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Deep learning based system for garment visual degradation prediction for longevity

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ABSTRACT

Prolonging garment longevity is a well-recognized key strategy to reduce the overall environmental impact in the textile and clothing sector. In this context, change or degradation in esthetic or visual appeal of a garment with usage is an important factor that largely influence its longevity. Therefore, to engineer the garments for a required lifetime or prolong longevity, there is a need for predictive systems that can forecast the trajectory of visual degradation based on material/structural parameters or use conditions that can guide the practitioners for an optimal design. This paper develops a deep learning based predictive system for washing-induced visual change or degradation of selected garment areas. The study follows a systematic experimental design to generate and capture visual degradation in garment and equivalent fabric samples through 70 cycles in a controlled environment following guideline from relevant washing standards. Further, the generated data is utilized to train conditional Generative Adversarial Network-based deep learning model that learns the degradation pattern and links it to washing cycles and other seam properties. In addition, the predicted results are compared with experimental data using Frechet Inception Distance, to ascertain that the system prediction are visually similar to the experimental data and the prediction quality improves with training process.

1. Introduction

To compensate overall environmental impacts stemming from the surging consumption of consumer goods, several emerging strategies are being practiced aiming towards a sustainable paradigm of production and consumption (Akenji et al., 2015). Prolonging or extending the product lifetime is one such key strategy (Rogers et al., 2015; Goworek et al., 2020). It aims at meeting the global consumer demand by extending the product lifetime that also leads to slowing-down the consumption cycle, reducing new products, and consequently decreasing the demand for raw materials (Rogers et al., 2015). In addition, extending product longevity has been identified as an important facilitating factor for circular business models (Gillabel et al., 2021).

Currently, textiles and clothing are estimated as the fourth highest-pressure category in terms of using the primary raw material consumption (Manshoven et al., 2019) and less than one percent of recycled textiles are reused in new clothing (Ellen MacArthur Foundation, 2017). In this context, clothing longevity is argued to be the single most critical strategy that can help in substantial reduction of the environmental footprint (Cooper et al., 2013). According to a UK based study by Downes et al. (2011), about 100,000 tonnes of CO_2-eq and 2000 tonnes of waste per year can be reduced by extending the lifespan of 10% of t-shirts. On the contrary, the utilization of clothing has almost halved (or the disposal rate has almost doubled) between 2000 and 2015 (Ellen MacArthur Foundation, 2017). With this trajectory, the textile and clothing industry is expected to account for nearly 26% of the carbon emission budget on the 2-degree Celsius pathway as per Paris agreement by the year 2050 (Ellen MacArthur Foundation, 2017).

For garment longevity, previous studies have highlighted numerous barriers related to businesses, product development, and usage that hinder prolonging the lifetime (Jensen et al., 2021; Goworek et al., 2020; Oxborrow et al., 2015). Additionally, the inability to judge or predict longevity is a key concern for retailers, which in turn hinders the ability to communicate its benefit to consumers in a meaningful way, thus resulting in opportunity loss. For instance, extant studies (e.g. Langley et al. (2013), BSR/NICE (2012)) have found how customer preference and even willingness to pay can be considerably higher for long-life, durable products. According to Jacobs and Hörisch (2021), the lack of information on longevity leads to information asymmetry

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between consumers and retailers that may result in adverse selection problems, such as the increased risk of purchasing a short-lived item by misjudging it to be long-lasting. Jensen et al. (2021) highlighted how this can hinder consumers in not only purchasing an appropriate product to meet their demand but also in optimally using the product before disposal.

While there are different ways to determine product lifetime or longevity, e.g. in terms of degradation of different functionalities over time or usage frequency, in different product types; predicting garment longevity is complex due to its multi-scalar nature. Besides functional properties, visual appearance is a vital factor in determining garment longevity (Gnanapragasam et al., 2018). Consequently, how such visual appearance, which in turn influences the garment's esthetic appeal, degrades over time is an important factor that decides the end-of-life (Wakes et al., 2020), yet difficult to determine. Further, while studies on garment longevity encompassing various closely related concepts of product durability – which include the aspects of material durability, design, etc. – as well as consumer use behavior can be found (eg. (McLaren et al., 2015; Laitala and Klepp, 2021) to mention a few), exploring longevity in terms of visual or esthetic degradation is scantly explored in extant literature so far.

The absence of information that provides a projection of how expected longevity changes over time is a critical barrier that not only hinders the consumers to make an informed purchasing decision but also makes it difficult for the consumers to use the garment. At the most, companies rely on practices such as product development iterations to improve the performance or for setting high-performance standards (Jensen et al., 2021), which may require extensive hit-and-trial experiments before reaching an optimal design and materials parameters for a pre-decided lifetime. Thus longevity predictive systems are not only of critical importance for prolonging garment longevity or designing garments for the desired lifetime but also for the consumers to make an informed purchase decision.

In light to this, our study focuses on developing a model for predicting the degradation of visual appearance of garments that mainly occurs due to washing-induced visual changes. A clear premise for our research lies in the axiom that a garment that degrades faster in visual appearance is expected to lose its esthetic appeal, and thus gets discarded earlier in comparison to a similar garment that loses its appearance slowly. It is further in line with the findings of multiple studies (e.g. Chapman (2021)) which reveal garment esthetic appeal and how it degrades over time as an important factor for longevity. The overall visual changes in a garment can be attributed to various factors, such as changes in shade, color, texture, luster etc. However, to build a predictive system based on these parameters, one may require additional effort to predict each of these parameters individually, and subsequently to re-create overall visual change to make it comprehensible to the end-users, it requires an aggregated system that can combine all these parameters. Therefore, in order to reduce the complexity, our study adopts a pragmatic approach that employs machine learning models which are trained for predicting the overall visualization for given degradation conditions.

The predictive system is based on the deep-learning-based conditional Generative Adversarial Network (GAN) that is trained for predicting and rendering the visual degradation in the seam area joining two fabric pieces. The key contribution of this paper is linked to the novel way of predicting and visualizing garment degradation by the application of artificial intelligence. While in this study, a limited number of parameters are used for demonstrating a novel way of representing visual degradation, the process and method can be followed for scaling up the model for incorporating additional parameters. Therefore this paper makes a critical contribution by laying down the foundation for the prediction of visual degradation in garments, and covers an important research gap.

The rest of the study follows the following structure. Section 2 presents related literature, and Section 3 discusses the materials and methods – including the experimental procedure for empirical data generation and labeling, and the description of GAN model development along with the training process – used in this study. Further Section 4 presents the results and finally Section 5 discusses the main conclusions and future research directions.

2. Garment longevity and visual degradation

2.1. Garment longevity

Prolonging garment longevity has been widely acknowledged as an effective strategy to prevent waste and overall reduce the product's environmental impact (Klepp et al., 2020; Oxborrow et al., 2015). Existing literature has focused on understanding garment longevity from a wide range of aspects, ranging from identifying the concept of clothing longevity or lifespan (Klepp et al., 2020) and understanding consumer behviour around longevity (Laitala and Klepp, 2020, 2021; Klepp et al., 2020; Langley et al., 2013), to strategies for prolonging it by involving different stakeholders and paths (Gwilt and Pal, 2017; Cooper et al., 2016). While the overall lifetime of a garment is decided by a combination of parameters including consumer's acceptance and willingness to actively use the product, the product durability – which is an important component for prolonging product longevity – is closely linked with the material degradation over use and time.

Garments are predominantly made of textiles that complex structures of fibers assemblies manufactured either by forming web-like layers of fibers or by assembling fibers into yarns that are then interlaced or inter-looped to form 2D sheet-like textile fabrics (Lomov and Verpoest, 2005). Clothes or garments, in this context, are next in the level of structural hierarchy that are formed by cutting and sewing textile fabrics in a defined fashion. The physical, mechanical, and visual characteristics and their changes/degradation/aging are the results of a complex interaction of material components on different levels of structure hierarchy, and their interaction with the external actions or the environment.

Drawing upon the complex material mechanics and a large number of variables, measurement or testing of durability in real life is a complex task besides being time-consuming, expensive, and difficult (Bide, 2012). Therefore, instead of using real-life conditions, one way to understand or predict the durability is approached by the standard mechanical or chemical tests in laboratory conditions in which the prime focus is testing if the selected attributes meet certain pre-defined quality criteria(Thiry, 2004). This approach is, therefore, primarily emphasizes on conforming to the performance specification rather than looking into the degradation behavior. Another experimental approach that many studies have followed is iterative measurements of properties under the incremental cycles of actions or events in a laboratory or real-life conditions that lead to degradation. For example, Agarwal et al. (2011) investigate the degradation of a series of mechanical properties of knitted textiles with washing, where the testing or measurements were made at certain washing intervals to track the change in mechanical properties. Similarly, Schlich and Neuss (2019) have investigated the effect of up to 50 times of home washing and drying on degradation or change in various mechanical and visual properties of denim fabrics. In addition, often statistical models are used which primarily focus on learning the material behavior from experimental data to state the durability. For example, Slater (1986) models the degradation of a garment that follows declining power curves i.e. $P = C_1(1-t/100)^{k_1} + C_2(1-t/100)^{k_2} + \ldots + C_n(1-t/100)^{k_n}$ where P is the instantaneous value of the residual property (that varies between 0% – 100%), t is the elapsed garment lifetime (varies between 0% – 100%), and $C_1, \cdots, C_n$ and $k_1, \cdots, k_n$ are the statistical fitting constants. Therefore, as t increases, the value of residual property P decreases. Mashaly and Hussein (2011) use factorial design to investigate the effect of structural and material parameters and subsequently develop a predictive model for the performance of elastic bands in garments.

However, another critical aspect of garment longevity that transcends such physical durability properties is related to its esthetic appeal which is largely influenced by the garment visual appearance - but as highlighted above is scantly explored in extant studies due to technical limitations, such as data insufficiency, lack of methods etc. For visual or esthetic changes, most of the existing studies have focused on changes in color or shade to express in certain numerical units e.g. percentage change in color (Sharma et al., 2012), average chroma change (Toscani et al., 2020; Agarwal et al., 2011) and, color shade change in terms of rating (Mondal and Khan, 2014). Measuring visual properties with a numerical measure – which can be subjective (e.g. panel assessment) or objective (e.g. chroma change) in nature – reduces the complexity to express the change and make it possible to use regression models for the prediction of degradation behavior. However, the main challenge is related to converting, connecting, or visualizing the adopted numerical scale into the real visual degradation without having an explicit reference scale or examples.

2.2. Artificial intelligence for visual predictions

In recent times, a new stem of research in artificial has focused on the development of predictive systems for realistic visuals i.e. in the form of images, by the application of Generative Neural Networks or GANs based deep learning models(Creswell et al., 2018). A GAN, in general, comprises of two neural networks namely generator – which is trained for generating images, and discriminator – which is trained for classifying real images from synthetic or the generator produced images (ibid). The purpose of the discriminator is to provide feedback to the generator in the training process. Interestingly, GANs have been used to predict the human face visual changes with aging where the training was carried out by exposing the GANs to training image datasets of human faces that are tagged with age information which allows the system to learn the human face as a function of age (Antipov et al., 2017; Tang et al., 2018). Papadopoulos et al. (2021) have further presented a model for material aging by the application of GANs which maps the input materials to degraded material over a time axis. Within the field of textiles, GAN-based systems have been demonstrated for predicting and rendering a range of complex visual properties of textiles such as wrinkles, deformation, and virtual fitting (Han et al., 2018; Wu et al., 2021; Yuan and Moghaddam, 2020; Lahner et al., 2018). These systems are trained by exposing them to the target dataset i.e. image labeled with input parameters or properties, while allowing the neural networks to adjust the internal parameters which allow the generator to produce the realistic images conditioned to the input labels. Further, a stem of research has focused on developing GAN-based systems (e.g. TailorGAN (Chen et al., 2020), ClothGAN (Wu et al., 2021)) that aim at assisting the designers by simulating realistic visuals of garments based on theoretical changes made in the design. While the GANs have found great popularity for simulating visuals in the field of textile and clothing, the investigation or development of predictive-system for garment visual degradation or aging has remained rather elusive. Most studies have focused on textile or garment visualization from design or dynamics perspective. This can be linked to the fact that training GANs require big datasets which require a lot of human effort (Nuha and Afiahayati, 2018). There are existing image-based open databases available for textile and clothing (such as DeepFashion (Liu et al., 2016), Fashion-minst (Xiao et al., 2017)) which have been used for training GANs in many studies. However, to the best of authors' knowledge, there is no database in the public domain that has garment images which show the time-scale-based visual degradation – which can be linked to the lack of studies on utilizing generative networks based deep learning models for investigating garment visual degradation.

3. Materials and methods

3.1. Materials

In real-life situations, garment degradation is not uniform in all locations. The expected degradation or visual changes can be broadly connected with parameters such as the location of the component and used material, and construction. The visual degradation varies with the location as the mechanical stress and abrasion connected with use condition are not uniform on all parts as some parts or locations (e.g. trousers part on or near to the knee) tend to have high stress because of interactions with wearer's body parts or external objects or environment as compared to other parts or locations, resulting in a differential rate of visual or mechanical degradation (Toresson Grip and Gatzwiller, 2020). In addition, there is a range of sources which contribute to the degradation. For example, garment washing not only induces abrasion and mechanical stresses but also exposes the materials to chemicals (such as cleaning agents) and water that result in the visual and mechanical degradation of the garments. Similarly, textiles having different physical properties and construction parameters are joined together to construct various parts of garments, which degrade differently or at different rates during the use of a garment and result in visual changes on seams (Yıldız and Pamuk, 2021; Kamali et al., 2020).

In this study, we focus on the visual degradation of the garment seams where garment washing is taken as a degradation simulating parameter. The selection of washing as degradation parameter is motivated by the fact that washing-induced color change is enlisted as one of the main causes of clothing disposal accounting to nearly 5% of the reasons for clothing disposal due to durability failure/faults (Bauer et al., 2018). Further, garment washing can be easily controlled in laboratory environment by controlling the washing conditions, treatment time and using the same washing machines for different washing cycles. Whereas other degradation drivers such as human body movement or degradation under real use conditions are either difficult to replicate in a laboratory environment or difficult to control if conducted in real-life scenario. Similarly, seam area is selected for study as garment seam appearance is not only considered as an important quality aspect for customer acceptance (Kamali et al., 2020), but also one of the most vulnerable positions in terms of visual changes when subjected to washing.

For our study, 17 pairs of trousers (as experimental garment samples) were supplied by a Swedish outdoor retail brand from the same stock keeping unit that were produced from fabric from the same production lot (experimental fabric samples), in order to minimize the material variations and their impact on the outcome. These samples were exposed to a systematic plan of washing and hand drying to monitor the incremental degradation over time and progressive wash cycles, as explained in Section 3.2.1. We focus on three seam locations coded as *AA*, *AB*, and *BA*, as shown in Fig. 1(a). The coding assigned originated from the type of fabrics joined over the seams (*A* and *B*), where the first letter of the coding indicates on which fabric the double stitching is placed, this is also the fabric perceived as "on top". For example *AB* indicates that the fabric *A* is joined with another fabric *B* where *A* is placed on the top of *B*. It should be noted that the fabric *A* is composed of 65% polyester and 35% cotton with areal density of $194g/m^2$, whereas fabric *B* is composed of 63% polyamide, 26% polyester and 11% elastane with areal density of $237g/m^2$. The location of the seams is indicated is indicated in Fig. 1(a), where the white fabric indicates fabric *A* and gray fabric indicates fabric *B*. In addition, fabric samples were also developed by joining fabric having same characteristics as that of the garments in terms fabric, threads, seam stitch etc.

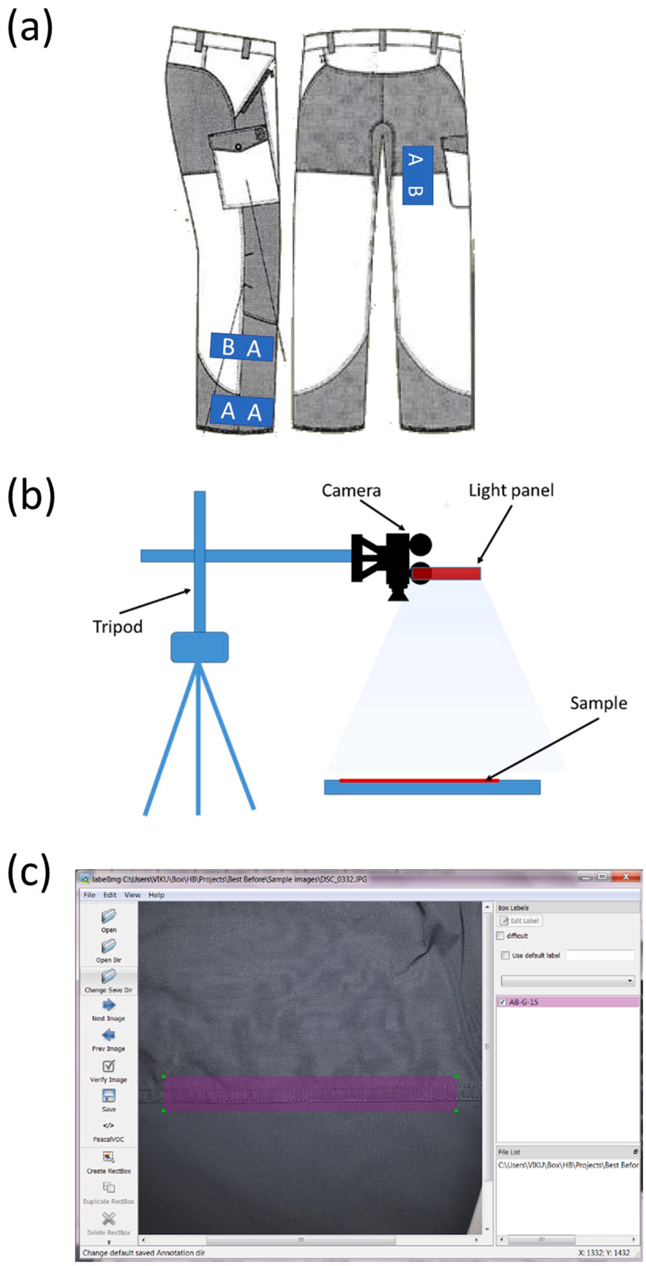

Fig. 1. Illustration of (a) the selected seam area on garments (b) experimental setup for image acquisition and (c) procedure for labeling the seam area.

3.2. Methods

3.2.1. Experimental setup

The degradation simulation, i.e. garment washing and hang drying was carried out with certain modifications as per guidelines for home washing from Swedish Standard SS-EN ISO 6330:2012[1]. The temperature of each washing cycle was 40 C° and with a regular domestic detergent for color garments. Each wash load contains three trousers, three pieces of fabric, and enough ballast to make the load weigh 2.0 ± 0.1 kgs. A specific washing scheme was implemented to distribute the trousers and fabrics throughout the washing cycles, as shown in Table 1. Each column in Table 1 represents a wash-run that consists of five wash cycles and one overnight hang-drying cycle. In the washing process, we used two washing machines represented by W_1 and W_2 and the samples loading in washing machine are presented by ✓ and $\times$ for W_1 and W_2, respectively. It must be noted that samples t_{15}, t_{16}, f_{15} and f_{16} were introduced to make the load even for wash runs 18 and 19.

3.2.2. Data acquisition

According to the design of experiment, the fabric- and garment-sample images were captured in a room with controlled light conditions after each wash-run. The setup included a digital camera, a light panel with controllable light intensity fixed on a tripod stand facing vertically on the horizontal plane, as shown in Fig. 1(b). The samples were placed on the plane and the images were captured of all fabrics and garments sampled on selected position for zero (i.e. no wash) to 70 washes on a regular interval of five washes. To ensure uniformity in imaging of the samples, the camera was fixed at the tripod and a reference scale template was used to calibrate the camera zooming. The light panel is every time calibrated to the same light intensity to ensure uniform brightness during the whole image acquisition process.

3.2.3. Labeling

In this step, the images acquired in Section 3.2.2 were tagged for seam positions. The tagging was carried out by an open-source application named LabelImg[2]. The images were first imported and then the seam area was tagged on the fabric samples and selected seam positions on garments, as shown in Fig. 1(c). Further, the tagged position of seam in the images was labeled for three parameters namely, sample type (fabric, garment), the seam joining fabric (*AA*, *AB*, *BA*), wash number $(0 - 70)$ for which the images were captured. Further, a python program was developed to extract the images from random positions along the tagged seam line of required dimensions, which were subsequently used for visual feature mapping and machine learning purposes. For the model development, originally, image patches of dimensions 512×512 pixels were extracted for multiple random positions along the seam line that resulted in a labeled dataset of ~ 9000 image patches. The extracted images were further down-sampled to dimensions of 128×128 pixels for faster processing in the machine learning process. It must be noted that all image patches are not unique because when the random positions of extraction are close to each other, it resulted in some image patches with the overlapping area. An example dataset of image patches is shown in Fig. 2.

3.3. Model specification

Generative Adversarial Networks or *GANs*, as aforementioned, consists of a combination of two deep neural networks, namely Generator (G) and Discriminator (D). The function of G is to generate a synthetic image based on given inputs. The input consists of two parts, namely random noise (R) and conditions (C), therefore the aim of G is to generate the images for given condition C. The discriminator D takes the synthetic images S and real images I input along with conditions C, identify some measure to calculate the difference between the real and synthetic images, and subsequently provides training feedback to G to improve the quality of synthetic images. In short, G trains with the help of D to generate synthetic images such that the latter cannot make a distinction between real images and synthetic images for given conditional inputs. At the same time, D trains separately to identify the difference between real and synthetic images so that it can provide improvement feedback to G. It should be noted that the GANs with conditional inputs isare also known as conditional GANs. The GAN setup used in this research is shown in Fig. 3.

The reader is directed to Fig. S1 and Fig. S2 in supplementary information for the detailed structure for G and D respectively. C in our

[1] https://www.sis.se/produkter/textil–och-laderteknik-d5f82ac0/produkter-fran-textilindustrin/allmant/sseniso63302012/

[2] https://github.com/tzutalin/labelImg

Table 1
Experimental design for washing.

	Wash run																			
Sample IDs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Total washes
t_1,f_1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓						70
t_2,f_2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓							65
t_3,f_3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓								60
t_4,f_4	X	X	X	X	X	X	X	X	X	X	X									55
t_5,f_5	X	X	X	X	X	X	X	X	X	X										50
t_6,f_6	X	X	X	X	X	X	X	X	X											45
t_7,f_7										X	X	X	X	X	X	X	X			40
t_8,f_8											X	X	X	X	X	X	X			35
t_9,f_9												X	X	X	X	X	X			30
t_{10},f_{10}													✓	✓	✓	✓	✓			25
t_{11},f_{11}														✓	✓	✓	✓			20
t_{12},f_{12}															✓	✓	✓			15
t_{13},f_{13}																		✓	✓	10
t_{14},f_{14}																		✓		5
t_{15},f_{15}																		✓	✓	10
t_{16},f_{16}																			✓	5
t_{17},f_{17}																				0
Total samples in W_1	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	
Total samples in W_2	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	0	0	

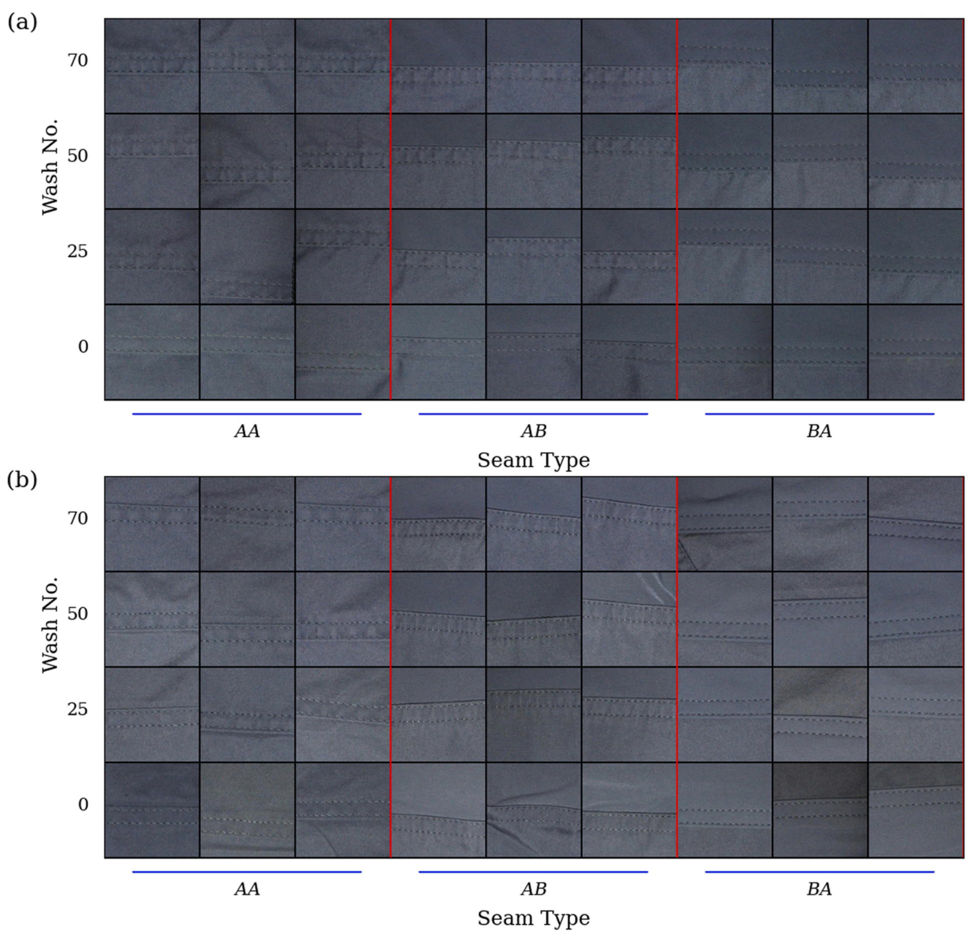

Fig. 2. Example image patches for extracted form (a) fabric and (b) garment samples. For each wash number, three representative image patches are illustrate to distribution in visual features.

research is a six bit parameter combining three conditions associated with labeled image i.e. sample type, seam joining fabrics, wash number. One-hot encoding is used for categorical conditions i.e. sample type (expressed as $AA = [0,0,1]$, $AB = [0,1,0]$, $BA = [1,0,0]$) and seam joining (expressed as 'fabric' or $F = [0,1]$, 'garment' or $G = [1,0]$), whereas wash number is a numerical value. Thus, a sample image labeled as AA on 'fabric' for wash number 35 is expressed as a six-bit parameter as $[35,0,0,1,0,1]$.

As aforementioned, the purpose of training D is to maximize the capacity to identify synthetic images from real images, the training of G is focused to produce synthetic images that look similar to the real images. Therefore, G is focused on generating the synthetic images that can

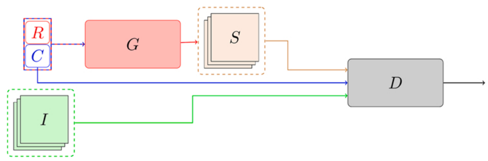

Fig. 3. Schematic of conditional Generative Adversarial Network(GAN).

fool D. Accordingly the training process of a GAN involves maximal and minimal game problem, as shown below (Mirza and Osindero, 2014; Gulrajani et al., 2017),

$$\min_G \max_D (D,G) = \mathop{\mathbb{E}}_{\mathbf{x}\sim\mathbb{P}_r}[\log(D(\mathbf{x}))] - \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_g}[\log(1-D(\tilde{\mathbf{x}}))]$$

where, $\mathbb{P}_r$ is the distribution of real data, whereas $\mathbb{P}_g$ is the distribution of generated data, which is implicitly defined $\tilde{\mathbf{x}} = G(z)$ where $z \sim p(z)$ is the prior input noise.

The above objective function is further extended to train D and G with conditional input parameter by feeding the conditional inputs $\mathbf{y}$ along with prior noise. In other words, the above-mentioned objective function is modified as (Mirza and Osindero, 2014),

$$\min_G \max_D (D,G) = \mathop{\mathbb{E}}_{\mathbf{x}\sim\mathbb{P}_r}[\log(D(\mathbf{x}|\mathbf{y}))] - \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_g}[\log(1-D(\tilde{\mathbf{x}}|\mathbf{y}))]$$

However, it has been highlighted that the originally objective function is equivalent to minimizing the Jensen-Shannon divergence between the data and model distributions, which exhibits problems such as mode collapse and vanishing gradient (Arjovsky et al., 2017; Gulrajani et al., 2017). In order to improve the training process, Arjovsky et al. (2017) proposed using Wasserstein distance, also known as Earth-Mover distance reconstructed using the Kantorovich-Rubinstein duality, as a measuring parameter for D to identify the difference between the real and synthetic images. This solves the issues associated with Jensen-Shannon divergence (ibid). In addition, Gulrajani et al. (2017) proposed the use of gradient penalty with Wasserstein distance in the objective function, that helps in stabilizing the training process and further improve the quality of generated images. Therefore, Gulrajani et al. (2017) proposed an objective function for GANs with Wasserstein distance and gradient penalty, also known as Wasserstein Generative Adversarial Network with Gradient Penelty or WGAN-GP, as shown below,

$$\min_G \max_{D\in\mathscr{D}} (D,G) = \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_g}[D(\tilde{\mathbf{x}})] - \mathop{\mathbb{E}}_{\mathbf{x}\sim\mathbb{P}_r}[D(\tilde{\mathbf{x}})] + \lambda \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_{\hat{\mathbf{x}}}}\left[\left(||\nabla_{\hat{\mathbf{x}}} D(\hat{\mathbf{x}})||_2 - 1\right)^2\right]$$

where, $\mathscr{D}$ is the set of 1-Lipschitz functions, λ is the gradient penalty coefficient, $\hat{\mathbf{x}}$ is sampling along straight lines between the true data distribution $\mathbb{P}_{\hat{\mathbf{x}}}$ is the sampling along the straight line between $\mathbb{P}_g$ and $\mathbb{P}_r$.

In our study, we want to generate the visual degradation in garment images, where the generator also needs to take the certain input conditional parameters while generating the images. Therefore, we use the WGAN-GP that uses conditional parameters as additional information supplied with prior noise. Accordingly, we use the following objective function that incorporate conditional parameters (Zheng et al., 2020),

$$\min_G \max_{D\in\mathscr{D}} (D,G) = \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_g}[D(\tilde{\mathbf{x}}|\mathbf{y})] - \mathop{\mathbb{E}}_{\mathbf{x}\sim\mathbb{P}_r}[D(\tilde{\mathbf{x}}|\mathbf{y})] + \lambda \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_{\hat{\mathbf{x}}}}\left[\left(||\nabla_{\hat{\mathbf{x}}} D(\hat{\mathbf{x}}|\mathbf{y})||_2 - 1\right)^2\right]$$

4. Results and analysis

The effect of washing is noticeable for samples *AA* and *AB* for both fabric and garment samples, as there is a visible change with an increase in wash number as shown in Fig. 2. However, no significant change is observed for *BA* samples in both cases i.e. fabric and garment. This indicates that the degradation of a textile component not only depends on its inherent properties but also on the other connected components. Hence in order to develop a predictive system that can learn such variations, the GAN model (described in Section 3.3) is trained with the experimental data.

The GAN model was trained with a batch-size of 64 images in each iteration. The training process was evaluated using *Frechet Inception Distance* (FID) proposed by Heusel et al. (2017). FID estimates the similarity of the synthetically generated images to the real images by using a pre-trained network that classifies each image for similarity with 1000 known objects. The minimum FID score is zero for two image sets that are same, which further increases as the difference occurs among the image sets. In our study, we use the pretrained network inception_v3[3] available with PyTorch[4]. Further, FID is calculated using the following equation (Borji, 2019),

$$\mathrm{FID}(r,g) = ||\mu_r - \mu_g||^2 + \mathrm{Tr}\left(\Sigma_r + \Sigma_g - 2\left(\Sigma_r \Sigma_g\right)^{1/2}\right)$$

where (μ_r, Σ_r) and $\left(\mu_g, \Sigma_g\right)$ are the mean and variance of real and generated image datasets.

As mentioned, the calculation of *FID* involves both real images and correspondeing synthetic images that are required to be generated for same conditions or labels as that of real images. However, one may not expect a huge improvement in the image quality in one iteration of learning as it involves a limited image-set and the learning rate is controlled by the learning hyperparameter. Therefore, it is reasonable not to calculate *FID* score after every training iteration in order to save computation time. In the training process, the *FID* score was calculated after a gap of 200 training iterations starting from 100th training iteration. The variation of *FID* score with training iteration is shown in Fig. 4 of each iteration consisting of 64 images.

It is evident from the graph that the *FID* score drops suddenly in first 1500 iteration to about 75 after which the marginal drop starts decreasing with increasing training iteration. The *FID* score after 25000 training iterations becomes almost steady with the value approximately ranging between 13 and 19. The inset images in Fig. 4 show the evolution of generated images with the same input conditions and noise, where an improvement in the quality of images can be clearly observed. Considering the near saturation in improvement in *FID* score, the training was carried out until 33100 iterations. The comparison of real images with synthetic images generated on different training iterations

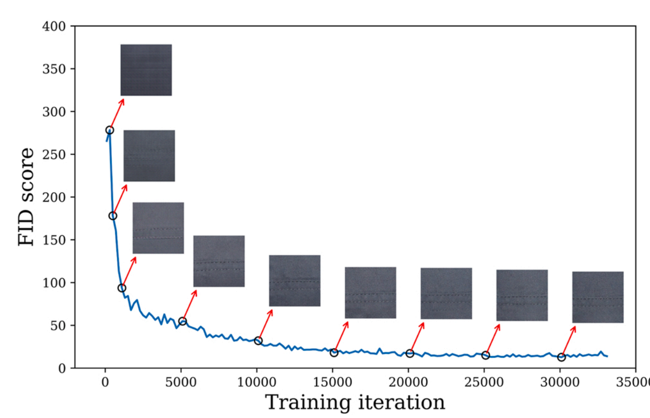

Fig. 4. Variation of the FID score with training iteration.

[3] https://pytorch.org/hub/pytorch_vision_inception_v3/
[4] https://pytorch.org/

is shown in Fig. S3 in supplementary information.

In order to check the quality of prediction for different conditions, we calculated the *FID* score for different conditions: *sample type* and *seam joining*. In this analysis, a set of real images is taken first and then synthetic images were generated for all combinations related to *sample type* and *seam joining* while keeping the *wash label* sequence the same for set of images in order make the *FID* score comparable. The calculated *FID* score for different conditions is shown in Fig. 5. The FID score for same set of real and synthetic images varies between ~21 and ~45. When comparing the real image-sets with synthetic image-sets generated for different conditions, except for synthetic image set *G* –*AB* (i.e. sample type = *AB* and seam joining = *G*) and synthetic image set *G* – *BA*, minimum FID score has resulted for the synthetic image-set that is generated conditions that matches with the real image-set. This implies that the synthetic images are influenced by the provided conditions on the sample type and seam joining which are learned by the model to a certain extent. However, for the synthetic image set *G* – *AB* minimum FID is obtained with real image set *G* –*AA* (and similar for synthetic image set *G* – *BA* which has minimum FID with real image set *F-BA*), which implies that further improvements are required in the model for better prediction where the conditions are more clearly interpreted by the system.

The visual degradation in the sample in comparison with the synthetic image set produced by the trained model is shown further shown in Fig. 6 and Fig. 7, for fabric and garment samples respectively. In the figures, *R* and *S* indicate the real images and synthetic or model-generated images respectively for different seam combinations namely *AA*, *AB*, and *BA*. In general, there is not much difference observed in the visual changes for fabric and garment samples, which indicates that the visual degradation follows the same pattern in both cases. In case of model prediction, there are certain visible differences between real and model generated images. For example, from simple visual inspection of the images, it can be inferred that the seam texture variations with washing for samples *AA* and *AB* are higher in real images as compared with the model-generated images. Nonetheless, the change in seam texture – i.e. increasing waviness in the seam area that indicates the visual changes – for model-generated images for *AA* and *AB* follows the pattern observed in the real images. On the other hand, there is no significant texture variation observed in the real images for *BA* samples, which indicates that no significant visual degradation has occurred in the samples for 70 wash cycles. Interestingly, the model-generated images also follow the same pattern i.e. no significant change in seam texture is observed in the model-generated images, which indicates the trained model has learned about conditions. It must be noted that the above observations of seam texture change are based on simple visual analysis of Fig. 6 and Fig. 7. For further analysis of texture change that is linked to visual degradation of the samples, suitable quantitative measures may be further required.

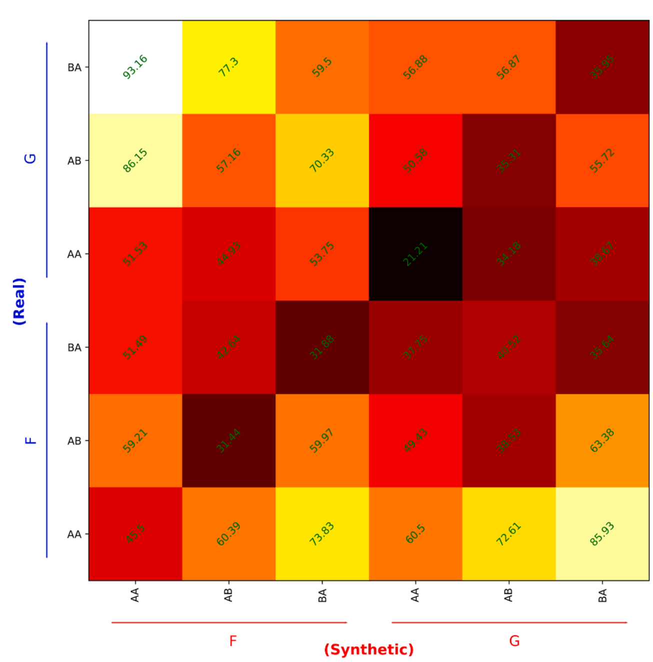

Fig. 5. FID score for seam type and seam joining conditions.

5. Conclusions

In this paper, we introduce a predictive system for garment visual degradation. The predictive system is based on the conditional GAN that is trained to predict or simulate the realistic visuals of garments seams based on three input parameters namely wash number, seam type, and seam location. The trained system is tested using the *FID* score to quantify the quality of simulated visuals. Further, the application of the trained system is shown with the help of the simulated garments visuals for different wash cycles that are compared against the actual visual changes in the garment and fabric samples. In general, from visual analysis, the predictive system appears to follow the visual degradation pattern for increasing wash as observed in the real images which indicates that the predictive system simulates the visual degradation similar to real degradation. Therefore, as a first step toward the development of a system prediction for generating data for garment visual degradation that can help in estimating the garment longevity is successfully demonstrated.

However, there are certain limitations associated with the study that need to be addressed in order to implement or exploit such systems in real application scenarios. While the study demonstrates the application of conditional GAN for generating the data for visual degradation analysis, at this stage no garment visual degradation measure or scale is used that maps the garment longevity or measure the system performance. To improve the system or establish the quality of prediction performance of the system, it is important to use objective measures that quantify the garment visual degradation. Therefore, the current work is limited to the feasibility of deep learning based GAN in creating visual data that can be used to assess the garment degradation and longevity. In addition, no physical or structural parameter of the textile is considered in this study. In practice, textile materials are characterized for various mechanical and chemical properties that can be achieved by controlling different design, structural and/or manufacturing parameters. Therefore, for the implementation of conditional GANs based predictive system, it is important to consider textile material characterization parameters as input for predicting visual degradation. This will allow the practitioners to not only estimate but also tune the garment visual degradation by changing the impacting material or manufacturing parameters. In addition, to develop a comprehensive system for longevity, it is important to combine visual degradation behavior with the degradation of mechanical and functional degradation of the garments as the end-of-life of a garment is not limited to the visual aspects. In this direction, further research is required that can first predict the functional degradation and then maps it with the visual degradation of the garment. In addition, to gauze the system performance, suitable objective visual degradation measures need to be devised that can be used to check the quality of GAN predictions.

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CRediT authorship contribution statement

Vijay Kumar: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Niina Hernández:** Conceptualization,

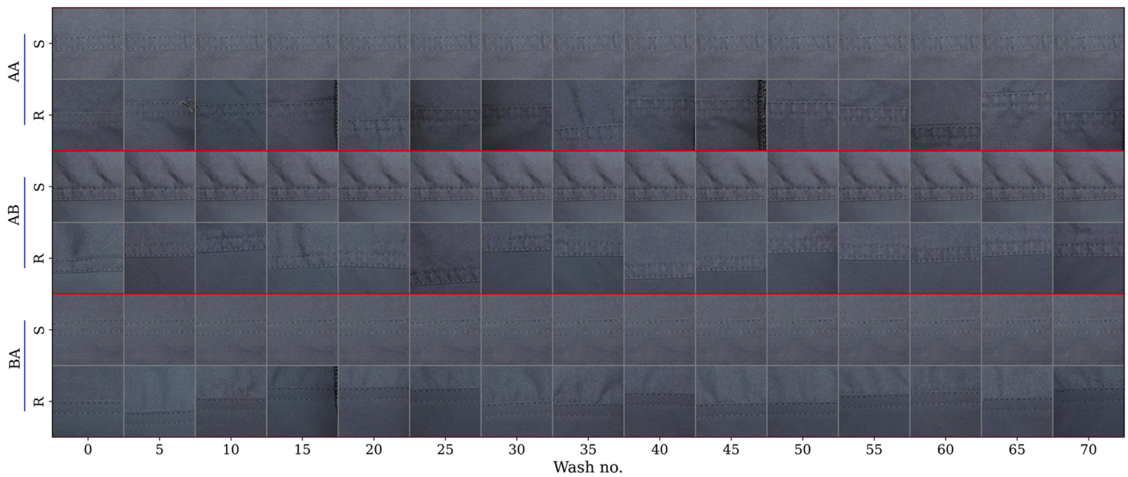

Fig. 6. Variation of visual degradation in real image-sets and synthetic image-sets.

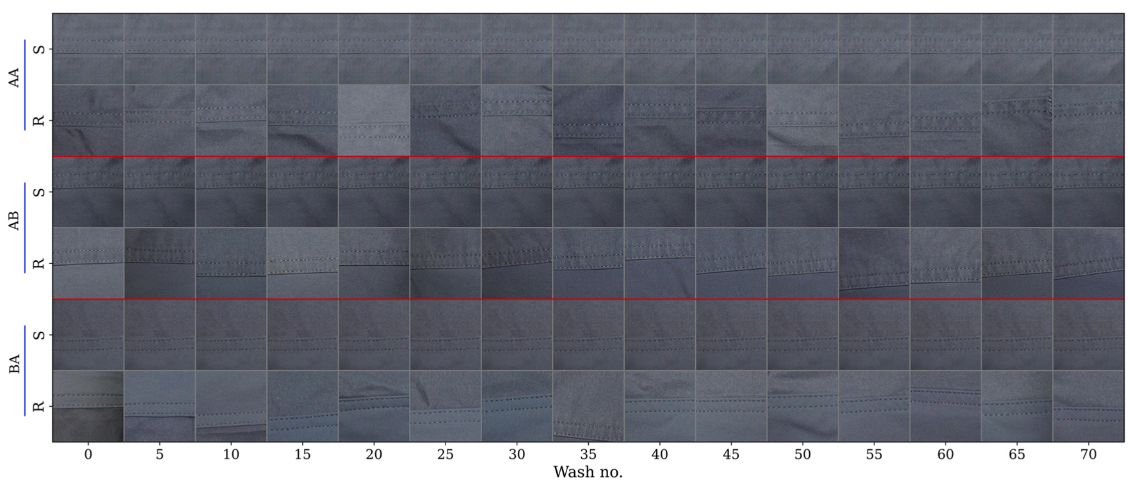

Fig. 7. Variation of visual degradation in real image-sets and synthetic image-sets.

Methodology, Investigation, Writing – review & editing. **Michelle Jensen:** Investigation, Writing – review & editing. **Rudrajeet Pal:** Conceptualization, Investigation, Writing – review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.compind.2022.103779.

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