Pattern Recognition in Islamic Architecture: Machine Learning Perspective

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Abstract: *The aim of this research is to evaluate the efficiency of the Machine Learning (ML) models and Deep Learning (DL) models for automatic identification of basic elements of the architectural world of Islam. The study is carried out on limited Islamic architecture images of 2000 images, covering five different classes (common features) of architecture. The study is done on a set of selected 2,000 images from various categories of prevalent features found in Islamic architecture. Works attentive to the various feature extraction approaches such handcrafted methods as, Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP) to automated feature learning using Convolutional Neural Networks (CNNs) are compared. Both Support Vector Machines (SVM) and Random Forest (RF) models and different CNN models, namely EfficientNetB0, were trained and tested following standard pre-processing (grayscale conversion, resizing to 64×64 coordinates, and augmentation). The results clearly show that DL models outperform the best traditional model (SVM with a Radial Basis Function (RBF) kernel) with 85% accuracy as best, surpassing the 83% accuracy level attained by the other traditional models. The results also illustrate the significant performance improvement provided by DL models, and they have managed to improve their accuracy by 12 points compared with the best traditional model (SVM with an RBF kernel, achieving 85%). In the Islamic architecture domain, which has less previous ML application, the novelty of this study is the specific evaluation of classical and DL methods for the classification of Islamic architecture elements. The results validate the efficacy of CNNs for automatically learning discriminative features, laying important groundwork related to architectural heritage classification and paving the way for future studies.*

Keywords: *Islamic architecture, deep learning, machine learning classifiers, HOG, LBP, CNNs, image classification.*

Received November 09,2025; accepted January 02, 2026
https://doi.org/10.34028/iajit/23/5/5

1. Introduction

Islamic architecture is noted for its cultural, historical, and aesthetic importance and reflects the artistic and spiritual achievements of the Muslim civilizations throughout the centuries. Elaborate geometric patterns, intricate arabesques, profuse calligraphy, majestic domes, and distinctive structural elements such as arches, minarets, and muqarnas characterize it. Islamic architecture, with its intricate craftsmanship, reflects the idiosyncratic values, beliefs, and identities of societies across various time periods and geographies, from Egypt to Morocco to India [2, 3]. While the architectural forms themselves are not aesthetically neutral, they represent cultural and spiritual symbolism that spans countless years through adaptation and innovation [1]. Mounted on the western wall of the mosque court are the mihrab, mashrabiyas, and muqarnas, elements of Islamic architecture with symbolic and functional relationships to these structures, and they are the synthesis of art, mathematics, and spirituality. However, Omer [18] and Rabbat [20, 21] have emphasized that form, function, and meaning are intricately intertwined in Islamic architectural design.

Baydoun *et al*. [6], Khan *et al*. [12], and Ummah *et al*. [27] have examined this complexity in detail, showing how it is encoded in the geometric and calligraphic motifs that adorn mosques, palaces, and other edifices. Despite the cultural significance of Islamic architecture, manual classification of architectural elements is time-consuming, subjective, and lacks scalability. This creates challenges for digital preservation, architectural education, and large-scale heritage documentation projects. The arches, mihrabs, and muqarnas of Islamic architecture differ from one another in ways that are visually complex and often subtle, so identifying them has traditionally depended on expert judgment. That approach does not scale to the large datasets that comprehensive digital archiving demands. Automated computational methods are therefore needed to identify and categorize these architectural components reliably, so that this heritage can be documented and conserved. Saeid *et al*. [22] applied classical image processing to shape and pattern recognition, and Güzelci *et al*. [9] used Machine Learning (ML) to model architectural heritage; more recent work has moved to Deep Learning (DL).

As Hussain *et al*. [11] and Aoulalay *et al*. [5] show, ML offers a repeatable, quantifiable alternative to manual analysis, which is slow, error-prone, and dependent on individual interpretation. Micklewright [15] makes a parallel argument for digital methods in architectural history.

Sukkar *et al*. [26] and Bölek *et al*. [7] document the rapid uptake of DL in architectural research, while Li and Wang [13] and Ananth and Gangashetty [4] show that Convolutional Neural Networks (CNNs) learn image features automatically and improve the classification of complex visual content. Through this, we have used modern computational methods, to classify the essential components of Islamic architecture, contributing to architectural research and heritage conservation.

In this study, ML and DL models are investigated for discriminating fundamental elements of Islamic architecture with various feature extraction approaches such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), CNN. This study's dataset comprises images of different architectural elements that are significant in the Islamic architecture such as arches, mihrab, mashrabiya, minaret and muqarnas, identified by Petruccioli and Pirani [19] and Shafiq [24] as characteristic elements of Islamic architecture. These include gradient orientation quantification, automated learning using CNNs, and texture pattern characterization, which all help extract the fine details that are crucial for the correct classification of the many forms and motifs of Islamic buildings. In addition to DL models like CNNs [7, 26] some traditional ML classifiers are used as models [23]: Support Vector Machine (SVM), decision tree, Random Forest (RF), gradient boosting, K-Nearest Neighbors (KNN), naive bayes and SVM with Radial Basis Function (RBF) kernel.

Aoulalay *et al*. [5] classified Islamic geometric patterns using SVM and RF classifiers built on texture descriptors, Mahmudnejad *et al*. [14] clustered Ilkhanid ornamental geometry, and Sukkar *et al*. [26] examined CNN-based approaches within Islamic architecture. Taken together, these studies establish that ML and DL can recognise architectural patterns reliably. This work extends their methods by comparing a broader set of models to decide which of the models is best suited to the classification of complex Islamic architectural elements. The analysis of the architectural data using computational techniques can uncover patterns that cannot be perceived visually, trace the stylistic influences in the region and the time, and aid in the digital preservation of the architecture. These tools provide the researcher a better understanding of the fine workmanship of Islamic architecture and a practical tool to enable preservation of Islamic architecture.

The primary contributions of this work are summarized as follows:

- We present the first systematic comparative study of a broad range of ML and DL methodologies applied to the classification of fundamental Islamic architectural elements.
- We introduce a new, curated dataset built for this classification task, covering five prevalent architectural elements: arches, mihrabs, mashrabiyas, minarets, and muqarnas.
- We evaluate 11 computational models, spanning traditional classifiers and modern CNN architectures, against multiple performance metrics to determine the most effective approach.
- We analyse the performance of different feature extraction techniques (HOG, LBP, and automated CNN features) to identify which visual characteristics are most discriminative for these elements.

In summary, this paper examines Islamic architectural elements through the lens of ML and DL. Through systematic experimentation with a diverse set of classifiers, we propose a framework for the automated classification of architectural imagery. The results are relevant to architectural heritage conservation, digital humanities, and education, and they contribute to the documentation and archiving of the architectural traditions of the Islamic world.

2. Related Work

Interpretation of the features and meanings that each of the elements of Islamic architectural heritage conveys has been the focus of research for years. The ways of this work have evolved over time, and each stage has brought its own strengths and limitations.

2.1. Art Historical and Manual Analysis

The earliest was in art history, where careful visual examination and expert classification were used to determine stylistic sequences and chronology [6]. Elements like domes, arches and calligraphy were given spiritual and cultural meaning by scholars like Omer [18] and Rabbat [20, 21]. This type of analysis yields careful and profound readings, but is subjective, poorly scalable, and requires expertise and considerable time. It cannot cope with the large digitized corpora of architectural data now available.

2.2. The Shift to Computational and Machine Learning Methods

Manual analysis techniques were reaching their limits, and computational methods were emerging in the field. Basic image processing, including edge detection for shape and pattern recognition [22] and the introduction of digital tools into the architectural history field [15] were some of the early applications, followed by ML. In the field of studies, clustering has been applied to the analysis of Ilkhanid geometric patterns [14] and to create predictive models, such as Pix2Pix-type approaches, for recovering missing parts of historical monuments [9]. Aoulalay *et al*. [5] showed the usefulness of texture analysis and feature extraction techniques (such as the Gabor filter and Gray-Level Co-occurrence Matrix (GLCM)) for the classification of geometric patterns. These techniques allowed tasks which were once manually performed to be automated and analysis was able to be conducted at a larger scale and quantitative level.

2.3. The Emergence of Deep Learning and AI

In recent years, DL has made its way into this domain, as well as a growing inter-disciplinary focus on Artificial Intelligence in Islamic Architecture (AIIA) [26]. CNNs extract features directly from the images as opposed to hand-crafted features like HOG and LBP. Bölek *et al*. [7], in their systematic review, document the growing role of AI across architectural practice, and Cantemir and Kandemir [8] determined building style using convolutional networks. Aoulalay *et al*. [5] used RF and SVM classifiers to classify Islamic geometric patterns and reported the strongest results using CNN-based transfer-learning features with SVM. Natesan *et al*. [17] applied neural style transfer to architectural imagery, and Han *et al*. [10] assembled a dedicated dataset for classifying the architectural styles of Chinese traditional settlements.

2.4. Identified Research Gap and Proposed Approach

Despite this progress, a gap remains. Many computational studies address a single narrow task, such as pattern classification [5, 14] or element restoration [9]. No comparative framework yet evaluates a diverse set of ML and DL models on a unified task of elemental classification in Islamic architecture. In addition, DL models are rarely benchmarked directly against strong traditional classifiers (e.g., SVM, RF) using well-established handcrafted features (e.g., HOG, LBP) within the same study, so the actual marginal benefit of deep architectures for this kind of classification is hard to judge. This study addresses that gap by systematically evaluating multiple algorithmic approaches. We propose a unified framework that integrates and compares:

- Traditional ML models (SVM, decision tree, RF, gradient boosting) powered by robust feature extraction methods (HOG, LBP).
- End-to-end DL models (CNNs) capable of automated feature learning.

By benchmarking these approaches for the classification of key Islamic architectural elements, this work seeks to identify the most effective and efficient methodologies. This comparative analysis not only provides a robust, automated tool for scalable architectural analysis and cultural heritage preservation but also offers critical insights into the conditions under which different computational paradigms are most advantageous for the study of Islamic architectural heritage. The overall framework of the proposed comparative approach is illustrated in Figure 1.

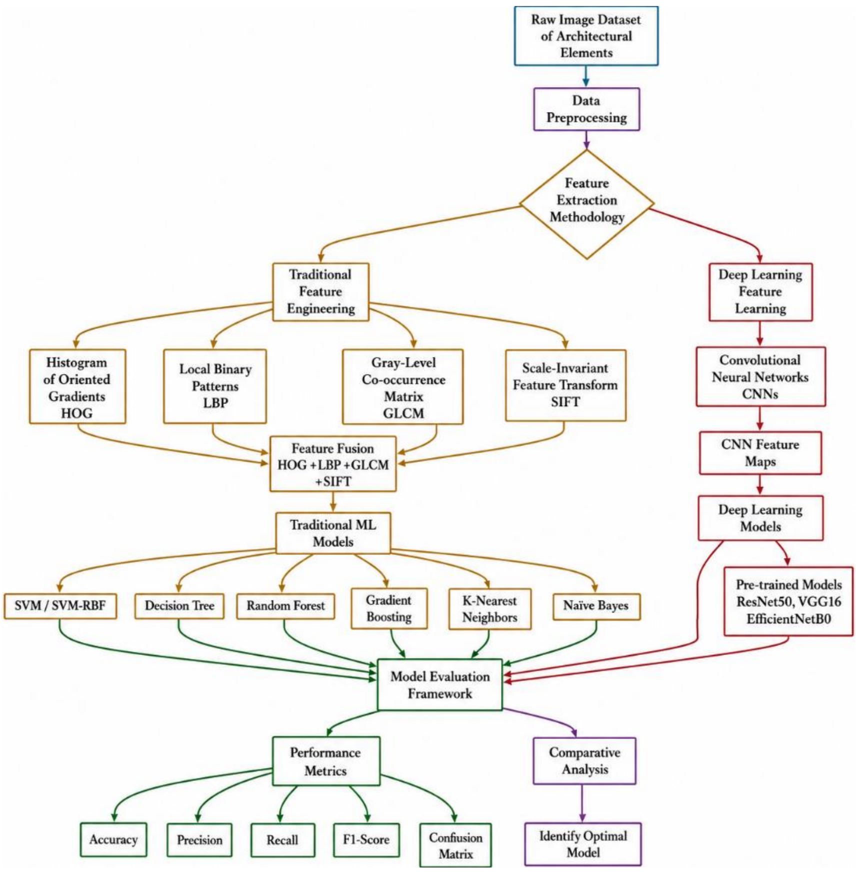

Figure 1. Research methodology flowchart illustrating the comparative framework between traditional ML and DL approaches for classifying Islamic architectural elements.

3. Methodology

For this study, the proposed methodology involves acquiring a dataset, preprocessing, feature extraction, model training, and evaluation. As illustrated in Figure 1, the proposed methodology involves dataset acquisition, preprocessing, feature extraction, model training, and evaluation. The process begins with dataset acquisition and preprocessing, then diverges into parallel tracks for feature extraction (handcrafted vs. deep feature learning), and finally converges for model training, evaluation, and the selection of an optimal classifier.

3.1. Dataset Acquisition and Preprocessing

The purpose of this study is to provide a data set of images of Islamic architectural features such as arches, minarets, mashrabiyas, mihrabs and muqarnas (refer to Figure 2). Images were obtained by public databases and web searches. Table 1 shows the description of the data. To make the images computationally efficient, have uniform input dimensions for training models, and accentuate structural and textural differences rather than colour differences, the images were all uniformly resized to an image size of 64x64 pixels, and converted to grayscale. To ensure diversity and robustness of the model, data augmentation techniques were used. The training set was enlarged with random rotations up to 20 degrees (with 0.7 probability) and horizontal flips (with probability 0.5) to account for real world photographic changes, and Gaussian noise (mean=0, std=0.05) to improve the model's generalisation [25].

Figure 2. Sample images of different elements in the dataset, including arches, minarets, mashrabiyas, mihrabs, and muqarnas.

Table 1. Dataset details.

Element type	Number of images	Description
Arches	500	Images of different types of arches
Minarets	450	Various minaret styles from different regions
Mashrabiyas	400	Detailed wooden latticework designs
Mihrabs	350	Different mihrabs with intricate carvings
Muqarnas	300	Ornamented vaulting, typical in domes

3.2. Feature Extraction

Feature extraction was performed using a combination of traditional and DL-based methods:

- HOG: Gradient-based features based on edge orientations comprising architectural structures were extracted through use of HOG. We used standard parameters: 8x8 pixel cells, 2x2 cells per block, and 9 orientation bins.
- LBP: texture pattern, which of great use for recognizing fine details in Islamic ornamental features, was extracted using the LBP. We employed a uniform LBP operator with P=8 neighbors and R=1 radius.
- CNNs: the use of CNNs was to auto extract features, taking advantage of its ability to learn discriminative features from the images without human interaction.

3.3. Model Training and Hyperparameters

To classify architectural elements, we trained multiple models like traditional ML classifiers (SVM, decision tree, RF, gradient boosting, KNN, naive bayes) and DL models (CNNs). Traditional classifiers were implemented with scikit-learn library using their default parameters for the initial comparative baseline. The CNNs was built using TensorFlow and Keras in the form of a sequential model with three convolutional layers (32, 64, and 64 filters each with 3x3 kernels and ReLU activation) and each convolutional layer is followed by a 2x2 maximum-pooling layer, with the final layer being a fully connected layer with softmax output. Adam optimizer was engaged in the compilation of the model with a learning rate of 0.001 and categorical cross-entropy loss was used to train the model over 50 epochs. The data was divided into 80% of training and 20% of testing. Another 20 percent of the training set was then taken as a validation split when training CNN to keep an eye on overfitting.

3.4. Model Evaluation

Several performance metric measures [16], such as accuracy, precision, recall, and F1-score, were used to evaluate the models. Each classifier was then compared using metrics to assess its effectiveness at detecting different architectural elements.

4. Results and Discussion

This paper provides a comparative study of some ML and DL models in architectural elements classification. The output was strictly measured using the mentioned metrics. The research was broken down into two broad paradigms that are: 1) the traditional machine-based models that used handcrafted features and 2) end-to-end deep learning models that can automatically extract features.

4.1. Performance of Traditional Machine Learning Models

The efficacy of traditional models is intrinsically linked to the feature descriptors used. Figure 3 details the performance of each model across five feature set configurations: HOG, LBP, GLCM, Scale-Invariant Feature Transform (SIFT), and a combination of all four (HOG+LBP+GLCM+SIFT).

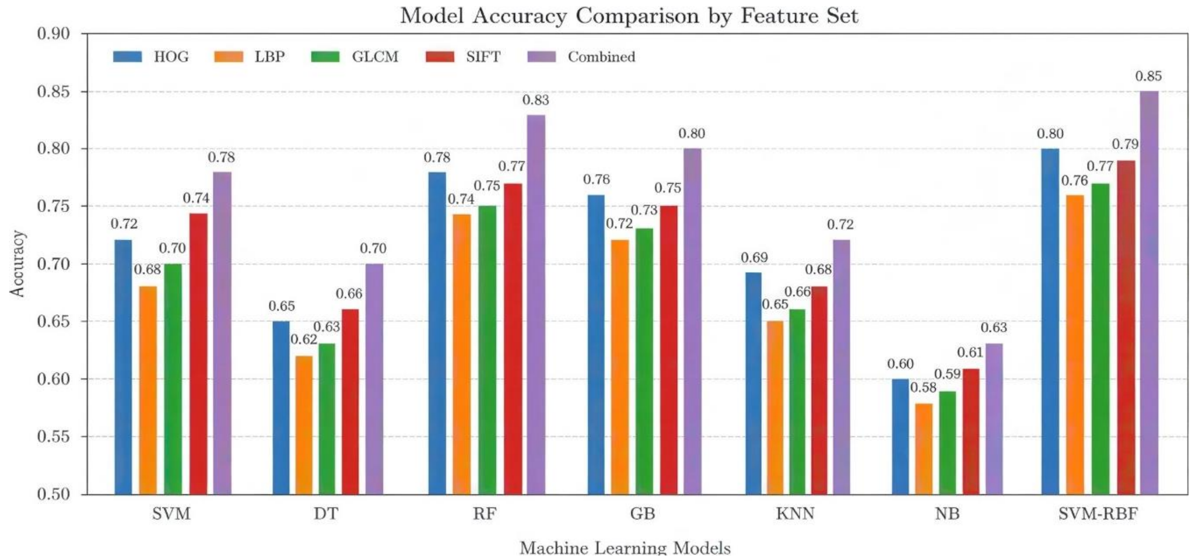

Figure 3. The grouped bars represent performance using various feature sets.

Figure 4. Heatmap of all model and feature combinations, measured on four metrics: accuracy, precision, recall and F1-score. The red to green color scale (low to high) produces a visual representation of the efficacy of the model in an intuitive way.

A consistent trend across all models is the superior performance achieved using the combined feature set. This synergy suggests that HOG, LBP, GLCM, and SIFT capture complementary information, respectively, shape, texture, statistical texture, and key point-based features which, when combined, provide a more robust and discriminative representation of the architectural elements. Moreover, Figure 4 shows performance heatmap of all model-feature combinations across four evaluation metrics. The matrix reveals that SVM-RBF and RF with combined features achieve the highest overall performance among traditional models, and that the combined feature set consistently outperforms any single descriptor across all metrics and classifiers.

The SVM with RBF kernel proved to be the best model among the traditional models with a combined accuracy of features of 85, closely followed by the RF with an 83 accuracy. These models have strong performance because they have the capability to model complex and non-linear decision boundary in the high-dimensional feature space formed by a combination of the descriptors. On the other hand, the naive bayes was found to be least effective with all sets of features and the highest accuracy of only 63% was obtained. It means that the assumption of the conditional independence present in the naive bayes algorithm does not fit the interdependent nature of visual features in this area very well.

4.2. Performance of Deep Learning Models

Table 2 summarizes the performance of the DL models which learn features directly through the data. These models grossly outperformed every other conventional ML method. EfficientNetB0 had the best overall performance with the accuracy of 95% and F1-score of 0.94. The other DL structures, such as ResNet50 and VGG16 and a standard CNN also achieved excellent results with all achieving a better than 92 percent accuracy level. This high performance is graphically summed up in Figure 5 which compares the accuracy of the best models of the two paradigms.

Table 2. Performance of DL models.

Model	Accuracy	Precision	Recall	F1-score
CNN	0.92	0.91	0.90	0.91
ResNet50	0.94	0.93	0.92	0.93
VGG16	0.93	0.92	0.91	0.92
EfficientNetB0	0.95	0.94	0.93	0.94

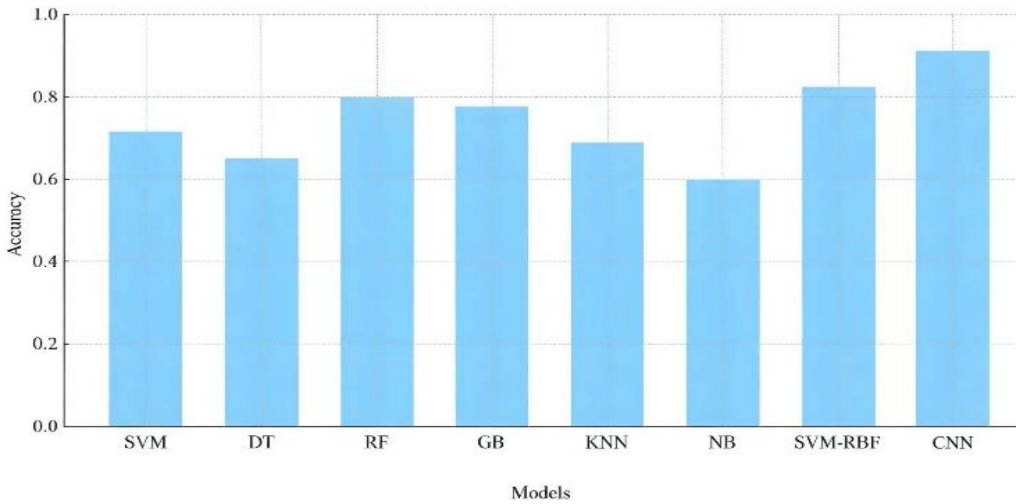

Figure 5. Model accuracy comparison.

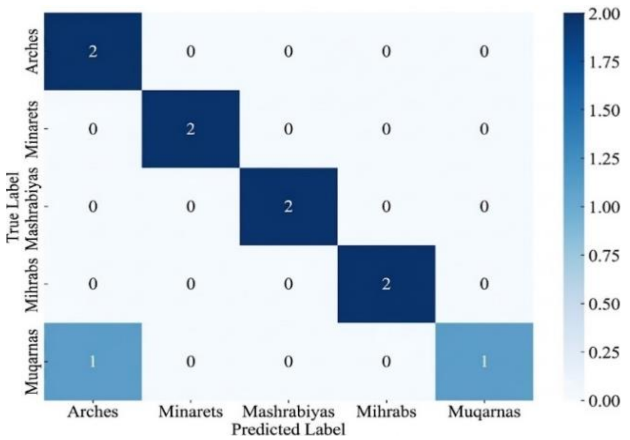

Figure 6. Confusion matrix for CNN model.

Figure 6 shows the confusion matrix of CNN model, which represents the classification effectiveness of the model further, as it is observed that there is a high concentration of correct prediction at the center (diagonal) and low confusion between the classes.

4.3. Comparative Analysis and Discussion

The performance difference between the two paradigms reveals a highly important result: DL models outperform it significantly in this architectural element classification task. The main cause of such superiority is their ability to learn features automatically. Whereas conventional techniques rely on those features, defined manually and crafted by hand, which might not be able to capture the complex and diverse patterns in historic architecture fully, CNNs acquire prior information directly at the level of the raw pixels. This enables them to acquire complex, abstract, and discriminative features that they are usually not discernible in manual engineering. Moreover, the DL method eliminates the feature selection and integration process, which is labor-intensive and requires experts. The findings indicate that a regular CNN architecture can be used to achieve higher accuracy by far (7 percentage points) in comparison to the most efficient traditional model (SVM-RBF using composite features). This performance can be further extended with the use of powerful, pre-trained models, such as EfficientNetB0, to use the experience gained on large datasets to produce the state-of-the-art performance. Finally, ensemble methods and kernel based-SVMs with extensive feature engineering seem to have a respectable performance, but their performance seems to be limited by its nature. DL offers a more effective, efficient and accurate route to complex image classification such as in cultural heritage as the most relevant features to the task are automatically discovered.

5. Conclusions

The current research is a comparative study of traditional ML and DL methods to the automated classification of five typical elements of Islamic architecture. By comparing a wide range of classifiers using handcrafted descriptors (HOG, LBP, GLCM, SIFT) and the deep-learned features, the study develops a strong framework of high-precision recognitions of architectural images. The main result highlights the improved effectiveness of DL in this complex visual task. In particular, EfficientNetB0 model got the best overall accuracy of 95% while all the traditional classifiers got accuracy of 85% or less. This number difference highlights how CNNs can automatically learn highly discriminative hierarchical features for visually complex architecture structures. Furthermore, the use of all four hand crafted descriptors was essential for high performance in the conventional ML pipeline, and complementary information about structure, texture and local geometry was found to be essential to achieve high performance.

The performance analysis of the class-specific features provided helpful clues as to the architecture: the minarets of the architecture were classified most accurately (98%) because they have a distinct structural profile. The greatest difficulty came from the mashrabiya which had an accuracy of 89% with many of them being extremely geometrically complex and using subtle texture patterns that were dependent upon the photographic conditions.

The resulting automatic classification system provides an objective and scalable solution to the shortcomings of the manual architectural evaluation and has substantial implications for projects of digital heritage conservation and documentation. However, future work will build upon this comparative methodology by adding a wider variety of cutting-edge deep architectures to further broaden and improve the generality and performance of the classification approach, including vision transformer and DenseNet.

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