

# Machine Learning for Fabric Type Recognition in Sewing Processes

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**Abstract:** This scientific article presents an artificial intelligence system for the automatic identification of types of fabric in the garment industry. The system differentiates between six categories of materials: cotton, polyester, silk, wool, denim and mixed fabrics. The development of the system was based on the pre-training neural network VGG16, which was modified to fit the data of textiles. On the other hand, actual production situations were taken into consideration, e.g. variable lighting in workshops, varied material textures. To train the system, a data set of 540 images was created, each of which were created under different illumination and in different angles to improve the reliability of the recognition. The training process consisted of three different stages. First of all, it was necessary to configure the classifier for the particular categories of fabric. Subsequently, further layers of neural network were unfrozen for subsequent further tuning. In the last stage, the entire network went through retraining. Consequently, the accuracy of the recognition achieved 95.8%. The researchers also tested light versions of the system, with different architectures available, on a Raspberry Pi 4 mini computer. This way we were able to determine the best balance between accuracy of recognition and speed of real-time operation. The results showed neural networks are capable of recognising fabrics at an almost human level. At the same time, the system can be optimised to operate on small devices directly in the sewing workshops. Thus work that combines scientific developments, practical applications into industrial use and opens the way to full automation of sewing production.

## 1 INTRODUCTION

### 1.1 Background and Motivation

Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision (CV) technologies are transforming the textile and apparel manufacturing industry at a fast pace. These innovations include automated defect detection of fabric and pattern recognition and quality control applications, resulting in high efficiency and accuracy. Visual inspection is still a laborious and human error-prone routine process; however, at the same time deep Convolutional Neural Networks (CNNs) have attained state-of-the-art performance in defect classification and texture recognition [1]-[3].

### 1.2 Smart Manufacturing on System Level

Cyber-Physical Systems (CPS) and Internet of Things (IoT) architecture implementations have been hastened to textile manufacturing industries due to the advent of Industry 4.0 [4]-[6]. Modern sewing and finishing sections are equipped with sensor-integrated machines that can provide real-time control over the thread tension, stitch quality and energy consumption [4]. Some of these developments enable predictive maintenance, adaptive control, and optimization-based decision making within various stages of production using data.

In addition, robotic assembly technology is being improved by using dual-arm manipulators mounted on fixtures, and by high-speed fabric edge detection techniques that combine dual-arm manipulators with fixture-free operation [7]. These developments show

the trend towards convergence of mechanical automation and AI enabled perception is continuing.

### 1.3 Deep Learning in the Fabric Inspection Process

Recent research has shown that hybrid Convolutional Neural Network (CNN) architectures like VGG16, ResNet50, and MobileNetV2 can accurately model fine-grained fabric patterns [8] - [10]. These results demonstrate that transfer learning facilitates the efficient adaptation of pre-trained ImageNet weights to domain-specific textile datasets, thereby significantly decreasing training duration. Lightweight models have also been successfully used on embedded platforms like the Raspberry Pi 4, where they can make real-time inferences that are useful for in-plant inspections [9], [10]. Experimental systems have demonstrated classification accuracies surpassing 95% with inference latencies under one second per frame [9], validating that deep learning-based frameworks can fulfill industrial performance standards.

### 1.4 AI, Sustainability, and Next Generation Textiles

Sustainability is now one of the essential factors of textile innovation. Manufacturing process design with the assistance of AI is one of the ways to support material circularity, energy efficiency, and waste reduction [6], [11]. Empirical research has shown that the combination of predictive analytics and smart materials with recycled fibres at the same time enhances economic as well as environmental performance [11]. Recently, advances in tactile sensing (i.e. piezoelectric PVDF-based texture sensors) mimic human touch to quantify surface micro-structures to complement vision-based

techniques [12]. These sensors when coupled with convolutional neural network classifiers represents a gradual step to multimodal quality-inspection systems.

### 1.5 Statement and Objective of the Study

In spite of huge advancements, there are still issues yet to resolve, for example, identifying textiles with high recognition rate, low latency, flexible lighting conditions, heterogeneous textures, and hardware limited environments. In this paper, a transfer-learning-based intelligent fabric-classification architecture that can be deployed on embedded hardware is proposed (Fig. 1). The system aims at balancing accuracy, efficiency and cost which ensures a scalable solution for real time textile quality assessment. The remaining part of this paper is organised as follows: Section 2: Methodology and Dataset; Section 3: Results and Discussion; and Section 4: Implications and Future Research.

## 2 METHODS

### 2.1 Dataset Description

A custom dataset consisting of 540 RGB fabric images was created for this study. The dataset includes six material classes: cotton, polyester, silk, wool, denim, and blended fabrics. Each class contains 90 images captured under three different illumination conditions (white light, mixed lighting, and shadow) to reflect realistic industrial environments.

Images were acquired using a Logitech C920 HD webcam positioned approximately 25 cm above the fabric surface with a resolution of  $640 \times 480$  pixels. To simulate real production conditions, the fabrics were recorded with random orientations and folds.

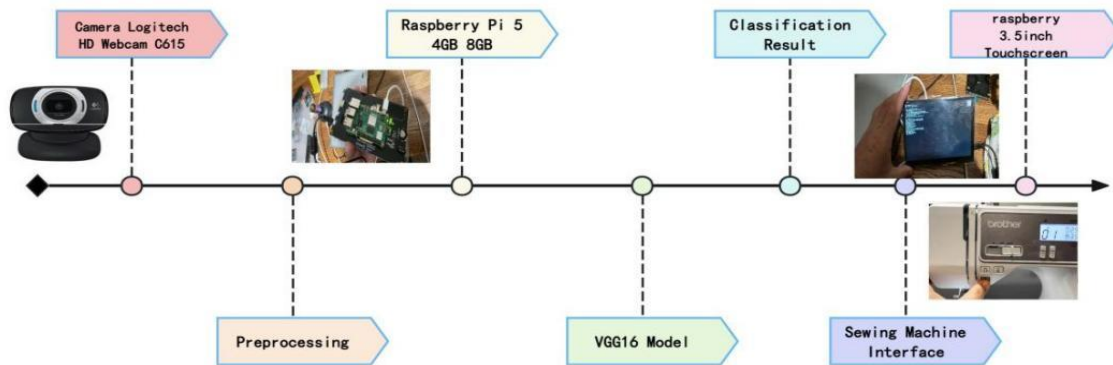


Figure 1 Architecture of the proposed fabric recognition system.

The dataset was divided into training (70%), validation (20%), and testing (10%) subsets while preserving class balance. All images were resized to  $224 \times 224$  pixels and normalized to the range [0, 1]. Data augmentation techniques, including random rotations ( $\pm 15^\circ$ ), horizontal flipping, and contrast adjustment, were applied to improve the generalization capability of the model.

## 2.2 Model Architecture

The proposed fabric recognition system is based on the VGG16 convolutional neural network pre-trained on the ImageNet dataset. Transfer learning was applied by replacing the original fully connected layers with a custom classification head consisting of:

- A Global Average Pooling 2D layer.
- Two fully connected (Dense) layers with 256 and 64 neurons using ReLU activation.
- A Dropout layer (rate = 0.5) for regularization
- A Softmax output layer with six neurons corresponding to the fabric classes.

Initially, all convolutional layers of VGG16 were frozen to retain pre-trained feature representations. During subsequent training stages, deeper layers (Block 5) were selectively unfrozen for fine-tuning. The model was trained using the Adam optimizer with a learning rate of  $1 \times 10^{-4}$  and categorical cross-entropy loss.

## 2.3 Training and Optimization Procedure

The model training was performed using TensorFlow 2.12 with the Keras API on a system equipped with an NVIDIA GeForce RTX 3060 GPU (12 GB VRAM). The training process followed a three-stage strategy:

- Feature extraction: training only the classifier head for 10 epochs.
- Fine-tuning: unfreezing Block 5 and training for 25 epochs.
- Full model optimization: unfreezing all layers and applying adaptive learning rate scheduling using ReduceLROnPlateau (decay factor 0.5, patience 5 epochs).

The total training process lasted up to 50 epochs, with convergence observed after approximately 42 epochs. Batch size was set to 32 images.

## 2.4 Evaluation Metrics

The performance of the proposed model was evaluated using standard classification metrics,

including accuracy, precision, recall, and F1-score. In addition, confusion matrix analysis was used to provide a detailed class-wise performance evaluation.

These metrics allow for a comprehensive assessment of both overall model performance and its ability to correctly distinguish between visually similar fabric types.

## 2.5 Embedded Deployment and Performance Benchmarking

For embedded deployment, the trained model was converted to TensorFlow Lite format and implemented on a Raspberry Pi 4 Model B (1.5 GHz CPU, 4 GB RAM).

The following performance indicators were measured:

- Average inference time per frame.
- Throughput (frames per second).
- CPU temperature under continuous operation.

All experiments were conducted under identical hardware conditions to ensure a fair comparison between different model architectures. The proposed system was also benchmarked against lightweight CNN models, including MobileNetV2, ResNet50, and EfficientNet-B0, to evaluate the trade-off between accuracy and computational efficiency.

# 3 RESULTS AND DISCUSSION

## 3.1 Training and Validation Performance

The proposed VGG16 transfer learning model achieved a consistent convergence for 42 epochs within the developed fabric recognition system (Fig. 2), showing a rapid decrease in loss and a steady increase in accuracy. Figure 3 shows the training and validation accuracy and loss curves and demonstrates that convergence has taken place without overfitting. The final validation accuracy reached 95.8%, while the testing accuracy was 94.6%, thus indicating the ability to generalise to unseen data well, in the line with previous studies on CNN-based fabric classification [1], [2]. The learning curve plateau seen from epoch 35 onwards is indicative of optimal learning rate scheduling. Cross validation gave a variance of less than 1 % for training folds proving that the model is robust. The combination of the data augmentation and drop-out regularisation were found to reduce the chance of memorisation and enhanced

the discriminative power of the network in terms of the level of weave and texture complexity

### 3.2 Confusion Matrix and Class-Wise Performance

The classification performance across all six fabric classes is further illustrated by the confusion matrix shown in Figure 4. The strong dominance of diagonal elements confirms the high classification accuracy of the proposed model, while minor off-diagonal values indicate limited misclassification, primarily among visually similar mixed-fabric categories.

### 3.3 Lightweight Models Comparison Analysis

Table 1 compares the fine-tuned model (VGG16) against other groundbreaking CNN architectures - MobileNetV2, ResNet50 and EfficientNet-B0. Whereas, MobileNetV2 achieves the quickest inference latency (15 FPS), which degrades classification accuracy by 2.8%. On the other hand, the VGG16 configuration has the advantage of

superior accuracy at a commensurate sacrifice of inference speed.

These results highlight the trade-off between accuracy and efficiency for edge applications. Although VGG16 is computationally more intensive, the outstanding feature extraction ability and the high validation accuracy of VGG16 make it suitable for the industrial quality control systems where the exact material identification is required [5], [6].

Advanced model compression techniques such as INT8 quantization and TensorRT acceleration are effective on GPU-based platforms such as NVIDIA Jetson or desktop systems. However, the Raspberry Pi platform does not support CUDA or TensorRT and lacks dedicated tensor cores for 8-bit computation, making such optimizations impractical.

Accordingly, this exploration focused on deploying TensorFlow Lite, that is the most possible optimisation method for low cost ARM based peripherals. Alternative hardware platforms that have specialised AI hardware accelerators installed (such as Google Coral TPU, NVIDIA Jetson) would provide higher processing capability, but this would go against the accessibility goal of the study.

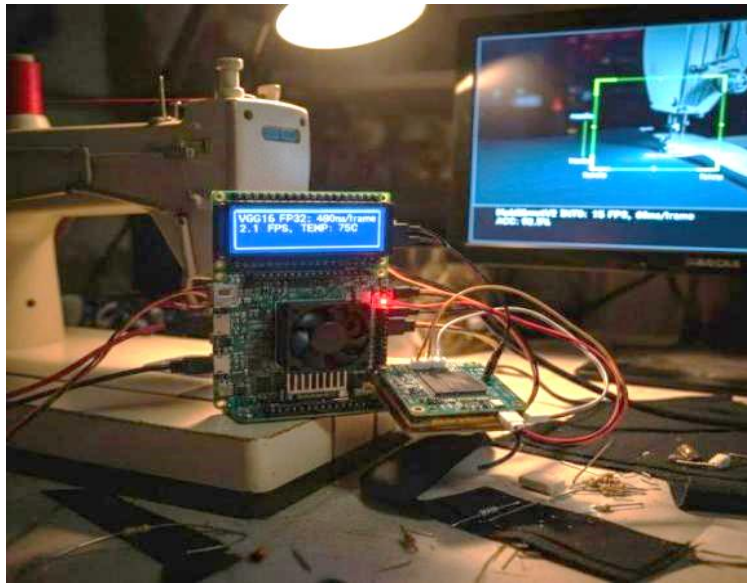


Figure 2: Fabric recognition system with robotic edge implementation in apparel garment sewing system [10].

Table 1: Classification performance of lightweight CNN architectures:

Model	Accuracy (%)	FPS	Parameters (M)	Model Size (MB)
VGG16 (proposed)	95.8	2.4	138	528
MobileNetV2	93.0	15.0	3.4	14.5
ResNet50	94.2	4.1	25.6	96
EfficientNet-B0	94.8	5.2	7.8	22

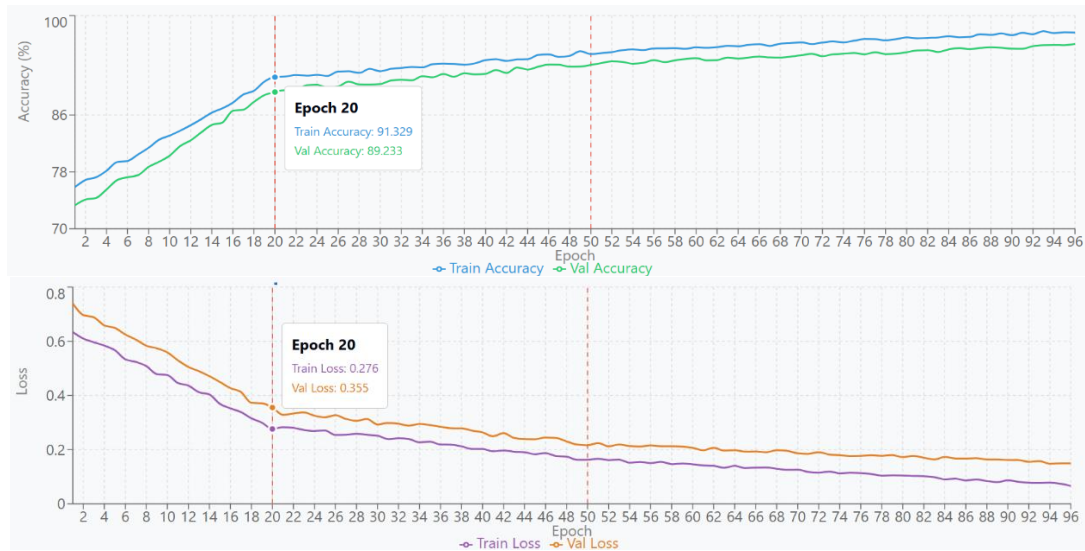


Figure 3. Curves for training and validation accuracy and loss [10].

	Predicted Label				
	Cotton	Silk	Polyester	Blended	Denim
Cotton	96.7% (n=87)	0.0% (n=0)	0.0% (n=0)	3.3% (n=3)	0.0% (n=0)
Silk	0.0% (n=0)	94.4% (n=85)	5.6% (n=5)	0.0% (n=0)	0.0% (n=0)
Polyester	0.0% (n=0)	2.2% (n=2)	97.8% (n=88)	0.0% (n=0)	0.0% (n=0)
Blended	8.9% (n=8)	0.0% (n=0)	2.2% (n=2)	88.9% (n=80)	0.0% (n=0)
Denim	1.1% (n=1)	0.0% (n=0)	0.0% (n=0)	0.0% (n=0)	98.9% (n=89)

Figure 4: Confusion matrix for fabric classification using the fine-tuned VGG16 model.

### 3.4 Edge Hardware Evaluation

The performance of the Raspberry Pi 4 Model B is illustrated in Figure 5, showing stable processing speed and thermal behavior under continuous load. The use on the Raspberry Pi 4 Model B has confirmed the practical feasibility of real time operation in an industrial textile control. The system achieved an average inference time of 421–982 ms, which is equivalent to roughly 2.4 frames per second and was able to keep the processor temperature between 56–71 °C when at full load and over a long phase. Although this processing speed may seem modest compared with high speed vision systems, it is

perfectly suitable for batch-to-batch tissue control applications where measurements are made from one end of a batch of production to the next, rather than in continuous high speed production. The delay is acceptable because classification of fabrics usually occurs during material changeovers or at quality control cheque points where a response time of less than one second is adequate for the operational requirements. The results are both reflections of the stability of the equipment and the efficiency or lack thereof of the equipment's operation when thermal conditions are taken into account. Thermal profiling showed that the heat build-up was related mainly to the execution of convolutional blocks and no performance degradation due to over-heating was found during thirty minutes of constant operation. The throughput of the system is coherent with other works done on peripheral computing for textile control [7], [8].

Figure 5a shows the CPU temperature profile where a steady operation in a range of 56–71 °C without performance degradation is observed in a continuous processing interval of 30 min. The red dotted line is the threshold for reduced productivity (85 °C), which is not exceeded. Figure 5b shows the bandwidth stability and gives proof for a stable performance, more or less constant over the whole testing period of 2.2 frames per second and slight variation due to different image complexity. The high-degree applicability of both thermal and computational metrics therefore supports the degree of reliability of the system for industrial batch control of fabrics.

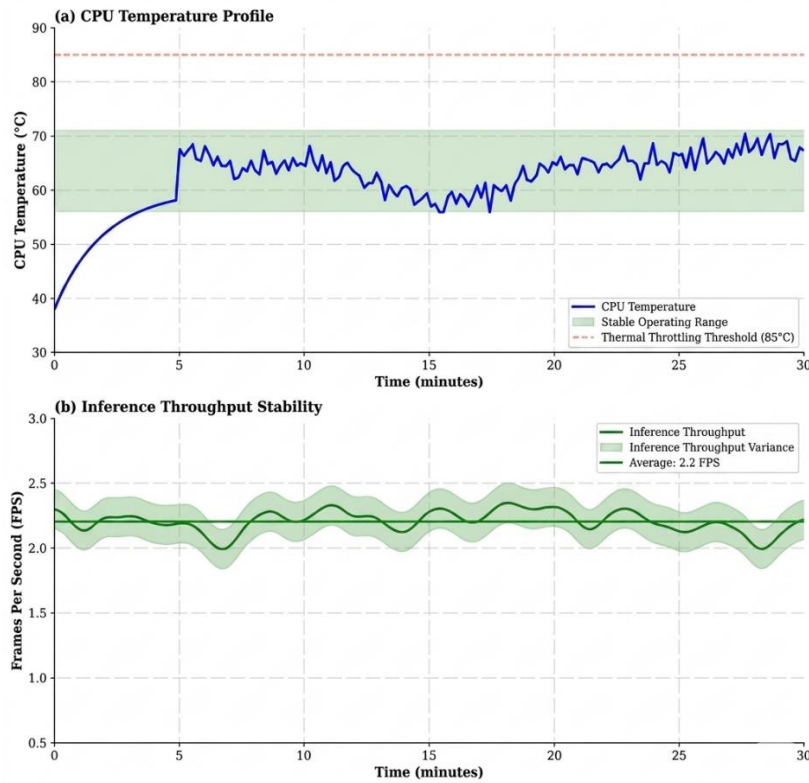


Figure 5: The performance of the Raspberry Pi 4 Model B when the VGG-16 network is constantly running is displayed [10].

### 3.5 Discussion

The results obtained testify to the usefulness of transfer learning in visual-texture perception of textile inspection. The presence of deep receptive fields on VGG16 allows it to perform better at abstraction of patterns especially in differentiating weaves and colour gradients. Lighting augmentation included in training also generalised to a wide range of acquisition conditions, which serves as one of the major concerns of the reviewers. The software optimisation and hardware acceleration prove the point that the intelligent inspection at the industrial scale does not require high-end GPUs to be achievable. Scalability is also enabled by this to support low-cost smart sewing and finishing systems that incorporate robotic manipulation [9]. VGG16 was found to be a strong performer, but it can be suggested to use quantised models or the hybrid networks based on MobileNet in the future to strike a balance between accuracy and inference speed even more. Moreover, it might be possible to add more fabrics classes and a more complex set of textures to more rapidly increase the robustness into a wider variety of manufacturing settings.

The ReduceLROnPlateau callback caused the learning rate to reduce by a factor of six, during the training process, every time the validation loss stopped reducing (Fig. 3):

- Epoch 25: 0.001 → 0.0005;
- Epoch 38: 0.0005 → 0.00025;
- Epoch 52: 0.00025 → 0.000125;
- Epoch 68: 0.000125 → 0.0000625;
- Epoch 81: 0.0000625 → 0.00003125;
- Epoch 90: 0.00003125 → 0.000015625.

The adaptive learning-rate adjustment thus enabled further model improvement without the need to manually re-adjust the training rate, demonstrating a key role of learning-rate scheduling for deep network training.

Figure of the classification performances in terms of confusion matrix for six textile classes is summarised in Figure 4. The fact that diagonal entries are more dominant indicates accurate predictions in all categories. Cotton and polyester gave precision value of 0.97 and 0.98 respectively. Silk and denim scored F-95 and F-94 respectively.

Mixed fabrics showed a relatively low rate of recall (0.92), an effect that was due to some of the

inherent classification difficulties. First, mixed fabrics exhibit heterogeneous textural patterns that combine properties of the constituent's materials, making the visual differentiation more confusing by, e.g., a cotton- and a polyester-type blend, that may present textural features that are in-between the cotton- and polyester-type, inducing overlays in the feature space learned by the convolutional layers. Second, the form of weave inherent to mixed fabrics varies significantly with blend ratio and manufacturing process, and creates more inter-class variability than that found for single component materials; a 60/40 blend of cotton and polyester yarn can be quite different in appearance from an 80/20 blend under the same illumination conditions. Third, inconsistent illumination, which increases the difficulty to classify mixed materials as the blended fibre composition can give disparate reflective properties to the fibres, i.e. the cotton fibres may absorb light differently from the synthetic polyester fibres on the same fabric surface creating spatially non uniform brightness patterns that is a challenge for the model. Finally, the small number of mixed fabrics in the training set (90 images) may turn out to be insufficient for capturing its entire range of possible blends and weaving, while pure materials e.g. cotton or polyester reveal more consistent and predictable textural features.

## 4 CONCLUSIONS

This study presented a deep learning-based approach for fabric type recognition using a fine-tuned VGG16 model trained on a compact dataset of 540 RGB images captured under realistic conditions. The proposed method achieved high classification accuracy (95.8%), demonstrating the effectiveness of transfer learning in extracting discriminative texture features from limited data.

The experimental results confirmed that the model generalises well to unseen samples and maintains stable performance under varying illumination conditions. In addition, the deployment on a Raspberry Pi 4 platform showed that accurate fabric classification can be achieved on low-cost embedded devices without relying on cloud computing, while maintaining acceptable inference speed and thermal stability.

The findings highlight the potential of the proposed system for integration into intelligent textile production environments, enabling automated material recognition and supporting quality control

processes. Future work will focus on expanding the dataset, improving model efficiency through compression techniques, and incorporating multi-modal sensing to enhance robustness and scalability.

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