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RESEARCH

Prediction of Star Polygon Types in Islamic Geometric Patterns with Deep Learning

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Abstract

Historical buildings in the Eastern world of architecture host many Islamic geometric patterns which are known as mathematically sophisticated patterns regarding their period of creation. This study focuses on the preparation of a model that can be helpful for the analysis and restoration/maintenance of these patterns. For this, a deep learning model to detect and classify star types in Islamic geometric patterns has been proposed, and the trials were evaluated. Accordingly, this study presents a database containing 5-pointed, 6-pointed, 8-pointed and 12-pointed star types. The database consists of 600 Islamic geometric patterns. A mask RCNN algorithm was trained to detect and classify star types using the prepared database. The results of the training indicate that the loss value is 0.90 and the validation loss value is 0.85. The algorithm was tested using images that it had not seen before and the results were evaluated. This paper presents a discussion on the pros and cons of the trained algorithm.

Keywords Islamic geometric patterns · Mask RCNN · Deep learning · Star polygons

Introduction

Throughout history, portraying living beings was avoided in Islamic art, and floral, written and geometric elements were used in decorations (Altın 2020). There are mathematical rules underlying the Islamic geometric patterns used in different parts of the Islamic geography throughout history. This mathematical infrastructure, especially used in ancient times, requires great expertise. Today, the application

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of this type of geometric patterns is almost non-existent. That explains why there are no experts trained in this field. Therefore, errors may occur in restorations. As a result of his research, Altın (2020) identified 120 incorrectly restored geometric panels or borders in 35 Seljuk architectural works. These errors generally arise from the problems in geometric construction.

Today, these artifacts need to be repaired and restored from time to time. It is necessary to quickly and practically solve what kind of mathematical system these patterns have, some parts of which have been lost or distorted. It is possible to divide these patterns into various classes. For example, the number of star arms can be considered as a classification. Different star types come together to form a tessellation. For example, the regular arrangement of 12-pointed stars and the formation of 6-pointed stars in the empty parts may be an example of the tessellation. These tessellations can be very diverse and complex. Therefore, in this study, a model based on deep learning is proposed for the prediction of star polygon types in Islamic geometric patterns.

The studies have been carried out about the classification and prediction of Islamic geometric patterns according to various parameters. For example, Aoulalay et al. (2022) proposed a machine learning-based classification model using grey level co-occurrence matrix, Gabor filter bank and CNN in order to determine symmetric groups (frieze, wallpaper and rosette) of Islamic geometric patterns, and used texture periodicity for the differentiation of the patterns. Similarly, Djibril and Thami (2008) proposed an Islamic geometric pattern classification model with taking account symmetric features. Ahadian and Bastanfard (2011) proposed a model using Zernike moments for feature extraction, K-nearest neighbor rule and feed forward neural network for shape based classification in Islamic geometric patterns. Similarly, Hajebi and Hajebi (2021) proposed a Islamic geometric pattern prediction model using Zernike moments for feature extraction, and back-propagation neural network for prediction of vanished patterns. In this study, in order to to detect star types and to mask the related object, we proposed and tested a model that is based on Mask RCNN (Mask Region Convolutional Neural Network) (He et al. 2017) algorithm. The model is based on the application of an instance segmentation technique with the state-of-the-art convolutional neural network model Mask RCNN to detect and distinguish star polygons in Islamic geometric patterns.

Background

Islamic Geometric Patterns

The patterns containing star motifs that are found around the Eastern world are usually called Islamic geometric patterns in the literature. The motifs in these patterns have a geometric substructure. Various star units come together to form a tessellation. Connections in the combinations of star units can be different. This connection unit type may be, for example, another star unit, or it may be a simpler geometric setup. The arrangement of the main units also has an important place in the formation of the tessellation setup. This arrangement may be, for example, a gridal arrangement, or it may be a radial arrangement (Schneider 1980). The number of star arms in the main units of the tessellations and the type of connection units determine the scheme of the tessellation. Different geometric tessellations can be created with different setups. One of the first known example of Islamic geometric pattern studies conducted by Bourgoin (1879) who had analysed patterns in the Eastern world. Broug (2008) and Bonner (2017) also analyzed many Islamic geometric patterns with their potential drawing techniques. Furthermore, Schneider (1980) gives information about the knotting principles in the 3rd dimension of the patterns in his drawings while showing which architectural artifacts contained these tessellations. Islamic geometric patterns, although applied in the 2nd dimension, contain the knot principle in the 3rd dimension (Agirbas 2020).

As mentioned in the Introduction section, there are limited studies about the recognition and classification of the pattern types in the Islamic geometric pattern tessellations. As it can be found in the review article of Ranjazmay Azari et al. (2023), the studies about the Islamic geometric patterns are mostly related to the method proposals for creation of Islamic geometric patterns. For example, Khamjane et al. (2023) proposed a polygonal method for creation of various Islamic geometric tilings, Khamjane et al. (2020) proposed a method for creation of decagonal self-similar Islamic geometric patterns, Khamjane and Benslimane (2018) proposed a method for creation of Islamic quasi-periodic patterns, El Ouaazizi et al. (2015) and Nasri et al. (2014) proposed a genetic algorithm-based method for Islamic geometric pattern characterization, Nasri and Benslimane (2014) presented method for symmetrical motif extraction in periodic Islamic geometric patterns, Lahcen et al. (2021) presented a method for creation of Islamic geometric patterns based in the traditional HASBA Method, mostly used by Moroccan craftsmen, Rasouli et al. (2008), Nadyrshine et al. (2021) and Izadi et al. (2010) developed algorithms to create Islamic geometric patterns.

Apart from the knot principle, we encounter the lifting of star patterns to the 3rd dimension in the creation of muqarnas geometries. Many authors agree that the muqarnas are lifted to the 3rd dimension after the plan drawings are made. In the muqarnas drawings in the Topkapı Scroll (Necipoglu 1995), it is clearly seen that there are star units in muqarnas plans. The star units in the plans of muqarnas were analyzed by Uluengin (2018) and Takahashi (2023). In these star units, some stars have equal arm lengths and some have unequal arm lengths. Agirbas and Yildiz (2021) and Agirbas et al. (2022) have investigated the geometric reasons for the unequal length of the star arms in the muqarnas plans. Moreover, the stars draw attention in the principle of ascension to the 3rd dimension of the muqarnas which are made up of layers. If we consider a type of star, some of the arms of the star are in one layer of the muqarnas and the other arms of the star are in the other layer of the muqarnas. In other words, cells in different layers come together to form the whole of the star. Algorithmic methods for creation of muqarnas geometry have been developed by various researchers. For example, 3D construction of muqarnas geometry has been studied by Senhaji and Benslimane (2022), Senhaji and Benslimane (2019), Gherardini and Leali (2016) and Hamekasi et al. (2011).

There are also current studies on lifting the star patterns to the 3rd dimension in different forms. For example, Agirbas (2020) has created parametric Islamic geometric knits through visual programming language by considering the knotting principles in Islamic geometric patterns. Agirbas and Basogul (2021), on the other hand, created reciprocal frame structures based on the knotting forms of Islamic geometric patterns and made their structural analysis using different variables. There are also studies on creating new variations by coding the mathematical infrastructure of Islamic geometric patterns (Agirbas 2017).

Deep Learning and the Mask RCNN Algorithm

Machine learning is a field of artificial intelligence that focuses on the development of algorithms that enable computers to learn and make predictions or decisions based on data. Deep learning is a branch of machine learning that involves training artificial neural networks on large amounts of data to recognize patterns and to make predictions. Deep learning algorithms consist of multiple layers of nodes that allow algorithm to learn from complex data (LeCun et al. 2015). These algorithms learn to perform tasks by adjusting the weights and connections between these nodes. The logic behind the deep learning algorithm structures are similar to human brain interconnected neurons. Deep learning algorithms are being widely used for many speech recognition and computer vision tasks.

The artificial intelligence based algorithms are increasing and diversing so fast. Therefore, researchers prepare review articles focusing on specific type of algorithms. For example, Sultana et al. (2020) and Masita et al. (2020) have investigated deep learning based object detection algorithms in detail, and Chen et al. (2021a) has reviewed almost 50 Convolutional Neural Networks (CNN) algorithms with their characteristics. CNNs are used mainly in computer vision tasks. There are many CNN algorithms mainly used for object detection (such as Yolo), image classification (such as GoogLeNet, VGGNet, LeNet-5, AlexNet, ViT), semantic segmentation together with image classification and object detection (such as DenseNet, MobileNet). Unlike these algorithms, Mask RCNN (Mask Region Convolutional Neural Network) (He et al. 2017), which is an improved version of Faster RCNN, can make pixel level segmentation. Therefore, it can create patches on the detected objects related to various classification categories. Mask RCNN was created by Facebook AI Research and many researchers interpreted the algorithm according to the specified tasks. In this study, Matterport's (Abdulla 2017; Johnson 2020) Mask RCNN interpretation with ResNet 101 FPN architecture was used. The algorithm architecture has parts such as Region Proposal Network (RPN), RoIAlign, Fully convolutional networks (FCN) to detect objects, classify them and make the final mask creation (Zhang et al. 2022; Chen et al. 2021b). Masks are the results of the generation of pixel-level segmentation for objects detected in the images. The loss values (classification loss, bounding box loss, mask loss) are calculated on multiple parts in the algorithm. The loss values refer to the metrics used to quantify discrepancy between the model's predictions and the truth. Per pixel sigmoid and SGD Keras optimizer was used in the algorithm.

Mask RCNN has been used in various branches of science. But the common point of the studies using this algorithm is to capture the specific details in the images. Wu et al. (2020) for particle characterization, Pustokhina et al. (2021) for anomaly detection in pedestrian walkways, Jin et al (2021) for detection of highway guardrail, Sadhukhan et al. (2020) to estimate surface temperature from thermal imagery of building, Tran et al. (2022) for detecting and identifying cracks in pavements, Shaodan et al. (2019) for ship detection, Al-Shaibani et al. (2021) for airplane type identification, Sizkouhi et al. (2020) for boundary extraction of photovoltaic plants, Chen et al. (2021c) for narrow gap deviation detection in welding, Fan et al. (2021) for detection and segmentation of underwater objects, Rahman et al. (2022) for filler detection in Scanning Electron Microscopic images, Raoofi and Motamedi (2020) for detection of construction machinery, Htet and Sein (2021) for classification of palm trees, Prados-Privado et al. (2021) for radiographic detection of teeth, Johnson (2020) for the detection of cell nuclei in the medical images, An et al (2021) for the automatic diagnosis of tongue.

Material and Methods

For this study, firstly, an Islamic geometric pattern database was created. The patterns in this database were drawn by the authors (Fig. 1). The software Illustrator allows designer to create vector based images and was used to create patterns in the dataset. These database patterns include 5-pointed, 6-pointed, 8-pointed, and 12-pointed stars, which are the most common star types in Islamic geometric pattern tessellations. Various colors and patterns with different scales were used in the images.

Supervised learning was used as a basis for the deep learning process. Accordingly, the patterns in all images in this database are labeled. Labeling consists of four classes: 5-pointed star, 6-pointed star, 8-pointed star and 12-pointed star. While this labeling was being done, the intertwined stars were also labeled so that they overlapped each other. The half stars at the corners of the images were eliminated from the labeling. Labeling was done with VGG Image Annotator 1.0.0 (Dutta and Zisserman 2019). Polygonal labeling was used to label stars based on their edges. Database was divided into two groups: train and validation data.

The patterns in the database are based on patterns found in the historical buildings containing star forms. Many variations of the patterns were produced by drawing them in different colors and sizes, keeping their geometric structures the same. The patterns in the database are generally chosen from the geography of Turkey (such as patterns found in Sehzade Mosque, Beyazit Mosque, Suleymaniye Mosque, Selimiye Mosque in Istanbul, Bursa Yesil Mosque in Bursa and Esrefoglu Mosque in Beysehir).

A new environment with Python language infrastructure has been prepared in Anaconda to perform deep learning training using the Mask RCNN algorithm developed by Matterport (Abdulla 2017). Environment includes imgaug, Keras, Tensorflow, scikit-image, numpy, opencv-python libraries. COCO (Common Objects in Context) was used for transfer learning in the training. Mask RCNN code has been modified to have four classes. The training result was monitored with the help of Tensorboard.

The validation tests were done with the use of different images (the images different from the train and validation data). The test data include various types

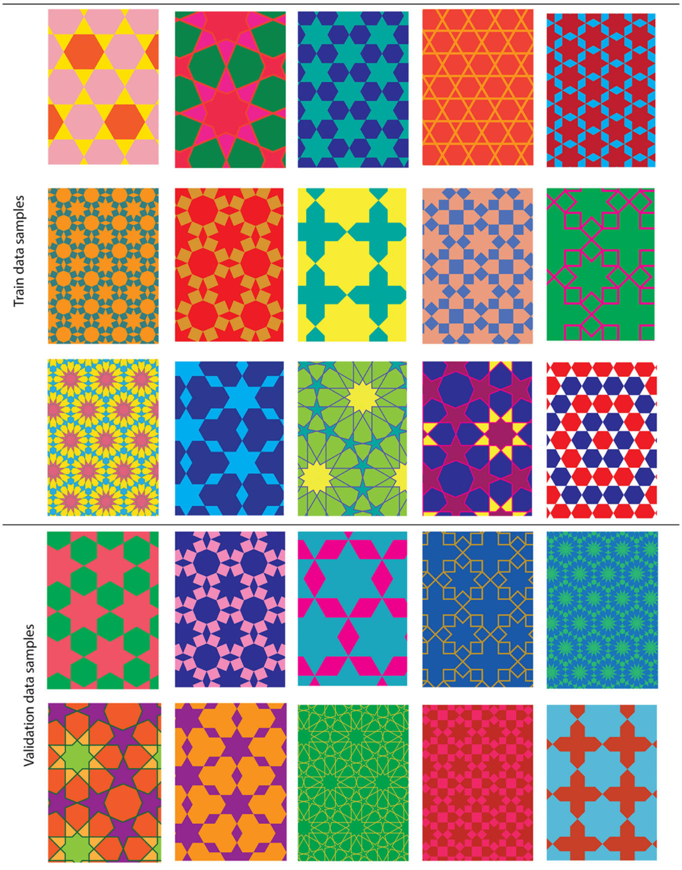


Fig. 1 Train and validation data samples of the prepared database

of images with various backgrounds, various scales of the patterns and various colors. The Jupyter Notebook platform was used to make these tests. The inspection algorithm has been modified to use the trained network. The weighted file obtained at the end of the training was used in the inspection tests.

Results and Discussion

Case 1

Train data of the database used for the Case 1 contains 300 elements, and validation data contains 100 elements. Additionally, augmentation (translate, rotate, Gaussian Blur) was used to increase the number of images in the database.

After the deep learning training was completed (epochs = 30, steps per epoch = 100, min confidence = 0.9, learning rate = 0.0005), the result values were

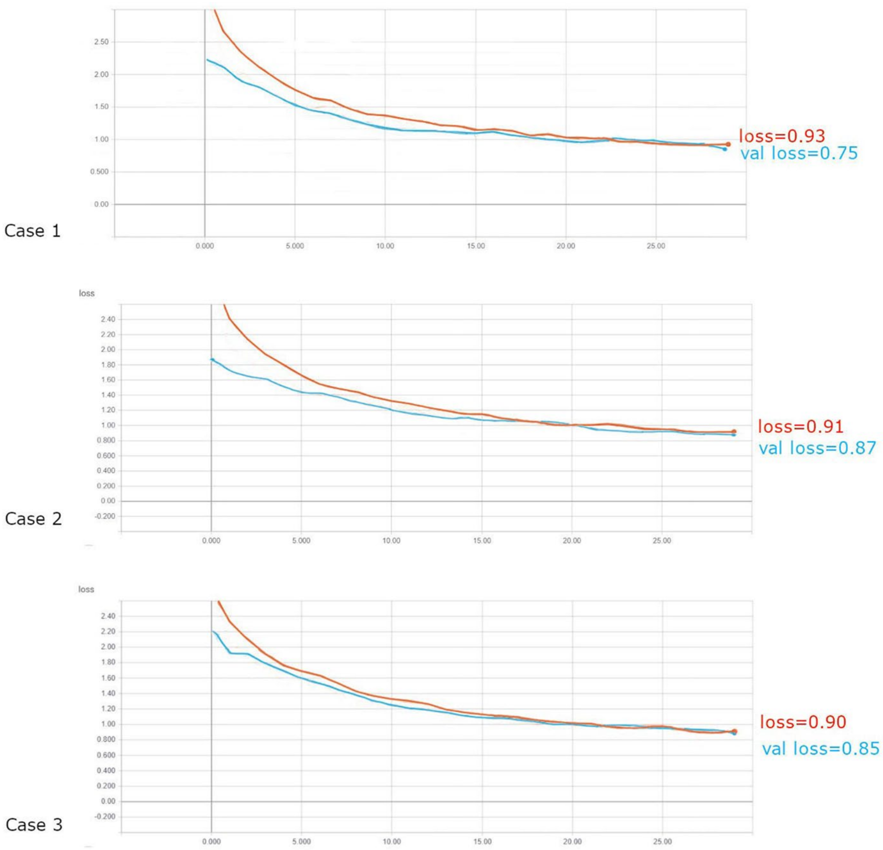


Fig. 2 Train and Validation loss graphs found at the end of the deep learning training with a Mask RCNN

monitored with the help of Tensorboard. Accordingly, the loss value is 0.93 and the validation loss value is 0.75 (Fig. 2, Table 1). Inspection tests were performed using test images that the algorithm had never seen before. According to these tests, the trained deep learning algorithm can classify stars according to their types. As can be seen in Sample 1, which includes random lines and figures at the background, the deep learning algorithm has detected 8-pointed stars in the pattern (Fig. 3). Also, as can be seen in Sample 2, which includes lines and a background color, the algorithm has detected 8-pointed stars in the pattern. In the Sample 3, the algorithm was able to detect 6-pointed stars in the pattern (Fig. 3).

Even though the algorithm can detect specific types of stars, there are limitations of the algorithm in the tested cases. The following problems were detected in the tests:

- Although the algorithm can correctly detect and classify 6-pointed and 8-pointed stars in the images, it generally cannot correctly detect and classify

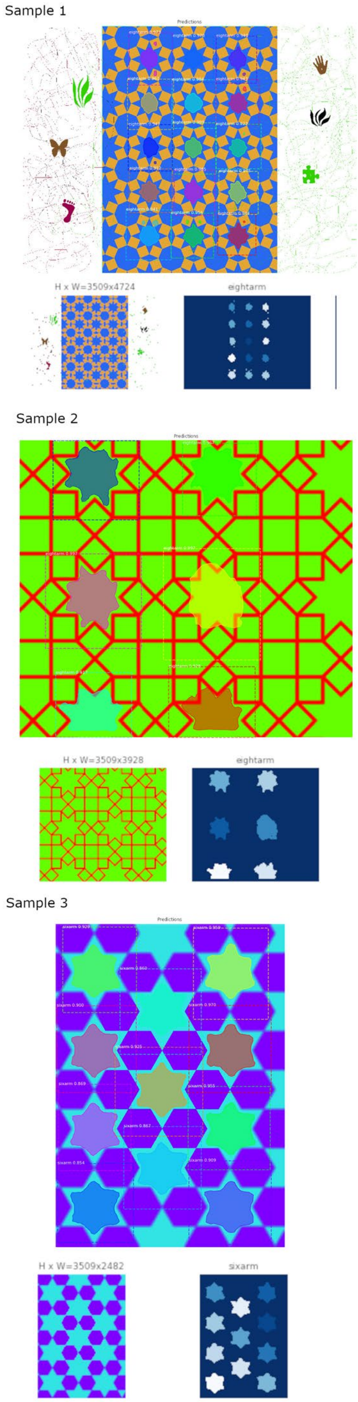
Table 1 The details of the tests

Properties of the deep learning process		Case 1		Case 2		Case 3	
Min confidence		0.9		0.9		0.2	
Epochs		30		30		30	
Steps per epoch		100		100		100	
Learning rate		0.0005		0.0005		0.0005	
Total images in the database		400		600		600	
Number of train data		300		460		460	
Number of val data		100		140		140	
Resulted loss value		0.93		0.91		0.90	
Resulted val loss value		0.75		0.87		0.85	
Details of the database content		Train	Val	Train	Val	Train	Val
Image details	Images with 5-pointed star	25	10	130	35	130	35
	Images with 6-pointed star	105	30	105	30	105	30
	Images with 8-pointed star	170	61	220	71	220	71
	Images with 12-pointed star	25	10	135	40	135	40
Number of labelled stars	5-pointed star	610	299	1359	530	1359	530
	6-pointed star	556	114	556	114	556	114
	8-pointed star	1323	364	1354	376	1354	376
	12-pointed star	373	159	791	298	791	298

5-pointed and 12-pointed stars in the images. The images containing 5-pointed and 12-pointed stars should be increased in the database.

- It has been determined that masking cannot be done in some of the images containing 12-pointed stars, even if the 12-pointed stars are detected in the related images (Fig. 4).
- It has been determined that although most of the stars can be detected and classified in the images of star pattern tessellations placed in the larger canvas (larger image sizes and more repetitive star patterns), some stars cannot be detected and classified (Fig. 5).
- It has been observed that star detection and classification cannot be done in images with very complex backgrounds. The database, which was used to train the deep learning algorithm, does not contain images with complex backgrounds. Therefore, images with complex backgrounds should be added to the database (Fig. 6).
- Star detection with masks could not be made in the images where the stars were drawn as lines (Fig. 7).
- The algorithm performs masking for stars. However, since this masking cannot be done from the exact edges of the stars, the masking cannot be in full star form. It is thought that ensuring exact masking can be useful for possible tessellation layouts creations.

Fig. 3 The star type prediction results



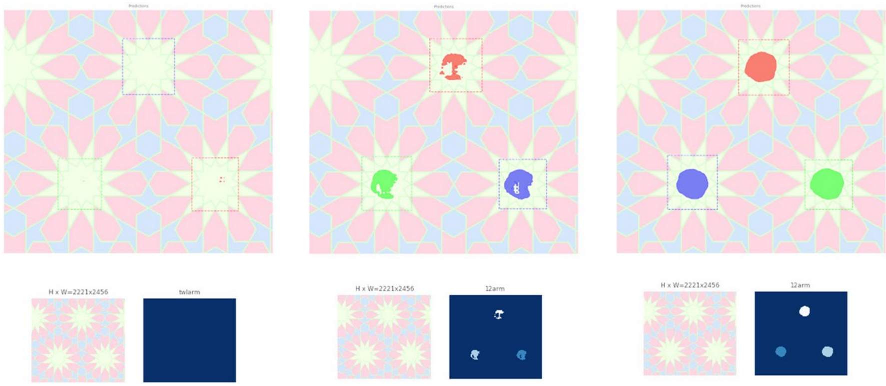


Fig. 4 12-pointed star detection results of Case 1, 2 and 3 respectively

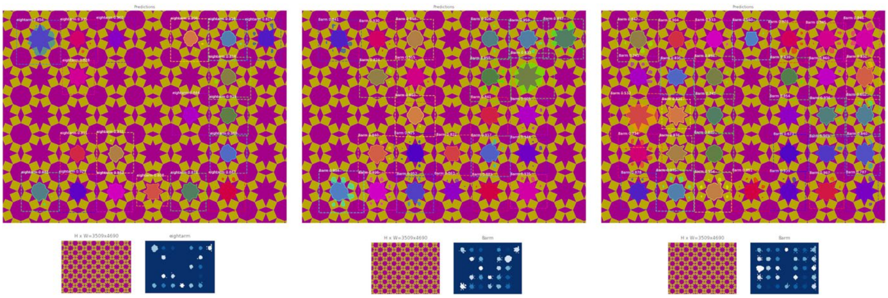


Fig. 5 The repetitive 8-pointed star pattern detection in larger canvas (results of Case 1, 2 and 3 respectively)

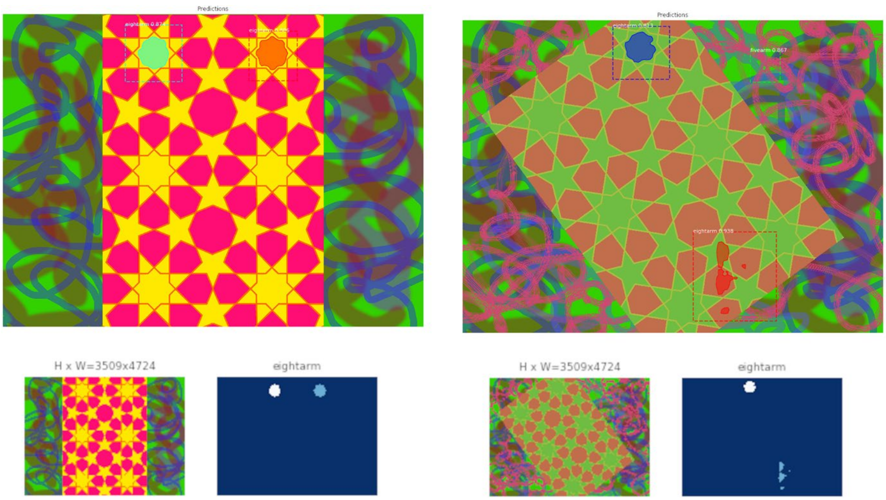


Fig. 6 The star type prediction problems in the complex backgrounds

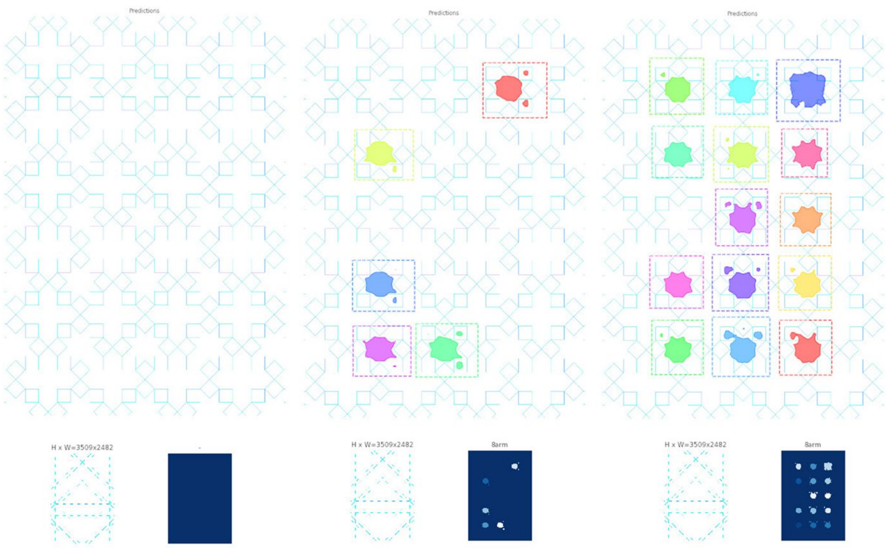


Fig. 7 8-pointed star pattern detection in linear drawings (results of Case 1,2 and 3 respectively)

Case 2

In Case 1, the number of labeled 5-pointed stars and 12-pointed stars is not very small compared to the others (Table 2). However, the number of images containing the number of 5-pointed stars and 12-pointed stars is less than other stars (train data contains 25 5-pointed stars, 105 6-pointed stars, 170 8-pointed stars and 25 12-pointed stars, while validation data contains 10 5-pointed stars, 30 6-pointed stars, 61 8-pointed stars and 10 12-pointed stars). In other words, because a few images contain a large number of 5-pointed stars or 12-pointed stars, the number of labeled 5-pointed stars and 12-pointed stars appears to be large. In response to this situation, it was decided to increase the number of images containing 5-pointed stars and 12-pointed stars and prepare a new dataset.

New images containing 5-pointed and 12-pointed stars have been added to the dataset. This database contains 460 train data and 140 validation data. Additionally, augmentation (translate, rotate, Gaussian Blur) was used to increase the number of images in the database. In the new dataset, train data contains 130 5-pointed stars, 105 6-pointed stars, 220 8-pointed stars and 135 12-pointed stars, while validation data contains 35 5-pointed stars, 30 6-pointed stars, 71 8-pointed stars and 40 12-point stars (Table 2).

At the end of the deep learning training with this database (epochs = 30, steps per epoch = 100, min confidence = 0.9, learning rate = 0.0005), similar to the previous test; the loss value: 0.91 and the validation loss value: 0.87 were found

Table 2 The results of the earlier tests

No.	Dataset information	Total data	Train data	Validation data	Number of labelled stars (train + val)				Loss value	Val loss value
					5-pointed	6-pointed	8-pointed	12-pointed		
Test 1	Photographs	257	200	57	411 + 136	374 + 372	99 + 52	18 + 10	0.89	2.04
Test 2	Photographs + drawings	657	500	157	1022 + 173	930 + 215	1422 + 247	390 + 62	0.98	1.20

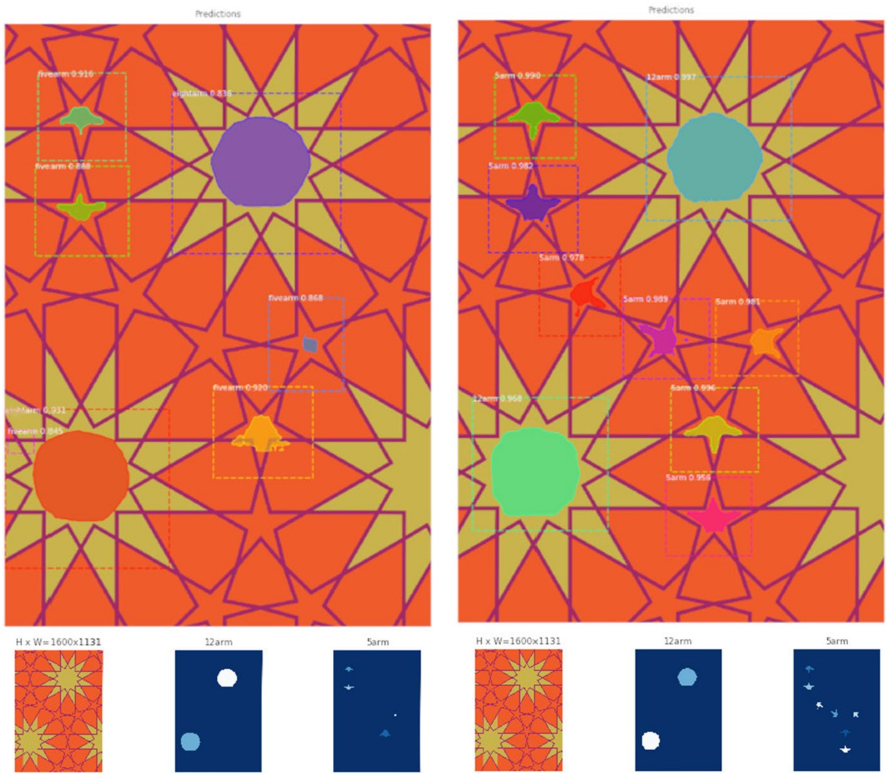


Fig. 8 Comparison of the 5-pointed star detection results of Case 2 (left side) and Case 3 (right side)

(Fig. 2, Table 1). The algorithm can find 6-pointed and 8-pointed stars, as in the previous test. In addition, the algorithm was improved by being able to find 5-pointed stars and 12-pointed stars to a certain extent (Fig. 8, Fig. 9).

Even though the algorithm can detect types of stars, there are limitations of the algorithm in the tested cases. The following problems were detected in the tests:

- In this test, 5-pointed stars started to be detected. However, not all the 5-pointed stars in an image are detected (Fig. 8).
- 12-pointed stars are also detected, but there isn't enough masking in the images (Fig. 9).
- Although a progress has been made in star detection in the images with large canvases and star detection in linear drawings, the final results are not fully successful (Figs. 5, 7).

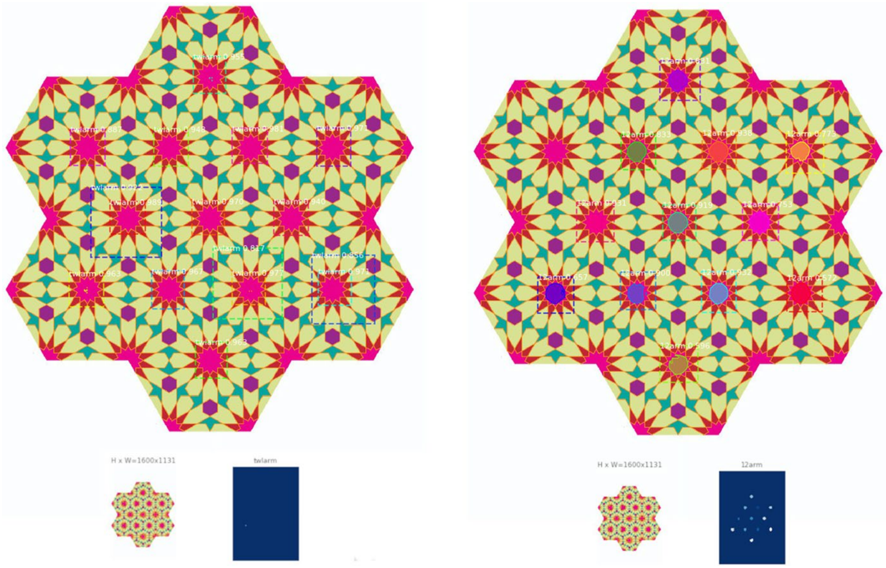


Fig. 9 Comparison of the 12-pointed star detection results of Case 2 (left side) and Case 3 (right side)

Case 3

The min confidence parameter was changed (epochs = 30, steps per epoch = 100, min confidence = 0.2, learning rate = 0.0005) and another test was performed. At the end of this deep learning training, similar to the previous test; the loss value was 0.90 and the validation loss value was 0.85 (Fig. 2, Table 1).

The algorithm can detect 6-pointed and 8-pointed stars, as in the previous test. Additionally, the rate of detecting 5-pointed stars and 12-pointed stars increased together with masking (Figs. 4, 8, 9). In Fig. 8, all of the 5-pointed stars and 12-pointed stars are detected and masked. As can be seen in Fig. 9, 12-pointed star detection can be achieved even with a larger canvas. Furthermore, various star detection in the images with large canvases and star detection in linear drawings are also increased (Figs. 5 and 7). Better results can be obtained at the end of the training by increasing the variations of images of the same concept in the database. The detection problem in very complex backgrounds can also be improved by adding images with a similar concept to the database.

Although the algorithm does not yet provide perfect detection and masking results, it is open to improvement. The authors believe that the experiments carried out in this study, which is a preliminary study on the subject, will shed light on future studies.

Comparison with Earlier Tests

In this study, apart from the database whose results were mentioned, other databases were also prepared and tested. As a result of these tests, the val loss value was high, and the obtained results of the tests were not satisfactory (Table 2). It is important that the loss and val loss values obtained at the end of the Mask RCNN training are close to 1 or less. In their studies using Mask RCNN, Davis et al. (2021), Sahin et al. (2023) and Wang et al. (2023) observed that the loss values were below 1.

Compared with earlier tests, the observation shows that the database used for training requires specific preparation. For example, in Test 1 with 257 data, a database consisting only of various Islamic geometric pattern photographs was prepared and labeled. The result of the tests were not successful. In Test 2, in addition to these photographs, Islamic geometric patterns drawn by the author were added to the database and a database with 657 data was prepared. However, the tests performed at the end of this training were not successful. The drawings prepared by the author have the same concept (linear features, coloring style, repetition, style). The tests in this study (mentioned as Case 1, 2, 3) were conducted only with the database prepared using these Islamic geometric patterns drawn by the author. As mentioned in the results section, this test was successful.

Accordingly, it has been observed that the tests performed with the database consisting of images containing a wide variety of different types were not successful, but the tests performed with the database consisting of images with similar styles and increased diversity were partially successful. With this result, the star detection mechanism with Mask RCNN has been tested and experienced.

It has been determined that for a database containing a wide variety of images, it must contain a large number of images close to each style. In this case, in order to achieve the best results, a database containing tens of thousands of images must be prepared. For this, using significant existing Islamic geometric pattern databases may be a good alternative. Examples of these databases are Wade Photo Archive (2024) and Brian Wichmann's (2024) archive, which contains versions of geometric constructions of these images.

There are a few Islamic pattern tessellations that include 9-pointed stars, 10-pointed stars and 16-pointed stars. Images containing these star types can be added to the database. By performing deep learning training, once more using the expanded database, the star types in Islamic pattern tessellations including 9-pointed stars, 10-pointed stars, and 16-pointed stars can also be classified.

Islamic geometric patterns are very diverse. Even though the patterns are different, they can be very similar to one another. In order for the deep learning algorithm to predict these patterns more precisely and give more accurate results, training it with a large number and variety of data will be necessary. A common platform can be created to create such a dataset to be used for deep learning algorithm training. Images can be added to this database by different people from different parts of the world. However, a systematic approach is needed to create such a platform.

Conclusion

Islamic geometric patterns are found in many historical artefacts in Eastern architecture. However, the applications of the patterns to the modern buildings are almost non existent. Therefore, the experts on this subject are very limited. This makes the restoration/maintenance of these patterns very difficult. Hence, the ways should be searched to make this process automated and easier. In this study, it is suggested to use the deep learning algorithm for the detection and classification of Islamic geometric pattern tessellation type. The contributions of this study are as follows:

- A database containing 600 Islamic geometric pattern images has been prepared.
- The deep learning algorithm was trained and a weighted file was created. This file is ready to use.
- The results were tested by giving test images to the trained algorithm. Thus, the operability of the trained deep learning algorithm has been confirmed.
- The system of creating Islamic geometric patterns is not widely known because it is not often used in architecture anymore. For this reason, it is known that mistakes were made in the relevant restorations. An attempt has been made to produce alternative auxiliary solutions to this situation by searching for artificial intelligence-based solutions.
- It is thought that the positive and negative test results in this study using Mask RCNN will contribute to the development of the algorithm.

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Availability of Data and Material Data will be made available on request.

Code Availability Not applicable.

Declarations

Conflicts of İnterest The authors declare no confict of interest.

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

References

Abdulla, Waleed. 2017. Mask R-CNN for object detection and instance segmentation on Keras and TensorFlow. https://waleedka.github.io/ (Accessed 10 January 2022)

Agirbas, Asli. 2017. Teaching Design by Coding in Architecture Undergraduate Education: A Case Study with Islamic Patterns. *CAADFutures 2017 Proceedings*, 12–14 July, Istanbul, Turkey: 249–258.

Agirbas, Asli. 2020. Algorithmic Decomposition of Geometric Islamic Patterns: A Case Study with Star Polygon Design in The Tombstones of Ahlat. *Nexus Network Journal.* 22: 113–137.

Agirbas, Asli and Elif Feyza Basogul. 2021. Structural Performance of Reciprocal Structures formed by using Islamic Geometrical Patterns. *Proceedings of the 39th eCAADe Conference*, 8–10 September, Novi Sad, Serbia: 391–400. https://doi.org/10.52842/conf.ecaade.2021.2.391

Agirbas, Asli and Gulnur Yildiz. 2021. Origin of Irregular Star Polygons in Ground Projection Plans of Muqarnas. *Nexus Network Journal.* 23: 507-548.

Agirbas, Asli, Gulnur Yildiz and Murat Sahin. 2022. Interrelation between grid systems and star polygons of muqarnas ground projection plans. *Heritage Science:* 10 (12). https://doi.org/10.1186/s40494-022-00647-z

Ahadian, Maryam and Azam Bastanfard. 2011. Classification of Islamic Geometric Pattern Images Using Zernike Moments. *Proceedings of Eighth International Conference Computer Graphics, Imaging and Visualization*, Singapore: 19–24. https://doi.org/10.1109/CGIV.2011.11

Altın, Alper. 2020. *Anadolu Selçuklu Mimarisindeki Geometrik Süslemelerde Restorasyon Hataları.* Konya: Literatürk.

Al-Shaibani, W.T., Mustafa Helvaci, Ibraheem Shayea and Azizul Azizan. 2021. Airplane Type Identification Based on Mask RCNN; An Approach to Reduce Airport Traffic Congestion. *IEEE Microwave Theory and Techniques in Wireless Communications (MTTW)*, 07–08 October, Riga, Latvia: 154–159. https://ieeexplore.ieee.org/document/9607203

An, Zhenyu, Emiri Nonaka, Ren Wu, Mitsuru Nakata and Qi-Wei Ge. 2021. Automatic Diagnosis of Tongue Using Mask-RCNN. *36th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC)*, 27–30 June, Jeju, Korea (South): 1–4. https://ieeexplore.ieee.org/document/9501265

Aoulalay, Ayoub, Abderrahim El Mhouti and Mohammed Massar. 2022. Classification of Islamic Geometric Patterns based on Machine Learning Techniques. *Proceedings of 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, 03–04 March, Meknes, Morocco: 1–6. https://doi.org/10.1109/IRASET52964.2022.9737839

Bonner, Jay. 2017. *Islamic Geometric Patterns: Their Historical Development and Traditional Methods of Construction*. NY: Springer.

Bourgoin, Jules. 1879. *Les Eléments de l'Art Arabe: Le Trait des Entrelacs*. Paris: Firmin-Didot.

Brian Wichmann Archive. 2024. https://tilingsearch.mit.edu/ (Accessed 20 April 2024)

Broug, Eric. 2008. *Islamic Geometric Patterns*. London: Thames and Hudson.

Chen, Leiyu, Shaobo Li, Qiang Bai, Jing Yang, Sanlong Jiang and Yanming Miao. 2021a. Review of Image Classification Algorithms Based on Convolutional Neural Networks. *Remote Sensing* 13(22): 4712. https://doi.org/https://doi.org/10.3390/rs13224712

Chen, Miaomiao, Fengshan Bai and Z. Gerile. 2021b. Special Object Detection Based on Mask RCNN. *17th International Conference on Computational Intelligence and Security (CIS)*, 19–22 November, Chengdu, China: 128–132. https://ieeexplore.ieee.org/document/9701686

Chen, Yunke, Yonghua Shi, Yanxin Cui and Xiyin Chen. 2021*c*. Narrow gap deviation detection in Keyhole TIG welding using image processing method based on Mask-RCNN model. The International Journal of Advanced Manufacturing Technology *112*: 2015-2025. https://doi.org/10.1007/s00170-020-06466-5

Davis, Dylan S., Gino Caspari, Carl P. Lipo and Matthew C. Sanger. 2021. Deep learning reveals extent of Archaic Native American shell-ring building practices. *Journal of Archaeological Science* 132: 105433. https://doi.org/10.1016/j.jas.2021.105433

Djibril, Mohamed Ould and Rachid Oulad Haj Thami. 2008. Islamic geometrical patterns indexing and classification using discrete symmetry groups. *Journal on Computing and Cultural Heritage* 1(2): 1-14. https://doi.org/10.1145/1434763.1434767

Dutta, Abhishek and Andrew Zisserman. *2019.* The VIA Annotation Software for Images, Audio and Video. Proceedings of the 27th ACM International Conference on Multimedia (MM '19), October 21–25, Nice, France: 2276–2279. https://doi.org/10.1145/3343031.3350535

El Ouaazizi, Aziza, Abdelbar Nasri and Rachid Benslimane. 2015. A rotation symmetry group detection technique for the characterization of Islamic Rosette Patterns. *Pattern Recognition Letters* 68: 111-117. https://doi.org/10.1016/j.patrec.2015.08.021

Fan, Zhimiao, Weijie Xia, Xue Liu and Hailin Li. 2021. Detection and segmentation of underwater objects from forward-looking sonar based on a modified Mask RCNN. *Signal, Image and Video Processing* 15: 1135–1143. https://doi.org/10.1007/s11760-020-01841-x

Gherardini, Francesco and Francesco Leali. 2016. A Framework for 3D Pattern Analysis and Reconstruction of Persian Architectural Elements. *Nexus Network Journal* 18: 133–167. https://doi.org/10.1007/s00004-015-0287-z

Hajebi, Bita and Pooya Hajebi. 2021. Intelligent Restoration of Historical Parametric Geometric Patterns by Zernike Moments and Neural Networks. *Journal on Computing and Cultural Heritage* 14 (4): 1-27. https://doi.org/10.1145/3459607

Hamekasi, N., F.F. Samavati and A.H. Nasri. 2011. Interactive modeling of muqarnas. *Proceedings of Computational Aesthetics in Graphics, Visualization, and Imaging*: 129–136. https://doi.org/10.1145/2030441.2030469

He, Kaiming, Georgia Gkioxari, Piotr Dollar and Ross Girshick. 2017. Mask R-CNN. *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, Venice, Italy: 2980–2988. https://doi.org/10.1109/ICCV.2017.322

Htet, Khaing Suu and Myint Myint Sein. 2021. Toddy Palm Trees Classification and Counting Using Drone Video: Retuning Hyperparameter Mask-RCNN. *7th International Conference on Control, Automation and Robotics (ICCAR)*, 23–26 April, Singapore: 196–200. https://ieeexplore.ieee.org/abstract/document/9463466

Izadi, Ali, Mahdi Rezaei (Ghahroudi) and Azam Bastanfard. 2010. A computerized method to generate complex symmetric and geometric tiling patterns. In *Intelligent computer graphics, Studies in Computational Intelligence,* D. Plemenos and G. Miaoulis (eds.), vol 321: 185–210. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-15690-8_10

Jin, Hao, Zhangli Lan and Xu He. 2021. On Highway Guardrail Detection Algorithm Based on Mask RCNN in Complex Environments. *Proceedings of 7th International Conference on Systems and Informatics (ICSAI)*, 13–15 November, Chongqing, China: 1–6. https://ieeexplore.ieee.org/document/9664044

Johnson, Jeremiah W. 2020. Automatic Nucleus Segmentation with Mask-RCNN. In: *Advances in Computer Vision, CVC 2019, Advances in Intelligent Systems and Computing,* K. Arai and S. Kapoor (eds.), vol 944: 399–407, Springer, Cham. https://doi.org/10.1007/978-3-030-17798-0_32

Khamjane, Aziz, Zouhair Ouazene, Abderrazak Taime, Imad Badi, Khalid El Fazazy and Rachid Benslimane. 2023. The Polygonal Technique for Constructing Islamic Geometric Patterns. In: *Digital Technologies and Applications, ICDTA 2023, Lecture Notes in Networks and Systems,* S. Motahhir and B. Bossoufi (eds), vol 669: 521–530, Springer, Cham. https://doi.org/10.1007/978-3-031-29860-8_53

Khamjane, Aziz, Rachid Benslimane and Zouhair Ouazene. 2020. Method of Construction of Decagonal Self-Similar Patterns. *Nexus Network Journal* 22: 507–520. https://doi.org/10.1007/s00004-019-00461-4

Khamjane, Aziz and Rachid Benslimane. 2018. Generating Islamic Quasi-Periodic Patterns: A New Method. *Journal on Computing and Cultural Heritage* 11 (3): 1-18. https://doi.org/10.1145/3127090

Lahcen, Yassine Ait, Abdelaziz Jali, Ahmed El Oirrak, Youssef Aboufadil and Abdelmalek Thalal. 2021. New Approach to Construct a New Islamic Geometric Patterns Using The HASBA Method. *Journal of Theoretical and Applied Information Technology* 99 (14): 3663-3672.

LeCun, Yann, Yoshua Bengio and Geoffrey Hinton. 2015. Deep learning. *Nature* 521: 436–444. https://doi.org/10.1038/nature14539

Masita, Katleho L., Ali N. Hasan and Thokozani Shongwe. 2020. Deep Learning in Object Detection: a Review. *International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*, 06–07 August, Durban, South Africa: 1–11. https://doi.org/10.1109/icABCD49160.2020.9183866

Nadyrshine, Neil, Lilia Nadyrshine, Rafik Khafizov, Nailia Ibragimova and Karine Mkhitarian. 2021. Parametric methods for constructing the Islamic ornament. *E3S Web of Conferences*, 274, 09009. https://doi.org/10.1051/e3sconf/202127409009

Nasri, Abdelbar, Rachid Benslimane and Aziza El Ouaazizi. 2014. A Genetic Based Algorithm for Automatic Motif Detection of Periodic Patterns. *Proceedings of Tenth International Conference* *on Signal-Image Technology and Internet-Based Systems*, 23–27 November, Marrakech, Morocco: 112–118. https://doi.org/10.1109/SITIS.2014.88

Nasri, Abdelbar and Rachid Benslimane. 2014. Symmetrical motif extraction for periodic ornamental patterns. *Proceedings of International Conference on Multimedia Computing and Systems (ICMCS)*, 14–16 April, Marrakech, Morocco: 99–104. https://doi.org/10.1109/ICMCS.2014.6911210

Necipoglu, Gülru. 1995. *The Topkapi scroll: Geometry and ornament in Islamic Architecture: Topkapi Palace Museum Library MS H. 1956*. Santa Monica: The Getty Center for the History of Art and the Humanities.

Prados-Privado, María, Javier García Villalón, Antonio Blázquez Torres, Carlos Hugo Martínez-Martínez and Carlos Ivorra. 2021. A Validation Employing Convolutional Neural Network for the Radiographic Detection of Absence or Presence of Teeth. *Journal of Clinical Medicine* 10 (6): 1186. https://doi.org/10.3390/jcm10061186

Pustokhina, Irina V., Denis A. Pustokhin, Thavavel Vaiyapuri, Deepak Gupta, Sachin Kumar and K. Shankar. 2021. An automated deep learning based anomaly detection in pedestrian walkways for vulnerable road users safety. *Safety Science* 142, 105356. https://doi.org/10.1016/j.ssci.2021.105356

Rahman, Fashiar, Tzu-Liang (Bill) Tseng, Jianguo Wu, Yuxin Wen and Yirong Lin. 2022. A deep learning-based approach to extraction of filler morphology in SEM images with the application of automated quality inspection. *AI EDAM* 36: e15 https://doi.org/10.1017/S0890060421000330

Ranjazmay Azari, Mohammadreza, Mohammadreza Bemanian, Mohammadjavad Mahdavinejad, Axel Körner and Jan Knippers. 2023. Application-based principles of islamic geometric patterns; state-of-the-art, and future trends in computer science/technologies: A review. *Heritage Science* 11: 22. https://doi.org/10.1186/s40494-022-00852-w

Raoofi, Hamed and Ali Motamedi. 2020. Mask R-CNN Deep Learning-based Approach to Detect Construction Machinery on Jobsites. *Proceedings of 37th International Symposium on Automation and Robotics in Construction (ISARC 2020),* Kitakyushu, Japan: 1122–1127. https://doi.org/10.22260/ISARC2020/0154

Rasouli, Peyman, Azam Bastanfard, Alireza Rezvanian and Omid Jalilian. 2008. Fast Algorithms for Computer Generated Islamic Patterns of 8-ZOHREH and 8-SILI. In: *Advances in Multimedia Information Processing - PCM 2008, Lecture Notes in Computer Science,* YM.R Huang et al. (eds) vol 5353: 825–829, Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-540-89796-5_91

Sadhukhan, Debanjan, Sai Peri, Niroop Sugunaraj, Avhishek Biswas, Daisy Flora Selvaraj, Katelyn Koiner, Andrew Rosener, Matt Dunlevy, Neena Goveas, David Flynn and Prakash Ranganathan. 2020. Estimating surface temperature from thermal imagery of buildings for accurate thermal transmittance (U-value): A machine learning perspective. *Journal of Building Engineering* 32: 101637. https://doi.org/10.1016/j.jobe.2020.101637

Sahin, M. Emin, Hasan Ulutas, Esra Yuce and Mustafa Fatih Erkoc. 2023. Detection and classification of COVID-19 by using faster R-CNN and mask R-CNN on CT images. *Neural Computing and Applications* 35: 13597–13611. https://doi.org/10.1007/s00521-023-08450-y

Schneider, Gerd. 1980. *Geometrische Bauornamente der Seldschuken in Kleinasien*. Wiesbaden: Reichert.

Senhaji, Mohammed and Rachid Benslimane. 2022. 3D Reconstruction of Moroccan-Andalusian Muqarnas Domes. *Journal on Computing and Cultural Heritage* 15 (2): 1-27. https://doi.org/10.1145/3479712

Senhaji, Mohammed and Rachid Benslimane. 2019. Automatic 3D muqarnas architectural patterns reconstruction using plane representation. *Journal of Cultural Heritage* 35: 25-40. https://doi.org/10.1016/j.culher.2017.12.004

Shaodan, Lin, Feng Chen and Chen Zhide. 2019. A Ship Target Location and Mask Generation Algorithms Base on Mask RCNN. *International Journal of Computational Intelligence Systems* 12 (2): 1134–1143. https://doi.org/10.2991/ijcis.d.191008.001

Sizkouhi, Amir Mohammad Moradi, Mohammadreza Aghaei, Sayyed Majid Esmailifar, Mohammad Reza Mohammadi and Francesco Grimaccia. 2020. Automatic Boundary Extraction of Large-Scale Photovoltaic Plants Using a Fully Convolutional Network on Aerial Imagery. *IEEE Journal of Photovoltaics* 10 (4): 1061-1067. https://doi.org/10.1109/JPHOTOV.2020.2992339

Sultana, F., A. Sufian and P. Dutta, 2020. A Review of Object Detection Models Based on Convolutional Neural Network. In: *Intelligent Computing: Image Processing Based Applications, Advances in Intelligent Systems and Computing,* J. Mandal and S. Banerjee (eds), vol 1157: 1–6. Springer, Singapore, https://doi.org/10.1007/978-981-15-4288-6_1

Takahashi, Shiro. 2023. Muqarnas: A three-dimensional decoration of Islamic Architecture. http://www.shiro1000.jp/muqarnas/default-.htm (Accessed at 30 October 2023).

Tran, Thai Son, Van Phuc Tran, Hyun Jong Lee, Julius Marvin Flores and Van Phuc Le. 2022. A two-step sequential automated crack detection and severity classification process for asphalt pavements. *International Journal of Pavement Engineering* 23 (6): 2019-2033. https://doi.org/10.1080/10298436.2020.1836561

Uluengin, Fatin M. 2018. *Mukarnas.* Istanbul: Istanbul Fetih Cemiyeti.

Wade Photo Archive. 2024. https://patterninislamicart.com/s/collections/main-archive (Accessed 20 April 2024)

Wang, Tao, Kunming Zhang, Wu Zhang, Ruiqing Wang, Shengmin Wan, Yuan Rao, Zhaohui Jiang and Lichuan Gu. 2023. Tea picking point detection and location based on Mask-RCNN. *Information Processing in Agriculture* 10 (2): 267-275. https://doi.org/10.1016/j.inpa.2021.12.004

Wu, Yuanyi, Mengxing Lin and Sohrab Rohani. 2020. Particle characterization with on-line imaging and neural network image analysis. *Chemical Engineering Research and Design* 157: 114–125. https://doi.org/10.1016/j.cherd.2020.03.004

Zhang, Zhiyong, Xiaolei Yin and Zhiyuan Yan. 2022. Rapid data annotation for sand-like granular instance segmentation using mask-RCNN. *Automation in Construction* 133: 103994. https://doi.org/10.1016/j.autcon.2021.103994

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