Iranian Architectural Styles Recognition Using Image Processing and Deep Learning

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Abstract

Iranian architecture or Persian architecture is the design of buildings of Iran and parts of the rest of West Asia, the Caucasus, and Central Asia. Its history with its unique characteristics goes back to at least 5,000 BC. As regards, Iran is located in the Middle East and the Middle East is in danger of possible wars, such as Iraq, Afghanistan, and Syria. Always during war, some historical monuments are unintentionally damaged or bombed and easily destroyed or suffer a lot of damage, and since the historical monuments of each country belong to all the people of the world, so weed to try to preserve them. In this paper, we propose a system for the automatic detection and recognition of Monuments based on Deep Learning methods. This system can be activated on the attacker's war equipment and the attacker can find out the date of construction of the building according to its architectural style and receive the necessary warning not to target the building. We have also prepared a dataset with about 3000 photos according to six styles of Iranian architecture of Iranian historical monuments that can be used in other sciences and applications. Also, this way can be helpful for tourists to familiarize themselves with Iranian historical monuments without the need of a guide to present by using cellphone photos to get information about the period of the historical monument and the style of that architectural building.

Keywords: Iranian architecture, Deep learning, Image classification, Image processing

Introduction

The emergence of Persian architecture dates back to the seventh millennium BC (1). Iran has been a pioneer in the application of mathematics, geometry, and astronomy in architecture. Persian architecture is extensive as well as diverse in both structural and aesthetic, moving beyond prior traditions and experiences gradually and precisely (2) traditionally, the guiding, formative, motif of Persian architecture has been famous due to its cosmic symbolism, "by which man is brought into communication and participation with the powers of heaven" (3). Iran ranks 7th in the world based on the number of famous landmarks and monuments registered in UNESCO's World Heritage list (4).

As stated by Arthur Pope, a Persian historian and archaeologist, architecture is considered the paramount Iranian art, in the proper meaning of the word. The superiority of architecture has been observed in both the ancient period and the Islamic era (5). People and students cannot easily make a distinction between the period and architectural style of Iranian historical monuments due to the significance of Iranian architecture. Moreover, reviewing a large number of documents linked to each monument is a time-consuming task for cultural and tourism organizations.

There are millions of images and videos available on the internet which encourage some advanced semantic analysis applications and algorithms that examine (6) images and videos for the purpose of providing the user with better search content and their summarization. Many world's researchers reported innovative breakthroughs in the areas of image labeling, object detection, and scene classification (7, 8). This causes to facilitate formulation approaches regarding object detection and scene classification issues. While artificial neural networks have demonstrated achievements in the implementation of object detection, scene classification, and especially convolutional neural networks, deep learning analyses a great deal of data through neural networks which are so challenging to be learned what users prefer online (9-11). Torch is a popular deep learning framework that focused on techniques and strategies of deep learning and neural networks (12, 13).

Background research

The present study aims to examine the approach of recognizing Iranian architectural styles through deep learning for the first time. Similarly, Jose et al. applied Deep Learning Techniques to generate a new dataset with about 4000 images that can Classify Architectural Heritage Images. Promising results of his study have been obtained based on accuracy and it can be assumed that these techniques can be employed extensively in the digital documentation of architectural heritage (14). Husain et al. also offered a method by which a powerful model can be designed to detect and classify multi-class defects accurately given relatively small datasets (15). Furthermore, a system for the automatic detection and identification of urban buildings was designed by Konstantinos et al. They exploited a framework in deep learning in terms of convolutional neural networks to address this drawback, which automatically creates highly detailed factors directly from source data. They explored the implementation of their method in the identification of half-timbered constructed buildings in Calw city in Germany (16).

Abraham et al. employed sparse features at the network's input in conjunction with primary color pixel values and designed a convolutional neural network to classify buildings' images. Consequently, they developed a neuronal model of classifying the architectural styles of Mexican buildings across three categories: prehispanic, colonial, and modern with an accuracy of 88.01% (17). A research work undertaken by Aditya et al. sought to extract the high-level image features from low-level visual features under the controlled condition that the test image does fit one of the categories. Their aim is to deal with multi–classes by blending two-class classifiers into a single hierarchical classifier. They have revealed that learning certain high-level semantic categories can be achieved through the application of particular low-level visual features under the restraint that the images do relate to one of the under-controlled classes (18).

In another study, a deep learning-based solution approach was proposed by Sebastian et al. with the aim of table detection in document images. Additionally, it presented a novel deep learning-based model to identify table structure, i.e. recognizing rows, columns, and cell locations in detected tables (19). A hieratical deep learning network with a symmetric loss formula was designed by Gaowei et al. aiming to identify exterior façade elements of buildings from images. This framework can practically be contributed to the realization of the automatic and precise identification of different building façade elements in sophisticated environments, which can be probably useful in infrastructure monitoring and maintenance operations (20).

Materials and Methods

Computer vision techniques are progressively being utilized to simplify and progress the process of documenting, conserving, and rebuilding architectural legacy. We use deep-learning in image classification for documenting architectural cultural legacy. We have trained our model about 3k images, and we have divided our dataset into a train and a test, since we had a little quantity of information we consider 90% of images for the training stage and 10% of images as a test (50 chosen images each class at random), it should be pointed out that we have divided our information on the train (90%) and the validation (10%), we operate validation information for optimizing our hyper-parameter in the training stage. As far as we are concerned, the principal goal looked for is the software program of deep learning-based Computer vision techniques to classify whatever technical knowledge was used to acquire images of the architectural legacy, in any case, the innovation is utilized to get them and as of now specified, particularly the convolutional neural networks are a utility for these assignments.

In this paper, we applied Fine-tuning to get conclusions more quickly. The training of a convolutional neural network consists of a set of pre-trained weights, which is named Fine-tuning so, as noted above, has been effectively utilized in many different applications. Since the quantity of information is little, we use diverse augmentations to images like horizontal flip, random brightness shift, shear, and so on.

It is important to note that we have applied models that have as of now been trained and have been fine-tuned. As we outlined above we utilize transfer-learning, which implies that we apply well-known architectures (like ResNet (21, 22)) as a classifier model and operate weights that they have trained on ImageNet (23-26). The special case is the final completely associated layer where the number of nods is dependent on the number of classes within the data set we need to categorize. One usual practice is to substitute the last Fully- connected layer of pre-trained CNN (27, 28) with a late Fully-connected layer containing as numerous neurons as the class number in the new app. Therefore, these models were made for 1000 classifications, changes were created on the final layer of MLP. As an example: we changed the final layer of MLP out-features to 6 rather than 1000 or in a few models we changed out-feature to 64, then included a fully connected layer that connected from 64 to 6.

Activation Function

In this model, we apply SoftMax (29-31) as a final activation function because we need to categorize buildings. Because we utilize PyTorch (32, 33), we can also use Cross-Entropy Loss (34, 35) which is equal to combining Log-Softmax (36, 37) and NLLLoss (38, 39). We have too made drop-out layers (40, 41) that keep away the network from Overfitting (42, 43). We apply Linux (Ubuntu) and Nvidia 1080-Titan for training the model and drawing conclusions.

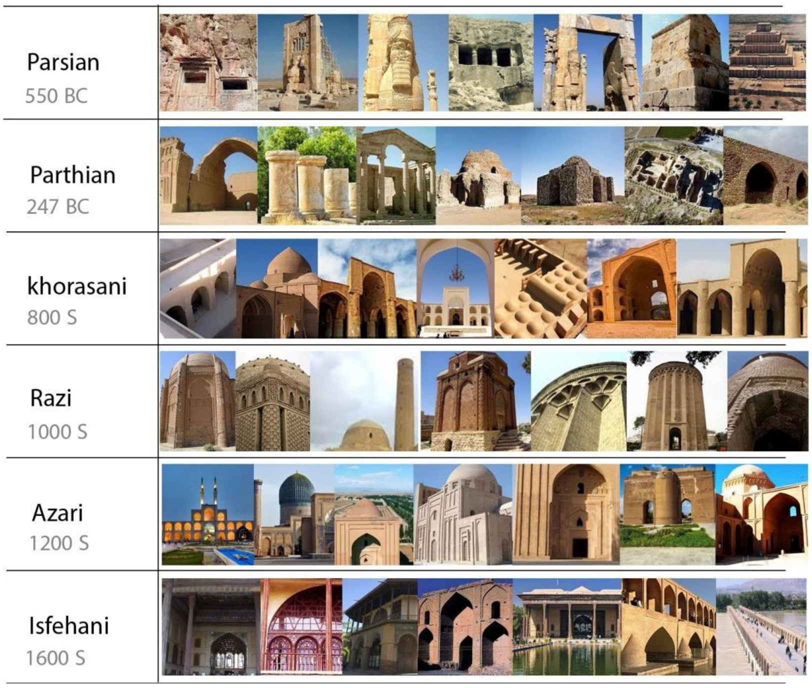


Figure 1 Division of Iranian architectural styles

Examples of images of Iranian old architectural constructions with the amount of building oldness and the classification of Iranian architectural styles are shown in Figure 1 from an architectural view. In addition, it should be mentioned that all the photos used in this article were taken and collected by us. Mohammad Karim Pirnia (a senior and well-known Iranian planner) classifies the classical architecture of the Iranian lands all through the ages in the six taking after classes or styles (44).

1. The style of the Persian (up to the 3rd century B.C.)
2. The style of the Parthian
3. The style of the Khorasani (from the late 7th to the late 10th century)
4. The style of the Razi (from the 11th century to the time of the Mongolian attack)
5. The style of the Azari (from the end of the 13th century until the presentation of the Safavid Dynasty in the 16th century)
6. The style of the Isfahani extends throughout the Safavid, Afsharid, Zand, and Qajar dynasties beginning from the 16th century forward.

Results

The primary purpose is to assess the appropriateness of these techniques in automatically classifying images of building legacy items. We have chosen to apply distinctive kinds of networks since the tests carried out to be able to recognize a few of the various choices as of now utilized, networks of convolutional neurons (CNN) (45, 46) especially and multi-layer perceptron (MLP) (47, 48). Our model is trained with 5 different architectures:

1. ResNet50 (49, 50)
2. MobilenetV3-Large (51, 52)
3. Inception-V4 (53, 54)
4. Inception-ResNet-V2 (55, 56)
5. EfficientNet-B3 (57, 58)

Figure 2 shows the highest level of validation accuracy in ResNet50 and the second one, MobileNet-V3 is approximately 0.02% less than ResNet50.

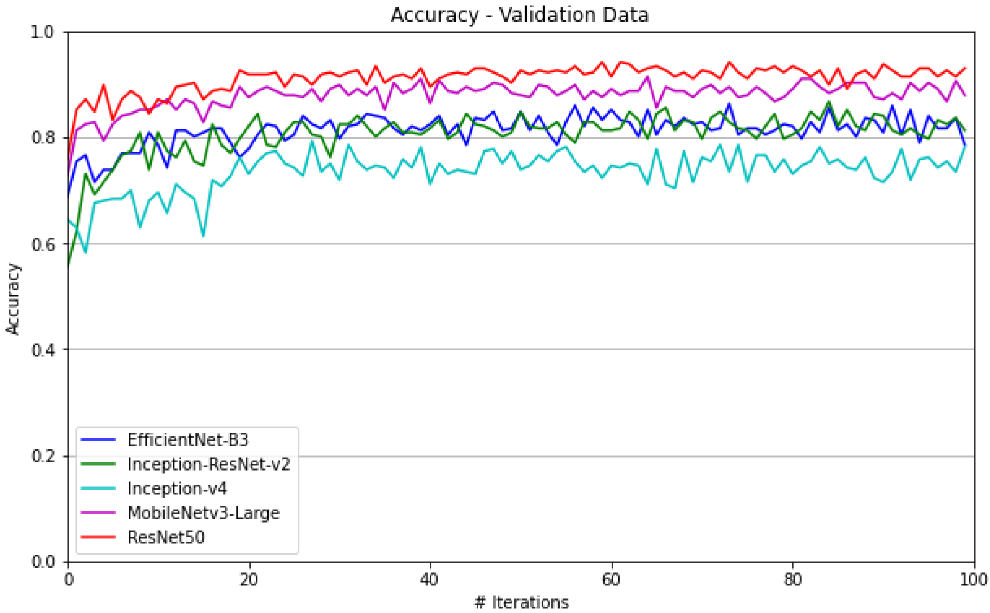


Figure 2 Accuracy- Validation Data

Figure 3 indicates that with Inception-ResNet-V2, the loss count is up to 40 periods, but it has the largest loss after MobileNetv3-large. Moreover, the loss lies at the lowest level of ResNet50 and is meaningfully different.

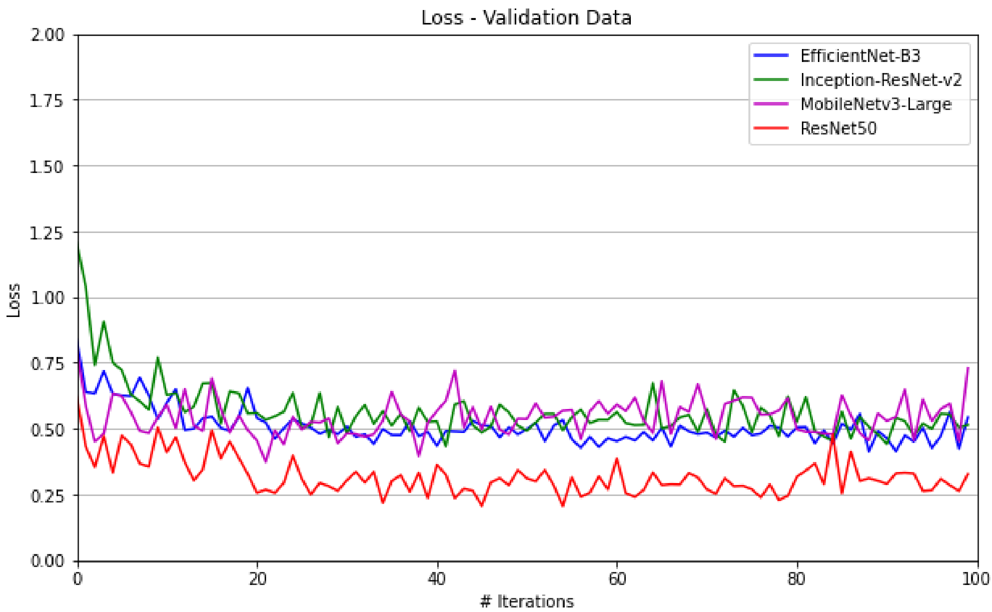


Figure 3 Loss- Validation Data

Figure 4 appears the accuracy of training information, which has come to its maximum level in ResNet50 and is next to MobileNetv3-Large's second location. All along processing, the accuracy among Inception-v4 and Inception-Resnet-v2 may be very same and near to one

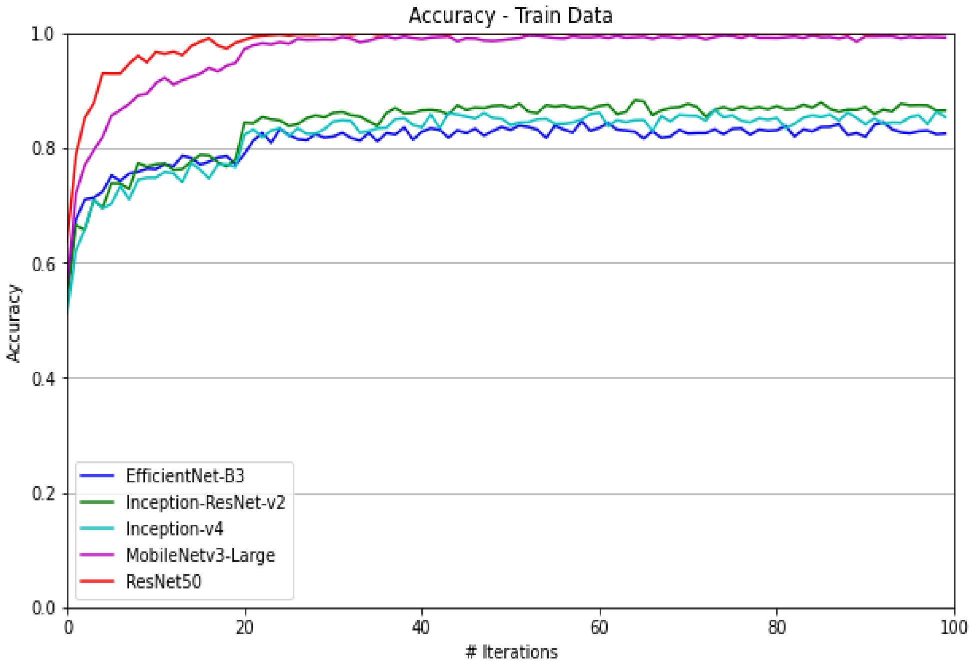


Figure 4 Accuracy-Train data

another, as well as in the final analysis, the lowest accuracy is displayed in EfficientNet-B3. As you can see in Table 1, ResNet has the highest accuracy and the lowest loss and Inception-v4 has the lowest accuracy and the greatest loss.

Table 1 compares train and test

	Train		Test	
	Loss	**Accuracy**	**Loss**	**Accuracy**
EfficientNet-B3	0.4793	82.50%	0.8617	83.11%
Inception-ResNet-v2	0.3848	86.47%	2.1547	51.09%
Inception-v4	0.3927	85.35%	18.7749	48.79%
MobileNetv3-Large	0.026	99.19%	0.6143	88.37%
ResNet	0.0019	99.41%	0.2794	95.06%

Table 2 Precision of Iranian styles

	Precision	Recall	F1-score	Support
Azari	0.96	1.00	0.98	50
Isfehani	0.98	0.90	0.94	50
Khorasani	0.87	0.96	0.91	50
Parsian	0.96	0.96	0.96	50
Parthian	0.98	0.90	0.94	50
Razi	0.96	0.98	0.97	50
Accuracy		95		300

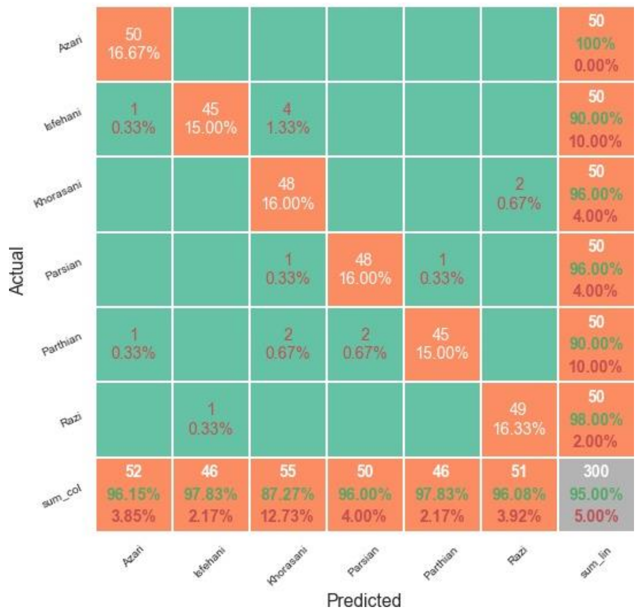
Moreover, in Table 2, we can see the standard metrics of the point-based classification: we show Precision, Recall, and F1-Score (59, 60) for each class along with the mean averages of these metrics. The formula for the standard F1-score is the harmonic mean of the precision and recall. A perfect model has an F-score of 1.

Table 3 Image sizes

	Size	Inference time	Epochs
EfficientNet-B3	300*300	0.011	100
Inception-ResNet-v2	299*299	0.006	100
Inception-v4	299*299	0.003	100
MobileNetv3-Large	224*224	0.001	100
ResNet50	224*224	0.001	100

Table 3 shows the resolution of dataset images in different ways. The confusion matrix is displayed in Table.

Table 4 Confusion Matrix



Conclusion

Taking into account the significance of Iranian architecture and classifying its styles, it is necessary to classify archives in a few offices like Tourism and cultural heritage organization, particularly in circumstances where it is necessary to rapidly distinguish the style and the age of the buildings. We identify the cultural legacy of Iran in circumstances like the war in a short term to avoid the harm and ruination of those precious buildings. In conclusion, we were able to categorize buildings through a deep-learning system and contrast various architectures, with an accuracy of 95% achieved with ResNet50.

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