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Integrating AI and 3D Digital Technologies to Assist in the Stylistic Analysis of Taiwanese Artisan Paintings: A Case Study on Door God Imagery

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Abstract

In Taiwanese temple decorative arts, door god paintings serve not only religious purposes but also reflect the distinct styles of individual artisans. With the advancement of digital preservation, Artificial Intelligence (AI) offers new opportunities for identifying and preserving traditional stylistic lineages. This study investigates Pan-style door god paintings, a prominent artistic lineage, and proposes a classification framework combining image feature extraction and machine learning.Fuzzy Color and Texture Histogram (FCTH) is used as the primary image descriptor. Models are trained and validated using the WEKA platform with two supervised algorithms: J48 decision tree and Random Forest. J48 offers interpretable classification logic, while Random Forest improves overall stability and accuracy through ensemble voting.Experimental results demonstrate that Random Forest outperforms J48, achieving an average accuracy of 91.2% versus 85.6%. Feature importance analysis highlights edge texture and color saturation—particularly in red and gold—as key indicators of Pan-style characteristics, which typically feature rich coloration and symmetrical composition.This study confirms that AI-driven classifiers are effective for distinguishing Pan-style aesthetics in temple paintings and can support restoration decision-making. The methodology offers a scalable model for polychrome heritage classification and preservation, adaptable to broader cultural heritage contexts.

1. Introduction

In Taiwanese temple architecture, door god paintings serve not only as sacred symbols of protection and religious belief, but also as prominent carriers of regional aesthetic expression and artisan lineage. Beyond their visual appeal, these painted figures reflect the cultural history and craftsmanship traditions of local communities across generations.

Since the Qing Dynasty, Taiwan has gradually developed multiple stylistic schools of door god painting. Among them, the Pan school stands out as one of the most iconic and influential, particularly due to the works of master painters Pan Yuexiong and Pan Lishui, whose stylistic legacy continues to shape the door god imagery seen in temples across central and southern Taiwan (Figure 1). The Pan school is characterized by dignified expressions, symmetrical compositions, refined brushwork, and strong color contrasts. These visual features are not only distinct but also carry significant cultural and artistic value.

However, the stylistic continuity of the Pan school is under threat due to the progressive decline of elder artisans and the fading of the traditional master-apprentice system. In addition, the lack of systematic visual archiving and analytical methods has made it increasingly difficult to preserve, study, and interpret the finer stylistic elements of these works. Existing conservation practices—primarily manual tracing, static photography, or textual documentation—can preserve the general appearance of the artwork but often fail to capture critical details such as brushstroke textures, spatial depth, and pigment layering. These limitations hinder quantitative analysis for style classification, technique comparison, and restoration guidance.

In recent years, Artificial Intelligence (AI) and photogrammetry have shown great promise in the field of cultural heritage preservation. AI, particularly when combined with image recognition and machine learning algorithms, enables the extraction of stylistic features—such as brushstroke direction, color palette, and compositional structure—from large-scale image datasets. This allows for automated style classification and lineage inference. At the same time, photogrammetry enables the creation of high-resolution 3D models using multi-view imagery, effectively preserving dimensional details such as relief brushwork, wooden textures, and paint layering. Compared to laser scanning, photogrammetry offers greater flexibility and cost-efficiency in field documentation, making it especially suitable for painted door panels.

Given these developments, this study centers on the stylistic recognition and digital preservation of Pan-style door god paintings. We propose an integrated workflow that combines AI-based image classification with photogrammetric 3D reconstruction. Using the WEKA platform, we implement two machine learning algorithms—J48 decision tree and Random Forest—to conduct comparative experiments. Classification performance is evaluated through cross-validation, with particular attention to accuracy, interpretability, and stability.

This study does not seek to develop new machine learning algorithms but rather adapts and applies existing AI and photogrammetric techniques to the context of Taiwanese cultural heritage, specifically Pan-style door god paintings. The contribution lies in its domain-specific adaptation and integration of these tools for cultural preservation.

The objectives of this research are twofold: to construct a reliable and interpretable recognition model for Pan-style door god imagery, and to develop a scalable and reproducible digital archiving system. The resulting framework can support future applications in artwork restoration, heritage education, and cultural exhibitions.

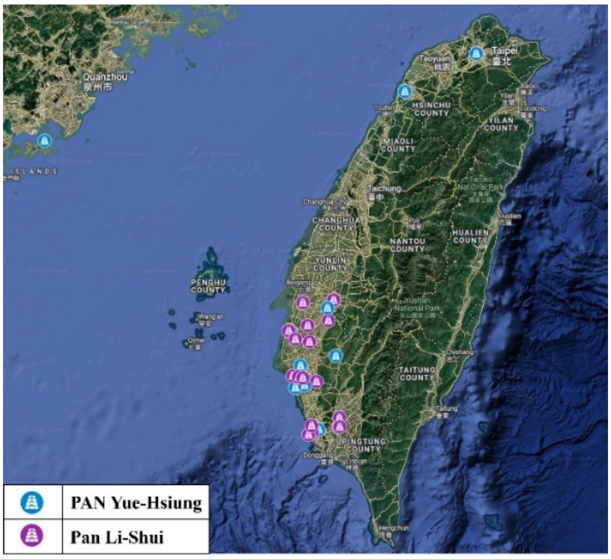

Figure 1. Wedding Palanquin, Civil Deity Palanquin, Martial Deity Palanquin (from left to right).

2. Related Work

The Pan school is one of the most representative traditional painting lineages in the development of Taiwanese door god art, particularly rooted in Tainan. According to Chen Y.-Z. (2011), the Pan style originated from the nianhua woodblock print tradition of Tangshan, China, and evolved into a localized artistic expression by blending regional Taiwanese culture with the techniques of local painters. Alongside the Chen school, founded by master artist Chen Yufeng, the Pan school has emerged as one of the two major painting styles since the Japanese colonial period.

Among contemporary inheritors of the Pan school, Su Tianfu is a pivotal figure. As a direct disciple of Pan Lishui, Su is regarded as one of the few remaining artisans whose works closely embody the original Pan aesthetic. His paintings are widely seen in temples across southern Taiwan. Guo (2017) conducted an in-depth study of Su’s work, identifying core stylistic elements such as meticulous linework, rigorous compositional symmetry, expressive facial features, and the use of prominent wavy beard patterns, all of which reflect both the continuity and creative evolution of the Pan school tradition.

From an aesthetic perspective, Lai (2005) analyzed the visual characteristics of door god paintings and summarized four key expressive traits: robust figuration, saturated coloration, ornate decorative detail, and a vivid divine aura. These align closely with the visual grammar of the Pan school, particularly in its bold compositions, rich coloring, and expressive human forms—qualities that embody the school’s core artistic philosophy.

Based on these studies, the stylistic framework of the Pan school can be categorized into five primary dimensions:

1. Figural Representation: Deities are depicted with solemn facial expressions, well-balanced features, and a dignified presence. Subjects frequently include the military generals Qin Shubao and Yuchi Gong (Figure 2), symbolizing temple guardianship.

Figure 2. Representative Pan-style Door God Painting featuring Yuchi Gong (left) and Qin Shubao (right).

2. Linework Technique: Outlines are bold and fluid, emphasizing contour clarity and motion. Wavy lines are often used to depict facial hair, becoming a hallmark of Pan-style brush technique.

3. Compositional Structure: Paintings adopt a symmetrical layout, with figures standing upright and centrally positioned, precisely aligned with door panel architecture. The resulting harmony reflects traditional aesthetic values of order and balance.

4. Color Application: Red, gold, and blue dominate the palette, often applied using layered coloring and gold foil accents. These create a visually rich, dimensional effect enhanced by the use of shadows.

5. Costume and Ornamentation: Detailed clothing elements—such as dragon robes, banners, boots, and chest armor—are paired with decorative motifs like spirals, cloud patterns, and auspicious symbols. These components are executed with precision and cultural symbolism. (Figure 3)

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Figure 3. Stylistic analysis using Qin Shubao as an example: Left, by Pan Yuexiong; right, by Pan Lishui. The comparison highlights differences in brushwork, composition, and color rendering.

A recent study by Li (2023) further demonstrated the feasibility of using AI techniques to recognize and restore Pan-style door god imagery. By selecting works from Pan Lishui and Pan Chunyuan as training samples, the study confirmed the suitability of Pan-style images for both classification and generative modeling tasks, underscoring their value in contemporary digital heritage applications.

In this context, our study proposes an integrated AI-based framework for recognizing and preserving Pan-style door god paintings, combining machine learning classification and photogrammetric modeling. Two algorithms, J48 decision tree and Random Forest, are implemented using the WEKA platform. Their performances are evaluated using cross-validation, with attention to classification accuracy, interpretability, and stability. The aim is to develop a Pan-style recognition model that is both scalable and reproducible, contributing to digital archiving strategies for future restoration, education, and exhibition purposes.

In the broader domain of image classification, both J48 and Random Forest are widely applied supervised learning algorithms. J48, based on the C4.5 algorithm by Quinlan (1993), offers transparent and interpretable decision rules. It has been successfully applied in medical diagnosis (Patil & Kumaraswamy, 2009), land-use classification (Pal, 2005), and image group analysis. In contrast, Random Forest, introduced by Breiman (2001), leverages an ensemble of randomized decision trees and a majority voting mechanism to enhance generalization and reduce overfitting. Belgiu and Drăguţ (2016), in a comprehensive review of remote sensing applications, highlighted Random Forest's stability and effectiveness in handling high-dimensional and nonlinear classification tasks. Rodríguez-Galiano et al. (2015) further validated its advantages in landscape classification and cultural image segmentation, affirming its role as a robust machine learning tool in heritage-related applications.

These studies collectively provide a theoretical foundation and practical framework for identifying visual logic and stylistic features in Pan-style door god paintings. When transformed into quantifiable image feature vectors, these stylistic characteristics form an ideal dataset for AI-based classification and style recognition in temple painting heritage.

Beyond Taiwanese door god paintings, image classification techniques have been widely applied to other cultural heritage domains, such as Buddhist statues (Renoust et al., 2023), frescoes, and Orthodox icons. These studies often use similar descriptors (e.g., texture histograms, CNN embeddings) for stylistic analysis. By aligning with these broader applications, this study contributes to the growing field of computational heritage analysis, with potential cross-cultural methodological relevance.

3. Results and Discussion

This study focuses on the Pan school of traditional Taiwanese temple door god paintings and proposes an integrated workflow for stylistic classification, digital preservation, and interpretive analysis by leveraging Artificial Intelligence (AI) and photogrammetry.The complete research methodology is structured as follows:

3.1 Field Survey and Image Acquisition

This study conducted field investigations on Pan-style door god paintings, selecting temples known for their stylistic fidelity—such as Hubei Temple (Tainan), Ciji Temple (Chiayi), and Xianse Temple (New Taipei City)—as data collection sites. A DSLR camera (e.g., Nikon D750) was mounted on a tripod and used with fixed-direction artificial lighting to capture multi-angle high-resolution images. This setup ensured consistent lighting, color fidelity, and visual detail across different temple environments (Figure 4). Although specific shooting time and white balance settings were not explicitly detailed, the use of artificial light and manual camera control minimized ambient variability and enhanced cross-site data consistency.

For 3D modeling, each door god painting was photographed from multiple overlapping angles, and image alignment and stitching were performed using photogrammetry software such as RealityCapture. While the AI classification phase employed cropped 2D images, these were derived from consistently scaled and well-aligned mosaicked datasets, ensuring a standardized basis for feature extraction.

Figure 4. High-resolution image dataset collected during fieldwork.

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3.2 Image Preprocessing and Feature Extraction

To enhance the consistency and clarity of the images, several preprocessing steps were applied, including color correction, noise reduction, and edge enhancement. Subsequently, Python and the OpenCV library were used to extract key visual features such as brushstroke direction, compositional symmetry, color saturation, and facial alignment. All images were manually annotated and categorized by style to build a labeled training and testing dataset.

For global image representation, the Fuzzy Color and Texture Histogram (FCTH) was chosen as the primary descriptor. FCTH integrates fuzzy logic-based color quantization and Haar wavelet-based texture analysis. Images are transformed into the HSV color space, classified into fuzzy sets, and represented by a fixed-length feature vector of 192 dimensions. This method effectively captures the richly saturated colors and intricate textures characteristic of Pan-style door god imagery (Figure 5).

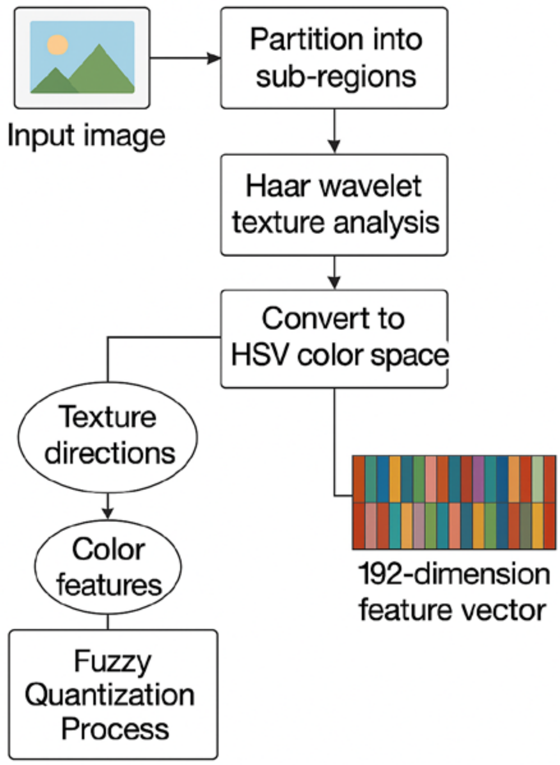

Figure 5. FCTH Feature Extraction Workflow: Input images undergo HSV conversion, texture analysis, and fuzzy classification to produce a 192-dimensional feature vector.

FCTH is particularly well-suited to the stylistic demands of door god imagery, which features high color saturation and complex ornamental patterns, providing robustness in distinguishing style through both color boundaries and textural variation.

3.3 AI Model Training and Classification Algorithms

The machine learning experiments were conducted using the WEKA platform (Waikato Environment for Knowledge Analysis). Two supervised classification algorithms were applied for comparative analysis of Pan-style recognition:

1. J48 Decision Tree:J48 is an implementation of the C4.5 decision tree algorithm, which recursively splits data based on information gain, constructing a readable, hierarchical tree where internal nodes represent decision conditions and leaf nodes represent classification results. The resulting if-then-else rules offer high interpretability and logical clarity.However, when handling high-dimensional data, J48 may suffer from overfitting. Appropriate tuning of parameters such as the confidence factor (-C) and minimum number of instances per leaf (-M) is essential to control model complexity.

2. Random Forest:Random Forest is an ensemble learning technique that builds multiple decision trees using random subsets of features. Through bagging (bootstrap aggregation), the model aggregates predictions via majority voting, enhancing classification robustness and reducing variance.While less interpretable than J48, Random Forest generally offers higher accuracy and generalization, making it more suitable for complex and large-scale image classification tasks.

3.4 Model Validation and Performance Metrics

Both models were evaluated using 10-fold cross-validation, and their performance was assessed using the following standard metrics:

Accuracy: Proportion of correctly classified instances.

$$\text{Accuracy}=\frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

Precision: Proportion of true positives among all predicted positives.

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (2)$$

Recall: Proportion of true positives among all actual positives.

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (3)$$

F1-score: Harmonic mean of precision and recall.

$$\text{F1}-\text{score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

Where TP (True Positive): Correctly predicted positive cases
Cases TN (True Negative): Correctly predicted negative
Cases FP (False Positive): Incorrectly predicted positive
Cases FN (False Negative): Incorrectly predicted negative

3.5 Performance Analysis and Visualization

To interpret and visualize classification results, Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) were applied to reduce the high-dimensional feature space into a two-dimensional projection, facilitating the observation of stylistic clustering among different samples.

In addition, the machine-predicted classifications were cross-verified with expert assessments from cultural heritage professionals to ensure alignment between AI-driven interpretation and domain-specific understanding.

This study establishes a reproducible and extensible AI-based model for Pan-style stylistic recognition and demonstrates the integration of AI in the digital preservation of cultural heritage. An overview of the proposed workflow is presented in Figure 6.

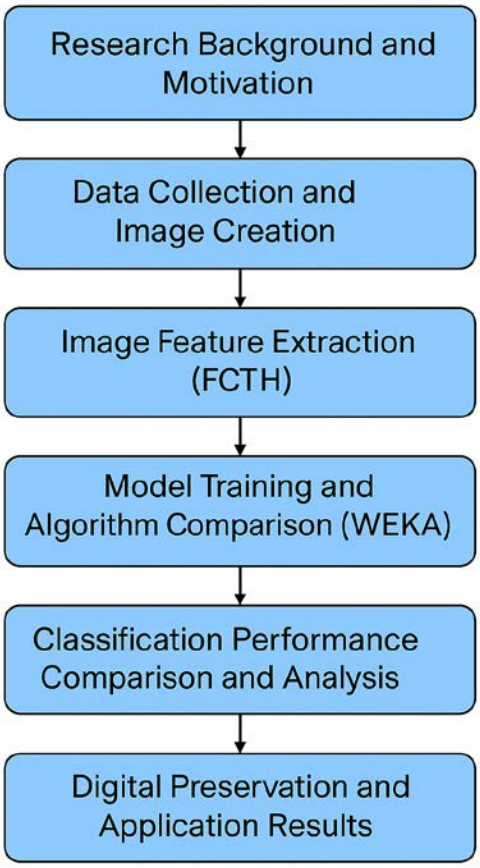

Figure 6. Research workflow for stylistic recognition and digital preservation of Pan-style door god paintings.

4. Results and Discussion

A series of classification experiments were conducted using the WEKA platform to evaluate the effectiveness of J48 decision tree and Random Forest algorithms in distinguishing stylistic features between two major schools of Taiwanese door god painting: HSIUNG (Pan school) and SHUI (Shui school). The dataset comprised 1,028 image samples processed with FCTH (Fuzzy Color and Texture Histogram) feature extraction. Model performance was assessed using 10-fold cross-validation, with evaluation results summarized in Table 1.

Classification Model	Accuracy (%)	Precision	Recall	F1-score	Kappa Statistic
J48 Decision Tree	90.76	0.908	0.908	0.908	0.8114
Random Forest	95.82	0.958	0.958	0.958	0.9148

Table 1. Evaluation of Classification Performance for Door God Style Recognition.

4.1 Performance of J48 Decision Tree

The J48 model offers interpretable decision rules, making it suitable for stylistic analysis and cultural knowledge interpretation. The model trained in this study consists of 51 leaf nodes and a total tree size of 101, with a training time of only 0.06 seconds, indicating computational efficiency. The overall classification accuracy reached 90.76%, and the Kappa statistic of 0.8114 reflects a high level of agreement beyond chance.

For the SHUI class, the recall, precision, and F1-score were 0.893, 0.891, and 0.892, respectively. For the HSIUNG class, they reached 0.918, 0.920, and 0.919. The weighted average F1-score was 0.908, confirming the model's balanced performance across both classes. However, the confusion matrix indicated misclassifications: 47 SHUI samples were labeled as HSIUNG and 48 HSIUNG samples were labeled as SHUI. These errors suggest the model's sensitivity to ambiguous samples with overlapping visual traits, particularly in borderline cases affected by feature thresholds.

4.2 Performance of Random Forest

The Random Forest model, comprising 100 decision trees, was selected based on its strong theoretical foundation in ensemble learning and its proven advantages in high-dimensional visual classification tasks. Introduced by Leo Breiman in 2001, Random Forest is an extension of the Bagging (Bootstrap Aggregating) technique. It constructs multiple decision trees by drawing bootstrap samples and selecting random subsets of features at each split, then integrates their predictions via majority voting. This approach effectively reduces overfitting and improves generalization performance.

The model training required only 0.2 seconds, maintaining high computational efficiency. It achieved an overall accuracy of 95.82% and a Kappa statistic of 0.9148, significantly outperforming J48. For the SHUI class, the recall and precision were 0.961 and 0.942, with an F1-score of 0.952. For HSIUNG, the values were 0.956, 0.971, and 0.963, respectively. The weighted average F1-score reached 0.958, making this the best-performing model in the study.

The confusion matrix indicated only 17 SHUI and 26 HSIUNG misclassifications, showing significantly fewer errors than the J48 model. Additionally, the area under the ROC curve (AUC) reached 0.992, and the precision-recall curve (PRC) also scored 0.992, confirming the model's outstanding ability to handle even ambiguous cases.

4.3 Model Comparison and Applicability

J48 excels in visual interpretability, making it ideal for use in cultural interpretation, heritage education, and interactive presentation. In contrast, Random Forest delivers superior classification accuracy, stability, and generalization, making it more appropriate for practical applications, including batch image analysis and automated recommendation systems for restoration.

Therefore, model selection should be based on specific application needs:

1. For interpretability and transparency, J48 is recommended.
2. For maximum accuracy and automation, Random Forest is preferable.

Although the current model focuses on clearly labeled Pan-style samples, its performance on ambiguous, faded, or stylistically hybrid samples remains an open question. Future training datasets may include mixed-style images to test the model's generalization beyond binary classification, such as recognizing transitional forms or differentiating additional stylistic schools like the Chen school.

5. Conclusion and Future Applications

This study confirms that AI-assisted methods are effective in identifying the visual characteristics of Pan-style door god paintings in Taiwanese temple art. By integrating traditional visual analysis, Fuzzy Color and Texture Histogram (FCTH) feature extraction, and machine learning classifiers, the proposed framework achieves promising classification results. Among the models evaluated, the Random Forest classifier demonstrated superior recognition performance, with outcomes closely aligned with the visually discernible traits of Pan-style artworks.

Based on the results, the following future applications are proposed:

1. Construction of a Digital Style Archive: A dedicated visual database of Pan-style door god paintings can be developed to support future model training, classification tasks, and aesthetic education.

2. AI-Assisted Restoration Tools: By integrating generative models such as Generative Adversarial Networks (GANs) with Random Forest classification outputs, the system could assist in reconstructing and restoring damaged artworks, providing data-driven guidance for heritage conservation. Furthermore, future studies may include robustness testing under varied lighting conditions, occlusions, and partial damages. These simulations would enhance the model’s reliability in real-world restoration tasks, especially when dealing with degraded or partially lost artifacts.

3. Online Style Recognition Platform: A user-friendly web-based interface could be developed to enable researchers and temple administrators to upload images and receive real-time feedback on stylistic attribution to the Pan school.

4. 3D Modeling and Virtual Exhibition: Using photogrammetry and AI-generated texture mapping, realistic VR temple environments can be created to offer immersive exhibitions featuring Pan-style aesthetics.

5. Cultural Education and Public Engagement: Visualization of classification results can be integrated into primary and secondary education curricula or online museum platforms to enhance public appreciation and understanding of Taiwanese traditional mural art.

The interdisciplinary integration model adopted in this study provides a novel direction for combining traditional craftsmanship with emerging AI technologies, demonstrating the innovative potential of "Traditional Art × Artificial Intelligence" in the field of cultural heritage preservation.

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