An enhanced fabric recognition algorithm utilizing advanced data processing techniques

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Abstract: Current fabric recognition techniques often struggle with complex real-world environments due to their limited adaptability and generalization capabilities. To address these challenges, this paper introduces an innovative data processing framework that applies three distinct augmentation methods to training and testing datasets. This approach enhances the model's ability to recognize fabrics in diverse conditions. An optimized MobileNetV3 model is proposed, integrating Early Neural Attention (ENA) to focus on essential image features at an early stage. Furthermore, the conventional bottleneck structure is modified, and the ReLU activation function is replaced with SELU to improve robustness and convergence speed. Comparative experiments validate the improved model's effectiveness, demonstrating notable enhancements in accuracy, precision, recall, and F1-score. These results confirm the model's ability to perform reliably in dynamic and challenging fabric recognition scenarios.

Keywords: Fabric recognition, Innovative data processing, MobileNetV3, ReLU, SELU.

1. Introduction

The increasing demand for personalized and diverse fabric products has driven rapid advancements in fabric design and manufacturing. As a result, fabric recognition has become essential for ensuring quality control and optimizing production management. Traditional fabric classification methods, which often rely on manual inspection or basic image processing techniques, suffer from inefficiencies and inaccuracies. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs) Kim, et al. [1] have revolutionized fabric recognition by enabling automated feature extraction and significantly improving accuracy and robustness.

Deep learning models surpass traditional approaches by effectively handling large-scale datasets and complex fabric patterns with enhanced generalization capabilities. Several notable research efforts have contributed to the progress of fabric recognition. For example, Meng, et al. [2] introduced a Multi-task and Multi-scale Convolutional Neural Network (MTMSnet) to localize yarns and recognize weave patterns with high accuracy. However, their approach requires extensive dataset construction and struggles with fabrics that exhibit significant bending or overlapping yarns. Similarly, Mahanta, et al. [3] proposed an improved VGG-based model for woven fabric recognition, which enables seamless deployment in various applications. However, this model may not perform well under occlusion and scale variations.

While existing fabric recognition methods have achieved considerable progress, they still face limitations in handling complex variations in real-world environments. To address these issues, this paper presents an advanced data processing strategy combined with an enhanced MobileNetV3 [4, 5]. The proposed approach ensures high recognition performance under varying conditions while maintaining computational efficiency and adaptability.

2. Theory and Methods

2.1. MobileNeV3 Overview

MobileNetV3 is a lightweight neural network optimized for mobile and embedded systems. Its key innovations include depth-wise separable convolutions, a linear bottleneck structure, and Neural Architecture Search (NAS)-optimized layers [6]. The Small variant of MobileNetV3, which offers efficient computations with minimal resource consumption, is selected as the base model for this study as shown in Fig.1.
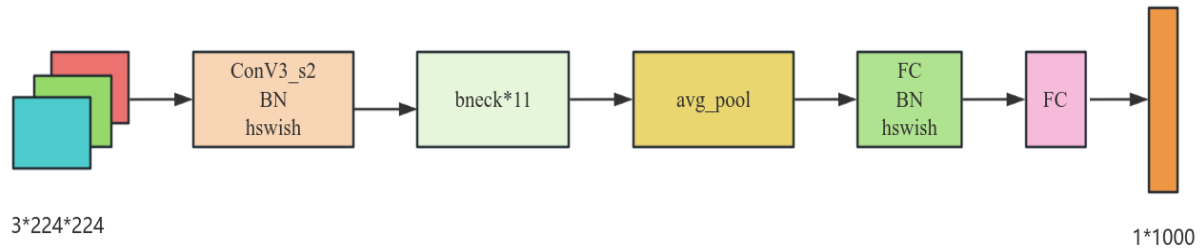

Figure 1.
The structure of MobileNetV3.

2.2. Proposed Model Enhancements

To meet the demands of real-time and accurate fabric classification, this study introduces multiple improvements to MobileNetV3, optimizing its structure (as shown in Fig.2) for enhanced performance in complex fabric recognition tasks.
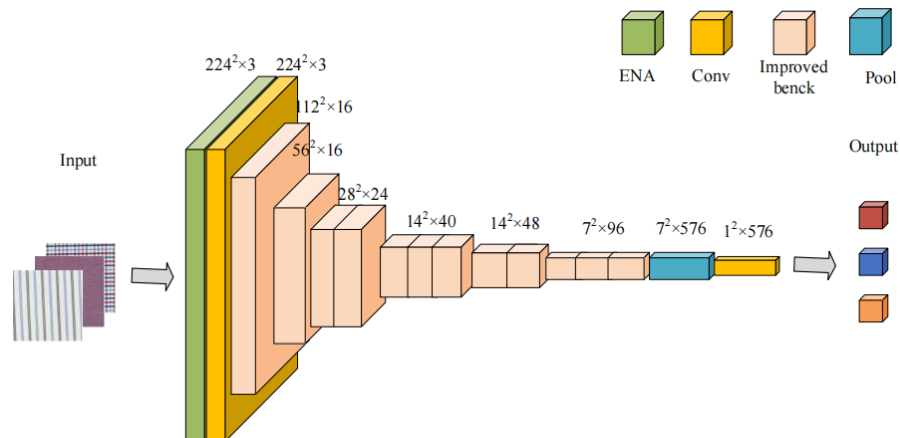

Figure 2.
Improved structure of MobileNetV3 model.

The enhancements are as follows:
- Early Neural Attention (ENA) for Feature Focus.
  To mitigate potential information loss in the standard MobileNetV3 model when processing complex fabric images, this paper integrates an Early Neural Attention (ENA) mechanism [7]. This is an adaptation of the Efficient Multi-Scale Attention framework Ouyang, et al. [8] which eliminates feature grouping while improving attention efficiency. By positioning ENA at the forefront of the model, it ensures that key image features are identified early in the processing pipeline. This improves both robustness and accuracy, allowing the model to focus on critical regions of fabric images with higher precision.
- Modification of the Bottleneck (Bneck) Structure.

To further refine the model, modifications are made to the bottleneck structure [9]. The traditional Squeeze-and-Excitation (SE) attention mechanism Zeng, et al. [10] is removed to simplify the model and reduce computational complexity. This adjustment minimizes the risk of overfitting while enhancing generalization. Additionally, a 7×7 grouped convolution, combined with a channel shuffling technique, replaces the conventional 1×1 convolution. This allows the model to capture a broader range of feature interactions, thereby improving pattern recognition efficiency across different fabric textures and patterns. Furthermore, the linear activation function is replaced with a Sigmoid activation function, which enhances the model's ability to learn nonlinear relationships present in fabric structures.

- Implementation of SELU Activation Function.
  The standard ReLU activation function Bai [11] is replaced with the Scaled Exponential Linear Unit (SELU) activation function [12]. This change addresses the vanishing gradient problem and improves the stability of deep networks by ensuring self-normalization. SELU also accelerates model convergence, leading to faster training times without compromising accuracy. This is particularly beneficial when deploying the model in real-world applications requiring real-time fabric classification.

3. Experimental Results

The dataset used in this study is derived from the YDFID-1 fabric image repository Zhang, et al. [13] containing 17 distinct pattern categories. The dataset is split into training and testing sets with an 8:2 ratio. The model is trained using the RMSprop optimizer Elshamy, et al. [14] with a dynamic learning rate, starting at 0.002. Training is conducted over 100 epochs with a batch size of 16. Cross-entropy loss is employed as the objective function.

3.1. Experimental Analysis

To evaluate the effectiveness of the proposed model modifications, an ablation study was conducted. The experiment compares the baseline MobileNetV3 model with progressively enhanced versions incorporating Early Neural Attention (ENA), modifications to the bottleneck structure, and the integration of different activation functions. The specific configurations and results are presented in Table 1.

Table 1.
Comparison results of models.

Method	Top-1 Accuracy	Precision	Recall	F1 Score
MobileNetV3	94.03	94.71	93.26	93.83
MobileNetV3 + ENA	95.69	96.78	94.86	96.65
MobileNetV3 + ENA + ReLU	96.64	97.27	96.03	96.58
MobileNetV3 + ENA + SELU	96.87	97.53	96.27	96.83

3.2. Performance Comparison

To further assess the generalization capability of the proposed model, additional experiments were conducted to compare the baseline MobileNetV3 model with the fully improved MobileNetV3 model. The results are summarized in Table 2.

Table 2.
Comparison results of MobileNetv3 and improved MobileNetv3.

Method	Top-1 Accuracy	Precision	Recall	F1 Score
MobileNetV3	97.53	97.50	97.44	97.44
Improved MobileNetV3	99.03	99.00	99.02	99.02

4. Conclusions

The results of this study demonstrate that integrating Early Neural Attention, modifying the bottleneck structure, and incorporating optimized activation functions significantly enhance the model's performance in fabric recognition tasks. The improved MobileNetV3 model exhibits higher accuracy, precision, recall, and robustness when dealing with complex and variable fabric patterns. Future research will explore the application of this enhanced framework to broader computer vision tasks, including object detection and semantic segmentation, to further validate its adaptability and efficiency in diverse scenarios.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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