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Adaptive Feature Learning in Transfer-Based Visual Garment Classification

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ABSTRACT

In the rapidly evolving field of fashion automation and textile manufacturing, accurate identification of garment types and stitching patterns is crucial for quality assurance, inventory management, and automated sorting. With increasing production demands, industries require intelligent systems capable of analyzing large volumes of garment images with high precision and consistency. Traditional methods based on manual inspection or basic image processing lack scalability, consistency, and the ability to detect fine-grained stitching variations under complex conditions. This work addresses the lack of a reliable automated system for dual-level garment classification, specifically identifying both fabric type and stitching condition from images. Conventional approaches rely heavily on human expertise, resulting in inconsistent outcomes, limited accuracy, and inefficiency in real-time applications. Additionally, these methods lack advanced feature extraction and automated learning, leading to poor generalization across diverse datasets. To overcome these challenges, the proposed system, FabricNet, introduces an intelligent framework for automated garment analysis deployed across two systems: Server and Client. The server extracts deep visual features using EfficientNetB0, which are then processed by models such as Deep Neural Network (DNN), Perceptron, and a proposed Multi-Layer Perceptron (MLP) for multi-output classification. A Tkinter-based graphical interface supports administrative tasks including dataset management, preprocessing, model training, and evaluation, while the user interface enables real-time image-based prediction. The system also incorporates explainable AI to interpret predictions. FabricNet enhances accuracy, reduces manual effort, and provides a scalable solution for modern smart garment industries.

Keywords: FabricNet, garment classification, EfficientNetB0, deep neural network (DNN), multi-layer perceptron (MLP), feature extraction, multi-output classification, automated garment analysis, real-time prediction, explainable AI (XAI).

1.INTRODUCTION

Garment retail companies and fashion industries have emerged as significant contributors to research in image processing and pattern recognition. In a highly competitive market, organizations continuously seek strategies to understand consumer preferences and current design trends in order to sustain and enhance their market position. Identifying popular garment styles and stitching patterns enables companies to optimize production, improve inventory planning, and align their offerings with customer demand. With the rapid growth of online shopping, the ability to automatically recognize garment designs and attributes has become increasingly important for both retailers and consumers. Recent studies in this domain have primarily focused on segmenting garments from real-world images and identifying basic categories such as shirts or jackets. While these contributions form a strong foundation, there is a growing need to move beyond basic classification toward more detailed analysis, including design-level and stitching-based categorization.

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According to recent industry reports, computer vision applications in manufacturing are experiencing significant growth, highlighting the importance of deploying intelligent systems for textile analysis. As shown as figure 1 the integration of data mining and machine learning has proven effective in extracting meaningful insights from large-scale data across various industries. Although the apparel sector has only recently begun adopting these technologies, there is substantial potential for their application in retail analytics, production optimization, and customer behavior analysis [1]. Leading platforms such as Myntra, Zalando, and StitchFix leverage data-driven models to understand user preferences and provide personalized recommendations. These systems utilize historical purchase data and interaction patterns to support decision-making, improve product design, and enhance customer engagement [2].

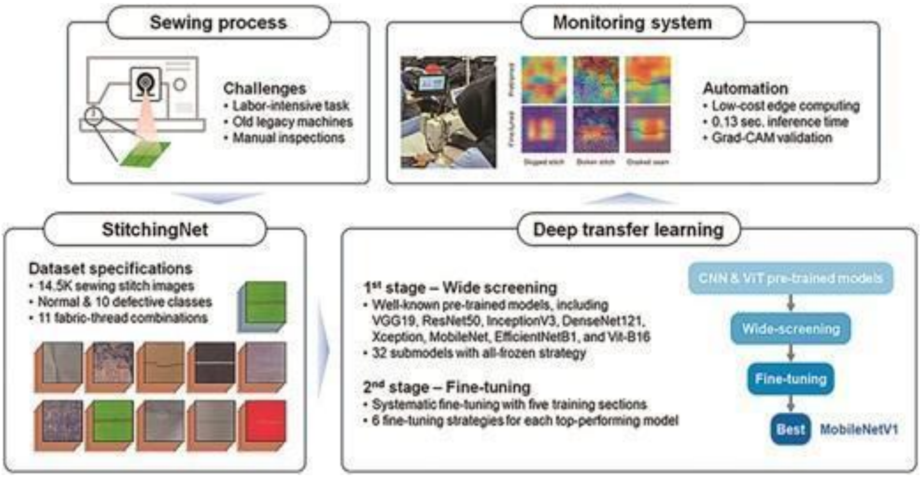

Figure 1: Workflow of transfer learning-based garment type classification using stitching net dataset.

With the expansion of digital platforms, including mobile commerce and social media-based retail, consumers generate vast amounts of data through their interactions. This growing availability of data necessitates the use of advanced technologies such as artificial intelligence, big data analytics, and machine learning to derive actionable insights. Intelligent systems can assist in recommending suitable garments, improving user experience, and supporting retailers in demand forecasting and assortment planning [3]. In this context, there is a clear need for automated systems capable of accurately classifying garments based on multiple attributes. Such systems serve as a foundational step toward building advanced decision support tools that benefit both consumers and businesses. Accurate garment classification directly influences customer satisfaction and retailer performance, as it ensures better product recommendations and improved shopping experiences [4]. Moreover, attribute-based classification supports efficient inventory management, demand forecasting, and comparative analysis for retailers and manufacturers [5]

2. LITERATURE SURVEY

Jain S, et al. [6] proposed the article which is devoted to the application of data mining on the industry's product data, i.e., data related to a garment, such as fabric, trim, print, shape, and form. The purpose of this article is to use data mining and symmetry-based learning techniques on product data to create a classification model that consists of two subsystems: (1) for predicting the garment category and (2) for predicting the garment sub-category. Classification techniques, such as Decision Trees, Naïve Bayes, Random Forest, and Bayesian Forest were applied to the 'Deep Fashion' open-source database. Medina, A.; et al. [7] proposed a CNN model classification for the implementation of these classifiers on cameras. First, the Fashion MNIST was analyzed and compared with the VGG16, Inceptionvv4,

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TinyYOLOv3, and ResNet18 classification algorithms to determine the best clo classifier. Then, for real-time analysis, a new dataset with 12,000 images was created and analyzed with the YOLOv3 and TinyYOLO. Finally, an Azure Kinect DT was employed to analyze the clo value in real-time. Moreover, real-time analysis can be employed with any other webcam. The model recognizes at least three garments of a clothing ensemble, proving that it identifies more than a single clothing garment. Besides, the model has at least 90% accuracy in the test dataset, ensuring that it can be generalized and is not overfitting.

Chen, X.; et al. [8] developed a paper that puts forward a style classification method combining fine-grained and coarse-grained techniques. Furthermore, a new deep neural network is proposed, which can improve the robustness of recognition and avoid the interference of image background through the pan learning and the background learning of image features. In order to study the relationship between the fine-grained attributes of clothing and the whole style, firstly, the clothing types are learned to realize the pre-training of model parameters. Secondly, through the transfer learning of the first stage of the pre-training model parameters, the model parameters are fine-tuned to make them more suitable for identifying the coarse-grained style types. Donati, L.; et al. [9] developed the work, made by using and testing the aforementioned approaches in collaboration with Adidas, describes a real-world study aimed at automatically recognizing and classifying logos, stripes, colors, and other features of clothing, solely from final rendering images of their products. Specifically, both deep learning and image processing techniques, such as template matching, were used. The result is a novel system for image recognition and feature extraction that has a high classification accuracy and which is reliable and robust enough to be used by a company like Adidas. This paper shows the main problems and proposed solutions in the development of this system, and the experimental results on the Adidas AG™ dataset.

Rocha, D.; et al. [10] aimed at categorizing and detecting the presence of stains on garments, using artificial intelligence algorithms. In their approach, transfer learning was used for category classification, where a benchmark was performed between convolutional neural networks (CNNs), with the best model achieving an F1 score of 91%. Stain detection was performed through the fine tuning of a deep learning object detector, i.e., the mask R (region-based)-CNN. This approach is also analyzed and discussed, as it allowed us to achieve better results than those available in the literature. Mukhamediev, R.I. et al. [11] described new results achieved with the Fashion-MNIST dataset using classical machine learning models and a relatively simple convolutional network. They present the state-of-the-art results obtained using the CNN-3-128 convolutional network and data augmentation. The developed CNN-3-128 model containing three convolutional layers achieved an accuracy of 99.65% in the Fashion-MNIST test image set. In addition, this paper presents the results of computational experiments demonstrated the dependence between the number of adjustable parameters of the convolutional network and the maximum acceptable classification quality, which allows us to optimise the computational cost of model training.

Paulauskaite-Taraseviciene, A.; et al. [12] presented the state-of-the-art results obtained using the CNN-3-128 convolutional network and data augmentation. The developed CNN-3-128 model containing three convolutional layers achieved an accuracy of 99.65% in the Fashion-MNIST test image set. In addition, this paper presents the results of computational experiments demonstrating the dependence between the number of adjustable parameters of the convolutional network and the maximum acceptable classification quality, which allows us to optimise the computational cost of model training. Nisa, H.; et al. [13] proposed the garment measurement solution based on image processing technologies, which is divided into two phases, garment segmentation and key points extraction. UNet as a backbone network has been used for mask retrieval. Separate algorithms have been developed to identify both general and specific garment key points from which the dimensions of the garment can be calculated by determining the distances between them. Using this approach, they have resulted in an average 1.27 cm measurement error for the prediction of the basic measurements of blazers, 0.747 cm for dresses and 1.012 cm for skirts.

Zulfiqar, A.; et al. [14] explored the systematic review with the applications of AI in evaluating clothing quality and condition within the framework of a circular economy, with a focus on supporting second-hand clothing resale, charitable donations by NGOs, and sustainable recycling practices. A total of 135 research resources were identified through searching academic databases including Google Scholar, Springer, ScienceDirect, IEEE, Taylor and Francis, and Sage journals. These publications were subsequently refined down to 49 based on selected inclusion criteria. The selection of these sources from diverse databases was undertaken to mitigate any potential bias in the selection process. Wilson, S.; et al. [15] described the efforts concerning prediction models related to the textile and polymer industry, especially garment seam strength, emphasizing critical parameters such as stitch density, fabric GSM, thread type, thread count, stitch classes, and seam types. These parameters play a pivotal role in determining the durability and overall quality of denim jeans based on cellulosic polymer. A significant focus is dedicated to the mathematical computational models employed for predicting seam strength in five-pocket denim jeans.

3. PROPOSED SYSTEM

The system designed as a distributed intelligent framework deployed across Laptop 1 (Admin/Server) and Laptop 2 (User/Client). Server handles all core processing tasks including dataset preparation, deep feature extraction using EfficientNetB0 (Efficient Network B0), and training of multiple classification models such as DNN, Perceptron, and the proposed MLP. These models are designed for multi-output classification to simultaneously predict fabric type and stitching condition. Client acts as the user interface where images are provided for prediction and results are visualized. The system also integrates an external generative artificial intelligence-based module for input validation and semantic interpretation. The overall architecture ensures efficient data flow from input acquisition to final prediction and visualization as illustrated in Figure 2, enabling accurate, scalable, and real-time garment analysis.

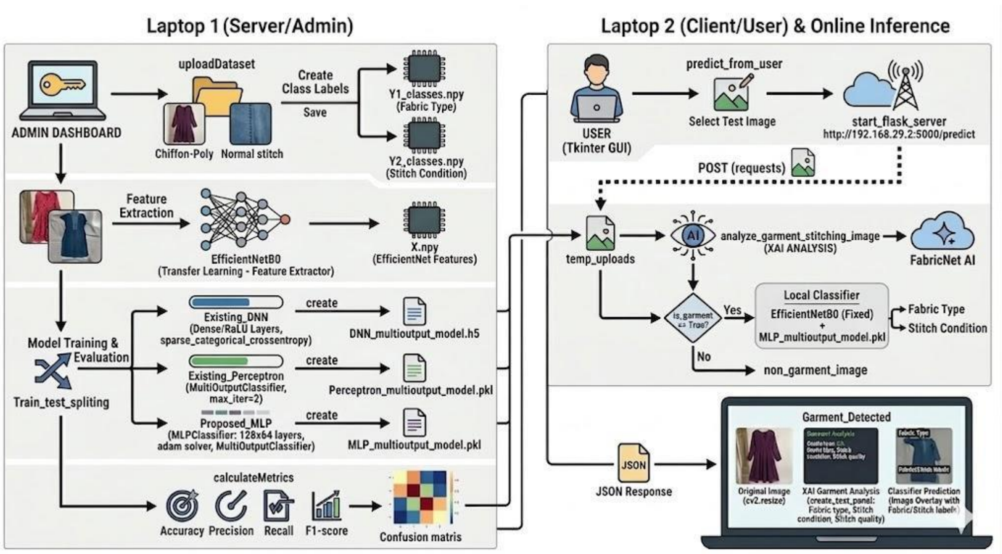

Figure 2: Proposed system architecture

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Step 1: Dataset Upload and Class Label Generation

The system begins with dataset upload through the admin interface on Laptop 1. Images are organized into hierarchical folders representing fabric categories (Y1) and stitching subclasses (Y2). The system automatically extracts and stores these labels as numerical mappings, which are later used during training and prediction. This structured labeling enables effective supervised learning for multi-output classification.

Step 2: Feature Extraction using EfficientNetB0

All images are processed through EfficientNetB0, a pre-trained convolutional neural network used as a feature extractor. It captures high-level visual patterns such as texture, edges, and stitching structures. The output features are stored as numerical vectors, reducing redundancy and improving computational efficiency. This step converts raw images into discriminative representations suitable for model training.

Step 3: Multi-Model Training and Evaluation

The extracted features are used to train three models: DNN, Perceptron, and the proposed MLP. Each model is configured for multi-output classification to predict both fabric and stitching labels simultaneously. Their performance is evaluated using metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis. This step identifies the most accurate and reliable model, with MLP performing best.

Step 4: Image Input and Intelligent Validation

On Laptop 2, users upload test images through the interface. The input image is first analyzed using an external generative AI-based module to verify whether it contains a valid garment and stitching pattern. This module also provides semantic insights such as stitching quality. This validation step prevents incorrect or irrelevant inputs from reaching the classification stage.

Step 5: Classification using Trained MLP Model

After validation, the image undergoes feature extraction and is passed to the trained MLP model. The model processes the feature vector and predicts both the fabric type and stitching condition. This step leverages learned patterns from training to perform accurate real-time classification on unseen data.

Step 6: Result Generation and Visualization

The final predictions, along with semantic analysis results, are presented to the user through the interface. The system displays fabric type, stitching condition, and additional insights in a clear format. This step ensures interpretability and enhances user experience by providing meaningful and actionable outputs.

4. RESULTS ANALYSIS

The results demonstrate that the system can accurately identify both fabric type and stitching subclass from garment images with high reliability. The use of deep feature extraction enables effective capture of fine visual details such as texture and stitch patterns. Among the tested models, the proposed MLP shows better performance in terms of accuracy and consistency compared to other approaches. The multi-output classification strategy efficiently handles dual predictions in a single pipeline, reducing computational effort. Performance metrics like precision, recall, and F1-score confirm the robustness

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of the model. The system proves to be efficient and suitable for real-time applications in automated garment analysis.

In figure 3 illustrates the GUI after dataset splitting, resulting in a total sample, with allocated to the training set and to the testing set, maintaining an 80-20 split. The feature shape aligns with EfficientNetB0's output after global average pooling, reflecting the dimensionality of the extracted features. The labels for y1 (category) and y2 (subcategory) training datasets are confirmed with shapes respectively, indicating a balanced split across the two target variables. This partitioning ensures that the models are trained on a representative subset of the data while reserving a sufficient portion for unbiased evaluation, adhering to best practices in machine learning for preventing overfitting.

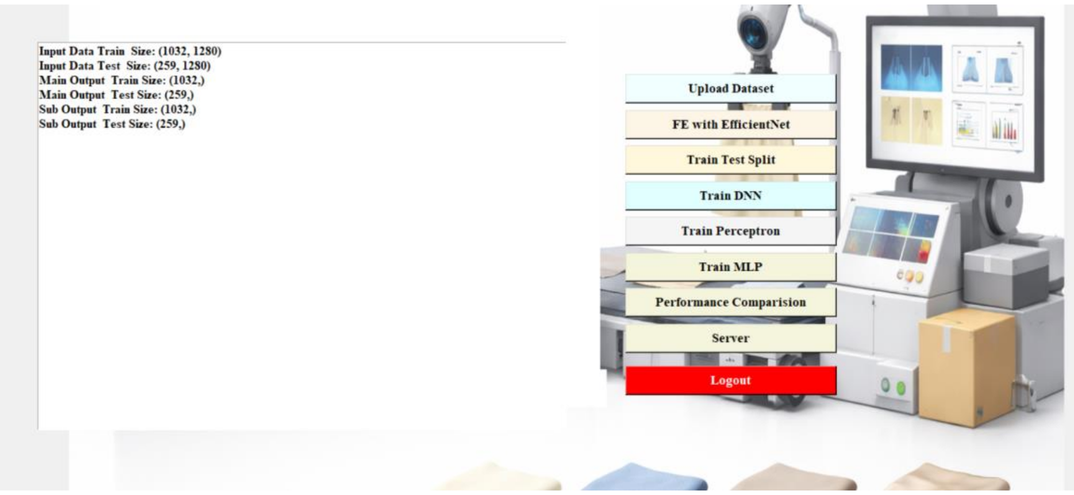
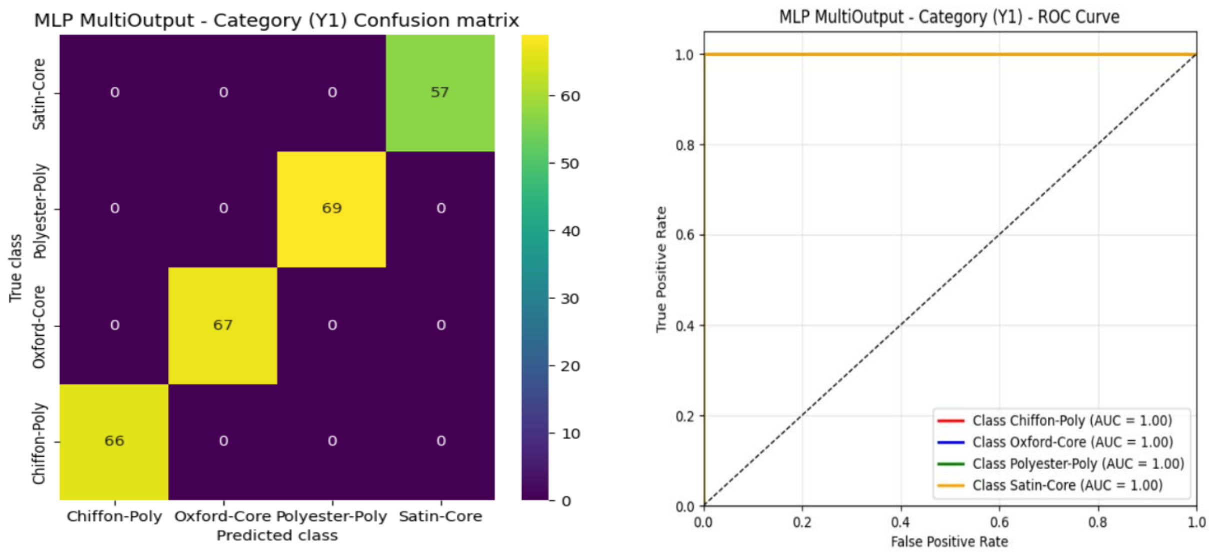


Figure 3: Dataset Splitting into Training and Testing Sets.



(a)

Figure 4 (a): Confusion matrix and ROC curve obtained using proposed MLP for main class Y1

The figure 4 (a) shows MLP multi-output model for category (Y1) classification exhibits perfect discrimination capability in the ROC curve, where all fabric classes such as Chiffon-Poly, Oxford-Core, Polyester-Poly, and Satin-Core achieved an AUC of 1.00, indicating the classifier can completely separate the garment categories without overlap. This ideal behavior is fully supported by the confusion

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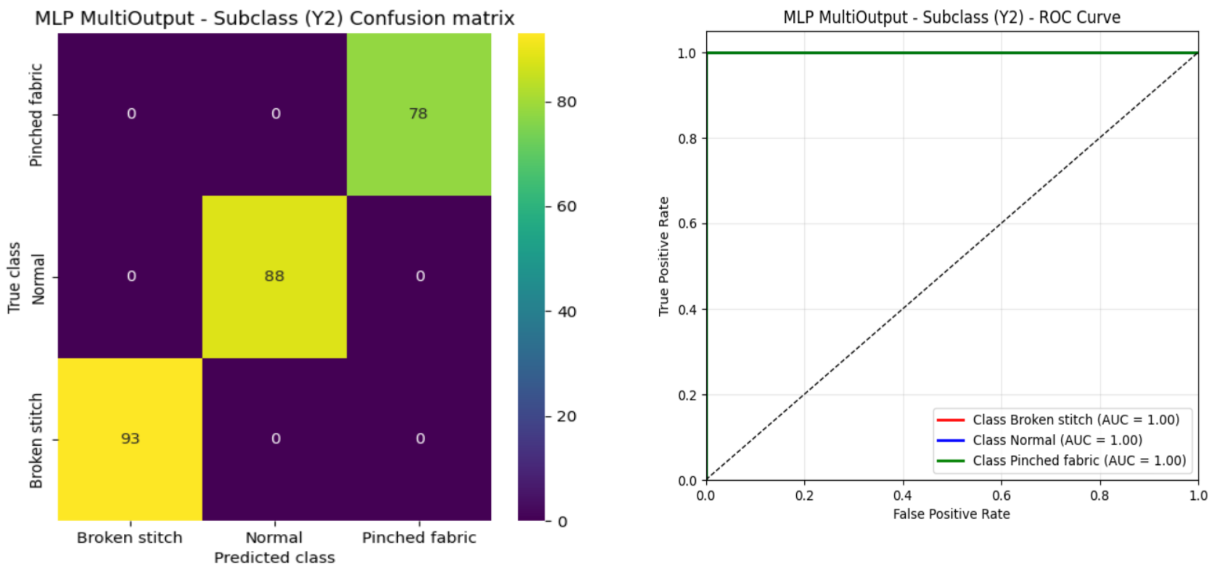
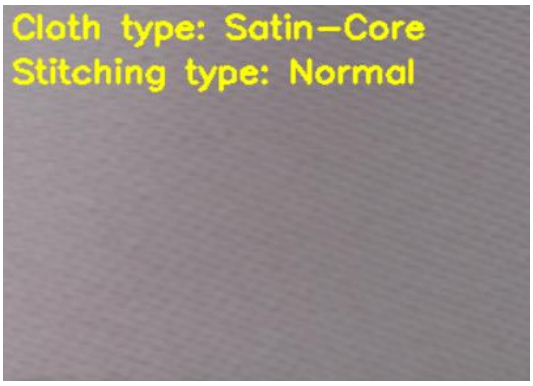
matrix, which shows every sample correctly predicted: Chiffon-Poly (66), Oxford-Core (67), Polyester-Poly (69), and Satin-Core (57) all fall exactly on the diagonal with zero misclassifications, demonstrating that the MLP model learns highly distinctive feature representations and provides flawless category recognition performance.



(b)

Figure 4 (b): Confusion matrix and ROC using proposed MLP for subclass Y2

The figure 4 (b) shows ROC and confusion matrix for MLP multi-output model for subclass (Y2) classification shows perfect separability in the ROC curves, where all stitching categories such as Broken stitch, Normal, and Pinched fabric achieve an AUC of 1.00, indicating complete discrimination without overlap between classes. This ideal performance is confirmed by the confusion matrix, in which every sample is correctly classified: Broken stitch (93), Normal (88), and Pinched fabric (78) all lie exactly on the diagonal with zero misclassification, demonstrating that the MLP model learns highly distinctive stitching features and delivers flawless subclass prediction accuracy.



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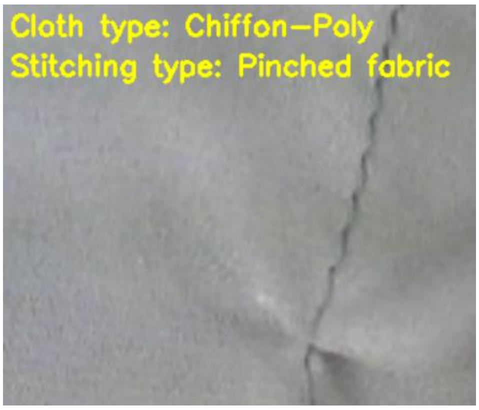

Figure 5: Prediction on test images using proposed MLP

The figure 5 shows predictions produced by the proposed MLP model on unseen test images demonstrate accurate joint recognition of both garment category and stitching type, correctly identifying Polyester-Poly with Pinched fabric stitching, Chiffon-Poly with Pinched fabric stitching, Oxford-Core with Normal stitching, and Satin-Core with Normal stitching; these results indicate that the model successfully captures distinctive texture patterns for fabric classification while simultaneously learning fine stitching characteristics, showing consistent real-time inference capability and confirming the reliability of the multi-output approach for practical garment inspection scenarios.

Table 1: Performance comparison for the DNN, Perceptron, and propsoed MLP model for main class Y1

Algorithms Name	Accuracy	Precision	Recall	F-score
DNN Model	98.45%	98.57%	98.24%	98.35%
Perceptron Model	99.61%	99.56%	99.62%	99.59%
MLP Model	100.0%	100.0%	100.0%	100.0%

Table 1 presents the comparative performance of the DNN, Perceptron, and proposed MLP models for the main garment category classification task (Y1), clearly showing a progressive improvement in predictive capability across the models. The DNN model achieves strong results with an accuracy of 98.45%, precision of 98.57%, recall of 98.24%, and F-score of 98.35%, indicating reliable classification but with minor misclassifications. The Perceptron model further enhances performance, reaching 99.61% accuracy, 99.56% precision, 99.62% recall, and 99.59% F-score, demonstrating better generalization and fewer errors compared to the DNN. However, the proposed MLP model outperforms both existing approaches by achieving perfect classification performance, recording 100% accuracy, precision, recall, and F-score, which indicates that the extracted EfficientNet features are highly separable and the MLP classifier can fully learn discriminative fabric patterns without any false predictions, making it the most effective model for main garment category recognition.

Table 2: Performance comparison for the DNN, Perceptron, and proposed MLP model for main class Y2

Algorithms Name	Accuracy	Precision	Recall	F-score

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DNN Model	93.82%	94.32%	94.13%	93.98%
Perceptron Model	95.36%	95.64%	95.49%	95.43%
MLP Model	100.0%	100.0%	100.0%	100.0%

Table 2 compares the performance of the DNN, Perceptron, and proposed MLP models for the stitching subclass classification task (Y2), demonstrating a clear improvement trend across the models. The DNN model achieves an accuracy of 93.82%, precision of 94.32%, recall of 94.13%, and F-score of 93.98%, indicating good recognition capability but with noticeable confusion among visually similar stitching patterns. The Perceptron model improves the classification results, obtaining 95.36% accuracy, 95.64% precision, 95.49% recall, and 95.43% F-score, which reflects better separation of stitching features and reduced misclassification compared to the DNN. The proposed MLP model significantly outperforms both methods by achieving perfect performance with 100% accuracy, precision, recall, and F-score, showing that the deep features extracted from EfficientNet are highly discriminative for stitching characteristics and that the MLP effectively learns fine-grained texture variations, making it the most reliable approach for subclass identification.

5. CONCLUSION

The research presents an intelligent garment inspection system developed using a transfer learning–based multi-output classification approach to identify both fabric type and stitching category from images. The system is deployed across Server and Client, where Laptop 1 performs feature extraction using EfficientNetB0 and classification using DNN, Perceptron, and the proposed MLP, while Laptop 2 enables user interaction and prediction visualization. Experimental results show that the proposed MLP achieves superior performance with high accuracy across both classification levels. Evaluation using confusion matrices and ROC curves confirms that the extracted features are highly discriminative. The system includes a graphical interface developed using Tkinter for dataset handling, training, and real-time prediction. In addition, an FabricNet, based module is incorporated to analyze input images and provide semantic interpretation, assisting in validating garment presence and stitching quality. Testing on unseen images demonstrates reliable performance in practical scenarios.

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