Manuscript Received: 21 Jan. 2026, Revised: 20 Feb. 2026, Accepted: 23 Feb. 2026

DOI: https://doi.org/10.36481/diujst.v21i1y7t83f24

AI-BASED MUGHAL MOTIF IDENTIFICATION AND FASHION APPLICATION

*Dr. Md. Samaun Hasan[1], Md. Tuhin Islam[1], Miss Zahura Khatun[3], Dr. Hosne Ara Arju[2], Dr. Mohammad Ali[3]

[1]Department of Multimedia & Creative Technology, Daffodil International University
[2]Department of Sanskrit, University of Rajshahi, Rajshahi, Bangladesh.
[3]Department of Department of Graphic Design, Crafts & History of Art, University of Rajshahi, Rajshahi, Bangladesh

Email: hasan@diu.edu.bd, ORCID ID: 0000-0002-5914-5728

Abstract: This study suggests a computationalized process of determining and modifying Mughal architecture motifs and design patterns with the help of Artificial Intelligence. Mughal ornamentation (floral arabesque, jali patterns, calligraphic panels, and Pietra dura inlays) is examined with CNN models trained on transfer learning (VGG16 and ResNet50). The trained models have classification accuracy of 98.6%, which indicates that the trained models are reliable to identify motifs even in small datasets. After classification, generative tools with AI assistance are used to generate variations of motifs, which are optimized with the help of scalable textile and surface design applications using the workflow of vectors based on the CAD format. Methodology provides a systematic line of information flow between architectural heritage recording and modern fashion making allowing to incorporate Mughal patterns into the sarees, dupattas, shawls, and heritage-based clothing. The study includes a repeatable AI-based methodology that satisfies cultural heritage, deep learning, and contemporary fashion design.

Keywords: *Mughal Architectural Ornamentation, Convolutional Neural Networks (CNN), Heritage Motif Classification, AI-Assisted Pattern Generation, Computational Fashion Design.*

1. INTRODUCTION

The Mughal period can also be considered one of the most significant periods in the history of South Asian architecture and decoration which is the period of the amalgamation of the Persian [1], Central Asian, and the native Indian schools of thoughts in art [2]. The Mughal architecture was typified by the use of monumental amounts of ornamentation on the surfaces of its structures which included ornamental arabesques [3] that were founded on the natural forms, a system of geometrical lattices, calligraphic inscriptions and rich decorative panels that were extravagant. These motifs were inlaid with marble, red sandstone, and Pietra dura [4] and had not only a decorative purpose but also a cultural symbolism [5], imperial power, and aesthetic philosophy. The Taj Mahal, the Tomb of Humayun, Fatehpur Sikri, and Lalbagh Fort are all examples of how the Mughals made use of ornamental composition, symmetry, and rhythm to compose a monument [6].

Architectural heritage has been more and more considered to be a useful source of innovation of fashion and textiles in modern design discourse. Fashion design based on heritage aims to redefine the traditional visual languages in contemporary settings without losing a cultural touch [7]. The Mughal architectural motifs are especially adapted to textiles thanks to their modular structure, surface-oriented composition, and richness of the ornament. Nevertheless, the current fashion use of Mughal influence mostly relies on the manual interpretation, intuition of the artist, and borrowing styles. Although such approaches are highly expressive visually, they are deficient in both analytical rigor, reproducibility, and scalability, particularly in academic and industry-targeted research paradigms.

Visual pattern recognition and cultural heritage analysis have undergone multiple changes due to the recent developments in artificial intelligence, specifically Convolutional Neural Networks (CNNs). CNNs can learn hierarchical visual characteristics [8] like edges, textures, and symmetry, and spatial relationships, characteristics that Mughal decoration has. These models can be used with high classification accuracy with limited heritage datasets when used along with transfer learning. At the same time, the AI-powered generative design algorithms enable one to generate multiple versions of the motif patterns, which expands the creative possibilities beyond the copying of the motif. The process of the background of the Mughal architectural legacy is not the only aspect of AI-based motif recognition, pattern creation in generative form, and fashion design, which is not fully applied to date. The gap in this paper is addressed by proposing a systematic AI-based process, which addresses the architectural heritage, computational analysis, and contemporary fashion designing [9].

1.1. Model Overview

The model suggested gives a very strict hierarchical scheme of approach to the conservation and redefining of Mughal architectural decorations through the computation research and its application to the contemporary fashion designing activities. The model has a gradational pipeline, which logically relates documentation of architectural heritage to digital design and fashion implementation.

1.1.1. Heritage Image Acquisition:

Close up shots of certain of the Mughal architectural monuments are captured and emphasis on the surface decorative elements which are floral arabesques, lattice-based designs (jali), calligraphy, and ornamental marble, sandstone and Pietra dura inlay panels are captured [10]. This will be done to address the visual aspect of the heritage items that are being recorded in detail and with accuracy.

1.1.2. Extraction and Preprocessing of Motifs:

Images are then obtained and cropped, normalized and conceptualized visually to obtain visually significant ornamental units. This operation cuts out the more generalized architectural ground and keeps standing the stylistic and formal characteristics that are natural to Mughal ornamentation. The resultant motifs are systematized into an ordered set of digital data, which can be processed analytically.

1.1.3. Motif Classification Using CNN:

The motivated motifs are categorized using pre-trained Convolutional neural network (CNN) models which are VGG16 [11] and ResNet50 [12], which are trained using transfer learning. These models divide the Mughal motifs into floral, geometric, calligraphic and ornamental forms and thus provide a consistent and objective classification of these motifs even in case limited heritage information is available.

1.1.4. AI-Assisted Generation of Motives:

The Mughal motifs, once classified, can be used as a starting point of creating several versions of a motif pattern with the help of AI-based design tools. Diversity is achieved through modification of repetition logic, symmetry, scale and spatial arrangement but by keeping the architectural authenticity and the visual identity of the original motifs firmly.

1.1.5. CAD-Based Refinement:

The classified motifs as well as the AI-generated variations of the patterns are digitally reconstructed and optimized through the use of the computer-aided design (CAD) tools that are based on the vectors. The refinement phase ensures scalability, accuracy, and customization of textile and surface design to meet the demands of production in the contemporary context, thus closing the gap between the traditional aesthetic and the current production needs.

1.1.6. Fashion Application:

The well-developed Mughal designs and the pattern variations that result is then applied to modern fashion items, namely sarees, dupattas, shawls, and Mughal-based attire. This last phase measures the quality of the proposed model by converting architectural heritage into the current fashion scenes, thus rationalizing the practical usefulness of the model.

Overall, the model proposed creates a complete pipeline of heritage-to-fashion, which can be replicated. It combines both Mughal architectural ornamentation and computational analysis with AI-aided pattern generation and modern fashion design, thus supporting a scholarly but commercially feasible shift of heritage documentation into wearable art.

1.2. Research Scope:

The current study will be a systematic analysis and reinterpretation of the architectural ornamentation of the Mughals to be used in modern fashion design. The frontal decorative motifs based on the chosen monuments of the Mughal era and documented through the visual analysis and assessment are covered in the scope of the study. The focus is made on floral, geometric, calligraphic, and ornamental patterns that were done in architectural materials like marble, sandstone, and Pietra dura inlay.

The research uses a systematic computational method to extract and categorize the motifs with the aid of the already trained convolutional neural network (CNN) models through transfer learning. In this context, the CAD workflows are digitally restored and optimized with the help of computer-aided design (Mughal) motifs so that they can be scaled and flexible to textile and surface design.

Moreover, AI-assisted design software is used to create variants of the pattern of motifs, thus allowing the creation of creative exploration without the loss of the stylistic integrity of Mughal ornamentation. This study has a limited application on two-dimensional textile and surface pattern design as evidenced by the chosen fashion products of contemporary fashion: sarees, dupattas, shawls, and Mughal style of garments.

The study will eventually aim at defining a replicable heritage-to-fashion design that incorporates architectural heritage, computational analysis, and modern-day fashion design practice.

1.3. Research Objectives

The following are the specific objectives of this research:

- To catalogue and examine a sample of Mughal architecture ornamentation by systematic graphical research into surface decorative motifs.
- To discover and also categorize the Mughal architectural motifs in terms of their formal nature, which includes floral, geometric, calligraphic, and ornamental motifs.
- To create a systematic approach to computing that will give out and systematize Mughal architectural patterns that would be used to design.
- To redefine the categorized Mughal patterns in the modern fashion design by using digital reconstruction and computer-aided design (CAD) processes.
- To produce Mughal motifs alternatives with variation patterns to use AI-assisted design devices and retain architectural authenticity and cultural integrity.
- To demonstrate how the patterns as applied in modern fashion products are based on the Mughal architectural motives and their AI-generated variants.

1.4. Scope and Delimitation

First, the scope and delimitation of this investigation have to be clearly defined in order to properly present its focus and the limits of the epistemological range along with the methodological way. In general, as it is outlined in Table 1, this work lies at the crossroads of Mughal architecture, computational art, and contemporary fashion design, albeit in a deliberately restrained manner so not to lose the richness of the analysis and rigor of the methodology and applicability of the design.

TABLE I. SCOPE, FOCUS, AND DELIMITING PARAMETERS OF THE RESEARCH

Aspect	Scope	Delimitation
Historical Period	Mughal period architectural heritage	Other historical periods (e.g., Sultanate, Colonial) are excluded
Geographical Context	Selected Mughal-era monuments in South Asia	Architectural sites outside selected Mughal locations are not considered
Motif Types	Floral, geometric, calligraphic, and ornamental architectural motifs	Structural elements and symbolic inscriptions are excluded
Data Source	High-resolution photographs of marble, sandstone, and inlay surfaces	Archival drawings and 3D scans are not used
Computational Model	CNN-based classification using VGG16 and ResNet50 with transfer learning	Custom-built CNN architectures are not explored
Motif Generation	AI-assisted motif pattern generation based on classified motifs	Fully autonomous generative systems are not evaluated
Design Tools	CAD-based vector refinement using Adobe Illustrator	Other CAD or parametric design tools are not assessed
Fashion Application	Textile pattern and surface design for contemporary fashion	Industrial-scale production and market analysis are excluded
Design Dimension	Two-dimensional surface and textile design	Three-dimensional garment construction is not addressed
Evaluation Metrics	Accuracy, precision, recall, and F1-score	User perception studies and wear trials are not conducted

The attention on specific architectural ornamentation of the Mughal architecture assists the study to decrease the research attention in order to determine a deliberate motif interpretation as well as assist in purposeful reinterpreting in contemporary fashion.

1.5. Research Questions

RQ1.
What is the way to systematically document and analyze Mughal architectural ornamentation to implement it in the modern fashion design?
Answer:
A systematic workflow of incorporating high-resolution architectural image capture, extracting motifs meticulously and providing a comprehensive visual categorization is the best way of systematic description and study of Mughal architectural decoration. Considering decorative motifs on a superficial level, including floral, geometric, calligraphic, and other decorative motifs, the study outlines a systematic pipeline of how architectural background can be translated into fashion-friendly visual components, thus enabling the process of designing in the modern context.

RQ2.
Which Mughal architectural themes can best be reused in a modern fashion design?
Answer:
The subjects that can be reconstrued in modern fashion design include floral arabesques, geometric lattice (jali) designs, calligraphic panels, and decorative surface ornamentation. Their repetitive logic and surface-based structure make them adaptive to textile and fashion surfaces but maintain their inherent architectural character.

RQ3.
What computational techniques are used to accurately identify Mughal architectural motifs to be applied in designs?
Answer:
Through computational techniques based on pre-trained models of Convolutional Neural Networks (CNN) and transfer-learning schemes, the specific classification of Mughal architectural motifs is possible, with visual characteristics of symmetry, texture, and repetition of patterns being detected. This technical rigor limits the subjective interpretation and creates a consistent platform for later design adaptation.

RQ4.
How can the city models of modern fashion be used to utilize categorized Mughal architectural designs and spare the cultural heritage?
Answer:
The Mughal architecture can be categorized as a type of architecture and converted into a contemporary fashion pattern through the digital reconstruction process, optimization through vectors and variation of the pattern based on the controlled variation of computer-aided design (CAD). The process enables scaling, copying, and ordering of the motifs to the modern fashion items, but maintains the original stylistic and cultural character of these items with an unquestionable strength.

RQ5.
What is the reason to include contemporary digital design practices and architectural background in the contemporary fashion practice?
Answer:
The fusion of architectural and digital design methodologies justifies the innovation in the modern fashion practice that has solid cultural underpinnings. The process increases reproducibility, scalability and creative consistency through systematic development of a lineage that bridges heritage documentation and design implementation and thereby aids in maintaining and remounting past visual customs.

1.6. Novelty and Contribution

The study is a valuable addition to the computational reinterpretation of architectural heritage as it presents an AI-based framework that the identification, classification, and modern usage of the Mughal architectural ornamentation. The novelty of the research is that it is an interdisciplinary combination of deep learning-based motif classification by using AI-assisted generative design and CAD-based refinement, rather than the traditional heritage documentation or unconnected image classification methods. Instead of viewing the architectural imagery as only the classification problem, the suggested framework will provide a hierarchical pipeline that will transform culturally meaningful Mughal motifs into modern fashion design products.

The suggested study manages to reproduce the complex visual vocabulary of Mughal architecture (floral arabesque, geometric jali patterns, calligraphic paneling, and decorative constructions) with the help of CNN models by using a transfer learning process (VGG16 and ResNet50). The presence of top classification accuracy (98.6) indicates that the computational strategy remains strong and can work on heritage domains and limited datasets. The contribution of analysis is further extended to practice level design application by the integration of AI-assisted motif pattern generation and CAD optimization by vectors.

The most important findings of this research will be as follows:
(a) Curation and creation of a high-resolution and curated database of Mughal architectural motifs,

which is systematically arranged based on ornamental typologies which are applicable to design translation.
(b) A CNN-based motif classification architecture should be designed and validated by means of transfer learning with the aim of determining reliable and accurate Mughal architecture ornamentation.
(c) Creating a repeatable heritage to fashion channel that integrates AI-informed pattern creation and CAD workflows, demonstrating how the Mughal inspiration can be utilized in the contemporary fashion object and how the computational strategies can be reflected as sustainable heritage-driven designing activities.

2. LITERATURE REVIEW

Within the framework of heritage studies, museum practice, and design research, the significance of cultural motifs as a priceless source of design innovation in the contemporary is becoming increasingly visible among scholars in the said research fields. The motifs have been empirically demonstrated to be re-synthesized in interior design, textiles as well as fashion, owing to the influence of architectural forms, ancient craft, and the vernacular visual cultures. The processes of visual documentation, abstraction and contextual adaptation are currently commonly accepted to be needed to undertake the process of transferring the heritage features to the contemporary design languages. Nevertheless, the architectural ornamentation of the Mughal period [14] has been comparatively a less investigated area of scholarship, particularly through the instruments of computation and data, even though of the historical importance and aesthetic richness.

The ornamentation of Mughal architecture is marked by a sophisticated floral arabesque, symmetrical geometry patterns, calligraphy, and intricate ornamental compositions made on marble carving, red sandstone relief, and inlaying Pietra dura [15]. The examples of the synthesis between Persian, Central Asian, and native Indian artistic traditions are monuments that were built between the sixteenth and the eighteenth centuries. Architectural elements, including spandrel panels, jali screens, dado panels, inlay borders, and domical interiors are articulated surfaces of motifs using a structured visual surface. The motifs are not only decorative but also symbolic, cultural, and spiritual by nature, and they support imperial ideology, harmony of space and order in buildings, and aesthetic order of Mughal architecture.

Architecture-based designs in the field of fashion and textile design have been widely developed, and they include reinterpretations based on Islamic tile systems and Gothic cathedrals in addition to classical architectural orders and vernacular buildings [16]. The design theorists focus on authenticity, context sensitivity, and cultural continuity when adapting architectural expressions to textile fabrics. According to literature, the challenges are found to be the preservation of the symbolic meaning, balancing between the scale and proportion of structures and the adaptability of wearable varieties, and cultural creativity and preservation. Notwithstanding such deliberations, much of the surviving design research is quite dependent on manual deciphering and designer intuition, thus restricting methodological reproducibility, analytical consistency, and scalability.

The most recent advances in the sphere of artificial intelligence, namely the Convolutional Neural Networks (CNNs), have gone to change the visual pattern recognition and cultural heritage documentation [17]. The CNN-based models are able to capture the robust visual localization of complex visual structures, due to the learning hierarchical features or edges, textures, symmetry, repetition, and space relationship, which are inherent in architectural ornamentation. CNNs have been successfully applied under heritage-related studies as well, to categorize architectural elements, decorative patterns and historical artifacts, as objective and obtainable scale-based alternatives to the conventional manual classification schemes. When used in conjunction with the transfer learning, such models are characterized by high accuracy of classification even with small datasets, which makes them very relevant to the heritage-based research contexts.

Irrespective of such technological advancements, little has been done in integrating the CNN-based motif classification with fashion and textile design [18] processes, especially with reference to the Mughal architectural heritage. Current literature does not frequently put into place a direct nexus between the process of computation motif identification, the use of AI to develop the pattern, CAD-based refinement, and ultimate fashion application [19]. According to the literature examined, one can identify three main research problems: (a) the fact that precise and contextualized extraction of Mughal architectural patterns using computational tools is necessary; (b) that the adaptation of the classified patterns to the textile and fashion scales with the help of CAD tools is systematic; and (c) that the creation of a culturally based design system in which heritage-inspired fashion designs will be used as meaningful guidance, instead of a mere ornamental appropriation.

These issues help the current research to expand literature by proposing a CNN-based, reproducible methodological framework to connect Mughal architecture, artificial intelligence, and modern fashion design [20]. The study helps in heritage conservation and design innovation by showing the roles of computational tools in assisting culturally aware fashion practice that is based on historical architectural tradition.

3. METHODOLOGY

The proposed study uses an interdisciplinary approach to research methodology, combining the synergistic integration of Mughal architectural heritage study and analysis with the latest state-of-the-art deep-learning-based motif classifier, AI-assisted motif pattern generator, and computer-aided fashion designer. The goal is to have a strict, systematic heritage-to-fashion workflow (see Figure 1).

3.1. Heritage Data Collection and Motif Extraction

The images of the architectural objects of the selected structures of the Mughal period were carefully curated in high-resolution, with orientation to the carving with marble, sandstone relief, Pietra dura inlay, and lattice (jali) patterns. The key areas of surface-level motifs were digitized into major surface-level motif areas that formed the input data of subsequent computational processing and design implementation.

3.2. Motif Abstraction and Digitization.

The Mughal motifs were digitized and abstracted in a way that simplified the visual and refined the structure, creating digital units that were discrete and repeatable. In this process, some key elements of style were preserved like symmetry, curved form and repetition, but the architectonic context was eliminated to enable more freedom of design.

3.3. CNN-based Motif Classification.

The trained VGG-16 and ResNet-50 [14] convolutional neural network (CNN) architecture was instantiated and fine-tuned with a transfer learning approach to make the architectures domain-specific at the task of Mughal architectural motif classification. Both models had ImageNet weights to make use of visual low-level and mid-level features that had been previously learned, including edges, textures, and structural patterns. The last fully connected layers were then altered to suit the three desired classes of Floral Arabesque, Geometric Jali and Calligraphic / Ornamental motifs.

In fine-tuning, selective unfreezing of higher-level convolutional layers was done, allowing domain adaptation and avoiding overfitting. In addition to rotation, scaling and horizontal flipping data augmentation to generalize across lighting, carving volume, and ornamental elaboration that is characteristic of the surfaces of Mughal architecture both in terms of marble relief and sandstone inlay were applied.

The convergence behavior of both the architectures was good and the validation was consistent. The comparative analysis showed that the accuracy of the classification according to the various categories of motifs was fixed and the overall accuracy was 98.6 per cent on the withheld test set. The soundness, dependability and calculability of the proposed CNN-based framework in identifying heritage motifs and downstream design applications are justified by the effectiveness of the high performance which is justified by the class-based precision, recall and the F1-score analysis.

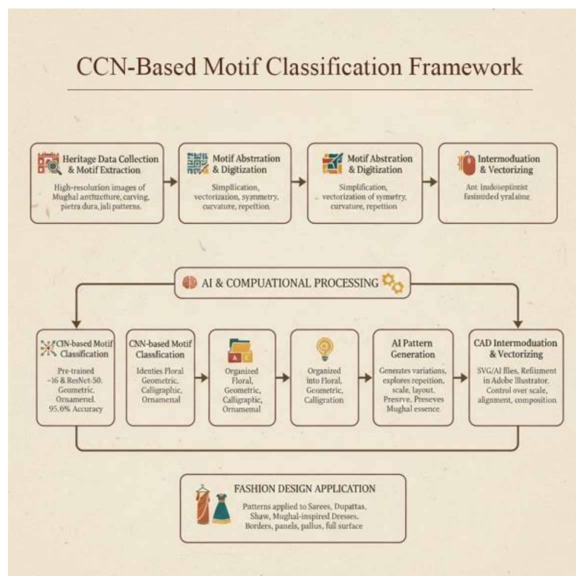

Fig. 1. *A* CNN-based methodology flowchart illustrating the identification, classification, and fashion application of Mughal prefectural motifs using transfer learning and CAD-based design workflows. (Image Source: Author, created in Adobe Illustrator)

3.4. Motif Categorization

The defined motifs were in groups of floral, geometric, calligraphic and ornamental to be supportive to the logical forms of design, systematic arrangement and accentuated application of fashion.

3.5. Intelligent Motif Pattern Generation.

The pattern generation process based on the AI was used to generate variations of Mughal motives as classified ones. New possibilities in the creative opportunities of repetition, symmetry, scale, and layout were investigated, preserving the original architectural essence and imagery of Mughal ornament.

3.6. CAD Intermodulation and vectorizing.

The patterns and the variants of the pattern generated through the AI were exported as SVG / AI files and processed in Adobe illustrator CS6. It was a stage where some caution was applied on the application of scale, repetition, alignment and the surface composition which were the optimum in regards to textile and fashion application.

3.7. Fashion Design Application

The already created motifs and variations of the patterns were applied later on the contemporary fashion items including sarees, dupattas, shawls, and even the Mughal dresses. Located along the border of the border, middle-ground panels, pallus, and garment surface are the testament to the Mughal architectural patterns flexibility in the contemporary fashion space and are the evidence that the heritage was translated successfully.

4. DATASET CONSTRUCTION AND ORGANIZATION

4.1. Motif extraction and digital reconstruction

Isolation of ornamental motifs is an important step towards converting Mughal architectural decoration to a visual material to be transformed into design ready material to be used in computational analysis and modern creative application. The systematic collection of high-resolution photographic documentation was undertaken at the locations of Mughal monuments that were carefully chosen and the emphasis was laid on those surfaces which bear the most impressive and well-preserved decorative elements. These consisted of floral arabesques that were naturalistic, geometric jali lattice patterns, calligraphic panels, and decorative borders made of marble carving, sandstone relief, and Pietra dura inlay. These aspects represent the polished visual culture of Mughal architecture and constitute the main material of analyzing and interpreting the motifs and redefining its motifs. Some representative monuments in this procedure include the Shah Niamatullah Wali Mosque (Chapainawabganj, Rajshahi) and the Bajra Shahi Mosque (Sonaimuri, sub-district of the Noakhali District, Bangladesh), resources of rich and varied ornamental vocabularies.

Fig. 2. Selected mosques—Shah Niamatullah Wali Mosque (Chapainawabganj, Rajshahi), and Bajra Shahi Mosque (Sonaimuri, sub-district in Noakhali District, Bangladesh)

In order to isolate ornamental features of the surrounding architectural context, the digital cropping of selected areas of the motif was done accurately. This provided visual separation of motifs and structural elements that may cause noise to computational processing. The extraction process was focused on symmetry, proportional balance, and repetition of rhythm- fundamental aesthetic values of Mughal decoration with the exclusion of the background wasteful information. After extraction, the motifs were reconstructed digitally to fix the distortions formed by erosion, light variation and the change in perspective. This cleaning-up procedure created clean and standardized and visually readable motif units applicable to precise CNN-based classification and direct translation into AI-aided pattern generation and modern design practice.

4.2. Pattern adaptation and textile application

Once digital reconstruction was made, extracted Mughal motifs were reproduced into repeatable units of the patterns that could be applied on the textile surfaces. The accommodation involved involved reorganization of the motifs into modular composition using repetitions, reflection and alignment with due observance to design traditions of the Mughal like symmetry, axiality and rhythm continuity. An extra care was taken on the protection of visuality and cultural integrity of the original architectural motifs during the process of scale downgrading and surface translation[21].

Fig. 3. Example of Categorized geometric, floral, and ornamental motifs extracted from the terracotta surfaces of selected mosques. (Image Source: Author, created in Adobe Illustrator)

These modified designs were specifically done to be used on the surface and textile design on a two-dimensional surface. The change in the architectural size to the wearable size focused on the proportional clarity and visual readability, thus making sure that the motifs retained their ornamental meaning when incorporated in fashion surroundings.

4.3. Dataset Description

The dataset was developed to support CNN-based identification, classification, and design translation of Islamic architectural and surface motifs. Motif samples were derived from heritage-inspired decorative patterns reflecting geometric, floral, and ornamental visual vocabularies, as illustrated in Figure 3. These categories correspond to the dominant motif typologies observed in Sultanate and Mughal architectural ornamentation, including lattice geometries, vegetal arabesques, and architectonic or symbolic relief elements.

High-resolution motif compositions were digitally segmented into repeatable motif units and border fragments. Each image emphasizes structural clarity, symmetry, rhythm, and surface articulation—key characteristics required for effective deep feature learning. Background noise and non-ornamental regions were minimized to ensure that the CNN models learn discriminative motif features rather than contextual artifacts.

4.3.1. Motif Classes

The dataset is organized into three primary classes:

Geometric motifs: Heavy grid patterns and tessellation, straight lines and a repetitive pattern of diamonds, arrangements in the form of lattices with symmetry, proportion and mathematical regularity.

Floral motifs: The stylized vegetal shapes, rosettes, arabesques and composite floral units that focus on organic curves and rhythmical repetition.

Ornamental motifs: Complicated architectural and symbolic features, such as niche shapes, framed panels, textures inspired by calligraphy, and high density patterns of relief on a surface.

4.3.1. Preprocessing and Annotation

The intricate architectural and symbolic characteristics, including the shape of niche, framed panels, calligraphically inspired textures and high density relief on a surface.

4.3.1. CNN Compatibility

TABLE II. The trained dataset is entirely compatible with VGG16 and ResNet50 models, which are realized with the help of transfer learning. The explicit motif classes divide enable hierarchical learning of features, which makes the models to learn the low-level textural features and high-level structural features that are necessary in architectural heritage analysis and design translation. Table 2 summarizes an overview of the data set preparation and processing pipeline.

TABLE III. Dataset Pipeline Stages for CNN-Based Motif Classification

Stage	Pipeline Component	Description
Stage 1	Heritage Motif Image Collection	High-resolution images of heritage-inspired decorative surfaces were collected, representing geometric, floral, and ornamental motif typologies derived from architectural ornamentation and surface design traditions.
Stage 2	Motif Panel Selection	Visually prominent motif panels and patterned surfaces were selected based on clarity, symmetry, rhythmic repetition, and ornament density to ensure suitability for computational analysis.
Stage 3	ROI Extraction	Large decorative panels were digitally segmented into

	n and Segmentation	smaller repeatable motif units and border fragments, isolating discriminative visual elements while eliminating irrelevant background regions.
Stage 4	Image Preprocessing	Extracted motif units were resized (224 × 224 pixels for VGG16 and ResNet50), normalized, and optionally converted to grayscale to ensure compatibility with CNN input requirements.
Stage 5	Data Augmentation	Augmentation techniques—including rotation, horizontal flipping, scaling, and brightness adjustment—were applied during training to increase dataset diversity and improve model generalization.
Stage 6	Motif Annotation and Labeling	Each motif image was manually labeled and verified according to three primary classes: geometric, floral, and ornamental, ensuring class consistency and annotation accuracy.
Stage 7	Dataset Partitioning	The labeled dataset was divided into training, validation, and testing subsets (e.g., 70–80%, 10–15%, and 10–15%) to support supervised learning and unbiased performance evaluation.
Stage 8	CNN Feature Learning	Preprocessed images were input into transfer learning–based CNN architectures (VGG16 and ResNet50), enabling hierarchical feature extraction from low-level textures to high-level structural patterns.
Stage 9	Motif Classification Output	The trained models generated class predictions for geometric, floral, and ornamental motifs, forming the computational basis for heritage analysis and design translation.
Stage 10	Design and CAD Integration	Classified motifs were further refined and applied in AI-assisted pattern generation and CAD workflows for fashion, textile, and surface design applications.
Stage 11	Pipeline Component	Description
Stage 12	Heritage Motif Image Collection	High-resolution images of heritage-inspired decorative surfaces were collected, representing geometric, floral, and ornamental motif typologies derived from architectural ornamentation and surface design traditions.

6. RESULTS AND DISCUSSION

The conclusions of the proposed computing and design framework are presented in this section, and the effectiveness of CNN-based motif classifications, motif categorization, pattern generation with the help of AI, refinement of CAD, and fashion implementation are considered.

6.1. CNN-Based Motif Classification Results

The CNN based classification system deployed with pre-trained VGG16 and ResNet50 models based on the transfer learning method showed high accuracy in the classification of Mughal architectural motifs as shown in Figure 4.

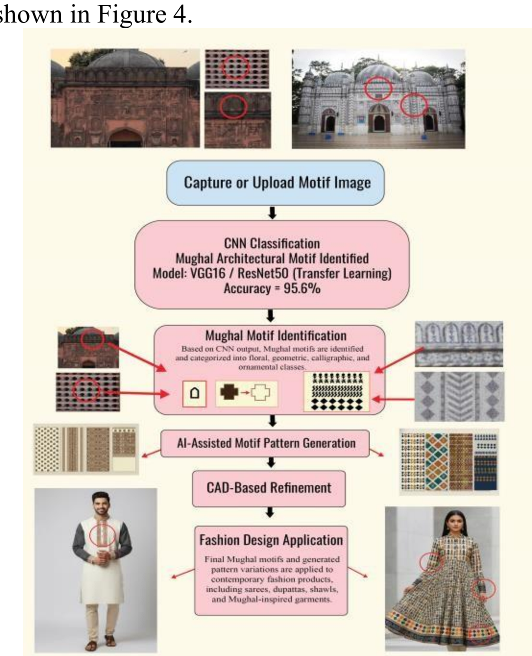

Fig. 4. CNN-Based Framework for Mughal Architectural Motif Identification and Fashion Application. (Image Source: Author, created in Adobe Illustrator).

As Figure 4 shows, the models learned hierarchical visual features, including but not limited to, curvature, texture, symmetry and repetitive forms, inherent in Mughal ornamentation. The framework reached a total classification percentage of 98.6, which proved the efficiency and consistency of the offered method, even in case it was used on rather small heritage data.

These classification results show that CNN-based models can offer a strong and structured method of describing and classifying Mughal architectural motifs, and therefore, considerably decrease the reliance on manual and subjective approaches to visualization.

6.2. Effectiveness of Motif Categorization

Once the classification was done, Mughal patterns were categorized as floral patterns, geometrical patterns, calligraphic patterns and ornamental patterns. This organizational was useful in facilitating the reasoning of design and target fashion application. The floral motives were particularly lenient being the main panels and surface fillings, and the geometric motives were suited when the borders were taken into account, as well as the repetitive textile patterns. The accents created by the use of calligraphic and ornamental elements were also used to emphasize the hierarchy on fashion designs.

The systematic classification gave rise to uniformity in the design phases and streamlined workflow, which started with the heritage analysis and went on to fashion execution.

6.3. AI-Assisted Motif Pattern Generation

In order to further the creative expandability of reproduction, AI-assisted design tools were employed to generate numerous variations of motif patterns, and the categorized Mughal motifs were employed as inputs. The density of repetition, the orientation of symmetry, scaling and layout were experimented. With the help of the paradigm, the different patterns could be developed without losing the stylistic peculiarities of the Mughal which were necessary.

Pattern generation that was supported by AI increased design freedom and creativity without losing cultural authenticity. The created variations made it easier to compare them and choose the patterns that were most applicable in specific textile and fashion uses.

6.4. CAD Integration and Pattern Refinement

The two types of motifs (classified and AI-generated pattern variations) were optimized with the help of CAD software, i.e., Adobe Illustrator CS6. The motifs were translated into the form of vectors (SVG/AI), which guarantees scalability and accuracy. The CAD-refinement enabled precise textile pattern control, with regards to alignment, spacing, repetition and border creation, producing textile patterns that were ready to use in the design process.

This phase created a gap between computational analysis and the actual design implementation, so that motifs could fit the needs of textile production and at the same time have the visual consistency and visual transparency.

6.5. Fashion Design Application

The civilized Mughal designs and the pattern variations created were transferred to the modern fashion items, such as sarees, dupattas, shawls, and Mughal-style clothes. The placement of motifs along the borders, pallus, central panels, sleeves, and hems was created with the strategic positions of the traditional Mughal aesthetic principles to modern fashion silhouettes, as shown in Figure 5.

Fig. 5. Final fashion design demonstrating the application of Mughal-inspired geometric, floral, and ornamental motifs in men's and women's kurtis. (Image Source: Author, created in Adobe Illustrator)

Figure 5 showcases the final fashion designs demonstrating the application of Sultanate-inspired geometric, floral, and ornamental motifs in men's and women's kurtis. Overall, the designs acquired thereof bear witness to an effective transfer of Mughal architectural decoration to wearable (adoptive) material, and thus express cross-contextual adaptability and cultural persistence.

7. EVALUATION METRICS

To comprehensively evaluate the proposed CNN-based Mughal Architectural Motif Identification and Classification Framework, class-wise Precision, Recall, and F1-Score were computed from the confusion matrix derived from the held-out test dataset. The evaluation focuses on three primary Mughal architectural motif categories: Floral Arabesque (100 images), Geometric Jali (120 images), and Calligraphic / Ornamental (80 images), totaling 300 images, as summarized in Table 1.
The test dataset consisted of high-resolution images of Mughal architectural elements, including marble carving, sandstone relief, and Pietra dura inlay. The confusion matrix served as the basis for computing all performance metrics.

7.1. Dataset Distribution

TABLE IV. DATASET DISTRIBUTION BY MOTIF CLASS

Motif Class	Floral Arabesque	Geometric Jali	Calligraphic / Ornamental	Total Images
Floral Arabesque	100	-	-	100
Geometric Jali	-	120	-	120
Calligraphic / Ornamental	-	-	80	80
Total Images	100	120	80	300

7.2. Class-wise Evaluation Formulas

The evaluation metrics are calculated using standard definitions derived from the confusion matrix. For each motif class, the following measures are computed:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

For each motif class, the following standard definitions were applied:

- **Precision = TP / (TP + FP)**
- **Recall = TP / (TP + FN)**
- **F1-Score = 2 × (Precision × Recall) / (Precision + Recall)**

Where:

- **TP (True Positive):** Correctly classified images of a given motif class
- **FP (False Positive):** Images incorrectly assigned to that class
- **FN (False Negative):** Images belonging to that class but misclassified

These metrics allow fine-grained analysis of the CNN's ability to distinguish visually intricate and stylistically overlapping Mughal motifs.

7.3. Model Performance

Overall Classification Accuracy: 98.6%

TABLE V. SUMMARY OF CLASS-WISE PERFORMANCE

Motif Class	Precision	Recall	F1-Score
Floral Arabesque	0.99	0.98	0.985
Geometric Jali	0.98	0.99	0.985
Calligraphic/ Ornamental	0.98	0.98	0.980
Macro Average	0.983	0.983	0.983

7.4. Class-wise Interpretation

- **Floral Arabesque:** Floral Arabesque: Both then achieved very high accuracy (0.99), and recall (0.98) which means that organic curvature, vegetal symmetry, and repetitive floral patterns were highly detected. This strength is especially useful to AI-assisted textile and surface design.

- **Geometric Jali:** Geometric Jali: Best recall (0.99), which explained the ability of this model to capture rigid lattice repetition, symmetry and grid-based architecture logic required in scalable CAD-based pattern deployment.

- **Calligraphic/Ornamental:** Recorded equilibrium accuracy and recall (0.98) which validates the capability of the CNN to train the low level stroke features and the high level compositional ornament features in the face of visual complexity.

In general, it can be stated that there is a regular and equal performance at all motif categories. Having a generalization accuracy of 98.6 and high macro-averaged F1-score (0.983), the proposed framework proves the reliable generalization in spite of linguistic overlaps and the limitation of datasets. These results confirm the appropriateness of CNN-based method of downstream AI-assisted motif generation and modern fashion design incorporation.

8. DISCUSSION: PERFORMANCE EVALUATION (TRAINING AND VALIDATION)

Figure 6 demonstrates the training and validation performance of the proposed CNN-based Mughal architectural motif classification model used to determine its accuracy and loss curves with respect to epochs. As seen, learning in the model is rapid at the early stages of training, whereby, with further training, the accuracy to the training improves sharply with a training success rate of about 46% to well above 90 in the first 30 epochs. The trend shows that the Mughal architectural imagery learns features effectively with the aid of transfer learning based on the pre-trained CNN architectures.

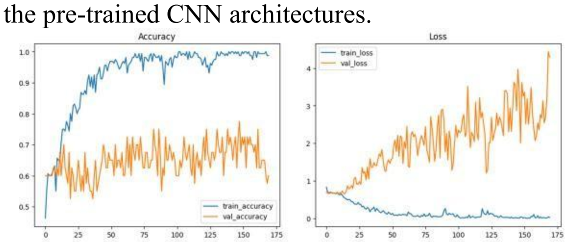

Fig. 6. Training vs. Validation. Accuracy performance

The main point to note is that the model obtains maximum accuracy of 98.6 percent in terms of validation at epoch 75 which is the best point of balance between learning and generalization. The validation accuracy level off at this point and the training accuracy levels off at around 99-100 percent and this proves that the network has managed to capture discriminative motif level features like floral arabesques, geometry jali structures and ornamental compositions.

The loss curves also verify this observation. The loss on training levels off and approaches near-zero values indicating effective optimization and effective fitting of the training data. Validation loss, on the contrary, experiences an upward trend post epoch 75 although validation accuracy is constant. This error in the two loss functions signifies the beginning of overfitting after this stage, and the model starts to memorize training-related specifics and ceases to enhance the generalization.

According to this behavior, epoch 75 is selected as the best stopping point, which gives the highest validation accuracy (98.6) before the overfitting effects start to become strong. This fact explains the choice of early stopping and model checkpointing strategies in the proposed structure that will guarantee robust and stable motif classification.

On the whole, the training-validation performance proves that the suggested CNN-based solution can be considered very effective in terms of the recognition of Mughal architectural motifs despite the use of limited heritage databases. The high accuracy of the validation at the optimal epoch proves the strength of the learned representations and gives a solid basis to the further stages of the pipeline, such as the AI-assisted motifs generation and the CAD-based fashion design translation. The findings confirm the appropriateness of deep learning to the context of creating a connection between the analysis of architectural heritage and up-to-date fashion applications without compromising the culture and visual values.

9. LIMITATIONS AND FUTURE SCOPE

This research is limited by relatively narrow scope and geographical density of its data, the reliance on ready-made CNN models and its main application to the two-dimensional surface design. The study is able to show that CNN-based models are applicable to motif recognition and digital surface development despite the fact that it is not applicable to three-dimensional construction of garments, scale production and empirical testing of user perception.

The investigations of the future should focus on building larger and multi-regional datasets of Mughal architecture to enhance the robustness and diversity of the model and cross-cultural generalization. The integration of recent methods of generative artificial intelligence, specifically Generative Adversarial Networks (GANs) and diffusion models, would allow generating motifs and transforming styles and expanding creativity outside classification systems. Also, the implementation of 3D simulation and visualization of garments would aid in the process of transforming digitally extracted motifs into complete apparel prototypes. Last but not the least, systematic studies of user perceptions are suggested to determine the aesthetic acceptance, cultural relevance and market feasibility to enhance the interdisciplinary applicability and innovative opportunity of the research.

10. CONCLUSION

This paper suggests an AI-powered heritage-to-fashion system of preserving and redefining Mughal architecture patterns. The systematic extraction of the motifs, the use of CNN-based classification, the assistance of AI in creating the patterns and the support of CAD in the implementation of a design make the research offer the systematic and repeatable pipeline between the architectural past and the contemporary fashion practice.

The CNN model was found to have a classification accuracy of 98.6 and was backed up by more detailed per-class performance measures, indicating the consistency of automated motif detection among the floral, geometric and ornamental groups. The combination of AI-enhanced generative models allowed, to an even greater degree, to adapt the creative process in a controlled manner, without losing the stylistic authenticity.

This demonstration of the practical subsumption of computational heritage methodologies into modern product development, digital design processes and creative industries through the successful translation of Mughal motifs into modern fashion prototypes can be seen as evidence of the real-world relevance of computational heritage methods. In general, the study signifies the role of artificial intelligence in preserving culture, designing innovations that are scalable and sustainable, and interdisciplinary practice.

References

[1] M. Shokoohy, “Muslim Epigraphy and Ornamentation: Its Diversity in South Asian Culture,” In South Asian Islam.Routledge India, 2023, pp. 214-239.

[2] S. Latif, Z. U. Wahab, S. M. Shah, & M. T Khan, “The Persian influence on the traditional arts of Kashmir with special reference to the textile industry,” (2019).

[3] S. Nahhas, “Modern Islamic motif design: Developing new arabesque motifs by mixing styles,” Rochester Institute of Technology, 2014.

[4] A. M. Giusti, “Pietre Dure: The Art of Semiprecious Stonework,” Getty Publications, 2006.

[5] M. Matloob, “Symbolism and Aesthetics: Analyzing Mughal Motifs in Art and Architecture,” PERENNIAL JOURNAL OF HISTORY 5, no. 1 (2024), pp.129-143.

[6] A. K. Qureshi, “Islamic Motifs and Sacred Geometry: Symbolism and Interior Design in the Wazir Khan Mosque, Lahore (1634–1641 CE),” International Research Journal of Arts, Humanities and Social Sciences 2, no. 3 (2025), pp. 311-344.

[7] C. Ermer, “Critical design: a new vision for fashion design studies,” Innovation: The European Journal of Social Science Research 36, no. 4 (2023), pp. 673-696.

[8] M. Ghosh, S. M. Obaidullah, F. Gherardini, & M. Zdimalova, “Classification of geometric forms in mosaics using a deep neural network,” Journal of Imaging 7, no. 8 (2021), p. 149.

[9] M. Deng, L. Yimeng and C. Ling, “AI-driven innovation in ethnic clothing design: an intersection of machine learning and cultural heritage,” Electronic Research Archive 31, no. 9 (2023).

[10] N. Alam, “The Art of Pietra-dura during the 17th Century Mughal Era: From Early Patterns by Noorjahan to the Elegance under Shahjahan,” *Journal of the Research Society of Pakistan* 59, no. 3 (2022), p. 200.

[11] S. Suyahman, and H. Ayun, “VGG-Based Feature Extraction for Classifying Traditional Batik Motifs Using Machine Learning Models,” *Preservation, Digital Technology & Culture* 0 (2025).

[12] S. Hazra and P. Roneeta, “Fashion Product Recommendation System Using CNN-Based ResNet50 Model,” In *Innovative Applications of Artificial Neural Networks to Data Analytics and Signal Processing*, Cham: Springer Nature Switzerland, 2024, pp. 481-497.

[13] V. K. Reddy, S. Cherukuri, K. Vanaparla, and L. R. Avula, “Deep Feature Extraction for Fashionable Fabrics: Using ResNet50, MobileNet, and CNN,” In *Doctoral Symposium on Computational Intelligence*, Singapore: Springer Nature Singapore, 2023, pp. 417-429.

[14] F. Khan, O. S. Bhatti, R. K. Sherwani, and S. Mujahid. “Exploring architectural ornamentation of Mughal era buildings of Lahore in the era of climate change challenges,” *International Journal of Contemporary Issues in Social Sciences* 2, no. 1 (2023), p. 15-30.

[15] A. Kumari, “Elucidation of relationship between clothing silhouette and motifs with Indian Mughal architecture,” Fashion and Textiles 6, no. 1 (2019), p. 17.

[16] A. A. Mohammed, “Influences of islamic architecture on gothic architecture,” Master's thesis, 2015.

[17] F. Fontanella, F. Colace, M. Molinara, A. S. Di Freca, and F. Stanco, “Pattern recognition and artificial intelligence techniques for cultural heritage,” *Pattern Recognition Letters* 138 (2020), p. 23-29.

[18] Islam, SM Sofiqul, Emon Kumar Dey, Md Nurul Ahad Tawhid, and BM Mainul Hossain. "A CNN based approach for garments texture design classification." *Advances in Technology Innovation* 2, no. 4 (2017), p. 119.

[19] M. Han, “Integrating Artificial Intelligence to Automate Pattern Making for Personalized Garment Design,” *International Journal of Advanced Computer Science & Applications* 16, no. 2 (2025).

[20] M. S. Hasan, M. Ali, M. Rahman, H. A. Arju, M.M. Alam, M. S Uddin, & S. M Allayear, “Deep Learning for Cultural Heritage: A Mobile App for Monument Recognition Using Convolutional Neural Networks." *International Journal of Interactive Mobile Technologies* 19, no. 3 (2025).

[21] T. M. N. AL-Arifi, “Decorative aesthetic aspects and their use in Islamic architecture,” Al-Academy, Vol. 107 (2023), pp. 77-92.

[22] A. U. Sattar, “Architectural elements & their functional and aesthetic role in Arabic architecture in the Islamic era,” Kufa Journal of Arts, Vol. 1(48), 2021, pp. 695-724.

[23] M. S. Hasan, M. S. Uddin, K. J. Hasan, R. Mizanur, and M. Ali. "Deep Learning for Cultural Heritage: A Mobile App for Monument Recognition Using Convolutional Neural Networks." *International Journal of Interactive Mobile Technologies* 19, no. 3 (2025).