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RESEARCH ARTICLE

Lightweight AI for Cultural Pattern Recognition: Safeguarding South Asian Regional Embroidery Heritage

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Abstract: The most important element of cultural heritage is the embroidery used in the ancient clothes. Embroidery used in the ancient clothes represents centuries of creative tradition, regional uniqueness, and the passing down of skills from one generation to the next. These elaborate textile practices, which have their roots in manual craftsmanship and oral instruction, are increasingly threatened by industrial production, globalization, and the slow decline of traditional artisans. By developing an automated identification structure based on MobileNetV2, an efficient yet highly effective convolutional neural network (CNN), this work presents an AI approach to support the preservation of regional embroidery. The model used in the paper was trained very carefully with a dataset of 5,200 high-resolution images that included a range of regional embroidery styles using pretrained ImageNet weights. With an identification accuracy of 97.3%, the suggested MobileNetV2 outperformed traditional CNN architectures like VGG16 and ResNet by over 2.3%. The results demonstrate how small AI models can make a significant contribution to the preservation of cultural heritage by providing a scalable method for storing and assessing textile arts for museums, scholars, and craftspeople. This methodology exhibits promise in fields such as digital archives, fashion technology, and cultural data analytics for heritage conservation.

Keywords: embroidery designs, MobileNetV2, CNN, cultural heritage, AI-driven heritage

1. Introduction

Embroidery is more than decorative stitching, and it is a vessel of cultural memory, regional identity, and artisanal knowledge. As a form of intangible cultural heritage recognized by UNESCO, traditional embroidery reflects social customs, spiritual beliefs, and historical narratives embedded in thread and fabric. Across many cultures, it serves not only as an art form but also as a means of storytelling, identity assertion, and intergenerational communication. However, with the rapid pace of globalization and mechanization, these living traditions face an alarming decline. Digital preservation and computational tools now offer new avenues to document, analyze, and revitalize such vulnerable cultural expressions. In many South Asian countries, embroidery is not just art, it is known as a language of identity. From the vibrant designs of Punjab to the delicate Sindhi Ajrak design patterns, each region's stitches tell stories of history, migration, and community [1]. Yet, as younger generations move away from traditional crafts, these designs risk becoming forgotten footnotes [2]. Because manually cataloguing thousands of needle work patterns is long-consuming, costly, and subject to human bias, museums and researchers are in a contest against time. As an instance, without months of instruction, even professionals have trouble telling identical geometric designs from various places apart. Existing computational methods fall short. Traditional image processing techniques [3], like edge detection [4] or color analysis, miss the nuanced cultural context of these designs. Meanwhile, bulky deep learning models (e.g., ResNet50) demand computing power that many heritage institutions across Asia lack [5]. Figure 1 shows the different embroidery designs of the four provinces of a South Asian country, Pakistan. These images were carefully selected from reputable heritage archives and publicly available sources dedicated to the preservation of traditional arts. Each photograph represents authentic, region-specific embroidery work, capturing the intricate craftsmanship and cultural symbolism embedded in these designs. The visual data used in this study were ethically sourced and reflect genuine textile artifacts, ensuring both the credibility and cultural integrity of the dataset.

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2. Literature Review

A review of previous studies indicates that researchers have employed a variety of methods to address similar problems. Which among them, transfer learning is more demanded [6]. In computer vision, deep learning that focuses on multi-layered neural networks has become a game-changing technology [7].

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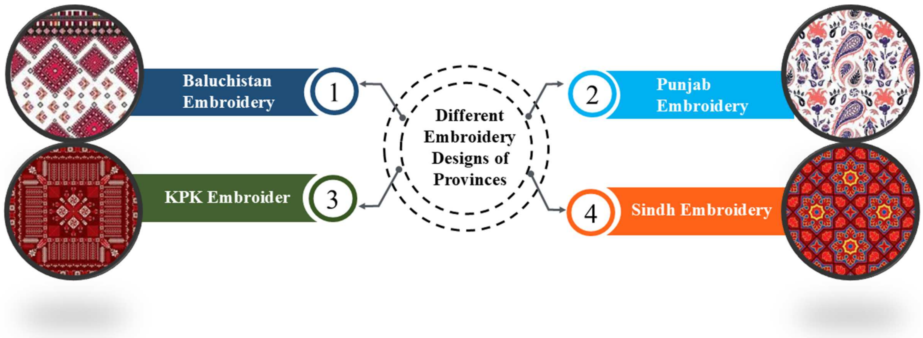
Figure 1
Different embroidery designs of provinces



It eliminates the need over manual feature engineering by allowing systems to directly learn intricate patterns and features from massive datasets [8]. Deep learning provides strong capabilities for automatically identifying, classifying, and analyzing complex patterns in embroidery designs and cultural heritage preservation that are frequently too complicated for conventional image processing methods [9]. Applications include pattern retrieval systems for the fashion and craft industries, computerized tagging and grouping of traditional designs, digitization of textile archives, and interactive educational resources for cultural studies. Because it can use pretrained models like MobileNetV2, transfer learning has drawn the most attention among different strategies because it can drastically cut down on training time without sacrificing accuracy [10]. In fields with little labeled data, like regional embroidery, where gathering and annotating big datasets can be resource-intensive, transfer learning is particularly helpful [11]. A pretrained model can be modified for an entirely novel but related task using this potent deep learning technique, which drastically cuts down on training time and boosts accuracy [12].

In order to address the difficulties associated with automatic dynasty classification in mural images that are brought on by the images' polysemy and stylistic variations among dynasties, Cao et al. [13] suggest an adaptive enhancement capsule network (AECN). The authors improve the original capsule network by adding a pre-convolution structure for extracting high-level features (like color and texture), adding an even activation operation to improve model performance, and using adaptive modifications to improve gradient smoothness in order to get around the drawbacks of conventional manual methods that mainly rely on texts and historical documents. The AECN demonstrated an accuracy of 84.44% when tested on the DH1926 dataset of mural images from the Mogao Grottoes, with all key performance metrics showing improvements of over 3% compared to both modified convolutional networks and the original capsule network. While the model effectively extracts multi-level semantic information and demonstrates robustness in dynasty recognition, its performance is sensitive to the resolution of mural images. Their future study work focuses on refining feature extraction methods and exploring the model's applicability to mural images from other cultural contexts [13].

An approach of Bezier curves & inverse distance weighted interpolation was used by Sun et al. [14]. Their method addresses challenges in restoring hard, irregular patterns with minimal prior information. The work done by the authors showed improved performance over existing inpainting techniques. The restored images from the work of the authors achieved an average SSIM of 0.977 and a PSNR of 39.16. The method used by the authors in the paper reported a classification accuracy of 93.5% [14].

In 2024, Zheng [15] used an augmented reality (AR) technology to preserve the Tang Dynasty tomb murals of cultural heritage. The author used 2D & 3D modeling, as seven murals from the Zhao Yigong Tomb were digitally restored and incorporated into an on-cloud augmented reality platform. For this research, the author has asked college students, researchers, and educators to participate in test and train of this process. From that testing and training, the results obtained increased cultural awareness and high acceptance. The method of the author estimated the effectiveness rating as it was 91.2%, which is the same as its classification accuracy [15].

Another work related to the ancient fashion of clothes, an art of the Guizhou Province in China, Quan et al. [16] tackle the threat that globalization poses to China's cultural legacy. Their work can digitally preserve and promote batik culture, and they suggest a dual channel mechanism that combines deep learning methods with knowledge graphs. The work done by the authors using an enhanced ResNet34 model classifies batik patterns with high accuracy of 94%, precision, recall, and F1-score. This work done by the authors proves that more powerful theoretical and practical backing of cultural heritage protection is the goal of their future research [16].

Using Yangxin Cloth Paste, a handcrafted craft from East Hubei Province, as a case study, Li et al. [17] present a study that uses digital twin technology in the 5G era to create a virtual experience platform for conserving and passing on cultural heritage. To build a comprehensive digital twin of the craft production process, the study used photogrammetric techniques and 3D reconstruction to collect both procedural and tangible data. This digital platform gives users an immersive, almost real-life experience of the cultural context of the craft by integrating systems for production, display, and transaction. The method's 90% accuracy rate and favorable user satisfaction ratings highlight the potential of virtual reality and digital twin technologies in the preservation of cultural heritage [17].

In 2024, Zhu and Zhu [18] presented a novel method for preserving the cultural heritage by employing CNNs to identify Shen embroidery. In this study, the recognition network was fine-tuned using transfer learning after the dataset was preprocessed. The author used spatial pyramid pooling (SPP) in place of the original MobileNet V1's average pooling layer in order to successfully fuse local and global features. The author gained a high recognition accuracy of 97.26%, and the enhanced MobileNet V1 model outperformed the baseline model by 2.3%. These findings demonstrate that the improved network can effectively and precisely recognize Shen embroidery, offering important technical assistance for the thoughtful creation and conservation of cultural heritage [18].

Ji et al. [19] propose an innovative classification technique for Zhuang ethnic clothing images that integrates supply-demand matching with convolutional neural networks. They first introduce an image resolution model that fuses visual style and label constraints to extract local features, leading to significant improvements in detection accuracy across various performance metrics achieving 90.5% pixel accuracy, 83.7% average precision, 80.1% average recall, and an 81.2% F1 score. Their study also highlights innovative approaches for handling the complex structure and unique visual style of Zhuang ethnic clothing. However, the authors note limitations such as the relatively small dataset and the need for improved generalization to other ethnic clothing, suggesting future work in expanding the dataset and optimizing the model structure [19].

As we can see that several previous studies have explored textile pattern classification using different machine learning and image processing techniques, most have focused on broader textile categories or fashion-related applications. But the studies related to the embroidery still remained relatively limited. Therefore, this paper will provide that foundation by narrowing the focus only on the regional embroidery designs, that holds deepest cultural meaning.

The main objective of the current proposed model is to develop a computational system that is not only accurate but also efficient and scalable to detect and classify the embroidery designs. To achieve this, the proposed research uses a MobileNetV2 method. The model is trained with MobileNetV2 to recognize and differentiate the complex patterns and motifs characteristic of traditional textile art. Contributing to the safeguarding and electronic documentation of cultural heritage which is becoming more and more endangered as a result of modernization and the decline of traditional craftsmanship is one of the main driving forces behind this work. Even in settings with limited resources, the method enables greater accessibility for institutions like museums, cultural organizations, and educational institutions by utilizing a model that requires comparatively little computational power. This work also demonstrates how contemporary artificial intelligence methods can be carefully incorporated into heritage preservation initiatives, promoting not only technological development but also cultural awareness and continuity.

Table 1 gives us a hint that why the automatic embroidery classification is important. As we can see that the manual embroidery classification is slow, inconsistent, and costly. Each design takes 45–60 min to classify, limiting daily output to 5–10 designs. Expert disagreement results in a 30% label mismatch, reducing reliability. Additionally, the cost per design ranges from 20 USD to 50 USD, making large-scale projects difficult to sustain. These challenges highlight the need for a more efficient and standardized approach.

The remainder of this paper is organized as follows: In Section 3 detail the dataset Preparation, image preprocessing, and data augmentation techniques employed. It also describes the architecture of MobileNetV2, including the modifications and custom layers added for our classification task, along with the training protocol. Section 4 presents the experimental results and discussion, comparing our method with existing approaches and highlighting its advantages. Finally, Section 5 concludes the paper by summarizing our findings and suggesting future research directions.

3. Research Methodology

The current research introduced a deep learning-based methodology for effectively identifying and categorizing regional embroidery designs. Collecting data, preprocessing, model selection, training, and evaluation are some of the steps in the process. Our method addresses the difficulties of high accuracy with constrained computational resources by utilizing transfer learning with MobileNetV2, a lightweight and effective convolutional neural network [20]. Our approach is made to manage the intricacies of regional embroidery designs, guaranteeing that the distinctive cultural traits of every design are maintained while attaining excellent classification results. The specific steps of the model methodology used in the paper are displayed in Figure 2.

MobileNetV2 was selected as the backbone architecture because it offers an optimal balance between computational efficiency, model size, and representational capability. While newer models such as MobileNetV3 and EfficientNet-B0 provide competitive accuracy, they are considerably more computationally intensive during training, especially on hardware without a dedicated GPU. MobileNetV2, by contrast, is specifically optimized for environments with limited processing power, making it highly suitable for cultural heritage institutions and researchers operating under similar constraints.

Since they are unable to capture the cultural and stylistic subtleties incorporated into the patterns, traditional computer vision techniques such as edge detection, color histogram analysis, or basic feature matching are inadequate for classifying embroidery designs [21]. Additionally, the majority of the deep learning models that were previously used, such as ResNet50 and VGG16, require a lot of computing power, which makes them unsuitable for researchers in resource-constrained areas like South Asia or Pakistan as well as small museums and cultural centers. Additionally, there is a dearth of high-quality, ethically sourced datasets specifically devoted to regional embroidery designs in the literature currently in publication. Furthermore, lightweight, real-time deployable models for this application have not received much attention [22].

To capture Pakistan's diverse embroidery heritage, the model was compiled with images from publicly available sources, including camera captures from own mobile phone, artisan social media profiles, cultural websites, and e-commerce platforms specializing

Table 1
Challenges in manual embroidery design cataloging

Issue	Manual approach	Consequence
Time per design	45–60 min	Only 5–10 designs cataloged daily
Expert disagreement	30% label mismatch	Reduced reliability for research
Cost	20–50 per design	Limits large-scale projects

in provincial crafts. The camera specifications on which these images were taken were 48 MP, f/2.2 aperture, 13 mm focal length, 120° field of view, hybrid focus pixels. And the high-resolution pictures were 8064 × 6048 pixels. For ethical transparency, only images with clear licensing (e.g., Creative Commons) or explicit merchant permissions were included. However, some provincial embroidery designs share very similar motifs, which naturally poses a challenge even for human experts. This similarity sometimes led the model to struggle in distinguishing between designs that are almost identical. To mitigate this, several augmentation techniques (such as rotations, shifts, and flips) were applied during training. These augmentations were crucial in improving the model's ability to recognize designs under varying conditions and contributed to the overall robustness of the system. Additionally, minor differences in precision and recall among provinces can be attributed to these design similarities, as certain motifs overlap in style and structure.

The final dataset consisted of 5200 images collected from four categories of sources: (i) 1480 images captured using a 48-MP mobile phone camera; (ii) 1320 images sourced from artisan social media pages with explicit permission; (iii) 1760 images from cultural heritage websites operating under Creative Commons licenses; and (iv) 640 images from e-commerce platforms specializing in regional crafts. This distribution is included to improve reproducibility and transparency. All data collection and experimental procedures complied with the ethical research guidelines of Wuhan Textile University. As the study involved only publicly available images and contained no identifiable human subjects, formal ethical board approval was not required. Permissions were obtained where necessary, and culturally sensitive material was handled in accordance with institutional and international standards for digital heritage research.

For the current dataset, a training was done to maximize the performance of the proposed model. As the dataset consisted of 5200 images, each province consisted of 1300 images each. For these 5200 Images in total, first, the dataset was split into 70% training (3640 images), 20% testing (1040 images), and then the remaining 10% validation (520 images) to ensure a robust evaluation of the model's performance. The Adam optimizer was optimized with a learning rate of 0.001. Because of the limited capacity of the computer, the batch size was set to 32 to ensure smooth training sessions. The model was trained for 15 epochs, during which the steady improvements were observed in accuracy. Notably, the model's performance stabilized after approximately 10 epochs, but extending the training to 15 epochs led to further increases in accuracy, confirming that additional training iterations helped fine-tune the model's performance.

To ensure full reproducibility, the training protocol was configured with the following hyperparameters: the Adam optimizer was used with a learning rate of 0.001; the batch size was set to 32 due to hardware constraints; and training proceeded for 15 epochs using early-stopping monitoring. All images were resized to 256 × 256 × 3 and normalized to [0,1]. The MobileNetV2 base was initialized with ImageNet-pretrained weights, while the custom classifier head included a 256-unit dense layer with ReLU activation and a dropout rate of 0.5. These hyperparameters, combined with the lightweight nature of MobileNetV2, enabled the model to be successfully trained on a standard Core i5 (7th Gen) CPU within approximately 4 h.

The HP Core i5 7th Gen laptop was equipped with 8GB of RAM and no dedicated GPU for the training of the dataset to highlight the efficiency of our model approach. For the programming language, the upgraded version of the Python 3.8.10 was utilized by us, with an upgraded TensorFlow 2.6.0 serving as our deep learning framework and OpenCV 4.5.4 for image processing tasks. Despite we had the limited hardware capabilities, the lightweight design of MobileNetV2 enabled us to complete the training process in approximately four hours, which demonstrate its suitability for environments with limited computational resources.

Significant differences in lighting and resolution were visible in the different pictures of embroidery designs for the different provinces, especially in Punjab's vivid phulkari and Baluchistan's darker textiles. Using OpenCV, every picture weas resized to a consistent 256 × 256 pixel size while keeping a 1:1 aspect ratio to guarantee the neural network's dependability and consistency. In order to scale the intensity to a range between 0 and 1, the pixel values were also normalized by dividing each value by 255. The model can concentrate on the key elements of the embroidery designs during training thanks to this standardization, which reduces disparities brought on by various lighting settings and picture resolutions.

Gaussian smoothing was applied as a light noise reduction step to mitigate inconsistencies introduced by variable lighting, sensor noise, and JPEG compression artifacts present in several raw images. To preserve fine embroidery details, a small kernel (3 × 3) and low σ value were selected. Preliminary experiments comparing training runs with and without smoothing showed a modest improvement of approximately 0.4% in classification accuracy, suggesting that smoothing reduced undesirable noise without blurring culturally significant motifs. Nonetheless, this preprocessing was applied conservatively to avoid weakening high-frequency texture patterns that are characteristic of regional embroidery.

Figure 2 shows the steps of methodology that are used in the proposed model. As it can be seen in the figure that the first step is dataset collection, after that the noise reduction methods are applied which are then augmented through augmentation method. The next step is the model architecture, then the training protocol is applied through Adam optimizer. After that in next step the model is implemented on the PC (personal computer) to test and get the results along with its percentage accuracy.

A common approach for noise reduction in image processing is Gaussian smoothing. The smoothed image $I_{\text{smooth}}(x, y)$ is obtained by convolving the input image $I(x, y)$ with a Gaussian kernel $G(i, j)$:

$$I_{Smooth}(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} G(i, j) \, . \, I(x + i, y + j) \tag{1}$$

where the Gaussian is defined as;

$$G(i, j) = \frac{1}{2\pi r^{s}} \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right) \tag{2}$$

Here, $I(x, y)$ shows original image at pixel (x, y), and $I_{\text{smooth}}(x, y)$ represents denoised version of the image at the same pixel. The $G(i, j)$ represents the kernel value at offset (i, j), with a standard deviation σ. The parameter k determines the kernel size, such that the full kernel has dimensions $(2k + 1) \times (2k + 1)$, covering a symmetric window around each pixel.

3.1. Data augmentation

By performing various modifications to the initial pictures, the data augmentation was also used in the proposed method, as

Figure 2
The steps of the methodology

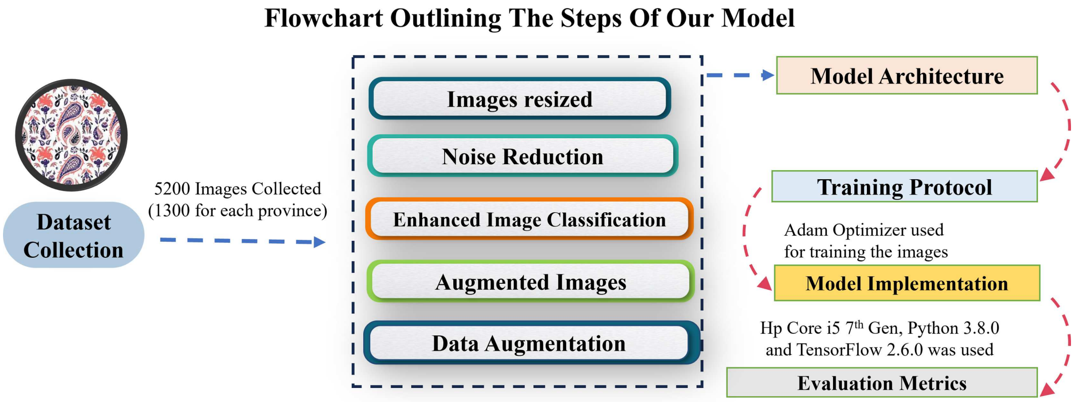
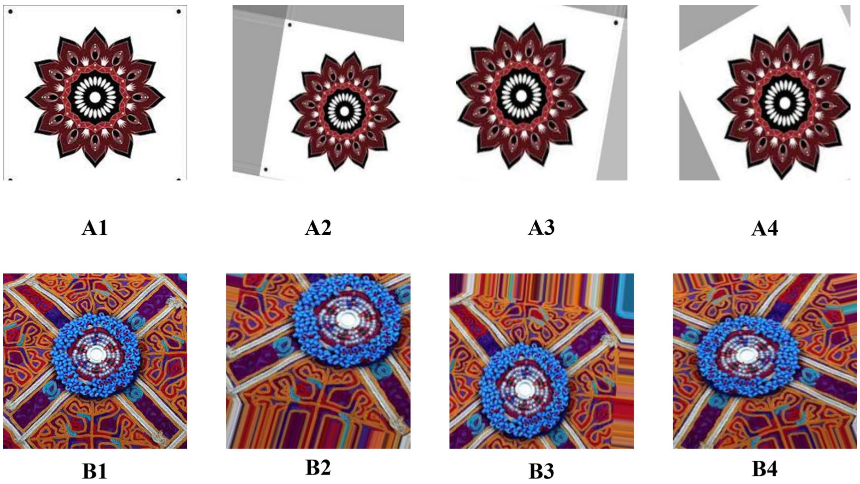


Figure 3
Data augmentation process image results



we know that data augmentation is a process that computationally expands the training dataset. This resembles the variety of conditions found in real-life situations, including rotated pictures and poor lighting [23, 24]. These methods successfully expanded the training data's diversity, which aids the model in learning to generalize more effectively in various orientations and lighting scenarios, ultimately improving the model's resilience and precision in identifying embroidery designs. We can see in Figure 3 how the data augmentation process can easily expand the dataset by rotating the picture at each angle.

Data augmentation techniques apply geometric transformations to images to increase dataset variability. One common transformation is rotation. The rotation of a point (x, y) by an angle θ is performed using the following transformation matrix:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{3}$$

where (x, y) are the original coordinates of a pixel, (x', y') are the coordinates after rotation, and θ is the rotation angle (in radians). Similarly, scaling is applied to simulate different sizes:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} s_x & 0 \\ 0 & s_y \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{4}$$

where s_x and s_y are the scaling factors in the x and y directions, respectively.

These transformations, along with translations and horizontal flips, diversify the training dataset, helping the model generalize better to real-world variations.

3.2. Applying MobileNetV2 model

The MobileNetV2 approach was used in the paper, which is a lightweight and efficient CNN method to classify regional embroidery designs [25]. MobileNetV2, which was initially trained on the ImageNet dataset, is perfect for uses where computational capacity is limited, like robotics or mobile devices, because of its resource-constrained architecture [26]. While the later layers of the network are tuned to recognize [27] the complex patterns unique to Asian embroidery, MobileNetV2 maintains its general feature extraction capabilities by freezing the first layers of the network. This method lessens the need for large custom datasets by enabling the model to develop both global characteristics and the fine details of textile motifs.

By using MobileNetV2 as the fundamental framework and storing its initial layers, the model can be adapted to a particular dataset while maintaining the important learned features. In accordance with the dimensions of our preprocessed image, the input design was defined as 256 x 256 x 3. The addition of custom layers included a flatten layer to convert the multi-dimensional feature maps into a one-dimensional vector, a Dense layer with 256 neurons and ReLU activation, and a Dropout rate of 0.5

to lessen overfitting. Lastly, for province classification, a Dense output layer with four neurons and softmax activation was used. With this altered architecture, the model can consistently capture and distinguish the minute differences in embroidery designs between provinces.

Apart from classification of images, MobileNetV2 is extensively employed for tasks involving object detection and recognition, which are crucial for sectors such as textile production and cultural heritage conservation [28, 29]. We can take advantage of robotic vision technologies that precisely analyze and catalog embroidery patterns by incorporating MobileNetV2 into automated systems [30, 31]. By guaranteeing that traditional designs are recognized and documented digitally, this can greatly aid in their preservation. Additionally, the model's effectiveness allows for real-time detection, which makes it appropriate for dynamic applications like on-site heritage preservation, where automated systems continuously gather and examine visual data from textiles and other cultural artifacts [32, 33].

Figure 4 illustrates the complete transfer learning process using MobileNetV2 for embroidery image classification. It begins with 5200 high-resolution images that are first preprocessed and augmented resized to 256 x 256 pixels, normalized, and subjected to various augmentations to create a robust dataset. After that, a MobileNetV2 model pretrained on ImageNet is used as the base, with its initial layers frozen to retain the valuable features learnt from a vast dataset. Custom layers are then added on top, including a Flatten layer to convert feature maps into a one-dimensional vector, a dense layer with 256 neurons and ReLU activation paired with dropout (0.5) to reduce overfitting, and a final Dense layer with softmax activation for classifying the images into one of four provinces. Finally, the modified model is fine-tuned over 15 epochs using the Adam optimizer with a batch size of 32.

3.3. Evaluation metrics

To assess the classification performance of our model, we employed a set of widely used evaluation metrics, namely accuracy, precision, recall, and F1-score. These metrics provide a balanced view of the model's behavior in correctly identifying embroidery patterns from various regions, particularly in scenarios where both false positives and false negatives are critical to evaluate. Accuracy reflects the overall effectiveness of the model in correctly classifying both positive and negative instances, and is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Here, TP (true positives) refers to the number of regional embroidery images correctly identified as belonging to their actual class. TN (true negatives) indicates the number of images correctly recognized as not belonging to a certain class. FP (false positives) represents the instances where the model incorrectly classified an image into a class it does not belong to, and FN (false negatives) are the cases where the model failed to detect the correct class of an image. The Recall in the method is also measured, which indicates the proportion of actual positive cases that were successfully identified by the model. In our context, it reflects the model's ability to detect embroidery patterns that are truly present in the image. Recall is calculated as:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

And then in order to evaluate the reliability of the positive classifications made by the model, we used the Precision metric, defined as:

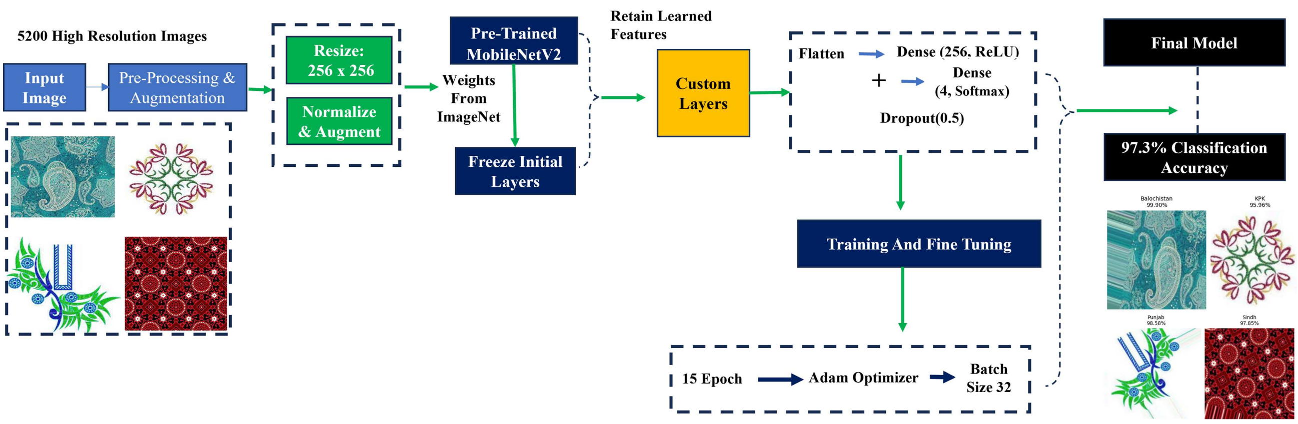
$$Precision = \frac{TP}{TP + FP} \tag{7}$$

Precision measures the proportion of positive identifications that were actually correct, which is essential in reducing false recognition of patterns, especially in systems aimed at documentation and archival purposes where accuracy is paramount. To balance both precision and recall, the F1-score was employed. The F1-score is the harmonic mean of precision and recall and provides a single measure that balances both false positives and false negatives:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

The F1-score becomes especially useful when the cost of false positives and false negatives is both significant, offering a comprehensive view of model performance. These metrics collectively offer a reliable assessment of the model's classification behavior, ensuring that its predictions are not only accurate but also culturally and contextually sensitive for applications in digital heritage preservation.

Figure 4
Transfer learning via MobileNetV2 process for classification



4. Results and Discussion

The experimental results of the proposed method demonstrate that the MobileNetV2-based model achieves an impressive accuracy of 97.3% on the curated dataset of 5200 high-resolution embroidery images. In addition to the overall accuracy, our analysis supported by precision, recall, and F1-score metrics across individual provinces confirms the robustness of the model, with all provinces scoring above 95%. The confusion matrix further reveals that while the model performs well overall, it occasionally confuses designs with similar motifs, such as Sindh's ajrak patterns with geometric motifs in Baluchistan. A closer examination of misclassified samples reveals that the confusion arises predominantly from shared geometric lattice motifs, including repeated diamond-shaped grids and alternating checkered patterns. Sindh's Ajrak designs often contain symmetrical star motifs and mirror-work reflections, which visually resemble the geometric mirror-embellished patterns of Baluchistan. Furthermore, under certain lighting conditions, the dark indigo-dominant Sindhi palettes appear similar to Baluchistan's muted earth-tone textiles after normalization, reducing color-based separability. These overlapping visual cues explain the specific difficulty the model encounters, mirroring the challenges reported by human embroidery experts when differentiating designs with shared cultural or historical roots.

Table 2 shows the substantial efficiency advantage of MobileNetV2. The model requires only 3.4 million parameters and 0.30 billion FLOPs—nearly 14× fewer FLOPs than ResNet50 and 50× fewer than VGG16. This reduction directly translates into faster inference times, with MobileNetV2 processing a single 256 × 256 embroidery image in 12.4 ms, compared to 42.7 ms for ResNet50 and 87.3 ms for VGG16. These values confirm that MobileNetV2 is not only highly accurate but also significantly more deployable in low-resource environments.

The study's embroidery dataset came solely from publicly accessible sources, and all original artists or institutions were fully credited for the photos that were gathered under suitable use guidelines. The data collection method did not have any sensitive or personal information. Most of the data usage regulations were examined and adhered to when traditional designs were sourced from cultural archives or museum collections. The information was only used for research-related reasons. An ethical committee's official permission was not necessary because the study did not include human beings. However, the study approach adhered to accepted standards for the responsible use of AI, paying special attention to cultural sensitivity, correct attribution, and avoiding bias or misrepresentation in the outputs produced.

The calculated area under the curve (AUC) of 0.98 reinforces the model's excellent capability in differentiating between classes. When compared with similar works such as the 97.26% accuracy achieved by an improved MobileNetV1 for Shen Embroidery recognition, and lower accuracies reported in studies using Adaptive Enhancement Capsule Networks for mural classification and Digital Twin approaches for handicraft preservation—our method not only competes effectively but also offers the advantages of lower computational resource requirements. These results underscore the potential of our approach as a cost-effective, efficient, and reliable tool for preserving and digitally documenting regional embroidery heritage.

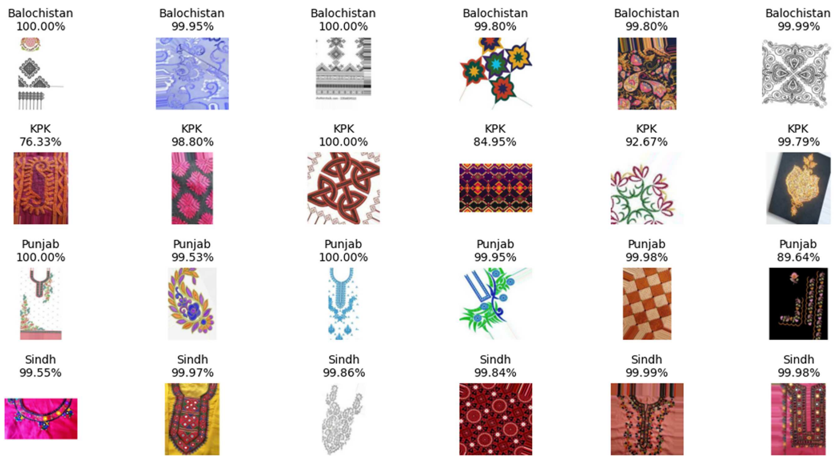
4.1. Model results

To see the results of the model, first see Figure 5 (Test Results on 24 Unseen Images), as Figure 5 shows the model's performance, that was tested on 24 different embroidery design images from different provinces that were not part of the training dataset. In this figure, each image is displayed alongside its

Table 2
Comparison of performance metrics for MobileNetV2, ResNet50, and VGG16

Model	Accuracy	Inference time (ms/image)	Parameters (M) (ms)	FLOPs (B)	Model size (MB)	Computational efficiency
MobileNetV2	97.3	12.4	12.4	0.30	14	High
ResNet50	96	42.7	42.7	4.10	98	Moderate
VGG16	95	87.3	87.3	15.5	528	Low

Figure 5
Results of the tested images showing model's performance



predicted class and accuracy percentage. This test shows how well the MobileNetV2 model generalizes to new and real-world examples. Most of the predictions show high confidence levels, which reinforces the model's robustness and reliability. The visual representation also helps to highlight subtle distinctions between similar designs, showcasing the model's capability to discern nuanced features that even challenge human experts. Overall, Figure 5 not only validates our experimental results but also emphasizes the potential of our approach for deployment in cultural heritage preservation projects.

This comprehensive evaluation, including the high AUC value, underscores the model's capability in effectively classifying regional embroidery designs. To further clarify the evaluation process, the four commonly used indicators were adopted, those were accuracy, precision, recall, and F1-score. The formulas used for these calculations are shown in Table 3.

As we can see from all these results, the proposed MobileNetV2 model has achieved an overall accuracy of 97.3% in classifying embroidery designs. In both training and validation, accuracy improved steadily over the 15 epochs, with the performance standing very firm after approximately 10 epochs. There were some very minor misclassifications though as well, but it was due to the reason that there were occasional cases where designs with very similar motifs led to minor confusion. In our experience, MobileNetV2 not only provided high accuracy but also demonstrated faster processing times and lower resource demands compared to heavier architectures like VGG16 and ResNet.

Table 4 compares various techniques from the literature with our approach. As shown, our proposed MobileNetV2-based CNN achieves an accuracy of 97.30%, matching or exceeding the performance reported by other studies. Moreover, its compact size of approximately 14 MB makes it ideal for deployment on devices with limited storage, whereas the other models are considerably larger and more resource-demanding. Overall, MobileNetV2's reduced computational requirements ensure greater efficiency and practicality for real-time applications.

Table 3
Performance metrics per province

Province	Precision	Recall	F1-score
Punjab	0.98	0.97	0.97
Sindh	0.96	0.96	0.96
KPK	0.97	0.98	0.97
Baluchistan	0.95	0.96	0.95

5. Conclusion

In this study, MobileNetV2 was used to create a lightweight classification system with the goal of automatically conserving and promoting South Asian, especially Pakistani, embroidery heritage. This model was selected to fill a significant research gap as most of the textile recognition studies only concentrated on fashion or other commercial classification tasks, but only few examine regional embroidery of cultural heritage.

The model was successful in differentiating complex embroidery patterns from Punjab, Sindh, Baluchistan, and Khyber Pakhtunkhwa, by its remarkable 97.3% classification accuracy. One significant issue that occasionally made classification more difficult was the existence of nearly identical motifs in different provinces. However, the system consistently distinguished important stylistic elements, like the geometric mirror-work of Sindh and the dense floral motifs of Punjab.

The model also revealed complex cultural trends. Several times, design elements that are usually associated with one province were seen in samples from another. For instance, some Punjabi designs contained motifs that resembled traditional Pashtun embroidery. These overlaps draw attention to the brittle lines separating regional artistic traditions and allude to past cultural exchanges. These early results suggest that AI-based tools can uncover subtle design influences that are consistent with more comprehensive understandings of shared heritage, even though domain experts were not formally consulted. Validating and enhancing these insights will require future research that incorporates expert opinion.

This project makes three key contributions: (1) it introduces a pioneering, ethically sourced dataset of regional Pakistani embroidery, carefully preprocessed for cultural analysis; (2) it provides a cheap solution that simplify digital preservation; (3) it offers new cultural insights by showing unexpected motif overlaps.

The study's findings show that AI can significantly contribute to the revival and preservation of traditional needlework techniques. The system contributes to the preservation of intangible heritage in the digital age by producing patterns that are stylistically in line with culturally significant motifs. Research and education can benefit from the archiving and use of these created designs in digital libraries. Additionally, by reviving obscure or dwindling designs, they can aid in the revival of crafts by providing artists with fresh inspiration. These AI-generated designs could be used in classrooms to teach embroidery by fusing conventional methods with cutting-edge teaching materials. The practical application of these outputs also extends to creative industries, where culturally inspired designs can be adapted into fashion or home

Table 4
Comparison of other techniques vs our proposed method

Study/Technique	Method used	Accuracy (%)	Refs.
Our proposed method	MobileNetV2-based CNN	97.30	–
Miao batik culture preservation	Improved ResNet34	94.46	[13]
Silk cultural relics	Bezier Curves	93.50	[14]
Heritage of tang dynasty	Augmented Reality Technology	94.46	[15]
Dynasty identification in murals	Adaptive Enhancement Capsule Network	84.44	[16]
Yangxin cloth paste digital twin	Digital Twin & VR Approach	90.00	[17]
Shen embroidery recognition	Improved MobileNetV1 with Spatial Pyramid Pooling	97.26	[18]
Zhuang ethnic clothing classification	Supply–Demand Matching & CNN	90.50	[19]

decor products, promoting economic sustainability while respecting heritage. These approaches offer concrete ways to integrate AI into embroidery protection efforts, ensuring the cultural legacy continues for future generations.

While the model occasionally misidentified designs within provinces, these inaccuracies should not be taken as conclusive proof of cultural interaction or common historical patterns without expert confirmation. Although some visual similarities indicate the possibility of cross-regional artistic influences, such conclusions are speculative. Confirming these cultural patterns would necessitate collaboration with textile historians, anthropologists, and cultural heritage experts, as well as a review of historical evidence that shows motif progression across areas. As a result, the findings given in this paper should be taken as preliminary insights that show the potential of AI models to supplement rather than replace scholarly cultural interpretation. Future research will explicitly include expert evaluation to see whether observed motif similarities correspond to known historical or cultural links.

Also, the collection of data should be enlarged, especially with images from missing regions, to increase accuracy and cultural depth. Additionally, transfer learning and hybrid approaches that incorporate expert input and AI should be used to improve the model. Finally, this research ensures the legacy of ancient embroidery for future generations by improving the complex, overlapping stories built into each stitch.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/ask1999/embroiderydataset.

Author Contribution Statement

Amir Sohail Khan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Junjie Zhang:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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