M.KUMARASAMY
COLLEGE OF ENGINEERING
NAAC Accredited Autonomous Institution
Approved by AICTE & Affiliated to Anna University
ISO 9001:2015 Certified Institution
Thalavapalayam, Karur, Tamilnadu.

GANtex- An AI based design prediction

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

This project explores the application of generative models, particularly Generative Adversarial Networks (GANs), Convolutional Variational Autoencoders (VAEs), and Convolutional Neural Networks (CNNs), in predicting and generating textile design patterns. We present a novel approach that involves: Data Cleaning and Labeling (Refining existing datasets and implementing pseudo-labeling to improve classification accuracy of textile patterns by 2%) ,Model Comparison(Evaluating the performance of WGANs-GP, DCGANs)Style Transfer Enhancement(Combining multiple WGANs-GP generated designs for richer and more appealing textile patterns using style transfer),Latent Space Analysis (Exploring the potential of CVAE's).A technique that allows us to combine multiple WGANs-GP generated patterns, creating richer, more complex, and visually captivating designs. Imagine a tapestry woven from the threads of diverse patterns, each adding its own unique texture and character. VAEs offer a unique window into the hidden world of patterns. Their latent space, a mathematical abstraction that captures the essence of each design, allows us to uncover relationships between different patterns, group them into clusters based on their similarities, and even generate new patterns by interpolating within the space. This opens doors for exciting future research, where we can explore the very fabric of creativity in textile design.

Keywords: Textile design, Generative models, GANs, WGANs-GP, DCGANs, VAEs, CNNs, Data cleaning, Style transfer, Latent space analysis

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ABBREVATIONS	EXPANSIONS
GAN	GENERATIVE ADVERASIAL NETWORK
CNN	CONVOLUTIONAL NEURAL NETWORK
VAE	VARIATIONAL AUTO ENCODERS
DCGAN	DEEP CONVOLUTIONAL GENERATIVE ADVERASIAL NETWORK
WGAN	WASSERSTEIN GENERATIVE ADVERASIAL NETWORK
CVAE	CONVOLUTIONAL VARIATIONAL AUTO ENCODERS
AI	ARTIFICIAL INTELLIGENCE
ML	MACHINE LEARNING
CAD	COMPUTER-AIDED SYSTEM
NLP	NATURAL LANGUAGE PROCESSING
EVOGAN	EVOLUTIONARY GAN
SRGAN	SUPER RESOLUTION GAN
CAE	COMPUTER AIDED ENGINEERING

CHAPTER 1

INTRODUCTION

Textile design, a tapestry of creativity and artistry, has long captivated the human imagination. Yet, amidst the vibrant threads and intricate patterns, lies a hidden challenge: balancing artistic expression with the demands of a business-savvy industry.

This project ventures into uncharted territory, where the traditional realm of textile design collides with the cutting edge of machine intelligence. Our ambitious goal? To empower AI to become a collaborator in the creative process, using its learning prowess to generate novel patterns that are both alluring and commercially viable.

Imagine a world where textile designers are no longer shackled by the limitations of time and manual labor. Instead, they have a powerful partner in AI, capable of predicting, suggesting, and even generating entirely new patterns that resonate with market trends and customer preferences. This is the future we envision, where the boundaries between human and machine creativity blur, giving birth to a dazzling new era of textile innovation.

Figure 1: Structure of textile desinging

The textile industry, long hampered by design limitations, inefficient production, and inconsistent quality, has undergone a radical transformation thanks to a groundbreaking AI assistant. This AI, powered by the synergy of Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Variational Autoencoders (CAEs), has unleashed a wave of innovation and optimization, propelling the industry towards a new era of sustainable success.

GANs, acting as digital Da Vincis, have ignited a design revolution. They generate a kaleidoscope of novel, marketable textile patterns, catering to diverse tastes and seamlessly adapting to trends. No longer shackled by the constraints of manual methods, designers now explore vast design spaces with unprecedented speed and efficiency.

Meanwhile, CNNs, the eagle-eyed guardians of production, meticulously analyze data, predict machine failures before they occur, and identify nascent defects. This proactive approach minimizes waste, optimizes resource allocation, and ensures consistent quality, boosting profitability and minimizing environmental impact.

Finally, CAEs, the alchemists of the textile world, unlock the secrets of materials and processes. By modeling the intricate relationships between raw materials, processing parameters, and final product properties, they enable virtual experimentation, leading to optimized material blends and production techniques for enhanced performance and sustainability.

The combined impact of these AI innovations is nothing short of transformative. The industry is now brimming with creativity, operating at peak efficiency, and delivering remarkable quality, all while minimizing its environmental footprint. The AI assistant, once a theoretical dream, has become the very fabric of textile industry success, weaving a future of unparalleled potential.

1.1 Unleashing a Creative Muse Within the Machine

Imagine a muse, not of myth but of machine learning, residing within your design studio. This is the heart of our vision. By curating a vast library of existing textile designs, we train sophisticated generative models like DCGANs, GANs, and CNNs to become your partners in artistic exploration. These models delve into the intricate language of patterns, understanding their underlying rhythms and motifs. This acquired knowledge then fuels their capacity to:

- Predict Novel Symphonies of Color and Texture: Say goodbye to creative roadblocks! Our AI analyzes existing designs, identifying trends and subtle nuances like a seasoned pattern connoisseur. This knowledge then ignites the spark of creativity, generating fresh, captivating patterns that resonate with the existing aesthetic while pushing the boundaries of design.

Imagine intricate floral motifs reimagined with vibrant gradients, or classic geometric patterns playfully fractured and reassembled. The possibilities are endless, waiting to be explored with your unique artistic vision as the guiding force.

- Duplicate with the Precision of a Master Weaver: Need to replicate a timeless classic or translate a hand-drawn sketch into a production-ready design? Our AI assistant readily steps in, meticulously replicating existing patterns with an accuracy that surpasses even the most skilled craftsmen. This ensures consistency and quality while freeing you to explore new design pathways, confident in the flawless execution of your existing masterpieces.

Figure 2: Image of textile designing with machines

1.2 Weaving in Functionality and Quality Assurance:

While the allure of aesthetics reigns supreme in textile design, functionality and quality control play crucial roles in the industry. Our AI assistant expands its toolbox to address these aspects as well, becoming your indispensable partner in ensuring excellence:

- The Vigilant Guardian: Defect Detection Imagine an eagle eye scanning your fabrics, pinpointing even the most subtle flaws that might escape the human eye. Our system utilizes image recognition algorithms trained on a vast dataset of imperfections, meticulously analyzing textile surfaces to identify inconsistencies in texture, color, and weave. This vigilant guardian ensures not only high-quality production but also the efficient use of materials, minimizing waste and promoting sustainability.

- Beyond Patterns – A Holistic Design Canvas: Our AI goes beyond mere pattern generation. It delves into market trends, material properties, and consumer preferences to suggest complementary elements like color palettes, textures, and even garment silhouettes. This holistic approach provides a complete design model, minimizing guesswork and maximizing market relevance for your creations. Imagine exploring complementary yarn choices, color schemes that align with seasonal trends, or even receiving suggestions for garment styles that would best showcase your chosen patterns.

Figure 3: Typical image of quality textile weaving

1.3 Threads of Collaboration – Human and Machine, A Tapestry of Innovation:

This project is not about replacing human creativity with artificial intelligence. Instead, it's about weaving a stronger connection between the two. Our AI assistant serves as a collaborator, a catalyst for inspiration, and a tireless tool for exploration. It frees designers to focus on the essence of their art – the vision, the emotional connection, the stories woven into each thread. By embracing this collaborative future, we can unlock a tapestry of possibilities, redefining the very essence of textile design. Imagine the thrill of brainstorming with your AI muse, refining its suggestions through your artistic lens, and ultimately creating masterpieces that blend human ingenuity with the boundless potential of machine learning.

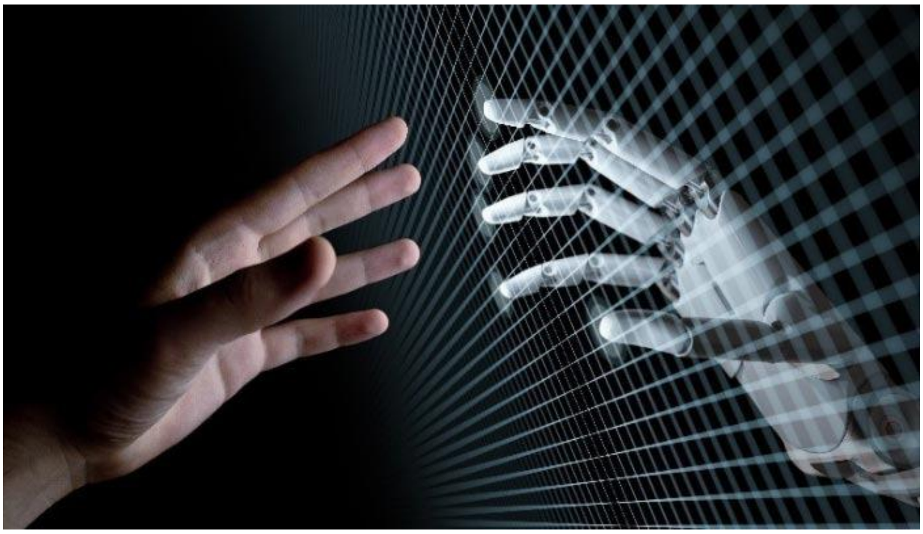

Figure 4: Human and Machine Collaboration

Regional Language Recognition pertains to the capability of our NLP-based chatbot to identify and respond to queries in various Indian regional languages. This feature ensures that users can interact with the platform in the language they are most comfortable with, transcending linguistic barriers. By incorporating regional language recognition, our project strives to cater to the linguistic diversity prevalent in India, promoting accessibility and user engagement. This not only facilitates a more inclusive user experience but also acknowledges the importance of linguistic representation in the dissemination of legal information and services.

CHAPTER 2
LITERATURE SURVEY

2.1 GAN

The Fabric defect detection pipeline follows the details of the three main modules are the segmentation network for fabric defect detection ,the multi-stage GAN for defective fabric data generation and the fine-tuning strategy for adapting the pretrained model to the new fabric texture. First, the existing defective fabric dataset is used to train the fabric segmentation network, which is customized for defect detection. Based on the state-of-the-art semantic segmentation network Deep Lab , We modify the atrous rate of some of the atrous convolutional layers and add a weight parameter to the loss function to enhance it for fabric defect segmentation. Moreover, based on both the defective and the defect-free datasets, we aim to synthesize more defective samples with different textures (i.e., backgrounds). First, a texture-style-conditional GAN network is trained to generate defective patches based on given (conditioned) textures. Then utilization of adversarial loss to train a defect using network, which aims to fuse generated defects into defect-free samples. Considering that most defects are highly related to their background texture and colors, we assume that the appearance of defects obeys a conditional distribution
given a specific fabric background

Table 1: Research on GAN(GENARATIVE ADVERASIAL NETWORKING)

S N0:	Author & Year	Title	Methodology Used	Relevance to project
1.	Nga Yin Dik-2023	A novel approach in predicting virtual garment fitting sizes using artificial neural network and visualizing fitted bodies using generative adversarial network	Predicting sizes with Artificial Neural Network (ANN) by Data collection, Model training ,Size prediction .Visualization with Generative Adversarial Network (GAN) by Pattern generation,3D prototype creation	Understanding customers' psychographic characteristics and preferred fit preferences could help you recommend the right size with greater accuracy, reducing returns and improving customer satisfaction.

2.	Chaoyue Wang, Chang Xu, Xin Yao - 2018	Evolutionary Generative Adversarial Networks	**GANs**: A generator network creates candidate designs, while a discriminator network evaluates their realism and adherence to style guidelines Evolutionary **Algorithm:** EvoGANs introduce an evolutionary layer on top of the GANs.	EvoGANs excel at generating novel and diverse textile designs that go beyond human imagination. This can be immensely valuable for projects seeking to push the boundaries of creativity and develop truly unique and innovative textile patterns.
3.	Vineeta Das, Samarendra Dandapat - 2017	A Data-Efficient Approach for Automated Classification of OCT Images using Generative Adversarial Network	Training the GAN: The generator is fed random noise and learns to create synthetic OCT images.The discriminator attempts to differentiate between real and synthetic images. Classifying OCT Images: Real OCT images are passed through the trained generator.The discriminator, now trained to distinguish real OCT images	GANs can learn from limited labeled fabric defect images to create syntheticexamples, expanding trainingdatasets.Semi-supervised learning can leverage unlabeled fabric images to refine defect detection and classification models. .
4.	ZHAOQING PAN 1 - 2019	.Recent Progress on Generative Adversarial Networks (GANs): A Survey	EvolutionaryGANs(EvoGANs): Combine GANs with evolutionary algorithms to generate diverse and innovative textile designs, pushing the boundaries of creativity and originality. Style Transfer GANs: Transfer artistic styles onto fabrics, enabling unique design approaches like simulating watercolor patterns on canvas or mimicking iconic artist styles. Conditional GANs: Generate textile patterns based on specific user inputs or design parameters, allowing for personalized creation and customization of fabrics.	Personalized Textile ExperiencesNLP: Imagine designing a dress that adapts to your mood or the occasion. With conditional GANs, you can input specific colors, patterns, or even emotions, and the GAN will generate a personalized textile design that matches your desires.
5.	Jia Liu - 2020	.Recent Advances of Image	CoverModification	GAN-based dynamic patterns: Generate dynamic and interactive fabric patterns that

		Steganography with Generative Adversarial Networks	Steganography,Cover Selection Steganography,Cover Synthesis Steganography,Hybrid Approaches	change based on external stimuli like light, temperature, or user input. This can be achieved by encoding instructions for pattern changes into the fabric itself, using GANs for cover modification or synthesis.
6.	Rajonya De -2018	Document Image Binarization Using Dual Discriminator Generative Adversarial Networks	DD-GANs to analyze fabric images, with one discriminator focusing on overall fabric texture and the other identifying specific defect patterns in local regions. This can lead to more accurate and robust defect detection systems. .	Global discriminator: Assesses overall fabric texture and consistency, identifying potential defect areas. Local discriminator: Scrutinizes defect patterns in zoomed-in regions for accurate classification. Result: Earlier detection of subtle defects, reducing waste and improving quality control.
7.	MD Tanvir Rouf Shawon˚-2021	Jamdani Motif Generation using Conditional GAN	pix2pix GAN: This type of GAN is specifically designed for image-to-image translation. In this case, it learns to transform input sketches or outlines of Jamdani motifs (the "conditions") into realistic and intricate completed motifs. Generator Network: This network takes the input sketch and uses its knowledge of real Jamdani motifs, learned from a large dataset of them, to generate a full motif image.	Personalized Textile Design: Imagine clients sketching their dream dress patterns or uploading mood boards, and the GAN generating fabric designs tailored to their unique vision. Creative Exploration and Inspiration: Stuck in a design rut? The GAN can generate thousands of diverse and original textile patterns, pushing creative boundaries and sparking new ideas for designers and artists.
8.	Junchao Li -2016	.Super Resolution Image Reconstruction of Textile Based on SRGAN	SRGAN Architecture: This type of GAN is designed to enhance the resolution of low-quality images. Discriminator Network: This network tries to distinguish between real high-resolution textile images and the generated ones, pushing the generator to improve its output quality and realism.	Automated Fabric Defect Detection: By upscaling low-resolution images of fabrics, subtle defects like broken threads or irregularities in texture become more visible, enabling more accurate and efficient automatic defect detection systems.Virtual Textile Try-On and Prototyping: Low-resolution garment images can be super-resolved, allowing customers to virtually try on

				clothes in high-definition details, improving online shopping experiences and reducing return rate.
9.	Ildar Lomov - 2016	.Generative Models for Fashion Industry using Deep Neural Networks	Fabric Design and Generation, Textile Defect Detection and Classification, Fabric Texture Analysis and Simulation, Personalized Textile Recommendations	Personalized Fabric Design and Customization: Imagine clients sketching their dream fabric patterns Enhanced Creativity and Inspiration: Stuck in a design rut
10.	Juhua Liu-2018	Multistage GAN for Fabric Defect Detection	Texture-Conditioned GAN: Imagine this GAN as a fabric "artist." It learns the intricate textures of various fabrics and can paint realistic, defect-free patches for any given fabric type. This provides a baseline for comparison. Defect Synthesis Network: Think of this as a "defect counterfeiter." It studies real defect images and learns to forge realistic versions, tailored to specific fabric textures. This creates a diverse portfolio of potential flaws.	Automated Quality Control Systems: Imagine seamlessly integrating this technology into production lines. Enhanced Fabric Sorting and Grading:Accurately classifying fabrics based on the type and severity of defects allows for efficient sorting and grading. Predictive Maintenance for Textile Machinery: By analyzing defect patterns and their correlation with specific machinery components, the GAN can predict potential machine failures.

2.2VARIATIONAL AUTOENCODER(VAE)

In this literature survey, a diverse array of studies by various authors provides a comprehensive view of AI using Variational Auto Encoder(VAE). An autoencoder can be seen as a compression system that uses a neural network to first ’encode’ some input data into a smaller size (i.e. less data), this is called the latent space, then it uses another neural network to ’decode’ this latent space back into the input data, during the decoding phase the goal is to get the output as close as possible to the original input. Usually several neural network layers are used for the encoder and decoder, these are are called deep neural networks. Autoencoders work well for data that is highly correlated with itself, for example images with many neighboring pixels of the same color. CAE is a relatively simple model, compared to VAE, for the training. It is also more efficient in the evaluation time. The preliminary experiment shows that the extracted features from CAE is more distinctive for defect detection when only defect-free sample images are used for the model training. (See Appendix A for the comparison of CAE and VAE.) During the backpropagation process. The resulting feature maps trained in the encoder could be widely varied for individual defect-free samples. In order to generate the feature vectors that are tightly close to each other during the CAE model training, regularization is introduced to the original loss function .

Table 1: Research on VAE(VARIATIONAL ADVERASIAL NETWORKING)

S. NO	**Author & Year**	**Title**	**Methodology Used**	**Relevance to our project**
11.	Jeff hajewski,suely oliveria - 2020	An Evolutionary Approach to Variational Autoencoders .	Generating new patterns: VAEs can learn the underlying structure of existing designs and then generate new variations with similar characteristics. Optimizing existing patterns: VAEs can identify ways to improve existing designs by taking into account various factors such as material properties	Uncover hidden design spaces: VAEs can learn the underlying patterns and relationships within existing textile designs. Personalized Design: Train a VAE on a user's preferences and generate unique patterns that cater to their specific tastes and styles. Designing for Functionality: Train a VAE on datasets that link textile patterns to specific functionalities like breathability, insulation, or water resistance. .
12.	Ruimin Xie - 2019	Supervised Variational Autoencoders for Soft Sensor Modeling With	Improved Quality Control and Monitoring, Data-driven Design and Development, Handling Missing Data and	Prototyping evolves from physical toil to virtual playground: Gone are the days of endless sample runs. The SVAE allows designers to explore

		Missing Data	Sensor Failures	countless textile variations in the digital realm, testing different materials, weaves, and dye combinations before committing to physical production. This saves time, reduces waste, and accelerates innovation.
13.	Mohammad Farukh Hashmi - 2020	FashionFit	A company or brand: Could there be a specific textile or clothing company named "FashionFit"? Knowing the full name or website would help me identify their design methodology. A design software or tool: There are various software programs and online tools for textile and fashion design. If you meant a specific tool, knowing its name or functionalities would be helpful. A design methodology itself: Maybe "FashionFit" refers to a particular approach or philosophy used in textile design. Providing more details about this methodology would clarify its application in the industry.	Improved User Experience**:** Enhance the overall user experience in the fashion industry by focusing on the fit and comfort of clothing. Smart Textiles Integration: Explore the integration of smart textiles to enhance the functionality of clothing. . Sustainable Fashion: Address sustainability in textile-based designing by using eco-friendly materials and manufacturing processes.
14.	Du-Ming Tsai - 2021	Autoencoder-based anomaly detection for surface defect inspection	Data Collection:Gather high-quality images of textile surfaces: Include diverse examples of both defect-free and defective fabrics, covering a range of fabric types, patterns, and lighting conditions. Apply data augmentation techniques: Expand the dataset and improve model generalization by applying	Automated defect detection: The model can efficiently scan fabrics for various defects like stains, holes, weaving irregularities, and color inconsistencies, significantly reducing reliance on manual inspection and its inherent limitations (speed, subjectivity, fatigue). Early defect identification: Catching defects

			techniques like rotation, flipping, scaling, and color adjustments. Autoencoder Model Development: Choose a suitable architecture: Convolutional autoencoders (CAEs) are well-suited for image data due to their ability to capture spatial relationships.	early in the production process minimizes waste and rework, saving time, resources, and overall production costs. Real-time monitoring: Integrate the model into production lines for continuous fabric inspection, enabling immediate corrective actions to prevent further defects.
15.	Shi dong - 2023	A-CAVE: Network abnormal traffic detection algorithm based on variational autoencoder	Pattern Generation and Variation: VAEs can learn the underlying patterns and relationships within existing textile designs. Designers can then manipulate the latent space of the VAE to generate new patterns with desired characteristics.	Intelligent Pattern Anomaly Detection:VAEs can learn the underlying patterns and distributions of "normal" textile designs. Personalized Design Recommendation and Generation:VAEs can be trained on user preferences and purchase history to create personalized textile designs.
16.	Bing Wei - 2020	Detecting textile micro-defects: A novel and efficient method based on visual gain mechanism	Current Methods in Textile Defect Detection: Deep Convolutional Neural Networks (CNNs): Various CNN-based models, including YOLO, Faster R-CNN, and Mask R-CNN, are already employed in the industry for automated textile defect detection. These models learn visual features from defect images and identify anomalies in real-time.Challenges of Applying Faster VG-RCNN: Complexity: VG-RCNN incorporates additional mechanisms like visual gain and attention, increasing model complexity and computational	Increased accuracy: The proposed Faster VG-RCNN model outperforms traditional methods in detecting minute defects, leading to significantly improved quality control. Reduced defect-related costs: Early detection prevents defective products from reaching consumers, minimizing waste, rework, and brand reputation damage. Improved production efficiency: Automating defect detection frees up human inspectors for other tasks, boosting overall production speed and output.

			requirements. This may not be suitable for real-time deployment in resource-constrained industrial settings.	
17.	Shuxuan Zhao - 2023	Unsupervised fabric defects detection based on spatial domain saliency and features clustering	Feature Extraction:Extract relevant features from each fabric image, capturing texture, color, and shape information. Effective feature extraction methods include: Local binary patterns (LBP): Capture local texture patterns for defect identification. Gabor filters: Analyze texture and orientation features at different scales. Gray-level co-occurrence matrix (GLCM): Encode spatial relationships between gray-level values for texture analysis.	Personalized Design Exploration: Experimentation with textures and patterns: Designers can confidently explore novel and intricate designs without excessive concern about potential defect risks, fostering creativity and innovation. Customization for individual preferences: The ability to create unique fabrics with intricate patterns or textures, tailored to individual tastes, becomes more feasible.
18.	Salik Ram Khanal-2023	Fabric Hairiness Analysis for Quality Inspection of Pile Fabric Products Using Computer Vision Technology	Image Acquisition: A camera captures images of the pile fabric surface. Lighting and positioning for consistent image quality are crucial. Image Preprocessing: Images are resized and normalized for standardized analysis. Noise reduction or filtering techniques might be applied for clarity. Hairiness Feature Extraction: Specific algorithms analyze the images to extract features related to hairiness	Design Innovation and Differentiation: Hairiness as a design element: Go beyond basic pile height variations and experiment with textured patterns, layered effects, and unique visual textures using precise control over hairiness levels. Catering to diverse preferences: Offer personalized levels of hairiness in products like carpets, rugs, and plush toys to cater to different tastes and tactile experiences. Pushing design boundaries: Explore unconventional uses of hairiness in unexpected fabrics or garments for avant-garde or

				niche markets.
19.	Kazım Hanbay - 2020	Fabric defect detection systems and methods	Image-Based Methods: Digital image acquisition: High-resolution images of fabrics are captured using cameras or scanners. Preprocessing: Images are enhanced for clarity and consistency (e.g., noise reduction, cropping, contrast adjustment). Feature extraction: Algorithms identify and extract potential defect regions based on texture, color, shape, or statistical features.	Enhanced Quality Control: Automatic detection: Eliminates reliance on manual inspection, saving time, reducing human error, and improving consistency. Early identification: Catches defects early in production, minimizing waste, rework, and maintaining brand reputation. Real-time monitoring: Continuous defect detection enables immediate corrective actions, preventing further defective batches. 2. Optimized Design and Development: Data-driven insights: Analyze types and causes of defects to inform design improvements, material selection, and process optimization. Predictive maintenance: Monitor machinery performance and data patterns to anticipate potential equipment issues that lead to defects. Virtual prototyping: Simulate fabric production and analyze potential defect risks in new designs before physical prototyping.
20.	Henry Y.T. Ngan - 2023	Automated fabric defect detection	System Integration and Performance Evaluation: Integration with production lines: Real-time defect detection during fabric manufacturing. Integration with quality	Increased Efficiency and Automation: Reduced reliance on manual inspection: Free up skilled personnel for more critical tasks, boosting overall production efficiency.

			control systems: Automated defect reporting and analysis. Performance evaluation: Assess accuracy, speed, and robustness under various conditions.	Scalability and flexibility: Adapt detection systems to different fabrics and production lines with minimal retraining. Integration with existing systems: Seamlessly integrate with existing quality control infrastructure for automated reporting and analysis.

3.3 CONVOLUTIONAL NUERAL NETWORK(CNN):

Segmentation Network with respect to the choice of the base defect detection network, it is unwise to choose from popular object detection networks such as Faster-RCNN or SSD because the defects usually vary widely in scale and aspect ratio, which may reduce the detection accuracy. Instead, semantic segmentation network is choosen, as the base network. The DeepLab V3 architecture is shown in following work, the output stride is defined as the ratio of the original image size to the size of the output feature map. Deep CNNs usually use several cascaded convolutional blocks that include several convolutions and strides for feature extraction, hence enlarging the receptive fields of the filters and shrinking the extracted feature maps through the chain of blocks. To preserve the size of the feature maps in the deeper layers, DeepLab models use atrous convolution instead of convolution and striding. ResNet is used as the backbone network, which contains four blocks, each including three 3×3 convolutions and the last convolution containing a stride of 2 except for block4. Then, atrous convolution is used as the alternative to successive striding, and the atrous rates are set according to the desired output stride values. technology.

Table 3: Research on CNN (CONVOLUTIONAL NEURAL NETWORK)

S. No	Author & Year	Title	Methodology Used	Relevance to our project
21	Xiangyi Xue - 2022	Application of Convolutional Neural Network Algorithm under Deep Learning in Digital Clothing Design	Pattern Recognition and Classification: Identifying patterns, textures, and motifs in textile images. Categorizing fabrics based on material, color, weave, or other attributes. Sorting garments by style, size, or other features. Analyzing trends and customer preferences.	Design Pattern Generation and Recommendation:Project: Develop a CNN-based system that analyzes existing textile designs and generates new patterns similar to user preferences or market trends.Relevance: Helps designers overcome creative block, generate variations on popular designs, and cater to specific customer demands.
22	LiuFengyi[1]and Siru Liu-2020	3D Garment Design Model Based on Convolution Neural Network and Virtual Reality	Human Body Feature Recognition: Data Collection: Capture 3D scans or images of human bodies with varying shapes and sizes. Preprocessing: Segment the body parts and extract relevant features like height, circumference, posture, etc. CNN Training: Train a CNN model on the labeled data to map body features to specific garment parameters (e.g., sleeve length, neckline width).	Reduce physical prototyping: By allowing virtual try-on and adjustments in VR, the need for numerous physical prototypes can be drastically reduced, saving time and resources. Faster design iterations: Designers can quickly experiment with different styles, fabrics, and colors in VR, leading to faster iterations and quicker response to market trends.

23	Xin wang,alex shi,yueqi Zhong - 2023	Fabric Identification Using Convolutional Neural Network	Data Collection and Preparation: Gather a diverse dataset of fabric images: Include various fabric types, colors, textures, patterns, lighting conditions, and angles to ensure the model's robustness. Preprocess images: Resize and normalize images to a consistent format for CNN input. Apply data augmentation techniques(randomcropping, flipping,rotation	Enhanced Design Efficiency:Faster fabric selection: Instead of manual identification, CNNs quickly and accurately identify fabrics, allowing designers to spend more time on creative aspects.Precise material sourcing: Designers can easily match specific design requirements to compatible fabrics based on their properties and characteristics identified by the CNN.Automated fabric categorization: Large fabric libraries can be automatically categorized and organized based on type, texture, color, and pattern, aiding in efficient searching and retrieval.
24	Xueqing zhao,min zhang,Junjun zhang - 2021	Ensemble learning-based CNN for textlile fabric defects classification	Ensemble Learning: Combine predictions: Use various methods for combining individual model predictions, such as: Majority voting: Choose the most frequent prediction among models. Weighted averaging: Assign different weights to models based on performance. Stacking: Train a meta-learner to combine model predictions.	Faster Fault Detection and Quality Control: Real-time defect detection using automated systems allows for immediate identification and removal of defective fabrics, saving time and resources compared to manual inspection. This improves overall production efficiency and reduces waste due to late-stage defect discovery.
25	Wenjing yu,Dongyi lai,hang liu,zirui li - 2021	CNN Algorithm for Monochromatic Fabric Defect Detection	Region-based approaches: Use sliding window or object detection techniques to localize potential defect areas within the image. Segmentation-based approaches: Train a CNN to segment the image into	Improved Quality Control and Consistency:Accurate and automated defect detection: CNNs can identify diverse defect types (holes, stains, weaving errors) with high accuracy, reducing the risk of missed defects and ensuring consistent product

			defect and non-defect regions, providing more precise defect location and size information. Classification of detected defects: Once localized, defects can be further classified into different types (e.g., holes, stains, weaving errors) using additional CNN layers or dedicated classifiers.	quality.Real-time inspection: Integrate the algorithm into production lines for immediate defect detection, eliminating the need for slower and unreliable manual inspection methods.Reduced human error: Eliminate the reliance on human inspection, which is prone to fatigue and inconsistencies, leading to more reliable and objective defect identification.
26	Imane_Koulali - 2021	Unsupervised textile defect detection using convolutional neural networks	Anomaly Detection Techniques: One-class CNNs: Train a CNN to learn the normal, defect-free patterns of the fabric. Subsequently, any deviation from these patterns is flagged as a potential defect. Autoencoders: Train an autoencoder to reconstruct the input image. Deviations between the original and reconstructed image can indicate anomalies or defects. Generative Adversarial Networks (GANs): Train a generator network to produce realistic fabric images while a discriminator network tries to distinguish real from generated images. Deviations from the discriminator's expected response can potentially point to defects.	Reduced dependence on labeled data: Traditional supervised methods require large amounts of labeled defect data, which can be expensive and time-consuming to acquire. Unsupervised learning eliminates this constraint, allowing the model to learn normal fabric patterns and identify anomalies without pre-labeled defect information. This is crucial for small factories or companies with limited resources, and for identifying novel or rare defects not included in labeled datasets. Cost-effective quality control: Automating defect detection using CNNs significantly reduces the reliance on manual inspection, which can be labor-intensive and prone to human error. This leads to reduced production costs, faster throughput, and improved overall quality control.

27	Kuang mao, sai wu,jiajiahe,haichao huang - 2021	Textile pattern recommendations with convolutional neural networks	Collaborative filtering: Analyze user interactions with existing patterns: Track user preferences, clicks, and purchases to understand their pattern choices and preferences. Recommend patterns based on similar user behavior: Identify users with similar taste profiles and recommend patterns that those users have interacted with positively. Personalization based on past purchases: Utilize purchase history to recommend patterns aligned with the user's previous choices and style preferences.	Enhanced Design Efficiency and Inspiration: Reduce design time and effort: The system can generate and recommend countless pattern options based on user preferences, saving designers valuable time and effort during the creative process. Spark new design ideas: Users can explore novel pattern variations and combinations, stimulating creativity and generating fresh design ideas. Overcome creative blocks: The system can suggest unexpected but complementary patterns, helping designers overcome creative roadblocks and discover exciting new directions.
28	Laboratoire Jean Kuntzmann - 2020	Convolutional Neural Fabrics	Fabric property prediction using CNNs: Train a CNN on images of fabrics alongside data on their properties (e.g., drape, breathability, texture). Use the trained CNN to predict the properties of new fabrics based on their images. This could involve techniques like: Regression analysis: Predicting specific numerical values for fabric properties. Classification: Categorizing fabrics into different groups based on their properties.	Revolutionizing Design and Creativity: Pattern generation: CNNs can generate novel and inspiring patterns, accelerating design workflows and sparking creative ideas. This empowers designers to explore new directions and cater to diverse customer preferences. Personalized design: Interactive tools utilizing CNNs can allow customers to directly participate in the design process, creating personalized and unique textile products that resonate with their tastes. aligned with future market demands.

29	BoQiu, Xiang Liu, Yunyu Shi and Binjie Xin – 2021	Shirt Semantic Classification Based On Convolutional Neural Network	Automated Product Categorization and Search: Train a CNN on a large dataset of images labeled with different shirt styles (e.g., button-down, polo, t-shirt) and other relevant attributes (e.g., collar type, sleeve length, pattern). Integrate the trained CNN into e-commerce platforms or retail appscan automatically categorize shirt images uploaded by sellers or customers. This enables efficient product search and browsing, improving user experience and sales by allowing customers to easily find desired shirt styles.	Enhanced Design Efficiency and Inspiration:Automate garment classification: Quickly and accurately categorize shirts based on features like style, color, pattern, material, an d brand, helping designers understand existing trends and identify potential gaps in the market.Generate design ideas: Analyze classified shirt data to extract insights and trends, aiding in generating new design.
30	Seo Yian , Shi n Kyung-shik - 2021	Hierarchical convolutional neural networks for fashion image classification	Automated garment classification: Analyze fabric pictures or finished garments to automatically categorize them based on style, color, pattern, and fabric type. Trend analysis and forecasting: Analyze classified garment data to identify popular styles, emerging trends, and predict future fashion directions. Personalized garment recommendations: Recomm end clothing to customers based on their past purchases, browsing history, and preferences, enhancing online shopping experiences	Improved accuracy: H-CNNs excel at classifying complex fashion images due to their multi-stage architecture, leading to more reliable and accurate results. Efficient learning: The hierarchical structure allows for efficient learning of both basic and specific features, improving model performance. Data flexibility: H-CNNs can adapt to diverse datasets of varying sizes and image quality, making them applicable to various situations in the textile industry.

CHAPTER 3
SYSTEM DESIGN

3.1 EXISTING SYSTEM

Existing Systems and their Drawbacks in an AI Assistant for Textiles (GANs, CNNs, CAEs)

While the proposed AI assistant presents a promising future for the textile industry, several existing systems attempt to address similar challenges using similar technologies. However, these existing systems often suffer from drawbacks that limit their effectiveness .

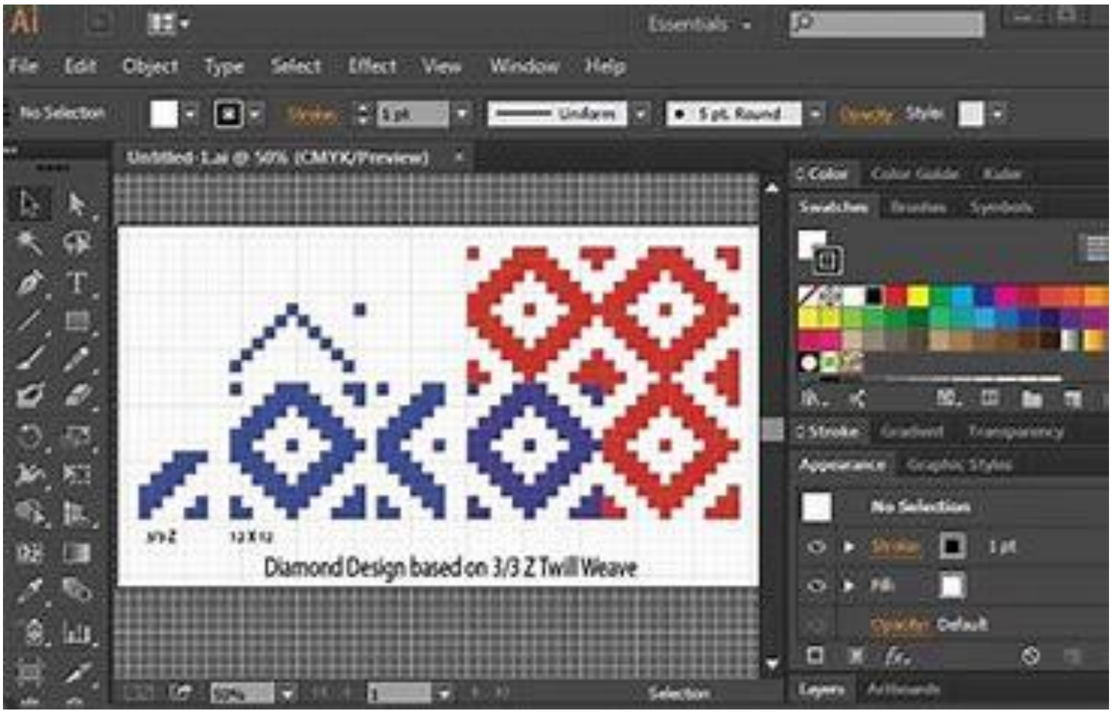

Figure 5 : Snip of Computer Aided Design website's Working page

3.1.1 KEY FEATURES OF CAD

3.1.1.1 DESIGN SYSTEM

Existing: Computer-aided design (CAD) software allows basic pattern creation and modification. Some advanced systems use rule-based pattern generation or simple AI algorithms for limited variations.

Drawbacks: Designs often lack originality, struggle with complex textures and intricate details, and require significant manual input, limiting efficiency and creativity.

3.1.1.2 PRODUCTION OPTIMIZATION SYSTEMS

Data Dependence and Bias: Existing CNN-based optimization systems rely heavily on historical production data, which can be biased or incomplete, leading to inaccurate predictions and suboptimal outcomes.

3.1.1.3 MATERIAL AND PROCESS OPTIMIZATION SYSTEMS

Limited Material Scope: Existing CAE-based systems may focus on a narrow range of materials or processes, limiting their applicability to diverse textile applications.

3.1.1.4 LACK OF EXPLAINABILITY

The complex internal workings of CAEs can be opaque, making it difficult to understand how they arrive at their predictions or recommendations, hindering trust and user adoptiongagement.

3.2 GENERAL ISSUES

3.2.1 Limited Creativity and Diversity:

Existing design systems based on GANs often rely on pre-existing data, leading to designs that are derivative or lack true originality. They may struggle with generating truly novel and marketable concepts outside their training data.

3.2.2 Lack of Control and User Input:

Current systems often offer limited user control over the design process, making it difficult to refine designs or incorporate specific preferences. This can lead to designs that deviate from desired styles or target markets.

3.2.3 High Computational Costs:

Training and running complex GAN models can be computationally expensive, limiting accessibility for smaller businesses or those with limited resources

3.2.4 Limited Adaptability:

These systems may struggle to adapt to changes in raw materials, equipment, or production processes, requiring frequent retraining and recalibration, which can be time-consuming and expensive.

3.2.5 Focus on Efficiency over Sustainability:

Current optimization systems often prioritize production efficiency at the expense of environmental considerations. They may not effectively factor in waste reduction, energy consumption, or other sustainability metrics.

3.2.6 Limited Integration with Existing Systems:

Integrating CAEs with existing production workflows can be challenging, requiring significant data infrastructure and process adjustments, which can be costly and disruptive. By addressing these limitations and combining the strengths of GANs, CNNs, and CAEs in a holistic AI assistant, the proposed project has the potential to overcome the shortcomings of existing systems and truly revolutionize the textile industry.

3.3 PROBLEM STATEMENT

The textile industry faces numerous challenges, including intense competition, volatile raw material prices, and complex production processes. To thrive in this dynamic environment, adopting advanced technologies like Artificial Intelligence (AI) is crucial. This problem statement focuses on utilizing Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Variational Autoencoders (VAEs) to develop an AI assistant that optimizes various aspects of textile production and design.

Challenges:

Design Creativity and Innovation: Generating novel and marketable textile designs that cater to diverse customer preferences and trends is a constant challenge. Traditional methods often rely on manual iterations and lack the ability to explore vast design spaces efficiently.

Production Efficiency and Optimization: Optimizing resource allocation, minimizing waste, and predicting potential defects during production are critical for maintaining profitability and sustainability. Traditional methods rely on historical data and expert knowledge, which may not capture all relevant factors or adapt to changes in raw materials or processes.

Quality Control and Assurance: Maintaining consistent quality across large production batches is essential for brand reputation and customer satisfaction. Manual inspection methods are often time-consuming and prone to human error.

3.4 PROPOSED SOLUTION

Generative adversarial networks (GAN) provides an excellent framework for learning deep generative models, which aim to capture probability distributions over the given data. Compared to other generative models, GAN is easily trained by alternately updating a generator and a discriminator using the back-propagation algorithm. In many generative tasks, GANs (GAN and its variants) produce better samples than other generative models . Besides image generation tasks, GANs have been introduced to more and more tasks, such as video generation , visual tracking , domain adaption , hashing coding , and feature learning. In these tasks, the adversarial training strategy also achieved promising performance. However, some problems still exist in the GANs training process. In the original GAN, training the generator was equal to minimizing the Jensen-Shannon divergence between the data distribution and the generated distribution, which easily resulted in the vanishing gradient problem. To solve this issue, a non-saturating heuristic objective (i.e., '− log D trick') replaced the minimax objective function to penalize the generator . Then, and designed specified network architectures (DCGAN) and proposed several heuristic tricks (e.g., feature matching, one-side label smoothing, virtual batch normalization) to improve training stability. Meanwhile, energy-based GAN and least-squares GAN improved training stability by employing different training objectives. Although these methods partly enhanced training stability, in practice, the network architectures and training procedure still required careful design to maintain the discriminator-generator

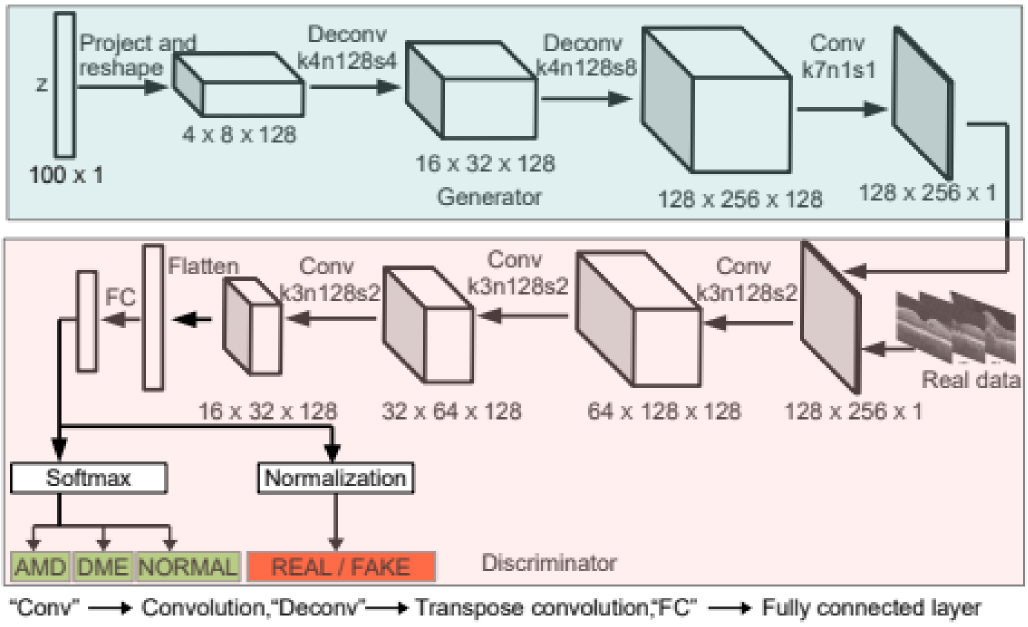

Figure 6 :Image showing levels in GAN

3.4.1 LEVELS OF GAN

3.4.1.1 Data Acquisition and Cleaning:

- We will acquire a dataset of textile pattern images for use in generating new designs.
- This dataset will consist of 6 classes: solid, checkered, dotted, striped, zigzag, and floral.
- Each class will have approximately 400 images, totaling 2500 images overall.
- We will obtain the dataset by searching Google for keywords like "checkered," "floral," and "stripes" and downloading the images.
- To ensure data quality, we will clean the dataset by removing faulty images like those shown in Fig. 7.

3.4.1.2 Pseudo Labeling for Improving and Cleaning Dataset:

- We will utilize pseudo labeling, a semi-supervised technique, to assign labels to unlabeled data.
- We will scrape mixed textile design images from the internet.
- Images with watermarks will be automatically identified and deleted using OCR technology.
- Images with text and website information at the bottom will be resized by removing the last 20 rows to maintain their integrity.
- A pre-trained Residual Network 50 on ImageNet will be fine-tuned on the labeled data and then used to predict category labels for the unlabeled data.
- Algorithm 1 will outline the pseudo labeling process for textile patterns.
- Through this process, we will acquire a large labeled dataset from a small labeled and a large unlabeled dataset.

3.4.1 LEVELS OF GAN

3.4.1.1 Data Acquisition and Cleaning:

3.4.1.2 Pseudo Labeling for Improving and Cleaning Dataset

3.4.1.3 Textile Patterns Generation Using Image Generative Models:

- We will experiment with WGANs GP, DCGANs, and convolutional VAEs for generating textile patterns.
- These models will be trained from scratch using standard architectures.
- The results of all three models will be presented in Table I.

3.4.1.4 Visualizing Latent Space of VAEs:

- Convolutional VAEs will be employed to generate textile patterns and visualize the captured latent space.
- The mean and standard deviation of the latent space for the testing set will be displayed in Fig. 3.
- Clusters of similar designs should be evident even if the textile designs are not well separated.
- This unsupervised method will further validate the proper labeling and distinctiveness of our proposed dataset.

3.4.1.5 Style Transfer

- Given the complexity of textile designs often featuring combinations of multiple patterns, we will explore style transfer to create more intricate designs.
- Since our dataset only includes single-pattern images, the generated WGAN designs may not be complex enough to qualify as genuine textile designs.
- Therefore, we will implement Gatys' approach [18] for neural style transfer to combine different styles.
- Designs generated using WGANs will be carefully selected to ensure contrasting styles and input image classes.

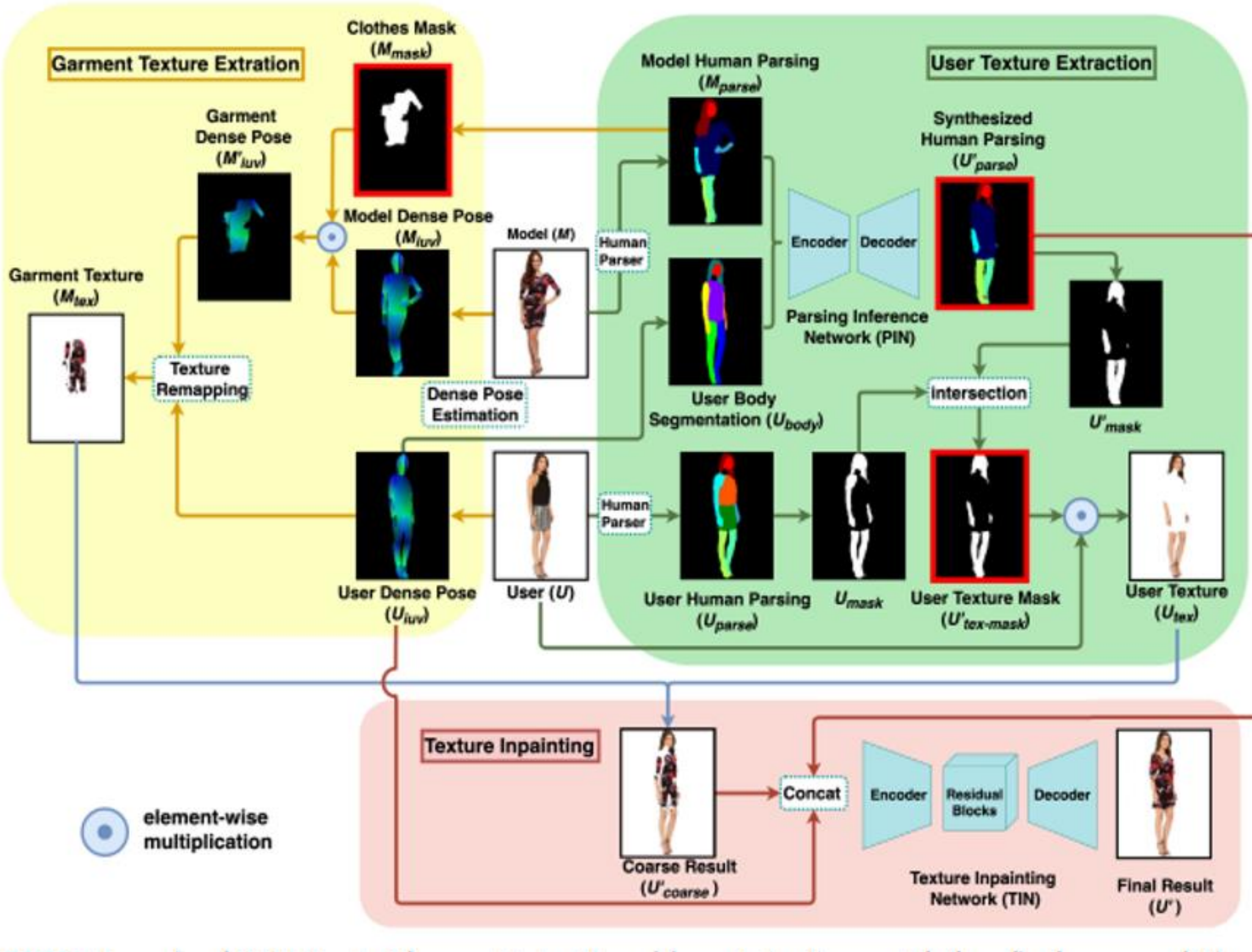

Figure 7 : image showing levels of GAN

3.4.2 IMAGE-BASED VIRTUAL TRY-ON

Early works for virtual try-on applications were mainly based on computer graphics technology. Though these works achieve precise physical simulation, most works require 3D measurements. Image-based virtual try-on, which can generate photo-realistic try-on results from 2D images, is more convenient and cheaper than the 3D based approaches. Existing works in image-based virtual try-on can be divided into two groups according to the type of input. The first group takes a user image and an in-shop clothes image as the input (user and article). The second group takes a user image and a model image as the input (user and model). Both groups aim to synthesize a new image of the user wearing the clothes from the product image or the model image.

3.4.2.1 Evaluation Metrics

In fabric defect detection, we are more concerned with whether the defects are detected than whether every pixel is predicted correctly. Therefore, we use an evaluation metric that classifies a defect as either detected or undetected. We use the intersection over union (IoU), which is the ratio of the intersection area to the union area for the ground truth and our detected polygonal region, as shown in Fig. 5. The IoU represents how closely our detection result matches the ground truth. As we do not need the resulting polygon to perfectly match its ground truth, we set the threshold for whether the defect is detected to 0.5.

Next, successfully detected defects are categorized as true positives (TPs), mistaken detections are categorized as false positives (FPs), and undetected defects are categorized as false negatives (FNs). With these three indicators, we calculate the precision, recall, and F −measure as the evaluation metrics, and their formulae are as follows:

$$precision = \frac{TP}{TP+FP} \ x\ 100\%$$

$$recall = \frac{TP}{TP+FN} \ x\ 100\%$$

$$F\text{-}measure = 2\ x\ \frac{precision\ \ X\, recall}{precision + recall} \ x\ 100\%$$

As the general rule, a higher F − measure reflects a better detection performance.

3.4.2.2 Experimental Steps

We next describe our experimental settings in detail. For clarity, we split our experiment into three parts according to our proposed detection system in Section III: detection model pretraining, defective sample generation for new textures, and model fine-tuning.

In the first step, we collect defective fabric images as our original dataset and categorize them according to the cause of the defect. We collected four defect types in both simple and complex texture fabrics. Due to different production processes and materials, the fabrics with simple textures and complex textures also have different defect types: color spot, oil stain, knot and broken end in simple texture fabric, and color spot, broken end, broken yarn, and white strip in complex texture fabric. We categorize these defect types with the aim of improving different aspects of our method. In short, color spots test the ability to detect small-scale defects, oil stains are used to enhance fuzzy edge detection, knots and broken yarn defects train our method for improving sharp edge detection, and broken ends and white strips require our model to have a wider field to capture large-scale defects. Note that our purpose is to detect defects not to classify the types of defects.

For data preprocessing, we randomly crop the defective samples to 512×512 according to the defect positions. Since our defective fabric dataset is not large enough to train a general model, to extend the variability of the dataset and avoid overfitting, we adopt data augmentation methods including hue, brightness, rotation, and mirroring to the defective samples. For clarity, we name this preprocessed dataset dataset0. After preparing the original defective fabric dataset, we use dataset0 to train our Deep Lab V3 network. When the training procedure is complete, we obtain the pretrained detection model as the output of step 1. This pretrained model detects defects in textures present in dataset0 well. However, as discussed above, because the background texture represents most of the fabric image, there is a significant difference between two fabrics when they have very different textures, which may cause the pretrained model to fail. In the second step, we focus on generating defective samples for the detected fabric, the texture of which may be very different from the textures in dataset0. For a given fabric to be detected, we can easily collect defect-free samples of this fabric and apply our multistage defect-generating module to generate defective samples for the detected fabric.

In stage 1, a conditional GAN is trained with style labels and real defects to generate different types of defects. In stage 2, another GAN is trained with composite images and real defective images to generate images with properly fused defects. A hinge reconstruction loss and perceptual loss are also applied to further constrain the generating module. After training, the module is fed with defect-free samples to generate defective dataset1 with new textures. Dataset1 is mixed with a random collection of dataset0 at a ratio of 1:5 to form the mixed dataset2. In the final step, we use the mixed-source dataset2 to finetune the pretrained model from step 1. Specifically, we use our pretrained model as the initialization of the Deep Lab V3 defect detection network, and then dataset2 is used as the training dataset to further fine-tune the network. The network is supposed to be able to extract different features for the detected fabric, so the detection ability of the final fine-tuned model, which is the output of step 3, is improved with regard to the new texture samples. Finally, we apply the fine-tuned model in the testing phase using real defective samples. The evaluation criteria are described above, and here we use these criteria to evaluate our detection results. The TPs, FPs, and FNs in different experimental settings are counted, and the corresponding assessment criteria, i.e., the precision, recall, and F − measure values, are calculated.

3.4.2.3 Results of Generating

Defective Samples We first train the proposed multistage defect-generating module to synthesize defective samples. Some generated fabric samples from both stages are reported, and we attempt to qualitatively analyze the effects and advantages of different stages. Since simple-textured fabrics are distinct from fabrics with complex textures, we divide the collected original defective fabric images into two categories: simple-textured fabric samples and complex-textured fabric samples.

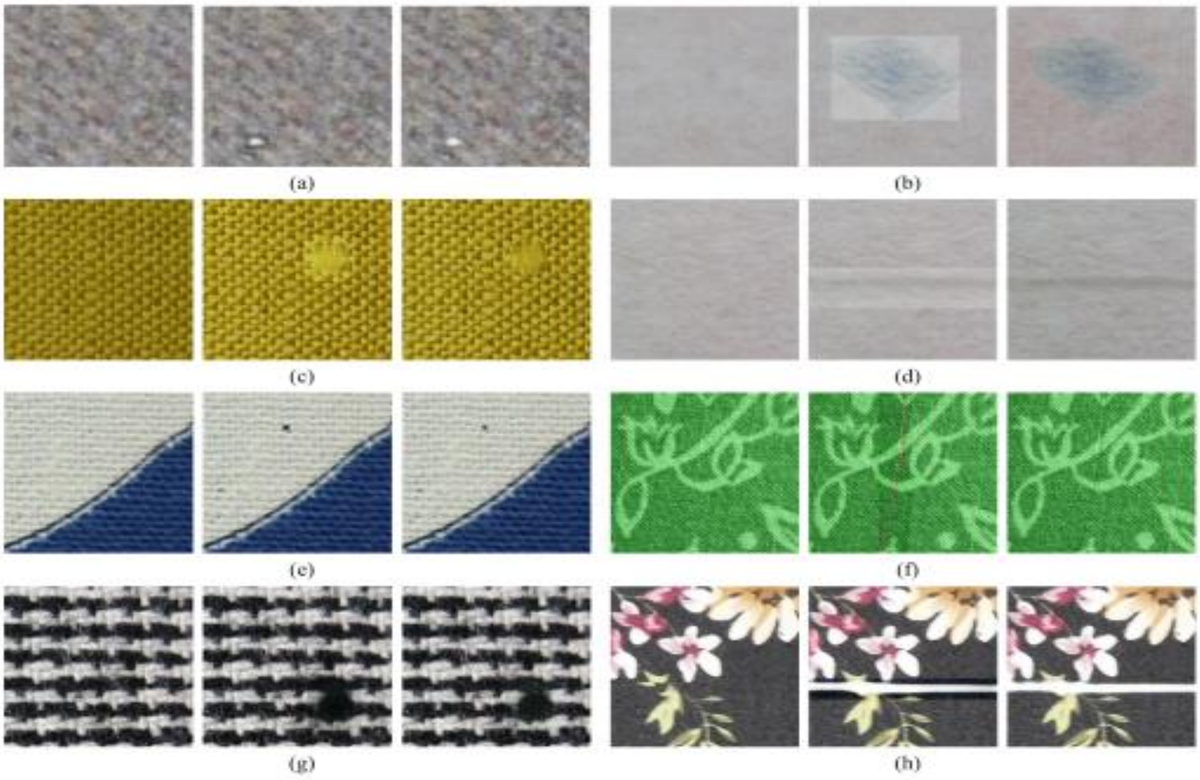

Figure 8: lists the number of defective images defects of each.

Each contains four different defect types. Our goal is to learn the patterns of different defect types and further add them into new defect-free images. Since these new synthesized 'defective' fabric images will be used to fine-tune the pretrained detection model, we hope that these synthesized fabric images are as realistic as possible.

3.4.2.4 Detection Results

In this section, we report the detailed testing results of the fine-tuned model under diverse settings. As mentioned above, we prepared one simple texture dataset and one complex texture dataset and then conducted experiments on both. According to our categorization, there are four defects in samples textured fabric (color spot, oil stain, knot, and broken end) and four defects in complex-textured fabric (color spot, broken end, broken yarn, and white strip). Detection results on the simple texture dataset: Table I lists the number of defective images and the number of defects of each type in our training and test datasets. As a single image can contain multiple defects, the number of defects is greater than the number of images. On average, knots are present more often in one image than the other defect types, while the oil stain and broken end defects mostly occur in only a single image. The test dataset shares a similar ratio between the number of images and number of defects to the training dataset for each defect type. The average size of the images is 5300×3000 pixels both during the training and test phases. For comparisons with other methods, we also implement a fast Fourier transform (FFT)-based method and train two

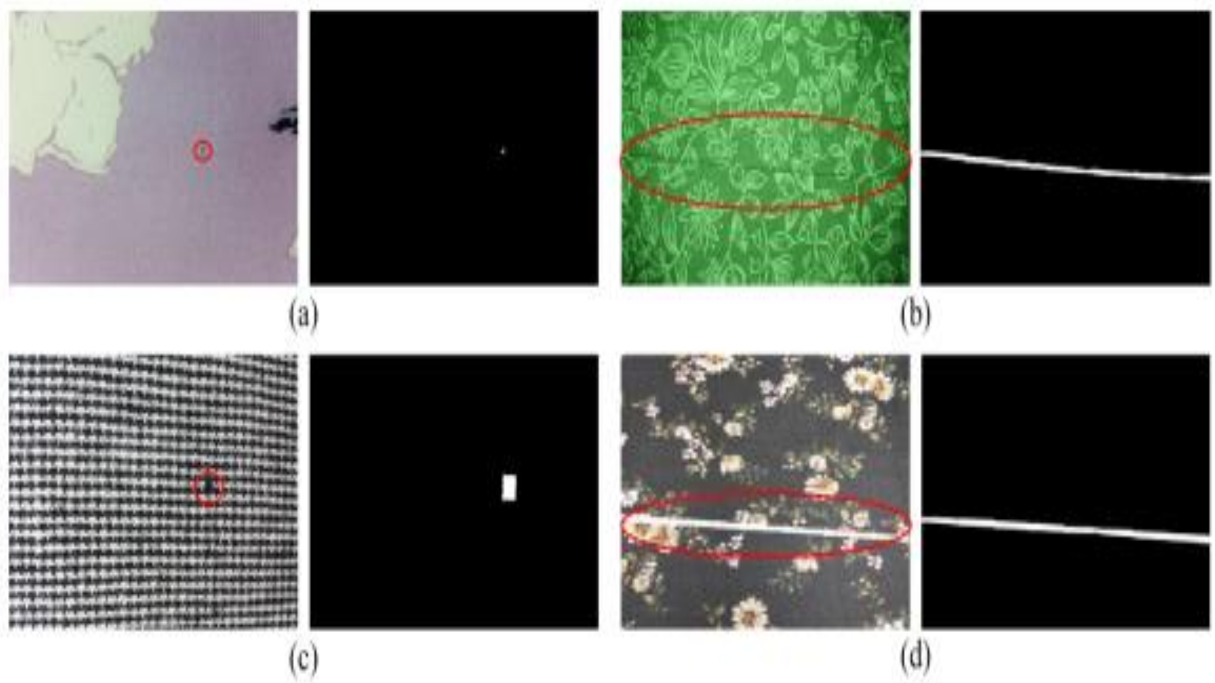

Figure 9: lists the number of defective images defects of each.

3.4.2.5 Attribute Selection

PWC items have dense, irregular and non-periodic patterns. We observe that the suitable attribute which can describe our PWC items is the ‘texture’. Moreover, the texture helps in supervised learning of features which is achieved by employing the SSDH technique in our framework. The features learnt using the basic patterns are further used to estimate the random patterns (as combination of basic patterns) of PWC. In the retrieval experiments, it is found that the 'texture' based description of PWC with SSDH feature learning shows promising results even though the variability of the patterns in Pakistani women's clothing is high. Furthermore, the design of a texture-based approach offers the following advantages: utilization of the image data of western women's clothing for training which has normally basic patterns; the approach is extendable to large datasets for evaluation. B. Binary Coded Feature Extraction In order to extract the binary coded texture features by supervised learning, we use the SSDH architecture as a feature extractor .The hierarchical ability of SSDH enables the extraction of low to high level features in corresponding initial to final layer . The learned features at each layer, break the complex non-linear task into a set of small linear tasks. The hierarchical feature extraction ability achieves the visual attributes detection by voting at each layer based on low, mid and high-level features which improves the classification accuracy significantly , in turn, the retrieval accuracy increases. The SSDH architecture learns the label consistent binary features by minimization of classification error. To make the binary codes informative the binarization error is minimized and entropy is maximized.

CHAPTER - 4

CONCLUSIONS AND FUTURE WORK

In this paper, we propose a compensation method of twostage image generation to help ordinary users create fashion design in AR environment. We designed and implemented a mobile application that enables non-professionals to create a early stage clothing design with everyday materials rapidly. The generative ability of the cGAN model and our compensation method provide novel tools for novices to produce graphical designs. Finally, through an online experiment and an offline use case study, we showcase the capability and usability of the proposed system. In this paper, we propose a GAN-based framework for fabric defect detection that can detect defects of various scales in both simple- and complex-textured fabrics. A pretrained semantic segmentation network is trained on an original dataset of defects to better address the fabric defect detection task. Using a multistage defect-generating GAN.

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