

Classifying Historical Azulejos from Belém, Pará, Using Convolutional Neural Networks

Wanderlany Fialho Abreu, Rafael Lima Rocha, Rafael Nascimento Sousa, Tiago Davi Oliveira Araújo, Bianchi Serique Meiguins, and Carlos Gustavo Resque Santos(✉)

Universidade Federal do Pará, Belém, Brazil
{wanderlany.abreu,rafael.lima,rafael.nascimento.sousa}@icen.ufpa.br,
{tiagoaraujo,bianchi,carlosresque}@ufpa.br

Abstract. The cultural heritage of a city is of great importance for the maintenance and enhancement of its history. Users can use innovative technologies such as Computer Vision to emphasize the city's treasures attractively and playfully. In Belém, Pará, azulejo is a meaningful cultural heritage case, which goes back to its foundation. The image recognition can facilitate and speed up the search for an azulejo and its historical information since, although cataloged, its visual appearance identifies it better than a name, which implies that the image-based search is much more natural than a text-based search. In this way, this work presents a prototype that uses Convolutional Neural Networks (CNN) to classify the azulejos from Belém by an image-based search. CNN's training used two image datasets. The first contains images that show azulejos and other environmental elements (for instance, walls, doors, streets, and people). The second dataset contains images that show only azulejos, and in both datasets, they only have one type of azulejo per image. The trained model consists of twelve different types of azulejos, representing the recognizable classes. Thus, after training, the tflite (Tensorflow Lite) model is generated with azulejos classes to be used in the mobile device image classification task. Finally, we developed an application in which the user takes a photo, and the system sends it to the classification module that contains the trained CNN model. After the image classification process, the module returns the five classes' values with the best accuracy and historical details about the azulejos.

Keywords: Image recognition · Cultural heritage · Azulejo · Convolutional neural networks

1 Introduction

Tourism is a fundamental activity for city economics and even cultural identity [4]. The visitation and presentation of a city's cultural heritage are among the tourism modality that most express the city's identity. The heritage can be

© Springer Nature Switzerland AG 2021
O. Gervasi et al. (Eds.): ICCSA 2021, LNCS 12950, pp. 84–98, 2021.
https://doi.org/10.1007/978-3-030-86960-1_7

physical (such as buildings, avenues, monuments) or exhibitions of their histories and traditions [29].

The Belém, Pará, Brazil, city has a vast cultural heritage, including physical heritage built at different times in the city's history. The collection of Azulejos is a prominent case of physical heritage. They were manufactured in Europe and imported to decorate the home of influential people between the 18th and 20th centuries [3]. The expressive amount of Azulejos in the heritage of Belém increased mainly in the period of economic growth of the city [1] when it ceases to be a subsistence economy and starts to be market-based.

Belém has an expressive diversity of different Azulejos patterns. Alcântara et al. [1] book, published by IPHAN (National Historical and Artistic Heritage Institute), is the most extensive catalog of Belém's Azulejos until now, containing various types, such as patterns, panels, and devotional art, along with its historical information.

This cultural treasure is already presented to the tourist in a narrated way or through books. However, new technologies could transmit this cultural heritage more interactively and playfully. The tourist activity itself is changing more and more by the visitor's independence with the help of technologies, such as mobile applications that assist the visitation and exploration of points of interest and associated content [18].

Mobile applications, smart cities, virtual and augmented reality, computer networks, image processing, and computer vision are among the areas of information technology that can assist visitors. This work focuses on applying computer vision techniques to facilitate the search for content of a particular Azulejo only from a photo of it obtained through a cell phone camera.

Therefore, this work uses one of the leading computer vision techniques, the Convolutional Neural Network (CNN). CNN combines parts of the images provided, making comparisons between these small parts called masks, which are patterns used to verify the new images. The set of masks forms a filter, and a convolution operation is performed on each layer where there are filters to reveal new patterns. The values for the masks in the filters are learned during the CNN training stage.

We used two datasets of Azulejos [28] to train our classifier. The first dataset contains images showing only Azulejos, and the second contains images showing Azulejos and adjacent environmental elements (such as streets, walls, and vegetation) in the image. Thus, the CNN model's training has used these datasets to classify Azulejos from new photos obtained by the user of the application. Additionally, we have implemented a prototype application to test the model's functioning on a mobile device.

The rest of the article is divided as follows: Sect. 2 describes the related works, Sect. 3 presents the datasets used for training the model and the dataset used to show historical content through the prototype application, Sect. 4 explains the training of the CNN model, Sect. 5 shows the mobile application developed to test the image-based search, and Sect. 6 concludes this work and draws directions for future work.

2 Related Works

This section presents works related to the main subjects addressed in this research, showing their objectives, techniques, and conclusions.

Table 1 presents an overview of the use of technologies concerning the related works, emphasizing Augmented Reality (AR), Computer Vision (CV) techniques, and the area of application.

Table 1. The overview of the related works.

Reference	Year	AR technique	CV technique	Area
[11]	2014	GPS-based	Image-recognition AR	Tourism
[20]	2015	GPS-based	–	Education
[24]	2015	GPS-based	–	Tourism
[27]	2015	QRcode	–	Journalism
[15]	2018	Augmenting immersive	–	Museum and art
[10]	2018	GPS-based	IFT, SURF	Tourism
[23]	2018	GPS-based	–	Tourism
[13]	2019	GPS-based	R-CNN	Tourism
[8]	2019	GPS-based	–	Tourism
[21]	2019	–	Machine learning, CNNs	Archaeology
[26]	2020	–	Point clouds, 3D reconstruction	Heritage
[12]	2020	Image-based	SURF, CNN model, SVM	Archaeology
[14]	2020	–	TU-DJ-Cluster and deep learning	Tourism
[16]	2020	–	Deep feature, image stitching	Tourism
[9]	2020	Image-based	–	Heritage
[22]	2020	–	VGG	Museum and Art
[17]	2021	Image-based	–	Tourism
[30]	2021	–	R-CNN	Archaeology
[25]	2021	Multisensory	–	Heritage
[2]	2021	3D Model	–	Tourism
[7]	2021	–	R-CNN	Archaeology

Rocha [27] analyzes augmented reality, aiming to improve journalism by innovating the presentation of news and proposing new ways of interacting with the reader. His work presents the chronological evolution of augmented reality technology and the uses in the journalistic medium, using mainly QRcode, for example, on magazine covers. As a result, the adherence to technology depends on the user's knowledge of how to use it, the different possible uses, and changes in society in the future.

Godoy et al. [13] present a mobile application focused on tourism, which allows the exploration and access to historical and cultural information in different places in Santiago, RS, Brazil. They used JavaScript, HTML, and CSS to create the application screens, in addition to the JavaScript framework Vue.Js. They used an API provided by Cordova (library) to implement the geolocation, while OpenCV was responsible for the computer vision techniques. The possibility of obtaining cultural and historical knowledge about the location during visitation is their main contribuiton.

Martins et al. [24] present a study on augmented reality and its use for tourism, which according to the authors, presents a significant growth in investments in technologies. Besides, they presented the project "Viseu na Palma da Mão" to better know the city by cell phone. In addition to visualizing, the tool allows manipulating virtual objects just by pointing the device at the real objects.

Various authors [15,22] present the use of augmented reality by immersion and image processing, using museum and art images as a database, showing the potential of augmented reality in creating innovative experiences in various sectors of museums and arts. The visitors' evaluation states that the more real the museum experience and visualization of the arts, the greater the interest in visiting and buying art.

Various authors [9,25,26] present immersive virtual reality, deep learning, and neural networks concerning images of cultural heritage sites to provide visitor experiences in various external cultural heritage environments.

Various authors [7,12,21,30] use new methods of deep neural networks, image processing, and augmented reality in archaeological images to detect unknown archaeological objects, from different places, in an innovative, accurate, and efficient way.

Kysela and Štorková [20] apply augmented reality technology to teaching history and tourism through a mobile application based on geolocation to offer innovative teaching methods attractively and effectively.

Various authors [2,8,10,11,14,17,23] use augmented reality resources, deep learning, and image recognition through images, geolocation, and immersion to provide sightseeing tours through various tourist spots.

3 Datasets

This section presents the datasets used in this work and their characteristics, structure, and purpose for their use. We have used two types of datasets to provide historical/cultural content about the Azulejos through the prototype application and another to train the CNN model.

3.1 Historical Content Dataset

Alcântara et al. book [1] provided the Belém, Pará, Azulejo's inventory that contains information on the cultural heritage of the Azulejos from Belém.

We transcribed the tables in the book (which are in printed format) to the digital format using a spreadsheet editor.

We created a spreadsheet for each table present in the book, containing a table with the information separated into the following columns: identification code, address, neighborhood, and information regarding the manufacture, characteristics, and application method. After registering all information in the spreadsheet editor, we have exported the datasets to the CSV (Comma-Separated Values) format to be easily imported into other applications. The aim of transforming this information into the digital format is to make it available for use by computer systems, thus facilitating further applications with this theme.

The historical/cultural dataset presents a total of 274 instances of Azulejos of pattern type, with eight attributes to describe each of them. The first column of Table 2 shows the attributes' name, the second has a brief description of that attribute, and the last column shows a sample of this dataset.

Table 2. Historical/Cultural dataset attributes on the Azulejos of pattern type

Attribute's name	Description	Sample
Azulejo-code	ID assigned for unique identification of records	Azulejo-PE1-1-1
Origin	Original manufacturing site of an Azulejo	Lisboa/Portugal
Factory	Original factory name	Viúva Lamego-Constância
Dimension-format	Size of individual tile piece	13.4 × 13.4 cm
Manufacturing technique	Material and techniques used in the manufacture of the Azulejo	Ceramic and glazed print
Address	Places in Belém where it is possible to find such Azulejos	Trav. Frutuso Guimarães n° 18/30/36, 257/259 ...
District	District containing the addresses	Cidade Velha, Campina
Use-application	Position and technique of tile application	Facade cladding, laid by compression against fresh mortar

A part of the information available in the historical/cultural dataset is used as visualized content in the prototype application of this work.

3.2 Azulejos Image Dataset for CNN Training

Despite the data and images obtained from the Azulejo's inventory, a larger amount of images with a variety of sizes, lighting, deformation, and distance is

necessary to create a suitable dataset for training the CNN so that the final result is reliable.

Considering the purpose of using CNNs to classify Azulejos, the selected dataset [28] has pictures of Azulejos in the city taken from three different cell phones. Being divided into two datasets, one containing 191 pictures showing Azulejos and environmental elements and the other 865 images showing only the Azulejos. Further, the current situation and the impossibility of visiting some places' interior have created an obstacle in obtaining new images.

The database has images of historic mansions in Belém, with Azulejos decorating the interiors and facades. Figure 1 shows two samples of images in the two datasets, which are used for training the CNN model.



Fig. 1. Sample images present in the 1st database, containing Azulejos and other elements (left), and in the 2nd database, containing only tiles (right). [28]

The 1st dataset contains 191 images collected using three different cell phones, and the images have different types of quality, angles, and shadows. Additionally, other environmental elements are shown, such as doors, windows, and elements of buildings' facades, making it challenging to identify the Azulejo shown in the image. In short, it is the one that best represents the use of the application by the final user.

The 2nd database contains 865 images, consisting of cropped images created from the 191 images in the 1st database. It aims to filter the images focusing on the Azulejos and discard environmental elements present in the first dataset.

Moreover, the dataset generated by the training presents twelve classes of different Azulejos. Figure 2 shows the twelve classes of Azulejos present in the dataset, presented in a 2×2 grid (4 tiles) to illustrate the training classes.

4 Model Training

This section presents the phases of model training, the image preprocessing, the selection of the convolutional neural network architecture, and the training itself.



Fig. 2. 2×2 (4 tiles) photo of the twelve classes of Azulejos present in the dataset. [28]

4.1 Preprocessing

This phase uses preprocessing to standardize the dimensions of the images in the dataset. The necessary data is loaded in the disk and is performed the standardization of dimensions, adding vertical or horizontal black padding to images at 256×256 pixels without stretching the tiles. Figure 3 presents a demonstrative compilation of four images of one of twelve tiles classes to show the images after the standardization process.

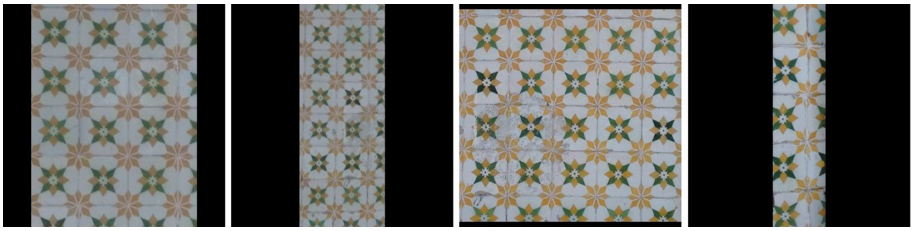

Fig. 3. Demonstrative compile of images from same tile class after the standardization of dimensions.

Besides, we used the Samplewise normalization of mean and standard deviation to normalize the network's input images. Each sample or image is normalized by subtraction of mean of image pixels values and then divided by the standard deviation of image pixels values. Finally, each input image will tend to zero mean and unit standard deviation of pixels values.

The Eq. 1 presents the normalization performed per image. The image before the normalization is represent by I, and μ and σ are the mean and standard deviation of image I, while I_n represent the normalized image witch the pixels values has zero mean and unit standard deviation.

$$I_n = \frac{I - \mu}{\sigma} \tag{1}$$

4.2 CNN Selection

We have performed a random search to find the best architecture and parameters to classify the Azulejos, where given a finite set o parameters, is investigated a random combinations of parameters to find the ones that best fit the proposed task in this work [5].

It was investigated the number of layers of the CNN and dense layers, besides the number of filters and neurons as shown in Table 3. For example, the Conv layers block 1 (Table 3) represents the first block of convolutional layers, varying between one to three layers, with steps of one, while Neurons represent the number of neurons in dense layers, starting with 128 until 1024, with increments of 128.

The predefined architectures ResNet50, VGG-19, and InceptionV3 also are evaluated to perform Azulejos classification.

Table 3. Set of parameters used in random search.

Search	Min	Max	Step
Conv layers block 1	1	3	1
Conv layers block 2	1	3	1
Conv layers block 3	1	3	1
Dense layers	1	3	1
Neurons	128	1024	128
Filters	16	128	16

The evaluation of predefined architectures suggests a poor classification performance of Azulejos. Nevertheless, the random search to find our architecture is successful. The obtained architecture has 18 layers, as shown in Table 4.

The selected architecture has seven convolutional layers, seven pooling layers (max pooling), and four dense layers, as shown in Table 4. The convolutional layers have filters of size 3×3, and have the number of filters present in the column filters/neurons in Table 4. The first three dense layers have 1024, 512, and 128 neurons, respectively. While the fourth and last dense layer present 12 neurons, expressing the twelve classes of Azulejos.

4.3 Training

We have added Azulejos' images taken from photos of the computer screen due to the pandemic situation that the world is currently experiencing, making it unfeasible to test the prototype in person. These images are sensitive to illumination interference, distortions, and others. Therefore, the model can learn to recognize images captured from a computer screen and in-loco visitation.

Table 4. Summary of selected architecture.

Layer	Type	Filters/neurons	Number of parameters
1	Convolutional	64	1792
2	Pooling		
3	Convolutional	64	36928
4	Pooling		
5	Convolutional	32	18464
6	Pooling		
7	Convolutional	32	9248
8	Pooling		
9	Convolutional	16	4624
10	Pooling		
11	Convolutional	16	2320
12	Pooling		
13	Convolutional	16	2320
14	Pooling		
15	Dense	1024	66560
16	Dense	512	524800
17	Dense	128	65664
18	Dense	12	1548
Total of parameters			734.268
Trainable parameters			734.268

The final dataset has 1164 images distributed in twelve classes of Azulejos. We divided the dataset into 80% of images for training and 20% of images for test the generated model, 931 and 233 images, respectively.

We used the RMSprop optimizer to minimize the cost function (known as loss function) to reduce the difference between the expected output and the network output [6]. The learning rate used is 0.001. We used 100 epochs and 16 batches of images.

The training image set is small to train a CNN accurately. Thus, we generated batches of synthetic images in real-time to the model training through the data augmentation approach [19]. The transformations applied were vertical and horizontal flips, translations of −30 to 30 pixels per axis, besides the scale transformation of 70–130% of image size per axis.

Figure 4 presents some transformations performed by data augmentation. The left image presents the original image, without transformations, of the Azulejo of the "soberano" class, and the subsequent images represent the transformations applied to the original image.

Table 5 presents the obtained results in terms of accuracy and loss after the Azulejos classification model generation. The values of training classification

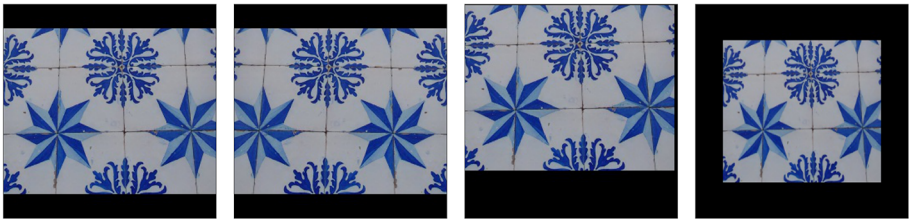

Fig. 4. Transformations applied by data augmentation. The left image shows the original, and the three right images show sample transformations applied by data augmentation.

results show that data is adjusted to model learning. The training set reaches an accuracy of 98.60%, indicating that almost all images are correctly classified. Furthermore, the loss value (0.0622) of Table 5 shows the efficiency of optimization performed by RMSprop with training data.

Table 5. Results of train and test sets.

	Accuracy (%)	Loss
Training	98.60	0.0622
Test	92.70	0.2875

The test results show the quality of both accuracy and loss results. The accuracy of 92.70%, shown in Table 5, indicates that 219 images are correctly classified of 233 available images. Besides, both training and test accuracies indicate no occurrence of model overfitting, i.e., the classification model of Azulejos showed up the efficiency to generalize and classify new images, which were not used in training. Finally, the loss value of the test set shows the optimization quality performed by RMSprop.

The database shows a certain level of imbalance between the number of Azulejo images per class. Therefore, to better elucidate the test images' results, the confusion matrix is generated, as shown in Fig. 5. The 'true class' shows the number of images that belong to a specific Azulejo class, while the 'predicted class' column represents the generated model's predictions.

Seventeen images are classified incorrectly, as shown in Fig. 5. The "pinho" class stands out, with five of twenty-five incorrectly classified. Two are classified as "particular2" and "sesc", while one is classified as "ihgp".

5 Prototype

In this section, we present the main activities of the azulejo recognition prototype. The application's main interactions are: take a picture of an azulejo,

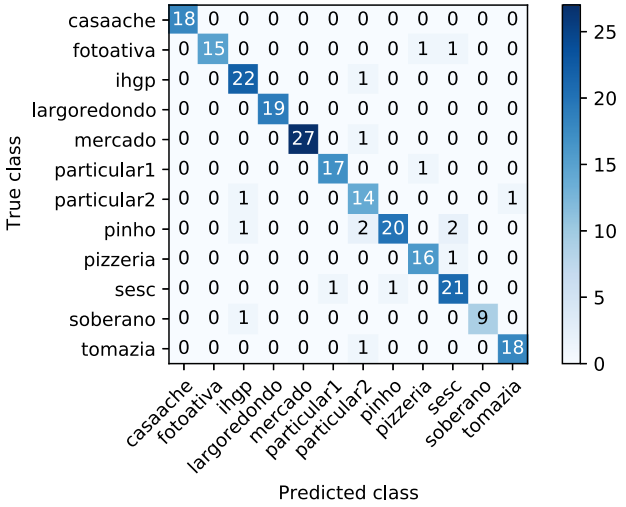

Fig. 5. Classification's confusion matrix of validation Azulejos images.

select the correct azulejo from the list of possibilities, and view content about the selected azulejo. Figure 6a presents the prototype's initial activity, showing the camera pointing to the image containing the azulejo to be recognized. After capturing the image, using the "FOTO" button, the smartphone screen displays the captured image.

Figure 6b shows the prototype's classification screen. It shows the four classes with the highest chance of being correct and their respective probability. The items on the screen are sorted from top to bottom in descending order of probability. In the example of Fig. 6b, the classes list shows "mercado" with ∼99% of probability, "casaache" with ∼0%, "pinho" with ∼0%, and "largoredondo" with ∼0%.

The activity of Fig. 6c presents the selected Azulejo's content of the classes list. This example shows the "mercado" class. This screen shows an Azulejo image alongside a textual description of its history, fabrication date, and location.

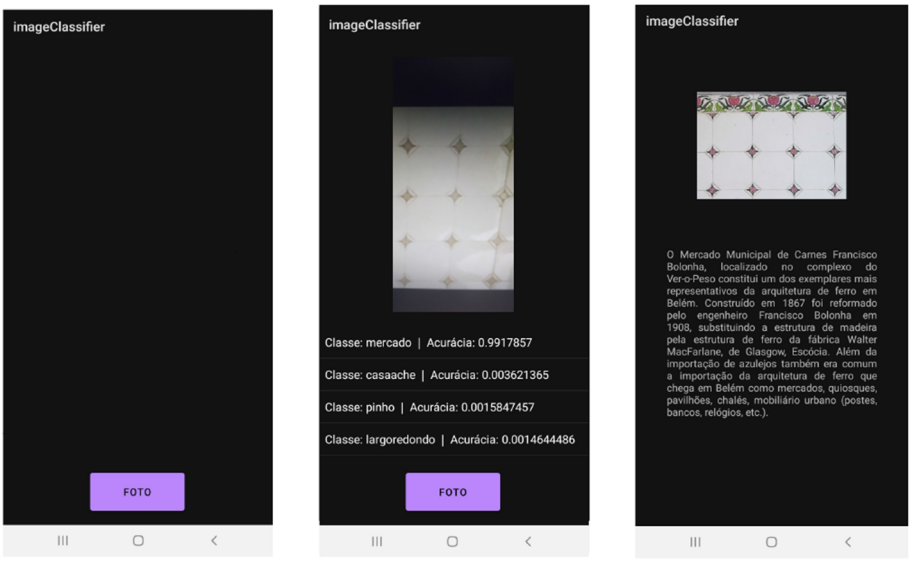

Fig. 6. Activities of the application in order of interaction. (A) The home screen has a button that opens the device's camera to take the picture. (B) Activity containing the taken photo and the name of the classes with the accuracy of the classification task. (C) Screen with details about the azulejos, accessed when the user clicks on an item listed in screen (B).

6 Conclusion

This work presents the application of a convolutional neural network in the city of Belém, Pará. We developed an image classification module using the Tensorflow environment libraries to reuse the created module in different projects that need the classification task. Besides, a table containing an inventory of the Azulejos from Belém, Pará, was transcribed into the digital format.

We researched several articles about other applications developed with similar themes aiming to acquire the necessary knowledge for the execution of the work. Besides, we detailed the technology they have used and the area of the application. to have a factual vision of what could be developed.

Regarding the use of a CNN for an image classification task, was used an eighteen layers architecture obtained through an exploratory search. The selected dataset for the training has twelve Azulejos classes, 1164 images taken from different cell phones, showing or not environmental elements, and having different angles, lighting, and shadow conditions.

The dataset was divided between images for the training itself, with 80%, and images for the model test, with 20%. Due to the relatively small number of images, we used the "Data Augmentation" technique to generate synthetic images (original images with subtle transformations).

Due to an in-loco test's unavailability, images of Azulejos taken from the computer monitor were inserted, making it necessary to use transformations related to lighting interference. During the training, the accuracy value was 98.60%, indicating that almost all training images were classified correctly, and the loss value was 0.0622%. During the test phase with the application, the accuracy and loss values marked the values of 92.70% and 0.2875% respectively, attesting to the training quality.

A confusion matrix was used to compare the obtained classification results with the true class. Additionally, we used the data augmentation technique to reduce repetition in deeper layers of training. As for the result obtained, among the exploratory search, our 18 layers architecture did better with the False Negative errors and the cost function and opened the possibility of future studies involving this architecture, using a larger dataset.

Regarding the coding contributions of this work, we decided to create a classification module, which brought together the necessary functions and interactions to perform the image classification task. The developed module aims to present only the necessary interfaces to other developers, leaving the details about classification encapsulated.

Besides, it is important to mention the transcription of the table present in the Azulejos' inventory from Belém, Pará, to the digital format, with 479 different specimens and various information about each of them. Thus, the table created can be used both concerning the information contained, offer a good source of data for building larger models, and the availability of information, which can be used in other projects for other purposes.

All used prototype code, trained CNN, and recognition module are available on the following link[1].

The future works are the integration of the prototype or the recognition module in other applications for tourism purposes, the integration with the location technology (GPS), the integration of the AR technology. Also, we will re-train the model with more classes when we could visit the local to take pictures.

References

1. Alcântara, D.M.E.S., Brito, S.R.S., Sanjad, T.A.B.C.: Azulejaria em Belém do Pará: Inventário - Arquitetura civil e religiosa - Século XVIII ao XX. Biblioteca Aloísio Magalhães IPHAN, Bras'ilia, DF (2016)
2. Marino Alfonso, J.L., Poblete Piedrabuena, M.Á., Beato Bergua, S., Herrera Arenas, D.: Geotourism Itineraries and Augmented Reality in the Geomorphosites of the Arribes del Duero Natural Park (Zamora Sector, Spain). Geoheritage **13**(1), 1–17 (2021). https://doi.org/10.1007/s12371-021-00539-x
3. Arruda, T.C., Sanjad, T.A.B.C.: Ornamentos de platibanda em edificações de belém entre os séculos XIX e XX: inventário e conservação. Anais do Museu Paulista: História e Cultura Material **25**(3), 341–388 (2017). https://doi.org/10.1590/1982-02672017v25n0310

[1] http://labvis.ufpa.br/AzulejAR/.

4. Awang, K.W., Hassan, W.M.W., Zahari, M.S.M.: Tourism development: a geographical perspective. Asian Soc. Sci. 5(5) (2009). https://doi.org/10.5539/ass.v5n5p67
5. Bergstra, J., Bengio, Y.: Random search for hyper-parameter optimization. J. Mach. Learn. Res. **13**(2), 281–305 (2012)
6. Bishop, C.M.: Pattern Recognition and Machine Learning, 5th edn. Information Science and Statistics. Springer, Heidelberg (2006)
7. Bonhage, A., Eltaher, M., Raab, T., Breuß, M., Raab, A., Schneider, A.: A modified mask region-based convolutional neural network approach for the automated detection of archaeological sites on high-resolution light detection and ranging-derived digital elevation models in the north German lowland. Archaeological Prospection, February 2021). https://doi.org/10.1002/arp.1806
8. Cauchi, M., Scerri, D.: Enriching tourist UX via a location based AR treasure hunt game. In: 2019 IEEE 9th International Conference on Consumer Electronics (ICCE-Berlin). IEEE, September 2019. https://doi.org/10.1109/icce-berlin47944.2019.8966141
9. Conde, M.B.: Nuevas tecnologías y difusión del turismo cultural: descubriendo a goya con realidad aumentada. ROTUR. Revista de Ocio y Turismo **14**(1), 81–93 (2020). https://doi.org/10.17979/rotur.2020.14.1.5945
10. Demir, O.F., Karaarslan, E.: Augmented reality application for smart tourism: GökovAR. In: 2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG). IEEE, April 2018. https://doi.org/10.1109/sgcf.2018.8408965
11. Fukada, H., Kasai, K., Ohtsu, S.: A field experiment of system to provide tourism information using image recognition type AR technology. In: Lecture Notes in Electrical Engineering, pp. 381–387. Springer International Publishing, November 2014. https://doi.org/10.1007/978-3-319-06764-3_47
12. Godewithana, N., Jayasena, K., Nagarawaththa, C., Croos, P., Harshanath, B., Alosius, J.: Historical places & monuments identification system. In: 2020 IEEE Region 10 Conference (TENCON). IEEE, November 2020. https://doi.org/10.1109/tencon50793.2020.9293882
13. Godoy, R.C., Cavalheiro, B.O., de Oliveira Castanho, C.L., da Silva, E.F., Spies, E.H., Alves, V.M.: Turismo e realidade aumentada: Desenvolvimento de um aplicativo para a cidade de santiago/rs. Anais da X edição do Encontro Anual de Tecnologia da Informação - EATI. **9**(1), 110–117 (2019). http://anais.eati.info:8080/index.php/2019/article/view/20/17
14. Han, S., Ren, F., Du, Q., Gui, D.: Extracting representative images of tourist attractions from Flickr by combining an improved cluster method and multiple deep learning models. ISPRS Int. J. Geo-Inf. **9**(2), 81 (2020). https://doi.org/10.3390/ijgi9020081
15. He, Z., Wu, L., Li, X.R.: When art meets tech: the role of augmented reality in enhancing museum experiences and purchase intentions. Tourism Manage. **68**, 127–139 (2018). https://doi.org/10.1016/j.tourman.2018.03.003
16. Hoang, V.D., Tran, D.P., Nhu, N.G., Pham, T.A., Pham, V.H.: Deep feature extraction for panoramic image stitching. In: Intelligent Information and Database Systems, pp. 141–151. Springer International Publishing (2020). https://doi.org/10.1007/978-3-030-42058-1_12
17. Huang, T.L.: Restorative experiences and online tourists' willingness to pay a price premium in an augmented reality environment. J. Retail. Consum. Serv. **58**, 102256 (2021). https://doi.org/10.1016/j.jretconser.2020.102256

18. Kounavis, C.D., Kasimati, A.E., Zamani, E.D.: Enhancing the tourism experience through mobile augmented reality: Challenges and prospects. Int. J. Eng. Bus. Manage. **4**, 10 (2012). https://doi.org/10.5772/51644
19. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097–1105 (2012)
20. Kysela, J., Štorková, P.: Using augmented reality as a medium for teaching history and tourism. Procedia - Soc. Behav. Sci. **174**, 926–931 (2015). https://doi.org/10.1016/j.sbspro.2015.01.713
21. Lambers, K., van der Vaart, W.V., Bourgeois, Q.: Integrating remote sensing, machine learning, and citizen science in Dutch archaeological prospection. Remote Sens. **11**(7), 794 (2019). https://doi.org/10.3390/rs11070794
22. Lei, Q., Wen, B., Ouyang, Z., Gan, J., Wei, K.: Research on image recognition method of ethnic costume based on VGG. In: Machine Learning for Cyber Security, pp. 312–325. Springer International Publishing (2020). https://doi.org/10.1007/978-3-030-62463-7_29
23. Llerena, J., Andina, M., Grijalva, J.: Mobile application to promote the Malecón 2000 tourism using augmented reality and geolocation. In: 2018 International Conference on Information Systems and Computer Science (INCISCOS). IEEE, November 2018. https://doi.org/10.1109/inciscos.2018.00038
24. Martins, M., Malta, C., Costa, V.: Viseu mobile: a location based augmented reality tour guide for mobile devices. Dos Algarves: a Multidisciplinary e-journal **26**(1), 8–26 (2015). DOi: https://doi.org/10.18089/damej.2015.26.1.1
25. Marto, A., Melo, M., Goncalves, A., Bessa, M.: Development and evaluation of an outdoor multisensory AR system for cultural heritage. IEEE Access **9**, 16419–16434 (2021). https://doi.org/10.1109/access.2021.3050974
26. Poux, F., Valembois, Q., Mattes, C., Kobbelt, L., Billen, R.: Initial user-centered design of a virtual reality heritage system: applications for digital tourism. Remote Sens. **12**(16), 2583 (2020). https://doi.org/10.3390/rs12162583
27. Rocha, P.M.A.: A exploração da realidade aumentada pelo jornalismo: a exposição da informação dos média num espaço aumentado. CECS - Centro de Estudos de Comunicação e Sociedade Universidade do MinhoBraga. Portugal. Literacia, Media e Cidadania - Livro de Atas do 4.° Congresso, pp. 475–491, November 2017
28. Santos, C., Junior, P.C., Araújo, T., Neto, N., Meiguins, B.: Recognizing and exploring azulejos on historic buildings facades by combining computer vision and geolocation in mobile augmented reality applications. J. Mob. Multimedia **13** (2017). https://dl.acm.org/doi/abs/10.5555/3177197.3177201
29. Williams, S., Lew, A.A.: Tourism Geography: Critical Understandings of Place, Space and Experience. Taylor and Francis Ltd. Abingdon (2014)
30. Trier, Ø.D., Reksten, J.H., Løseth, K.: Automated mapping of cultural heritage in Norway from airborne lidar data using faster r-CNN. Int. J. Appl. Earth Obs. Geoinf. **95**, 102241 (2021). https://doi.org/10.1016/j.jag.2020.102241