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Review of Machine and Deep Learning Methods for Phulkari Image Analysis and Classification

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Abstract

Phulkari embroidery, a traditional textile art of Punjab, represents a rich cultural heritage characterized by diverse patterns, motifs, and vibrant color compositions. With the growing interest in digital preservation and intelligent textile analysis, the application of machine learning (ML) and deep learning (DL) techniques has emerged as a promising approach for automated Phulkari image analysis and classification. This review paper presents a comprehensive analysis of existing ML and DL methods used in image processing and pattern recognition, with a focus on their applicability to Phulkari embroidery. It explores various feature extraction techniques such as texture, color, and shape descriptors, along with classification algorithms including Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Naïve Bayes (NB). The study also highlights the role of convolutional neural networks (CNNs) in learning complex visual patterns directly from images, enabling improved accuracy and efficiency in classification tasks. Furthermore, this review identifies key challenges in Phulkari image analysis, such as limited availability of labeled datasets, high intra-class variation, and similarities between different pattern types. By providing a structured analysis of current methodologies and future research directions, this study aims to guide researchers in developing efficient and intelligent systems for Phulkari image recognition and classification.

Keywords: Phulkari Embroidery, Image Classification, Machine Learning, Deep Learning, Pattern Recognition



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1. INTRODUCTION

Phulkari embroidery, a traditional textile art form originating from the Punjab region, is widely recognized for its vibrant colors, intricate stitch work, and rich cultural symbolism. Historically crafted by women, Phulkari represents not only artistic creativity but also the social, emotional, and cultural identity of Punjabi communities. The embroidery features a diverse range of patterns, including floral, geometric, and narrative motifs, each carrying unique meanings and traditional significance.

With the rapid advancement of digital technologies and artificial intelligence, there is a growing interest in applying image analysis techniques to traditional art forms. Machine learning (ML) [1-9] and deep learning (DL) [10-15] have emerged as powerful tools for image classification, pattern recognition, and feature extraction. These techniques have been successfully applied in various domains such as medical imaging, agriculture, and textile analysis. In the context of Phulkari embroidery, ML and DL methods offer the potential to automate the identification and classification of complex patterns, which are otherwise difficult to analyze manually due to their variability and intricate designs. Automated systems can significantly reduce human effort, improve accuracy, and enable large-scale digital documentation of embroidery patterns.

Traditional machine learning approaches rely on handcrafted feature extraction methods, where key visual attributes such as color distribution, texture, and shape are manually derived from images. Algorithms like Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Naïve Bayes (NB) are then used to classify these features into predefined categories. While these methods have shown promising results, they often struggle to capture the complex spatial relationships and fine-grained details present in Phulkari patterns. Additionally, their performance is highly dependent on the quality of feature engineering, which can be time-consuming and requires domain expertise.

In contrast, deep learning techniques, particularly Convolutional Neural Networks (CNNs) [27-46], have revolutionized the field of image analysis by enabling automatic feature learning directly from raw image data. CNNs are capable of extracting hierarchical features, capturing both low-level details such as edges and textures, as well as high-level semantic patterns. This makes them highly suitable for analyzing intricate embroidery designs like Phulkari. Recent advancements in deep learning, including transfer learning and hybrid



models, have further enhanced the capability of these systems, even when working with limited datasets. As a result, deep learning-based approaches have demonstrated superior performance compared to traditional methods in many image classification tasks.

Therefore, this review paper aims to provide a detailed analysis of machine learning and deep learning methods for Phulkari image analysis and classification. It explores various techniques, compares their performance, and highlights their strengths and limitations. Additionally, the study identifies research gaps and suggests future directions for developing more efficient and robust classification frameworks. By bridging the gap between traditional textile knowledge and modern computational techniques, this work contributes to the preservation, analysis, and promotion of Phulkari embroidery in the digital era.

2. REVIEW OF LITERATURE

The existing literature on textile image analysis and pattern classification reveals significant advancements in both machine learning and deep learning approaches. Early studies primarily focused on content-based image retrieval (CBIR) techniques using handcrafted features such as color, texture, and spatial descriptors, combined with classifiers like Support Vector Machines (SVM), which demonstrated improved performance in fabric classification tasks [1]–[5]. Further research explored advanced feature extraction methods, including fractal-based textures, Gabor filters, and PHOG descriptors, to enhance retrieval accuracy for complex textile patterns such as batik and embroidered fabrics [6]–[9]. With the emergence of deep learning, recent studies have shifted towards Convolutional Neural Networks (CNNs), multi-task learning, and deep similarity models, which enable automatic feature extraction and improved classification accuracy [10]–[15]. Hybrid approaches combining transfer learning with handcrafted features have also shown promising results in handling diverse textile datasets [16]. Despite these advancements, challenges such as high computational cost, limited availability of labeled datasets, and difficulty in capturing intricate pattern variations persist. These limitations highlight the need for more efficient and scalable frameworks, particularly for culturally rich and complex embroidery styles like Phulkari.

2.1 Handcrafted Methods based Feature Extraction

Feature extraction using handcrafted methods involves manually designing techniques to capture important visual characteristics from Phulkari images, such as color, texture, and shape. Common approaches include color histograms for capturing color distribution, Gray-



Level Co-occurrence Matrix (GLCM) for texture analysis, Histogram of Oriented Gradients (HOG) for edge and shape detection, and Gabor filters for frequency and orientation information. These features are then used as input to machine learning classifiers like Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbors (KNN) for pattern classification. While these methods are computationally efficient and interpretable, they heavily depend on domain knowledge and may struggle to capture complex and highly detailed variations present in intricate Phulkari embroidery patterns (Table 1).

Table 1: Review of literature on machine learning based Fulkari image classification

Ref.	Method	Key Contribution	Limitation
[1]	SVM, CBIR	Developed a CBIR system for textile classification using SVM with improved accuracy.	Limited to handcrafted features; not scalable for large datasets.
[2]	Geometric Similarity, Feedback	Improved patterned fabric retrieval using geometric similarity and relevance feedback.	Requires user interaction; increases computational complexity.
[3]	Color & Spatial Features	Enhanced retrieval performance using color and spatial descriptors.	Ineffective for complex texture variations.
[4]	Fractal Texture, HSV	Combined fractal texture and HSV color features for better retrieval.	Sensitive to noise and lighting variations.
[5]	Color Moments, GIST	Proposed hybrid feature-based retrieval method.	Limited ability to capture fine-grained patterns.
[6]	Texture Fusion	Improved batik motif recognition using texture fusion techniques.	Computationally intensive feature extraction.
[7]	PHOG Features	Enhanced CBIR performance using shape-based PHOG features.	Ignores color information; partial feature representation.
[8]	Gabor Filters	Used Gabor filters for robust texture-based retrieval.	High computational cost; parameter tuning required.
[9]	Robust Retrieval Methods	Developed a robust system for embroidered fabric retrieval.	Limited generalization across diverse datasets.
[19]	Eigenimage-based	Reduced dimensional features	Limited generalization



	classification		
[20]	Sparse classifier + scattering transform	Texture & frequency features	Limited adaptability
[21]	Naïve Bayes classifier	Statistical features	Low accuracy for complex images
[22]	Feature-based classification	Color & texture features	Limited feature representation

2.2 Automatic Deep Learning–Based Feature Extraction Methods

Automatic feature extraction using deep learning methods, particularly Convolutional Neural Networks (CNNs), eliminates the need for manual feature engineering by learning features directly from raw image data (Table 2). CNNs use multiple layers, including convolutional and pooling layers, to automatically extract hierarchical features ranging from low-level details like edges and textures to high-level representations of complex patterns and motifs. This approach is highly effective for analyzing intricate and diverse Phulkari designs, as it can capture subtle variations and spatial relationships within the patterns. Although deep learning methods require large datasets and higher computational resources, they generally achieve superior accuracy and robustness, making them well-suited for advanced image classification tasks.

Table 2: Review of literature on deep learning-based Fulkari image retrieval and classification

Ref.	Method	Key Contribution	Limitation
[10]	CNN, Hierarchical Search	Proposed a deep CNN-based hierarchical search system for fabric image retrieval with improved efficiency.	High computational cost; requires large dataset.
[11]	Multi-task Learning	Introduced multi-task learning for fabric retrieval, improving feature learning and accuracy.	Complex model design; difficult to optimize.
[12]	CNN-based Feature Extraction	Reviewed CNN-based feature extraction methods for textile retrieval systems.	Limited experimental validation; mostly theoretical.
[13]	Transfer Learning + Handcrafted	Combined transfer learning with handcrafted features for improved wool fabric retrieval.	Hybrid complexity; increased processing time.



	Features		
[14]	CNN	Applied CNN for batik image retrieval, achieving better classification accuracy.	Requires large labeled dataset; training intensive.
[15]	Deep Similarity Learning	Proposed deep similarity models using ranking techniques for fabric retrieval.	Sensitive to ranking strategy; training complexity.
[16]	Modified CNN (CBIR)	Developed a CNN-based CBIR system for traditional woven fabrics with improved retrieval performance.	Limited generalization across diverse textile types.
[17]	PCA-based Feature Descriptor	Used joint local PCA-based features for textile image retrieval.	May lose fine-grained details; dimensionality reduction issues.
[18]	Deep Learning-based CBIR	Applied deep learning features for CBIR, improving retrieval accuracy.	Requires high computational resources and training data.
[23]	GAN + Vision Transformer	Augmented deep features	High computational cost
[24]	DL + Knowledge Graph	Semantic + visual features	Complex implementation
[25]	CNN Fine-tuning	Deep visual features	Overfitting risk
[26]	Multi-scale Attention CNN	Attention-based features	High training time

3. COMPARATIVE ANALYSIS

The comparative analysis of machine learning, deep learning, transfer learning, and ensemble approaches reveals distinct performance characteristics in image classification tasks. Traditional machine learning methods, such as SVM and Naïve Bayes, rely on handcrafted features and offer lower computational complexity but achieve only moderate accuracy. In contrast, deep learning models, particularly CNN-based architectures, provide significantly higher accuracy due to their ability to automatically learn complex features, though they require large datasets and substantial computational resources. Transfer learning techniques further enhance performance by leveraging pre-trained models, making them effective for smaller datasets, but may suffer from domain adaptation issues. Ensemble and hybrid approaches combine multiple models or feature sets, resulting in improved accuracy and robustness;



however, they introduce increased system complexity and computational overhead. Overall, deep learning and ensemble methods demonstrate superior performance, making them more suitable for complex pattern classification tasks such as Phulkari image analysis.

Table 3: Comparative analysis of Phulkari image analysis and classification techniques

Approach	Algorithms	Feature Type	Accuracy Level	Advantages	Limitations
Machine Learning	SVM, KNN, Naïve Bayes	Handcrafted (color, texture, shape)	Moderate	Simple, low computational cost	Depends on feature engineering, lower accuracy
Machine Learning	Sparse Classifier	Statistical + texture features	Moderate	Efficient for small datasets	Limited scalability
Deep Learning	CNN	Automatic deep features	High	High accuracy, robust feature learning	Requires large dataset, high computation
Deep Learning	Attention-based CNN	Multi-scale deep features	High	Captures complex patterns	High training time
Deep Learning	GAN + Transformer	Augmented deep features	Very High	Improves data diversity	Complex training, unstable
Deep Learning	YOLO-based models	Spatial features	High	Fast detection	Not ideal for classification tasks
Transfer Learning	ResNet, VGG (fine-tuned)	Pre-trained deep features	Very High	Works well on small datasets	Domain mismatch issues
Transfer Learning	Feature Fusion Models	Hybrid features	High	Improves accuracy	Increased complexity
Ensemble Learning	Fusion-based methods	Combined features	Very High	Better generalization	High computational cost
Ensemble Learning	DL + Knowledge Graph	Semantic + visual features	Very High	Context-aware learning	Complex implementation
Hybrid Models	CNN + LSTM	Spatial + temporal	High	Captures sequential	Complex architecture



		features		patterns	
Self-Supervised Learning	Contrastive learning	Representation learning	Moderate –High	Reduces labeling effort	Requires careful tuning

4. RESEARCH CHALLENGES

The classification of Phulkari patterns using machine and deep learning techniques presents several significant challenges due to the intricate nature of the embroidery and variability in data. One of the primary challenges is the high intra-class similarity and inter-class variability among patterns, where different Phulkari types often share similar motifs, colors, and geometric arrangements, making it difficult for models to distinguish between them accurately. Additionally, the lack of a standardized and publicly available Phulkari dataset limits the development and benchmarking of robust models. Most available datasets are small, unbalanced, or collected under uncontrolled conditions, leading to poor generalization.

Another major challenge lies in the complexity of texture and color patterns, as Phulkari embroidery involves dense stitching, reflective silk threads, and vibrant color combinations that vary under different lighting conditions. This introduces noise, illumination variations, and background interference in images, affecting feature extraction and classification accuracy. Furthermore, traditional machine learning methods rely heavily on handcrafted features, which may fail to capture the deep structural and semantic characteristics of Phulkari designs. On the other hand, deep learning approaches, although powerful, require large labeled datasets, high computational resources, and careful parameter tuning, which may not always be feasible. Lastly, the absence of real-time classification systems and domain-specific models tailored specifically for Phulkari further complicates practical deployment in cultural preservation and textile industries.

5. RESEARCH GAP

Despite the growing advancements in image classification using machine learning and deep learning, there exists a notable research gap in the domain of Phulkari pattern recognition and analysis. Most existing studies focus on general textile or fabric classification, with very limited work specifically addressing the unique characteristics of Phulkari embroidery, such as its symbolic motifs, geometric symmetry, and cultural semantics. Moreover, current approaches often emphasize either handcrafted feature-based machine learning methods or



deep learning techniques independently, without effectively exploring hybrid frameworks that combine the strengths of both approaches.

Another critical gap is the absence of a well-annotated, large-scale Phulkari image dataset, which is essential for training robust deep learning models. Existing works also lack comprehensive comparative evaluations across different algorithms, making it difficult to determine the most suitable approach for Phulkari classification. Additionally, there is limited research on transfer learning and ensemble techniques specifically applied to Phulkari patterns, which could potentially improve classification accuracy and efficiency. Furthermore, most current models do not address real-world challenges such as varying lighting conditions, fabric distortions, and occlusions, leading to reduced performance in practical scenarios. Therefore, there is a strong need to develop an efficient, robust, and scalable machine learning-based framework that can accurately classify diverse Phulkari patterns while preserving their cultural significance.

6. CONCLUSION

The present study highlights the growing significance of machine learning and deep learning techniques in the domain of textile image analysis, with a particular focus on Phulkari pattern classification. Through a comprehensive review and comparative analysis, it is observed that traditional machine learning approaches, while computationally efficient, are limited by their dependence on handcrafted features and relatively lower accuracy. In contrast, deep learning models, especially convolutional neural networks, demonstrate superior performance by automatically extracting complex visual features from intricate embroidery patterns. Furthermore, transfer learning and ensemble methods have shown promising results in enhancing classification accuracy and robustness, particularly in scenarios with limited data availability. These advancements indicate the strong potential of intelligent systems in automating the recognition and preservation of culturally significant art forms like Phulkari. Despite these advancements, several challenges and research gaps persist, including the lack of standardized datasets, high variability in patterns, and the need for computationally efficient models suitable for real-world applications. The study emphasizes the necessity of developing hybrid frameworks that integrate the strengths of both machine learning and deep learning techniques to achieve improved performance. Future research should focus on creating large-scale annotated datasets, optimizing model architectures, and designing real-time classification systems. Such efforts will not only enhance the accuracy and efficiency of



Phulkari pattern classification but also contribute to the digital preservation and global recognition of this rich cultural heritage.

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