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Feature Recognition of Regional Architecture Forms Based on Machine Learning: A Case Study of Architecture Heritage in Hubei Province, China

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Abstract: Architecture form has been one of the hot areas in the field of architectural design, which reflects regional architectural features to some extent. However, most of the existing methods for architecture form belong to the field of qualitative analysis. Accordingly, quantitative methods are urgently required to extract regional architectural style, identify architecture form, and to and further provide the quantitative evaluation. Based on machine learning technology, this paper proposes a novel method to quantify the feature, form, and evaluation of regional architectures. First, we construct a training dataset—the Chinese Ancient Architecture Image Dataset (CAAID), in which each image is labeled by some experts as having at least one of three typical features such as "High Pedestal", "Deep Eave" and "Elegant Gable". Second, the CAAID is used to train our neural network model to identify three kinds of architectural features. In order to reveal the traditional forms of regional architecture in Hubei, we built the Hubei Architectural Heritage Image Dataset (HAHID) as our object dataset, in which we collected architectural images from four different regions including southeast, northeast, southwest, and northwest Hubei. Our object dataset is then fed into our neural network model to predict the typical features for those four regions in Hubei. The obtained quantitative results show that the feature identification of the architectural form is consistent with that of regional architectures in Hubei. Moreover, we can observe from the quantitative results that four geographic regions in Hubei show variation; for instance, the feature of the 'elegant gable' in southeastern Hubei is more evident, while the "Deep Eave" in the northwest is more evident. In addition, some new building images are selected to feed into our neural network model and the output quantitative results can effectively identify the corresponding feature style of regional architectures in Hubei. Therefore, our proposed method based on machine learning can be used not only as a quantitative tool to extract features of regional architectures, but also as an effective approach to evaluate architecture forms in the urban renewal process.

Keywords: architectural heritage; artificial intelligence; image recognition; regional architecture; architectural form

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1. Introduction

Since the 1960s, with the popularization of modern architectural forms and cultural "globalization", architecture homogenization has gradually become obvious, and modern architects have begun to consciously reflect on the relationship between architectural forms and their surroundings, i.e., the awakening to regionalism [1]. Robert Venturi once satirized that modernist architecture achieved formalism while rejecting form, elevated expressionism while ignoring decoration, and mythologized space while rejecting symbols [2]. Under this background, regionalism began to develop. In China, Liangyong Wu proposed "glocal architecture" ("glocal" is the abbreviation of "global" and "local"), suggesting that contemporary architecture should not only be global architecture but also new architecture with local characteristics [3]. Lewis Mumford also emphasized that the modern movement of architecture is regionalism in essence: it reflects on the differences between the local and other regions, as well as on its history and future, in order to find a balance between inheritance and development. Therefore, in this rapidly globalizing world, any research on architecture inevitably leads to reflections on regionalism [4,5]. Although the definition of regional architecture is broad, the spatiality and location of architecture determines that any architecture is regional. However, only those buildings that possess specific regional natural characteristics, construct the cultural spirit of the region, and adopt appropriate technical and economic conditions are regarded as regional architecture.

On the other hand, most regional architecture is a valuable cultural heritage of mankind which is a reliable medium for the transfer of history and knowledge [6]. Moreover, from the international 'Athens Charter' (1933) and the 'Florence Charter' (1981) to the UNESCO 'Washington Charter' (1987) and the 'Convention for the Safeguarding of Intangible Cultural Heritage' (2003), for the protection of cultural heritage, the first focus is the tangible and material historical remains, and next is the cultural value inherent in the heritage. Therefore, for a regional building belonging to a particular cultural heritage, its architectural components and overall form are preserved best and are most valuable for research. For example, the Ancient Building Complex in the Wudang Mountains, which is not only an excellent regional architecture but also a world cultural heritage site, has been completely preserved, especially its regional architectural form. Therefore, this paper selects the ancient architecture that belongs to the architectural heritage in the Hubei region as our research object.

In previous studies, there have been many studies on "architectural form" and "architectural style" that have been accepted by the majority of scholars. For example, "architectural morphology" developed from the concept of "morphology", which can be interpreted as the harmonization of "movement" from a historical perspective and from which the definition of architectural "style" is derived [7]. There is also "architectural typology", which specializes in the study of "archetypes" and "types" of architecture [8], and "semiotics", which has been proposed by Italian architectural theorists and architects [9]. As for the research on the features of regional architectural form, the regional architectural styles of each region have been studied and the stylistic elements refined by the experts of each country and region [10]. However, most of these methods are based on subjective summary and qualitative evaluation; for example, most people in China know that the typical characteristics of Huizhou-style architecture are white walls and grey tiles with Ma Tau walls [11], but they cannot summarize what percentage of white walls can be considered as "white walls" of Huizhou-style architecture, and what degree of grey color can be considered as "grey tile". Therefore, we urgently require quantitative methods to extract the regional architectural style and provide evaluation criteria for the protection of architectural heritage and the renewal of urban historic landscape areas.

With the development of technology, utilizing scientific tools, especially machine learning, to study "architectural form features" has become a new paradigm [12]. For example, the latest research results include Chinese scholars using a machine learning unsupervised field algorithm to automatically generate building forms and their combination schemes in urban design, providing more feasible references for designers [13]. In particular, image recognition techniques and convolutional neural networks in the field of machine learning have yielded a large number of research results on architectural forms, especially architectural styles, which have focused not only on historical buildings with large differences in styles, but also on modern buildings with more similar styles [14,15]. From the perspective of heritage conservation, with a more deep understanding of cultural heritage and more advanced technology adopted in cultural heritage conservation, digital conservation of cultural heritage has become a new trend in the conservation and development of historical heritage [16,17]. On the other hand, deep neural network learning technology has shown excellent performance for traditional tasks, i.e., image classification [18], feature extraction [19,20], etc.

Therefore, in this paper, we utilize the machine learning neural network Fast-R-CNN to study the feature of architecture form in regional architecture. Specifically, Fast-R-CNN is a quantitative method based only on existing visual elements from the images of regional architecture, which is much different from those qualitative methods depending on traditional culture and other subjective knowledge in architecture history and theory [15]. In sum, the contribution of this paper is fourfold.

(1) We propose to utilize Fast-R-CNN to extract the form feature of regional architecture and obtain a quantitative evaluation result. We construct a training dataset, known as the Chinese Ancient Architecture Image Dataset (CAAID), in which each image is labeled as having least one of three traditional and typical features such as 'High Pedestal', 'Deep Eave' and 'Elegant Gable'. The items of CAAID are fed into the Fast-R-CNN to train our neural network model.

(2) To reveal the traditional forms of regional architecture in Hubei, we built the Hubei Architectural Heritage Image Dataset (HAHID) as our object dataset, in which we collected architectural images from four different regions such as the southeast, northeast, southwest, and northwest of Hubei. The object dataset was fed into the Fast-R-CNN to identify the feature of architecture form. The obtained quantitative results showed that the recognized feature of architectural form based on Fast-R-CNN is consistent with that of the regional architectures in Hubei. Moreover, we can observe from the quantitative results that four geographic regions in Hubei show variation; for instance, the feature of the "elegant gable" in southeastern Hubei is more evident, while the "Deep Eave" in the northwest is more evident.

(3) We chose some images of new buildings that are located in Hubei and fed them into the Fast-R-CNN, and the output quantitative results can effectively identify the corresponding feature style of regional architectures in Hubei.

(4) This paper uses an object recognition model to process visual images, construct a sample set for machine learning, and then recognize a specific dataset and conduct a statistical analysis of the results. This research demonstrates the application of artificial intelligence in architectural heritage protection; based on computer vision technology to identify the architectural form features, we can evaluate whether the building conforms to the architectural style and architectural features we expect to get just by a building image or architectural design effect picture, in order to assess whether the new building design has the local architectural style features at the beginning of the architectural design and to promote the control of architectural style in urban renewal.

The paper is organized as follows: Section 2 provides a literature review including regional architectural form features and the application of machine learning techniques in the architectural area. Section 3 gives the detailed construction of the training dataset used in this paper and specific research methods. Section 4 states the quantitative results of the object dataset on the Fast-R-CNN. Section 5 discusses the results of this paper. Finally, a summary, recommendations, and future work are presented in Section 6.

2. Review of Literature

2.1. Feature of Regional Architectural Form

The concept of "morph" is widely used in the field of history, anthropology, and biology, while its subjective reflection in human consciousness is "form". In architectural design, the issue of form has unavoidably been a central problem, but it is a dizzying and confusing puzzle [21,22]. In a broad sense, the research aim of architectural form is to establish a human-oriented and sustainable view of architectural consciousness and elaborate on the relationship between humans and nature. In a narrow sense, the research object of architectural form is to investigate the spatial organization characterized by humans, architecture, society, technology, art, culture, and the environment, especially the natural environment [23,24].

When it comes to the architectural form of regional architecture, if we trace the origin of regionalism in the context of international-style modern architecture, the landscape gardening movement in England in the second half of the 18th century can be considered the beginning of regionalist architectural thinking. Modern regionalism was first active in the United States and Northern Europe in the early 20th century. Frank Lloyd Wright's Prairie Style, Taliesin West, and his organic architecture can be regarded as the pioneering inheritance of American regional architecture [25]. The Nordic influence is represented by the Finnish architect Alvar Aalto, combining the spirituality of modernism with the Finnish region and national sentiment to create a humanistic Finnish architecture [26]. In 1947, architectural theorist Lewis Mumford negated the international movement of the 1930s with the "Bay Area Architectural Form" in California, for example. At that time, the majority of regionalist architecture was located in Europe and their influence was limited.

After the 1950s, with the advancement of scientific technology, the development of modernist architecture reached its peak in Europe, but the indiscriminate and one-size-fits-all "modernist" style of architecture severed the cultural correlation between architecture and region, which urged architects of different regions and cultures to reach the climax in their exploration for regionalism. Jane Jacobs proposed that regional architecture should be diverse and include an appropriate proportion of older buildings [27]. Mario Botta created a unique and regional architectural language in Switzerland that is integrated into the local natural and social environment [28]. Based on the research of urban typology, Aldo Rossi (Italy) proposed a method to solve the historical succession of cities [8]. Indian architect Charles Correa proposed the concepts of "form following climate" and "open space" based on native culture and climate, combined with the technical and economic conditions of the region [29]. Japanese architect Tadao Ando created the Church of Light through a high abstraction of nature and the use of simple geometric forms in a Japanese "Zen" pursuit [30].

So far, many excellent architectural cases successfully expressed regional features and also many valuable studies on regional architecture and architectural form. However, few researchers utilize emerging digital methods to explore the feature of regional architecture form from the perspective of quantitative analysis. On one hand, the research of regional architecture has generally focused on conceptual, cultural, architectural design, and other architectural theoretical fields or specific case studies. For example, in terms of the concept of regional architecture, Abidin Kusno explored architectural regionalism in Southeast Asia in the 1980s [31]. Demessie Mekuria's research revealed the characteristics of the formation and development of the concept of architectural regionalism [32]. Stylianos Giamarelos adopted a long-term historical perspective to illustrate the emergence and significance of critical regionalism as the most celebrated moment in the history of twentieth-century modernism in Greek architecture [33]. As for regional culture, there exist various research perspectives. In terms of architectural design, some researchers examined how to reflect a local regional identity in modern commercial multi-functionality buildings and how to make a modern building to be regional in appearance, and there have also been some specific case studies on regional architecture in recent years [34]. In addition, Sanyam Bahga investigated the major architectural projects realized in India since 1947 that adhere to the ideology and principles of critical regionalism [35]. On the other hand, those studies on regional architecture or architectural form were mostly based on traditional qualitative methods [36]. For instance, the latest research explored the typology characteristics of the facade of colonial buildings in the Loji Wetan Area [37] and utilized social semiotics to study the relationship between the Gubang City Hall building and the surrounding social life context [38].

In summary, most current studies on the feature of the regional architectural form belong to the type of qualitative and case studies. Therefore, this paper seeks to use machine-learning technology to explore architectural form, which is only based on some existing visual elements of images from regional architecture, making it different from the previous qualitative studies that mostly depend on a priori historical knowledge and subjective summaries.

2.2. Machine Learning in Architectural Field

With the development and popularity of deep learning, some deep neural network models such as AlexNet, ZF-Net, and Deepval-Net have been successfully applied in the field of computer vision [39,40]. In 2006, a Professor at the University of Toronto, Geoffery Hinton, the "Godfather of Artificial Intelligence", and a few of his students published a paper in Science which first introduced the concept of deep learning. One of the main points of that paper can be summarized as follows: convolutional neural networks with multiple hidden layers have a very powerful feature learning capability; the trained models used for feature extraction have a more abstract and essential description for the original input data such that they can solve the problem of feature visualization or classification in a meaningful way [41,42]. As an extremely powerful image recognition tool, they were successfully used in many fields [43], such as aerial images [44], medical images [45], license plates and vehicle recognition [46], gait recognition [47], microbial classification [48], urban environment recognition [49], fruit recognition [50], etc.

Currently, in the field of architecture, image recognition is rarely applied to developing new methods in architectural research, but a few of the scholars have started to apply image recognition technology in architectural technology and architectural vision research [51,52]. In construction engineering, image recognition was widely used in predicting housing earthquake damage, engineering costs, urban density, and building volume ratio calculation. In architectural conservation, image recognition technology was used to automatically predict the age of buildings and automatically identify building defects [53,54].

As for architectural vision, the research is in the early stage. For example, the problem of image parsing in architectural scenes was addressed in order to analyze building areas on a more detailed level, such as determining the location of windows, doors, and roof lines, the color of walls, and the spatial extent of a particular piece of a building [55]. Yang et al. used a region classification method to classify building facades in natural images [56]. Shalunts et al. used a clustering method to classify the facade windows of different styles of buildings [57]. Mathias et al. proposed an algorithm to automatically classify architectural styles from building facade images [58]. Goel proposed a method to recognize salient features of architectural style categories in an unsupervised manner [59]. With the rapid development of the convolutional neural network (CNN), the research achievements of image recognition technology applied to architectural image classification have become increasingly plentiful, and also initially involved historic architectural heritage image classification research [39]. As for the architectural style, the convolutional neural network model not only can realize the classification of different styles of historical buildings but also classify modern buildings with high similarity in appearance [14,15]. Other researchers specifically discussed how to tackle the rich inter-class relationships between architectural styles in image classification tasks [60]. In addition, some researchers explored the limitation of different algorithmic models [51], solved the problem of lack of training samples [14], and investigated how to improve the efficiency and accuracy of algorithms [61,62], etc.

Architectural style classification faces numerous difficulties in feature extraction, such as finding different expressions in the same architectural style within the same architectural feature and, correspondingly, finding very similar expressions in the same architectural component without a different architectural style [40]. Furthermore, in conventional image recognition applications, the form features used to determine the style are learned entirely by the model itself, which has the advantage of reducing the influence caused by human subjectivity, but also leads to a reliance on high-quality datasets and requires a large number of images to train the model to capture the features [58,63]. Lastly, most of the current CNN models for image classification only studied the overall features of building facades or the distinction between various buildings, while none discuss how to extract the spatial features of different components of a single building [64], such as the roof on a building.

3. Materials and Methods

As mentioned before, the machine learning technique for image recognition is increasingly being successfully applied to architectural visualization. For instance, by training convolutional neural networks, the building age in an image could be automatically predicted, and the accuracy rate even exceeds that of human judgment [53].The main objective of this study is to apply image recognition techniques to find the presence or absence of an object feature in a building image as well as to output the location information and confidence coefficient of the object feature. The specific application of image recognition techniques to these tasks is also briefly described. This paper uses the object recognition model to detect the Hubei regional architecture images and obtain the results of the quantified form features of Hubei regional architecture. In this section, we used the image search engine of the Google platform to construct the Chinese Ancient Architecture Image Dataset (CAAID) and Hubei Architectural Heritage Image Dataset (HAHID) as the training dataset and object dataset, respectively.

3.1. Introduction of Object Area

Hubei Province is located in the center of Chinese geography, economy, and transportation, and is in the area of north-south climate transition. This unique geographical pattern makes "Chu" culture to be a convergence of characteristics from various directions. It has abundant natural resources and a well-connected transportation system, and the two major sources of Chinese civilization—the Yangtze River culture and the Central Plains culture intersect in this area. Over the years of formation and evolution, Hubei regional architecture has adopted various design strategies to adapt to the local climate and natural environment, thus gradually forming some specific regional styles. The long history and culture and the unique geographical environment create a variety of cultural landscapes in the province. More importantly, the province is also the location of many historical and cultural sites, and thousands of cultural relics, protection units, and historical and cultural style protection areas contain multiple types of cultural heritage, forming a unique historical and cultural style within the province. Therefore, this paper selects the Hubei region as the object to study the preservation and utilization of cultural heritage in the Hubei region.

Chinese regional architecture can be approximately divided into the following geographical subdivisions: northern architecture, which is included in the Central Plains Culture Circle, Qi-Lu Culture Circle, and the Northern Culture Circle; northwestern architecture, which is included in the Qin Culture Circle; central China architecture, which is included in the Chu Culture Circle; southwestern mountain architecture, which is included in the Ba-Shu-Dian Culture Circle; southern architecture, which is included in the Wu-Yue Culture Circle; and the Lingnan architecture, which is included in the Nan-Yue Culture Circle [65].

The object of this paper is the architecture of Central China, which belongs to the Chu culture circle. For the Hubei regional architecture, the geographical location of the thoroughfare relative to nine provinces and the long historical process cause its regional style to be formed by complex and variable influencing factors [66]. Therefore, it is more complicated to study the form features of Hubei regional architecture. As shown in Figure 1, the study area of this paper is roughly divided into four geographic divisions. The architectural heritage of these four geographical divisions is selected as the object of this paper.

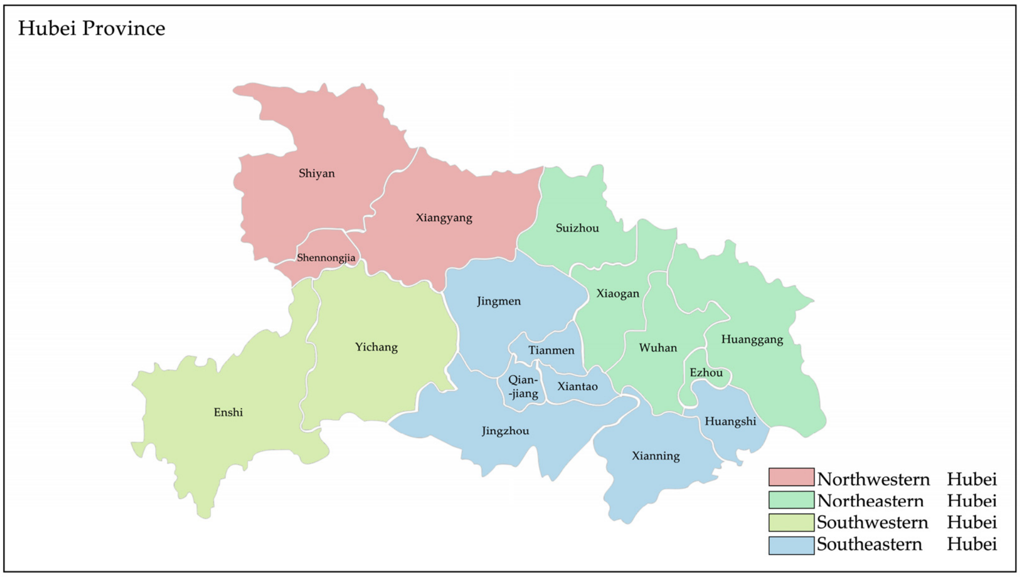


Figure 1. Location of the study area (http://datav.aliyun.com/portal/school/atlas/area_selector, accessed on 25 January 2023).

Table 1 lists the ancient Chinese buildings included in the four geographic divisions of Hubei, which are also the architectural heritage belonging to national or provincial key cultural relic protection units. A total of 96 architectural heritage sites are the main object of this paper. Considering the traditional regional culture of the Hubei region and the architectural regional features mainly formed in the Chu state during the pre-Qin period [67,68], the scope of "ancient Chinese architecture" here refers to the ancient ground buildings built and preserved in Hubei region after the Qin dynasty and before 1840.

Table 1. Hubei Regional Architectural Heritage.

Wuhan	Northeastern Hubei	Southeastern Hubei	Southwestern Hubei	Northwestern Hubei
Guiyuan Buddhist Temple	Xishui Confucian Temple	Jingzhou Confucian Temple	Wenchang Temple	Dacheng Hall (Yunyang, China)
Baotong Buddhist Temple	Yingcheng Confucian Temple	Taihui Buddhist Temple	Yuquan Temple	Ancient Building Complex in the Wudang Mountains
Gude Temple	Yunmeng Dacheng Hall	Kaiyuan Buddhist Temple	Huangling Temple	Mercury sets
Changchun Taoist Temple	Sizu Temple	Xuanmiao Buddhist Temple	Sanyuan Palace	Xiangfan Duobao Pagoda
Ancient Building Complex in the Mulan Mountains	Wuzu Temple	The Xianling Tomb of the Ming Dynasty	The Wang's Ancestral Hall (Yichang, China)	Longzhong Baoqi Pavilion
Yuji Palace	Sizhou Temple	Longevity Pagoda	the Yan's Ancestral Hall (Xianfeng County, China)	Longzhong Wuhou Temple
The Tomb of The King of The Ming Dynasty	Wushi Temple	Wenfeng Tower in Zhongxiang	Yuquan Temple and Iron Tower	Cheng'en Temple (Gucheng County, China)
Pagoda of Mt. Hongshan	Bharhut Pagoda	Chuanzhu Palace Theater	Yang Shoujing Farmhouse	Xiangfan Jiangxi Hall

Table 1. *Cont.*

Wuhan	Northeastern Hubei	Southeastern Hubei	Southwestern Hubei	Northwestern Hubei
Shengxiang Pagoda	Zhongsheng Pagoda	Lu, Fuzi Temple	Enshi Guanyu Temple	Xiangfan Shanxia Hall
Lute Platform	Baizi Tower	Xingwang Palace	Yichang Pangu Temple	Xiangfan Fuzhou Hall
Wenjin Academy	Denggong Tower	Jingzhou Ancient City	Lichuan Shilong Temple	Three temple (Gucheng County, China)
	Xudian Palace Theater	Yuanyou Palace	Rugao Academy	Sanlu Academy (Shennongjia Forestry District)
	Xiehe Palace Theater	Shaosima Memorial Archway	Dashuijing Lishi Temple	Shiyan Wuchang Hall
	Fuzhu Temple Palace Theater	Lantai Academy	Longshui Confucian Temple	Ancient city of Xiangyang
	Tung-po Chibi	Longquan Academy	Chen Man's Festival of Filial Piety	Shanshan Hall (Qiangang Village, China)
	Yuhuage Buddhist Stone Pillar	Baiyun Gate Tower	Naijiantianri Place	Furen City
	Ziweihou Temple	Wushi Temple	Shemihu Baishou Hall	
	Yuliang House	Liangshi Temple	Changyang Heshen Pavilion	
	Guanyin Pavilion	Li Shengshi Farmhouse	Laifeng Ox King Temple	
	Xianrentai Temple	Imperial Decree Memorial Archway	Jiangdu Temple	
	Jinling Academy	Mi Yingsheng Farmhouse	Shizhu Buddhist Temple	
	Wanniantai Scenic Area	Tangjarong Paihang House		
		Tanshi Temple		
		Tongshan Temple		

3.2. Data Collecting

The form features of the architectural style are mainly reflected in the facade appearance, space combination, color application, material selection, and interior environment of a building [37,69]. Among them, the determination of facade style is an important part of controlling the urban landscape and protecting cultural heritage buildings, especially for the facade renovation of cultural heritage buildings [70]. Therefore, this research mainly focuses on collecting the facade images of buildings to establish the dataset.

3.2.1. Construction of the Chinese Ancient Architecture Image Dataset (CAAID)

Considering that no image dataset is directly available for our study, we first need to build a Chinese ancient architecture image dataset that contains the architectural form features of the Chinese Hubei region. Generally, the most convenient way to obtain data is to access free resources on open platforms [39]. Therefore, we retrieved the ancient Chinese architectural facade images on the Internet open platform through the Google search engine. To enhance the relevance of image data to the architectural features of the Hubei region, we have collected as many images containing the architectural features of the Hubei region as possible through a keyword search. In particular, we searched images in Google Images with the keywords "high pedestal of Chinese ancient buildings", "deep eave of Chinese ancient buildings", and "elegant gable of Chinese ancient buildings" to collect the corresponding images of ancient building facades. Figure 2 shows the first search result in Google using the keywords "the high pedestal of Chinese architecture". For each keyword, approximately the first 1000 images were selected as feasible data. Through expert checking, the first 1000 images from the search mostly contain all of the states of the required keywords. Through an initial screening of the images, removing irrelevant images and duplicate images, we obtained 2345 valid images, plus 235 images taken by the authors of this paper; finally, we constructed a "Chinese Ancient Architecture Image Dataset" containing 2580 images.

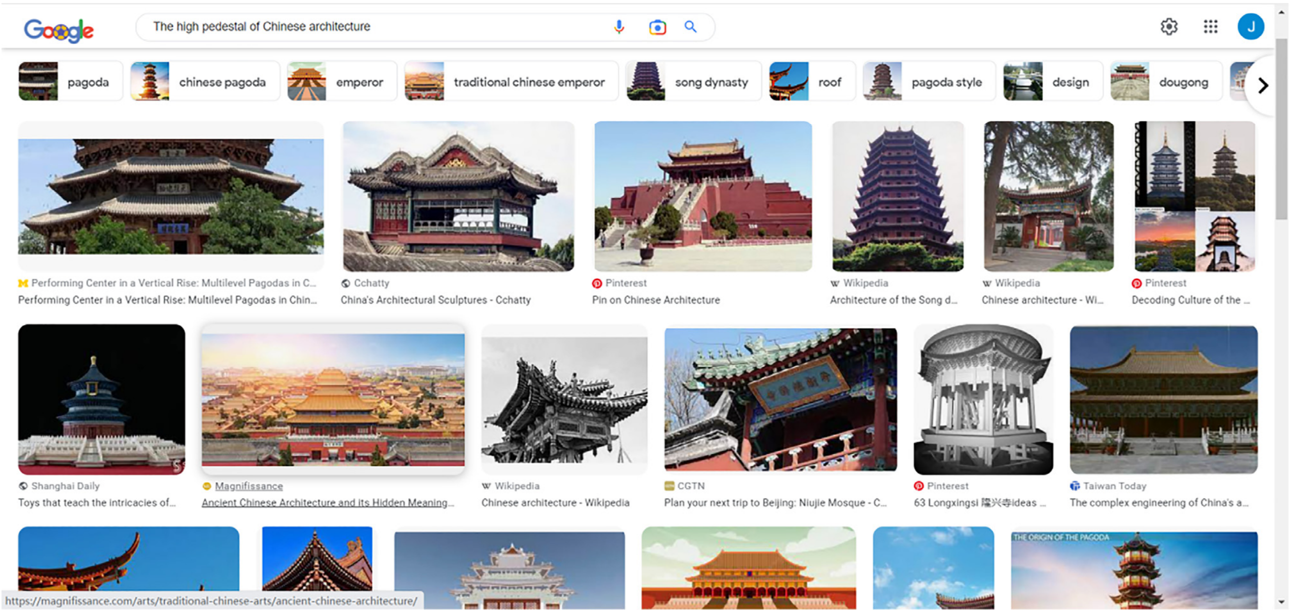


Figure 2. First search results for "the high pedestal of Chinese architecture".

3.2.2. Construction of the Hubei Architectural Heritage Image Dataset (HAHID)

To study the architectural form of architectural heritage in Hubei, we constructed a "Hubei Architectural Heritage Image Dataset", which is based on the existing ancient architectural heritage in Hubei, China. In the process of constructing this dataset, this architecture heritage is divided into four classes according to four geographic regions; that is, northeastern Hubei, southeastern Hubei, southwestern Hubei, and northwestern Hubei (Wuhan belongs to the northeastern Hubei region).

In Table 2, 33 types of architectural heritage are included in our dataset for the northeastern Hubei region (including Huanggang, Xiaogan, Suizhou, Wuhan, and Ezhou), 24 in the southeastern Hubei region (including Jingmen, Jingzhou, Qianjiang, Tianmen, Xiantao, Xianning, and Huangshi), 21 in the southwestern Hubei region (including Yichang and Enshi), and 18 in the northwestern Hubei region (including Shiyan, Shennongjia Forest Area and Xiangyang). To balance the number of images of each building in the dataset, we constructed this dataset according to the following principle, that is, the images of historical buildings were collected according to a certain proportion of the quantity. Taking the Guiyuan Buddhist Temple located in the Wuhan area as an example, we collected six images from its front facade and side facade, so that a total of 66 images of the architectural facade are collected for the 11 architectural heritage sites in the Wuhan area. As shown in Table 2, we built a "Hubei Architectural Heritage Image Dataset" which is composed of a total of 576 images.

Table 2. Hubei Architectural Heritage Image Dataset.

Geographic Division	Quantity of Architectural Heritages	Quantity of Images
Northwestern Hubei	18	108
Southwestern Hubei	21	126
Southeastern Hubei	24	144
Northeastern Hubei	33	198
In all	96	576

Some images of architecture heritage in this dataset are shown in Figure 3.

(a) (b)

Figure 3. Some images in the dataset of (**a**) Northeastern Hubei; (**b**) Northwestern Hubei.

3.2.3. Construction the Hubei Neo-Regionalism Architectural Image Dataset (HNAID)

New regionalism refers to the architecture forms synthesizing local, ethnic, or folkloric styles so that the specific style is reflected in the modern architecture of this region. Although Neo-regionalism is not equal to the antiquity and replication of regional traditional architecture, it is still a part of modern architecture which follows modern standards and demands in function and construction, but only partially absorbs traditional motives in the form [71]. Because of this, we established a Hubei Neo-regionalism Architectural Image Dataset and utilized machine-learning technology to scientifically and quantitatively evaluate whether those neo-regionalism architectures conform to the traditional architectural style of the Hubei region. In particular, this dataset includes buildings such as the Wuchang Railway Station, Hubei Museum, Hongshan Assembly Hall, and Jingzhou Railway Station.

To improve the efficiency of the machine-learning model, we collected images through the Internet according to the following principles: (1) In the screening process we only retained images containing the whole building elevation and removed images containing multiple building aerial images or images containing only partial building structures to ensure that the training of the machine-learning model focuses on the feature of building form rather than the pixel points containing the building or building components in a whole image. (2) In the construction process, we collect those images that contain buildings from different angles and scenes, i.e., front elevation, side elevation, overhead elevation, etc., and collect those images that contain different weather conditions, i.e., sunny, cloudy, etc. (3) We balanced the number gaps of each label [72].

3.3. Method

By extracting the features of architecture form through the machine-learning method, we can effectively eliminate the influence of subjective factors and reduce the bias of recognizing historical and characteristic information of buildings from different individuals. Moreover, the machine-learning method can process a huge amount of data repetitively, which is outside of human ability, and accurately classify target features which facilitate the human judgment of relevant information [73]. The deep learning method is able to extract the high-level features of buildings independently, learn the patterns of the data from a massive dataset, and effectively avoid inadequate descriptions of features from traditional statistical methods.

3.3.1. Research Design

In this section, we propose a machine-learning approach to extract the features of regional architectural forms in Hubei and evaluate architectural forms, which is different from previous methods based on subjective summaries of architectural history and theories [15], providing architects and historians with a new tool or possibility to verify some known theories and even discover new ones. The specific flow of our proposed method is shown in Figure 4. First, we initially summarized the traditional architectural form features of the Hubei region based on historical context and architectural theory. Second, two image datasets were established separately by collecting the open data from the Internet: the Chinese ancient architecture image dataset and the Hubei architectural heritage image dataset. Third, the Chinese ancient architecture image dataset is used as a training dataset for training our machine-learning model that can recognize the architectural form features of the Hubei region, and the Hubei architectural heritage image dataset is used as an object dataset to feed into our machine-learning model to obtain the quantitative recognition results of the features. Lastly, the model was also used to evaluate the new regional architectural form features and to evaluate whether the new buildings conform to the regional architectural style.

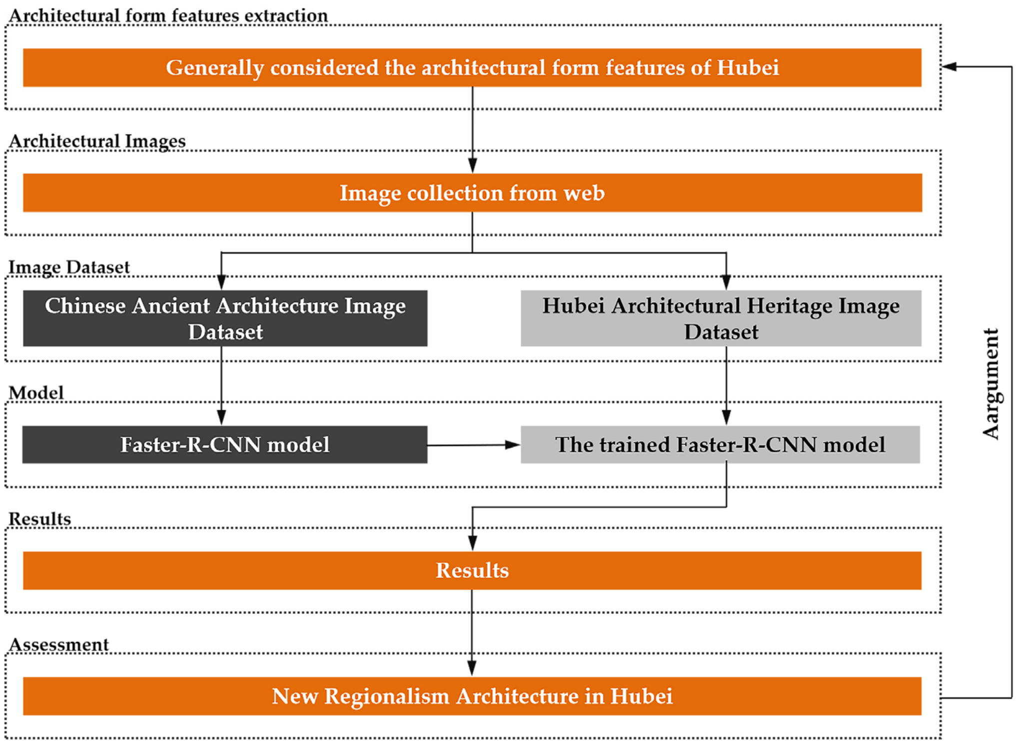


Figure 4. The flowchart of our proposed method.

3.3.2. Overview of the Hubei Regional Architectural Form Features

This paper adopts the classic book, *Cities and Architecture in the Chu Dynasty*, on the regional architecture in Hubei as a reference to extract architectural form features [67]. The architectural form features of the Hubei region discussed here specifically refer to the architectural form features created by the ancient Chinese Chu people in the area of modern Hubei, which are summarized into six classes as follows.

(1) Deep Eave

In ancient China, the roof used in the Hubei region, which is designed to withstand the local rainy and hot climate, formed a "deep eave" with a typical feature of a large roof, as shown in Figure 5. For the form of "deep eave", the elements, such as courtyard, overhanging gable roof, flush gable roof, gable, hip roof, etc., are the specific and concrete symbols to characterize "deep eave" [66].

Figure 5. Typical "deep eave" is illustrated in the box.

(2) High Pedestal

The architectural form of the "high pedestal", which is designed to withstand the humid and rainy climate of Hubei, which is known as the "province of a thousand lakes", is an essential regional feature that best reflects the features and craftsmanship of local architecture. It occupies an important position in Chinese architectural history. The high platform in the Chu Dynasty was used for various purposes such as observation of scenery, hunting, observing astronomical phenomena, hosting banquets, living, and as a military lookout. The high platforms of the buildings showed different styles and various architectural forms in different periods [74].

(3) Elegant Gable Wall

The form of the gable wall of the Hubei dwelling is unique, with a rounded and beautiful arc type, step-by-step ladder type, and various combination forms. The Chu people attach great significance to the aesthetic of curves in architectural activities, and the curved shape is dominated by the flowing and rhythmic sense, which is fully reflected in the gable wall of the building [66,74].

(4) Ingenious Construction

When dealing with complex structural problems, the Chu people were not only unconstrained by the norms, but also flexible and adaptable, and the subtlety of their construction was breathtaking. The skilled craftsmen created many exquisite architectural structures in Hubei traditional architecture, such as cantilevered beams, bracket sets, post and lintel construction, and column and tie construction [67,74].

(5) Quality Decoration

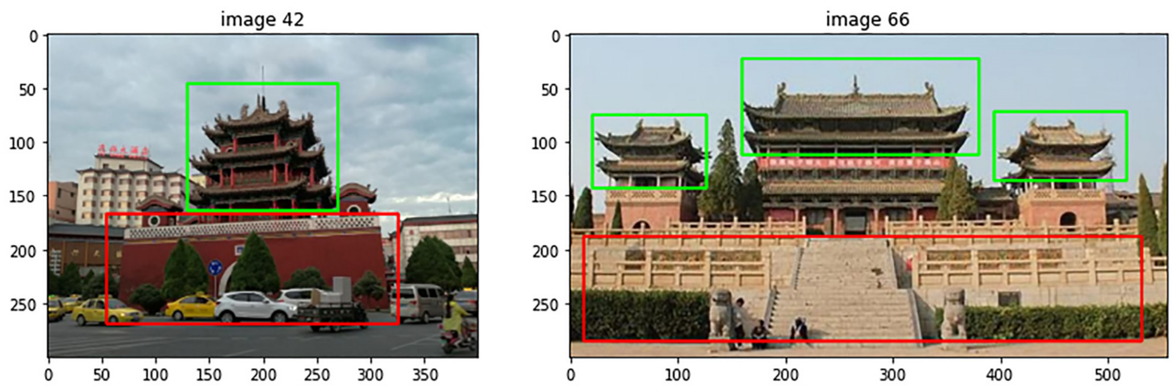
The historian Ban Gu wrote the "Han Dynasty-Records of Geography", which documented that the Chu region was fertile and vast, and since it was easier to survive, it was likely that more people would be freed from purely subsistence activities and put into more advanced and complex physical production. The architecture of the Jianghan region originally had a tradition of refinement. In primitive society, some humans used five different layers of soil, mud, and chalk on the indoor floor to prevent moisture, and the architecture of the Hubei region inherited this tradition of refinement [75].

(6) Red-Yellow-Black

From the description of "Chu Ci", it can be seen that most of the buildings in Chu are dominated by black and red. The Chu love for red originates from the ancient totem concept and the consciousness of ancestor worship. Red is the color of fire, symbolizing the south, which is the color of life and has a radical, romantic, and flamboyant effect. Black refers to the north, giving a stable and quiet feeling, and red and black have the intention of reconciling "yin" and "yang". With the strong contrast of red and black as the theme, in this tone and in addition to the local brown, bright yellow, diamond blue, pink, and green color combination, it forms a colorful, splendid, abundant color combination [66,76].

3.3.3. Processing of Dataset

Considering that the proposed machine-learning model is a supervised one, we know that the dataset should be labeled before use. "LabelImg" is an open-source data annotation tool and allows the labeling of files in three formats, in which labels are available for classification and object recognition [77]. Thus, we adopted the "LabelImg" tool to label the three forms "High Pedestal", "Deep Eave" and "Elegant Gable" for each item of the dataset. In particular, we mainly used the "VOC" tag format and saved it as an "XML" format file. The machine-learning model is trained to extract not only the features inside the "ground truth box" (Object boxes on manually labeled images) to learn localization and recognition, but also the features around them to learn other parts that do not feature objects. Therefore, the general principle of image labeling is that all the pixel points in an image meeting the labeling requirements should be included in the "ground truth box". Figure 6 shows some examples of the "ground truth box" output.



(a) (b)

Figure 6. Two examples of the "ground truth box" output: (**a**) An example of a "deep eave" (green box) and a "high pedestal" (red box); (**b**) Three examples of "deep eave" (green box) and one example of "high pedestal" (red box).

Second, although an imaging feeding to the convolutional layer can be of arbitrary size, to speed up the model training so that the size of the nine candidate boxes generated on the image can be better adapted to the size of the object, the image needs to be scaled down by the shortest side before being input to the model. In this paper, we reduced the shortest edge of all images to 300 pixels in size to speed up the training. Moreover, the model also needs to update the parameters based on small batches during training, i.e., inputting multiple images and then performing one gradient update. Even though the convolutional layer can input images of different sizes, the same batch of images must still be of the same size, and only then can the model update the parameters on that batch. In this paper, we used the method of zero padding, which means that we first calculate the maximum length and width of a batch of images as the size of this batch input and then expand all the images to this size, and zero padding is added in the blank places. The result of a batch of size 4 after expansion before input to the model is shown in Figure 7.

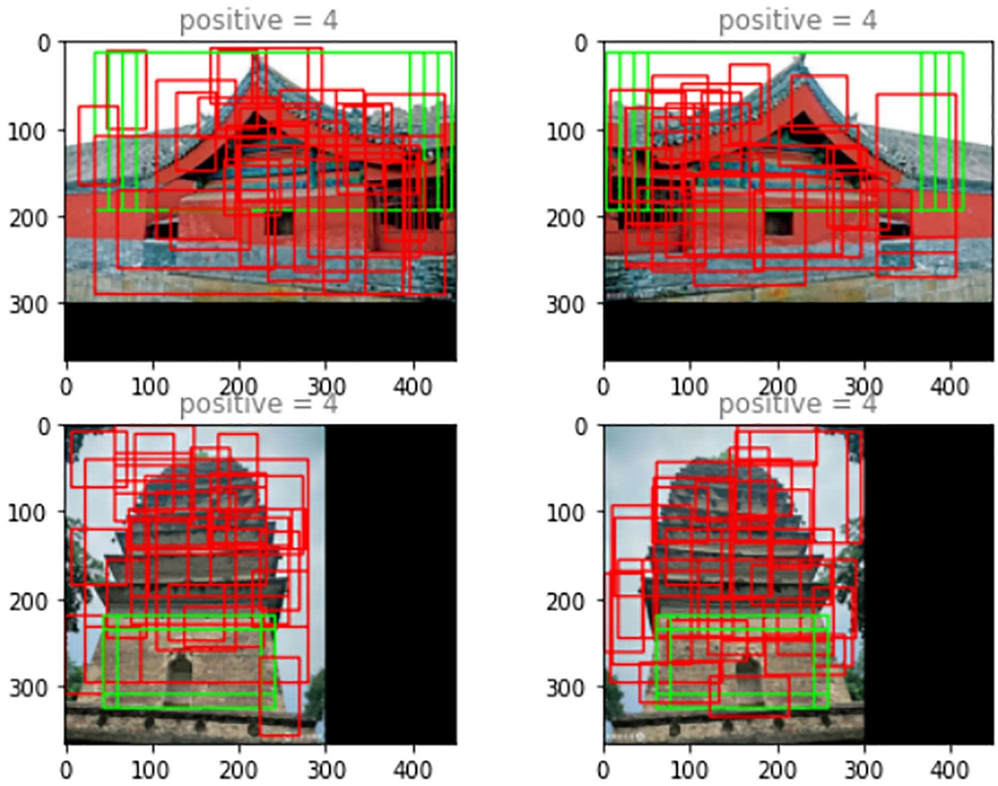


Figure 7. Image after expansion.

3.3.4. Training CNN Model

Convolutional neural networks are built to imitate biological visual perceptual mechanisms and are closely related to biological neural networks, which try to restore the way biological brains work by artificial design, acquiring knowledge from the external environment and interconnecting neurons to store the learned knowledge [17], with the main advantage of learning high-level features from low-level ones, while details unrelated to the target are ignored [40,78].

Object detection utilizes the learning of the annotated content in the image dataset by the computer to accurately detect the objects in the image based on different training labels, i.e., to extract the objects from the sequential images [79]. Since building form features are dependent on the visible image of the building and each feature has its uniqueness, they can be automatically detected and extracted by computer vision based on the building facade image and the local structure image.

Convolutional neural networks can be summarized into three main parts: the input layer, the hidden layer, and the output layer. They was simplified to work on the following principle: input the data to be trained in the input layer, complete the training of the training set in the hidden layer, and, finally, get the training results in the output layer. VGGNet and GoogLeNet both showed good performance in architectural style classification [80]. In this paper, we propose the use of VGGNet to extract the objective features, use the Chinese Ancient Architecture Image Dataset as the training set, and train the Faster-R-CNN model, thus obtaining the model for identifying the features of the Hubei regional architecture form. In this paper, the selected objective detection model is Faster-R-CNN [81], which is a two-stage algorithm. "Two-stage" means that the model first extracts all suggestion boxes in an image and then classifies the suggestion boxes. The main advantage of this model is a higher utilization efficiency of computational resources [77]. The model first extracts the image features by the convolutional neural network, generates all the candidate boxes containing the objectives by a Region Proposal Network (RPN) network and the position and size corrections of the candidate boxes, and these two parts are combined to become the proposed candidate boxes. The proposed candidate boxes are then classified using a neural network with several fully connected layers, and the proposed boxes are generated from the feature maps of the convolutional neural network by the pooling network layer.

Faster-R-CNN is a two-stage algorithm that generally needs to be trained separately. First, the RPN network needs to be trained to output high-quality region suggestions, and then the trained suggestion boxes are used as data to train the classification part to recognize the categories to which the suggestion boxes belong [81]. In the first part of training, it is necessary to train both the feature extraction network (VGG16 convolutional neural network) and the RPN network. However, the RPN network has two outputs, and the gradient update of the network parameters is performed using two loss functions respectively, which may cause the convolutional network not to converge easily. Therefore, this paper adopts a two-training method. The first training only uses the loss function of the one output from the RPN network to update the parameters, aiming to train the feature extraction ability of the convolutional neural network. The second training aims to train the proposed box classification and the correction regression ability of the RPN network based on the well-trained convolutional neural network.

(1) Training of RPN Network

The function of the RPN network is to extract candidate regions that contain the objectives from a large number of "anchor boxes", and these candidate regions are regression-adjusted. To train the RPN, each "anchor box" is assigned to the label of whether it contains the target or not, i.e., the label of positive and negative samples, and then trained.

Before training, we need to judge whether the candidate box is a positive sample (contains the objective), a negative sample (does not contain the objective), or a neutral sample (contains only part of the objective and does not participate in training) by the intersection over the union with the objective box. Assume the taking of −1, 0, and 1 as the values of positive samples, neutral samples, and negative samples to form a matrix, respectively. Furthermore, for the positive sample, the center coordinates and size corrections between this candidate box and the objective box are calculated to form another new matrix.

The loss function of the RPN network is written as follows.

$$L(p_i, t_i) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*). \tag{1}$$

where i is the index of the anchor; p_i is the probability that the i-th anchor will be predicted to be the objective; p_i* is the "ground truth box" label; t_i denotes the four parameterized prediction results of the positive sample anchor to the prediction region "bounding box"; and t_i* is the offset of the "ground truth box" corresponding to this positive sample anchor.

The predicted value is written as follows:

$$t_x = \frac{(x - x_a)}{w_a}, t_y = \frac{(y - y_a)}{h_a}, t_w = \log\frac{w}{w_a}, t_h = \log\frac{h}{h_a}. \tag{2}$$

The ground truth value is written as follows:

$$t_x^* = \frac{(x^* - x_a)}{w_a}, t_y^* = \frac{(y^* - y_a)}{h_a}, t_w^* = \log\frac{w^*}{w_a}, t_h^* = \log\frac{h^*}{h_a}. \tag{3}$$

where x, y, w, h denote the window center coordinates and the width and height dimensions of the window, and the variables x, x_a and x^* denote the coordinates of the "prediction box", "anchor box", and "ground truth box", respectively (y, w, h similarly).

(2) Training of Fast-R-CNN Network

In the training of Fast-R-CNN, the candidate regions with an intersection ratio greater than 0.5 in a "ground truth box" are set as positive samples, and the category objective value is the category of "ground truth box". The candidate regions with an intersection ratio less than 0.5 in a "ground truth box" are set as negative samples, and the category objective value is 0.

Each training candidate region is labeled with a classification target value "u" and a detection box regression target value "v". The background samples are denoted by "u = 0", For each labeled candidate region, a multi-task loss L is used to jointly train the classification and detection box regression as follows

$$L(p, u, t^u, v) = L_{cls}(p, u) + \lambda[u \geq 1]L_{loc}(t^u, v). \tag{4}$$

where $L_{cls}(.)$ denotes the cross-entropy loss; $L_{loc}(.)$ is the loss between the objective value and the "prediction box" of the quadruple; and the parameter λ is set to 1.

After two trainings, an example of the "prediction box" of the RPN network and the "prediction box" after non-maximum suppression is shown in Figure 8. It can be seen from the figure that after the correction, the "prediction box" is closer to the correct objective, and after non-maximum suppression, most of the redundant "prediction boxes" are eliminated, and only the optimal "prediction box" is left. The results are consistent with expectations at the beginning. Comparing the "prediction box" with the "ground truth box" can show that the model correctly identified the objective.

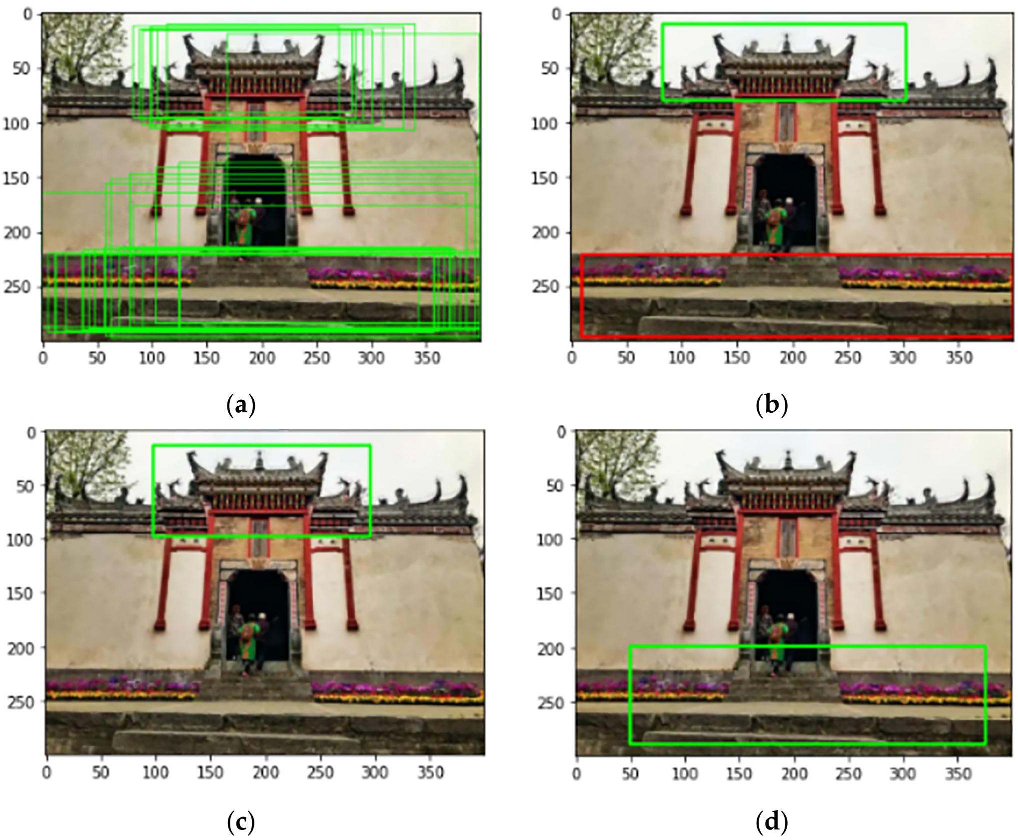


Figure 8. The "prediction box" of the RPN network after training and tuning: (**a**) All "prediction boxes"; (**b**) The "ground truth box"; (**c**) The "prediction box" 1 of the final output after non-extreme value suppression; (**d**) The "prediction box" 2 of the final output after non-extreme value suppression.

3.3.5. Sampling and Identifying Architectural Heritage Features in the Hubei Region

For the six features of the architectural heritage of the Hubei region, "deep eave", "high pedestal", "elegant gable", "ingenious construction", "quality decoration", and "red-yellow-black", these three features ("ingenious construction", "quality decoration" and "red-yellow-black") in an image cannot follow the principle of objective detection technology in labeling an image. Note that the principle is that all the pixel points in an image that meets the labeling requirements should be included in the “ground truth box” and the objective “ground truth box” of different images has the same standard completely. Two features (“ingenious construction” and “quality decoration”) are usually reflected in the space and structure of the building and cannot be fully reflected in the architectural facade image, so they cannot be correctly labeled manually. For “red-yellow-black”, this feature can be interpreted as the overall color of the Hubei region architecture, mainly being red, yellow, and black, which is not a spatial description of a certain component and cannot be labeled as a certain position on the architectural facade image. Therefore, this paper only focuses on three features of architectural form, i.e., “deep eave”, “high pedestal”, and “elegant gable”.

The identification process for the architectural heritage form features of the Hubei region can be broadly described as follows. In an image according to a certain step move to generate three fixed sizes and three sizes of “anchor boxes”, calculate the area intersection over the union of each “anchor box” and the labeled “ground truth box” according to which it can be determined whether the “anchor box” contains the labeled architectural form features, including whether it is a positive sample, does not contain that it is a negative sample, or the rest is a neutral sample. Whether it is a positive sample is used as the value, and the position of the “anchor box” in the image is used as the index to construct the “anchor box” matrix. We then use the “anchor box” matrix which corresponds to the dataset images as data to train the image recognition model and the RPN network classification part, the model outputs the image feature map and the network outputs the image “anchor box” matrix. Calculate the position and size corrections of each positive sample “anchor box” and the corresponding feature “ground truth box”, and use the position of the “anchor box” in the image as the index to construct the correction matrix. Using the correction matrix corresponding to the dataset images as data to train the regression part of the RPN network, the RPN network outputs the positive samples of the images as the correction matrix. Using the positive samples of the “anchor box” matrix, the positive samples of the “anchor box” are corrected by the corresponding correction amount in the correction matrix to generate the “prediction box”. Using the ROI Pooling layer, the feature map corresponding to the “prediction box” is generated based on the feature map of the image. The “ground truth box” is used as the suggestion box, and the corresponding feature map and architectural form feature category are used as data to train the fully connected neural network to output the prediction of the category to which the suggestion box belongs.

4. Results

In this section, we present the experimental results obtained by using the method proposed in this paper, i.e., the quantifying identification results of the architectural form features of the Hubei region using image recognition techniques. First, we are trying to capture the spatial features of the different components in the building elevation image, rather than focusing only on the overall features of the building or the overall style. Second, our research on the form features of Hubei regional architecture is based on geographic divisions, thus obtaining the differences in the performance of three form features of Hubei regional architecture in different geographic divisions within the study area, and finding that the architecture of the Hubei region has a clear convergence of architectural styles compared to that of its neighboring regions. In addition, we analyzed the experimental data based on building type as a statistical criterion and obtained the differences in the performance of the form features of Hubei regional architecture based on the classification criterion of building type. Last, this paper uses the trained model to identify two cases of new Hubei regional buildings and obtains the expected results.

4.1. Identification of Hubei Regional Architectural Form Features

In the object recognition task, besides finding the location of the object accurately, it is most important to identify which category the object is and label it with the corresponding confidence coefficient. The confidence coefficient is used to determine whether the object in the "bounding box" is a positive or negative sample. Those greater than the confidence coefficient threshold are judged as positive samples, and those less than the confidence coefficient threshold are judged as negative samples. Table 3 shows the results of object detection based on the self-built Hubei Architectural Heritage Image Dataset. Among them, the label "elegant gable" is labeled as a positive sample 230 times, including 46 times with a confidence coefficient ≥ 0.7, 61 times with a confidence coefficient ≥ 0.8, and 123 times with a confidence coefficient ≥ 0.9. The recognition results of the labels "high pedestal" and "deep eave" are also as positive as that of "elegant gable". It is sufficient to show that the ancient architecture of the Hubei region is indeed featured in three architectural forms: "elegant gable", "high pedestal" and "deep eave". On the other hand, the samples of the same building we collected when building the dataset tend to consist of its front and side elevations, however, for the feature of "elegant gable", the gable wall is defined as the horizontal facade at both sides of the building. Therefore, the "elegant gable" is not shown on the front facade of the building, i.e., not all of the 576 samples contain all of the objectives. In this case, the experimental results are far more satisfactory than what is seen.

Table 3. Identification Results of Hubei Regional Architectural Form Features.

Objective Feature	Training Sample	Confidence Coefficient $\geq$ 0.7	Confidence Coefficient $\geq$ 0.8	Confidence Coefficient $\geq$ 0.9	In All
"elegant gable"	576	46	61	123	230
"high pedestal"	576	43	51	142	236
"deep eave"	576	60	76	203	339

4.2. Identification of Architectural Form Feature by Geography and Building Type

4.2.1. Identification of Architectural Form Feature Based on 4 Geographical Divisions

Table 4 shows the identification results of four geographic divisions of the Hubei region and the number of positive sample results for the three regional architectural form features of the Hubei region, namely "elegant gable", "high pedestal" and "deep eave", are counted. For example, among the 108 valid images in northwestern Hubei, 172 "prediction boxes" are obtained and marked as positive samples, among which "elegant gable" is labeled as a positive sample 30 times, "high pedestal" is labeled as a positive sample 57 times, while "deep eave" is labeled as a positive sample 85 times.

Table 4. Identification results of architectural form feature based on four geographical divisions.

Geographical Division	Architectural Image	Total Positive Sample	"Elegant Gable" Positive Sample	"High Pedestal" Positive Sample	"Deep Eave" Positive Sample
Northwestern Hubei	108	172	30	57	85
Southwestern Hubei	126	163	51	40	72
Southeastern Hubei	144	193	91	48	54
Northeastern Hubei	198	277	58	91	128
In All	576	805	230	236	339

As shown in Figure 9, we can observe that the recognition rate of "deep eave" is higher in northwestern Hubei, at 78.7%, while the recognition rate of "elegant gable" is lower, at only 27.8%; the recognition rates of the three architectural form features in southwestern

Hubei are not very different, at 40.4%, 31.7%, and 57.1%, respectively, among which the recognition rate of "deep eaves" is the highest; the recognition rate of "elegant gable" in southeastern Hubei is higher, at 63.2%, while the recognition rates of "high pedestal" and "deep eave" are relatively lower, at 33.3% and 37.5%; the recognition rate of "deep eave" is also higher in northeastern Hubei, at 64.6%.

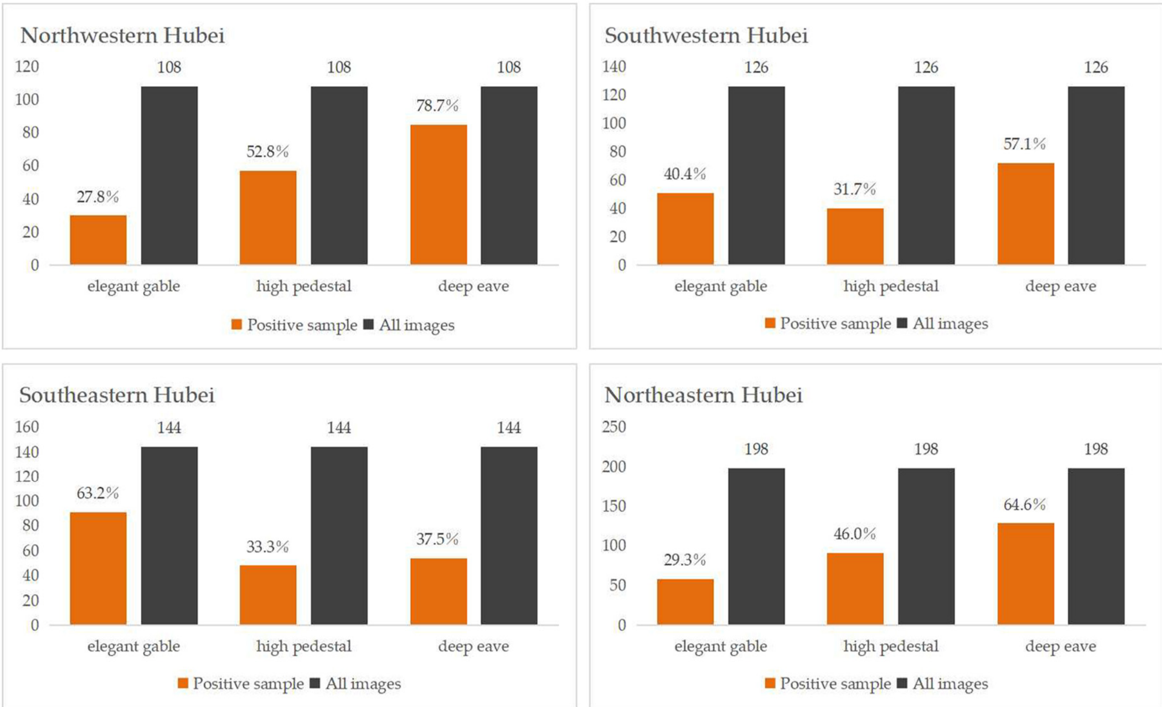


Figure 9. Identification results of architectural form feature based on four geographical divisions.

These results are traceable when viewed in the context of geographic location and climate characteristics. Northwestern Hubei is adjacent to southern Henan Province, so the architectural style has converged with that of southern Henan. While the southern Henan area has more rainfall and is mostly in the form of pitched roofs, and some halls are also made in the form of the double-hipped roof in the mezzanine part, the "deep eave" form feature is especially prominent in northwestern Hubei. Southeastern Hubei is adjacent to Anhui and Jiangxi, and the architectural style is close to the "Huizhou" style, so the form feature of the "elegant gable" is especially prominent. Northwestern Hubei and southwestern Hubei are adjacent to Chongqing and Sichuan, and the architectural style is close to eastern Sichuan architecture. The eastern Sichuan region is mountainous, and this folded terrain has a well-developed river network under the influence of a humid climate. Therefore, under the influence of the local weather, the eaves space becomes a semi-social occasion; whether it is for sheltering from the rain or for social gossip, these demands make the eaves a common choice for the design of residential buildings in the region. Based on this, the feature of "deep eave" is more prominent in both northwestern Hubei and southwestern Hubei, especially in the northwestern Hubei region, which is adjacent to the Henan region, which also has the climatic characteristic of heavy rainfall, reaching a 78.7% recognition rate for the feature "deep eave".

4.2.2. Identification of Architectural Form Feature Based on Building Type

The experimental data are analyzed according to the classification criterion of building type, and we obtain the results in Table 5.

Table 5. Identification results of architectural form feature based on building type.

Building Type	Architectural Image	Total Positive Sample	"Elegant Gable" Positive Sample	"High Pedestal" Positive Sample	"Deep Eave" Positive Sample
Confucian temple	48	74	10	26	38
Religious building	192	276	63	89	124
Mausoleum	12	25	1	12	12
Memorial temple	42	64	39	6	19
Tower	60	27	0	21	6
Academy of classical learning	36	48	16	7	25
Guildhall	30	42	15	5	22
Pailoo	36	45	14	4	27
Opera tower	30	52	9	13	30
City building	30	58	3	30	25
Former residences of celebrities	60	94	60	23	11
In all	576	805	230	236	339

From a longitudinal perspective, all buildings, except for those belonging to the "Former residences of celebrities" and "Tower" categories, have the highest recognition rate for the "deep eave" feature.

As shown in Figure 10, we can observe that both "Confucian temple" and "Religious building" rank first with 79.2% and 64.6% for "deep eave", respectively. This is because the Buddhist temple architecture in the Hubei region is between the north and the south, with the features of north-south integration of ancient architecture, and its roof style is inclined and the roof corners rise very high, the curvature of the roof is larger, and most of the hipped roof is flush with the gable roof. The recognition rate of "high pedestal" and "deep eave" of "mausoleum" buildings is 100%, but the recognition rate of "elegant gable" is 0%, which is due to the visual effect of the two existing mausoleum buildings in the Hubei region, the Fangcheng Minglou of the Mingxian mausoleum, and the Hanbaiyu stone steps and gable-end hip roof of the Chu King mausoleum, both of which have "high pedestal" and "deep eave" as the main visual features (Figure 11). The recognition rate of the feature "elegant gable" in the "Memorial temple" category was the highest, at 92.9%. The recognition rate of all three features of the "Tower" is low, at 0%, 35%, and 10%, because the "Tower" is a towering point building with a specific form and style (Figure 12), so building elements such as eaves, pedestals, and walls do not exist on the "Tower". The recognition rates of "Academy of classical learning" and "Guildhall" are similar in all three architectural form features, 44.4% and 50% for "elegant gable", 19.4% and 16.7% for "high pedestal", and 69.4% and 73.3% for "deep eave". This is because the architectural expressions of the academy of classical learning and the guildhall are roughly the same, with the main building being a flush gable roof building; only the guildhall demonstrates more exquisite architectural craftsmanship than the academy of classical learning due to its commercial character. The recognition rate of "deep eave" in the "Pailoo" category is the first of the three form features, at 75%. This is because "Pailoo" is similar to a memorial archway in that it is a door-shaped structure with columns, but unlike a memorial archway, "Pailoo" has a roof, and since the role of "Pailoo" is to recognize, commemorate, decorate, symbolize and guide, the roof is usually grand and magnificent. The recognition rate of "high pedestal" and "deep eave" in "City building" is as high as 100% and 83.3%, which is because the form city building is built on a gatehouse on the city wall for the main function of city military defense.

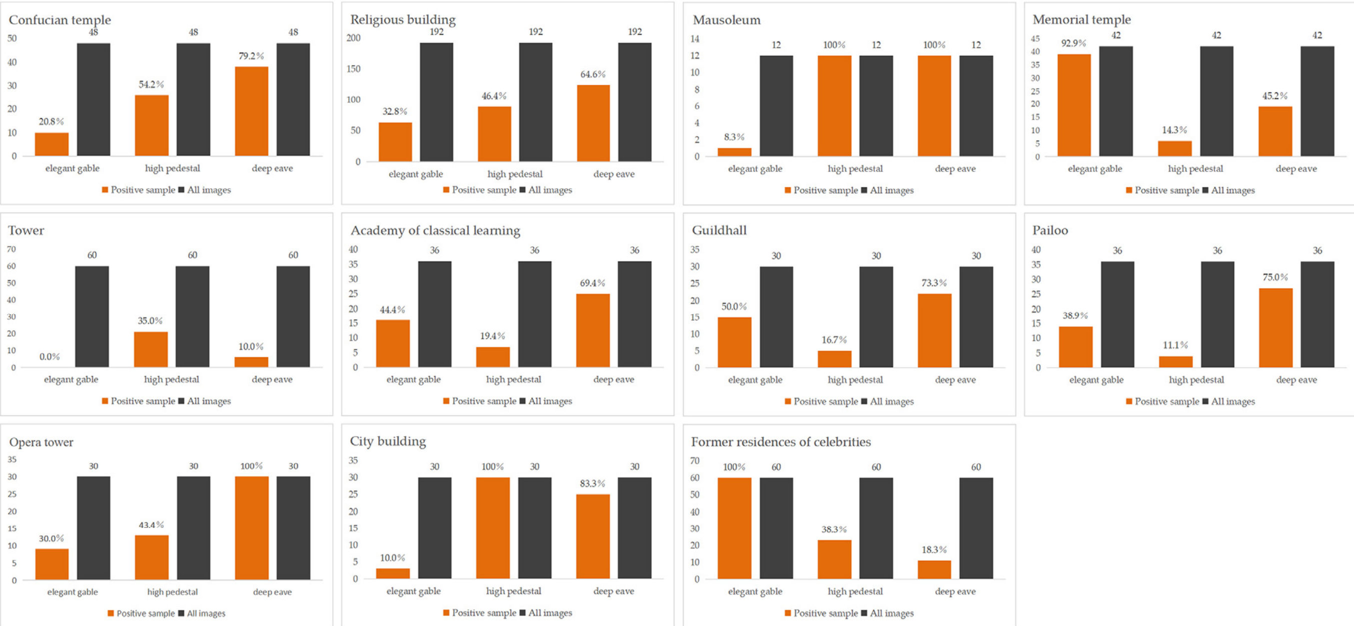


Figure 10. Identification results of architectural form feature based on building type.

(**a**)

(**b**)

Figure 11. Mausoleum type buildings: (**a**) The Tomb of The King of The Ming Dynasty; (**b**) The Xianling Tomb of the Ming Dynasty.

(**a**)

(**b**)

(**c**)

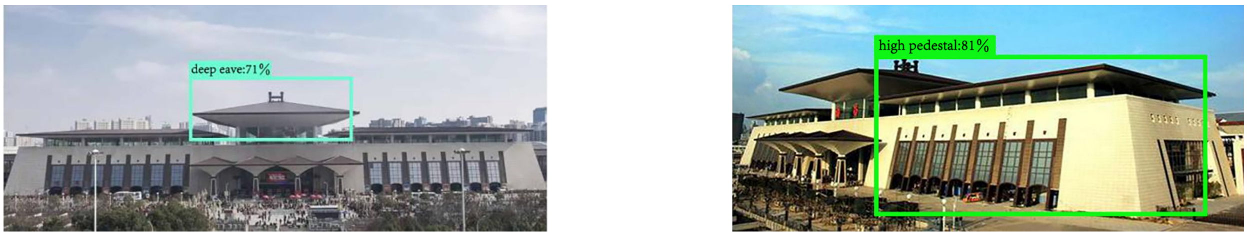
Figure 12. Tower buildings: (**a**) Yuquan Temple and Iron Tower; (**b**) Bharhut Pagoda; (**c**) Pagoda of Mt. Hongshan.

4.3. Identification of New Regionalism New Built Architecture

4.3.1. Wuchang Railway Station

The new Wuchang Railway Station abstractly uses the unique architectural forms of Hubei regional architecture such as axial symmetry, high pedestal, and deep eave. The large pitched roof above the main building of Wuchang Railway Station restores the architectural form of Hubei regional architecture with deep eaves in terms of "form" and highlights the lightness of Chu architecture in terms of "sense". The pattern of the carillon texture on the exterior wall of the building, the Chu decoration style of the interior space, and the carillon pattern on the entrance square pavement all highlight the cultural legacy. To sum up, Wuchang Railway Station is a well-designed and constructed building, known as the "Gate of Chu Culture", and is a very good example of newly built Hubei regional architecture [82].

As shown in Figure 13, we can see that the model correctly labels the feature of "deep eave", but the confidence coefficient is only 0.71. We can interpret that the data set we used in training the model are all ancient Chinese buildings, whose materials and colors are different from those of modern buildings. The model learns not only the spatial form of architectural features, but also the materials and textures of these features. Secondly, the model did not succeed in identifying the feature "high pedestal" in the front elevation of the building, and it only outputs the roughly accurate position in the image of another angle with a confidence coefficient of 0.73. In comparison, there is a large discrepancy between the identification of the "high pedestal" and "deep eave" architectural form features. For this result, we can interpret that the models tend to learn the form of the building features more in the figurative form and the relative spatial position of the label in the image, and the abstract representation of the form feature of the "high pedestal" in Wuchang Railway Station is not well recognized by the models.



(**a**) (**b**)

Figure 13. Quantitative recognition results of Wuchang Railway Station: (**a**) Results of "deep eave"; (**b**) Results of "high pedestal".

4.3.2. Hubei Museum

Hubei Museum is a typical antique-style Hubei regional architecture, and the overall architectural style highlights the multi-layer "deep eave", large pitched roofs and "high pedestal" and other architectural form features. The whole building is natural and harmonious, with the aesthetic sense of multi-layer, and from the form to the sense, it reminds one of the architectural forms of "multi tiers and pavilions" in the Chu Dynasty.

As shown in Figure 14, we can see that the model can correctly identify the two architectural form features of the "deep eave" and "high pedestal" in the Hubei Museum, and the confidence coefficient also reaches 95% and 0.81%, which is an ideal positive sample result. For this result, we can determine that the building itself belongs to the antique style and that it was designed to retain the "deep eave" and "high pedestal", which are two regional architectural form features of Hubei.

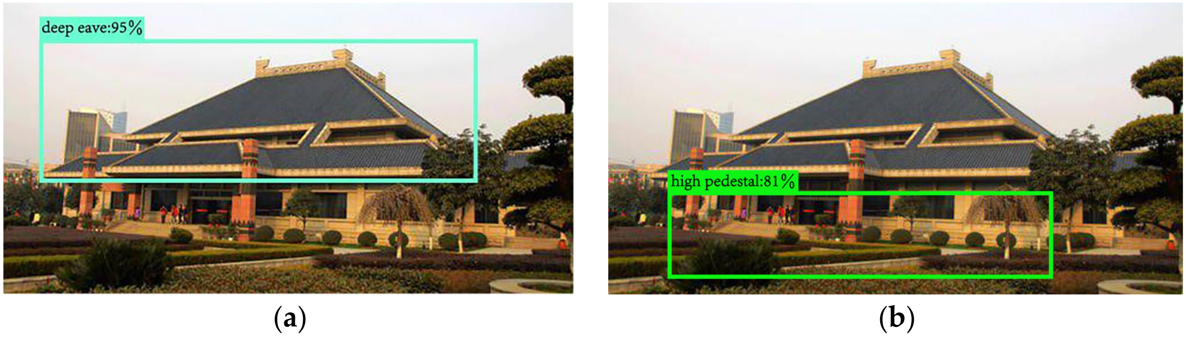


Figure 14. Quantitative recognition results of Hubei Museum: (**a**) Results of "deep eave"; (**b**) Results of "high pedestal".

5. Discussion

This paper explores the theory, methodology, and implementation process of utilizing image recognition technology as a tool for the research of Hubei regional architecture. Our results provide an alternative view to traditional architectural style research—using the results of the machine-learning analysis as a complementary and quantitative representation of the architectural history and theory-based findings. Although it is not a substitute for traditional research on the extraction of architectural form features, we show that our proposed method is not only a complementary illustration of traditional theoretical research but can also discover unknown aspects of traditional research. After compiling and analyzing the research data, we found the following contributions of image recognition technology applied to the architectural form feature research.

We constructed a method to quantify architectural features based on image recognition technology and summarized the traditional architectural features of the Hubei region. We built a Hubei Architectural Heritage Image Dataset and using the trained image recognition model, which correctly recognized the "high pedestal", "deep eave" and "elegant gable" of Hubei architecture.

This paper uses image recognition technology, which not only recognizes and labels the specific location of the object features in an image, but also outputs the computer's confidence coefficient for that feature. It can be determined that the image contains the objective features, and the possibility that it is indeed this feature suggests the confidence coefficient score. This transforms the definition of architectural form features into a degree of performance model, which is impossible via human definition.

Using the visual information quantification ability of the image recognition technology, we summarized the architectural form features of the Hubei region from a new perspective. We subdivided Hubei into four geographic regions and found that although Hubei's regional buildings have the same features of architectural form, their performance varies greatly in the four geographic regions. We classified the architectural heritage in the dataset by building type and found that the expression of these architectural form features also differed. All of these are good complements to the research of traditional architectural styles in the Hubei region.

Our findings, which are mostly consistent with the traditional descriptions of architectural historians and theorists, illustrate both the scientific validity of our method and the fact that this method can also provide architects and historians with new tools to verify known theories and even discover new ones. In the theoretical sense, we constructed a method for the quantitative recognition of architectural form features, while summarizing the traditional architectural form features of the Hubei region. In the practical sense, this study can be used as a tool not only to extract regional architectural form features, which are conducive to the conservation and utilization of architectural heritage, but also to evaluate whether new buildings fit the regional architectural style to facilitate the control of architectural style in urban renewal.

While this method provides definite value and novel perspectives for current research, it also has some limitations. First, due to the limited extent of architectural heritage in the study area, our sample size was limited, and although we tried to collect all of the existing buildings that meet the requirements to build the image dataset, the total number was only 96 historic buildings. This may have led to potential bias in the analysis. Second, some architectural features are abstract generalizations of the overall form of the building. For example, the feature of “red-yellow-black” of Hubei regional architecture refers to the preference of Hubei regional architecture using the three colors of red, yellow, and black, which is a regular summary of architectural color performance and cannot be labeled as a specific spatial location of the building, so the objective recognition method is not applicable in such features. Last, the accuracy of the model is still limited, which can be improved in the future by improving the model further and increasing the hardware computing capability.

6. Conclusions

The design of architectural forms in the present day is a complex procedure that combines elements of art, technology, science, and philosophy. In addition, the visual elements of the architectural form are vital for communicating the performance’s complexity. Any research on the architectural design must consider the socioeconomic-cultural trends that influenced the applied appearance, form, and technology [83]. This is because the architectural style should be viewed as a copy of the “archetype.” The application of image recognition technology in architecture and urban planning can help us obtain a greater understanding of this architectural “archetype” and provide original insights from a variety of new perspectives. Even though the findings of this research are preliminary, they provide a novel strategy that is both productive and efficient for studying the architectural form feature. It is frequently challenging for researchers to separate visual features from a priori knowledge, historical context, and personal imagination. This was crucial information that was unknown prior to the completion of this research.

In addition, this method applies to the study of morphological features of other types of buildings, such as in urban renewal work to identify the architectural morphological features of new buildings based on images or architectural model renderings, and to determine whether the architectural style meets the design expectations. Chongqing University professors have employed image recognition technology and online graphics to examine and analyze urban intentions at the level of urban planning. The identification method of architectural morphological features based on image recognition developed in this research can also be integrated with the network streetscape to examine the effect of new regionalism architecture on urban regeneration and an urban landscape at the city level. In conclusion, the application of image recognition technology to the study of architectural morphological traits can not only contribute significantly to the research and preservation of historical buildings, but also play a significant role in architectural design and urban planning.

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