Deep Learning Based Classification of Pashmina Fabric

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Abstract

This research presents a novel application of deep learning in the field of textile classification, specifically focusing on pashmina fabrics distinguished by their embroidery and designs. Leveraging the ResNet-50 architecture, we developed a deep-learning model capable of accurately classifying six distinct categories of pashmina fabrics. Our experiment utilised a dataset comprising 1585 images. The test set, comprising randomly chosen 10% of the overall dataset was utilised to evaluate the model's performance, resulting in a classification accuracy of 92.60%. This study highlights the effectiveness of deep learning techniques in automating the classification of pashmina fabrics, which would be helpful in the textile industry.

Keywords: Fabric, Pashmina, Artificial Intelligence, Deep Learning

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1. Introduction

Pashmina fabrics, renowned for their luxurious softness and intricate designs, are a cornerstone of South Asian textile heritage. A diverse array of pashmina apparel is available in the market, each characterised by unique textures, patterns and designs [1][2]. Identifying and classifying different types of pashmina apparel based on their embroidery and design patterns has traditionally relied on the expertise of seasoned artisans, a process often subjective and time-consuming. Recent years have seen a surge of interest in the applications of deep learning for the classification of apparel. One of the key motivations behind this research is the increasing demand for automated and efficient clothing recognition systems in various domains, such as fashion retail, e-commerce, and image-based recommendation systems. Several studies have investigated the use of deep learning models, particularly convolutional neural networks, for image classification tasks [3], [4], [5]. These models have demonstrated impressive performance in accurately categorising and classifying images based on their visual features. Deep learning has gained significant such attention due to its ability to learn hierarchical features from input data.

With the advent of deep learning, however, there arises an opportunity to automate and streamline the textile classification process. This research presents a deep learning model for the automated classification of pashmina apparel based on their embroidery and design. Utilising the powerful ResNet-50 [6] architecture, a prominent convolutional neural network (CNN) known for its effectiveness in image classification tasks, we trained and tested our model on a comprehensive dataset of 1585 images encompassing six distinct categories of pashmina fabrics. By leveraging deep learning to extract and learn inherent features from complex visual patterns, we aimed to achieve accurate and objective classification of pashmina fabrics, ultimately aiding in efficient management and market evaluation of pashmina products.

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2. Dataset and Preprocessing

We used pashmina datasets comprising a total of 1585 high-resolution images representing six distinct categories of pashmina apparel: Embroidered (568 images), Kani (313 images), Ombre (80 images), Patterned (211 images), Reversible (132 images), and Solid (311 images). To prepare the dataset for model training, several preprocessing steps were implemented. Firstly, all images were uniformly scaled to a standard dimension of 224x224 pixels to ensure consistency in input size across the dataset. Subsequently, images of low quality or containing irrelevant content were removed to maintain data integrity. Additionally, the ability of the models to generalise on variations of input data, the dataset was diversified by applying affine augmentation techniques including zooming, rotations and flipping. The augmented dataset was then partitioned into training, validation, and testing sub-datasets following a ratio of 70:20:10 respectively. This partitioning scheme enables effective model training, hyperparameter tuning, and unbiased evaluation of unseen data. Through these preprocessing steps, the dataset was optimised to facilitate accurate and robust classification of pashmina fabrics based on their distinctive embroidery and designs.

3. Methodology

Deep learning models have gained significant attention and success in image classification and other computer vision. Particularly, Convolutional Neural Networks have been extremely successful in this area due to their ability to automatically learn hierarchical features from raw image data. Our methodology employed a CNN-based approach for feature extraction and classification of pashmina fabrics. The input to our CNN model consisted of images resized to a standard dimension of 224x224 pixels with three colour channels. Within the CNN architecture, convolutional operations were performed to extract distinctive features from the input images. Rectified Linear Unit (ReLU) activation functions were applied to introduce non-linearity and enhance the model's capacity to capture complex patterns inherent in the data. Pooling operations were incorporated to downsample feature maps, thereby reducing computational complexity and enhancing the model's ability to generalise across different input variations [7]. The extracted features were subsequently fed into a customised Feed-Forward Neural Network (FFNN) for classification (see Figure 2). At the final layer of the FFNN, a softmax function was employed to compute the probabilities of each input image belonging to one of the predefined categories of pashmina fabrics.

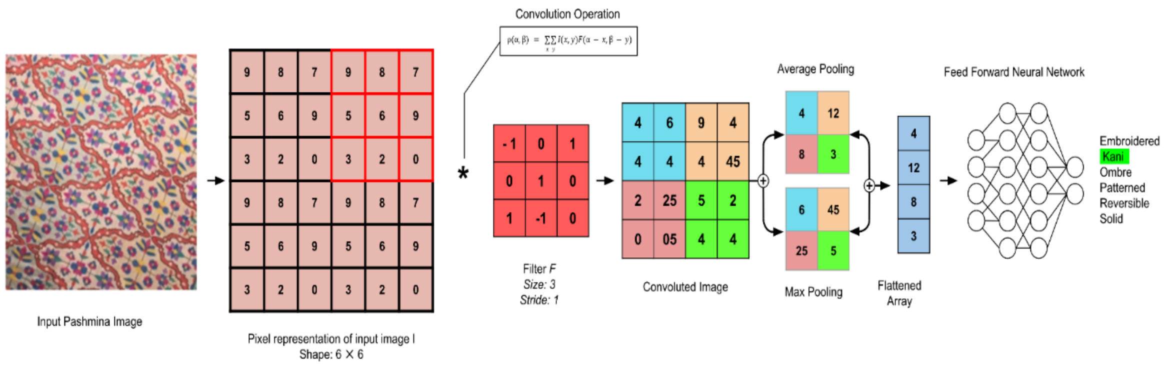

Figure 1: Convolutional Neural Networks (CNN) for Pashmina Embroidery classification

To accelerate model training and utilise pre-existing knowledge, we adopted the transfer learning technique. Specifically, we utilised the ResNet50 architecture, a renowned CNN architecture known for its depth and efficacy in image recognition tasks. Transfer learning enabled us to leverage the learned representations from the ResNet50 model, which had been trained on the ImageNet dataset, and fine-tune its parameters to suit our classification task of pashmina fabrics. By integrating these methodological components, our approach aimed to utilize the deep learning and transfer learning paradigms for the effective classification of pashmina fabrics based on their intricate embroidery and designs.

In our experimental setup, we configured the hyperparameters and training procedures to optimise the performance of our deep learning model for classifying pashmina fabrics. The learning rate was initialised at 0.001 and the decay was to be a factor of 20 after each epoch, ensuring gradual convergence towards an optimal solution. We employed the RMSprop optimizer, renowned for its effectiveness in adapting learning rates to individual parameters, thereby facilitating more efficient and stable convergence during training. With a batch size of 36, we made a balance between computational efficiency and model convergence. Our model underwent rigorous training over 100 epochs, allowing it to iteratively refine its parameters and learn intricate patterns within the dataset.

4. Results and Discussion

achieving an overall classification accuracy of 92.60% on the testset (10% of the overall dataset), the results of the experimentation show the impressive performance of our model in classifying different categories of pashmina fabrics. Throughout the training process, we observed a consistent trend wherein the model's accuracy continued to improve, while the training loss steadily decreased across epochs. This trend signifies that the model iteratively learned from the dataset, progressively enhancing its performance and refining its ability to classify pashmina fabrics, as illustrated in Figure 3 accurately.

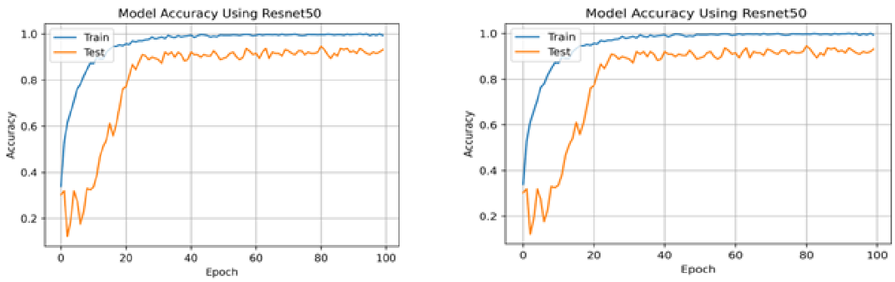

Figure 2: The iterative improvement of the model's accuracy and reduction in training loss across epochs

The test set, comprising 10% of the total dataset with 311 samples utilised for evaluating the model's predictive capabilities. The predictions generated by our model were further analysed and presented in a confusion matrix (see Figure 4), providing insights into the distribution of predicted labels across the different pashmina categories.

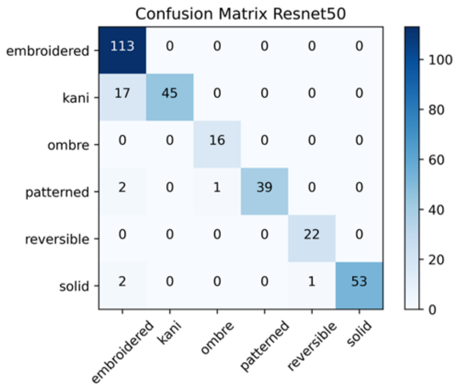

Figure 3: The distribution of predicted labels across various pashmina categories through a confusion matrix

To demonstrate a comprehensive assessment of the model's performance across individual categories, we have used the evaluation metrics of precision, recall, and F1-score offer as summarised in Table 1.

Table 1. Precision, Recall and f1-score of the classifier

Name	Precision	Recall	F1-Score
Embroidered	0.84	1.00	0.91
Kani	1.00	0.73	0.84
Ombre	0.94	1.00	0.97
Patterned	1.00	0.93	0.96
Reversible	0.96	1.00	0.98
Solid	1.00	0.95	0.97
Average	**0.96**	**0.94**	**0.94**

The precision scores indicate the proportion of correctly predicted instances within each category, with particularly high precision values observed across all categories, notably for Kani, Ombre, Patterned, Reversible, and Solid pashmina fabrics. Similarly, the recall scores reflect the ability of the model to correctly identify instances belonging to each category. The F1-score, provides a balanced measure of the model's performance, by calculating the harmonic mean of precision and recall, exhibiting consistently high values across all categories. These results underscore the robustness and reliability of our model in accurately classifying diverse pashmina fabrics based on their unique embroidery and designs. The model's exceptional performance, as evidenced by its high classification accuracy and comprehensive evaluation metrics, holds significant implications for the textile industry, offering a promising avenue for automating and enhancing the classification process of intricate textile patterns.

5. Discussion and Conclusion

This research presents a deep model to classify pashmina fabric designs using the ResNet-50 architecture. The results demonstrate that the classification process of pashmina fabric can be automated using deep learning with high accuracy, offering valuable insights for applications in the fashion industry and textile manufacturing sector. Future research endeavours could explore the integration of additional deep learning architectures and ensemble methods to further enhance classification performance. The development of real-time classification systems and integration with production workflows could streamline quality control processes and contribute to the advancement of smart textile manufacturing.

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