ICONARP
International Journal of Architecture and Planning
Received: 09.02.2024 Accepted: 15.12.2024
Volume 12, Issue 2/ Published: 31.12.2024
Research Article *DOI: 10.15320/ICONARP.2024.308 E- ISSN:2147-9380*
ICONARP

Deep Learning-Assisted Discovery of Analogy-Inspired Designs within Peter Collins' Analogical Architectural Design Classification Framework

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Abstract

This study focuses on analogical reasoning and deep learning models to enhance the innovative design process in architecture. By constructing multi-layered artificial neural networks, deep learning can derive analogical predictions from structured data to solve complex tasks. Deep learning models interact with analogical thinking patterns in the architectural design process, enabling designers to analyze and draw inspiration from analogical design examples. This study aims to develop a deep learning model that categorizes architectural design examples into specific analogical design classifications. For this purpose, a model based on Convolutional Neural Networks was developed and coded in the Google Colab environment using a dataset of 29,596 visual images, employing Peter Collins' classification system of biological, mechanical, gastronomic, and linguistic analogies. During the training process, the model was trained on images classified according to biological, mechanical, gastronomic, and linguistic categories, achieving an accuracy rate of 98%; however, this rate was recorded as 86% during the testing phase. It was observed that adjustments in the learning rate parameter balanced classification accuracy and training time; lower learning rates reduced accuracy while extending training time. Despite the complexity of architectural images indicated by the 86% accuracy rate on test data, the study emphasizes the model's capacity to achieve accuracy above 95% when confronted with distinct architectural features. In this case, the model allows designers to discover which analogical classification the architectural work to be tested is designed according to, allowing them to develop creative solutions to new design problems. Additionally, this research establishes an interdisciplinary dialogue between artificial intelligence and architecture, providing a foundation for future studies.

Keywords:
Analogical design, Architectural design, Deep learning, Peter Collins.

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To cite this article: Özdemir, H. (2024). Deep Learning-Assisted Discovery of Analogy-Inspired Designs within Peter Collins' Analogical Architectural Design Classification Framework. *ICONARP International Journal of Architecture and Planning,* 12 (2), 872-890. DOI: 10.15320/ICONARP.2024.308

INTRODUCTION

Deep learning represents a sophisticated methodology within machine learning, designed by constructing artificial neural networks with multiple processing layers to tackle complex tasks (Wong, 2021). This innovative approach focuses on leveraging the capabilities of deep neural networks, which can derive insights directly from structured data. The remarkable ability of these neural networks to replicate the complex connections between input data and the resulting output predictions is noteworthy. Deep neural networks often integrate architectural elements of convolutional, recurrent, and multilayer perceptrons in their design, drawing inspiration from the inner workings of the human brain (Chinnasamy et al., 2015). Pioneering research is being conducted in this field, exploring new models within this comprehensive framework (Jayakanna & Raju, 2022). The domain of deep learning algorithms is characterized by a continuous evolution involving the iterative fine-tuning of weights and biases connected to individual neurons. This gradual improvement process results in a step-by-step enhancement of cognitive abilities, enabling them to adeptly address previously considered complex and insurmountable challenges. Despite significant challenges related to the demand for extensive data and substantial computational resources, the profound potential of deep learning methodologies significantly enhances their flexibility and importance across various fields. These fields encompass recognition and image processing sectors, where deep learning techniques have delivered transformative results.

One of the primary advantages of using deep learning in architectural design is its ability to augment human creativity. As Petráková notes, a well-calibrated artificial intelligence can inspire architects without overshadowing their creative instincts, thus preserving the human touch in design processes (Petráková, 2023). This view is shared by Atwa and Saleh, who emphasize the necessity of understanding how artificial intelligence can impact creativity. It is suggested that architects increasingly leverage the capabilities of artificial intelligence to meet specific design demands (Atwa & Saleh, 2023). Furthermore, Rane states that including generative artificial intelligence in architectural theory represents a paradigm shift, expressing that machine intelligence is blended with human creativity, redefining the essence of creativity in design (Rane, 2023).

The evolution of artificial intelligence in architectural design has also brought about various algorithmic approaches that facilitate the exploration of abstract concepts and the generation of numerous design ideas. Hegazy and Saleh discuss how artificial intelligence has revolutionized the construction industry by providing tools capable of parametric explorations and generating design variations based on mathematically defined parameters (Hegazy & Saleh, 2023). This capability is also supported by Li and others, demonstrating how deep learning models contribute to the intelligent design of architectural

DOI: 10.15320/ICONARP.2024.308

spaces and enhance design processes suitable for three-dimensional features (Li, Wu, Xing, & Wang, 2023).

Moreover, the ethical dimensions of artificial intelligence in architecture must be considered. Tellios emphasizes that integrating artificial intelligence into architectural applications raises questions about biases in these technologies and that its impact on design innovation and production processes should be subject to critical scrutiny (Tellios, 2023). This concern is echoed in the work of Winiarti and others, who state that artificial intelligence should be used responsibly in digital architecture, addressing potential challenges while enhancing design capabilities (Winiarti, Pramono, & Pranolo, 2022).

Regarding practical applications, recent developments in generative design with artificial intelligence have enabled architects to create high-quality architectural designs from textual descriptions. Chen's research reveals an innovative artificial intelligence method that produces designs with specified features similar to the style and qualities of master architects, significantly enhancing the creativity and efficiency of the design process (Chen, 2023). These findings parallel the work of As and others, discussing the potential of deep learning to create conceptual designs by extracting fundamental building blocks based on functional performance criteria (As, Pal, & Basu, 2018).

Integrating artificial intelligence into architectural design processes also brings a new perspective to the historical roots of architectural theory. In this context, it has been observed that analogies have been used as a significant tool for thinking in architectural design throughout history and have been classified in various forms by experts. Peter Collins' categorization of analogies into biological, mechanical, gastronomic, and linguistic categories demonstrates that design processes can be approached with inspiration from different disciplines (Collins, 1965). On the other hand, Abel classifies analogy models from a broader perspective as spiritual, semantic, utopian, traditional, organic, military, commercial, and mechanical, revealing the transformation of architecture in different periods and contexts and the elements that influenced it (Abel, 1979). William Gordon's classification of analogies into symbolic, direct formal, individual, and cultural (Aydınlı, 1993), along with Tassoul's (2005) categories of personal, direct, paradoxical, natural, and fantastical analogies, provides a crucial framework for understanding the multifaceted use of analogy in architecture and its contribution to design processes.

In this context, integrating deep learning and artificial intelligence into architectural design processes interacts with analogical thinking styles, offering new creative possibilities. Classifications such as Peter Collins' biological, mechanical, and linguistic analogies allow architects to develop a historical and interdisciplinary perspective. While addressing modern challenges such as sustainability and cultural significance, this approach combines artificial intelligence's extensive data sets and analysis capacity, integrating interdisciplinary knowledge more effectively. Thus, integrating deep learning into architectural design should be considered a technological innovation and a holistic transformation that enriches the creative process and theoretical foundation.

Integrating deep learning and analogical thinking in architecture represents a new research area with the potential to transform traditional design methods. In architectural design, deep learning models can play a significant role in categorizing architectural design examples into specific classes of analogical design. These models allow designers to analyze analogical design examples and uncover sources of inspiration. Recognizing the source of inspiration enables designers to develop creative solutions to new design problems. This process can enhance both creativity and efficiency in architectural design processes. In this context, the study aims to innovate in the design process by incorporating Peter Collins' analogical architectural design classification system. Using a dataset of 29,596 visual images created according to Collins' analogical architectural design classification, a deep learning model based on Convolutional Neural Networks (CNN) was developed. The CNN model achieved a learning accuracy of up to 98%. However, the accuracy rate was 86% during the testing phase. The study synthesizes the relationship between analogical thinking and deep learning, highlighting the applicability of integrating deep learning models into architectural design processes and opening new horizons for enhancing creativity through automation.

THEORETICAL BACKGROUND

The analogy is a similar relationship between objects or concepts based on standard features. In this context, analogy has become a cognitive component, especially in philosophical fields such as epistemology and ontology. Aristotle's transformation of analogy from a physical similarity into a cognitive tool in logic and science emphasizes the intellectual importance of this concept. The conceptual power of analogy is helpful for understanding, interpreting, constructing arguments, examining, and expanding knowledge. Bartha (2013) notes that analogical arguments have shaped philosophical and scientific thought since ancient times. Analogy is a fundamental part of the design process in architecture. Architectural works can be created by taking inspiration from other objects, structures, or concepts. This approach encourages creativity and enables architectural works to emerge from various perspectives. Analogical design creates new forms inspired by known facts by making inferences from the specific to the general. Consequently, adopting an analogical approach in architectural design facilitates interdisciplinary collaboration and the generation of innovative solutions, which enhances the significance of architectural works and enables them to establish a profound connection with the public.

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Peter Collins' Classification of Analogical Design

Analogies have been significant in the architectural process since ancient times. They are used to express thoughts and beliefs through architectural formations. Therefore, analogy has become a common practice in architecture. Scientists specializing in analogies have classified them into various categories (Aydınlı, 1993; Collins, 1965; Tassoul, 2005; Uraz, 1993). This study focuses on Peter Collins' classification, commonly used in the literature, rather than considering all the experts' separate classifications. This approach provides a basis for future studies to improve different classifications. In his book 'Changing Ideals in Modern Architecture,' Peter Collins, an expert on analogy in architecture, classified analogies into four categories: Biological, Mechanical, Gastronomic, and Linguistic (Collins, 1965). This classification aids in comprehending the use of analogy in the design process. Analogous design involves generating new ideas inspired by existing known situations or objects. Collins' classification helps us understand designers' thinking processes and creative design outputs. Analogical thinking indicates that design is a cognitive activity (Ozkan & Dogan, 2013). This process demonstrates the designers' ability to apply existing knowledge to new problems, allowing for the emergence of creative solutions. Additionally, it has been observed that professionals working in design and engineering commonly use analogies (Goel, 1997). Analogy enables designers to generate innovative solutions.

Collins' classification is a significant reference for analogy in architecture and design. This classification aids in comprehending various aspects of using analogy in design thinking and provides a detailed examination of the design process.

Biological analogy

The relationship between architecture and biology has become more pronounced with the emergence of the organic architecture movement. Organic architecture emphasizes using natural forms and processes in building design to achieve a profound harmony between the building and its surroundings. The principle of functional adaptation observed in biological organisms is applied to building design in this context. Biological analogies have often been used to explain the formation of artistic and architectural products, from Herbert Spencer to Raymond Unwin and F.L. Wright (Uraz, 1993). Samuel Taylor Coleridge's concept of organic form emphasizes that buildings should have a structure resembling naturally evolved, unshaped structures, untouched by external interventions.

In modern architecture, organic architecture is a fundamental concept that emphasizes harmony with nature, respect for local materials, and the importance of environmental factors. For example, F.L. Wright's approach to organic architecture advocates integrating buildings with their surroundings and drawing inspiration from natural forms. This principle has also influenced the designs of contemporary architects (Ayyıldız, 2001). Architects such as Tadao Ando incorporate Japanese cultural and belief systems into their designs, thereby perpetuating the principle of organic architecture. This approach emphasizes the importance of a harmonious relationship between the built environment and nature.

In this context, using biological analogies in architecture ensures that architectural design is in harmony with the natural environment and shaped to respond to human needs. Organic architecture adheres to the functional adaptation principles observed in biological organisms, combining functionality and aesthetics in building design, thus establishing a solid foundation (Kortan, 1992). Therefore, using biological analogies in architecture highlights the significance of interdisciplinary collaboration and promotes innovative solutions in the field.

Mechanical analogy

Mechanical analogies refer to the comparison between architectural structures and mechanical devices. This concept emerged in 18th-century literature, highlighting the difference between mechanical and organic concepts (Collins, 1965). In architectural discourse, the debates surrounding mechanical analogies gained momentum towards the end of the 19th century. The early 20th century is widely regarded as a period in which technology played a significant role in architectural thought, often referred to as the 'age of the machine' (Artun & Balcıoğlu, 1982). During this period, architectural texts focused on technology-related themes, with architecture perceiving the machine as an aesthetic object. It was observed that the machine generated a 'mechanical aesthetic' within architectural space and became fetishized (Artun & Balcıoğlu, 1982). Antonio Sant Elia, a representative of Futurism in architecture, advocated for modern buildings to resemble giant machines (Kortan, 1991). Le Corbusier expressed his admiration for industrial products and emphasized the lessons to be learned from them in architectural creation (McLeod, 1996). In modern architecture, mechanical models were used to emphasize functional form. In High-tech architecture, these models acquired a complete machine-like appearance (Uraz, 1993). Norman Foster is a prominent architect in the field of High-tech design. He is known for incorporating technology into his structures and drawing analogies to machines (Uraz, 1993).

Gastronomic analogy

In architectural art, gastronomy has emerged from discussions surrounding flavor and taste, positioning these concepts at the center of aesthetic evaluations. Building upon Croce's emphasis on the creative taste of the artist, investigations have been conducted into the impact of architectural works on individuals and their gratifying qualities (Croce, 1983). This approach highlights the significance of aesthetic pleasure and preference in architecture. Within architectural literature, alongside

DOI: 10.15320/ICONARP.2024.308

gastronomic analogies, there is an examination of how aesthetic attitude and sentiment can be expressed in architectural works. According to Tunalı, aesthetic attitude entails not only adopting a stance for enjoyment but also experiencing aesthetic pleasure towards an object (Tunalı, 2012). In this context, the concepts of aesthetic taste and preference in architecture are utilized to comprehend and assess the positive effects of a work on individuals.

Gastronomic analogies are also employed to determine correct design principles in architecture. Fergusson has suggested that reading cookbooks can be beneficial in understanding architectural design principles (Alexander, 1979). This approach underscores the importance of flavor and taste concepts in architecture. The significance of Romantic and Picturesque influences in gastronomic discussions is also substantial. Picturesque denotes an artistic attitude aiming to mimic the randomness and diversity found in nature rather than adhering to mathematical arrangements, while Romanticism focuses on emotional and natural beauties (Tuğlacı, 1983). The influence of these movements in architecture has played a crucial role in determining how architectural works appeal to human emotions and sensations.

In the works of renowned architects such as Carlo Scarpa, it is observed that the sense of taste predominates in architectural production. The structures created by Scarpa convey a pronounced sensation of taste uncommon in architectural works (Ayyıldız, 2001), thus reinforcing the significance and influence of taste and flavor principles in architectural design. Consequently, gastronomic analogies form the foundation of aesthetic evaluations in architecture and provide a significant tool for understanding the effects of work on individuals. Considering flavor and taste concepts in the design of architectural works can contribute to creating aesthetically satisfying and gratifying spaces.

Linguistic analogy

In architectural literature, language is defined as a set of elements and rules that enable the transmission and interpretation of thoughts, emotions, and desires within society (Aksan, 2000). However, considering language as a category in architecture is a relatively recent phenomenon and only came to the fore in the middle of the 20th century (Yücel, 1981). Some art philosophers, such as Bruce Allsopp, have approached architecture by adapting R.G. Collingwood's aesthetic theory to architecture, leading to linguistic analogies in architectural philosophy. Linguistic analogies offer superiority over biological and mechanical analogies because they better explain the expression of structure and human emotion through language's structural and semantic nature (Collins, 1965). Particularly with the critique of modernism, architectural language's meaning and structural character began to intersect with disciplines such as linguistics, semiotics, structuralism, and semantics.

According to Şentürer (1995), architecture uses language to express and convey messages. The importance of architectural language is also emphasized in the works of Robert Venturi, who claims that architecture's autonomous language has an abstract and conceptual structure that expresses the meaning of structures (Venturi, Brown, & Izenour, 1968). In Venturi's applications, it is observed that architectural language conveys precise and mass-oriented meanings (Akın, 1990). Consequently, linguistic analogies provide an essential tool for understanding and explaining language's structural and semantic character in architecture. The influence of language on architecture plays a crucial role in determining the meaning and expression of structures, thus enhancing the communicative power of architectural works.

METHODOLOGY

In this study, a Convolutional Neural Network (CNN), an artificial neural network model used in deep learning for tasks such as image classification and object detection, was developed and coded in the Google Colab environment. This neural network model forms the methodology of the study.

Components of the Convolution Neural Network Model

The CNN model is significant among artificial neural networks based on image processing. This model comprises a series of specialized layers designed to extract features from data and perform classification tasks. The CNN model includes an input layer, a convolutional layer, a Rectified Linear Units (ReLU) layer, a pooling layer, a flattened layer, and a fully connected layer.

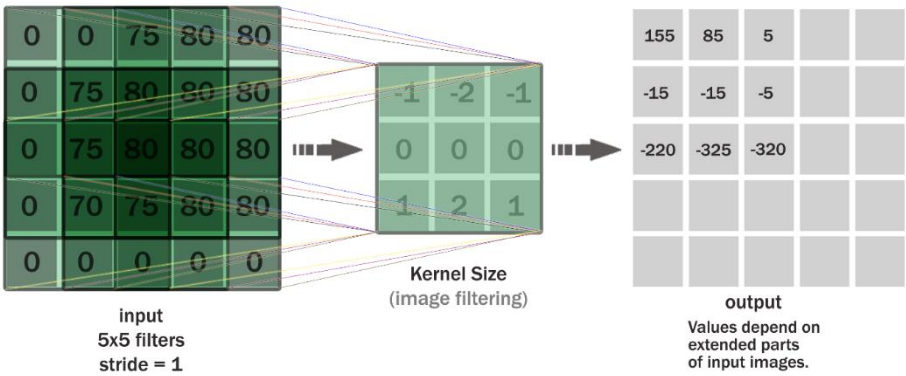

Figure 1. An example of kernel size 3x3 in the convolutional layer of channel 1.

The input layer serves as the initial stage, ensuring subsequent layers receive data in a format suitable for processing. Raw image data is typically prepared in this layer to be forwarded to other model layers.

The convolution layers are responsible for discovering the features of the object to be classified through elemental accumulations. Each filter aims to reveal a unique feature of the object. The output image obtained from these layers contains as many activation or feature maps as the number of filters used. The convolution layer typically applies to a

DOI: 10.15320/ICONARP.2024.308

matrix with dimensions of 3x3 or 5x5 as a filter to the input image (Figure 1).

This layer operates on an image input with dimensions of W1xH1xD1. The convolution layer is characterized by the parameters K number of filters, F spatial extension, S stepping, and P zero padding. Each filter on the input image undergoes a convolution process to learn specific features. Applying the specified stepping and zero padding in the convolution process obtains the W2 × H2 × D2 dimensions output. These output dimensions are determined by mathematical expressions calculated based on the width, height, and depth dimensions of the input image (Equ. [1]-[3]) (Hatir, Barstuğan, & İnce, 2020). The input image's width, height, and depth dimensions are essential components of the convolution layer that enable extracting features from the image.

$$\mathrm{W2} = \frac{\mathrm{W1} - \mathrm{F} + 2\mathrm{P}}{\mathrm{S}} + 1 \quad [1]$$

$$\mathrm{H2} = \frac{\mathrm{H1} - \mathrm{F} + 2\mathrm{P}}{\mathrm{S}} + 1 \quad [2]$$

$$\mathrm{D2} = \mathrm{K} \quad [3]$$

The Rectified Linear Units (ReLU) layer, widely used in CNN models, is applied to the previous layer's output by reducing negative values to zero and leaving positive values unchanged. In the designed model, this layer is integrated after the convolution and fully connected layers. The pooling layer is typically applied after the ReLU layer in Convolutional Neural Networks (CNNs) (Figure 2).

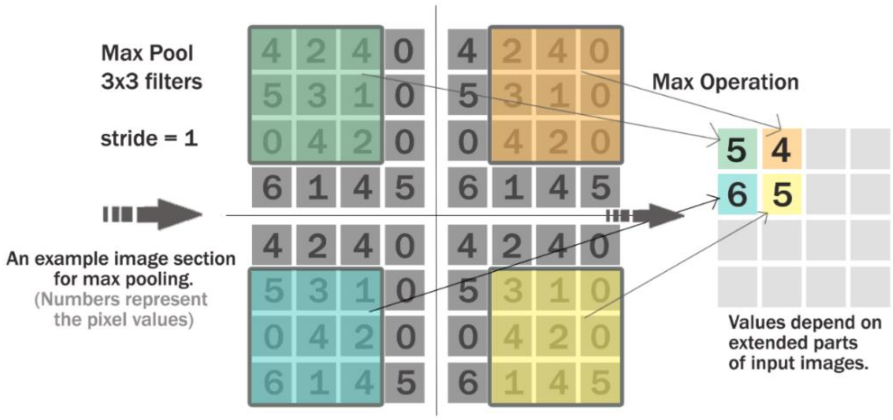

Figure 2. MaxPooling layer example with 3x3 filter.

The primary purpose is to reduce the size of the input image while maintaining the depth of the image. This reduction in input size leads to a loss of information about the image. However, this reduces the computational cost of the subsequent network layer and prevents model overfitting. Max pooling is generally preferred as it tends to exhibit better performance. The proposed CNN model includes a pooling layer. Max pooling achieves this by selecting the most enormous value within each region. This layer uses P (i, j) to represent the element at position (i, j) in the output of the pooling layer. I (i. s+m, j. s+n) represents the element at position (m, n) of the input matrix within the pooling region. The variable 's' represents the pooling step, and 'k' represents the size of the pooling region (Equ. [4]).

$$P(i, j) = \max_{m,n} I(i.s + m, j.s + n) \qquad [4]$$

The flattening layer in the CNN model is typically used to convert the input data from matrix form into a flattened vector (Figure 3). This layer is responsible for converting feature maps into a format that can be inputted into the following fully connected layers, enabling the model to learn more complex features.

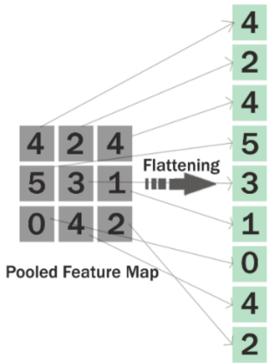

Figure 3. Flatten layer example with 3x3 pooled feature map.

The Fully Connected layer is usually positioned at the network's end and flattens the feature maps from previous convolutional and pooling layers. This process connects each pixel in the feature map to one another. These layers are commonly used for classification or regression tasks, utilizing the features learned by the network beforehand. However, when working with datasets with large input sizes, they may overfit and encounter factors such as computational intensity. Therefore, such networks often require regularization techniques (e.g., dropout, batch normalization) and architectural optimizations. The Fully Connected layer connects to all units in the preceding layer, with connections determined by weights. The general equation for fully connected layers is as follows (Equ. [5]):

$$y_i = f\left(\sum_{i=1}^{n} w_{ij}.x_i + b_j\right) \qquad [5]$$

In this equation:

- The output of the j-th unit in the fully connected layer is represented by y_i.
- The output of the i-th unit in the previous layer is represented by x_i.
- The weight of the connection from the i-th unit to the j-th unit is denoted by w_{ij}.
- The variable b_j represents the bias of the j-th.
- The activation function is represented by $f(.)$.

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The categorical layer constitutes a stage utilized by Convolutional Neural Network (CNN) models to classify or predict class identifications. This particular layer commonly employs a mathematical function called "SoftMax" to transform the outcomes of the CNN network into probability distributions associated with various classes. Consequently, this layer generates a vector containing probability values linked to class identifications. This layer typically provides a probability value for each class in multi-classification dilemmas. The probability distributions generated by the model enable it to allocate input information to the appropriate classes effectively. Typically positioned as the final layer of the model, the categorical layer serves to solidify the ultimate output of the model.

Data Collection

This study has prepared a specialized visual dataset for processing by a CNN model. This dataset is organized according to Peter Collins' four categorical classifications based on the concept of analogy in architecture: biological (based on the form and function of living organisms), mechanical (based on the operational principles of machines), gastronomic (drawing aesthetic inferences from gastronomic processes), and linguistic (referencing the structural rules of language). The images are 1024x768 pixels in size and have a resolution of 72 dpi, chosen to optimize the temporal processing of the model and ensure that the images are distinguishable and perceivable by the CNN model.

The dataset comprises 29,596 images, systematically organized into training, validation, and test sets. The training set contains 27,525 images, the validation set 1,009 images, and the test set 1,062 images. This distribution has been strategically implemented to facilitate effective learning and evaluation of the CNN model. The images are categorized according to Collins' four analogical design classes: 3,133 biological images, 8,352 mechanical images, 9,421 linguistic images, and 6,619 gastronomic images (Table 1). This categorization is crucial for the model to recognize and classify architectural elements based on analogical reasoning. Data augmentation techniques have been employed to enhance the diversity and volume of the dataset. These techniques include random horizontal and vertical shifts, rotations, zooming, and reflections, contributing to the model's learning capacity and accuracy in object prediction.

Table 1. A number of images used in analogy design classes.

Class	Number of images		
	Test	Train	Validation
Biological	474	3133	465
Mechanical	161	8352	113
Linguistic	118	9421	120
Gastronomic	309	6619	311
Total	1062	27525	1009

Data Analysis

As illustrated in Figure 4, the classified images are processed within the CNN model to enable the artificial neural network to analyze the data. This process begins with transferring images, which constitute the analysis data, to the input layer of the CNN model. Initially, the first convolutional layer is applied, utilizing 32 filters of size 3x3 to extract fundamental features. At this stage, the ReLU (Rectified Linear Unit) activation function is employed to zero out negative values and retain positive values in the feature maps. Subsequently, the first layer performs a max pooling operation with a 2x2 filter size, reducing the spatial dimensions by half.

In the second convolutional layer, 32 filters of size 5x5 are used to extract more complex and higher-level features. The ReLU activation function is again applied to zero out negative and preserve positive values. A second max pooling operation with a 2x2 filter size further halves the spatial dimensions.

The third convolutional layer employs 32 filters of size 3x3 to extract more detailed and specific features. The ReLU activation function is applied once more, and a third max pooling operation with a 2x2 filter size is performed, further compacting the feature maps. After completing the convolutional and pooling layers, the resulting two-dimensional feature maps are transformed into a one-dimensional vector through a flattening layer. This feature vector is fed into a fully connected layer, where class probabilities are calculated using four neurons. Finally, in the classification layer, the sigmoid activation function obtains probability values between 0 and 1 for each class, thus providing the classification result for the input data.

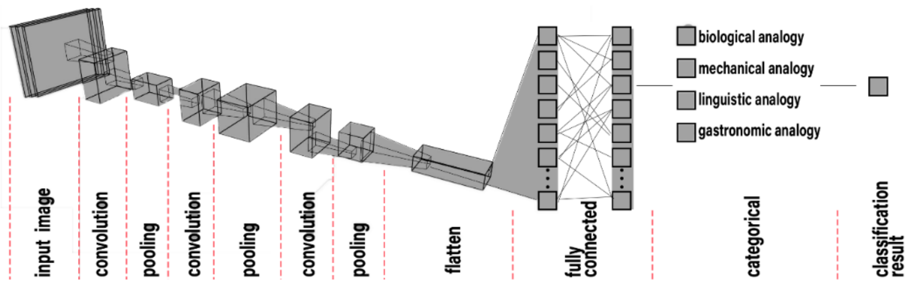

Figure 4. Proposed stages for deep learning processing.

EXPERIMENTAL FINDINGS

The dataset consists of 5000 visual images divided into four distinct classes: biological, mechanical, linguistic, and gastronomic. However, a larger dataset of 29,596 architectural images was generated to train the model effectively using data augmentation techniques, such as random horizontal and vertical shifting, rotation, zooming, and reflection (Figure 5). This augmentation aims to improve the model's learning capacity and increase the accuracy of object prediction. The CNN model was trained using 27,525 images, with 1,062 for testing and 1,009 for validation. The training dataset consists of 3,133 biological images, 8,352 mechanical images, 9,421 linguistic images, and 6,619

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gastronomic images. The test dataset includes 474 biological images, 161 mechanical images, 118 linguistic images, and 309 gastronomic images. Meanwhile, the validation dataset consists of 3,133 biological images, 465 mechanical images, 120 linguistic images, and 311 gastronomic images. The training process used a batch size of 64 and lasted 24 epochs.

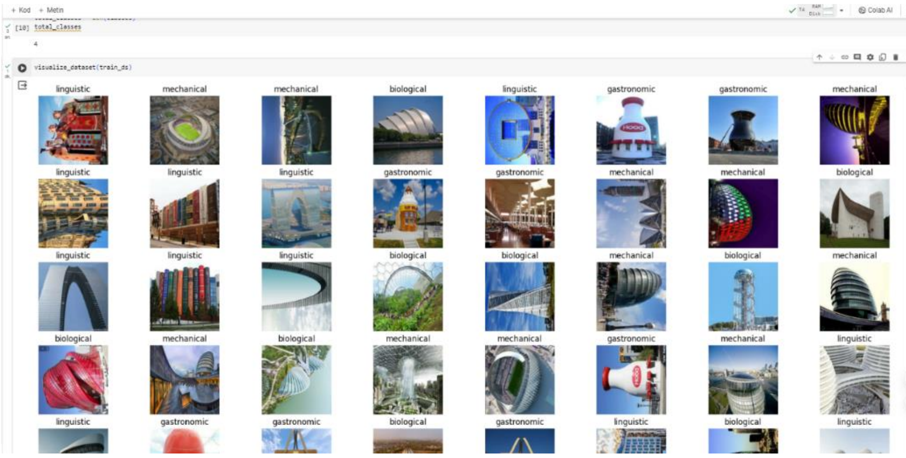

Figure 5. Training dataset in the deep learning process.

The Deep Learning model displays the convergence graph obtained due to the learning process performed on the training dataset in Figure 6. In the training phase, 98 % accuracy was achieved in four classes of 29596 images. The accuracy values in the validation data reached 80-86 % after the 20th epoch. Figure 6 displays the accuracy and loss plots of a CNN model trained over 25 epochs on a dataset containing analogy architectural classes.

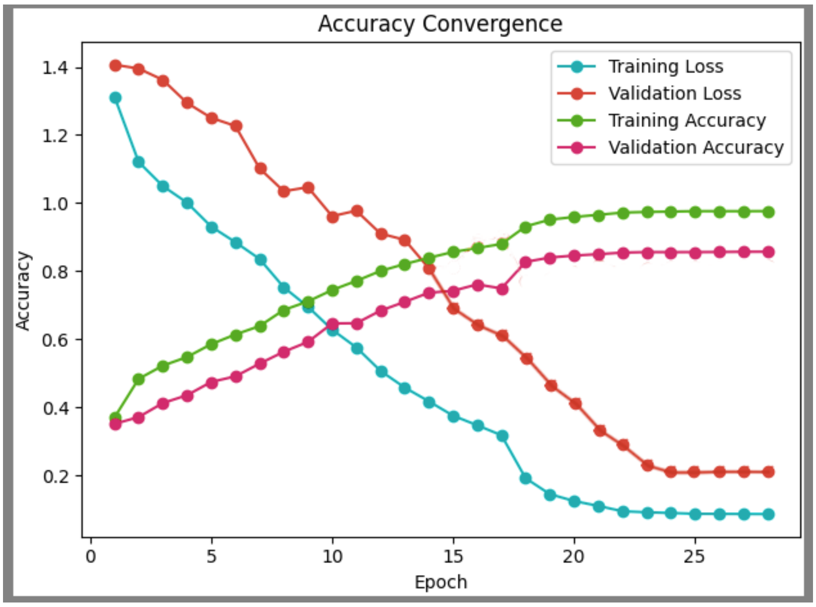

Figure 6. Accuracy and Loss of Convergence Graphs of CNN Model.

The model architecture includes convolutional, max pooling, flattened, and fully connected layers. The plots demonstrate that training and validation accuracy increases as training progresses while training and validation losses decrease. The model achieved high accuracy (1.2%) and low loss (0.2) on the training data, indicating effective learning. However, the higher training accuracy and loss compared to the validation accuracy (1%) and loss (0.4%) suggest a risk of overfitting. Overfitting happens when the model memorizes the training data and cannot generalize new data. Various methods can be employed to mitigate this risk. These include increasing the amount of training data, utilizing data augmentation techniques, exploring different model architectures, and applying regularization techniques. Additionally, it is essential to consider factors such as dataset size and complexity, the optimization algorithm used, and tuning the model's hyperparameters to evaluate its performance better.

The model achieved an accurate rate of 86% on the test data. The confusion matrix obtained at this stage is shown in Figure 7. The model faces difficulty extracting the intrinsic qualities of images when classifying architectural images of the four classes in the dataset due to the presence of concrete and abstractly designed architectural structures. Despite the challenge, the model successfully classified the four classes with the desired accuracy. The reduction of the learning rate parameter resulted in a decrease in both classification accuracy and training time. Graphs indicate that deep learning algorithms tend to learn more general features as the learning rate decreases. The model in this study presents training durations and accuracy values based on data weights. The classification results show a 98% accuracy rate. The best outcome was obtained using a learning rate parameter 10000e-04 and a batch size of 10.

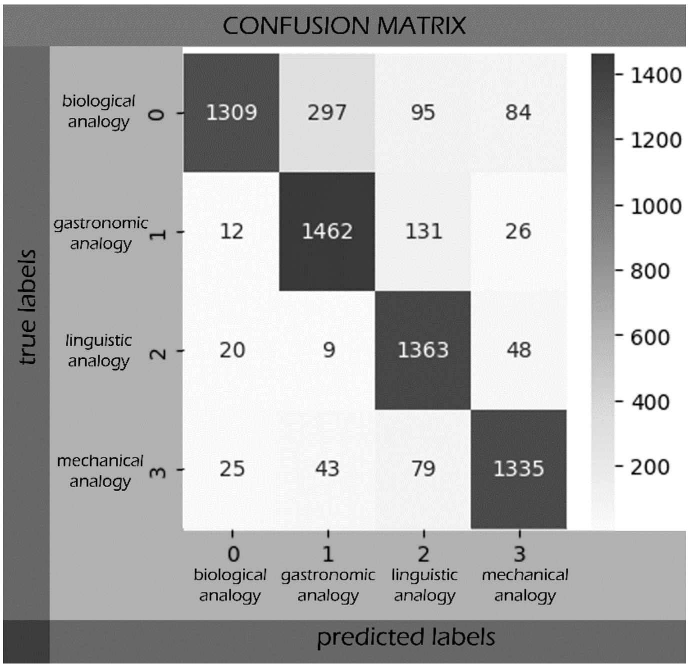

Figure 7. Understanding the Confusion Matrix in the CNN Model.

The CNN model produced analogical design classes as outlined by Collins. Table 2 displays its classification performance for the four classes: biological, gastronomic, linguistic, and mechanical. The precision, recall, and F-measure values yielded an average of 86-87%

DOI: 10.15320/ICONARP.2024.308

accuracy. In the Biological Analogy class, the model's classification achieved a precision of 0.96. However, the recall value was lower at 0.73, indicating that some biological analogies may not have been accurately recognized. The F-Measure, representing the balance between precision and recall, was 0.83. In the Gastronomic Analogy class, precision was measured at 0.81 and recall at 0.90. The model demonstrated balanced performance in recognizing gastronomic analogies with an F-measure of 0.85. In the Linguistic Analogy class, precision and recall values were 0.82 and 0.95, respectively, indicating a tendency to recognize linguistic analogies with high precision, resulting in an F-Measure of 0.88. Precision and recall values were measured at 0.89 and 0.90 for the Mechanical Analogy class, respectively. The model demonstrated a successful ability to recognize mechanical analogies, achieving an F-measure of 0.90.

Table 2. Performance values of the model according to analogical design classes

Class	Precision	Recall	F-Measure
Biological Analogy	0.96	0.73	0.83
Gastronomic Analogy	0.81	0.90	0.85
Linguistic Analogy	0.82	0.95	0.88
Mechanical Analogy	0.89	0.90	0.90
Macro Average	0.87	0.87	0.86
Weighted Average	0.87	0.86	0.86

The Macro Average and Weighted Average values summarized the performance across all classes. The Macro Average provided an equally weighted average for each class, while the Weighted Average indicated the weighted average based on the sample sizes of the classes. In this context, the model's average precision, recall, and F-Score were determined to be 0.87, 0.87, and 0.86, respectively.

DISCUSSION

Integrating artificial intelligence into architectural design processes transforms how architects conceptualize and execute projects. The studies by Hegazy and Saleh demonstrate that AI can facilitate parametric explorations by generating various design alternatives based on defined parameters, thereby expanding creative possibilities in architectural practice (Hegazy & Saleh, 2023). Zakariya's research highlights the innovative use of AI art platforms in mosque facade design, showcasing AI's role in enhancing aesthetic evaluations suitable for cultural contexts (Zakariya, 2023). This intersection of technology and creativity makes the design process more efficient and promotes a more inclusive approach to architectural expressions.

In light of these developments, integrating Peter Collins' analogical design classification with the deep learning model CNN presents a significant innovation in architecture. Achieving a training accuracy of 98% indicates that analogical thinking categories can be effectively combined with deep learning models. However, while this classification has been successful with biological and gastronomic analogies, it faces challenges with linguistic and mechanical analogies. The model's validation accuracy of 86% suggests that the distinctive features of classification, particularly in linguistic and mechanical analogies, have not been fully analyzed. Nevertheless, the accuracy of the 98% training demonstrates the successful integration of analogical thinking categories into the deep learning model.

This success could serve as an inspiration for future studies. The model's performance can be further enhanced by expanding the dataset and optimizing the learning rate. The broader application of AI in architecture, enabled by the model's versatility across various fields and architectural topics, facilitates the rapid classification of studies and the seamless integration of new information. The following could help bridge the gap between traditional and innovative design in architecture. However, there are limitations in extracting specific architectural features, necessitating further exploration in future research. Additionally, evaluating the model's performance across different architectural styles and expanding the categories of analogical design could be addressed in future studies.

In conclusion, this study successfully integrates the analogical thinking of architecture with deep learning models. However, further work is needed to achieve tremendous success in expanded application areas and to overcome specific challenges.

CONCLUSION

This study aims to develop a method for identifying architectural designs using deep learning within Peter Collins' analogy architectural design classification framework. The deep learning model extracts design patterns from a diverse architectural dataset and identifies significant similarities and differences between architectural styles. Collins' classification framework integrates design patterns and associates them with characteristics specific to different stages of the architectural design process. The model enables designers to improve the quality and diversity of their designs by using a data-driven and analytical approach to the architectural design process.

The study focused on understanding the importance of analogy designs in architectural design and evaluating the effectiveness of deep learning models. The results show that the deep learning model correctly classified architectural elements with 98% accuracy during the training phase. On test data, the model achieved 86% accuracy. When classifying the architectural images in the data set prepared for the deep learning model, particular and abstractly designed architectural works made it difficult to extract the essence of the images. This resulted in the model achieving 86% learning accuracy on the test data. The deep learning model can be increased to an accuracy level of 95% or more for classifications with entirely distinctive features. The successful performance of the model despite images lacking fully discriminative features was attributed to reducing the learning rate parameter and

DOI: 10.15320/ICONARP.2024.308

setting the fragment size to a specific value. Peter Collins divided the analogy designs into biological, mechanical, gastronomic, and linguistic categories. This made it easier for the deep learning model to identify similarities between architectural elements. The model's ability to draw inspiration from different aspects of architectural design and creatively integrate them into projects is demonstrated. The study demonstrates the contribution of the deep learning model to the architectural design process by identifying similar designs and adding unique elements to projects. It provides a valuable perspective on the dynamic relationships between tradition, innovation, and inspiration in the interaction between architecture and artificial intelligence disciplines.

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DOI: 10.15320/ICONARP.2024.308

Resume

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