Pertanika Proceedings 1 (5): 29 - 33 (2025)

PERTANIKA JOURNALS

PERTANIKA PROCEEDINGS

Journal homepage: http://www.pertanika.upm.edu.my/

Quantitative Assessment of Deep Learning and Metaheuristic Optimization Techniques in Fabric Defect Detection

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ABSTRACT

Advancements in fabric defect detection (FDD) are explored through the application of Deep Learning (DL) and Metaheuristic Optimization (MO) techniques in this study. As textile production becomes more automated, the need for precise and speedy defect detection systems grows. We look at contemporary works that combine different DL models with MO approaches like simulated annealing, particle swarm optimisation, and genetic algorithms. The work focusses on a complete statistical evaluation of several approaches across multiple datasets, including accuracy, precision, recall, and processing cost.

Keywords: Deep learning, fabric defect detection, , metaheuristic optimization, performance metrics, statistical analysis

INTRODUCTION

Fabric Defect Detection (FDD) is an important quality assurance tool in textile manufacturing since it detects faults in fabric that may damage both aesthetic appeal and functionality. Certified inspectors have typically performed FDD by hand, which, while speedy, is labour-intensive and prone to human error, particularly as inspector fatigue sets up over time. As the textile industry expands and changes, more dependable, cost, and effective flaw detecting approaches will undoubtedly become necessary. The advancement of automation technologies provides new opportunity to address these concerns. Among the most amazing advances are Deep Learning (DL) and Metaheuristic Optimization (MO). DL models are ideal for detecting fabric problems because they can learn from large amounts of data and draw exact judgements. Metaheuristic Optimization (MO) techniques, on the other hand, provide significant solutions to optimisation difficulties and aid in the optimisation of DL model performance,

ARTICLE INFO

Article history:
Received: 29 August 2025
Published: 31 October 2025

DOI: https://doi.org/10.47836/pp.1.5.006

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increasing their significance in real-world applications. The goal of this research is to investigate the recent advances in the application of DL and MO for FDD.

LITERATURE REVIEW

Conventional methods of fabric fault detection have primarily relied on hand inspection and basic automated systems using basic image processing methods including thresholding and filtering. However, as the complexity and variety of cloth patterns grow, these technologies often fell short in terms of consistency and efficiency. Deep Learning (DL) has revolutionised the field of fabric defect diagnosis by providing potent techniques for highly precise analysis of complex picturesRecent studies have automatically learnt the intricate characteristics of both defective and non-defective fabric samples using a range of architectures including Convolutional Neural Networks (CNNs). Training now includes MO techniques to enhance the performance of Deep Learning Models These approaches maximise neural network hyperparameters to raise model resilience and learning effectiveness. More accurate and efficient defect detection systems have come from methodically tuning parameters including learning rate, batch size, and layer number using genetic algorithms (GAs), particle swarm optimisation (PSO), and ant colony optimisation (ACO) (Sajitha & Priya, 2024). Table 1 summarises current studies in FDD using DL and MO, highlighting the models or techniques used, as well as the major aspects and developments that set each study apart. This compilation provides a detailed look at the advances and specific contributions made in the discipline over recent years.

Figure 1 visually depicts the performance of a variety of sophisticated techniques for identifying fabric flaws. While certain methods, such as Fourier Spectrum combined with GoogleNet and GoogleNet alone, achieve accuracies of 94.46% and 93.60%, respectively, models such as Few-shot learning achieve an accuracy of 96.04%, demonstrating excellent efficiency.

Using a Weight Initialised Adaptive Window, advanced models such as Alexnet and Pseudo-CNN are also compared to expose their performance measures. With 97.84% accuracy, CNN's Ensemble approach is more robust than others (Mewada et al. 2024). Figure 2 provides a comparative analysis of several Deep Learning models that have been employed to detect fabric defects, based on four primary criteria: accuracy, precision, recall, and F1-score. According to the graph, the conventional CNN model exhibits modest performance, with scores of 67% in Accuracy, 70% in Precision, 66% in Recall, and 79% in F1-Score. RestNet50v2 and DenseNet169v2 exhibit inferior performance in all metrics, which would indicate that they are inadequately suited for this application. In contrast, Feature Pyramid Networks (FPN) and their variants, demonstrate significant enhancements in Recall and Precision, which suggests that they can identify defects (Sajitha & Priya, 2024).

Table 1
Recent works on FDD using DL and MO

Author	Model/Approach	Features and Innovations
Kang (2024)	Utilizes the lightweight YOLOv5s model, integrating the Convolution Block Attention Module and Feature Enhancement Module, with CIoU_Loss for improved loss calculation. These modifications enhance information extraction, prediction speed, and accuracy.	Achieves mAPs of 86.4% and 75.8% for raw and patterned fabrics, respectively, marking improvements of 7.6% and 1.7%. The detection speed reaches 102 FPS, fulfilling the real-time requirements of industrial applications.
Mewada et al. (2024)	Utilizes a pretrained ResNet50 fine-tuned for fabric defect classification into four categories (holes, objects, oil spots, thread errors) with cuckoo search optimization for parameter tuning, achieving a 95.36% accuracy and a 95.35% F1 score.	May struggle with extremely subtle or novel defect types not represented in the training set, potentially limiting generalization.
Mustafa et al. (2024)	Utilizes ACSA for optimizing monitoring variables and alarm thresholds in the TEP, enhancing fault identification and reducing false alarms by adapting to process variations and disturbances. Demonstrated superior fault detection and reliability through extensive simulations on the TEP dataset.	Potential limitations in scenarios with extremely erratic process behaviors or where the algorithm's adaptability may not fully capture highly complex or unusual disturbances.
Nasim et al. (2024)	Utilizes YOLOv8 on a dataset from Chenab Textiles, achieving a mAP of 84.8%, with precision of 0.818 and recall of 0.839. Demonstrates high accuracy and efficiency in defect detection across various fabric types.	Limited to fabric types included in the training dataset, with potential for improvement in detection accuracy under highly variable conditions.
Liu et al. (2024)	Used PRC-Light YOLO that enhances YOLOv7 with Extended-Efficient Layer Aggregation for optimized feature extraction, Receptive Field Block for feature fusion, and Content-Aware ReAssembly of Features for dynamic convolution kernels. Uses HardSwish activation and Wise-IOU v3 for bounding box optimization.	Compared to YOLOv7, the model reduces parameters by 18.03% and computational load by 20.53%, while improving mAP by 7.6%.

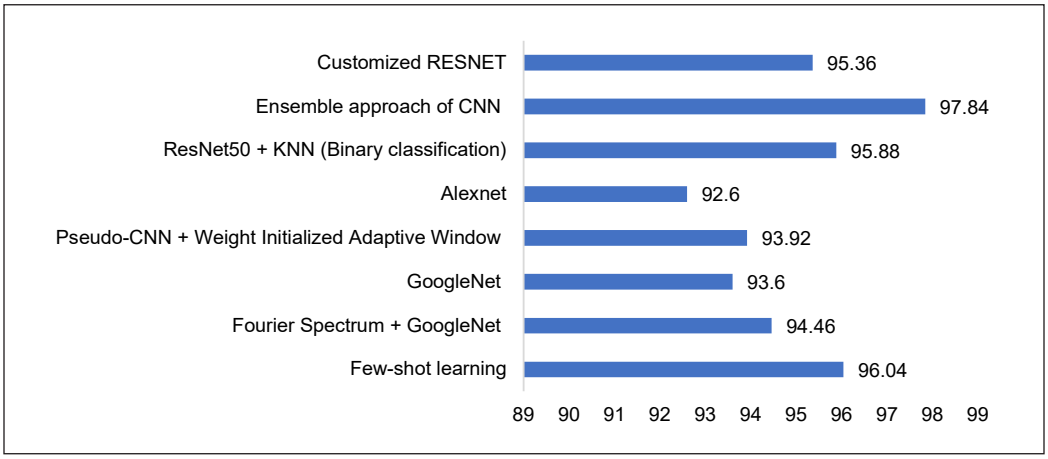

Figure 1. The statistical comparison of recent methods on FDD

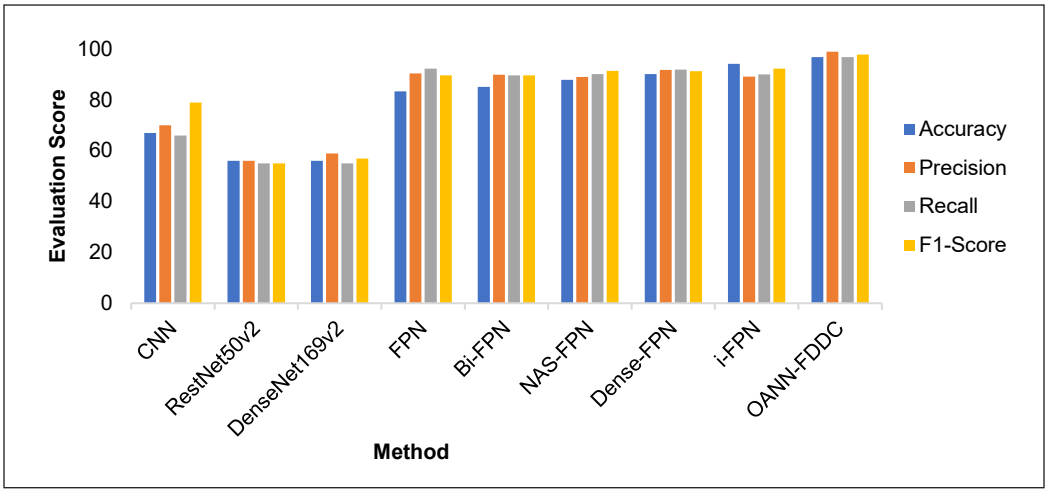

Figure 2. The comparison results of the FDD on different evaluation metrics

i-FPN achieves a well-balanced detection ability under numerous circumstances, as evidenced by its 94.2% Accuracy and 92.34% F1-Score. OANN-FDDC is the most exceptional model, with an Accuracy of 96.97%, Precision of 99.02%, Recall of 96.97%, and an F1-score of 97.92%, surpassing the top scores of nearly all categories. This model's exceptional performance underscores its potential for high-efficiency industrial applications, as it guarantees precise and consistent defect identification. The graph clearly illustrates the enhancements in model performance that have been achieved as a result of the implementation of the recent models, including OANN-FDDC and i-FPN.

CONCLUSION

This study indicated that FDD using DL and MO contributed industry growth. Modern computational techniques improved the detection systems' accuracy, efficiency, and dependability over inconsistent and laborious methods. Models such as OANN-FDDC and i-FPN demonstrated extraordinary performance increases, indicating their suitability for usage in industrial applications requiring high operating efficiency and precision. Furthermore, the acceptance of metaheuristic algorithms increased model performance under a variety of conditions, marking a significant milestone in the development of FDD technology. This study not only clarified efficient defect detection approaches, but also provided a solid foundation for future improvements in textile manufacturing quality control.

ACKNOWLEDGEMENT

The authors express their sincere gratitude to Mohan Babu University, India for providing the necessary facilities and support. throughout the research.

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