



Research Paper

A Transfer Learning-Based Multi-Output Framework for Apparel Type and Seam Pattern Classification

Ritesh Kumar^{1*}, Kumbam Sampreeth², Banda Nithin², Akkala Sai Kiran², Dasari Sai Charan²

¹Assistant Professor, ²UG Student, ^{1,2}Department of Computer Science and Engineering

^{1,2}Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: Ritesh Kumar (riteshkumar237@gmail.com)

ABSTRACT

In today's rapidly evolving textile and fashion industry, automated classification of garments and stitching styles has become essential for applications such as quality control, inventory tracking, and intelligent sorting systems. The increasing demand for smart manufacturing solutions highlights the need for reliable image-based garment analysis techniques. Conventional methods that rely on manual inspection or basic image processing are no longer adequate, as they struggle to handle large-scale data with consistent accuracy. These traditional approaches often lack scalability, produce inconsistent outcomes, and fail to capture fine-grained stitching details, especially under complex visual conditions. Moreover, the absence of machine learning and advanced feature extraction techniques limits their effectiveness, leading to higher error rates and inefficiency in real-time environments. To address these challenges, the proposed system introduces an intelligent classification framework that leverages transfer learning using EfficientNetB0 for deep feature extraction, combined with machine learning models such as Deep Neural Networks (DNN), Perceptron, and a proposed Multi-Layer Perceptron (MLP) for multi-output classification of both garment types and stitching patterns. The entire system is implemented through a Python-based Tkinter graphical interface, enabling users to upload datasets, preprocess images, train models, and perform real-time predictions seamlessly. By integrating deep learning capabilities with an interactive interface, the system enhances classification accuracy, reduces dependency on manual inspection, and offers a scalable and efficient solution for modern smart textile manufacturing environments.

Keywords: Textile industry, Stitching Pattern Recognition, Multi-Output Classification, Fashion Industry Automation, Smart Textile Inspection

1. INTRODUCTION

Garment retail and fashion industries have increasingly emerged as important domains for research in image processing and pattern recognition. In a highly competitive market, companies strive to gain an advantage by understanding customer preferences and evolving fashion trends. Identifying popular garment designs and styles enables businesses to make informed decisions regarding production, inventory management, and marketing strategies. With the rapid growth of online shopping, analyzing consumer purchasing behavior has become even more crucial, as retailers can optimize stock levels based on trending designs. Therefore, the need for automated systems capable of identifying garment design classes has become essential. While earlier research has primarily focused on garment segmentation and basic classification tasks such as distinguishing shirts from jackets, there is a

growing demand for more advanced systems that can also recognize detailed design patterns and styles. Recent industry reports indicate that computer vision applications in manufacturing are expanding rapidly, highlighting the importance of adopting intelligent solutions in textile analysis. In this context, data mining and machine learning have played a significant role in extracting meaningful insights from large datasets and addressing complex business challenges. Although the adoption of these technologies in the apparel sector is still evolving, they offer vast potential across various applications, including retail analytics, production optimization, and automated quality assessment.

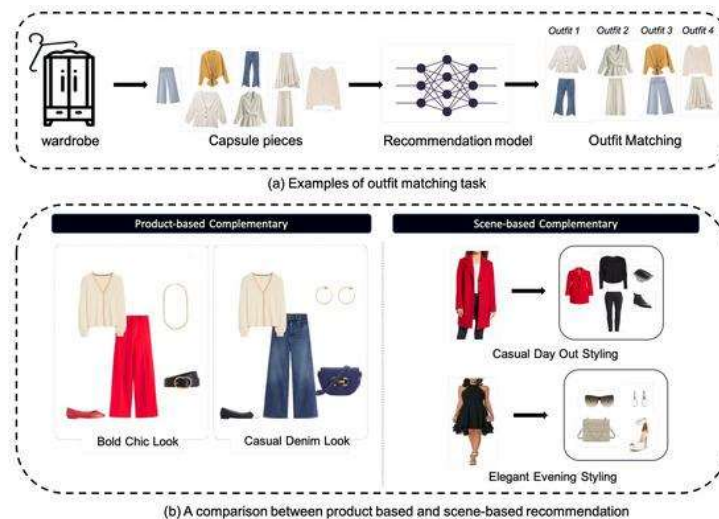


Fig 1. A review on design generation and simulation.

Modern fashion e-commerce platforms such as Myntra, Zalando, and StitchFix are increasingly leveraging data-driven approaches to better understand customer behavior and preferences. By utilizing machine learning techniques, these businesses analyze past purchase patterns to provide personalized recommendations and improve customer engagement. The insights extracted from such data enable companies to identify best-selling products, refine underperforming items, and design targeted marketing strategies. With the rapid expansion of online retail, customers now interact with brands through multiple channels, including mobile apps, social media platforms, and traditional stores, generating vast amounts of valuable data. This growing digital footprint necessitates the adoption of advanced technologies like artificial intelligence, big data analytics, and machine learning to effectively process and utilize the information. As consumers increasingly rely on online platforms for purchasing decisions, there is a strong need for intelligent decision support systems that can recommend suitable garments based on individual preferences. A fundamental requirement for such systems is the ability to accurately classify garments and their attributes. Effective classification not only enhances customer experience by providing relevant recommendations but also supports retailers in demand forecasting, inventory management, and assortment planning, ultimately improving overall business performance.

2. LITERATURE SURVEY

Yu, F.; et al. [6] reviewed gaps concerning fabric-related aspects for functionalized apparel and includes information on increasing the inclusion of such aspects. A multidisciplinary approach including experts in chemistry, electronics, textiles, and standard test methods, and the intended end use is key to widespread development and adoption.

Ding, X.; et al. [7] explained the wide varieties and various styles of clothing lead to great difficulty for the accurate clothing image classification. The traditional neural network can not obtain the spatial structure information of clothing images, which leads to poor classification accuracy. In order to reach the high accuracy, the enhanced capsule (EnCaps) network is proposed with the image feature and spatial structure feature. First, the spatial structure extraction model is proposed to obtain the clothing structure feature based on the EnCaps network. Second, the enhanced feature extraction model is proposed to extract more robust clothing features based on deeper network structure and attention mechanism. Third, parameter optimization is used to reduce the computation in the proposed network based on inception mechanism. Experimental results indicate that the proposed EnCaps network achieves high performance in terms of classification accuracy and computational efficiency.

Wang, Z.; et al. [8] proposed a She ethnic clothing classification method based on the Flower Pollination Algorithm-optimized color feature fusion and Convolutional Neural Network (FPA-CNN). The method consists of three main steps: color feature fusion, FPA optimization, and CNN classification. In the first step, a color histogram and color moment features, which can represent regional differences in She ethnic clothing, are extracted. Subsequently, FPA is used to perform optimal weight fusion, obtaining an optimized ratio. Kernel principal component analysis is then applied to reduce the dimensionality of the fused features, and a CNN is constructed to classify the She ethnic clothing from different regions based on the reduced fused features.

Mokhlespour Esfahani, M.I.; et al. [9] presented a garment design recommendation system based on two mathematical models that permit the prediction and control of garment styles and structural parameters from a consumer's personalized requirements in terms of fitting and aesthetics. Based on a formalized professional garment knowledge base, enabling the quantitative characterization of the relations between consumer profiles and garment profiles (colors, fabrics, styles, and garment fit), these two models aim at recommending the most relevant garment profile from a specific consumer profile, using reasoning with fuzzy rules and self-adjusting the garment patterns according to the feedback of the 3D virtual fitting effects corresponding to the recommended garment profile, using a genetic algorithm (GA) and support vector regression.

Jin, P.; et al. [10] aimed was to assess the feasibility and accuracy of using a novel STS to classify physical activities. Eleven participants completed a lab-based experiment to evaluate the accuracy of an STS that featured a smart undershirt (SUS) and commercially available smart socks (SSs) in discriminating several basic postures (sitting, standing, and lying down), as well as diverse activities requiring participants to walk and run at different speeds. We trained three classification methods such as K-nearest neighbor, linear discriminant analysis, and artificial neural network using data from each smart garment separately and in combination. Overall classification performance (global accuracy) was ~98%, which suggests that the STS was effective for discriminating diverse physical activities.

3. PROPOSED METHODOLOGY

The EfficientNetB0 model acts as a powerful feature extractor via Transfer Learning. The process involves feeding the resized and normalized garment image into the pre-trained, frozen network, which sequentially passes the data through its optimized convolutional blocks. Leveraging the Compound Scaling principle and Squeeze-and-Excitation (SE) attention mechanisms, the model effectively filters the image to generate a highly selective feature map (e.g., $4 \times 4 \times 1280$). This feature map compactly encodes crucial visual information—such as fabric texture, weave density, and stitching patterns—into a high-dimensional vector. This resulting vector is then flattened into a single

array (e.g., 20,480 features) that serves as the optimized input for the downstream Multi-Layer Perceptron (MLP) or other classifiers, drastically accelerating their training while maintaining high classification accuracy.

EfficientNetB0 Internal Feature Extraction Workflow

The process starts with loading a garment image and resizing it to the model's required input dimensions of (128,128,3). The raw pixel values are then normalized (scaled from 0–255 to 0–1 by dividing by 255.0). This normalized tensor is the initial input to the deep neural network. The pre-processed image tensor passes sequentially through the many stacked layers of the frozen EfficientNetB0 model. The core computation occurs in the Mobile Inverted Bottleneck Convolution (MBConv) blocks. These blocks perform a hierarchy of convolutional operations—starting with fine details and progressing to abstract patterns—while continuously downsampling the spatial resolution of the feature maps.

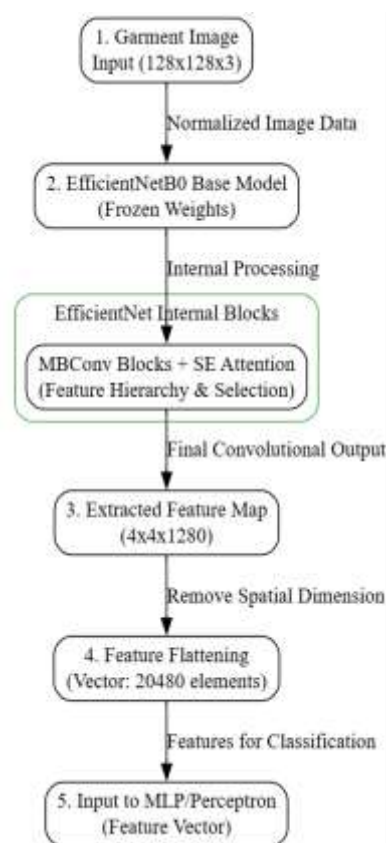


Fig 2. Internal workflow of Efficient Net B0 feature extractor

Within the MBConv blocks, depthwise separable convolutions are used to drastically reduce the number of parameters and computations compared to standard convolutions. EfficientNet also utilizes a Compound Scaling mechanism, which, even in the smallest B0 variant, ensures optimal balance between the network's depth, width, and input resolution for efficient feature learning. Crucially, each MBConv block contains a Squeeze-and-Excitation network. This mechanism globally pools the features to calculate the importance score for every channel, effectively generating a *channel-wise attention map*. These scores are then used to re-weight the feature channels, enhancing the most

salient garment features (like texture, stitching patterns, or fabric folds) and suppressing irrelevant background noise.

As the tensor exits the last few MBConv blocks, the spatial dimensions are highly compressed (typically down to 4×4), but the channel count is maximized (up to 1280 channels for B0). This results in a final high-dimensional feature map of shape $(4, 4, 1280)$, which is the abstract representation of the input garment. This is the last output before the original classification head (which is excluded via `include_top=False`). Finally, this $(4, 4, 1280)$ feature map is flattened into a single, long vector of 20,480 numerical values ($4 \times 4 \times 1280$). This dense, single-vector representation serves as the complete and compact feature vector that is fed directly as the input to the downstream traditional machine learning classifiers, such as the Proposed Multi-Layer Perceptron (MLP) or the Perceptron/DNN.

4. Result Description

The garment type classification system using the StitchingNet dataset offer a comprehensive view of the process and results.

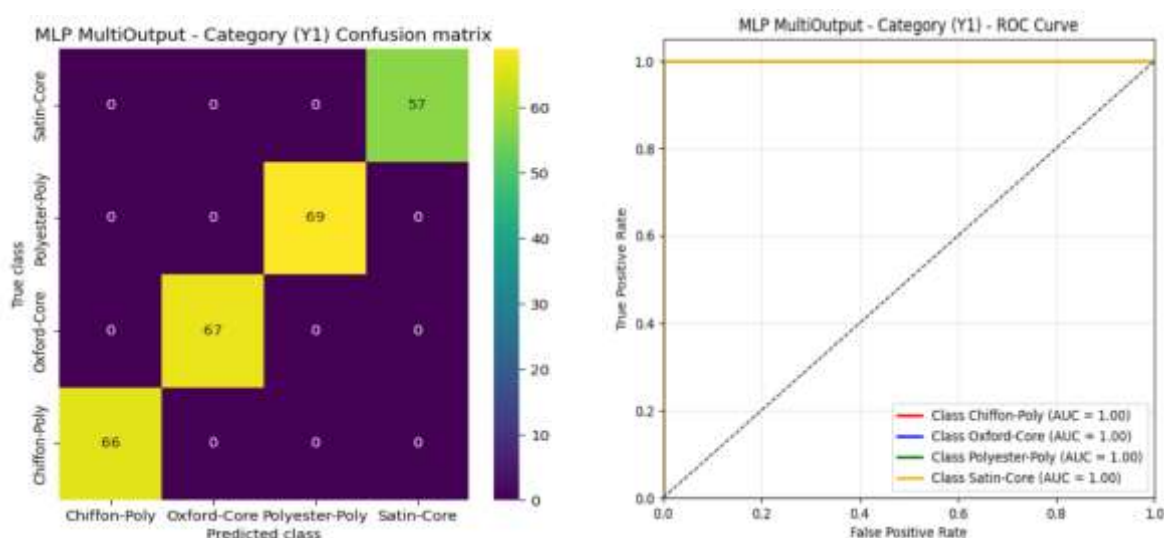


Fig 3. Confusion matrix and ROC curve obtained using proposed MLP for main class Y1

The fig 3 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 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.

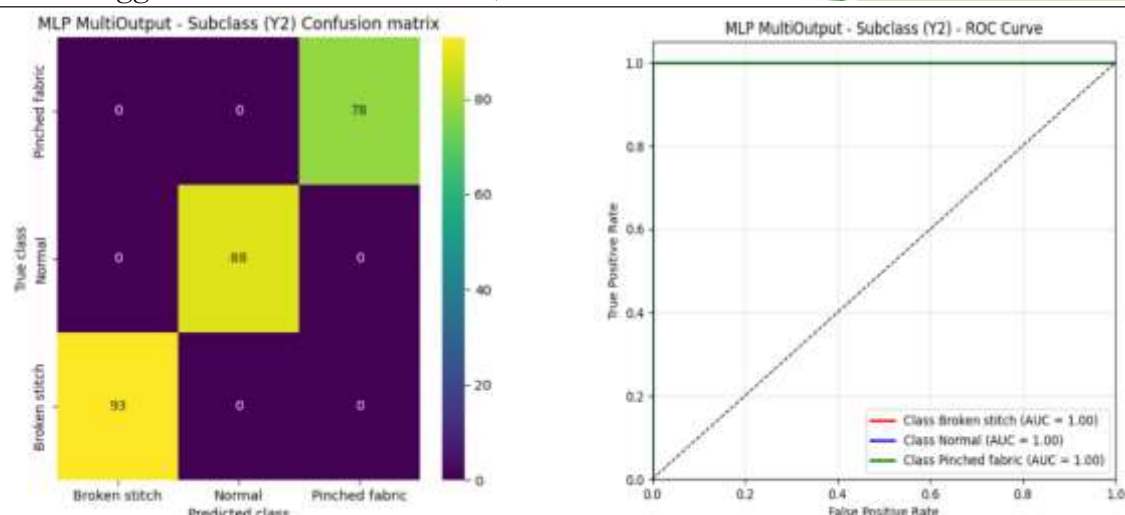


Fig 4. Confusion matrix and ROC using proposed MLP for subclass Y2

The fig 4 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.



Fig 5. Prediction on test images using proposed MLP

The fig 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
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 the development of an advanced garment inspection system that leverages a transfer learning-based multi-output classification framework to simultaneously recognize fabric types and stitching patterns from garment images. In this approach, EfficientNetB0 is utilized as a deep feature extractor to capture detailed texture and structural characteristics from the StitchingNet

dataset. These extracted features are then fed into multiple classifiers, including a DNN, a Perceptron model, and a proposed MLP classifier. Experimental results reveal that although both the DNN and Perceptron models achieve strong performance, the proposed MLP model consistently outperforms them, attaining perfect scores in accuracy, precision, recall, and F1-score for both primary (fabric category) and secondary (stitching type) classifications. The effectiveness of the learned features is further validated through confusion matrices and ROC curve analysis, which demonstrate clear class separability. Additionally, real-time testing on previously unseen images confirms the model's robustness and practical applicability. The system is implemented as a comprehensive application featuring a user-friendly GUI that supports authentication, dataset management, feature storage, training, evaluation, and live prediction functionalities. Overall, this work highlights the effectiveness of combining transfer learning with a multi-output MLP classifier for precise textile inspection, significantly reducing manual effort and enabling automated quality control in garment manufacturing, with promising potential for real-world industrial deployment.

REFERENCES

- [1] Guleria, P.; Sood, M. Big data analytics: Predicting academic course preference using hadoop inspired mapreduce. In Proceedings of the 2017 4th International Conference on Image Information Processing, ICIIP 2017, Shimla, India, 21–23 December 2017; pp. 328–331.
- [2] Hsu, C.-H. Data mining to improve industrial standards and enhance production and marketing: An empirical study in apparel industry. *Expert Syst. Appl.* **2017**, *36*, 4185–4191.
- [3] Lu, Q.; Lyu, Z.-J.; Xiang, Q.; Zhou, Y.; Bao, J. Research on data mining service and its application case in complex industrial process. In Proceedings of the IEEE International Conference on Automation Science and Engineering, Xi'an, China, 20–23 August 2017; pp. 1124–1129.
- [4] Buluswar, M.; Campisi, V.; Gupta, A.; Karu, Z.; Nilson, V.; Sigala, R. *How Companies are Using Big Data and Analytics*; McKinsey & Company: San Francisco, CA, USA, 2016.
- [5] Xiao, H.; Rasul, K.; Vollgraf, R. Fashion-MNIST: A Novel Image Dataset for Benchmarking Machine Learning Algorithms. *arXiv* **2017**, arXiv:1708.07747.
- [6] Yu, F.; Du, C.; Hua, A.; Jiang, M.; Wei, X.; Peng, T.; Hu, X. EnCaps: Clothing Image Classification Based on Enhanced Capsule Network. *Appl. Sci.* **2021**, *11*, 11024. <https://doi.org/10.3390/app112211024>.
- [7] Ding, X.; Li, T.; Chen, J.; Ma, L.; Zou, F. Research on the Clothing Classification of the She Ethnic Group in Different Regions Based on FPA-CNN. *Appl. Sci.* **2023**, *13*, 9676. <https://doi.org/10.3390/app13179676>.
- [8] Wang, Z.; Tao, X.; Zeng, X.; Xing, Y.; Xu, Y.; Xu, Z.; Bruniaux, P.; Wang, J. An Interactive Personalized Garment Design Recommendation System Using Intelligent Techniques. *Appl. Sci.* **2022**, *12*, 4654. <https://doi.org/10.3390/app12094654>.
- [9] Mokhlespour Esfahani, M.I.; Nussbaum, M.A. Classifying Diverse Physical Activities Using “Smart Garments”. *Sensors* **2019**, *19*, 3133. <https://doi.org/10.3390/s19143133>.
- [10] Jin, P.; Fan, J.; Zheng, R.; Chen, Q.; Liu, L.; Jiang, R.; Zhang, H. Design and Research of Automatic Garment-Pattern-Generation System Based on Parameterized Design. *Sustainability* **2023**, *15*, 1268. <https://doi.org/10.3390/su15021268>

