

DOI: 10.5281/zenodo.12426744

# AI-DRIVEN MATERIAL OPTIMIZATION IN ARCHITECTURAL IMAGE MODELLING: ENHANCING DURABILITY AND AESTHETIC PRECISION

Prabu Sekar<sup>\*1</sup> Geeta rani<sup>2</sup> Krishna Kumar<sup>3</sup> Ajay Kumar Kushwaha<sup>4</sup> Ashutosh kumar<sup>5</sup> Ngu Wah  
Zan<sup>6</sup> Debmalya Mukherjee<sup>7</sup>

<sup>1</sup>Assistant Professor, Specialization in Architecture, School of Environment Architecture and Design, SRM Institute of Science and Technology, Ramapuram, Chennai-600089, Email Id: prabus@srmist.edu.in

<sup>2</sup>Assistant professor, Department of computer science, Specialization in AI, ML, DBMS, C language, Python, Kasturi Ram college of higher education, Delhi-110036, Orcid Id: 0009-0008-9346-8003, Email Id: ratwat.geeta9@gmail.com

<sup>3</sup>Professor, Institute of Technology & Management, GIDA, Gorakhpur (Uttar Pradesh), India, Email Id: kk\_gkp@rediffmail.com

<sup>4</sup>Associate Professor, Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune, Maharashtra, Email Id: akkushwaha@bvucoep.edu.in, Orcid Id: 0000-0002-9666-2214

<sup>5</sup>Assistant professor, Mechanical Usha Martin University, Ranchi, Email Id: ashutosh@umu.ac.in

<sup>6</sup>Research scholar, Department of Master of Science in Construction Management, Faculty of Engineering and Quantity Surveying, Inti International University, Malaysia, Email Id: i25034426@student.newinti.edu.my, Orcid Id: 0009-0009-1225-9726

<sup>7</sup>Assistant Professor, Department of Computational Sciences, Specialization in Machine Learning, Brainware University, Email id: dbml.mukherjee@gmail.com, Orcid Id: 0009-0006-9946-0964

Received: 14/11/2025

Accepted: 15/03/2026

Corresponding Author: Prabu Sekar  
(prabus@srmist.edu.in)

## ABSTRACT

Artificial intelligence is becoming more widely used in the field of architectural design, but the analysis of aesthetic value and the durability of materials is commonly considered as two independent processes. This paper fills this gap by suggesting an AI-based architectural image modelling model that concurrently assesses aesthetic accuracy and perceived material longevity through exterior architectural pictures. The dataset of 27,168 exterior images was locked and separated into training, validation and test sets with full data integrity. Embeddings of ImageNet-pretrained ResNet-50 were used to extract deep visual features in 2048-dimensional form that were L2-normalized and clustered unsupervised to determine the dominating aesthetic modes. The perceived material durability was measured using interpretable pixel-based proxies which included edge density, texture energy, mean saturation, and brightness which were summed together to form a train-normalized composite durability measure. The findings show moderate world visual coherence and significant aesthetic diversity, and stable and aesthetically interpretable clusters. The proxy scores of durability were almost a Gaussian distribution with high variance, which implied that there was a large variety of the material conditions both weathered and in a visual state of perfection. The cluster-level analysis showed that there were systematic differences in durability perception and weak negative relationship between aesthetic

*compactness and perceived durability. On the whole, the results prove that image analysis by AI can offer early-stage and material-conscious architectural assessment by combining aesthetic structure and visually inferred durability indicators.*

---

**KEYWORDS:** Artificial Intelligence; Architectural Image Modelling; Aesthetic Precision; Material Durability; Computer Vision.

---

## 1. Introduction

Artificial Intelligence (AI) is a phenomenon that has gained more and more power in the sphere of architectural design and has altered the way buildings are conceptualized, assessed, and optimized. Modern studies show that AI has developed beyond the automation and drafting functions to become an agent in architectural thinking, able to interact with design aesthetics, materialism, and performance evaluation (Albukhari, 2025). The development of machine learning and computer vision has made AI systems capable of processing and interpreting complex visual information, which places architectural imagery at the center of a new field of application of architectural knowledge, where it can be analyzed computationally. With the architectural practice still being dependent on the digital visual representation, the image-based AI solutions provide the new possibilities to comprehend the way architectural qualities are perceived and evaluated. Architectural images contain high-quality visual information about the material texture, the status of the surface, the light, and the structure of the composition, which affects the evaluation of the architectural quality. Recent research shows that AI-based image analysis can make sustainability-focused design more effective and efficient by increasing the precision of the correspondence of architectural forms and material manifestations with the contextual and cultural conditions, especially in the visually complex environment (Chen et al., 2024). This accumulation of literature highlights into the possibilities of image-based AI to not rely on formal or stylistic classification but instead on other insights about material behavior and visual performance. Meanwhile, aesthetic intelligence has become one of the primary fields of AI study in architecture. There is an observed growing ability in deep learning models to recognize and produce architecturally coherent visual results that are consistent with human perceptions of aesthetic quality. The studies of AI-based generative and diffusion models demonstrate that the aesthetic principles can be encoded and learned by a computational system and that aesthetics can be considered as a structured and learnable field instead of a subjective one (Chen et al., 2024). In a similar vein, the research on AI-based virtual-real architecture environments points to the fact that architectural interaction and evaluation are inherently mediated by visual perception, which is why images are so central to the process of architectural decision-making (Chen et al., 2024). AI is

increasingly transforming the architectural processes in the professional practice, bringing in new types of visual analysis, predictive modeling and optimization. Instead of substituting the architectural knowledge, AI is being increasingly imagined as a developing collaborator that complements the design thinking, especially in early exploration stage and material decision-making (El Moussaoui, 2025). The creation of validated AI-based design processes, including the integration of architectural and engineering ones, also indicates the ability of AI to aid complex design analysis, such as design analysis of material performance and visual effects (Fichera et al., 2025). In spite of these developments, AI application in architecture is not well distributed across various design issues. One of the key gaps that remain critical is how AI can be used to solve the problem of material durability and aesthetic precision. The evaluation of material durability is conventionally considered by physical testing, engineering simulation, or lifecycle assessment, but aesthetic judgment is mostly subjective and qualitative. Most of the current methods consider durability and aesthetic as distinct areas of analysis, despite the fact that AI has been extensively used to improve the efficiency of design and automate visual processes in architecture. Thematic reviews of AI applications in architectural design indicate that although AI is more effective in form generation and efficiency optimization, little focus has been on the visual perception and evaluation of material aging and degradation in the architectural image (Jin et al., 2025).

This division restricts the possibilities of AI to aid the overall material optimization in the architectural design. The visual information in architectural images touches on surface fragmentation, texture change, color change, and loss of brightness-elements that human beings subconsciously equate to old age, weathering, and longevity. Nevertheless, such hints are hardly measured or incorporated into the design processes powered by AI. Consequently, the decisions that are made about materials based on AI tend to ignore the indicators of perception that affect architectural judgment, user experience, and long-term acceptance of built environments.

To address this gap, the current research pays attention to the AI-based architectural image modelling as the way of collectively studying aesthetic accuracy and perceived material stability. This study uses deep convolutional neural networks to extract visual features and combine them with computer vision methods to analyse pixels at the pixel level to treat architectural images as data rich

artifacts and not as a static representation. The paper focuses on perceived durability, the visual interpretation of material strength and aging, as opposed to physical durability, as determined by engineering tests, in recognition of the primary importance of visual perception in architectural appraisal.

The range of this study is chosen with the purpose of balancing the analytical rigor and practical relevance. The discussion is limited to exterior architectural photographs, in which material surfaces are directly exposed to the environment, and where signs of durability are best manifested visually. Although the research is not aimed at substituting physical material testing or structural analysis, it provides a complementary, image-based point of view that may be used to inform the initial design and material choice.

The aims of this paper are, therefore:

- To create an AI-based architectural image modelling system to provide aesthetic accuracy in the form of deep visual feature representations.
- To build interpretable image based proxy measures of perceived material durability with surface texture, edge complexity, brightness and color characteristics.
- To examine how aesthetic coherence and perceived durability are related in the architectural imagery, with implications on material optimization on architectural design.

## 2. Literature Review

The last developments in the field of artificial intelligence have profoundly transformed architectural studies and practice, especially using machine learning algorithms in the assessment of designs, environmental regulation, and optimization of materials. Researchers have underscored the fact that AI has long stopped being a tool of automation and has found its way into the conceptual, analytical, and evaluative parts of architectural design, which have undergone a fundamental overhaul, putting architects in a new way of interacting with form, performance, and decision-making processes (Kurcusz & Stefańska, 2025). This has made AI one of the most fundamental elements of modern architectural innovation.

The use of AI to make buildings adaptive and dynamically optimized in terms of visual perception and environmental comfort has been one of the most notable directions of this evolution. Studies on AI-based systems of facades show how machine learning and genetic optimization can be used to make visual comfort and the responsiveness of

adaptive facades more effective, and how AI systems are increasingly responsive to visual performance requirements in real-time, and how visual data plays an increasingly important role in architectural decisions (Manesh *et al.*, 2025).

In line with these architectural advances, there is massive advancements in the field of AI-based materials research. The use of machine learning methods to speed up materials discovery and predict material behaviour has become common, and allows exploration of materials with next-generation functionality. Surveys of materials discovery using machine learning demonstrate how data-based models may reveal the complexity within the relationship between material composition and performance, which forms a background knowledge of the possibility of AI-mediated material optimization processes that could eventually be reflected in architectural applications (Nematov and Hojamberdiev, 2025).

The issues of ethical and sustainability as well as optimization have become popular in AI-based architecture discourse. Students at AI-based building architecture focus on the necessity to balance the objectives of performance enhancement and the sustainability goal, ethical considerations, and focused on the long-term viability of the material lifecycle, environmental effects, and overall long-term sustainability (Ojelabi and Adekunle, 2024). This approach highlights durability as one of the main design challenges and emphasizes the need of AI approaches, which are not limited to the aesthetic value of the short term.

Wider scans of the state-of-the-art technology in building design also put AI into more perspective as it exists in a growing digital ecosystem. The overall analysis of new technologies, including the use of AI, parametric and simulation models implies that, although AI has already been used massively to improve efficiency and generate forms, relatively little has been done to apply this technology to perceptual assessment and material aging (Rane *et al.*, 2023). This discontinuity demonstrates the lack of connection between the technological capability and its application in the visually informative material judgment.

Multi-disciplinary approach to AI-assisted building design has also been discussed in the view of a combination of architectural design, material science, and computational intelligence. Research on AI-assisted design practices emphasizes the capability of the AI to serve as a bridge between aesthetics, functionality, and material behavior and observes that most existing strategies are overly dependent on

numerical simulations and performance measurements, and not visual data (Saad et al., 2024). In materials science, AI has been useful in discovering the trends in material behavior and performance. It has been shown that the evolution of artificial intelligence can transform the design of materials by detecting the connection between microstructure, processing, and performance, which can be applied to architectural materials, the properties of which affect the appearance and texture on the surfaces and degradation with time (Badini et al., 2023).

The effect of AI on intelligent built environments has also been extended by the extensive reviews on architecture, urban systems, and intelligent infrastructure. These works highlight that AI is becoming the mediator in the process of building design, monitoring and experience and demand AI systems that can understand human-centric concepts of visual perception and experience quality instead of basing their concepts on technical performance alone (Talebian et al., 2025).

Recent developments in the field of deep learning materials prediction frameworks are another example of the growing analytical ability of AI. They suggest that any given architecture of deep learning frameworks can be deployed to predict a wide range of material properties by adopting a modular structure, in which neural systems can be reconfigured and redesigned to accept other types of data and open possibilities of how these frameworks can be extended to retrieve visually implied material indicators in architectural settings (Wang et al., 2025). The workflow of architecture has been reinvented by generative AI, as well, due to the possibility of exploration and the visual synthesis of new forms of design. Studies regarding the generative deep learning models reveal the escalating integration of AI in architectural processes to form, style as well as creative procedures, and also introducing issues regarding the objective measurement of aesthetic accuracy and material expression in generated and real-world images (Yiannoudes, 2025; Liu and Deng, 2025).

Lastly, preliminary studies on AI-based simulation of material fatigue and degradation contain valuable information on the durability evaluation. Neural network models have shown good predictive models of both short- and long-term fatigue crack propagation in materials, which, when designed to be applied in architectural contexts as the visible surface aging and degradation are the observable results of durability-associated phenomena (Mortazavi and Ince, 2020).

On the whole, the literature reviewed proves that AI has already contributed significantly to architectural design, material science, and optimization of performance. Nevertheless, there is still a visible gap in the unification of visual aesthetics, perceived material durability, and AI analysis of images. Current literature either gives too much attention to the material property of items without attention to visual perception or too much to aesthetics without paying much attention to the material durability. The given gap is what encourages the current research, which aims to bridge the gap between the architectural image modelling and the AI-based material optimization with the help of the joint analysis of aesthetic accuracy and perceived stability based on the visual data.

### 3. Methodology

#### 3.1 Research Design

The present study has chosen a methodology of quantitative research design that uses AI and visual-analytic interpretation to examine material optimization in architectural image modelling. The study is both an exploratory-analytical one, and it aims at comprehending how deep learning-based visual representations are capable of describing, at the same time, aesthetic accuracy and aesthetic permanence as perceived with regard to architectural imagery. Seeing that there are no annotations of ground-truth material durability, the study focuses on the use of representation learning, unsupervised clustering, and proxy-based perception modeling, instead of supervised prediction. The methodological process is organized into four consecutive stages, i.e. dataset locking and preprocessing, deep visual features extraction, aesthetic precision analysis, and durability perception modeling, and finally a correlational analysis between aesthetic structure and durability perception.

#### 3.2 Data Collection Methods

The data is one of RGB architectural images in their native 128x128 pixels, representing external architectural scenes in terms of building facades, massing arrangements, and surface dominated views. The source of the pictures was a publicly accessible architectural image repository, and they were stored locally to achieve reproducibility and controlled access (Paulat, T. 2022). All paths to images were checked programmatically, and those pictures whose file existence was verified were stored.

An analytical dataset of 27,168 images extracted was locked and filtered and validated. This frozen dataset was regarded as the ultimate corpus of further

experiments. The physical layout of the images was done into training, validation and testing directories and integrity checks were done to ensure that existence rate across all splits was 100 percent. Although the images were downsized to 224x 224 pixels during the extraction of deep features to fit the pretrained network input format, all of the durability proxy calculations were made on the original 128 x 128 images to maintain the original texture and surface features.

### 3.3 Population and Sampling

The study population will include all exterior architectural images in the chosen database. The locked subset was created out of this population by means of validation and preprocessing. Since the images were of the same top-level directory, it was not possible to sample based on groups. Rather, stratified random sampling approach was used to separate the dataset into training (70%), validation (15%), and testing (15%) subsets, and obtained 19,017 training images, 4,075 validation images, and 4,076 test images.

Clustering stratification was done in terms of cluster derived strata to maintain visual diversity as well as distributional consistency between splits. This will reduce possible sampling bias and provide that patterns about aesthetics and durability factors acquired during the training set are also similar in the validation and test subsets.

### 3.4 Data Analysis Techniques

#### 3.4.1 Deep Visual Feature Extraction

A fixed feature extractor comprising a ResNet-50 convolutional neural network that was trained on ImageNet was employed to extract high-level architectural visual characteristics. Embedding vectors of each image were generated at 2048 dimensions and the classification head was removed. The extraction of features was performed in batches, which guaranteed the efficiency of memory and the stability of calculations. Embeddings were all stored in disk so as to facilitate reproducibility and downstream analysis. The embeddings were L2-normalized before analysis, which allowed the easy calculation of the cosine similarity.

#### 3.4.2 Aesthetic Precision Analysis

Unsupervised clustering and compactness of the clustering was used to model aesthetic precision. K = 20 Minich incremental KMeans applying to normalized training embeddings was used to discover prevailing aesthetic modes in the architectural imagery. The silhouette score showed a moderate separation - being continuous in nature as

represented by the architectural visual space - but the clusters gave it a meaningful organization through which they could be compared.

Cluster compactness was measured as the mean similarity of cosine between images and their respective cluster centres, where a high compactness (correspondingly) depicts a high visual coherence and hence a high aesthetic preciseness. False positives were visually checked by means of representative images that were nearest to each centroid to aid the qualitative interpretation of the detected aesthetic modes.

#### 3.4.3 Durability Perception Modeling

The study used pixel-based visual proxies to derive the perceived material durability in the absence of physical durability labelling. Each image had four calculable measures, which included density of edges (surface fragmentation proxy), texture energy (roughness and weathering proxy), mean saturation, and mean brightness (aging and staining proxies). These measurements were calculated with the standard computer vision methods that were applied directly to the native 128x128 images.

A composite score of durability perception was formed by weighted z-scores of the metrics with more weight given to edge density and texture energy and less weight given to saturation and brightness. Normalization parameters were also trained on the training set and used uniformly on the validation and test sets in order to guarantee cross-split comparability.

#### 3.4.4 Linking Aesthetics and Durability

The computed cluster-wise means, medians, variances and sample counts were computed on durability scores that were aggregated at the aesthetic cluster level. The results were then subjected to a correlation test between aesthetic compactness and average scores of perception of durability, which made the relationship between visual consistency and the perception of material aging and robustness to be assessed quantitatively. The statistical summaries and various visualizations such as histograms, boxplots, scatter plots, and representative image panels were used to support the findings.

### 3.5 Ethical Considerations

This research does not use human subjects or personal identifiers and any sensitive information since the data used is images published publicly. The durability results are clearly put as perceptual proxies and not physical performance results which

can be misleading. Every step of analysis is clear, replicable, and consistent with the responsible AI research practices in architectural research.

## 4. Results

### 4.1 Data Presentation

The last analytical dataset included 27,168 exterior architectural images, which were randomly sampled into 19,017 training, 4,075 validation and 4,076 test samples through stratified random sampling (Paulat, T. 2022). File integrity tests ensured that there were no missing data that would affect the analysis by confirming that there was a 100% image availability rate among all splits.

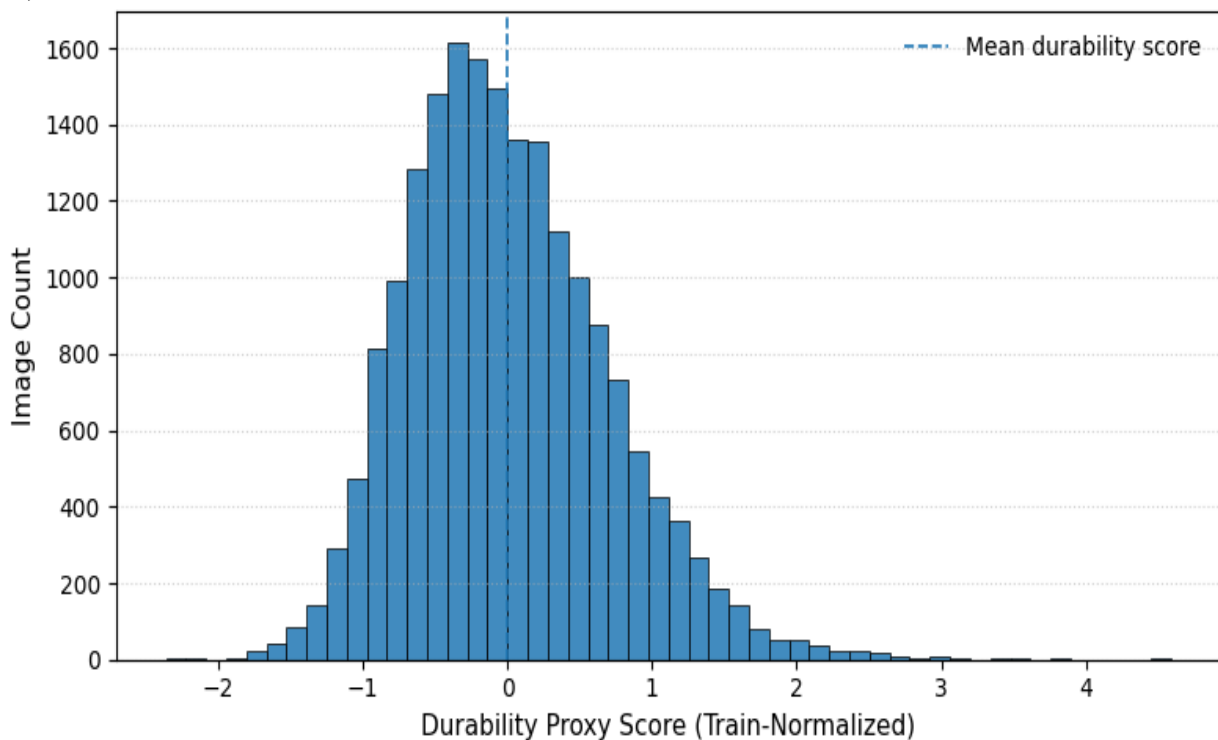
A ResNet-50 ImageNet-pretrained convolutional neural network was used to extract deep visual features, which were in the form of 2048-dimensional embeddings of each image. The matrices of resulting features were (19017, 2048), (4075, 2048) and (4076, 2048) of training, validation and test sets respectively. Similarity computation and clustering were done with L2-normalized all embeddings.

Random pairwise cosine similarity analysis between training embeddings produced a mean similarity of 0.447, with a standard deviation of 0.127 which is

moderate global visual coherence but does not imply significant architectural diversity. This proves the fact that there are visually consistent typologies of the façade and heterogeneous architectural programs in the dataset.

MiniBatchKMeans ( $K = 20$ ) was used to do unsupervised clustering of the normalized training embeddings. Despite the fact that the silhouette score was small ( $\approx 0.015$ ), such a result is aligned with the continuity and overlap of architectural visual space. There were good distributions of the cluster sizes and none of the clusters had a critically low sample counts.

The proxies of durability perception were calculated on the original unresized 128x128 images based on the pixel-level measures in the computer vision. Summary statistics revealed significant differences among all the proxies, which validated that the data set represents a broad range of textures on the surface and visual aging situations. The composite durability proxy score was almost distributed using a near-Gaussian distribution with meaning equal to zero with standard deviation of about 0.70 as shown in Figure 1.



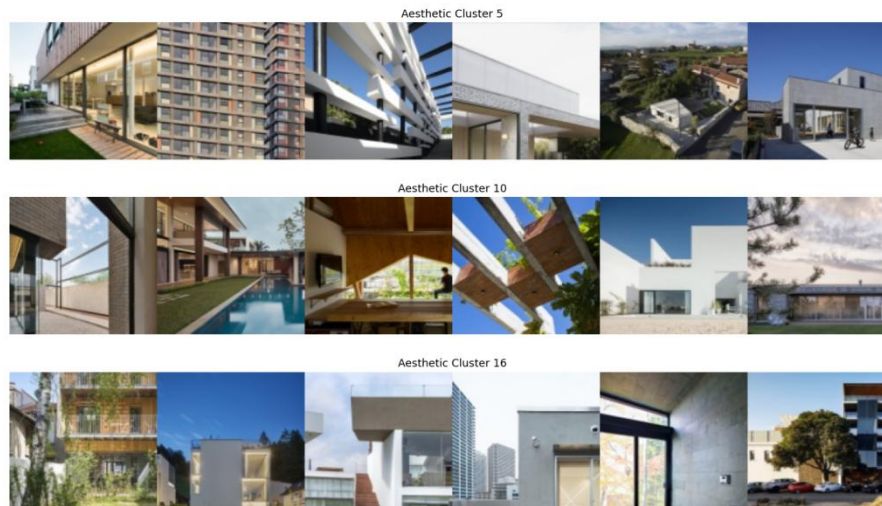
**Figure 1.** Distribution of train-normalized durability perception scores showing sufficient variance.

## 4.2 Key Findings

### 4.2.1 Aesthetic Clusters and Visual Precision

Clustering analysis showed that there were specific modes of aesthetics in the corpus of architectural images. Figure 2 shows sample images that are

closest to the centroid of three clusters (Clusters 5, 10, and 16). Such clusters have coherent structure in their architecture such as regularity of facades, regularity of materials, lighting and structure of composition.



**Figure 2.** Representative images from three aesthetic clusters (Clusters 5, 10, and 16) derived from deep feature clustering.

Cluster compactness as the mean cosine similarity of images and their cluster centroid differed between clusters. Some of the clusters obtained the compactness values of more than 0.80, which was a very high level of aesthetic accuracy, whereas other clusters had lower compactness, which was a higher level of internal variability of form and surface treatment. These findings prove that deep visual representations can be very useful in grouping architectural images into meaningful aesthetic categories even in the lack of clear semantic descriptors.

#### 4.2.2 Durability Perception Distribution

The composite score on the proxy of durability had a balanced and continuous distribution throughout the

data. As presented in Figures 4, the scores fell in between strongly negative scores, which represented a visually smooth, clean and less worn appearance, to strongly positive scores that represented a rough, old or heavily textured material appearance.

Figure 3 is qualitative evidence of these findings and compares the highest and lowest training set durability perception scores. Images with high scores (high score) have thick edge characteristics, high texture energy, dull saturation and less bright visual signals, which are aesthetically related to old or worn surfaces. Conversely, low-score pictures have smoother surfaces, are brighter and more uniform in chroma, which is expected to be true of more recent and less weathered material.



**Figure 3.** Images illustrating highest and lowest durability perception scores in the training set.

#### 4.2.3 Cluster-wise Durability Profiles

The scores of durability were summed at the aesthetic cluster level showing systematic differences among clusters. Table 1 presents cluster-level

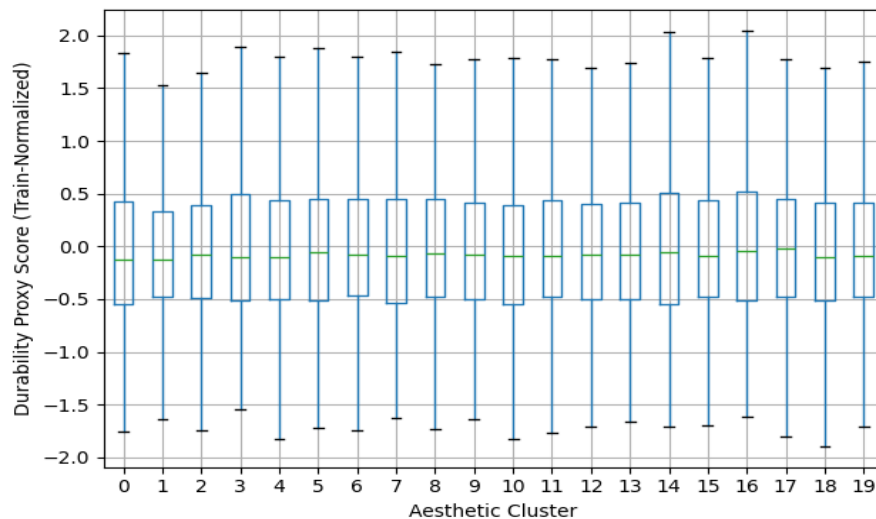
summary statistics, such as standard deviation, standard deviation, sample size, mean, and median of the training set.

**Table 1.** Cluster-wise durability proxy statistics (training set).

Aesthetic Cluster	Mean	Std. Dev.	Median	Count
16	0.038	0.724	-0.044	1251
17	0.035	0.737	-0.021	1254
14	0.018	0.753	-0.049	548
6	0.008	0.673	-0.076	905
8	0.008	0.662	-0.065	764
15	0.007	0.694	-0.085	1004
7	0.006	0.731	-0.089	523
9	0.005	0.711	-0.079	852
11	0.004	0.710	-0.085	1320
13	0.003	0.711	-0.074	1284

These differences at cluster level are also depicted in the boxplots that are presented in Figure 4 that

indicate variability and median durability perception among aesthetic clusters.

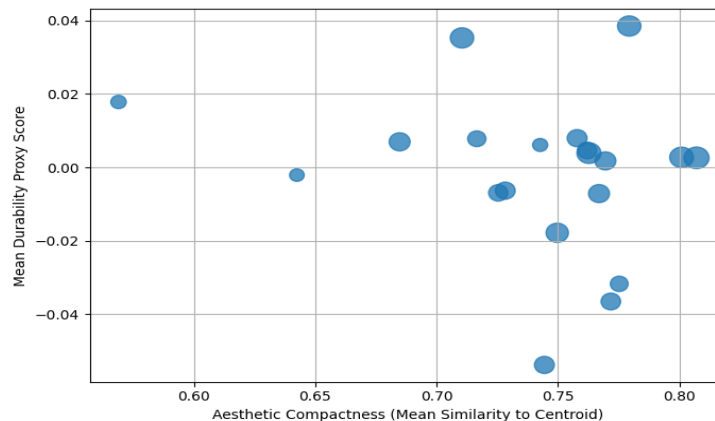
**Figure 4.** Boxplots of train-normalized durability proxy scores across 20 aesthetic clusters.

### 4.3 Patterns and Trends

#### 4.3.1 Relationship Between Aesthetic Precision and Durability

One of the objectives of the present research was to test the connection between the aesthetic precision

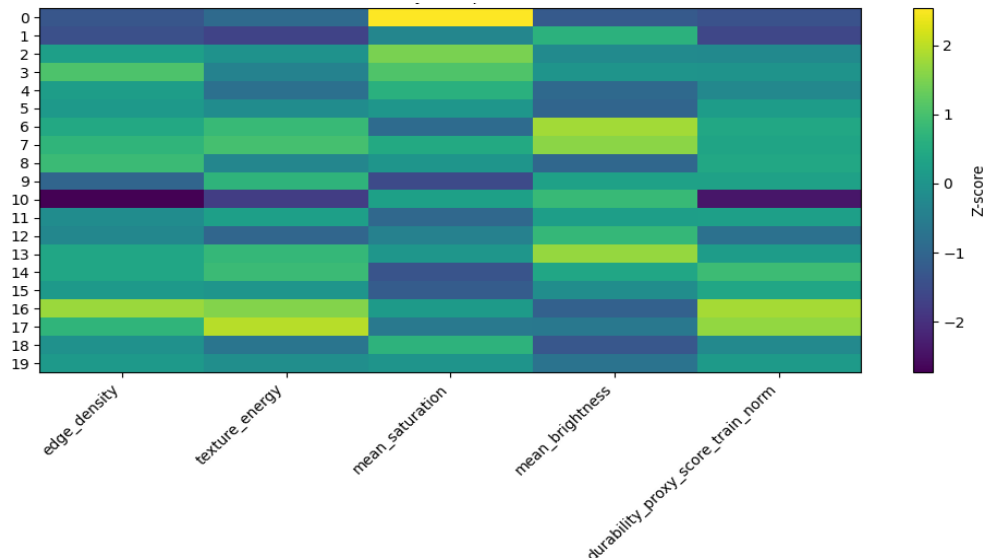
and perceived durability. Correlation analysis was done at the cluster level between the cluster compactness and mean durability proxy score. The resultant relationship is illustrated in Figure 5.

**Figure 5.** Relationship between aesthetic compactness and mean durability proxy score at the cluster level.

The analysis indicates that there is a weak but consistent negative correlation and therefore clusters having high aesthetic compactness are likely to have slightly low scores on the proxy of durability. Architectural designs that are visually homogeneous and extremely consistent are thus more frequently linked with cleaner, smoother, and less weathered facades of materials, as compared to clusters with higher internal visual heterogeneity, which involve old or materially expressive surfaces.

### 4.3.2 Proxy Composition Patterns

The cluster-wise proxy composition heatmap in Figure 6 further illuminates further information on the durability perception. Clusters that have higher scores in terms of durability always have high edge density and texture energy, alongside lower mean saturation and brightness.



**Figure 6.** Cluster-wise heatmap of z-scored durability proxy components and composite score.

This illusion proves that perception of durability is a result of an integrated region of surface and color indications, and not an individual measure, confirming the authenticity of the composite proxy measure.

### 4.3.3 Consistency Across Data Splits

There was consistency in score distributions in durability and aesthetic clusters in training, validation, and test sets. The similarity of the means and standard deviations of the train-normalized durability scores of all splits suggests that the learned representations and proxy models are applicable to the training data far beyond and also validates the robustness of the analytical pipeline.

### Discussion

The findings of the current research can shed significant light on how AI-based architectural image modelling can be used to combine both aesthetic structure and perceived material sustainability through visual data. It can be seen in the analysis that deep visual representations based on a pretrained ResNet-50 model can arrange a large set of exterior architecture images into consistent aesthetic modes,

even where semantic labels are not provided. Even though the low score of silhouette which was obtained when clustering shows that the architectural visual space is not discrete and can be separated, the consistency of cluster sizes and the aesthetic integrity of centroid-nearest exemplars both confirm that the clusters serve well as aesthetic groupings. This observation supports the idea that aesthetic specificity in architecture should be viewed as a range of visual regularity instead of a set of stylistically defined categories.

This knowledge is further enhanced by the durability perception analysis which demonstrates that the architectural images have measurable visual information on the material aging and the condition of surface. The composite score of durability proxy composites, which were built on interpolable pixel-based measurements, including edge density, texture energy, saturation, and brightness, had a wide and near-Gaussian distribution within the dataset. It means that the image corpus is very diverse in terms of visually pristine and weathered surfaces, and it could be useful in making meaningful comparisons. The quantitative measures were supported by

qualitative examination of pictures at either end of the distribution of durability scores indicating that the suggested proxies are reflecting perceptually significant durability indicators and not arbitrary image artifacts.

The clustering together of the durability proxy scores on the cluster level indicated systematic variations in aesthetic modes. Some clusters were always more perceived as durable whereas others were connected to either cleaner or less weathered looks, meaning that aesthetic organization is not neutral when it comes to material perception. The weak negative correlation between aesthetic compactness and durability perception can be seen as a sign of a trade-off between visual homogeneity and the material expressiveness, which can be identified in studies of adaptive facade systems where learning-based control techniques are used to achieve visual performance (Manesh et al., 2025).

The results are also consistent with the general literature on AI-assisted materials research that proves that machine learning can identify complex correlations between the geometry of the materials and their performance (Badini et al., 2023). The current research however adds a perceptual approach to this argument by highlighting visually formed durability as opposed to physically quantified properties. The understandability of the used proxies is essential especially based on the ethical and sustainability concerns because the scholars have stated the necessity of transparency and responsibility in the AI-driven architectural decisions (Ojelabi and Adekunle, 2024).

In a greater sense, the research is a complement to the existing studies of AI-based modeling of material degradation, the neural network is employed to forecast fatigue and failure through the physical information (Mortazavi and Ince, 2020). Although these methods emphasize the mechanical behavior, this work concerns early-stage design situations by emphasizing those visually evident manifestations of aging and wear. The study is restricted due to scope of the dataset and vulnerability to photographic environments. Typical diversity is to be broadened in

future studies, expert calibration of perception on durability is to be incorporated, and visual analysis is to be intertwined with lifecycle and material performance data to achieve material optimization is to be further enhanced by AI in architectural design.

## Conclusion

This paper shows that architectural image modelling with the help of AI has the potential of optimizing materials through the collaborative quantification of aesthetic accuracy and perceived material longevity based on outer building architectural visuals. A locked dataset of the 27,168 exterior images was then decomposed into training, validation and testing sets containing the full file integrity that were then processed to obtain deep visual features with a pretrained ResNet-50 network and then grouped through unsupervised clustering to organize the aesthetic modes. In spite of the continuity and overlap of architectural visual space, the clustering procedure indicated consistent and understandable aesthetic clusters in terms of differences in façade composition, material consistency, and surface articulation. Material perceived durability was also operationalized with interpretable pixel level proxies of density of edges, density of texture energy, mean saturation, and mean brightness that were averaged together to produce a composite, train-normalized durability perception score. The resulting distribution of scores was significantly varied, which proved that architectural images convey some valuable visual representations of surface aging and material condition. The cluster-level analysis showed that there were systematic differences in the durability perception across aesthetic modes, which showed that both visual organization and material expression are not independent of each other. The implications of the findings to the architectural practice are significant because the proposed framework allows designers to consider material appearance and possible aging behavior at the early design phases to supplement the conventional engineering-based durability tests to early-stage architectural material selections across the world.

## References

1. Albukhari, I. N. (2025). The role of artificial intelligence (AI) in architectural design: A systematic review of emerging technologies and applications. *Journal of Umm Al-Qura University for Engineering and Architecture*, 1-20.
2. Chen, F., Mai, M., Huang, X., & Li, Y. (2024). Enhancing the sustainability of AI technology in architectural design: improving the matching accuracy of Chinese-style buildings. *Sustainability*, 16(19), 8414.
3. Chen, J., Shao, Z., Zheng, X., Zhang, K., & Yin, J. (2024). Integrating aesthetics and efficiency: AI-driven diffusion models for visually pleasing interior design generation. *Scientific Reports*, 14(1), 3496.

4. Chen, X., Gao, W., Chu, Y., & Song, Y. (2024). Enhancing interaction in virtual-real architectural environments: A comparative analysis of generative AI-driven reality approaches. *Building and Environment*, 266, 112113.
5. El Moussaoui, M. (2025). Architectural practice process and artificial intelligence—an evolving practice. *Open Engineering*, 15(1), 20240098.
6. Fichera, G., Guardo, V., Frazzetto, L. R., Rodonò, G., & Margani, G. (2025, June). Architecture and Engineering in the AI Era: Definition and Validation of a New AI-Driven Design Workflow. In *International Conference of Ar. Tec. (Scientific Society of Architectural Engineering)* (pp. 406-424). Cham: Springer Nature Switzerland.
7. Jin, D., Zairul, M., & Salih, S. A. (2025). Artificial Intelligence (AI) and its Application in Architecture Design: A Thematic Review. *Alam Cipta: International Journal on Sustainable Tropical Design Research & Practice*, 18(1).
8. Kurcusz, M., & Stefańska, A. (2025). Transformative integration of Artificial Intelligence in architectural design. *Architectus*, 81(1).
9. Li, Y., Chen, H., Yu, P., & Yang, L. (2025). A review of artificial intelligence in enhancing architectural design efficiency. *Applied Sciences*, 15(3).
10. Liu, F., & Deng, K. (2025). AI knows Aesthetics: AI-Generated Interior design Identification using Deep Learning Algorithms. *IEEE Access*.
11. Manesh, M. T., Hoonejani, M. R., Gousheh, S. G., Abdolmaleki, A., Dehnavi, A. N., & Shahrashoob, A. (2025). AI-driven control algorithm using machine learning and genetic optimization for enhancing visual comfort in adaptive façades. *Automation in Construction*, 179, 106474.
12. Nematov, D., & Hojamberdiev, M. (2025). Machine learning-driven materials discovery: unlocking next-generation functional materials—a minireview. *Available at SSRN 5219988*.
13. Ojelabi, E. T., & Adekunle, E. O. (2024). AI-Driven Building Architecture: Ethics, Sustainability and Optimization. *Brolly*, 5(2), 235-248.
14. Rane, N., Choudhary, S., & Rane, J. (2023). Leading-edge technologies for architectural design: a comprehensive review. *Available at SSRN 4637891*.
15. Saad, S., Haris, M., Ammad, S., & Rasheed, K. (2024). AI-assisted building design. In *AI in material science* (pp. 143-168). CRC Press.
16. Badini, S., Regondi, S., & Pugliese, R. (2023). Unleashing the power of artificial intelligence in materials design. *Materials*, 16(17), 5927.
17. Talebian, S., Golkarieh, A., Eshraghi, S., Naseri, M., & Naseri, S. (2025). Artificial intelligence impacts on architecture and smart built environments: a comprehensive review. *Advances in Civil Engineering and Environmental Science*, 2(1), 45-56.
18. Wang, B., Ouyang, Y., Li, Y., Wang, Y., Cui, H., Zhang, J., ... & Zhou, H. (2025). MoMa: A Modular Deep Learning Framework for Material Property Prediction. *arXiv preprint arXiv:2502.15483*.
19. Yiannoudes, S. (2025). Shaping architecture with generative artificial intelligence: Deep learning models in architectural design workflow. *Architecture*, 5(4), 94.
20. Mortazavi, S. N. S., & Ince, A. (2020). An artificial neural network modeling approach for short and long fatigue crack propagation. *Computational Materials Science*, 185, 109962.
21. Paulat, T. (2022). *Modern architecture (100k small images)* [Data set]. <https://www.kaggle.com/datasets/tompaulat/modern-architecture-100k-small-images>