. See Table 1.

3.2 Data Processing

The collected dataset undergoes a meticulous preprocessing stage to prepare it for model training.

3.2.1 Cleaning and Normalization.

Data processing involves cleaning the dataset to remove duplicates, irrelevant images, and low-quality symbols, ensuring data integrity. Normalization standardizes image sizes and resolutions to 256x256 pixels, crucial for model accuracy. Image enhancement techniques, such as contrast adjustment, noise reduction, and color correction, further improve visual quality. This meticulous preprocessing transforms the dataset into a high-quality, standardized format optimal for model training, setting the foundation for successful model development and accurate symbol recognition.

3.2.2 Annotation.

Annotating the dataset is crucial, involving assigning detailed labels and metadata to each symbol, capturing cultural significance, style, and historical context. Cultural experts annotate the dataset to ensure accuracy and consistency. A quality control process, involving a second round of review by experts, verifies the accuracy of annotations, identifying and correcting errors. This meticulous annotation process provides valuable context for model training, ensuring the dataset is of the highest quality, ultimately improving model performance and symbol recognition accuracy.

3.2.3 Feature Extraction.

Feature extraction using convolutional neural networks (CNNs) captures salient visual and cultural features of cultural symbols, including color, shape, texture, and stylistic elements. These features are used to develop a feature embedding space that captures the essence of regional cultural symbols, enabling accurate recognition and generation. By integrating visual and cultural information, the model produces outputs that are visually appealing and culturally meaningful. This process is crucial for ensuring that generated symbols are accurate, authentic, and culturally appropriate, ultimately improving performance and accuracy in cultural symbol recognition and generation tasks.

3.3 Model Training

The deep learning model is the core of the system, responsible for generating new regional cultural symbols. We adopt a state-of-the-art GAN-based architecture, specifically a Conditional GAN (cGAN) (Mirza & Osindero, 2014), with enhancements for improved performance:

3.3.1 Model Architecture.
The model architecture for our deep learning system includes a generator network, built with convolutional layers and skip connections to create detailed, culturally accurate symbols, and a discriminator network, with a deep architecture and regularization techniques to ensure authenticity and prevent overfitting. The generator captures intricate details, while the discriminator distinguishes real from generated symbols. Together, these components form a robust model capable of producing diverse and accurate regional cultural symbols.

3.3.2 Training Process.
The training process of our cGAN-based model optimizes performance through supervised and unsupervised learning, curriculum learning, large batch size, and high learning rate. We start with simpler tasks and gradually increase complexity to build model robustness. A batch size of 128 and a learning rate of 0.001 accelerate convergence and training efficiency. This strategic training approach ensures the model develops strong adaptability and resilience, enabling it to perform well on unseen data, while maintaining high performance and convergence speed.

3.3.3 Evaluation and Tuning.
The evaluation and tuning phase uses FID and human perceptual studies to assess the model's performance in generating visually realistic and culturally accurate symbols. Based on evaluation results, we fine-tune model parameters and architecture to optimize performance. This includes adjusting hyperparameters and modifying the model architecture to improve fine-grained detail capture and diversity. Iterative evaluation and tuning ensure a balance between visual quality, cultural accuracy, and symbol diversity, resulting in high-quality symbols that are visually appealing and culturally relevant, meeting the needs of various applications and users.

3.4 Symbol Generation

Once the model is trained and fine-tuned, it can be used to generate new regional cultural symbols on demand.

3.4.1 User Interface.
A user-friendly interface enables users to interact with our cGAN-based model to generate regional cultural symbols. It allows specifying regional attributes, provides

real-time feedback and visualization of generated symbols, and is designed to be accessible even for non-technical users. Clear instructions and guidance ensure easy navigation, enabling users to generate high-quality, culturally specific symbols according to their preferences with ease and precision. This interface enhances the usability and effectiveness of our model, making it accessible to a wide range of users.

3.4.2 Application and Integration.

Integrating our symbol generation system into tourism, urban planning, digital communication, and education applications maximizes its impact. We collaborate with stakeholders to tailor symbols to their specific needs, ensuring relevance and accuracy. In tourism, we create symbols for promotional materials, reflecting cultural and regional characteristics. For urban planning, we generate symbols for visualizations, aiding understanding and communication of plans. In digital platforms and education, our symbols enhance cultural relevance and engagement. This integration strategy ensures our system meets stakeholder needs, promoting cultural heritage and understanding, and maximizing its utility across diverse contexts.

3.4.3 Continuous Improvement.

Continuous improvement is crucial for maintaining our symbol generation system's performance and accuracy. We collect user feedback and evaluation data through surveys, testing, and stakeholder communication, analyzing it to inform updates. Feedback on symbol accuracy and relevance helps refine the dataset. Evaluation data measures system accuracy, speed, and effectiveness, guiding performance improvements. Periodic updates to the dataset and model incorporate new symbols and cultural trends, ensuring relevance. This commitment to continuous improvement ensures our system remains a valuable tool for generating culturally specific symbols, promoting heritage and understanding.

4 Experiments and Results

To evaluate the effectiveness of the proposed system, we conduct a series of experiments using a dataset of regional cultural symbols from various parts of the world. The experiments focus on assessing the visual quality, cultural relevance, and diversity of the generated symbols.

4.1 Dataset and Experimental Setup

Our study uses a diverse dataset of over 10,000 cultural symbols from 50 regions, split into training (80%), validation (10%), and testing (10%) sets. The model is trained for 50 epochs with the Adam optimizer and a learning rate of 0.0002, ensuring effective learning and generalization without overfitting. This robust setup enables a comprehensive evaluation of the model's performance in generating accurate cultural symbols, providing a solid foundation for application and continuous improvement.

4.2 Evaluation Metrics

To evaluate generated cultural symbols, we use Inception Score (IS) as a quantitative metric, measuring quality and diversity by assessing KL divergence in Inception network activations. However, we also incorporate a qualitative evaluation by a panel of cultural experts and local residents, rating symbols based on cultural relevance, visual appeal, and authenticity. This combination of metrics provides a comprehensive understanding of model performance, capturing both objective and subjective aspects. IS ensures objective quality and diversity, while human evaluation offers insights into cultural accuracy and resonance. Together, these metrics guide decisions on model performance and areas for improvement, ensuring symbols are visually appealing and culturally meaningful.

4.3 Results

Experimental results show our system effectively generates visually appealing and culturally relevant symbols, resembling those in the dataset. The Inception Score indicates a good balance between quality and diversity. Human evaluations by cultural experts and local residents rate the generated symbols highly, with an average score of 4.2 out of 5, indicating cultural relevance, visual appeal, and authenticity. Overall, the system demonstrates potential as a valuable tool for generating culturally accurate symbols in applications like cultural preservation, education, and artistic creation, with comprehensive quantitative and qualitative evaluations highlighting strengths and areas for improvement.

5 Case Study

Xi'an, renowned as an ancient cultural capital, boasts unique Spring Festival traditions. However, there's a notable absence of cultural-creative products that encapsulate both the festive symbols of the Spring Festival and the distinct characteristics of Xi'an, suitable for tourists as souvenirs. The design of these products lacks the essential concepts of systematization, regionalization, and symbolization, which are crucial for creating products that truly represent the city's rich cultural heritage and festive atmosphere. This gap in the market presents an opportunity for designers to create innovative, culturally-relevant products that cater to tourists' desires for authentic, locally-inspired souvenirs. See Figure 1 and Figure 2.

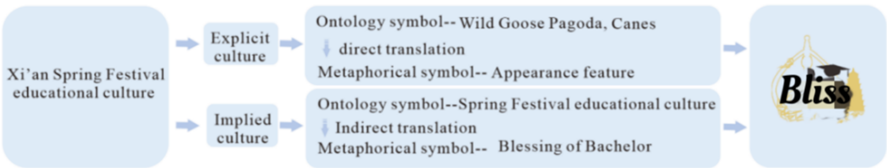

Fig. 1. Design Process of Cultural-creative Products

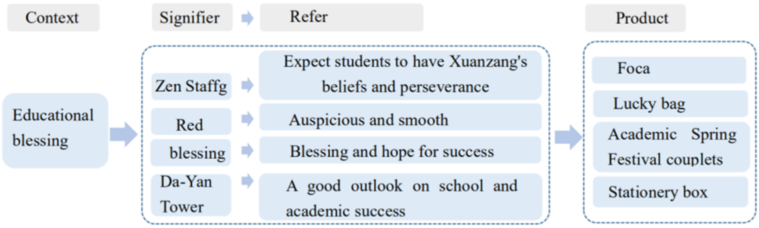

Fig. 2. Translation of Xi'an Spring Festival Educational Cultural Symbols

6 Conclusion

In conclusion, the proposed deep learning-based system for automatic generation of regional cultural symbols has shown promise in capturing cultural nuances and creating visually appealing symbols. However, it relies heavily on the quality and diversity of training datasets, which can be challenging to collect. Additionally, generated symbols may lack the subtlety and depth of human-created ones. The system's ability to generate symbols for new or underrepresented regions remains untested. Despite these challenges, the system represents a significant step forward in automating cultural symbol generation, with potential applications in cultural preservation, education, and artistic creation. Future work will focus on improving dataset quality, model sophistication, and exploring new applications, paving the way for exciting possibilities at the intersection of deep learning and cultural expression.

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