

Article

Construction-Period Classification of Traditional Dwellings in the Guanzhong Region Based on Support Vector Machine

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Abstract

Construction period is a core item of information for the heritage conservation of traditional dwellings, supporting building archive compilation, historical character zoning, conservation grading, and restoration strategy formulation in traditional villages. However, accurately determining the construction period of traditional dwellings remains difficult. Existing methods rely heavily on expert judgment and field surveys and are limited by low efficiency, subjectivity, and weak scalability. This study focuses on surface-built traditional dwellings in the Guanzhong region. UAV image acquisition and field photography were used to collect dwelling images, while resident interviews were used to verify construction-period information. Architectural components with chronological relevance were then annotated. On this basis, a construction-period classification model was developed using a support vector machine (SVM). Model performance was evaluated through classifier comparison, RBF parameter optimization, and repeated dwelling-level test-set evaluation. The optimized SVM model achieved an average classification accuracy of 81.9%. Qing-dynasty and post-1980 dwellings showed the highest and nearly identical classification performance, with F1-scores of 87.2% and 87.0%, respectively. Republican-period dwellings also achieved relatively good performance, with an F1-score of 82.9%, whereas dwellings built between 1949 and 1979 showed the lowest performance, with an F1-score of 75.4%. These findings indicate that construction-period classification based on architectural component features and SVM can support preliminary screening of dwelling construction periods, providing auxiliary technical support for digital archiving, period-based classification, character control, conservation planning, and targeted restoration in traditional villages.

Keywords: support vector machine; Guanzhong traditional dwellings; architectural components; construction-period classification



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1. Introduction

Traditional dwellings are material carriers of regional culture. They record construction techniques and social transformations from specific historical periods and constitute an important subject in architectural heritage conservation and rural sustainable development research [1,2]. In the conservation of traditional dwellings, construction period provides fundamental information for assessing historical value, historical layers, and conservation priority. Accurate construction-period classification helps establish more complete village-level building archives and provides a basis for historical character zoning, conservation grading, and the formulation of restoration strategies. This classification task is not merely

a form of architectural information recording but also a key procedure in the refined conservation and renewal management of traditional villages [3].

However, construction-period information for traditional dwellings is often difficult to obtain in rural heritage settings. Rural buildings are frequently spatially dispersed, morphologically complex, and poorly documented, which increases the difficulty of construction-period classification and conservation management [4,5]. Historical archives of rural buildings are usually incomplete, and many dwellings lack clear construction records. Conventional dating methods mainly rely on on-site architectural surveys, literature review, and resident interviews. These methods can provide important historical clues, but they are often time-consuming, costly, and dependent on expert judgment. When traditional village conservation requires large-scale surveys, grading, and the ongoing management of numerous dwellings, manual classification alone can hardly meet the needs of refined conservation practice [6]. In addition, traditional dwellings often undergo repeated repairs, extensions, or component replacement during long-term use, leading to the coexistence of period-related information from different phases within the same building. For example, the main timber frame, wall foundation, doors, windows, and decorative components may not necessarily share a consistent chronological relationship. This complexity further increases the difficulty of construction-period classification.

In recent years, digital heritage conservation has provided new technical approaches for the documentation and management of traditional villages. Heritage Building Information Modeling, point-cloud processing, UAV-based surveys, street-view imagery, and machine learning have been applied to architectural heritage documentation, traditional village landscape evaluation, architectural style recognition, and building deterioration assessment [7–11]. These studies have improved the efficiency of traditional building surveys and supported the transition of heritage information management from manual recording to digital and structured approaches. Existing research has mainly focused on traditional building recognition [12,13], landscape-character assessment [14–16], visual quality evaluation [17,18], street-view image analysis [19], heritage-element identification [20], and building damage detection [21,22]. Recent studies have also begun to apply deep learning methods to the construction-period classification of traditional dwellings [23]. However, the use of component-level architectural features for construction-period classification within regional heritage contexts has not yet been sufficiently examined.

Classifying traditional dwellings by construction period is a distinct architectural heritage task. Period-related information is not always expressed through the overall building outline or macro-scale stylistic features, but is often reflected in component-level details, such as roof form, wall construction, foundation form, timber-frame systems, fenestration, and decorative elements [24]. These components are closely related to regional construction practices and historical changes in materials, structural systems, and craftsmanship. Compared with whole-building image classification, component-level analysis is better suited to capturing the architectural evidence used in construction-period classification, especially when later repairs, partial replacements, or additions have altered the appearance of the building.

Although deep learning methods have strong capabilities in large-scale image classification tasks, their application to traditional dwelling datasets may be constrained by limited verified samples, uneven class distributions, and limited interpretability [9,25]. Traditional dwellings in regional heritage contexts often present these challenges, because verified period labels are difficult to obtain and component features vary across local construction traditions. Support Vector Machine (SVM) can handle nonlinear classification problems in high-dimensional feature spaces through kernel functions and is generally suitable for limited-sample classification tasks [26–30]. Therefore, this study adopts an SVM-based clas-

sification approach to test whether annotated component images can support preliminary construction-period classification of traditional dwellings.

The Guanzhong region is one of the areas in China where traditional villages and regionally distinctive dwellings are relatively concentrated. Traditional dwellings in this region show distinct regional characteristics in architectural form, construction techniques, material use, and decorative expression, while dwellings from different periods also show observable patterns of component change. Based on this context, this study focuses on traditional dwellings in the Guanzhong region. Image data were collected through unmanned aerial vehicle (UAV) imaging and on-site photography, and construction-period information was cross-verified using resident interviews, traditional village archival records, conservation planning documents, and field surveys. Architectural components with chronological relevance were then annotated and cropped, and the resulting component images were used as inputs for an SVM model. This study examines whether component-level architectural features can support the construction-period classification of traditional Guanzhong dwellings, evaluates the recognition performance of the proposed model, and discusses the potential application of this workflow in building archive compilation, period-based classification, and differentiated conservation practice.

2. Materials and Methods

2.1. Study Area and Construction-Period Classification

The Guanzhong region has a long history and contains the largest number of nationally listed traditional villages in Shaanxi Province. Its settlement patterns and dwelling typologies are diverse and have considerable historical and cultural value, making it a suitable case for studying the construction-period classification of traditional dwellings. Traditional dwellings in Guanzhong can generally be divided into surface-built traditional dwellings and cave dwellings. In this study, surface-built traditional dwellings refer to house-type dwellings constructed above the ground surface, including courtyard dwellings and single-row dwellings.

This study focuses on surface-built dwellings. Cave dwellings, including cliffside cave dwellings and sunken courtyard cave dwellings, were excluded because their spatial organization, visible components, and construction-period indicators differ substantially from those of surface-built dwellings. This exclusion helps maintain consistency in building type, feature annotation, and classification process.

The diversity of surface-built dwellings in Guanzhong provides a regionally specific sample basis for construction-period classification. This study mainly selected traditional villages in Guanzhong from the first three batches of the List of Chinese Traditional Villages, as these villages generally retain more traditional dwellings and show relatively complete conservation conditions. Field surveys showed that the selected villages from the first three batches contained courtyard dwellings but lacked single-row dwelling samples. To cover all house-type dwelling types within the typological framework adopted in this study, Shichuangou Village, which was included in the fourth batch, was further incorporated to provide single-row dwelling samples. The distribution of the study sites is shown in Figure 1.

For construction-period classification, the Guanzhong dwelling samples include both earlier historical remains and buildings constructed or substantially altered in modern periods. Because many traditional dwellings have undergone repeated repairs, extensions, or component replacement during long-term use, construction period cannot always be determined by a single feature. The period labels in this study were assigned with reference to existing research on architectural period classification of traditional dwellings [23] and the construction-period scoring criteria in the Evaluation and Identification Index System of Traditional Villages (Trial), issued in 2012 [31]. This official system evaluates

traditional buildings partly according to their construction periods, assigning 3 points to Qing-dynasty dwellings, 2 points to Republican-period dwellings, and 1 point to dwellings built between 1949 and 1979. Based on this framework and the field-verified construction-period information, the samples were divided into four categories: C1-1 for Qing-dynasty dwellings, C1-2 for Republican-period dwellings, C1-3 for dwellings built between 1949 and 1979, and C1-4 for dwellings built after 1980. As shown in Figure 2, the final dataset comprised 351 dwellings, including 53 in C1-1, 124 in C1-2, 114 in C1-3, and 60 in C1-4.

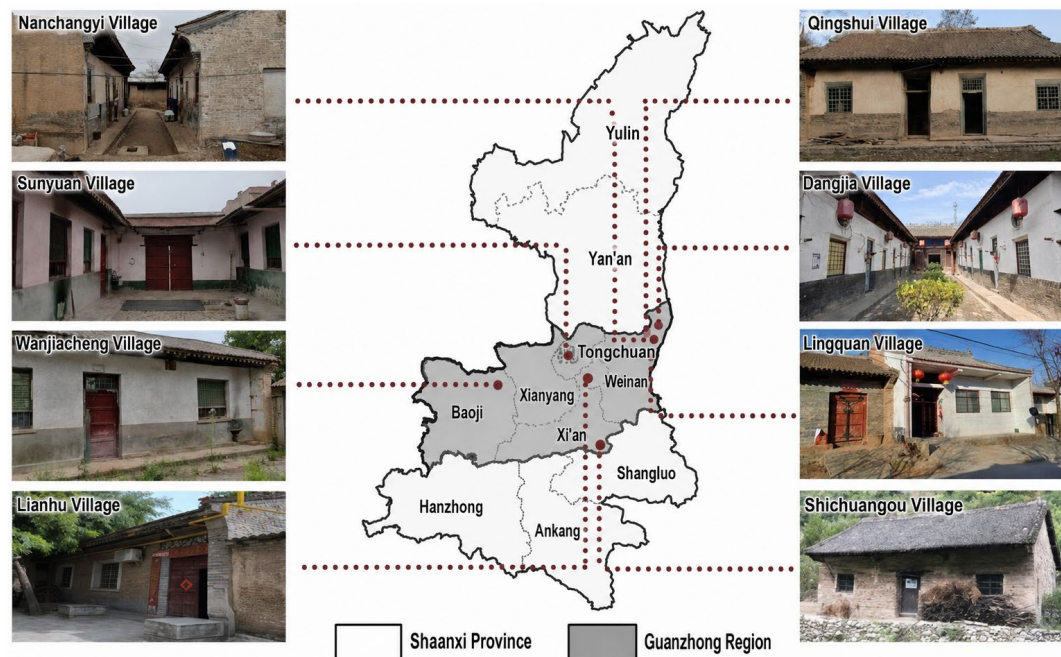


Figure 1. Geographical Distribution of the Surveyed Traditional Villages in Shaanxi Province.

Construction-period Category	Examples		Architectural Characteristics	Sample Distribution
C1-1 (1644–1911)			Timber framework structure is common, with brick and wood carvings and fine decorative elements. Door and window styles are diverse, and the main wall material is brick.	$n = 53$ (15.10%)
C1-2 (1912–1948)			Structures are mainly of wood and brick, with walls commonly made of earth and stone. The materials are a mixture of earth, timber, and stone. The overall style is relatively simple, and decorative elements are minimal.	$n = 124$ (35.33%)
C1-3 (1949–1979)			Mainly built with brick, gray tiles, and cement plastering. The facade is simple with standardized treatment and tends toward uniformity. Traditional decorative elements are relatively few.	$n = 114$ (32.48%)
C1-4 (After 1980)			Architectural forms show modern characteristics. Walls are often made of brick or finished with paint or tile. Roofs are usually covered with colored metal panels. Doors and windows are made of modern materials, and the glazed area is relatively large.	$n = 60$ (17.09%)

Figure 2. Construction-period classification, representative examples, architectural characteristics, and sample distribution of traditional dwellings.

2.2. Data Collection and Image Annotation

To support construction-period classification, this study first screened the regionally characteristic architectural elements of Guanzhong traditional dwellings. Based on previous studies on the architectural characteristics, landscape-character elements, and spatial configuration of traditional dwellings [32,33], together with field survey results, three

groups of features with potential chronological relevance were identified: facade features, structural features, and decorative features. Facade features include externally visible components such as roofs, walls, and foundations. Structural features reflect differences in construction techniques, structural systems, and material use across different periods. Decorative features involve stylistic changes and cultural meanings expressed through patterns, symbols, inscriptions, and detailed components.

Four approaches to feature identification were used to guide image annotation: element identification, pattern identification, structural feature identification, and cultural-semantic interpretation. Element identification focused on representative architectural components such as doors, windows, beams, and columns. Pattern identification focused on decorative motifs and their stylistic changes. Structural feature identification emphasized building structure and spatial layout, while cultural-semantic interpretation focused on historical and cultural information embedded in building location, layout, and decoration. These feature categories provided the basis for image annotation and subsequent classification.

Because construction-period information for traditional dwellings is difficult to obtain from public online sources and existing records are often incomplete, this study collected both image data and period information through field surveys. From 2023 to 2026, the research team conducted five field surveys in eight traditional villages in the Guanzhong region. After preliminary screening, 351 dwelling records and 1110 original photographs were retained for verification. Construction-period information was cross-verified using resident interviews, traditional village archival records, conservation planning documents, and visible chronological clues recorded during fieldwork, including beam-frame inscriptions, facade inscriptions, and texts on screen walls. Records with inconsistent or unverifiable period information had been excluded during preliminary screening.

To ensure that the images were suitable for subsequent annotation and modeling, photographs with poor image quality, unsuitable lighting, inappropriate shooting angles, or unclear component information were excluded. The remaining dwelling photographs were annotated using the Labellng1.8.6 image annotation tool (Figure 3). During annotation, regions containing period-related architectural components, such as columns, doors, windows, and decorative details, were delineated and assigned corresponding period labels, generating XML-formatted annotation files. The annotated regions were then cropped into independent component images. A total of 21,040 valid component images were obtained and used to establish the component-image database.



Figure 3. Example of image annotation using Labellng.

2.3. Model Construction and Evaluation

After image acquisition, sample screening, and component annotation, the component-image database was divided into training and test sets at a ratio of approximately 85:15 at the dwelling level. To reduce potential data leakage, the split was constrained by dwelling identity. All original photographs and cropped component images derived from the same dwelling were assigned to the same subset, so that no dwelling appeared simultaneously in the training and test sets. The resulting training and test component images were then used for model construction and evaluation.

As shown in Figure 4, the model construction and evaluation workflow included sample screening, component annotation, dataset preprocessing, SVM-based classification, and performance evaluation.

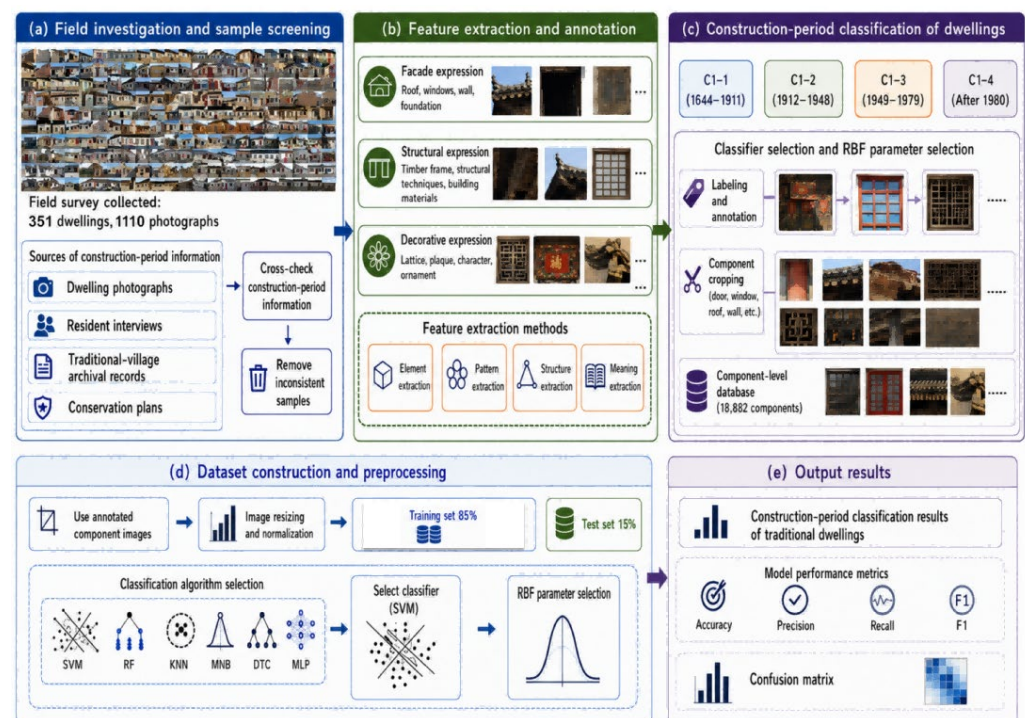


Figure 4. Technical workflow for construction-period classification of traditional dwellings in the Guanzhong region.

In this study, construction period refers to the period when the main dwelling structure was formed, renovation period refers to later maintenance, expansion, or partial modification, and component period refers to the formation or replacement period of individual architectural components. Since later repairs and component replacement may obscure the construction period of the main dwelling body, the selection of component categories was based on previous studies on traditional building identification and evaluation, together with findings from field surveys from the Guanzhong region. Existing studies and evaluation criteria commonly regard structural systems, roof forms, facade materials, and decorative details as important indicators for identifying and assessing traditional architecture [34,35]. Accordingly, this study selected roofs, walls, foundations, timber frames, doors, windows, and decorative components as the main observable elements.

Among these components, roofs, walls, foundations, and timber frames are generally more closely related to the initial construction of the main dwelling body and are less likely to be completely replaced during later restoration than doors, windows, and decorative details [36,37]. Their materials, forms, and structural configurations are therefore more likely to retain information about the original construction period. Accordingly, roofs, walls,

foundations, and timber frames were used as primary indicators for construction-period classification, while doors, windows, and decorative components were used as supplementary indicators because they are more susceptible to later replacement, modification, or redecoration.

After component labeling and cropping, each annotated architectural component was converted into an independent component image. All cropped component images were resized to 128×128 pixels and processed in RGB format. Pixel values were normalized to the range $[0, 1]$. Each resized image was then flattened into a 49,152-dimensional numerical vector and used as input to the SVM classifier. No dimensionality reduction was performed. Model training and testing were implemented in Python 3.10.

In the classifier-selection phase, six commonly used classifiers were compared: Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Multinomial Naive Bayes (MNB), Decision Tree Classifier (DTC), and Multi-Layer Perceptron (MLP). The comparison was conducted using only the training data, with five repeated runs used to calculate the average accuracy, average running time, and corresponding variances of each classifier. After SVM was selected as the core classifier, different radial basis function (RBF) kernel parameter combinations were further evaluated using only the training data. The selected classifier and parameter combination were subsequently evaluated on the independent test set.

Model performance was evaluated using accuracy, precision, recall, and F1-score [38]. In the final evaluation, these metrics were calculated at the dwelling-sample level. Accuracy measures the proportion of correctly classified test dwellings among all test dwellings and reflects the overall recognition performance of the model. Precision measures the proportion of correctly identified samples within a predicted category and reflects the reliability of the model's positive predictions. In Formula (1), (P) denotes precision:

$$P = \frac{TP}{TP + FP} \quad (1)$$

Here, (TP) denotes true positives, namely test dwellings that belong to a given category and are correctly classified into that category; (FP) denotes false positives, namely test dwellings that belong to other categories but are incorrectly classified into that category (Table 1). Precision therefore indicates the correctness of predictions for a given category. Recall ((R)) measures the proportion of test dwellings in a given category that are correctly identified by the model, as shown in Formula (2):

$$R = \frac{TP}{TP + FN} \quad (2)$$

Table 1. Confusion matrix for binary classification evaluation.

Confusion Matrix		Predicted Value	
		Class 1	Non-Class 1
Actual value	Class 1	True Positive (TP)	False Negative (FN)
	Non-Class 1	False Positive (FP)	True Negative (TN)

Here, (FN) denotes false negatives, namely test dwellings that belong to a given category but are incorrectly classified into another category (Table 1). Recall therefore reflects the model's ability to identify the dwellings that actually belong to a given category.

The F1-score is the harmonic mean of precision and recall. It balances prediction correctness and category coverage, and is therefore useful when the sample distribution across construction-period categories is uneven. Its calculation is shown in Formula (3):

$$F1 = \frac{2PR}{P + R} \quad (3)$$

In the construction-period classification task, the sample distribution varied across the four period categories. Therefore, a single metric may not fully reflect model performance. The F1-score was used to evaluate the balance between precision and recall for each category, especially under uneven class distributions. A confusion matrix was also used to examine misclassification patterns among period categories and to further assess the model's category-level recognition performance.

3. Results

3.1. Classifier Selection and Parameter Optimization

To select a classifier suitable for construction-period classification of Guanzhong traditional dwellings, six commonly used classifiers were evaluated. Table 2 presents the mean results of five repeated runs. Among the evaluated classifiers, SVM achieved the highest mean accuracy of 62.5%, exceeding the corresponding values of RF, KNN, MNB, DTC, and MLP. SVM also exhibited relatively low accuracy variance, indicating comparatively consistent performance across the five runs. Therefore, SVM was selected as the core classifier for subsequent parameter optimization.

Table 2. Classifier comparison results.

Classifier	Accuracy	Running Time (s)	Accuracy Variance	Time Variance
SVM	0.63	48.94	0.09	8.84
RF	0.58	5.87	0.06	0.79
KNN	0.53	1.01	0.09	0.16
MNB	0.41	0.71	0.05	0.16
DTC	0.39	38.59	0.09	5.52
MLP	0.29	448.61	0.11	884.08

After SVM was selected as the core classifier, this study further tested the effects of different RBF kernel parameter combinations on model performance. The parameter test results are shown in Table 3. Overall, changes in the value of (C) did not lead to a linear increase in accuracy; instead, model performance fluctuated across different parameter settings. This result indicates that the SVM model was sensitive to parameter settings and that parameter testing was necessary for the current dataset. Among the seven tested parameter combinations, the model achieved the best performance when kernel = 'rbf', C = 100,000, and gamma = 'scale', with an average accuracy of 68.8% and an accuracy variance of 0.05. Therefore, this parameter setting was adopted for the subsequent construction-period classification experiments.

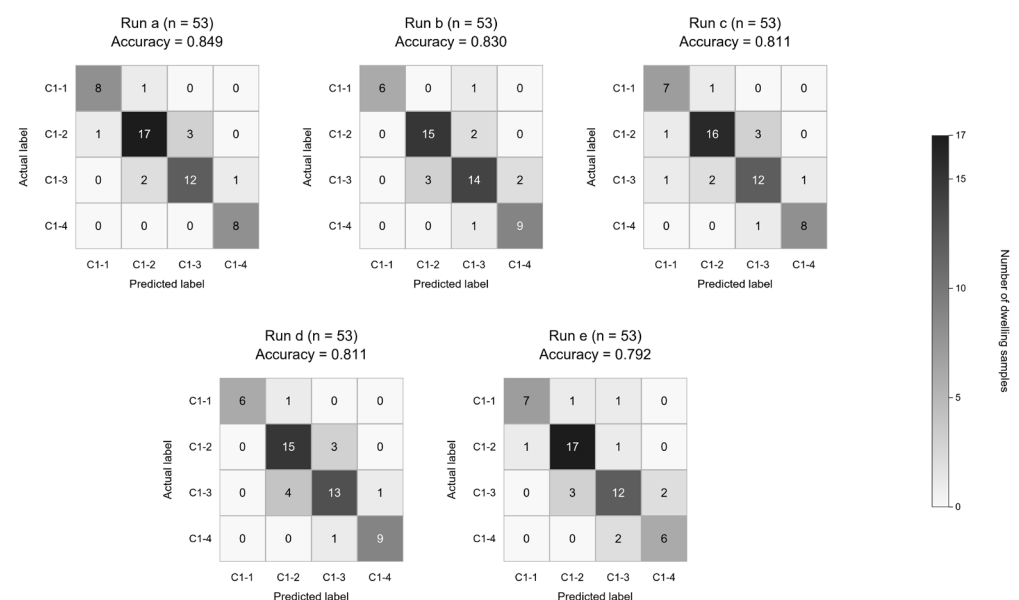
Table 3. Parameter test results for the RBF kernel.

Parameter Setting	Accuracy	Time (s)	Accuracy Variance
kernel = 'rbf', C = 10,000, gamma = 'scale'	0.66	39.38	0.08
kernel = 'rbf', C = 1000, gamma = 'scale'	0.64	39.05	0.04
kernel = 'rbf', C = 10, gamma = 'scale'	0.61	38.57	0.04
kernel = 'rbf', C = 100, gamma = 'scale'	0.64	39.61	0.09
kernel = 'rbf', C = 1, gamma = 'scale'	0.58	37.79	0.10
kernel = 'rbf', C = 100,000, gamma = 'scale'	0.69	38.15	0.05
kernel = 'rbf', C = 1,000,000, gamma = 'scale'	0.64	38.06	0.05

3.2. Overall Recognition Performance

After classifier selection and parameter optimization the optimized SVM model was trained and tested in five repeated runs. In each run, the final recognition results were summarized at the dwelling-sample level, with 53 test dwellings included in each run. The model achieved an average recognition accuracy of 81.9% and an average running time of 58.52 s. This result indicates that the optimized SVM model could complete the construction-period classification task within a relatively short time and showed consistent overall performance across the repeated runs.

To further examine class-specific performance and misclassification patterns, the dwelling-level predictions from the five runs were aggregated into a confusion matrix (Figure 5). The results show that the model generally distinguished the four construction-period categories, C1-1, C1-2, C1-3, and C1-4, indicating that the annotated architectural components contained visual information relevant to construction-period classification. Misclassification occurred primarily between C1-2 and C1-3, while smaller numbers of errors were observed between the other categories.

**Figure 5.** Confusion matrices of the construction-period classification results period-identification.

The dwelling-level classification accuracy and running time across the five repeated runs are shown in Figure 6. Classification accuracy ranged from 79.2% to 84.9%, with a mean of 81.9%, while running time ranged from 56.92 to 60.37 s, with a mean of 58.52 s. The relatively limited variation across the five runs indicates that the final SVM model achieved comparatively consistent performance under different data splits. Although computation time may vary depending on hardware and implementation conditions, the observed

running times suggest that the model could support preliminary construction-period screening and building archive compilation for traditional dwellings.

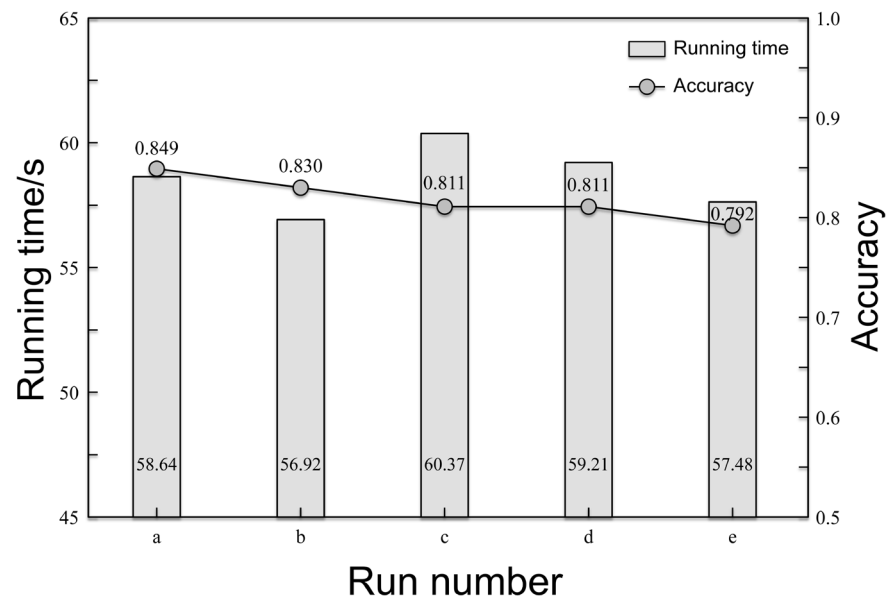


Figure 6. Classification accuracy and running time over five runs.

3.3. Recognition Differences Among Construction-Period Categories

To further examine the model's performance across different construction-period categories, this study aggregated the confusion matrices from the five repeated runs. The F1-score was then calculated for each category (Figure 7). The F1-scores for C1-1, C1-2, C1-3, and C1-4 were 87.2%, 82.9%, 75.4%, and 87.0%, respectively. C1-1 and C1-4 showed the highest and nearly identical classification performance, followed by C1-2, while C1-3 had the lowest F1-score.

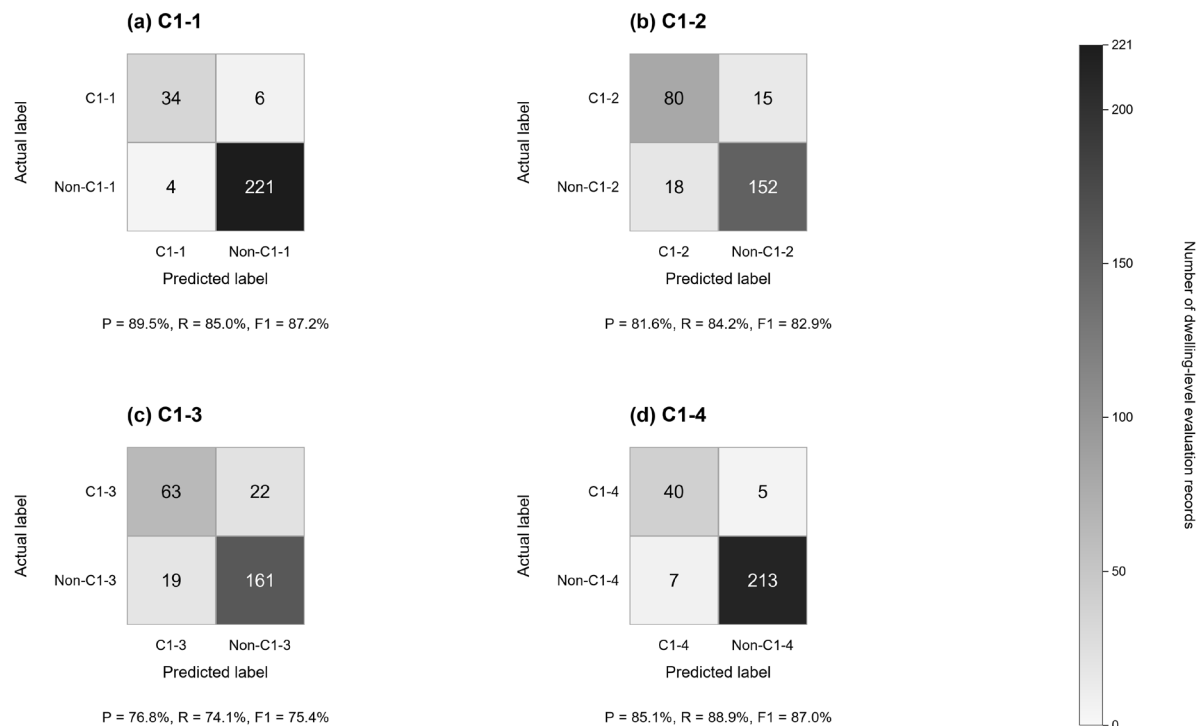


Figure 7. Confusion matrices and performance metrics for the four construction-period categories.

4. Discussion

4.1. From Building Recognition to Construction-Period Identification

Existing digital studies on traditional villages have applied image recognition, remote-sensing imagery, UAV-based surveys, three-dimensional point clouds, and machine learning to village investigation and architectural information extraction. These studies can be broadly grouped into three directions. The first focuses on extracting village spatial patterns, building objects, and building types to improve the efficiency of traditional village surveys and documentation [39–41]. The second converts visible features, such as street space, architectural texture, color, and exterior quality, into indicators for landscape-character or visual-quality evaluation [18,19,42–44]. The third uses deep learning, computer vision, or UAV-based data acquisition to identify heritage-related attributes, building defects, and damage types, providing automated or semi-automated support for the conservation of traditional villages and architectural heritage [45,46]. Together, these studies have contributed to the transition of traditional village conservation from predominantly experience-based manual recording toward image-based analysis and quantitative evaluation.

Construction-period classification differs from these tasks. Building-object recognition mainly determines whether a particular building type or architectural object appears in an image; character assessment evaluates the visual quality or landscape character of buildings and spaces; and damage detection identifies deterioration or defects. By contrast, construction-period classification examines chronological information reflected in visible architectural components. The construction period of a traditional dwelling is an important attribute related to historical layering, period-based classification, conservation priority, and restoration strategy formulation. Therefore, compared with general building recognition, this task places greater emphasis on the relationship between architectural components and historical periods. The construction-period categories adopted in this study are operational intervals intended to support conservation-oriented analysis and should not be interpreted as natural or absolute morphological boundaries.

The results of this study indicate that visual information contained in annotated component images can provide auxiliary evidence for preliminary dwelling-level construction-period classification. However, such evidence should be interpreted in relation to the period when the main dwelling structure was formed. As discussed in the component-selection procedure, relatively stable structural elements are more likely to preserve information related to the original construction period, whereas later repairs, extensions, and component replacement may introduce visual information from other periods. Therefore, visible architectural components should not be treated as equally reliable chronological evidence; their relationship to the initial formation and subsequent transformation of the dwelling should also be considered.

This study does not aim to propose a new machine-learning algorithm. Instead, it examines whether the relationship between architectural components and construction periods can be translated into a component-image-based classification workflow. Through image collection, component annotation, SVM model construction, and dwelling-level prediction, this study provides a preliminary assessment of whether annotated component images can support the construction-period classification of traditional dwellings.

4.2. Interpretation of Recognition Results

The differences in classification performance across construction-period categories indicate that construction-period classification of traditional dwellings cannot be understood solely as a general image classification task. Model performance depends not only on visual separability, but may also be affected by the stability of architectural components, material replacement, repair history, and changes in local construction practices. Previ-

ous studies on traditional dwelling classification, vernacular facade morphology, and the visual-quality assessment of traditional villages have shown that visible elements, such as roofs, walls, facade composition, materials, doors, windows, colors, and decorations, can reflect regional characteristics, character differences, and visual-perception features of traditional architecture [47–50]. The results of this study indicate that visible architectural components can provide useful evidence for preliminary construction-period classification, although the strength of this evidence varies across period categories.

The classification results show that Qing-dynasty dwellings and post-1980 dwellings achieved the highest and nearly identical F1-scores, although their classification performance may be associated with different architectural characteristics. For C1-1, the relatively high classification performance may be related to the preservation of stable components, such as timber frames and foundation walls. Most Qing-dynasty dwellings included in the survey sample had also been documented in cultural heritage protection materials or traditional village archives, and their primary structural components and overall architectural character were relatively well preserved. Therefore, the relatively high F1-score of C1-1 may reflect both the distinctiveness of early dwelling components and the comparatively clear chronological information of the selected samples.

The classification performance of C1-4 may be associated with the visibility of modern materials and construction methods. Post-1980 dwellings are more clearly influenced by modern construction technologies, and their walls, structural expression, and overall appearance differ more directly from those of traditional timber-frame dwellings. Unlike C1-1, the relatively high performance of C1-4 may reflect the visual contrast between modern construction expression and earlier traditional dwelling forms rather than the preservation of historical components.

By contrast, Republican-period dwellings and dwellings built between 1949 and 1979 demonstrate the transitional nature of construction-period classification. C1-2 dwellings often combine traditional frames, newer materials, and partial changes in architectural form. This mixed character retains some period-related features, which may explain the relatively good classification performance of C1-2, but it also weakens the visual boundary between C1-2 and adjacent period categories. The results therefore suggest that transitional-period dwellings are classified through a combination of component-level information rather than a single, clearly distinguishable visual marker.

C1-3 showed the lowest classification performance among the four categories. This category represents a stage between traditional dwellings and more clearly modernized dwellings. Its architectural form, material use, and spatial organization may retain similarities with both earlier and later periods while lacking consistently distinctive period-related features comparable to Qing-dynasty timber frames or post-1980 modern wall materials. Repairs, extensions, and component replacement may further increase the overlap between the visible characteristics of C1-3 and those of adjacent categories. The lower F1-score of C1-3 may therefore be associated with both model limitations and the relatively weak visual boundaries of this period category.

Overall, these results indicate that the key issue in construction-period classification is not whether all visible components correspond to the same period, but which components more reliably reflect the main construction period of the dwelling. Stable components can provide stronger chronological evidence, whereas replaceable components may introduce information from later repairs or modifications. This finding supports the need to distinguish original construction features from later repair features in future model optimization.

4.3. Application Potential and Limitations

The construction-period identification method proposed in this study has potential applications in traditional village conservation. In conservation practice, construction period is an important basis for building archives, historical character zoning, conservation grading, and restoration strategy formulation. Manual field survey can provide detailed judgments, but village-scale surveys and dynamic updates are often constrained by time costs, expert availability, and incomplete historical records. The image-feature-based SVM workflow developed in this study can provide auxiliary support for preliminary screening at the village scale, thereby improving the efficiency of architectural information organization and period-based classification.

Compared with recent studies that have applied deep learning methods to the construction-period classification of traditional dwellings, this study focuses on component-level image features rather than whole-building images [24]. This focus is relevant because period-related information in traditional dwellings is often embedded in specific architectural components, while whole-building images may contain mixed information caused by later repairs or component replacement. The use of SVM also provides a practical option for limited-sample and high-dimensional image classification tasks, especially when large-scale labeled datasets required by deep learning models are difficult to obtain [26–30].

At the application level, the proposed workflow can be integrated into traditional dwelling archive construction by organizing dwelling images, component annotation information, and model recognition results into structured construction-period data. For categories with relatively stable recognition results, it can assist period-based classification, historical character zoning, preliminary conservation grading, and restoration priority assessment. However, the method should be understood as an auxiliary tool rather than a substitute for expert judgment. Construction-period identification involves architectural history, local construction traditions, repair records, resident interviews, and field experience. When buildings have undergone repeated repairs or component replacement, model results still need to be verified through field survey, historical records, and expert assessment.

This study also has several limitations. First, although 21,040 valid component images were obtained, the number of verified dwelling samples remains limited. The generalization ability of the model therefore needs to be further tested with larger and more balanced datasets. Second, the present study focuses on surface-built traditional dwellings in the Guanzhong region. Future research should include more villages and regional dwelling types to examine the cross-regional applicability of the workflow. Third, the current model mainly uses flattened pixel values as input features, and no dimensionality reduction or multi-level feature representation was applied. Future studies may further distinguish original construction features from later repair features, introduce richer image features, and integrate recognition results with village spatial data, conservation grades, and repair records. Such improvements may help transform construction-period identification from an image classification task into a more complete information-management tool for the refined conservation of traditional villages.

5. Conclusions

This study developed an SVM-based workflow for construction-period identification of surface-built traditional dwellings in the Guanzhong region. Dwelling images and construction-period information were collected through UAV imaging, field photography, resident interviews, traditional village archival records, and conservation planning documents. Based on the regional architectural characteristics of Guanzhong traditional dwellings, architectural components with chronological relevance were annotated and

converted into component images. On this basis, multiple classifiers were compared, and an SVM-based construction-period identification model was constructed through classifier selection and parameter optimization.

Across five repeated evaluations, the final SVM model achieved a mean dwelling-level classification accuracy of 81.9%. Classification performance varied across the four construction-period categories. Qing-dynasty dwellings (C1-1) and post-1980 dwellings (C1-4) achieved the highest and nearly identical F1-scores of 87.2% and 87.0%, respectively. Republican-period dwellings (C1-2) also showed relatively good performance, with an F1-score of 82.9%, whereas dwellings built between 1949 and 1979 (C1-3) showed the lowest performance, with an F1-score of 75.4%. These differences may be associated with the stability of architectural components, the visibility of modern materials, transitions in local construction practices, and the effects of later repairs or component replacement.

The main contribution of this study is that it transforms construction-period identification of traditional dwellings into a recognition task based on image features and a classification model, and verifies the feasibility of SVM for construction-period identification of Guanzhong traditional dwellings. This method can provide auxiliary support for traditional dwelling archive compilation, period-based classification, and preliminary screening in traditional village conservation. Future research should further expand the sample range and improve the model's applicability to dwellings with complex repair histories and regional variations.

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Institutional Review Board Statement: Formal institutional ethical approval was not obtained because this study was conducted as a non-interventional architectural heritage survey. The resident interviews were used only to verify dwelling construction periods, renovation histories, and building-use information. No biomedical data, health information, personal identification numbers, financial information, or other sensitive personal information were collected. Privacy protection measures were adopted during data processing and manuscript preparation, including the removal of household names, detailed addresses, and other privacy-sensitive information.

Informed Consent Statement: Written informed consent forms were not collected. Before resident interviews or dwelling photography, the research purpose and academic use of the collected information were explained to residents, and interviews or photography were conducted only when residents agreed to cooperate. The images included in the manuscript were selected or cropped to show architectural components and dwelling features. No identifiable residents are shown in the manuscript.

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and field survey restrictions.

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Abbreviations

The following abbreviations are used in this manuscript:

SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
RBF	Radial Basis Function
RF	Random Forest
KNN	K-Nearest Neighbors
MNB	Multinomial Naive Bayes
DTC	Decision Tree Classifier
MLP	Multilayer Perceptron
TP	True Positive
FP	False Positive
FN	False Negative
TN	True Negative
P	Precision
R	Recall
F1-score	Harmonic mean of precision and recall

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