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A Deep Learning Approach for Classifying Generated Geometric Pattern Datasets

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Abstract Deep learning is now widely recognized as a powerful method for solving complex problems, such as image classification and object detection. This study focuses on applying deep learning to classify a custom-generated dataset of geometric patterns. We have implemented a binary classification system to distinguish between acceptable and non-acceptable geometric patterns based on criteria established by artisans working with wood. Due to the absence of a standard dataset, we created our own dataset, adhering to the construction rules for these patterns. In this study, two pre-trained CNN-driven models (Inception-V3 and ResNetV2) have been suggested in this paper for the classification. Numerous criteria, including precision, accuracy, recall, and F1 score, are used to illustrate this superiority. The experimental system focuses on evaluations based on loss, precision, and confusion matrices and uses Jupyter Notebook, Python, TensorFlow, and Keras.The pre-trained Inception-V3 model achieves the best classification performance, with an accuracy of 97.80%, according to the experimental results.

Keywords CNN Architecture, IGPs, pre-trained models, Classification

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1. Introduction

Geometric pattern creation has always captivated scholars and designers alike. Historically, geometric patterns have been a characteristic of Islamic art and architecture, with intricate designs that often incorporate mathematical principles [1]. In recent years, the advent of computer graphics and algorithmic approaches has opened innovative routes for the exploration and generation of these patterns, particularly around deep learning frameworks [2].

Islamic ornamental art appears on various materials like tiles, bricks, wood, brass, and plaster. It can be classified into two main types: three-dimensional ornamental art known as *'Muqarnas'* (stalactites) and flat ornamental Arabesque, further divided into two categories: *'Floral'* and *'Tastir'*, or Islamic Geometric Patterns (IGPs). [3].

These patterns often incorporate repeating motifs aligned along various geometric paths, including lines, circular arcs, and splines [4]. Artisans working in this field have utilised intricate geometric patterns to produce remarkable visual compositions in mosques and similar environments. The complexity of Islamic patterns is most evident in those constructed from grids derived from lines and circles. Artisans still employ the historical methods of *Hasba* and *Zellij* in their woodwork. Previous research has shown that deep learning frameworks can be effective in classifying various types of data, including images and text [5].

Nonetheless, classifying geometric patterns for different purposes is now a significant field of research. This study is intended to address this gap by examining the application of deep learning techniques. Frameworks for categorizing produced geometric pattern datasets. After a discussion with the craftsmen working on these kinds

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of geometric patterns, we found that there is a subset of patterns that are technically valid but not accepted for aesthetics and beauty. However, there are others that are both valid and acceptable.

Among the criteria that artisans use to distinguish between the two categories of geometric patterns (acceptable and unacceptable) are: As shown in Figure 1 below, patterns that are too simple may be deemed unacceptable, while complex and well-detailed patterns are often preferred.

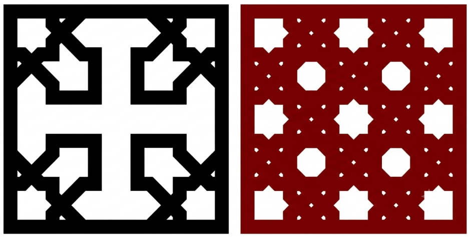

Figure 1. IGPs from both classes: unacceptable (left) vs. acceptable (right).

The purpose of this study is to identify the category that an Islamic geometric pattern falls within. We suggest employing Convolutional Neural Network (CNN) techniques to enhance the geometric pattern classification procedure. Over the past few years, CNNs have demonstrated remarkable capability and performance across multiple applications, notably in image classification [6], handwritten character recognition [7], scene segmentation [8], and various other tasks. In the last few years, CNNs have consistently delivered leading performance in the grouping of large-scale images, particularly through models such as InceptionV3 and ResNetV2 [9]. In our scenario, the constructed dataset comprises 10,149 images used for training a CNN from scratch. CNNs aim to learn efficient feature representations from input images. In the convolutional part of the CNN, features are extracted from the image, which are subsequently classified by the fully connected layers. Transfer learning [10, 11] involves leveraging the knowledge of a pre-trained network for a different classification task. In our study, we employ transfer learning with the convolutional layers of advanced networks like ResNetV2 as well as *InceptionV3*. This approach helps achieve higher prediction accuracies when classifying binary datasets containing images of IGPs.

The structure of this document is as follows. The relevant work is reviewed in Section II. The materials and techniques employed in this study are presented in Section III. It includes the proposed methodology, the dataset description, the data preprocessing steps, and the deep transfer learning architecture. The experimental results and a thorough explanation are presented in Section IV. Section V describes the experimental setup as well as the evaluation in terms of loss and accuracy. The paper is finally concluded in Section VI, which also provides guidance for upcoming studies.

2. Related Work

Classification is the method of determining an object's characteristics and categorizing it into different classes. The classification problem of IGPs has not received extensive study; several works that have focused on this problem in their work [12]. PGIs are divided into three symmetry categories by the authors: frieze, wallpaper, and rosette based on symmetry features. There are two phases to the categorization phase. In the initial phase, the center is identified to find out if a pattern is classified as part of the rosette group or as a periodic pattern (frieze and wallpaper). In the subsequent step, *frieze* and *wallpaper* patterns are differentiated via lattice detection. However, in our work, we attempt to classify our generated dataset into two categories (acceptable and unacceptable), geometric patterns, and references to the craftsmen.

The authors in [6] suggested a method for classifying Islamic motifs based on any regular pattern or texture. The author provides computer methods for the analysis of periodic patterns based on wallpaper and frieze symmetries in the work [13]. These models use algorithms to identify the underlying lattice, symmetry group, and representative motifs of a given pattern.

Islamic geometric art has received considerable attention from researchers for many years. Several authors focused their work on classification. Aljamali [14] proposes an approach to classify (7-frieze or 17-wallpaper pattern) and design IGP using computer graphics. In other work, the same author [15] introduces a novel approach to classify and generate IGPs through computational methods, building on existing classification systems and distinguishing between classifying patterns vs. individual designs.

Hankin's "polygons-in-contact" method provides the foundation for Islamic star patterns, which use a geometric tiling modification to increase the range of feasible designs, according to C. Kaplan [16]. M.Ahadian [17] proposes an approach for classifying IGPs, highlighting the representation and recognition stages. In the work [18], analyse and identify similar geometric shape families in Islamic patterns created using the *"Hasba"* method.

Several studies have focused on the classification of batik patterns. Y. Sari [19] divided batik designs into two groups in order to differentiate between coastal and inland batik patterns. The Euclidean distance method was applied, yielding accuracy, precision, and recall rates of 44.44%, 50%, and 40%, respectively. In [20], Y. Sari applied the grey-level co-occurrence matrix (GLCM) method combined with Canberra distance to categorise batik into two classes, obtaining an accuracy of 41.67%. Additionally, the classification is also used in [21] where the authors present a method using Zernike moments and two classifiers to classify Islamic geometric pattern images, achieving a 96.03% correct recognition rate.

To overcome these limitations, we need a new approach capable of deeply analyzing geometric patterns to classify them into two categories (acceptable and unacceptable). Deep learning (DL) [22], a branch of artificial intelligence that uses deep neural networks with multiple hidden layers to directly learn representations from input [23], is one technique for categorizing IGP patterns. One commonly used DL-based method for classification purposes, CNN is employed [24].

CNNs can automatically group and detect objects in images by processing input data of size m×n [25]. Multiple studies have utilised CNNs in classification tasks. For example, S. Deepak [26] classified brain tumours into two categories using the CNN-based VGG16 method, achieving accuracy and F1 scores of 90%. Another work by M. Nawaz [27] used a CNN-based variant of DenseNet to classify breast cancer into two classifications with an accuracy of 96%. Furthermore, H. A. Elnemr [28] classified plant seeds into twelve categories using the CNN method, achieving accuracy, recall, precision, and F1 scores of 94.38%, 93.1%, 94.83%, and 93.57%, respectively.

In this article, IGPs are classified into two categories: acceptable and unacceptable. These two types of motifs belong to IGPs derived from the *"Hasba"* method. IGPs are commonly used by Moroccan craftsmen, who employ rulers and compasses for their construction. The literature shows that CNN-based models achieve high classification performance, with average results exceeding 90%.A pre-trained deep CNN with transfer learning is used in this study to classify IGP patterns. The evaluation of the proposed CNN-based approach was carried out using accuracy, precision, recall, and F1-score for Islamic geometric pattern classification. In addition, this work seeks to assist craftsmen in identifying and classifying *"Hasba"* motifs within the Moroccan tradition, considered a cultural heritage that must be preserved.

3. Materials And Methods

3.1. Proposed Methodologies

A pre-trained model is one that has already been taught to carry out a particular task, such as image classification, using a sizeable dataset. The primary benefit of transfer learning is that it makes it possible to train models with smaller datasets while utilizing less computing power. In this paper, we develop deep CNN-based models, namely ResNetV2 and InceptionV3, for the binary classification of IGP images into two classes: acceptable and unacceptable. Moreover, we applied transfer learning by using our generated dataset. Then, this dataset will be resized and split (processing data). Afterwards, the refined dataset is fed into pre-trained CNN models, where feature extraction is performed using convolutional layers, followed by Global Average Pooling (GlobalAveragePooling2D) and activation functions such as ReLU and Softmax. The model's evaluation is the next stage. Figure 2 provides a complete methodology for this study.

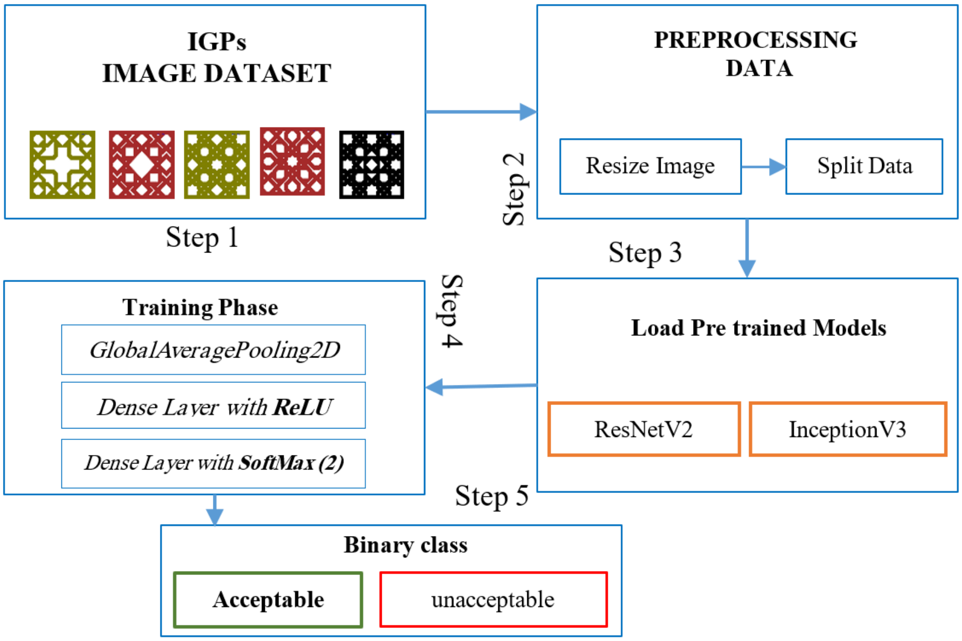

Figure 2. Proposed classification pipeline for Islamic Geometric Patterns using deep transfer learning.

3.2. Dataset

The IGPs, which are automatically created from our earlier publication [1], the guidelines for creating an Islamic geometric pattern utilizing the *'Hasba'* approach, are the data used in this study. The procedure of creating this pattern is shown with some examples in Figure 3 and 4. We must examine the 10,149 photos in the IGPs collection, which are separated into 5,350 acceptable motifs and 4,799 undesirable motifs.

- Building the underlying grid in a frame with dimensions L = h*q; h = 16 will be used in this work.
- Identifying the essential area.
- Sketching the fundamental region's threads.
- The final IGP obtained by applying the symmetry of the rule (axial symmetry and rotations of 90°, 180°, and 270°).

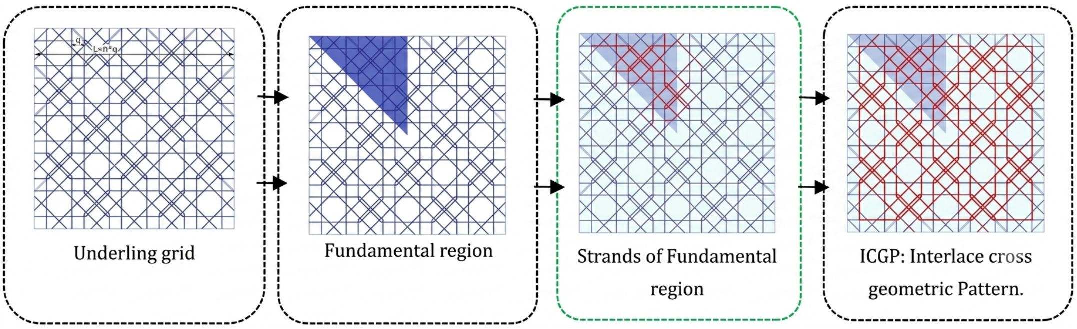

Figure 3. Step-by-step construction process of an Islamic Geometric Pattern following the *'Hasba'* method.

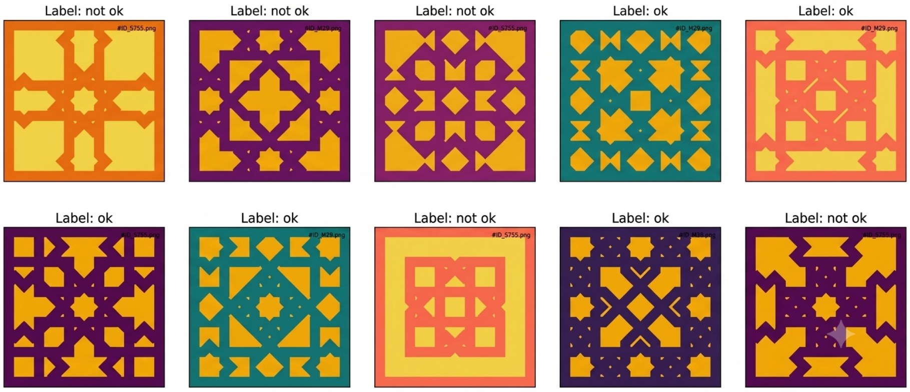

Figure 4. Examples of automatically generated Islamic Geometric Patterns.

3.3. *Preprocessing Data*

In this step, the image data are preprocessed by applying a resizing technique to reduce the size of IGP images. Additionally, the dataset is divided into training, validation, and test sets.

The training dataset consists of 7,004 PNG-formatted IGP patterns. Separate datasets with 1,236 and 1,909 patterns, respectively, are used to assess the validation and test sets. Figure 5 provides a graphical representation of the dataset arrangement.

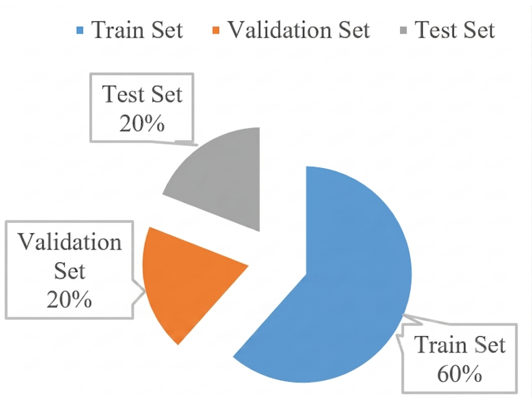

Figure 5. Splitting datasets for assessment, validation, and training

3.4. *Architecture of Deep Transfer Learning*

Figure 6 depicts a typical deep learning pipeline for picture classification. The process begins with an input image, which undergoes pre-processing to enhance and normalize the data. The processed image is then passed through a convolutional layer and a pooling layer in order to extract and minimize high-level feature representations. Once these traits have been flattened, a fully connected layer performs high-level reasoning. A Softmax activation function then produces the output probabilities, allowing the model to classify the image into two groups: acceptable and unacceptable.

1) Convolutional Layer

A feature map is produced by the convolutional layer, which is composed of a collection of learnable filters (kernels) (Alzubaidi et al. [24]). Using predetermined settings, the incoming image is separated into local receptive fields.

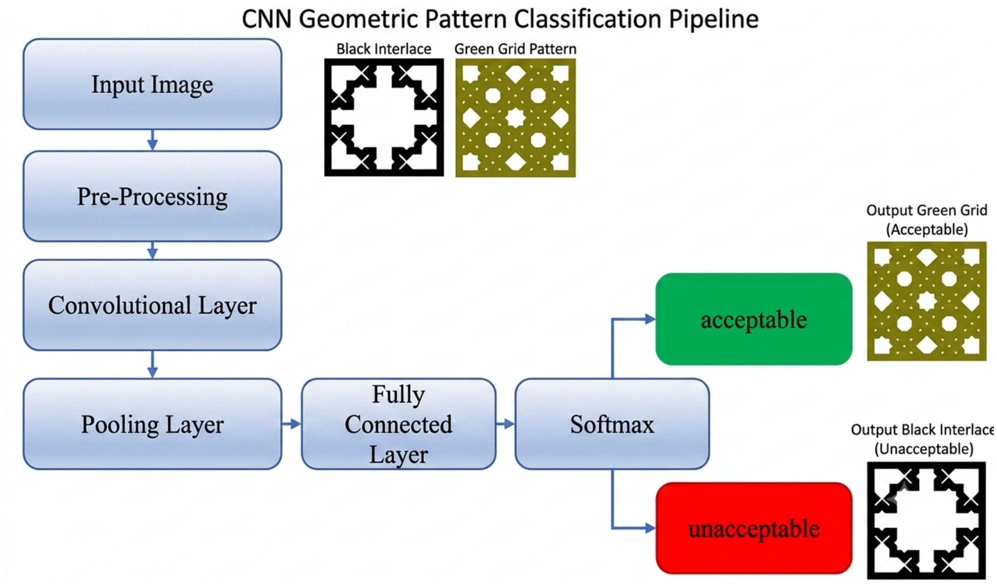

Figure 6. Deep transfer learning architecture for binary IGPs classification.

As a result of the convolution operation, The output feature map may be smaller or maintain the same spatial dimensions as the original image, while its depth is increased according to the number of filters applied. The computation of the output feature map resulting from the convolution operation is given in Equation (1):

$$a_{(i,j)} = \left(\sum_{u=0}^{m-1} \sum_{v=0}^{n-1} \left(C_{(i+u,j+v)} \times K_{(u,v)} \right) \right) + b_q \tag{1}$$

where C denotes the input matrix, K represents the convolution kernel, m and n denote the kernel dimensions, and b_q is the bias term associated with the filter.

2) Pooling Layer

Global average pooling is used to extract representative features from the feature maps by computing the average value of each feature channel. Additionally, the global average pooling approach is used to reduce the size of the image, preserving the most discriminative information while reducing spatial dimensionality to facilitate the subsequent CNN phase. The conventional and global average pooling processes are performed multiple times to achieve a feature map of the desired size. This feature map will be the input of the Fully Connected Layer (Dense Layer) process, which has been transformed into a single-dimensional array for classification.

3) Fully Connected Layer (Dense Layer)

The crucial CNN layer is the dense layer. Every node in the previous layer is linked to every activation function. To speed up training, the fully linked layer applies the Rectified Linear Unit (ReLU) activation function. All negative pixel values in the image are mapped to zero by this activation function, which is represented by $f(x)$ and defined in Equation (2).

$$f(x) = \max(0, x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \tag{2}$$

The flattening process is used to reshape the output feature maps into a one-dimensional vector, which serves as input to the fully connected layer. The Softmax activation function, denoted as $\int(x_j)$ and defined in Equation (3), produces probability values for classification.

$$\int (x_j) = \frac{e^{x_j}}{\sum_{y=1}^{m} e^{x_y}} \tag{3}$$

Where m and x_j represent respectively the number of classes and the input data.

4) Performance Metrics

Several performance criteria are used in this study to evaluate prediction. Equations (4), (5), (6), (7), and (8) [26] show the calculation formula for performance metrics, which are used to assess the performance of the suggested model:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \times 100\% \tag{4}$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100\% \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100\% \tag{6}$$

$$\text{F1-score} = \frac{2 \times TP}{2 \times TP + FN + FP} \times 100\% \tag{7}$$

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{8}$$

4. Results And Discussion

The primary objective of this project is to develop a classification model for images with geometric patterns. Dense layers with 1024, 512, 256, and 30 neurons, respectively, were used to refine and freeze the network layers.

The performance metrics for many pre-trained models, each of which underwent 30 training epochs, are shown in Table 1, for the classification of geometric images. Notably, the InceptionV3 model stands out as the most effective, with an accuracy rate of 97.80%, demonstrating its ability to accurately classify geometric images. The ResNetV2 model also demonstrates remarkable performance, with an accuracy rate of 96.53%. *InceptionV3* continuously outperforms other models in terms of precision, recall, F1 score, and Matthews Correlation Coefficient (MCC). These results show that the *InceptionV3* model works quite well for IGPs classification tasks.

Table 1. Performance comparison of transfer learning models for geometric pattern classification.

Model	Epochs	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC (%)
InceptionV3	30	**97.80**	**97.80**	**97.80**	**97.80**	**95.51**
Xception	30	97.15	97.12	97.15	97.13	94.30
EfficientNetB0	30	96.85	96.88	96.85	96.86	93.70
ResNetV2	30	96.53	96.54	96.53	96.53	93.05
VGG16	30	95.42	95.38	95.42	95.40	90.85

5. Experimental Setup and Evaluation

1) Experimental Setup

Jupyter Notebook and Python tools like OpenCV, NumPy, and Pandas were utilized in the experimental setup for image processing tasks. Classifiers were implemented using Anaconda, Scikit-Learn, and Python 3.10.

In order to improve computational capabilities, pre-trained models were trained and tested using Keras and TensorFlow, utilizing a Google Colab PRO T4-GPU with a claimed memory of 51GB and storage capacity of 166.77GB. CNN models *InceptionV3* were trained. It is trained using the ImageNet dataset. And ResNetV2: is a deep convolutional network that was trained on the ImageNet-2012 dataset using the ResNetV2 architecture. The model's input is a 299x299 image, and its output is a list of predicted class probabilities that were pre-trained using random initialization weights by optimizing the cross-entropy function using adaptive moment estimation (Adam) [29].

For each experiment, the batch size, learning rate, and number of epochs have been empirically set to 16, 1e-5, and 30, respectively. The dataset was split into two separate sets at random, with 68% going toward training, 12% going toward validation, and 20% going toward testing.

2) Loss and Accuracy

Both the training and validation datasets receive accuracy and loss numbers from the training procedure. For each pre-trained model.

Figures 7 and 8 display the prediction accuracy and loss curves of the proposed model for the training and validation datasets. One iteration of the training image collection to update the weights is represented by an epoch in Figure 7. To find the ideal weights to utilize as model parameters, The total errors made for every image during the training phase are displayed via the loss function.

Figure 7. Graph of loss per epochs

According to the curve in Figure 8, accuracy starts to rise noticeably after the first epoch. It can be observed that the training process undergoes a sharp change in gradient while still achieving convergence to a satisfactory level, reaching a peak accuracy of approximately 97% on the training data using the *InceptionV3* model.

The loss curves in Figure 7 show potential overfitting on both the training and validation datasets, but the training procedure is still steady and efficient overall.

The model's overall accuracy for classifying IGP motifs is assessed in Table 1. The percentage of accurately predicted positive samples among all predicted positives is known as precision. Recall measures how well the model can locate pertinent examples in the dataset. In addition to balancing recall and precision, the F1-score can be used as an extra benchmark for assessing model performance. As shown in Table 2, the average accuracy

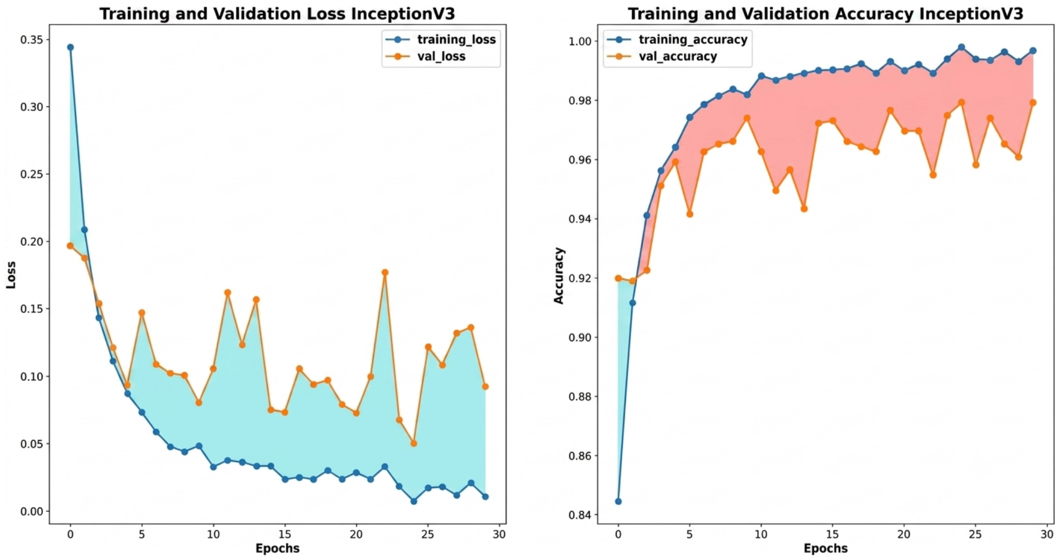

Figure 8. Graph of accuracy per epochs.

achieved is **97.80**% for the two classes, demonstrating how successfully the CNN model classifies different types of IGP motifs. The analysis and interpretation of the findings come after the evaluation phase.

The evaluation findings of IGPs' motifs classification using the suggested CNN architecture are now compared with those from previous studies. Table 2 displays the comparison of performance evaluations. The comparison

Table 2. Comparison of Classification Results with Previous Research

Authors	**[29]**	**Our Work**
Model	CNN	InceptionV3 / ResNetV2
Epochs	30	30
Accuracy (%)	96.74	**97.80 / 96.53**

of performance evaluation results is presented in Table 2. Based on this table, the proposed method achieves an accuracy of 97.80%. The method is therefore capable of classifying IGP motif types into two classes within the dataset. In this instance, IGP motifs congruent with the dataset can be validated using the model produced from the classification results.

3) Confusion Matrix Roc Curves

To further evaluate the classification performance of the best-performing model, Figure 9 presents the confusion matrix and the Receiver Operating Characteristic (ROC) curves obtained by InceptionV3 on the test set (1,909 images). As shown in the confusion matrix, the model correctly classified 791 out of 818 acceptable patterns (True Positives) and 1,076 out of 1,091 not-acceptable patterns (True Negatives), yielding only 27 false negatives and 15 false positives. These values correspond to a per-class precision of 98.14% and a recall of 96.70% for the acceptable class, and a precision of 97.56% and a recall of 98.63% for the not-acceptable class, confirming the model's strong and balanced discriminative capability across both categories.

The ROC curves further corroborate these results: both the per-class curves (class 0 and class 1) and the micro- and macro-average curves reach an Area Under the Curve (AUC) of 1.00, indicating that InceptionV3 achieves near-perfect class separation on the IGP binary classification task. Taken together, the confusion matrix and ROC analysis demonstrate that the proposed transfer learning approach not only achieves high overall accuracy but

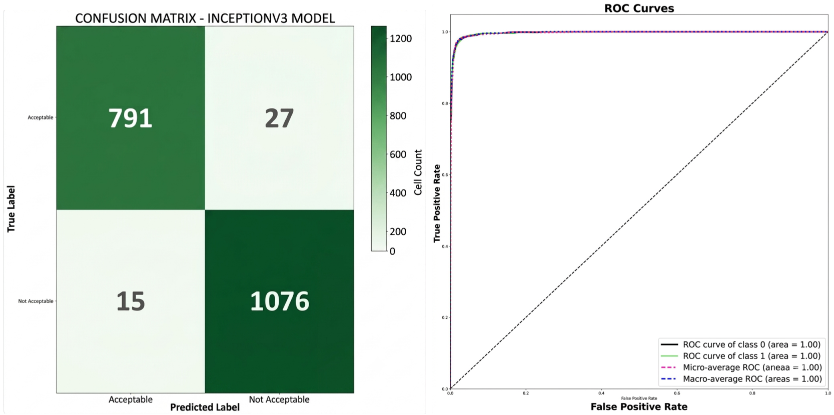

Figure 9. Confusion Matrix & Roc Curves for InceptionV3 model (30 Epochs)

also maintains consistent performance across both the acceptable and not-acceptable pattern categories, with no significant bias toward either class.

4) Evaluation of the InceptionV3 classifier

Ten example IGP images from the test dataset are shown in Figure 10 along with their ground-truth labels and the InceptionV3 model's matching predictions. The model assigned prediction probabilities of 100.00% for nine images and 99.99% for the final image, properly classifying all ten samples with incredibly high confidence.

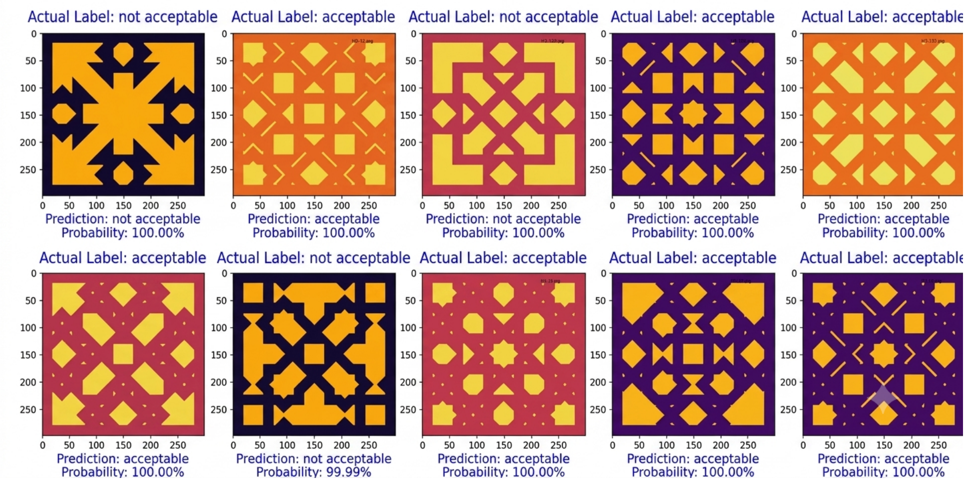

Figure 10. Predictions of InceptionV3 model

The chosen examples show both acceptable and unacceptable (not ok) geometric patterns with different geometric structures and color combinations (such as orange/navy, orange/dark red, and yellow/purple). This variety shows that, in spite of differences in color distribution and visual composition, the suggested model retains strong classification performance.

These qualitative observations further show that transfer learning based on InceptionV3 successfully captures the artisan-defined aesthetic characteristics underpinning the binary classification of Moroccan geometric designs, and they are in line with the quantitative results presented in Table 1.

6. Conclusion

The experimental results demonstrate the strong classification capabilities of the proposed method, with InceptionV3 achieving an overall accuracy of 97.80% along with consistently good precision, recall, and F1-score across both IGP categories. These findings confirm deep transfer learning's efficacy and reliability as a framework for the "Hasba" method's binary classification of Islamic geometric patterns. Despite these promising results, the current study has several flaws that present chances for additional investigation. In particular, the model's fixed membership functions and reliance on a single color-based representation suggest that incorporating symmetry group theory could enhance the model's classification accuracy and generalizability to previously unseen pattern configurations by explicitly encoding frieze and wallpaper group constraints as training signals.

REFERENCES

1. Y. Ait Lahcen, A. Jali, and A. EL Oirrak, *NEW APPROACH TO CONSTRUCT A NEW ISLAMIC GEOMETRIC PATTERNS USING THE HASBA METHOD*, Journal of Theoretical and Applied Information Technology, vol. 99, no. 14, p. 10, 2021.
2. M. Hussain, J. J. Bird, and D. R. Faria, *A Study on CNN Transfer Learning for Image Classification*, in Advances in Computational Intelligence Systems, vol. 840, A. Lotfi, H. Bouchachia, A. Gegov, C. Langensiepen, and M. McGinnity, Eds., in Advances in Intelligent Systems and Computing, vol. 840, Cham: Springer International Publishing, pp. 191–202, 2019. doi: 10.1007/978-3-319-97982-3_16.
3. Y. Ait Lahcen, A. Jali, and A. El Oirrak, *Approach of Constructing an Islamic Pattern Respecting the "HASBA" Method*, Proceedings of the 3rd International Conference on Networking, Information Systems & Security, pp. 1–9, 2020. doi: 10.1145/3386723.3387872.
4. Y. A. Lahcen, A. El Gourari, E. Elbachari, and M. J. Eddine Benatia, *Design Analysis and Generation of Islamic Patterns Using Artificial Intelligence*, in 2024 International Conference on Global Aeronautical Engineering and Satellite Technology (GAST), Marrakesh, Morocco: IEEE, pp. 1–6, 2024. doi: 10.1109/GAST60528.2024.10520795.
5. J. Wang, Y. Fan, and Z. Li, *Texture Image Recognition Based on Deep Convolutional Neural Network and Transfer Learning*, J Comput-Aided Design Comput Graphics, vol. 34, no. 05, pp. 701–710, May 2022. doi: 10.3724/SP.J.1089.2022.18986.
6. A. Aoulalay, A. El Mhouti, and M. Massar, *Classification of Islamic Geometric Patterns based on Machine Learning Techniques*, in 2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco: IEEE, pp. 1–6, Mar. 2022. doi: 10.1109/IRASET52964.2022.9737839.
7. S. Kolte and B. Gupta, *Modi Script Character Recognition Using Convolutional Neural Networks and Attention-Based CNN Architecture*, IJARSCT, pp. 54–62, Apr. 2025. doi: 10.48175/IJARSCT-25309.
8. Z. Guo, L. Bian, X. Huang, H. Wei, J. Li, and H. Ni, *DSNet: A Novel Way to Use Atrous Convolutions in Semantic Segmentation*, arXiv, 2024. doi: 10.48550/ARXIV.2406.03702.
9. Z. Wu, C. Shen, and A. van den Hengel, *Wider or Deeper: Revisiting the ResNet Model for Visual Recognition*, Pattern Recognition, vol. 90, pp. 119–133, Jun. 2019. doi: 10.1016/j.patcog.2019.01.006.
10. S. Yuvaraj, J. V. Franklin, V. S. Prakash, A. Anandaraj, and R. Subha, *A Survey on Human Face Emotion Recognition using Machine Learning Models*, in 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India: IEEE, pp. 1993–1996, Mar. 2023. doi: 10.1109/ICACCS57279.2023.10112955.
11. F. Leno da Silva and A. H. R. Costa, *A Survey on Transfer Learning for Multiagent Reinforcement Learning Systems*, Journal of Artificial Intelligence Research, vol. 64, pp. 645–703, Mar. 2019. doi: 10.1613/jair.1.11396.
12. M. O. Djibril and R. O. H. Thami, *Islamic geometrical patterns indexing and classification using discrete symmetry groups*, Journal of Computing and Cultural Heritage, vol. 1, no. 2, pp. 1–14, Oct. 2008. doi: 10.1145/1434763.1434767.
13. Y. Liu, R. T. Collins, and Y. Tsin, *A computational model for periodic pattern perception based on frieze and wallpaper groups*, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 26, no. 3, pp. 354–371, Mar. 2004. doi: 10.1109/TPAMI.2004.1262332.
14. A. Aljamali and M. Fakir, *AN EXPERT SYSTEM FOR THE DESIGN AND CLASSIFICATION OF ISLAMIC GEOMETRIC PATTERNS USING COMPUTER GRAPHICS*, 2019.
15. A. M. Aljamali, *Classification and Design of Islamic Geometric Patterns Using Computer Graphics*, in 2009 Second International Conference in Visualisation, pp. 253–258, Jul. 2009. doi: 10.1109/viz.2009.46.
16. C. S. Kaplan, *Islamic star patterns from polygons in contact*, in Proceedings of Graphics Interface 2005 (GI '05), Canadian Human-Computer Communications Society, School of Computer Science, University of Waterloo, Waterloo, Ontario, Canada, pp. 177–185, 2005.
17. M. Ahadian and A. Bastanfard, *Islamic Star Pattern Images Recognition by Central Moment Invariants*, 2011.
18. A. L. Yassine, J. Abdelaziz, and E. Oirrak, *New Approach for the Detection of Family of Geometric Shapes in the Islamic Geometric Patterns*, International Journal of Advanced Computer Science and Applications (IJACSA), vol. 11, no. 3, 2020. doi: 10.14569/IJACSA.2020.0110343.
19. Y. Sari, M. Alkaff, and R. A. Pramunendar, *Classification of coastal and Inland Batik using GLCM and Canberra Distance*, vol. 1977, no. 1, p. 020045, Jun. 2018. doi: 10.1063/1.5042901.
20. Y. Sari, *KLASIFIKASI PENGENALAN MOTIF BATIK BERBASIS IMAGE RETRIVAL*, Jukung, vol. 4, no. 2, Sep. 2018. doi: 10.20527/jukung.v4i2.6581.

21. M. Ahadian and A. Bastanfard, *Classification of Islamic Geometric Pattern Images Using Zernike Moments*, in 2011 Eighth International Conference on Computer Graphics, Imaging and Visualization (CGIV), Singapore: IEEE, pp. 19–24, Aug. 2011. doi: 10.1109/CGIV.2011.11.
22. Y. LeCun, Y. Bengio, and G. E. Hinton, *Deep Learning*, Nature, vol. 521, pp. 436–444, 2015. doi: 10.1038/nature14539.
23. W. Chen, B. Yang, J. Li, and J. Wang, *An Approach to Detecting Diabetic Retinopathy Based on Integrated Shallow Convolutional Neural Networks*, IEEE Access, vol. 8, pp. 178552–178562, 2020. doi: 10.1109/ACCESS.2020.3027794.
24. L. Alzubaidi et al., *Review of deep learning: concepts, CNN architectures, challenges, applications, future directions*, Journal of Big Data, vol. 8, no. 1, p. 53, Mar. 2021. doi: 10.1186/s40537-021-00444-8.
25. A. Desiani, B. Suprihatin, S. Yahdin, A. I. Putri, and F. R. Husein, *Bi-path Architecture of CNN Segmentation and Classification Method for Cervical Cancer Disorders Based on Pap-smear Images*, vol. 48, no. 3, 2021.
26. S. Deepak and P. M. Ameer, *Brain tumor classification using deep CNN features via transfer learning*, Computers in Biology and Medicine, vol. 111, p. 103345, Aug. 2019. doi: 10.1016/j.compbiomed.2019.103345.
27. M. Nawaz, A. A., and T. Hassan, *Multi-Class Breast Cancer Classification using Deep Learning Convolutional Neural Network*, International Journal of Advanced Computer Science and Applications (IJACSA), vol. 9, no. 6, 2018. doi: 10.14569/IJACSA.2018.090645.
28. H. A. Elnemr, *Convolutional Neural Network Architecture for Plant Seedling Classification*, International Journal of Advanced Computer Science and Applications (IJACSA), vol. 10, no. 8, 2019. doi: 10.14569/IJACSA.2019.0100841.
29. M. W. Ilahi et al., *Classification of Geometric Batik Motif Typical of Indonesian Using Convolutional Neural Network*, Jurnal Teknik Informatika, vol. 15, no. 1, pp. 91–100, Jun. 2022. doi: 10.15408/jti.v15i1.24968.