

Deep Learning Approaches for Automatic Recognition of Textile Weave Structures

*Pugazhenthir T.¹ & Pravin P Chavan.²

¹National Institute of Fashion Technology, Textile Design Department, Kannur, Kerala, India

²National Institute of Fashion Technology, Knitwear Design Department, Kannur, Kerala, India

DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150600060>

Received: 14 June 2026; Accepted: 19 June 2026; Published: 06 July 2026

ABSTRACT

The Fabric weave structure is an essential component in the design and manufacture of premium fabric. The structure or pattern used in the fabric's weaving significantly impacts its overall appearance, texture, durability, and drape. Traditional methods of Weave pattern recognition are relied heavily on manual visual inspection, which is time-consuming, prone to human error, struggles with complex patterns and sensitive to lighting conditions. Therefore, an automated system is necessary for the classification of woven cloth to improve production efficiency. In this paper we proposed a deep learning model particularly Transfer Learning model that employs data augmentation and transfer learning methods for the classification and identification of woven textiles and compared with other models. The model uses a MobileNet-V2 to autonomously extract and categorize fabric texture features in an end-to-end fashion. The model is trained using a custom dataset with various weave types, including plain, twill and satin. The experimental findings indicate that the suggested model is resilient and attains cutting-edge precision. We compared our findings with other baseline methods, demonstrating that the suggested technique attained superior accuracy when accounting for rotational orientations in fabric and appropriate illumination conditions.

Keywords: Deep learning, MobileNet-V2, Pattern recognition, ResNet-50, Transfer learning, Woven fabric

INTRODUCTION

Pattern recognition in weaving is an essential function within the textile industry, influencing fabric quality, design, and manufacturing efficiency. It is regarded as a crucial process prior to fabric production. The importance of classifying textile weave patterns stems from its considerable influence on fabric aesthetics, textural evaluation, and design modification. Conventional methods for weave categorization rely heavily on manual visual evaluation, which is laborious and prone to human error. This approach may lead to discrepancies, especially when dealing with complex patterns (Das et al., 2022). Some traditional methods are very dependent on controlled lighting conditions.

Fluctuations in lighting can markedly influence the precision of texture analysis and pattern identification (Akram et al., 2024; Kuo et al., 2010). Certain conventional techniques necessitate the physical extraction of yarns from the fabric to examine the weave pattern, which may compromise the fabric and is inappropriate for non-destructive testing (Sabuncu et al., 2016; Kuo et al., 2016). Conventional techniques frequently encounter challenges regarding precision and consistency, especially when addressing complex or non-repetitive weaving patterns. These approaches may inadequately capture the nuanced differences in fabric textures, resulting in misclassification (Kuo et al., 2010; Meng et al., 2020). To enhance the efficiency of textile production, numerous researchers have dedicated themselves to employing image processing and artificial intelligence technologies for the automatic identification of weave patterns. Over the years, various image processing techniques have been developed to automate this process, reducing reliance on manual inspection and improving accuracy.

METHODS

CONVOLUTIONAL NEURAL NETWORKS ARCHITECTURE (CNN)

CNNs have emerged as a powerful tool for fabric weave pattern recognition. These deep learning models excel in identifying patterns in textile images due to their ability to learn hierarchical features directly from data. Several studies have utilized CNNs for this purpose. A basic CNN model was used to classify three textile weave patterns (plain, twill, and satin) with an average accuracy of 72%. However, the model performed differently across patterns, achieving 100% accuracy for plain weave but only 50% for satin weave (Pasha et al., 2024).

VGG16 Model

A modified VGG16 model with additional pooling layers was proposed to improve accuracy and reduce computational requirements. This model achieved 90% accuracy and an F1-score ranging from 0.8 to 1 (Akram et al., 2024).

Resnet Architecture

Rauf et al. (2022) used ResNet, a pre-trained CNN architecture, in combination with texture features extracted via the gray-level co-occurrence matrix (GLCM) and Gabor wavelets, achieving a high accuracy of 96.15%. CNNs have proven to be highly effective for texture-based classification tasks, though their performance can vary depending on the complexity of the weave patterns and the quality of the training data.

Transfer Learning

The choice of pre-trained model architecture significantly impacts the accuracy of textile weave pattern classification using transfer learning, as evidenced by various studies. DenseNet121, for instance, has been shown to achieve high accuracy in classifying woven fabric patterns, with a reported accuracy of 92.58% and a loss of 29.62%, outperforming other model such as MobileNetV2 in specific applications (Maur et al., 2023). The model's efficiency is attributed to its compact size and effective feature propagation, making it suitable for mobile applications.

Proposed Model

We designed our deep learning model as a pipeline based approach which includes basic CNN and MobileNet-V2 model. The pipeline was structured to have a certain number of phases, with the first stage including the fabric images and the last stage encompassing the model categorization. The output of one step served as the input for the subsequent stage. The planned pipeline is seen in Figure 1 and delineated as follows:

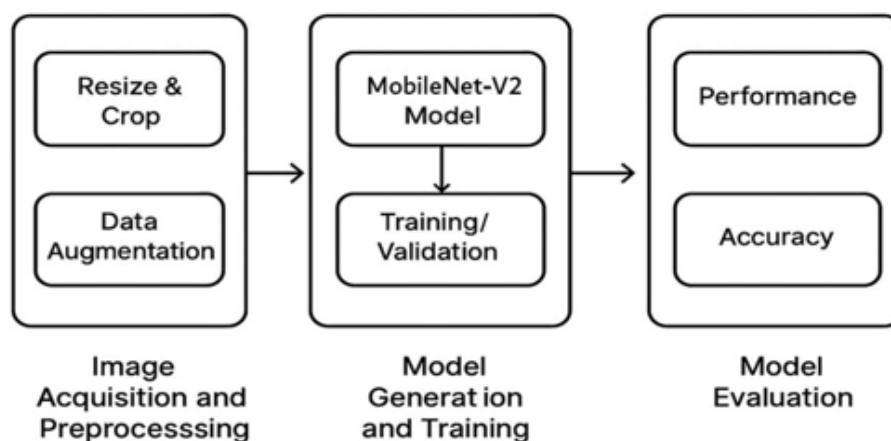


Figure 1. Proposed pipeline approach.

Data Collection and Preprocessing

The woven fabric images were collected into a database and stored as 2 dataset namely training and testing. The data set needed appropriate conversions, image resize and preprocessing for training and testing the data. As the number of images is still a relatively small, it is important to expand the dataset and we applied some augmentation methods to expand the data set to help the model have a good generalization, achieve the better identification.

Model Generation and Training

A learning method that processes input data that mapped to characteristics corresponding to the goal and predict the output class is referred to as a model. We used the MobileNet-V2 architecture for our model. During the training process, the initial convolutional layers were left alone, and only the custom layer linked to the base network was trained.

Model Evaluation

Our proposed model is evaluated across a range of performance metrics including accuracy, balanced accuracy, precision, recall, and F1-score.

Dataset

The model was trained and tested on a Digital Microscope with Camera Endoscope 8-LED Light Magnifying Glass Magnifier (1000× zoom) of woven fabric texture images. Total 1182 images have been taken for three kinds of fabrics which includes 532 images for Plain cloth, 504 images for Twill and 146 images for Satin. Of total 1182 images, 20% images are used as validation images and remaining 80% images are as train images. where 80% and 20% from 1182 images means 946 images are as training image and 236 images from total 1182 are as validation images.

Preprocessing

During preprocessing, each image is first converted from RGB (color) to grayscale so that the model learns the fabric weave pattern instead of the color. The grayscale image is then converted back to a 3-channel image because MobileNet requires a 3-channel input. Finally, the pixel values are normalized to the range -1 to 1, which helps the model train more effectively. The same preprocessing steps are applied to both the training and validation datasets to ensure consistency.

According to Shorten and Khoshgoftaar (2019), data augmentation is a group of methods that make training datasets larger and more diverse, thereby improving deep learning model performance. Hussain et al. (2020) reported that the limitation of a small training dataset can be addressed through data augmentation techniques. Data augmentation applies various transformations, including zoom in, zoom out, scaling, skew, flip, and intensities to the whole dataset to obtain a diverse set of images thereby enlarging the dataset

Deep learning models perform particularly well when trained on large datasets. Data augmentation increases the size of the training dataset, enabling the model to learn more effectively. Data warping techniques generate additional samples by applying various transformations to the original data, thereby enhancing the diversity of the training set (Wong et al., 2016).

This process helps reduce overfitting and improves the model's generalization capability without altering the underlying data characteristics. In this study, several augmentation techniques were applied to the images, including horizontal and vertical flipping, shifting, rotation, zooming, shearing, and brightness adjustment.

RESULTS AND DISCUSSION

The MobileNet transfer learning framework, that was discussed about earlier, was used to build our model for classifying the images. The proposed pre-trained transfer learning model, MobileNet-V2, classifies woven fabric images into three categories. The quantity of training and testing images in the woven fabric dataset, after augmentation, has been elevated to 1182. This article utilizes 80% of the training images (946) for model training, while the remaining 20% (236) is designated as a validation subset to assess the model during data training. The deep learning model's performance was evaluated using the test set.

Experimental Framework

Initially, all woven fabric images were resized to 224×224 pixels. MobileNetV2 was selected as the base model because of its lightweight architecture and reduced number of parameters. The pretrained MobileNetV2 model was trained using the woven fabric dataset presented in this study. In the first modification, the last two dense layers of the original MobileNetV2 architecture were removed and replaced with customized dense layers. Transfer learning was employed to train the newly added layers while keeping the weights of the remaining layers frozen. Freezing these layers helped accelerate convergence and prevented gradient explosion during training. In the second modification, to reduce overfitting, the final dense layer was retrained using additional data, and a dropout layer was inserted between the last two dense layers (Mahanta et al., 2024).

A global average pooling layer followed by batch normalization, two fully connected layers, and two dropout layers were stacked on the base network. The dense layers contained 128 and 64 neurons, respectively. Each fully connected layer employed a ReLU activation function, while dropout was used to prevent the network from relying excessively on specific neurons and to encourage the learning of more robust and generalized features (Mahanta et al., 2024).

The training efficiency and stability of the pre-trained model were further enhanced through the incorporation of batch normalization layers (Hidajat et al., 2025). In addition, the combination of global average pooling and dropout layers helped mitigate overfitting. By randomly deactivating redundant neurons during training, the dropout layers improved the model's generalization performance. Overfitting is a common challenge in deep learning architectures, often resulting in poor performance on unseen test data. Finally, a Softmax layer was employed as the output layer to classify woven fabric images into three categories. A high-level architecture of the customized deep learning model is presented in Figure 2.

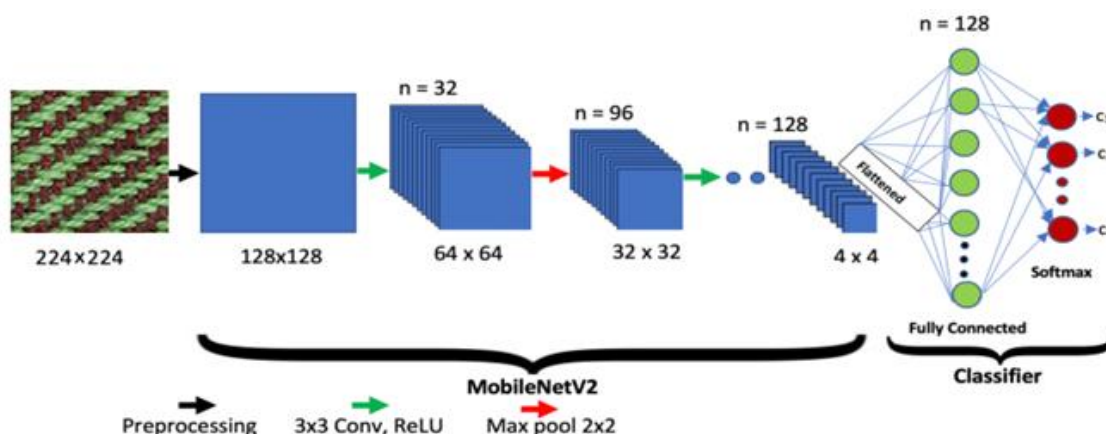


Figure 2. Architecture of the Proposed Model

After feature selection, classification was performed for predicted class against actual class. The model under consideration had an optimizer (the optimizer to train the parameters, here Adam) and a loss function for stochastic optimization. The learning rate was initialized to 0.0051. The dropout proportions for the two dropout layers were set to 0.550. The batch size was set to 32.

Result

The model was trained and tested on a Digital Microscope with Camera Endoscope 8-LED Light Magnifying Glass Magnifier (1000× zoom) for extraction of woven fabric texture images. The model was implemented in Python 3.9 with Keras serving as a frontend and a Tensorflow backend.

Evaluation Metrics

Accuracy is the primary metric used to measure the performance of a classification model. It represents the percentage of correctly classified instances out of the total instances.

Higher accuracy in a model indicates reliability, while large accuracy in an imbalanced dataset suggests bias favoring the class with more images. The confusion matrix was calculated to visualize the model's predictions on test data and understand the total number of correctly and misclassified images, with rows and columns presented in Figure 3.

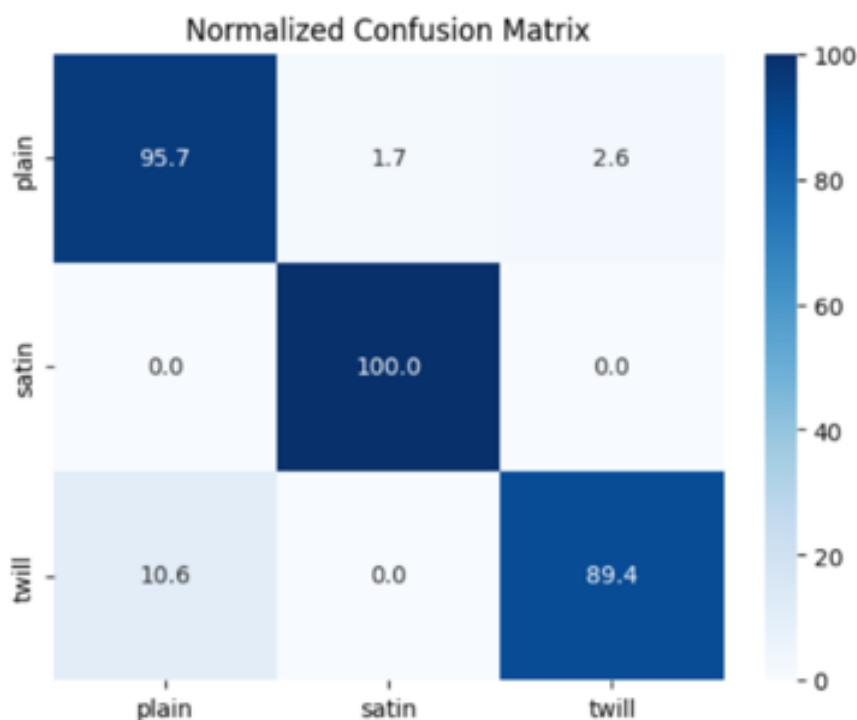


Figure 3. Architecture of the Proposed Model

Table 1. Precision, recall, and F1-score

Name of the weave	Precision	Recall	F1-score	Support
Plain	0.92	0.96	0.94	115
Satin	0.95	1	0.97	36
Twill	0.96	0.89	0.93	85

The precision, recall, and F1-score of the proposed model were averaged over the test set. Performance analysis of these values in terms of each class is shown in Table 1. Average precision, recall and F1-score were 94.66 %.

DISCUSSION

In previous works, researchers proposed methods that employed traditional machine learning models with hand-crafted features, in a way being more laborious and time-consuming.

Akram et al. (2024) employed a modified VGG-16 algorithm to extract image features and classify various kinds of woven fabrics. Their proposed method achieved an accuracy of 90%. Xiao et al. (2018) proposed another method based on Transform Invariant Low-rank Textures (TILT) and Histogram of Oriented Gradients (HOG), achieving an accuracy of 94.57% in identifying woven fabric patterns. However, these methodologies were developed using datasets containing a limited number of images. The authors did not account for physical factors such as yarn diameter variation, fabric deformation, fabric rotation during image acquisition, uneven illumination, and other real-world imaging conditions.

With our proposed model, we were able to achieve validation accuracies far superior to random guessing, providing us with confidence in its effectiveness for our classification task. Furthermore, the data augmentation techniques increased the diversity of the available data, and as a result, improved the overall performance of the model. The computational efficiency of this model also made it ideal for deployment in real-world scenarios, as it minimized processing time and resource usage. Overall, our decision to use our own custom model proved to be the right one, as it outperformed the pretrained architectures in every aspect important to our project's success.

A MobileNet-V2 architecture (MobileNet-V2)-based pretrained convolutional neural network (CNN) model was employed as a deep model. The woven fabric images that we had developed were utilized by the proposed model to execute end-to-end fabric feature extraction and classification.

CONCLUSIONS

In this paper, we proposed a customized deep learning model for the recognition and classification of woven fabrics. The MobileNet-V2 model clearly outperforms the CNN in the categorization and identification of fundamental fabric images, including plain, twill and satin. A survey of the current literature indicates that many authors have contributed to the case study of deep learning in fabric categorization. The primary justification for endorsing convolutional neural networks (CNN) is the inadequate assessment of fabric by traditional manual visual techniques, which are inefficient and unlikely to be sustainable in the long term within industrial and textile sectors. The MobileNet-V2 method effectively reduces computing costs by extracting essential information throughout the training phase following the addition of additional layers. The experimental findings indicate that the MobileNet-V2 algorithm outperforms others in accuracy, speed, initial learning rate, and dropout rate.

REFERENCES

1. Das, S., Das, S. K., Shanmugaraja, K., & Shanmugaraja, K. (2022). Application of artificial neural network in determining the fabric weave pattern. *Zaštita Materijala*. <https://doi.org/10.5937/zasmat2203291d>
2. Akram, N., Butt, R. A., & Qureshi, M. A. (2024). Modification of a convolutional neural network for the weave pattern classification. *Mehran University Research Journal of Engineering and Technology*. <https://doi.org/10.22581/muet1982.2998>
3. Kuo, C.-F. J., et al. (2010). Application of computer vision in the automatic identification and classification of woven fabric weave patterns. *Textile Research Journal*. <https://doi.org/10.1177/0040517510373630>
4. Sabuncu, M., Sabuncu, M., Özdemir, H., & Özdemir, H. (2016). Recognition of fabric weave patterns using optical coherence tomography. *Journal of The Textile Institute*. <https://doi.org/10.1080/00405000.2015.1114791>
5. Kuo, C.-F. J., Shih, C.-Y., Huang, C.-C., Su, T.-L., & Liao, I.-C. (2016). A novel image processing technology for recognizing the weave of fabrics. *Textile Research Journal*, 86(3), 288–301. <https://doi.org/10.1177/0040517514549982>
6. Meng, S., et al. (2020). A multi-task and multi-scale convolutional neural network for automatic recognition of woven fabric pattern. *Journal of Intelligent Manufacturing*. <https://doi.org/10.1007/s10845-020-01607-9>
7. Pasha, Q., Akram, N., Rafique, A., Akber, A., & Abbasi, M. (2024). An automated model for fabric weave pattern recognition and classification using deep learning based image processing. In 2024 Global Conference on Wireless and Optical Technologies (GCWOT). IEEE. <https://doi.org/10.1109/GCWOT63882.2024.10805736>
8. Rauf, M. A., et al. (2022). Fabric weave pattern recognition and classification by machine learning. In 2022 2nd International Conference of Smart Systems and Emerging Technologies (SMARTTECH). IEEE. <https://doi.org/10.1109/SMARTTECH54121.2022.00026>
9. Maur, Y. E. H., Santoso, A., & Pranowo. (2023). Fine tuned DenseNet121 to classify NTT weaving motifs on mobile application. *International Journal on Advanced Science, Engineering and Information Technology*. <https://doi.org/10.18517/ijaseit.13.6.18314>
10. Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6(1), 60. <https://doi.org/10.1186/s40537-019-0197-0>
11. Hussain, M. A. I., Khan, B., Wang, Z., & Ding, S. (2020). Woven fabric pattern recognition and classification based on deep convolutional neural networks. *Electronics*, 9(6), 1048. <https://doi.org/10.3390/electronics9061048>
12. Wong, S. C., Gatt, A., Stamatescu, V., & McDonnell, M. D. (2016). Understanding data augmentation for classification: When to warp? In 2016 International Conference on Digital Image Computing: Techniques and Applications (DICTA) (pp. 1–6). IEEE. <https://doi.org/10.1109/DICTA.2016.7797091>
13. Mahanta, L. B., Mahanta, D. R., Rahman, T., & Chakraborty, C. (2024). Handloomed fabrics recognition with deep learning. *Scientific Reports*, 14(1), 7974. <https://doi.org/10.1038/s41598-024-58750-z>
14. Hidajat, M. S., Wibowo, D. A., & Mintorini, E. (2025). Performance comparison of machine learning algorithms for ikat weaving classification. *KINETIK*. <https://doi.org/10.22219/kinetik.v10i1.2059>
15. Xiao, Z., et al. (2018). Automatic recognition of woven fabric pattern based on TILT. *Mathematical Problems in Engineering*, 2018, 1–12. <https://doi.org/10.1155/2018/9707104>