

Combining AI and Creative Design for Automated Fabric Defect Analysis and Pattern Generation from Common Imperfections

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Abstract

Common perception holds that fabric imperfections are unavoidable and contribute to economic losses and degradation of the environment. This study offers a new perspective by reimagining these shortcomings as opportunities for innovative design. This study takes an approach, using Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) to not only identify fabric defects but also transform them into the unique visual designs. The dataset of 3,000 fabric defects from local and open datasets has been added unbiasedly and equally.

The CNN model, developed using Keras, attains an excellent accuracy of 81.65% over 11 defect types, encompassing structural concerns as well as surface and seam anomalies. The GAN subsequently converts these defects into innovative patterns, while the CNN is employed once more to identify and categorize each defect in the newly created designs. This unique technique connects with SDG 12: Responsible Consumption and Production, fostering sustainable textile practices, minimizing waste, and appreciating beauty in imperfection.

Keywords: Artificial Intelligence; Creative Design; Fabric Defect Analysis; Pattern Generation

Introduction

The textile industry plays a crucial role in the global economy, contributing to employment and having an impact on the worldwide GDP[1]. The challenges facing the industry are as intricate as the effects of the global economy. One of the major problems is the pre-production waste and the fabric defects, which result in the majority of the issues and losses[2]. There is a clear correlation between the scale of the textile sector and the rise in the number of mistakes and the amount of waste produced[3].

Consequently, we have arrived to the most important problem that our human community is currently confronted with, which is the greenhouse effect and the phenomenon of global warming[4]. Waste from textiles has a significant influence on the surrounding ecosystem. By the year 2030, it is anticipated that the clothing industry would have produced roughly 134 million tons of trash, which is an increase from the current annual amount of approximately 92 million tons[5]. In light of the fact that this garbage contributes to landfill overflows and environmental damage, there is an urgent need for new solutions to reduce waste and reinvent the value of defects.

Traditional techniques of inspecting fabrics have always depended significantly on operations that are performed manually[6]. Despite the fact that human inspectors are capable of locating flaws, this method is laborious, time-consuming, and prone to mistakes. Due to the increased complexity and volume of modern textile manufacturing, these manual processes are being put under additional strain, leaving them unable to satisfy the expectations of the industry at the present time[7]. As a consequence of this, faulty textiles may make their way through the supply chain, ultimately resulting in waste or items of inferior quality being delivered to customers[8].

As a solution, the research of automated detection methods has evolved as a solution, enabling an improvement in precision, quicker, more cost-efficient, and the flexibility to adapt to a variety of different types of fabric [9]. This work makes a contribution to the achievement of Sustainable Development Goal 12 by recasting fabric flaws as distinctive design components. Within the scope of Sustainable Development Goal 12 (SDG12), the recommendation of a method for prolonging the life cycle of textile materials and minimizing waste has been granted [10]. In addition, reducing the amount of trash produced by manufacturing helps to indirectly promote friendly Development Goal 13: Climate Action by reducing the carbon footprint of the company and supporting behaviors that are environmentally friendly [11].

As consumers become more aware of the importance of sustainability, there is a growing desire for one-of-a-kind, environmentally friendly items that are in line with principles such as the reduction of waste and the conservation of resources [12]. The findings of this study reframe the concept of fabric faults as chances for creative expression and design innovation rather than as indicators of waste. In order to improve the value of the cloth and its visual appeal, artificial intelligence has the ability to creatively repurpose these defects into deliberate design components. The Japanese concept of wabi-sabi, which celebrates beauty in imperfection, serves as a source of inspiration for this technique. It advocates a shift in vision, shifting from perceiving defects as undesirable to considering them as distinctive features that tell a narrative [13]. This study is in line with the ideals of sustainable design since it converts faults into patterns that can be used. It also helps to reduce waste while simultaneously satisfying the need of consumers for items that are unique and significant.

Research Objectives

The objectives of this research are as follows:

1. To develop an AI-based framework using Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) for identifying and repurposing fabric defects into innovative visual patterns.
2. To evaluate the classification performance of the CNN in accurately identifying defect types across multiple classes.
3. To generate new fabric patterns using GANs that creatively incorporate identified defects.
4. To explore the sustainability implications of AI-driven defect detection and pattern generation, aligning with Sustainable Development Goals (SDG) 12 and 13.

Research Methodology

1. Dataset and Defect Classes

Fabric flaws came from industry partners and open-source platforms. Each form of flaw was picked for its distinct visual characteristics, which aid in AI classification and subsequent pattern development. The collection consists of 11 distinct defect classes and 3,000 tagged pictures depicting commonly occurring textile flaws. To ensure correct labeling and classification, industry specialists reviewed and annotated the dataset, offering domain-specific insights on each fault type [9].

1.1 Hole: Absence of material, typically circular or uneven in shape.

1.2 Knot: Fibers that are situated or gathered due to manufacturing flaws.

1.3 Stain: All visible damage resulting from spills, dyes, or contaminants.

1.4 Loose Threads: Hanging or misplaced threads can disrupt fabric continuity.

1.5 Seam-Puckering: Layers or gathers in seams caused by tension mismatches during stitching.

1.6 Skipped Stitches: Unstitched areas along a seam that leave gaps in the stitch line.

1.7 Seam slippage: The partial separation of fabric layers at the seam caused by strain or faulty stitching.

1.8 Misalignment: Alignment variations that interrupt fabric design symmetry.

1.9 Slub: Thicker thread segments create irregular texture on fabric surfaces.

1.10 Snags: Pushed threads that cause distortion in the weave as a result of sharp objects or strain.

1.11 Weaving defects: Broken or missing threads.

2. Sampling Methodology

The dataset was collected using a random sampling strategy to ensure variety and impartial representation of fabric defects[10]. This method reduced sample bias while also ensuring the inclusion of diverse defect types such as structural, surface, and seam abnormalities. The random sample strategy guaranteed that around 3,000 photos were evenly distributed among the 11 defect classes, allowing the CNN and GAN models to effectively generalize to previously unknown data during validation and testing.

3. Keras-based CNN for Defect Classification

The Keras-based CNN was created to categorize 11 defect classes using a structured sequence of layers optimized for picture classification tasks. The design starts with convolutional layers that apply numerous filters to the input images, extracting key properties like edges, textures, and patterns that can be used to identify fabric flaws. Each convolutional layer is followed by a ReLU activation function, which adds nonlinearity to the model and allows it to learn complex patterns successfully[11][12]. Max-pooling layers are added after the convolutional layers to minimize the spatial dimensions of the feature maps, lowering computational complexity while preserving the most important information[13]. This pooling procedure allows the network to focus on the most important features while also making it more resistant to fluctuations in the input data[14]. The feature maps produced by the convolutional and pooling layers are then sent into a flatten layer, which converts the multidimensional tensor into a one-dimensional vector[15]. This data vector is supplied into fully connected layers, which function as a decision-making component through combining and mapping extracted data to output classes[16].

The CNN was trained on 80% of the dataset, allowing the remaining 20% for validation. Return propagation was used during the training phase to update the network's weights, which improved its capacity to distinguish between distinct errors classes[17].

4. GAN for Pattern Generation

A Generative Adversarial Network (GAN) was used to transform fabric defects into appealing patterns[18]. The GAN carefully combined a variety of defects[19]. This leading to complex designs that could be evaluated for artistic value. The method reimagines defects as deliberate design aspects, transforming blemishes into something functional and aesthetically beautiful[20].

The GAN architecture comprises two networks: the generator and the discriminator. The generator network generates patterns by combining faults from different classes, seeking to develop designs that are both distinctive and cohesive[21][22]. Meanwhile, the discriminator network assesses the generator's outputs, offering feedback to assist refine and improve the patterns formed over time[23]. This continuous interaction between the two networks allows the GAN to learn and improve its outputs, producing designs that showcase the creative potential of fabric flaws[24].

5. Labeling and Error Percentage Analysis

After creating new patterns with the GAN, the trained CNN was used to label the generated pictures. This approach included combining the CNN predictions over the GAN-generated patterns to determine the nature and position of each defect in the designs. The CNN labeling enabled a pixel-by-pixel analysis, designating every defect and allowing for a precise knowledge of how different forms of defects were distributed across the patterns[25][26].

6. Conceptual Framework

For this study combines modern AI technology to address both flaw detection and sustainable textile design. It operates on three main components

1. Defect Classification

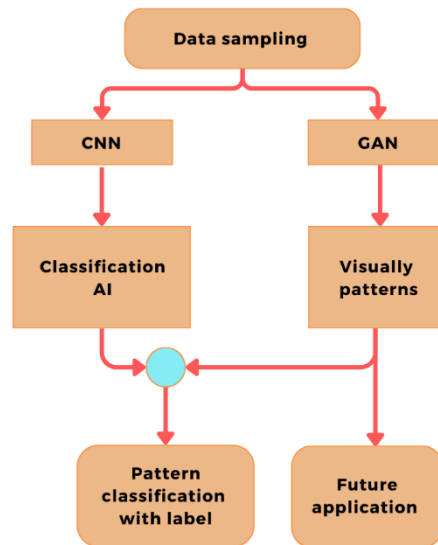
Using CNN to correctly identify and classify fabric flaws across 11 categories, assuring precision and dependability.

2. Pattern Generation

Using GAN to create unique visual patterns that are both creative and functional.

3. Sustainability Integration

Aligning AI-based strategy with global sustainability targets like SDG 12 and SDG 13 to reduce waste and encourage responsible consumption.



Results

1. Classification Accuracy

The Keras library was used to create the CNN architecture, with RGB picture inputs measuring 224x224 pixels. The network consisted of three convolutional layers, followed by max-pooling layers, a flatten layer, and two fully connected layers. The convolutional layers used 32, 64, and 128 filters, respectively, with a kernel size of 3x3 and ReLU activation functions to capture intricate patterns in the defect images. Max-pooling layers lowered spatial dimensions, increasing computational efficiency while retaining essential characteristics.

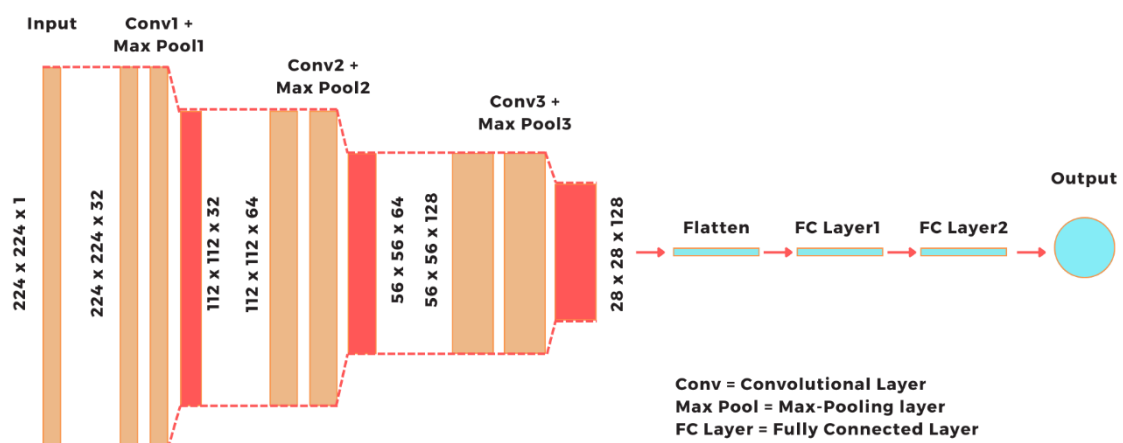


Figure 1: Visualization of CNN classification accuracy across the 11 defect classes.

The model was trained with a batch size of 32 over 45 epochs, using the Adam optimizer and categorical cross-entropy loss function. Data augmentation techniques, including rotation, zoom, and flipping, were applied to the training data to increase the diversity of input images and improve generalization. Early stopping, model checkpoints, and learning rate reduction strategies were employed to prevent overfitting and enhance performance.

Table 1: Confusion matrix displaying the classification accuracy for the 11 defect classes.

accuracy	loss	val_accuracy	val_loss	learning_rate
0.332826734	2.369426966	0.113733903	2.376540184	0.001000
0.462006092	1.690731883	0.435622305	2.221219063	0.001000
0.492401212	1.534138918	0.094420604	2.379912853	0.001000
0.523556232	1.441597819	0.579399168	2.078232527	0.001000
0.543313086	1.383414745	0.407725334	2.04981041	0.001000
0.618541062	1.225633025	0.278969944	2.064217806	0.001000
0.610942245	1.231050611	0.523605168	1.948122382	0.001000
0.613981783	1.20954895	0.489270389	1.737505436	0.001000
0.65577507	1.070107579	0.489270389	1.718495607	0.001000
0.669452906	1.037566543	0.648068666	1.556826115	0.001000
0.680091202	1.03859818	0.532188833	1.836373687	0.001000
0.676291764	1.005176306	0.497854084	1.753246784	0.001000
0.680851042	0.986656964	0.590128779	1.566355586	0.001000
0.717325211	0.886477828	0.590128779	1.757009268	0.001000
0.702887535	0.909740031	0.607296109	1.420908093	0.001000
0.722644389	0.8964867	0.605150223	1.399523377	0.001000
0.708966553	0.892713368	0.42703864	1.744126081	0.001000
0.712765932	0.865985274	0.493562222	1.56475389	0.001000
0.737841964	0.793861568	0.225321889	2.254143	0.001000
0.7507599	0.774361014	0.289699584	2.082658529	0.001000
0.68617022	0.965304554	0.570815444	1.447069526	0.001000
0.758358657	0.753072321	0.61802578	1.293449044	0.000200
0.762158036	0.699026644	0.624463499	1.284235597	0.000200
0.78039515	0.672835469	0.57296139	1.448554158	0.000200
0.793313086	0.637286782	0.575107276	1.508919358	0.000200
0.797872365	0.613129735	0.512875557	1.678878546	0.000200
0.791793287	0.623691797	0.484978527	1.731726289	0.000200
0.791793287	0.608093679	0.551502168	1.596917987	0.000200
0.809270501	0.572158396	0.527897	1.636138439	0.000040
0.808510661	0.580787539	0.538626611	1.63095057	0.000040
0.806231022	0.574210286	0.562231779	1.563812852	0.000040
0.810030401	0.576669276	0.547210276	1.610363364	0.000040
0.805471122	0.581760943	0.532188833	1.654515862	0.000040
0.81231004	0.571452558	0.534334779	1.635042667	0.000010
0.802431583	0.584775686	0.530042946	1.654054523	0.000010

0.814589679	0.559331775	0.530042946	1.679548621	0.000010
0.809270501	0.553373396	0.540772557	1.622317314	0.000010
0.803951383	0.575209141	0.532188833	1.655038714	0.000010
0.825227976	0.548741102	0.523605168	1.654763937	0.000010
0.810030401	0.562165499	0.527897	1.656260014	0.000010
0.81155014	0.566143394	0.538626611	1.635235667	0.000010
0.810030401	0.564367592	0.527897	1.673851609	0.000010
0.81382978	0.570172846	0.519313276	1.732593536	0.000010
0.814083079	0.570924064	0.50929896	1.77791814	0.000010
0.816522899	0.57293879	0.499642293	1.826597075	0.000010

Continuous monitoring of the training and validation accuracy as well as loss was performed throughout the epochs. Callback routines made certain that the model with the highest level of performance, as determined by validation loss, was preserved. Convergence behavior of the model was displayed in a history file that was created as part of the training procedure. This file may be used for further study.

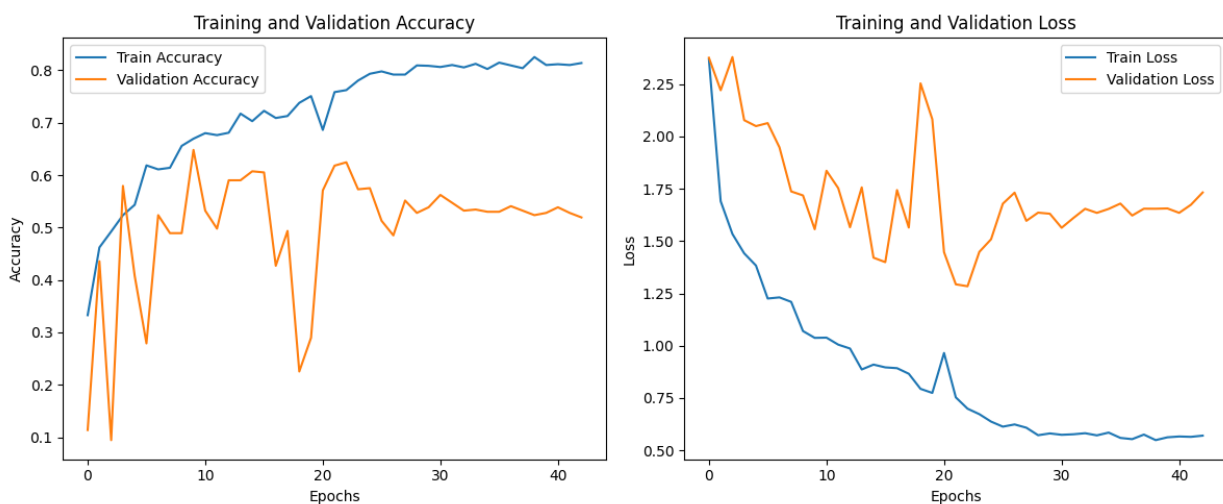


Figure 2: Training and validation accuracy and loss curves illustrating the model's learning progress over the epochs.

These results provide a thorough perspective of the CNN's training dynamics and performance metrics, as well as a reflection of the usefulness of the CNN in classifying fabric faults within the dataset.

2. GAN-Generated Patterns

To effectively generate patterns, the GAN was able to integrate defects from a variety of different classes in an imaginative manner. This allowed the GAN to successfully construct patterns. In order to demonstrate the creative potential of these patterns, the transformation of flaws into designs that were cohesive and visually pleasing was demonstrated. Bringing to light the prospect of recycling faults for innovative textile applications is the utilization of this method, which demonstrates the possibility.

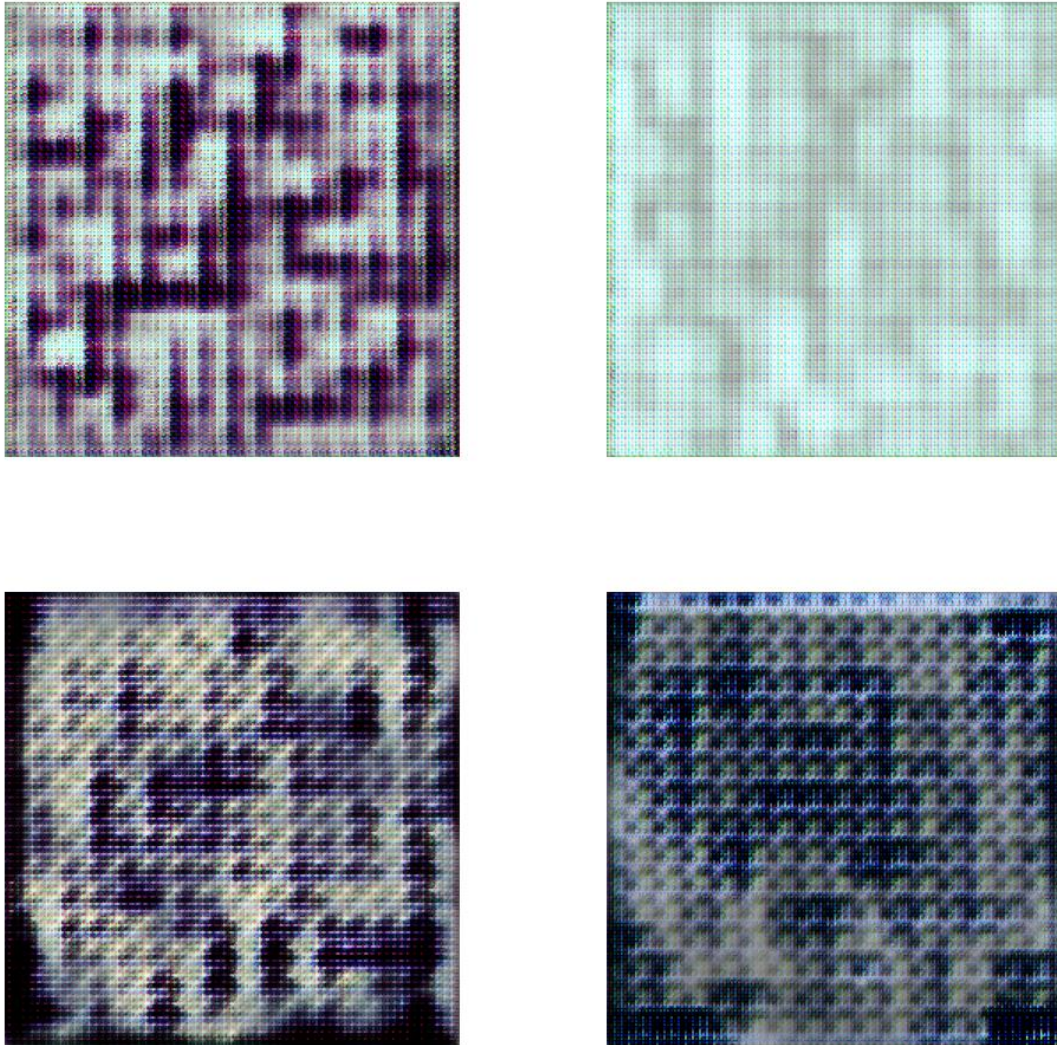
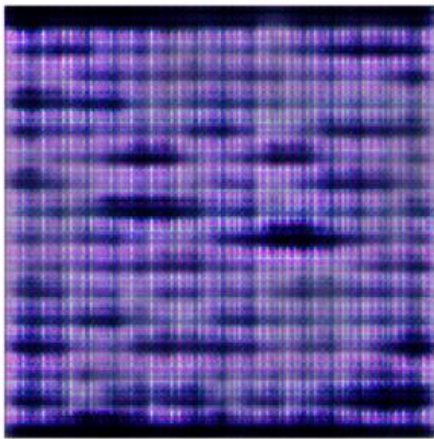


Figure 3: Sample GAN-Generated Patterns

Examples of patterns generated by the GAN, illustrating how multiple defect types were blended to create unique designs.

3. Defect Labeling on GAN Patterns

The use of CNN to the designate GAN-generated patterns enabled an in-depth investigation of defect location and distribution within each unique design. The CNN labeling showed the spatial distribution of defects in GAN-generated patterns, which improved understanding of the function each defect distribute in the overall composition.



Hole: 0.57%, Knot: 0.00%, Loose thread: 0.00%, Misalignment: 99.31%, Seam slippage: 0.00%, Seam-puckering: 0.00%, Skipped stitches: 0.00%, Slub: 0.05%, Snag: 0.02%, Stain: 0.00%, Weaving defect: 0.04%



Hole: 9.31%, Knot: 4.85%, Loose thread: 44.51%, Misalignment: 0.31%, Seam slippage: 6.01%, Seam-puckering: 0.04%, Skipped stitches: 9.96%, Slub: 1.14%, Snag: 5.47%, Stain: 6.47%, Weaving defect: 11.93%

Figure 4: CNN-Labeled GAN Patterns

Discussion

The research demonstrates the effectiveness of CNN and GAN in transforming fabric defects into visually patterns[27]. The Keras-based CNN's classification shows accuracy of 81.65% with 11 classes, classification accuracy shows the importance of visually diverse categories for AI defect analysis while the previous research normally has up to 7 classes[28]. Ensemble learning improves textile fault analysis classification. The use of a GAN to creatively combine defects adds an artistic dimension to the textile manufacturing, showcasing AI's potential to affect both quality control and design innovation. Future research could focus on the GAN's generative powers[29], increasing the variety of patterns produced and investigating possible applications in sustainable textile design.

This study's approach to textile waste reduction is clearly in line with SDG 12: Responsible Consumption and Production. By reimagining faults as design components, this study contributes to the development of a circular economy model in the fashion industry, reducing the environmental effect of textile waste[30]. The transforming of fabric defects to visually patterns support more sustainable manufacturing processes by proposing a new method of utilizing materials efficiently[31].

Furthermore, by reducing waste, this research indirectly supports SDG 13: Climate Action. Waste reduction in manufacturing helps to minimize carbon emissions by using fewer resources to produce more materials, matching our work with climate action goals.

Conclusion

This research illustrates the effective collaboration of AI techniques including CNN and GAN, and their utilization in defect analysis and creative pattern development. By focusing on visibly recognized fabric imperfections, researchers facilitate precise categorization and generate unique designs that emphasize the aesthetic and functional value of imperfection. This methodology provides a distinctive addition to textile manufacturing by integrating technical efficiency with creative expression, perhaps inspiring sustainable methods in addressing production defects.

This research illustrates the innovative capacity of AI in textile production. Utilizing CNNs and GANs, fabric imperfections are reinterpreted as assets instead of liabilities, in accordance with SDG 12 by fostering sustainable production methods. The use of fabric imperfections as design features promotes responsible consumption and indirectly advances SDG 13 by decreasing the use of resources and emission. The combination of AI-driven methodologies with sustainability objectives presents an achievable foundation for environmentally responsible innovation in textiles.

Recommendations

1. Future research should explore into the integration of several AI classification models to enhance the classification accuracy of the complex pattern.
2. Comparative analyses of different machine learning models for fabric defect detection will improve comprehension of the trade-offs between performance and computational efficiency.
3. Working with textile designers to investigate the usability and creative benefits of GAN-generated patterns might broaden the study into practical applications.

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