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Analysis of Image Filters for Binary Fabric Classification

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Abstract— ***The precise classification of fabrics as either synthetic or natural is crucial for various industrial and consumer applications, ranging from textile recycling to healthcare product development. This study investigates the efficacy of an ensemble of image processing filters combined with machine learning models in achieving accurate fabric classification. We propose a novel approach that leverages the complementary strengths of various image processing techniques - namely, Local Binary Pattern and Gabor filter - to extract textural features from fabric images. These features are then fed into distinct machine learning models - namely, SVM, Naive Bayes Classifier, Random Forest, CatBoost, and XGBoost - to perform the classification task. The performance of each model is evaluated individually without the filters and with filters, using a comprehensive dataset of fabric images encompassing a wide range of synthetic and natural materials. Our findings demonstrate that the proposed combination of image filters significantly impact the performance of specific classification models. This research paves the way for the development of more robust and reliable fabric classification systems with potential applications in diverse fields.***

Index Terms— ***Fabric Classification, Image Processing, Texture Analysis, Machine Learning, Ensemble Methods, Synthetic Fabrics, Natural Fabrics***

I. INTRODUCTION

The textile industry is a major part of global commerce, playing a crucial role in economic development and individual well-being. However, with the rise of synthetic fabrics, concerns have emerged regarding their environmental impact and potential health risks. Accurately classifying fabrics as natural or synthetic is essential for addressing these concerns, enabling sustainable practices and informed consumer choices. Machine Learning (ML) models have emerged as powerful tools for fabric classification, offering high accuracy and the ability to learn from complex data patterns. However, the performance of these models can be significantly influenced by the quality of the input data, which is often influenced negatively by noise and inconsistencies inherent in real-world fabric images.

This study investigates the effectiveness of an ensemble of image processing filters in enhancing the performance of ML models for classifying fabrics as synthetic or natural. We hypothesize that by pre-processing fabric images with a combination of carefully chosen filters, the accuracy and robustness of ML models can be improved. Specifically, the focus is on filters that address common challenges in fabric image analysis, such as noise reduction, illumination variations and texture enhancement. The performance of the filter combination on a diverse dataset of fabric images is measured, comparing their impact on the accuracy of various ML models.

The real-world objective of this study is to aid and enhance the existing fabric quality control methods and create a more accessible and reliable fabric identification system with the use of macroscopic mobile images, image processing and machine learning methods. This study can further be expanded to identify individual types of fabrics and blended fabrics to improve the diversity of the identification system.

First, we explore the potential of ensemble image processing filters to enhance fabric classification accuracy by improving the performance of ML models. Second, we provide a comprehensive evaluation of a particular filter combination and their impact on various ML models, providing valuable insights. Finally, our findings can inform the development of robust and reliable fabric classification systems for various applications.

This paper is structured as follows: Section 2 presents a review of existing literature on fabric classification using ML models and the challenges associated with image processing. Section 3 details the experimental methodology, including the dataset, image filter ensemble, ML models, and evaluation metrics. Section 5 presents the results and analysis of the experiments, highlighting the impact of filters on model performance. Finally, Section 6 concludes the paper by summarizing the key findings, discussing limitations, and suggesting future research directions.

II. LITERATURE REVIEW

Several studies have successfully employed image filters for highlighting defect features in fabrics. Some of the most commonly used filters for enhancing the features of fabrics

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are Median filter, Gabor filter and Local Binary Pattern. These filters are often combined with other machine learning and deep learning algorithms to show exceptional results for defect detection tasks. *Khwakhali et al.* [1] proposed an image classification method that converts images to grayscale, extracts GLCM and LBP features, and uses various models to achieve high validation accuracy on unseen data. A validation accuracy up to 83.9% and test accuracy up to 70% was achieved. Similarly, *Uzen et al.* [2] propose a method to use a median filter for denoising and pooling processes with deep learning methods to identify defects in fabrics. This method produced an accuracy of 95.82%. These filters demonstrate the potential of image preprocessing for improving defect detection sensitivity.

Pattern recognition techniques play a crucial role in fabric analysis. There are many image processing filters that serve the purpose of pattern recognition. The image classification method proposed by *Huang et al.* [3] preprocesses fabric images by filtering (smoothing using Direct Fourier Transformation method combined with Gaussian filtering and compressing using Daubechies wavelet method) and binarizing them, then extracts pilling features (number of pilling points, area, etc.) using image processing techniques. Finally, machine learning models (ANN and SVM) are trained to classify the level of pilling in the fabric. The Artificial Neural Network (ANN) consistently achieved higher accuracy than the Support Vector Machine (SVM) across different image processing methods. The ANN reached a peak accuracy of 96.8% using the Fourier transform with Gaussian filter, while the SVM's best accuracy was 95.3% with the same method. Additionally, there have been works using just Deep Learning methods which have produced considerable results. The work of *Iqbal et al.* [4] describes the use of transfer learning where new layers are added to an already trained model and only the new layers are trained with the specific pattern data. The high-level texture features are extracted, and then finally classified based on the types of woven fabric (plain, twill, and satin). The proposed transfer learning method achieved an accuracy of 99.3%. These techniques offer valuable insights into defect pattern analysis, potentially complementing the chosen ML and DL models.

Deep learning, particularly Convolutional Neural Networks (CNNs), has garnered attention for its automatic feature extraction capabilities in fabric classification tasks. CNNs can be designed for specific tasks by altering already existing architectures or creating a new one altogether. Sometimes, multiple architectures and methods are combined to form a new architecture. One such architecture designed for the purpose of identifying different fabric materials is the FabricNet [5]. The architecture of FabricNet consists of two main modules: Head model and Ensemble models. The head model directly fetches the input images and generates lower dimension embeddings. The embeddings derived by the head model are passed to the ensemble models. Each of the ensemble models is assigned to identify only a single type of fabric fibers or class, and each class's prediction is independent of the other class-based ensemble. Therefore, the number of ensemble models must be similar to the number of possible categories.

Since, the main focus is to study the impact of image processing filters, understanding the underlying mechanism of transforming images to enhance specific features is important. Specific filters are used for enhancing specific features in the image. Multiple filters can be combined and used for any specific task. *Yildiz et al.* [6] used LBP filters to extract texture information from images of wool and mohair fabrics. The proposed image classification pipeline converts images to grayscale, then extracts LBP features for classification using various methods, including Nearest Neighbor, Deep Learning with CNN models, and even the pre-trained Inception V3 model. This method produced around 98% accuracy with CNN classifier. The work proposed by *Zhao et al.* [7] uses a similar approach to extract the texture of wrinkles to identify fabrics. It converts images to grayscale and binary formats similar to LBP, removes noise, then extracts data like wrinkle width-to-length ratio, area-to-perimeter ratio, and area-to-height ratio. Using these features, the system can effectively differentiate various clothing fabrics. Another instance where the LBP filter proved to be effective is when combined with GLCM and Hu Moments to extract features from fabric images. *Da Silva et al.* [8] explored various approaches for fabric classification using image features like texture (GLCM, LBP, Hu Moments) and deep learning models (VGG, MobileNet, InceptionV3 etc.). They also compared different classification algorithms like Naive Bayes, MLP, kNN, Random Forest and SVM. Denoising is an important preprocessing step for images. Image denoising filters aim to remove unwanted noise from pictures, like grain or speckles, while preserving important details like edges and textures. Different types of filters exist, some working by averaging surrounding pixels (mean filter), while others use more advanced techniques like wavelets to selectively target noise without blurring the image. *Kumar et al.* [9] lay down a detailed comparison between the performance of median, gaussian and Denoise Auto-encoder. For speed, the median filter performed best with few iterations. However, for better image quality based on PSNR and SSIM metrics, the Denoising Autoencoder offered superior performance compared to Gaussian and median filters. Texture and edges are features that distinguish different classes of fabrics from each other. Another important filter used mainly for edge detection, feature extraction, and texture analysis is the Gabor filter [10].

The reviewed literature highlights the potential of image preprocessing filters and how they can be effectively used for fabric defect detection. While studies showcase various combinations of individual models and filters, the most commonly used image preprocessing step for fabrics is

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enhancing the edges and analyzing the textures. This provides the motivation to study the effect of a specific combination of filters namely Local Binary Pattern and Gabor filter paired with ML models to identify fabrics.

III. METHODOLOGY

In this section we describe the proposed methodology that uses enhanced image processing techniques to classify the fabrics, in response to the growing demand for efficient fabric identification systems. First, we preprocess the input images with the necessary filters, which is detailed in Section-B: Data Preprocessing. The pre-processed images are then used to train the model. The model is then tested and evaluated. The training and testing are explained in Section-C: Experimental Setup. This flow of information is represented in the block diagram Fig. 1 below:

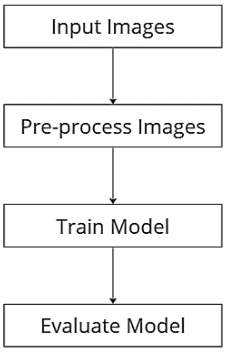

Fig 1: Data flow diagram

A. Dataset

The dataset used in this study is the Fabrics dataset [11], obtained from the Intelligent Behavioral Understanding Group (iBUG) repository. This dataset is a carefully curated collection of images of fabrics with different textures, patterns, and types. The data set originally consisted of 7877 images across 24 different classes. It was carefully restructured into 2 classes - Synthetic (2142 images) and Natural (4047). The imbalance between the 2 classes was eliminated by the method of Data Augmentation. The images are collected using custom portable photometric stereo sensors, thus ensuring high quality and standardized data. Sample images from both the classes are as in Fig. 2 and Fig. 3.

Fig 2. Sample image of Natural fabric class

Fig 3. Sample image of Synthetic fabric class

B. Data preprocessing

Prior to model training, all images undergo a preprocessing stage as mentioned in methodology to ensure standardized input and improve the suitability of the dataset for our study. First, we uniformly reduce the images to a size of 128 x 128 pixels.

1) Gabor Filter

The Gabor filter is applied on the resized image. This filtering improves textural features that are critical for accurate identification of fabrics. A complex Gabor filter is defined as the product of a Gaussian kernel and a complex sinusoid function. The overall function is considered as a combination of a real filter component Eq. 1 and an imaginary filter component Eq. 2.

$$g_r(t) = \omega(t)\, \sin(2\pi f_0 t + \theta) \qquad \text{Eq. 1}$$

$$g_i(t) = \omega(t)\, \cos(2\pi f_0 t + \theta) \qquad \text{Eq. 2}$$

2) LBP Filter

After Gabor filtering, a local binary pattern (LBP) filter is applied to the processed image. This filter effectively thresholds each pixel's neighboring pixels, further improving unique features within the image. The image is first loaded as a grayscale image. For each pixel in the grayscale image, the function defines a circular neighborhood with radius R and P sampling points. The coordinates of each sample point are calculated based on its angle around the circle. The intensity value (gc) of the center pixel is compared with the intensity (gp) of each neighbor. The function assigns a 1 if the neighbor's intensity is greater than or equal to the center, otherwise assigns a 0. Combining these binary assignments (0s and 1s) from the neighborhood into a single binary number, create the LBP code for that central pixel. This code essentially captures the local textural pattern around the center pixel.

The pre-processed images are then input into the classification model to facilitate the training process.

C. Experimental Setup

After the preprocessing of the fabric images, the dataset was split into training and test sets in a ratio of 80:20 to evaluate the classification model. Different classification models namely - SVM, Naive Bayes, Random Forest, XGBoost and CatBoost were tested upon as a part of the study. The models in their default values were first trained and tested on raw, unprocessed images to provide a baseline for their performance. Then the models were trained and tested again with the preprocessed images. This two-stage approach allows comparative evaluation and provides insights into the impact of preprocessing on model performance. The evaluation produces two sets of results: the model’s performance on the original images and the model’s performance on the pre-processed images. The latter frequently exhibits better classification metrics, such as

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improved precision, recall and F1-score. This systematic approach ensures a comprehensive understanding of the benefits and improvements resulting from the preprocessing techniques employed in the suggested fabric identification methodology.

IV. RESULTS AND DISCUSSION

This experiment was performed to investigate the impact of using image preprocessing filters on the performance of machine learning models for fabric classification. Different algorithms, including XGBoost, Random Forest, Naive Bayes, CatBoost, and SVM, were evaluated with and without image preprocessing filters.

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Table I. Classification Scores with and without image preprocessing

Classification Models	Accuracy	
	Without Filtering	With Filtering
Naive Bayes	55%	68%
SVM	64%	71%
CatBoost	72%	72%
Random Forest	71%	68%
XGBoost	75%	69%

The results shown in Table I demonstrate that image preprocessing filters generally provide marginal to moderate improvements in classification accuracy for three out of the five models tested.

Overall, these findings suggest that the combination of LBP and Gabor filters when paired with specific classification models have a significant improvement in classification accuracy. While Naive Bayes showed a notable improvement, other models saw little to no change or even a slight decrease in accuracy. This can be observed clearly in the graph represented in Fig. 4. Further study is needed to understand and analyze the underlying reasons for these variations to potentially optimize filtering strategies for different algorithms and fabric classification tasks.

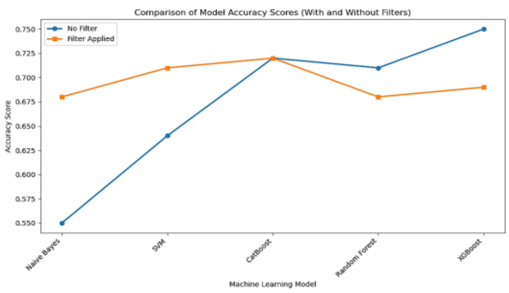

Fig 4: Graphical analysis of the results

Further study is needed to understand the underlying reasons for these variations and potentially optimize filtering strategies for different algorithms and fabric classification tasks.

V. CONCLUSION AND FUTURE WORK

This study examined the impact of feature filtering on the performance of various machine learning models for fabric classification. Five representative algorithms, namely XGBoost, Random Forest, Naive Bayes, CatBoost and SVM, were evaluated with and without prior feature filtering.

The results revealed mixed effects of filtering on classification accuracy across the different models. While Naive Bayes demonstrated a clear improvement with filtering (13% increase), other models experienced negligible changes or even slight decreases. These findings suggest that the effectiveness of filtering hinges on the specific algorithm and potentially the properties of the dataset.

Several avenues for future research emerge from this study:

Studying the impact of filtering for Deep Learning algorithms and observing the results.

Increasing the size of dataset to include diverse types of fabrics.

Explore various other filtering methods beyond the ones used in this study to see if they yield different results.

Diversify the classification to multiple classes of fabrics and blended types of fabrics.

Extending from research to successfully deploying in practical applications and scenarios.

In conclusion, while this study provided basic insights into the impact of feature filtering on fabric classification with machine learning, it opens up several exciting areas for further research. By studying deeper into the relationships between filtering, specific algorithms, and fabric properties, we can continuously improve the accuracy and efficiency of automated fabric classification systems.

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