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AN APPROACH WITH DEEP CONVOLUTIONAL NEURAL NETWORKS FOR ACCURATE ARCHITECTURAL STYLE CLASSIFICATION

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Abstract. Unlike other studies, this study aims to examine the effect of data diversity and quantity on the performance of a model rather than solely focusing on classifying architectural styles. It also seeks to emphasize the importance of selecting the appropriate number of classes in architectural style classification and to explore how determining the optimal number of classes affects the model's success. The first dataset comprises the original images (4776 images), the second dataset (10091 images) includes additional data and the third dataset (9552 images) is obtained through data augmentation. Using these three datasets, models were developed by reducing the number of classes with convolutional neural networks (CNNs), which utilize convolution layers to identify local features in the images and classify them by summarizing these features. The results of the developed models show that the method of adding data and increasing data decreased the success of architectural style classification, whereas reducing the number of styles increased it. This study may lay the groundwork for the development of deep learning models for future architectural style classification. The findings of this study can significantly impact various application areas, such as analyzing architectural styles, identifying historical periods and integrating them into architectural education.

Keywords: *Architectural styles, image classification, digital documentation, deep learning, cultural heritage.*

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1. Introduction

Architectural style represents a certain understanding and aesthetics, as architectural movements or philosophies, which generally include innovative elements in architectural design, become widespread in certain periods or in a culture to change the existing architectural understanding. Each architectural style is determined according to the cultural, historical, social, political, technological, economic and natural characteristics of the region or period to which it belongs and has common design features consisting of various elements such as materials used, structural elements, forms, ornaments, proportions and other design elements. Therefore, they change over time and may have different characteristics. Architectural style contains certain unique elements and features and thanks to these features, it can be understood which architectural style a building belongs to. Architectural style classification, which helps us understand and preserve their historical, cultural and aesthetic contexts by determining the design and structural features of buildings, provides important

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information in many areas such as urban planning, preservation of cultural heritage, restoration projects and sustainable urban development (Siountri & Anagnostopoulos, 2023). Architectural style classification is important for many reasons. These reasons can be listed as follows:

- ✓ To help understand the historical and cultural context of buildings,
- ✓ To understand the architectural heritage of the past and different cultures by learning different architectural styles,
- ✓ To understand and analyze the architectural character of a particular period or culture,
- ✓ To ensure the protection of cultural heritage by correctly classifying the style of a building and guiding restoration or conservation efforts,
- ✓ Determining the style of a building, as each style has common design features, helping to understand which features and design principles the architect uses in the design process,
- ✓ Examining architectural projects and helping to analyze architectural developments,
- ✓ To provide guidance and inspiration to architects during the design process,
- ✓ To stimulate creative thinking by learning the characteristics of different styles and design approaches
- ✓ Learning the characteristics of architectural styles helps making more conscious decisions and generating different ideas during the design process,
- ✓ To contribute to the formation of a common language in the field of architecture and
- ✓ To present several terms and concepts used to analyze, present or report architectural projects.

In summary, architectural style classification in the discipline of architecture; It helps us understand the architectural heritage, protect it, get inspired and make sense of social identity. Therefore, this information allows architects to make more informed and effective design decisions.

Correct classification of architectural styles allows not only to understand the architectural civilization, but also to reflect the historical and cultural information of that period more effectively; however, this process includes complex elements such as historical identity, building materials, regional characteristics and architectural structures, making classification difficult (Wang *et al.*, 2023). Nowadays, visual data is increasingly increasing with the development of technology and sharing on social media. The constant increase of this data makes the task of classifying architectural styles, which requires expert knowledge, very difficult. The main challenge in traditional Machine Learning models for architectural style classification is the feature extraction phase because there are many visual features in these styles that need to be extracted, enhanced and optimized and all these operations are done at the discretion of the researcher (Rababaah & Rababah, 2022). Especially with the increase in hardware power, the success of deep learning methods also increases. The ability of deep learning methods to process visual data can facilitate obtaining appropriate and useful data through shape recognition among many data in the architectural design process, especially during the information gathering phase. Deep learning method, which has been successful in many areas recently, seems to be a suitable method for analyzing and correctly classifying this increasing data.

Ways to increase performance regardless of the model are called Regularization. Although regularization methods are generally used to prevent overlearning to increase the performance of the designed model, they are also used to reduce the complexity of the model without decreasing the performance. Data Augmentation, Adding Noise, Synthetic Data Generation, Early Stopping, Dropout, Transfer Learning, Dense-Sparse-Dense Training are among the Regularization methods. In this study, the success of the model was evaluated using data augmentation.

The purpose of this study is to examine the effect of data diversity and quantity on the performance of a model, to emphasize the importance of choosing the number of classes in architectural style classification and to investigate the effect of determining the optimum number of classes on the success of the model. Within the scope of the study, a model was developed with 3 data sets to examine how adding and increasing data affects the model and to understand how much convolutional neural networks, a deep learning method, learn the features of styles in architectural style classification. In this study, images of various architectural structures were used for architectural style classification. These images were collected from public databases. The first data set used for this purpose is the original data set (4776 images), the second data set (10091 images) is the data set with data addition and the third data set (9552 images) is the data set obtained by data augmentation. First, a classification model was developed for 25 architectural styles in these data sets. Later, the models were developed by reducing the number of styles to 14, 6, 5 and 4, respectively. The images were subjected to pre-processing such as "sizing, normalization and data augmentation" to make them suitable for the convolutional neural networks model. Within the scope of the study, Convolutional Neural Networks, a deep learning method, was used in image classification, as it provides high accuracy rates, especially in cases where complex features need to be extracted. The model is divided into training (80%), validation (10%) and testing (10%) datasets. Training data was used to realize the basic learning process of the model. Validation data was used to evaluate the model's performance during training and tune hyperparameters. Test data that was not used during training was used to objectively evaluate the overall performance and generalization ability of the model. Model performance was evaluated using metrics such as accuracy, precision, sensitivity and F1 score. With this study, it is expected to develop a model that can classify different architectural styles with high accuracy. The resulting model is intended to be a valuable tool for architectural historians, academics and architects and to provide a method that can be used in the automatic classification of architectural works.

This study seeks to investigate the following hypotheses:

✓ RQ1: Does adding data and using data augmentation methods improve the performance of a model?

✓ RQ2: How does the number of classes used in architectural style classification affect the accuracy of the model?

Data addition is the inclusion of new samples into the existing training dataset. This method increases the model's data diversity, reduces overfitting and improves its generalization ability. For these reasons, it is expected that the success of the model will increase with data increase. Data augmentation is a technique used to increase data diversity by adding new data points to an existing dataset. This technique is especially important when working with limited data or when the model does not have enough data to learn certain patterns. Methods include "geometric transformations, random transformations, synthetic data generation and transfer learning". This allows the model to perform better on new and unseen data points, learn general features and train with more data. Therefore, it improves the overall performance of the model. In the case of little data, the tendency of the model is to overfit the training data. Data augmentation reduces model overfitting and helps achieve a more general and useful model. Considering these features, data augmentation is expected to be more successful than adding data.

In classification problems, decreasing the number of classes can affect the performance of the model in various ways. The reduced number of classes allows the model to learn more general features with fewer parameters and predict specific classes more accurately. However, in cases where rare classes are important or there is a data balance issue, the reduced number of classes can further increase the imbalance. Additionally, the decreasing number of classes may perhaps cause it to ignore some important details or differences, which may reduce the generalization ability of the model. As a result, decreasing or increasing the number of classes may be a factor affecting the performance of the model and needs to be determined carefully. Decreasing the number of architectural styles may cause the model to become simpler as it will enable learning with fewer parameters. Therefore, it can generalize better. Therefore, reducing the number of classes is expected to positively affect the performance of the model.

2. Related work

Architectural styles that have developed over time by completing the development of the social, economic and religious aspects of society are determined and examined by architects and architectural historians according to the structure, material, decorations, form and context of architectural elements of buildings. Because architectural styles are subjective and can be affected by various external conditions, their determination is complex and uncertain (Xia *et al*., 2020). The classification of architectural styles is one of the most challenging problems in the history of architecture due to the temporal interclass relationships between different styles and the geographical variation within a style (Wang *et al*., 2019). Traditional studies in determining the architectural styles of buildings involve specialization around architectural styles that require extensive knowledge of the social and economic context and thus, the long-time span and wide geographical distribution of architectural styles and dates make it difficult to express the evolution of styles and types on a large scale (Sun *et al*., 2022). Despite efforts to predict architectural styles, there are still limitations, which can be listed as follows (Sun *et al*., 2022):

- ✓ Most studies have adopted low-level feature extraction to represent buildings. These efforts may provide some level of performance, but the approach they use does not allow for a comprehensive, cognitive level understanding of buildings.
- ✓ LiDAR, 3D GIS model and DSM used in previous studies are not easily accessible and available in many cities.
- ✓ Scalability remains challenging due to the complexity of the above data and the manual process required.

Among image classification problems, the problem of recognizing architectural styles is interesting (Obeso *et al*., 2018), because architectural styles have many similarities and requires techniques that can finely distinguish between different instances of the styles (Zhang & Košecká, 2007). Determining architectural styles has an important place in the residential building design and project process; however, due to the complexity and uncertainty of styles in practice, style determination is often based on the subjective judgments of designers and lacks scientificity and therefore it is an imperative requirement to propose a new method to better understand the connection between morphological elements and styles and how they are affected by design conditions (Xia *et al*., 2020). As a result of a comparative evaluation of different traditional classification techniques for architectural style classification, stronger visual features are needed for architectural style classification (Xu *et al*., 2014). Architectural style classification and extraction is a developing research field in the field of computer vision that has attracted attention in recent years (Xu *et al*., 2014).

Image classification and content-based image retrieval (CBIR) are important problems in the field of computer vision and in recent years, convolutional neural networks (CNNs) have become the preferred tool for creating state-of-the-art image classification systems (Meltser *et al*., 2017). In research in various fields, deep learning has been applied to tackle image classification tasks and some general-purpose networks with strong ability to extract features have been used in these studies (Krizhevsky *et al*., 2012; Simonyan & Zisserman, 2014; Zeiler & Fergus, 2014; Szegedy *et al*., 2015; He *et al*., 2016; Huang *et al*., 2017; Zhou *et al*., 2018; Cui *et al*., 2018).

In recent years, 'deep convolutional neural networks' from the computer vision field of artificial intelligence (AI) have produced simple yet effective models of the visual system (Lindsay, 2021). Studies in the field of image classification have made great progress in accurately recognizing and distinguishing different images and in some cases, these systems can outperform humans (Rawat & Wang, 2017). Classification studies carried out to perform a specific learning task also include satellite images (Shafaey & Salem, 2018; Kadhim & Abed, 2020; Diker & Erkan, 2022), technical drawings (Huang & Zheng), street view images (Liu *et al*., 2017), design principles (Demir *et al*., 2021) and sketches (Karimi *et al*., 2020) were used. While artificial intelligence has already been used for visual aesthetic analysis in art, its use in architecture is quite low (Demir *et al*., 2021).

Various machine learning methods are used to visually classify architectural designs and elements using computer vision techniques. Learning distinctive features for classification also helps explain design differences and similarities. Each architectural style has several unique and distinctive features (Dunlop, 2003); It allows automatic classification of facades and decorations using computer vision methods (Meltser *et al*., 2017). Since the same proportions or similar elements can be used in different architectural styles, one of the problems of classifying architectural styles is their similarities and therefore a convoluted neural network was used to recognize the distinctive architectural features of styles belonging to different historical periods, cultures, nations and countries (Dautov & Astafeva, 2021). Combining features in CNNs is known as a good strategy to reduce data dimensionality, computational complexity and summarize representative features for subsequent layers (Obeso *et al*., 2018). Recent studies have used Convolutional Neural Networks for prediction and classification of architectural styles (Doersch *et al*., 2012; Lee *et al*., 2015; Llamas *et al*., 2017; Obeso *et al*., 2017; Perez *et al*., 2019; Yoshimura *et al*., 2019; Zhao *et al*., 2019;).

Yoshimura et al. (2019) used a deep convolutional neural network (DCNN) model to classify the works of 34 different architects and this model divided the images into classes depending on the visual similarities measured by the algorithm. Llamas et al. (2017) used convolutional neural networks to classify architectural heritage images and stated that the application of these techniques can significantly contribute to the digital documentation of architectural heritage. Similarly, Obeso et al. (2017) used a Convolutional Neural Network to classify the architectural styles of buildings in digital photographs of Mexican cultural heritage and stated that style identification with this technique can make a broad contribution to video annotation tasks, especially in the automatic documentation of cultural heritages. Wang et al. (2019) emphasized that high impact was achieved on the CNN output by highlighting identifiable parts of the input image with the visualization method in their in-class classification study of Gothic architecture based on geographical location. Additionally, the CNN method was used to detect building defects (Perez *et al*., 2019).

As deep neural networks develop and are applied in different fields, there are research studies on architectural styles. Architectural style classification is based on different features in space, details, materials and construction technology, among which basic building elements such as roof, door, window, column, dome, tower, arch are the most prominent (Xia *et al*., 2020). Some studies have focused on the architectural style of building facade windows (Shalunts *et al*., 2011), the architectural style of domes (Shalunts *et al*., 2012) and the architectural style of towers (Shalunts, 2015). In another study, the nearest neighbor technique was used to find architectural features of windows, lamps, etc. (Doersch *et al*., 2012). Additionally, a real estate cadastral map has been combined to date building facades to explore the evolution of architectural elements over time, using image patches to find features associated with a building's construction time (Lee *et al*., 2015). Goel et al. (2012) classified images by grouping 25 European monuments into five architectural styles and developed an unsupervised method to identify the characteristic features of each style.

The classification process is used to automate some tasks during the architectural design phase. With the development of technology, as the building becomes more sophisticated in 3D modeling, the number of architectural elements increases and therefore architects generally divide each geometry into semantically correct layers after the draft model is completed to model faster in the first stage of schematic drawings. Separating and labeling geometries into individual layers is a simple task that does not require special knowledge. Yetiş et al. (2018) aimed to automate this work to reduce this workload of architects and designers and improve work performance. For this purpose, they applied and compared logistic, K-NN, SVM, Naive Bayes and decision trees machine learning models to label architectural elements in various parametric design environments (Rhinoceros, Grasshopper, Grasshopper Python and Grasshopper Python Remote). Additionally, Yetiş et al. (2018) focused only on the automation of labeling and layering of structural elements using X, Y, Z dimensions, while Armeni et al. (2016), in their research, large-scale point cloud data covers broader aspects of the task, from void and mass detection to architectural element and furniture detection.

Recent developments have revealed the potential to develop a model that can identify architectural styles without expert intervention using deep learning-based object classification algorithms, which can help users find houses that suit their preferences and provide architects with design solutions for their preferences (Yi *et al*., 2020). Recent advances in deep learning and the increasing scope of street view services make street view images an ideal approach for building style prediction (Sun *et al*., 2022).

It is important to carefully choose which images should be used to represent an architectural style to define the architectural style and demonstrate that there is a clear relationship between styles more clearly (Yi *et al*., 2020). The choice of the appropriate representation of the class and its scalability to many samples is also important in classification problems (Zhang & Košecká, 2007).

Learning and understanding the architectural style, which is an important element that determines the identity, character and feature of a building, enables examining the history of architecture and structures from different periods, making design decisions, creating a common structure, getting inspiration and creativity. Additionally, knowing the style of a building means we know what types of elements we look for during reconstruction and their typical appearance (Mathias *et al*., 2012). To provide an alternative perspective for architectural research, a CNN model was developed with 3 datasets to demonstrate the potential of deep learning in classifying architectural styles.

3. Methods

Architectural style classification is made to describe, categorize and analyze the stylistic features of buildings and other structures. However, due to increasing data, it is becoming increasingly difficult to do it manually. Within the scope of this study, models with convolutional neural networks were developed to classify architectural styles. The developed models aim to provide an alternative perspective for architectural research and also to demonstrate the potential of deep learning in classifying architectural styles. Accurate classification of architectural styles is important to preserve architectural heritage, guide restoration projects, provide information for education and research purposes and optimize design processes. This study consists of the stages of organizing the data, developing the model, reducing the number of styles and developing the model again and evaluating the performance of the models. The flow diagram applied for the study is as follows (Figure 1):

1. 3 data sets were used to see the model performance of data addition and data augmentation methods. The first dataset is the original data containing images from 25 different architectural styles. The second data set is the data set created by adding data to the first data set. The data added is data from Google images. The third data set was created by increasing the data in the first data set. There are a total of 4776 images in the first dataset, 10091 images in the second dataset and 9552 images in the third dataset. The images were subjected to pre-processing such as “sizing, normalization and data augmentation” to make them suitable for the convolutional neural networks model.

2. A classification model was developed with 3 data sets using convolutional neural networks.

3. Models were developed for 14 architectural styles with a 30% accuracy rate across three data sets. Then, a model was developed for 6 architectural styles with a 50% accuracy rate in three data sets. By removing the least successful style, a model was developed for 5 and then 4 architectural styles.

4. Data not previously used in training was used to test the performance of the three developed models.

5. The performances of the models were evaluated.

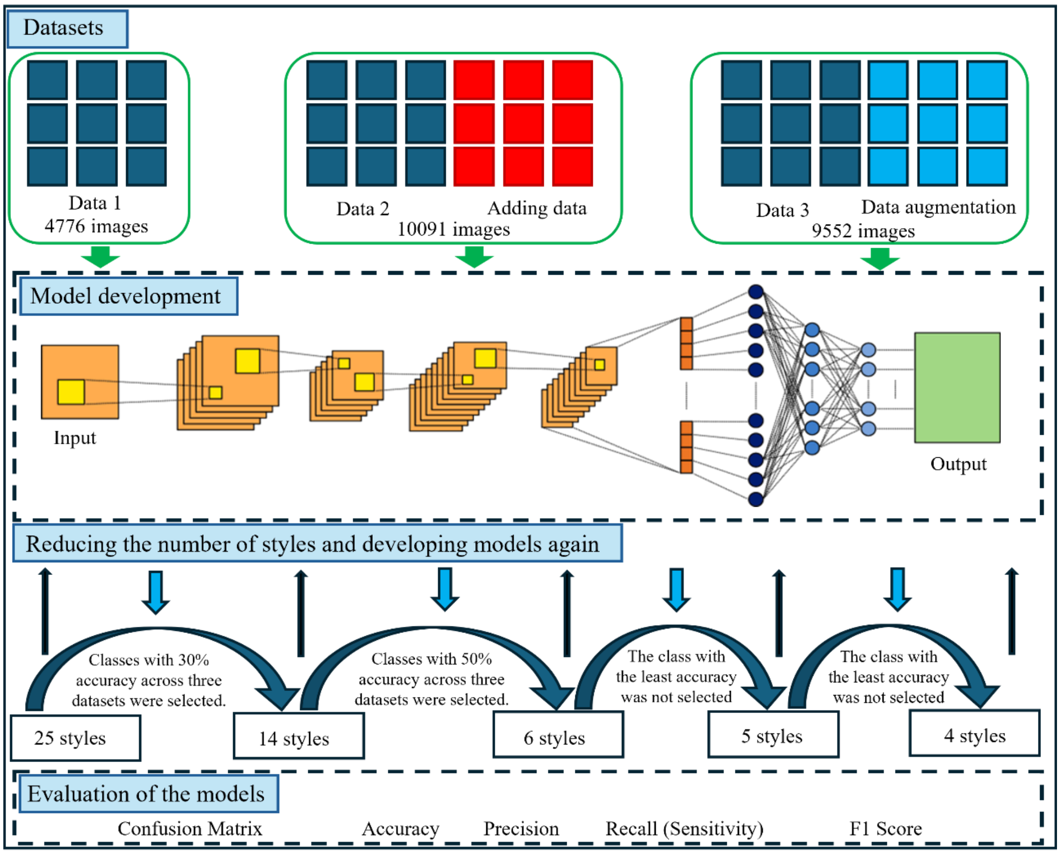

Figure 1. Flow diagram of the study

3.1. Construction of the data set

For the study, 3 group data sets were used. In the first data group, images of 25 architectural styles in the dataset in the article "Architectural Style Classification Using Multinomial Latent Logistic Regression" (ECCV2014) prepared by Xu et al. (2014) were used. In the second data group, images taken from Google Images shared on the "Kaggle" platform have been added to the first data group. The last data group was created by increasing the data in the first data group. There are a total of 4776 images in the first data set, a total of 10091 in the second data set and a total of 9552 images in the third data set (Figure 2) and sample images of the classes from the data set used are shown in Figure 3.

Augmented data were used in the same model to understand whether architectural styles learned distinctive or similar features. The parameters used to augment the data are:

- ✓ Random rotation angle range: -20 to 20 degrees
- ✓ Shifting range on width: 10%
- ✓ Shifting range on height: 10%
- ✓ Shearing range: 20 degrees
- ✓ Zooming range: 20%
- ✓ Horizontal flipping: Yes
- ✓ Fill missing pixels using nearest neighbor.

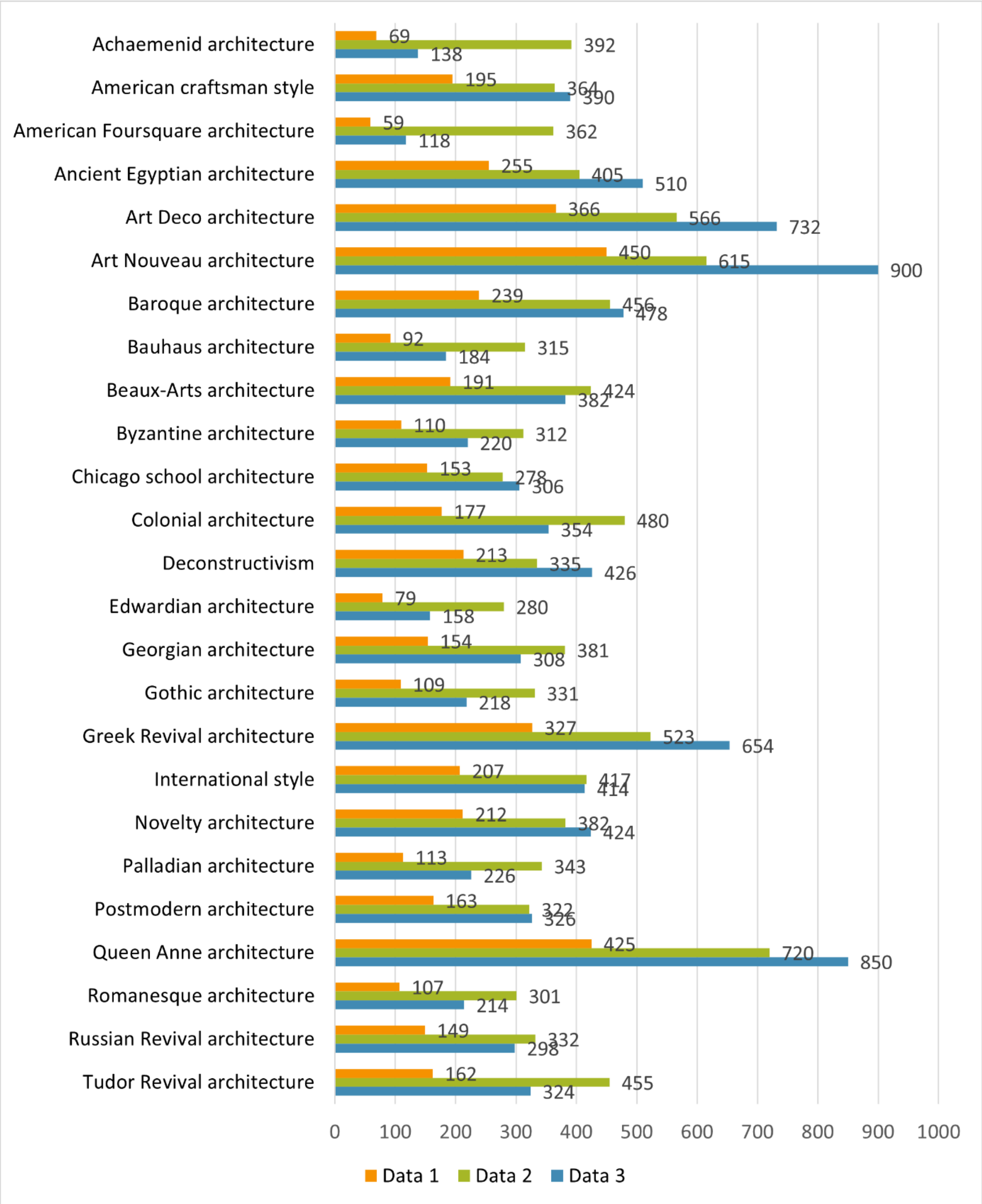

Figure 2. Number of data available for each class

Figure 3. Sample images of the architectural styles used

Some sample images of classes from the augmented data set are shown in Figure 4.

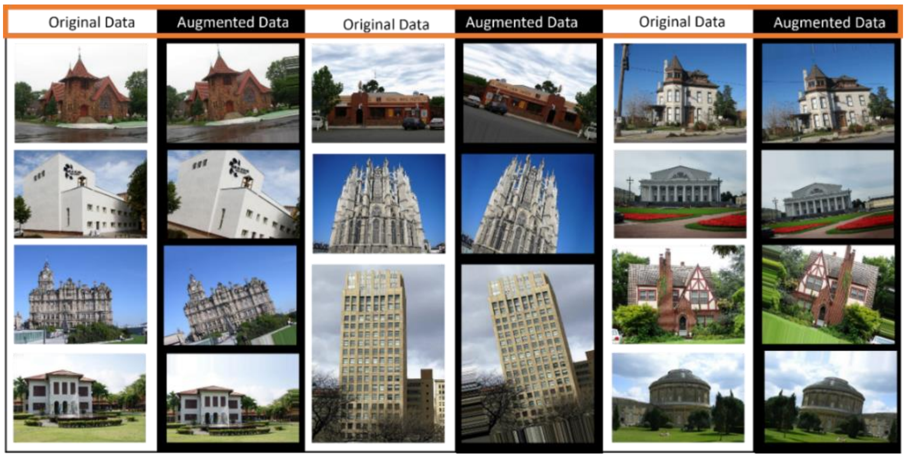

Figure 4. Sample images of the augmented data set

3.2. Development of models

Deep convolutional neural networks contain 3 basic layers convolution, pooling and full connection, as well as some hyperparameters such as Strid, Pixel Padding, Kernel and Activation Functions (Figure 5).

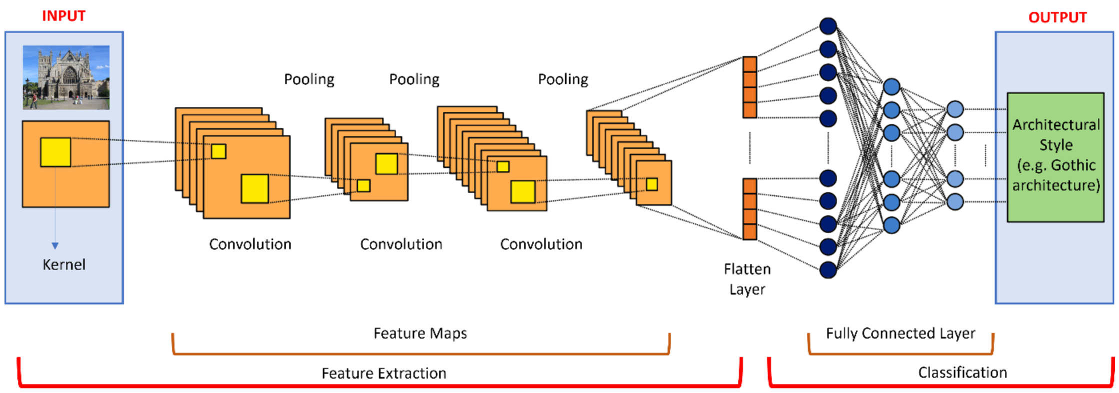

Figure 5. General structure of deep convolutional neural network

In the convolution layer, features are extracted from the input image. This inference is made through filters that act on the input data, perform dot multiplication with these regions and receive the output as a dot product matrix. Filters perform matrix multiplications by moving them over the images and the result value is obtained by adding the values obtained from the multiplications.

As a result of the convolution process, a size difference occurs between the input matrix and the output matrix. If the size of the feature map is not desired to decrease after each convolution process, pixels are added to the outer edge of the input image by either copying the pixels consisting of zeros or the pixels around the image to prevent the size difference. The image is transferred to the pooling layer after the convolution layer. There is no learning process in this layer. The purpose of this layer is to reduce the size of the input matrix based on width and height by keeping the number of channels constant. As the size decreases, information loss occurs and this loss provides less computational load on the next network layer and prevents the system from being memorized. This layer uses the incoming data to create an output vector containing smaller and meaningful information. A sizing matrix of the specified size is applied in the pooling layer. This sizing matrix is applied on the image according to the step shift value.

If the maximum values in the matrix are taken, the maximum pooling method is applied, or if the average of the values is taken, the average pooling method is applied. As a result of the Flattening process applied to the data obtained after the convolution and pooling layer, input data for the fully connected layer (dense layer) is obtained. In this way, the process for the relevant learning process begins. In this layer, each neuron is connected to every neuron after it. This fully connected layer processes the weights and data from the previous hidden layers. As a result of these operations, the data is combined with a selected activation function and the output value is created. The output layer represents the result of the network and is used in tasks such as classification or prediction.

The design of the developed deep convolutional neural networks consists of 6 double of convolutional layers and a maximum pooling layer repeated 6 times, followed by a flattening layer and 2 densely connected layers. The kernel size for all convolutional layers is 3 × 3 and the kernel size for all max-pooling layers is 2 × 2. Rectified Linear Unit (ReLU) activation function was used as an activation function in the hidden layers. Since the output layer has 25 different classes, the Softmax function was used as the activation function. Python programming language and the Google Collaboratory program, offered free of charge by Google, were used to develop the deep convolutional neural network model. The general architecture of the developed deep convolutional neural network model is shown in Figure 6.

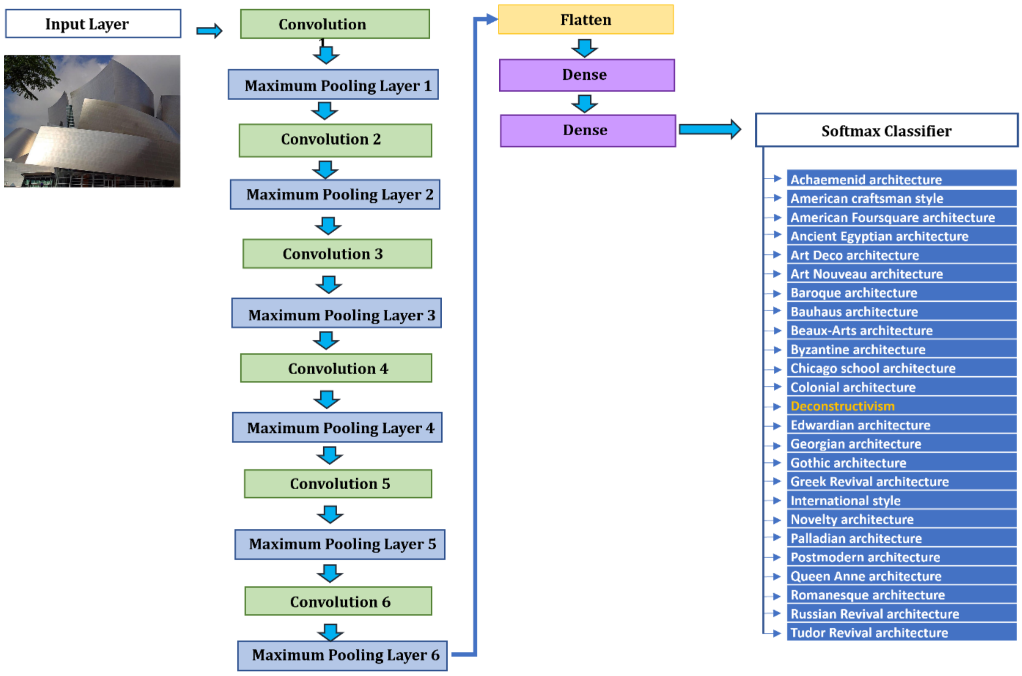

Figure 6. Architecture of the Developed Deep Convolutional Neural Network

3.3. Performance Evaluation Criteria

To measure the predictive ability, accuracy, reliability and success of the developed classification models and to decide whether the model is a good model or not, the performance of the models must be evaluated. Some of the most common metrics used to evaluate classification model performance include:

✓ Confusion Matrix: It is a matrix that visually displays actual and predicted classes. If the number of class labels in the data set is n, the matrix size is n*n. The following four evaluations are used for classification predictions:

- True Positive (TP): These are positive class labels that are correctly predicted by the model.
- True Negative (TN): These are negative class labels that are correctly predicted by the model.
- False Positive (FP): These are positive class labels that were incorrectly predicted by the model.
- False Negative (FN): These are negative class labels that are incorrectly predicted by the model.

✓ Accuracy: It is expressed as the ratio of correct predictions to all predictions.

✓ Precision: It is a measure of success that expresses the ratio of data predicted as positive by the model to actually be positive.

✓ Recall (Sensitivity): It is a measure that shows how successfully positive situations are predicted.

✓ F1 Score: Precision and sensitivity are the harmonic mean of the measures.

Performance metrics may vary depending on different applications and problems. Therefore, choosing the appropriate criteria for the problem and evaluating the model according to these criteria is of critical importance to determine that the model is working effectively. Since architectural style classification is a classification task in which visual data is analyzed, criteria suitable for visual classification problems should be considered when choosing performance criteria. Since an unbalanced data set was used in this study, the F1 score performance evaluation criterion was used.

4. Results

The success of the model was evaluated with the developed model 3 data set and by reducing the number of architectural styles. First, 25 architectural style classifications were evaluated with the developed model. It was evaluated again in the same model with 14 architectural styles that had a 30% accuracy rate in three data sets. Then, 6 architectural styles with an accuracy rate of 50% were evaluated in three data sets. By removing the least successful style, 5 and then 4 architectural styles were evaluated. The purpose here is to see how decreasing the number of classes affects the success of the model.

Based on the Pareto principle (80-20 principle) in the use of data sets, 80% of each data set is reserved for training, 10% for testing and the remaining 10% for validation. In the training of the developed model, 100 epochs, 0.001 learning rate and Adam optimization algorithm were used. The accuracy and loss rates in training and validation during the epochs are shown in Figure 7-11.

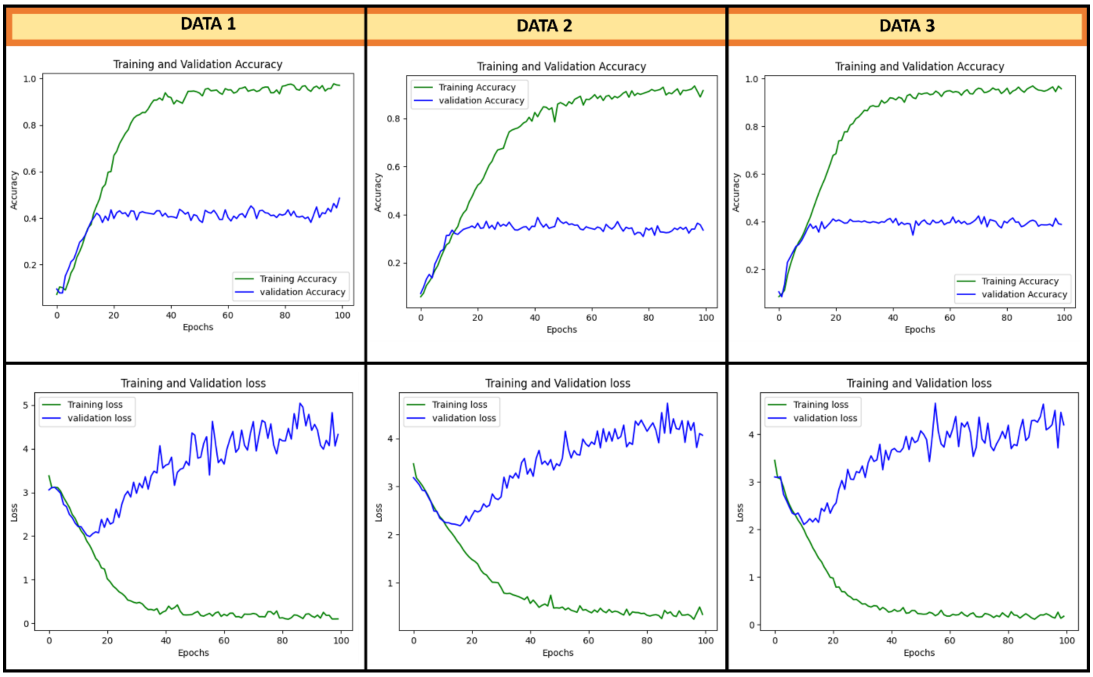

Figure 7. Training and validation accuracy graph obtained from the developed model (25 Classes)

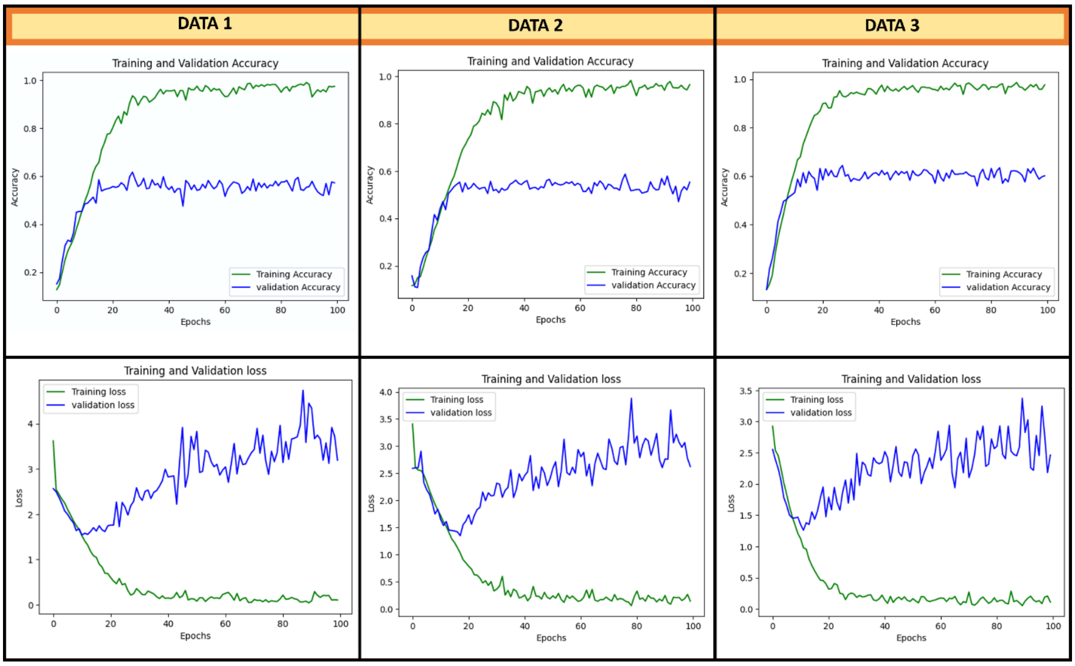

Figure 8. Training and validation accuracy graph obtained from the developed model (14 Classes)

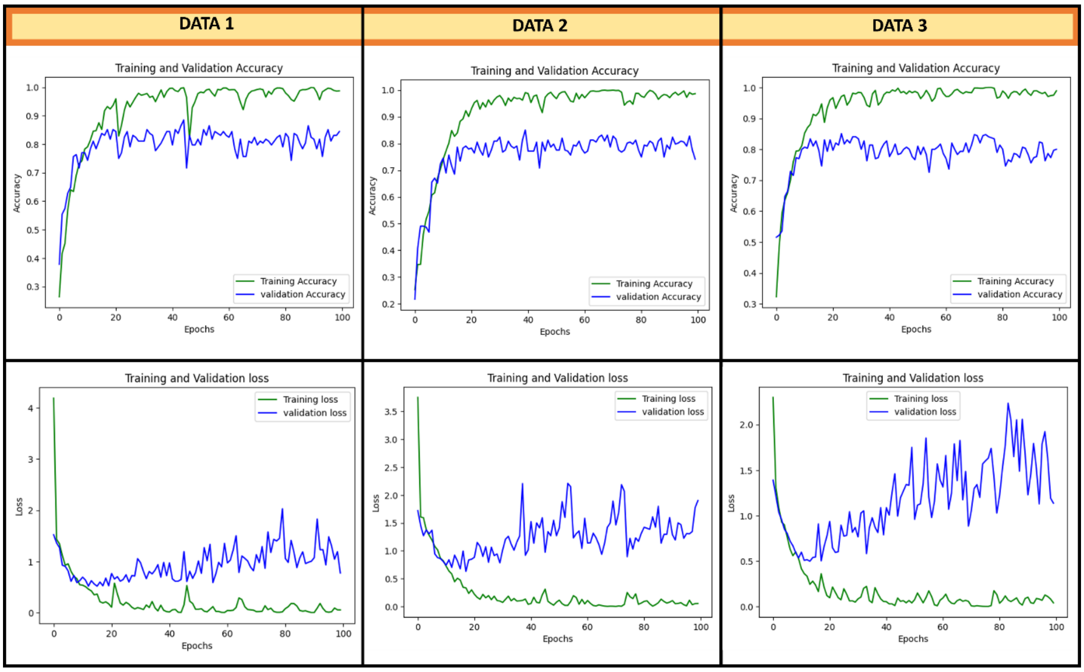

Figure 9. Training and validation accuracy graph obtained from the developed model (6 Classes)

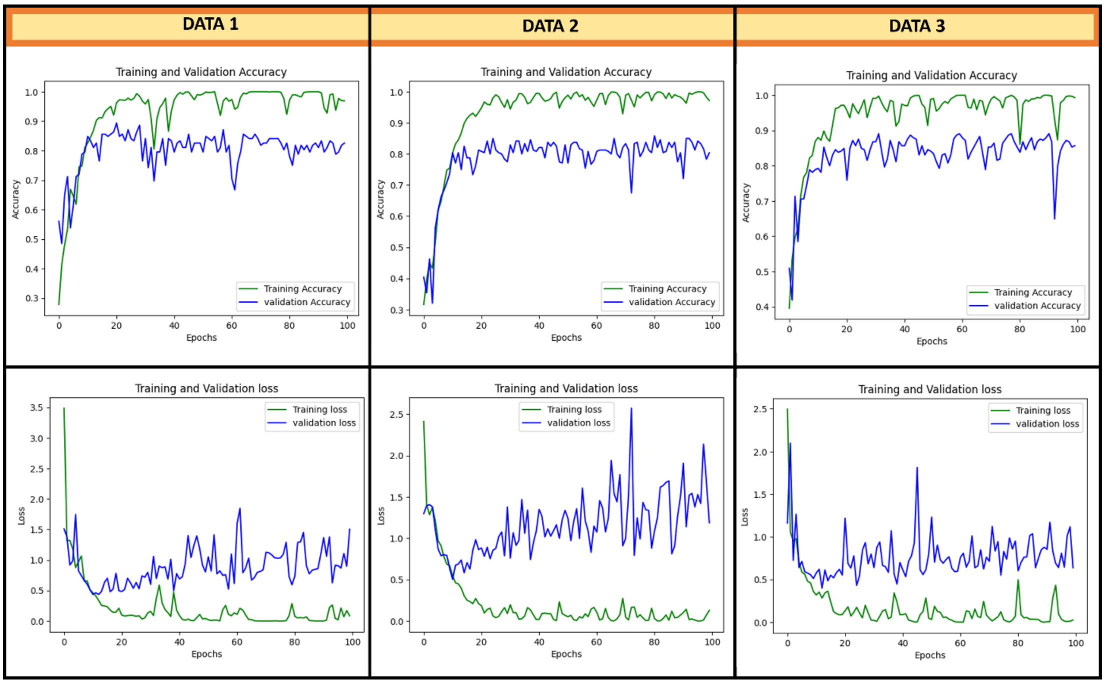

Figure 10. Training and validation accuracy graph obtained from the developed model (5 Classes)

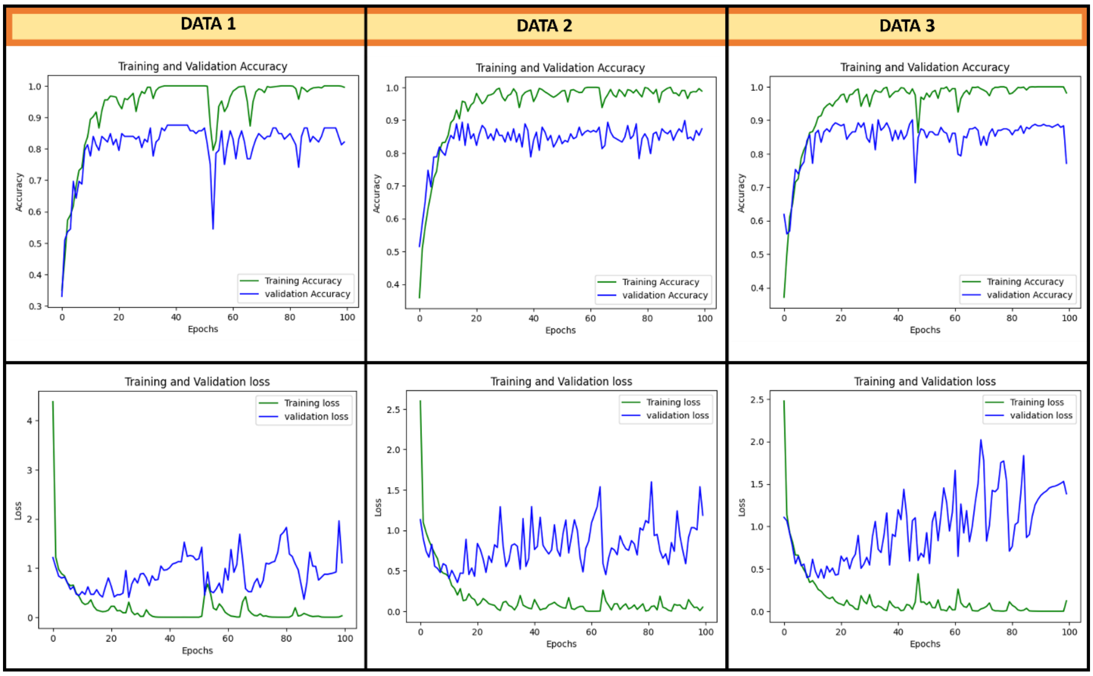

Figure 11. Training and validation accuracy graph obtained from the developed model (4 Classes)

4.1. Performance results of the developed models

4.1.1. 25 architectural style classification results

The confusion matrix obtained from the developed models is shown in Figure 12 and the distribution of the F1 score results of the models in 3 data sets is shown in Figure 13. The results of the performance criteria evaluated according to this matrix are shown in Table 1.

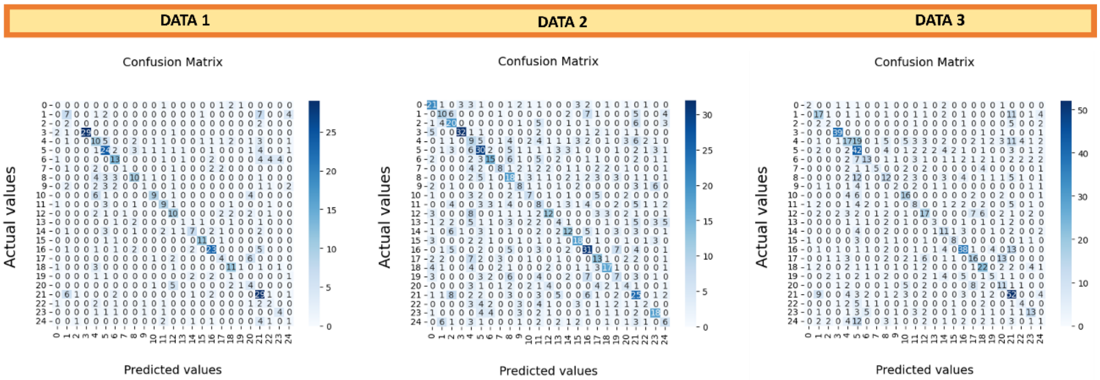

Figure 12. Confusion matrix obtained from the developed model

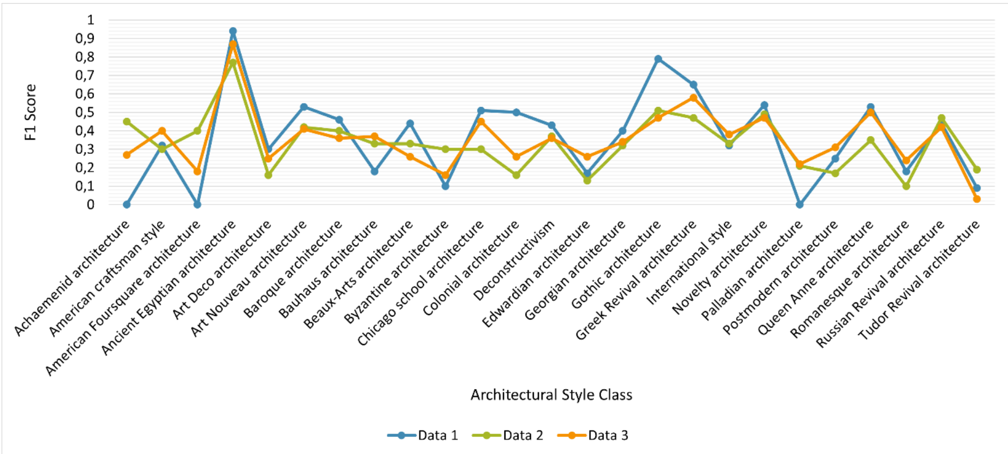

Figure 13. F1 score distribution obtained from the developed model (25 classes)

Table 1. Performance results of the developed model (25 classes)

	Precision			Recall			F1 Score		
Architectural Style	D 1	D 2	D 3	D 1	D 2	D 3	D 1	D 2	D 3
Achaemenid architecture	0,00	0,41	0,40	0,00	0,50	0,20	0,00	0,45	0,27
American craftsman style	0,32	0,33	0,40	0,32	0,28	0,40	0,32	0,30	0,40
American Foursquare architecture	0,00	0,35	0,22	0,00	0,48	0,15	0,00	0,40	0,18
Ancient Egyptian architecture	1,00	0,89	0,81	0,88	0,68	0,93	0,94	0,77	0,87
Art Deco architecture	0,28	0,13	0,31	0,33	0,19	0,20	0,30	0,16	0,25
Art Nouveau architecture	0,50	0,39	0,31	0,57	0,45	0,59	0,53	0,42	0,41
Baroque architecture	0,48	0,45	0,45	0,43	0,36	0,30	0,46	0,40	0,36
Bauhaus architecture	0,50	0,44	0,56	0,11	0,27	0,28	0,18	0,33	0,37

Beaux-Arts architecture	0,48	0,28	0,27	0,42	0,39	0,25	0,44	0,33	0,26
Byzantine architecture	0,20	0,31	0,22	0,07	0,29	0,12	0,10	0,30	0,16
Chicago school architecture	0,64	0,32	0,41	0,43	0,28	0,50	0,51	0,30	0,45
Colonial architecture	0,47	0,14	0,28	0,53	0,19	0,25	0,50	0,16	0,26
Deconstructivism	0,38	0,46	0,37	0,48	0,31	0,35	0,43	0,37	0,36
Edwardian architecture	0,25	0,17	0,33	0,12	0,10	0,21	0,17	0,13	0,26
Georgian architecture	0,50	0,38	0,30	0,33	0,29	0,41	0,40	0,32	0,34
Gothic architecture	0,79	0,50	0,47	0,79	0,51	0,47	0,79	0,51	0,47
Greek Revival architecture	0,64	0,44	0,60	0,66	0,51	0,56	0,65	0,47	0,58
International style	0,33	0,32	0,42	0,31	0,35	0,34	0,32	0,33	0,38
Novelty architecture	0,50	0,53	0,44	0,58	0,45	0,50	0,54	0,49	0,47
Palladian architecture	0,00	0,23	0,28	0,00	0,18	0,18	0,00	0,21	0,22
Postmodern architecture	0,21	0,20	0,29	0,31	0,15	0,32	0,25	0,17	0,31
Queen Anne architecture	0,44	0,31	0,43	0,67	0,40	0,59	0,53	0,35	0,50
Romanesque architecture	0,18	0,18	0,29	0,18	0,07	0,21	0,18	0,10	0,24
Russian Revival architecture	0,44	0,47	0,46	0,44	0,47	0,38	0,44	0,47	0,42
Tudor Revival architecture	0,09	0,19	0,04	0,09	0,19	0,03	0,09	0,19	0,03
Average	0,38	0,35	0,37	0,36	0,33	0,35	0,36	0,34	0,35

Note: Since precision and accuracy values are the same, accuracy is not added separately
D 1: Data 1 D 2: Data 2 D 3: Data 3

While Data 3 was expected to be more successful than the other two data in the classification of 25 architectural styles since it was augmented data, Data 3 was more successful in 10 classes from Data 1 and 14 classes from Data 2 according to the F1 score criterion. Similarly, since Data 2 contains more visual data, the model is expected to learn better. According to the F1 score criterion, Data 2 was only more successful in 8 classes than Data 1.

4.1.2. 14 architectural style classification results

The confusion matrix obtained from the developed models is shown in Figure 14 and the distribution of the F1 score results of the models in 3 data sets is shown in Figure 15. The results of the performance criteria evaluated according to this matrix are shown in Table 2.

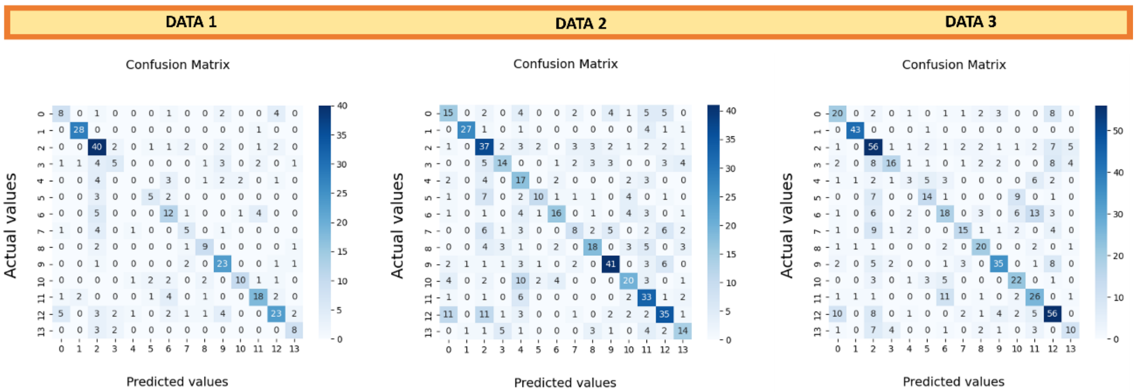

Figure 14. Confusion matrix obtained from the developed model

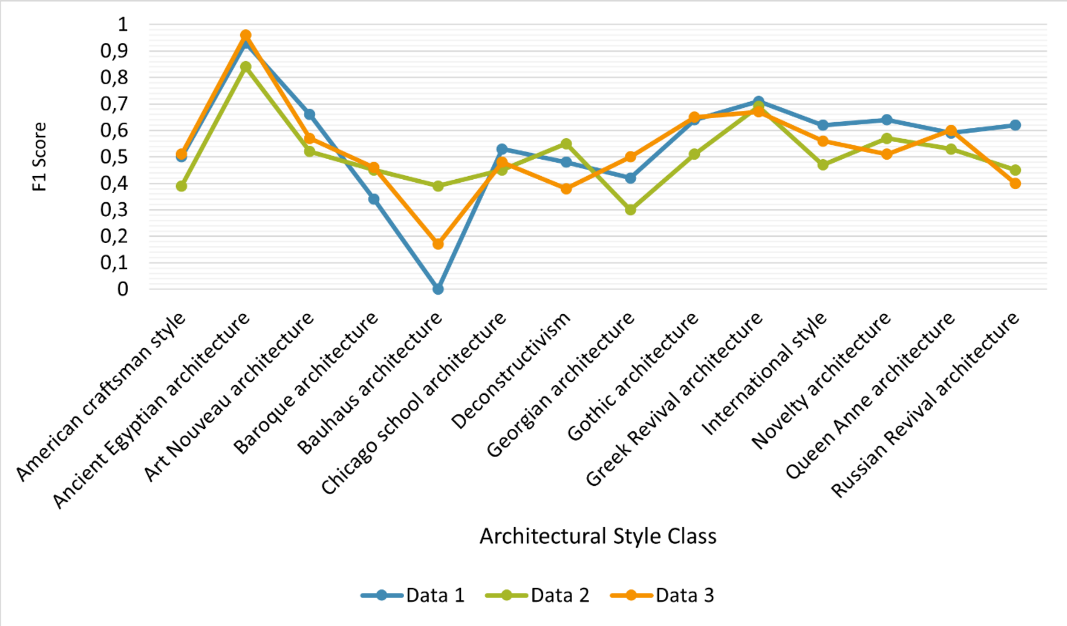

Figure 15. F1 score distribution obtained from the developed model (14 classes)

Table 2. Performance results of the developed model (14 classes)

	Precision			Recall			F1 Score		
Architectural Style	D 1	D 2	D 3	D 1	D 2	D 3	D 1	D 2	D 3
American craftsman style	0,50	0,39	0,49	0,50	0,39	0,53	0,50	0,39	0,51
Ancient Egyptian architecture	0,90	0,93	0,93	0,97	0,77	0,98	0,93	0,84	0,96
Art Nouveau architecture	0,57	0,45	0,49	0,78	0,63	0,68	0,66	0,52	0,57
Baroque architecture	0,45	0,52	0,64	0,28	0,40	0,36	0,34	0,45	0,46
Bauhaus architecture	0,00	0,29	0,25	0,00	0,57	0,12	0,00	0,39	0,17
Chicago school architecture	0,56	0,62	0,54	0,50	0,36	0,44	0,53	0,45	0,48
Deconstructivism	0,44	0,62	0,41	0,52	0,50	0,35	0,48	0,55	0,38
Georgian architecture	0,42	0,42	0,62	0,42	0,23	0,42	0,42	0,30	0,50
Gothic architecture	0,60	0,58	0,59	0,69	0,46	0,71	0,64	0,51	0,65
Greek Revival architecture	0,62	0,71	0,74	0,82	0,67	0,61	0,71	0,69	0,67
International style	0,77	0,51	0,50	0,53	0,43	0,63	0,62	0,47	0,56
Novelty architecture	0,67	0,48	0,45	0,62	0,72	0,59	0,64	0,57	0,51
Queen Anne architecture	0,68	0,56	0,57	0,52	0,51	0,63	0,59	0,53	0,60
Russian Revival architecture	0,62	0,47	0,48	0,62	0,44	0,34	0,62	0,45	0,40
Average	0,56	0,54	0,55	0,56	0,51	0,53	0,55	0,51	0,53

Note: Since precision and accuracy values are the same, accuracy is not added separately
D 1: Data 1 D 2: Data 2 D 3: Data 3

In the classification of 14 architectural styles, Data 3 was more successful than Data 1 in 7 classes and Data 2 in 9 classes according to the F1 score criterion. According to the F1 score criterion, Data 2 was more successful than Data 1 in only 3 classes.

4.1.3. 6 architectural style classification results

The confusion matrix obtained from the developed models is shown in Figure 16 and the distribution of the F1 score results of the models in 3 data sets is shown in Figure 17. The results of the performance criteria evaluated according to this matrix are shown in Table 3.

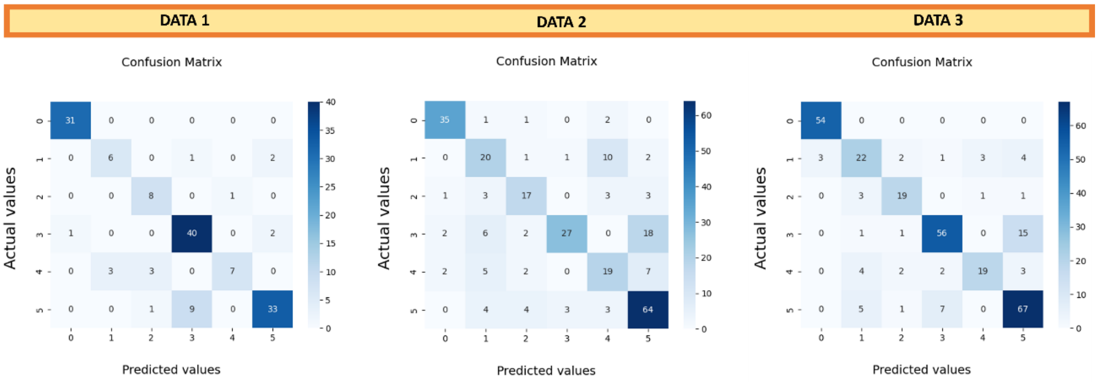

Figure 16. Confusion matrix obtained from the developed model

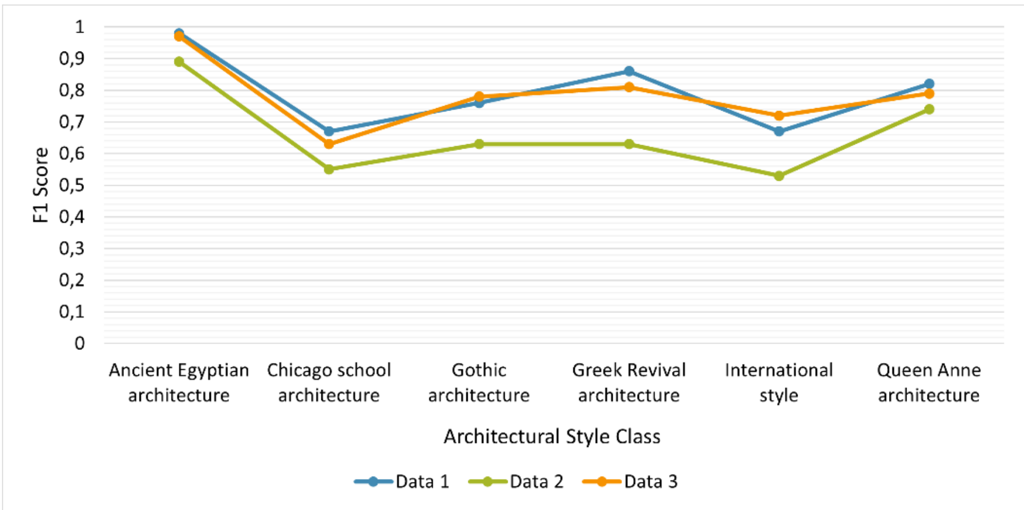

Figure 17. F1 score distribution obtained from the developed model (6 classes)

Table 3. Performance results of the developed model (6 classes)

	Precision			Recall			F1 Score		
Architectural Style	D 1	D 2	D 3	D 1	D 2	D 3	D 1	D 2	D 3
Ancient Egyptian architecture	0,97	0,88	0,95	1	0,9	1	0,98	0,89	0,97
Chicago school architecture	0,67	0,51	0,63	0,67	0,59	0,63	0,67	0,55	0,63
Gothic architecture	0,67	0,63	0,76	0,89	0,63	0,79	0,76	0,63	0,78
Greek Revival architecture	0,8	0,87	0,85	0,93	0,49	0,77	0,86	0,63	0,81
International style	0,88	0,51	0,83	0,54	0,54	0,63	0,67	0,53	0,72
Queen Anne architecture	0,89	0,68	0,74	0,77	0,82	0,84	0,82	0,74	0,79
Average	0,81	0,68	0,79	0,80	0,66	0,78	0,79	0,66	0,78

Note: Since precision and accuracy values are the same, accuracy is not added separately
D 1: Data 1 D 2: Data 2 D 3: Data

In the classification of 6 architectural styles, Data 3 was more successful in 2 classes than Data 1 and in 6 classes than Data 2, that is, in all of them, according to the F1 score criterion. According to the F1 score criterion, Data 2 was not more successful than Data 1 in any class.

4.1.4. 5 architectural style classification results

The confusion matrix obtained from the developed models is shown in Figure 18 and the distribution of the F1 score results of the models in 3 data sets is shown in Figure 19. The results of the performance criteria evaluated according to this matrix are shown in Table 4.

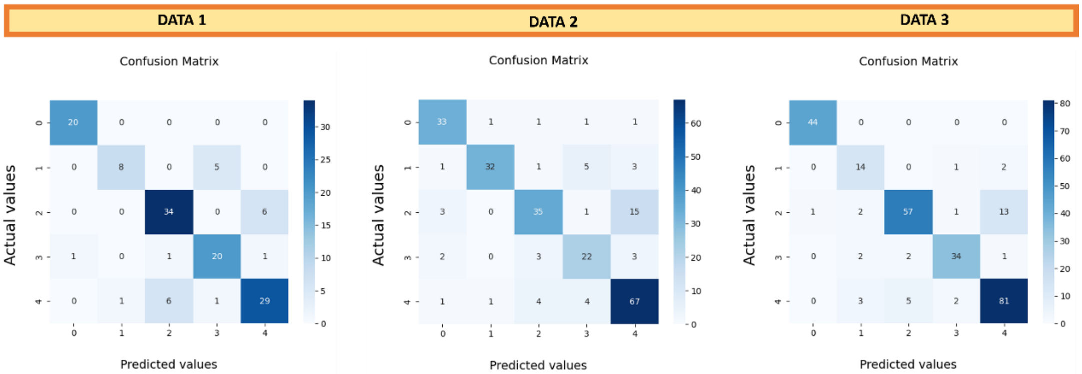

Figure 18. Confusion matrix obtained from the developed model

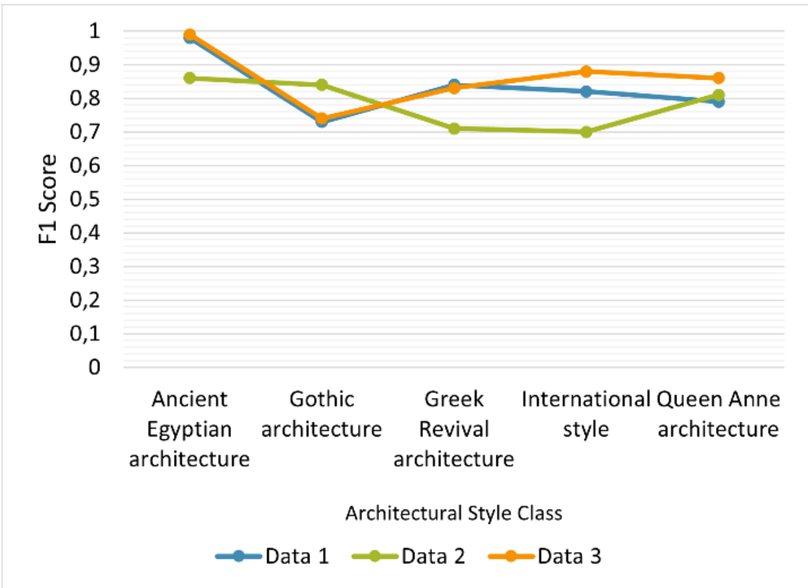

Figure 19. F1 score distribution obtained from the developed model (5 classes)

Table 4. Performance results of the developed model (5 classes)

	Precision			Recall			F1 Score		
Architectural Style	D 1	D 2	D 3	D 1	D 2	D 3	D 1	D 2	D 3
Ancient Egyptian architecture	0,95	0,82	0,98	1	0,89	1	0,98	0,86	0,99
Gothic architecture	0,89	0,94	0,67	0,62	0,76	0,82	0,73	0,84	0,74
Greek Revival architecture	0,83	0,8	0,89	0,85	0,65	0,77	0,84	0,71	0,83
International style	0,77	0,67	0,89	0,87	0,73	0,87	0,82	0,7	0,88
Queen Anne architecture	0,81	0,75	0,84	0,78	0,87	0,89	0,79	0,81	0,86
Average	0,85	0,80	0,85	0,82	0,78	0,87	0,83	0,78	0,86

Note: Since precision and accuracy values are the same, accuracy is not added separately
D 1: Data 1 D 2: Data 2 D 3: Data

In the classification of 5 architectural styles, Data 3 was more successful than Data 1 in 4 classes and Data 2 was more successful in 4 classes according to the F1 score criterion. According to the F1 score criterion, Data 2 was more successful than Data 1 in only 2 classes.

4.1.5. 4 architectural style classification results

The confusion matrix obtained from the developed models is shown in Figure 20 and the distribution of the F1 score results of the models in 3 data sets is shown in Figure 21. The results of the performance criteria evaluated according to this matrix are shown in Table 5.

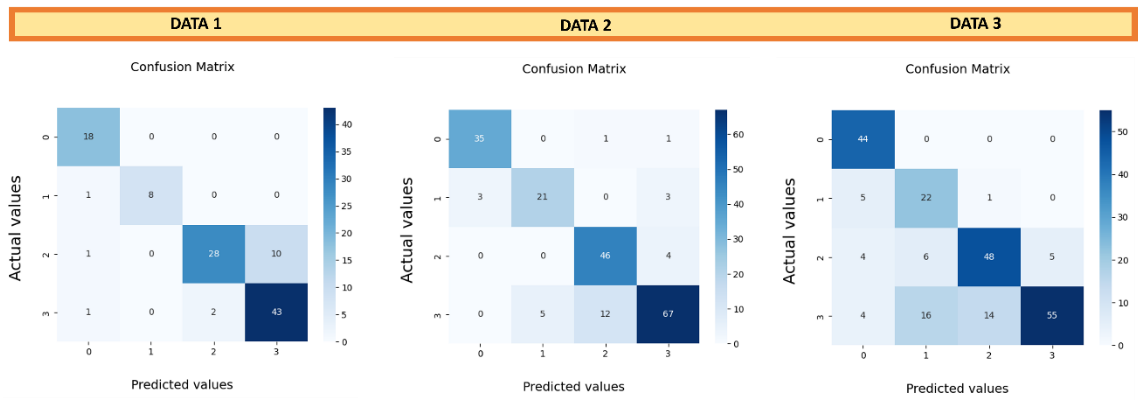

Figure 20. Confusion matrix obtained from the developed model

In the classification of 4 architectural styles, Data 3 was not more successful than any of the classes of Data 1 and Data 2 according to the F1 score criterion. According to the F1 score criterion, Data 2 was more successful than Data 1 in only 2 classes.

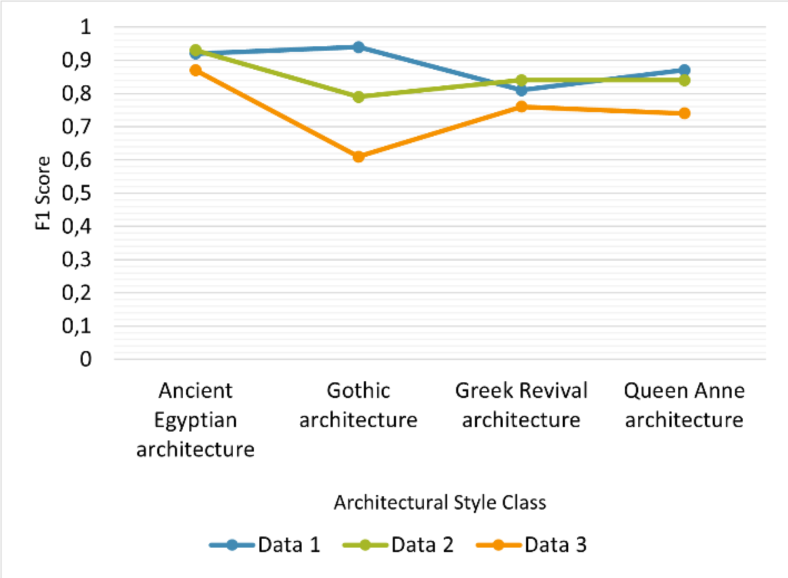

Figure 21. F1 score distribution obtained from the developed model (4 classes)

Table 5. Performance results of the developed model (4 classes)

	Precision			Recall			F1 Score		
Architectural Style	D 1	D 2	D 3	D 1	D 2	D 3	D 1	D 2	D 3
Ancient Egyptian architecture	0,86	0,92	0,77	1	0,95	1	0,92	0,93	0,87
Gothic architecture	1	0,81	0,5	0,89	0,78	0,79	0,94	0,79	0,61
Greek Revival architecture	0,93	0,78	0,76	0,72	0,92	0,76	0,81	0,84	0,76
Queen Anne architecture	0,81	0,89	0,92	0,93	0,8	0,62	0,87	0,84	0,74
Average	0,90	0,85	0,74	0,89	0,86	0,79	0,89	0,85	0,75

Note: Since precision and accuracy values are the same, accuracy is not added separately
D 1: Data 1 D 2: Data 2 D 3: Data

4.2. Discussion

While the success achieved from Data 2 and Data 3 is expected to be more successful than Data 1, Data 1 has been more successful than Data 2 and Data 3. In the model that classifies only 5 classes, it has been more successful in Data 3 Recall and F1 Score. It has achieved the same success in the precision and accuracy criteria. In general, it is observed that Data 2 and Data 3 failed more than Data 1 in all performance criteria. This indicates that the DCNN model is not successful in increasing data and data augmentation from the Regularization methods applied to increase its success. In addition, this study has once again emphasized the importance of data selection by considering the complexity of architectural style learning.

In the classification of 25 architectural styles, 19 classes showed either an increase or decrease in the same way in all three data sets. In the classification of 14 architectural styles, 9 classes showed either an increase or decrease in the same way in all three data sets. In the classification of 6 architectural styles, 6 classes showed either an increase or decrease in the same way in all three data sets. In the classification of 5 and 4 architectural styles, no class showed either an increase or decrease in the same way in all three data sets. The quantity of data in the classification of 6 architectural styles is 100%; 76% in 25 architectural styles; 62% gave the same effect in 14 architectural styles. However, 5 and 4 showed no similarity in the classification of architectural styles. This situation emphasizes the importance of the optimum number of classes.

As the number of architectural style classes decreased (except for Data 3 in 4 architectural style classification), the success rate increased. This shows that the increase in the number of architectural styles reduces the learning rate in the DCNN model.

In a study conducted in the classification of 3 architectural styles, 77% accuracy was obtained in test data (Mathias *et al*., 2012). Similarly, in a study conducted to classify 3 architectural styles, 84.66% accuracy was obtained (Cantemir & Kandemir, 2024). In this study, an average accuracy of 83% was obtained in the classification of 5 architectural styles and an average accuracy of 89% in 4 architectural styles. These findings make significant contributions to the existing literature by providing high accuracy rates despite the larger number of classes. This study shows that the DCNN model is an effective tool in architectural style classification and its performance can be increased with optimum data selection and number of classes.

5. Conclusions

Classification of architectural styles has a considerable important place in subjects such as understanding the history of architecture, preserving cultural heritage, analyzing structures, making design decisions and creating more creative designs. Since expert knowledge is necessary in the classification of architectural styles, the role of architects and historians in image classification is significant to find structures suitable for styles. However, with the development of technology, it becomes increasingly difficult to manually classify the increasing data correctly.

With the development of technology and hardware, deep learning has made significant improvements in object classification algorithms to classify according to their own learning without human intervention. This study aims to provide researchers and practitioners interested in architectural style classification in data mining or machine learning with a better understanding of data addition, data augmentation and choice of number of classes. Answers to these questions can contribute to more effective and accurate solving of architectural style classification problems. Accordingly, in this study, the success of the data addition and data augmentation method to increase the accuracy of the model in architectural style classification was examined. In addition, the effect of reducing the number of classes on the success of the model was evaluated. However, data addition and data augmentation architectural styles failed to classify. This shows that the DCNN model is not successful in learning various features of a particular entity in the image, such as pose (position, size, direction), deformation, tone, texture. It was concluded that the DCNN model failed to understand the locations of objects in the image or the relationship between parts of the object. In addition, the selection of data in architectural style classification is quite difficult and therefore it is concluded that the data is of great importance in the success of the model. More successful models can be developed by improving the data set or other deep learning networks.

This study may provide an infrastructure for the development of deep learning models for future architectural style classification. This is a research and development study that aims to use deep convolutional neural networks to identify complex structures and features, going beyond traditional methods of identifying architectural styles. This modeling approach can be valuable in many application areas in the field of architecture, such as analyzing architectural styles, identifying historical periods and predicting future style trends. Finally, the use of such approaches in architectural practice; It will provide many benefits, including understanding historical buildings, directing restoration processes, providing inspiration for new designs and understanding history and development in architectural education. In addition, it can provide practical benefits in areas such as tourism, real estate marketing, urban planning and management.

Accurate architectural classification with the developed models can offer students a historical, cultural, aesthetic and technical perspective in architectural education and this can make them more conscious and competent architects. These knowledge and skills can help students be more successful in future design projects and contribute to the process of preserving and recreating architectural heritage.

This study emphasizes the importance of optimal data selection and number of classes in increasing the success of the DCNN model in architectural style classification. Decreasing the number of architectural styles increases the generalization and learning performance of the model. While data addition and data augmentation were expected to increase the performance of the model, a higher success rate was achieved in the original data. These findings will guide future research and provide new perspectives to the literature on complexity management and model optimization.

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