



Data Driven Patternmaking: Automated Generation of Stretch-Knit Patterns for Different Fabric Stretch

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Abstract

Patterns serve as the blueprint for garment production; therefore, accurate patternmaking is crucial for producing well-fitted garments with minimal trial and error. Patternmaking is time consuming and requires specialized expertise and proficiency. Current research in automated patternmaking has increasingly focused on enhancing pattern precision through computational methods. Recent developments have addressed data driven modeling and machine learning in automated pattern creation. Yet, the influence of fabric stretch on pattern adjustment has not been studied. This study examined how fabric stretch characteristics apply to garment fit and developed predictive models to create pattern shapes of womenswear upper torso stretch garments. The research objectives were to review existing data driven approaches for automated patternmaking techniques, create CAD patterns based on the sizes and fabric stretch values, develop a machine learning model to predict pattern shapes, and validate the predicted patterns through digital fit assessments. Adopting a machine learning approach, this study applied multiple linear regression to predict pattern alterations based on size and fabric stretch values. Furthermore, the same framework is improved to automate the pattern generation with fabric stretch values and size inputs provided. The findings contribute to the development of more accurate, automated patternmaking systems that account for fabric stretch, enhancing efficiency and fit consistency in apparel production.

Keywords: Automated Patternmaking; Digital Prototyping; Machine Learning; Multiple Linear Regression
Stretch knit fabrics.

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1. Introduction

Garment manufacturing is a complex process involving many stages spanning from design conceptualizing, fabric and other raw material production, product development, and garment production and shipment. While most raw material production processes, such as yarn spinning and fabric weaving or knitting, involve high levels of automation, garment product development and manufacturing are still labor intensive. Yet with the introduction of new computer-aided technologies such as Computer-aided design (CAD), Computer-aided manufacturing (CAM), 3D scanning, and robotics, the industry is becoming more productive and efficient [1].

Patternmaking is a crucial task in the apparel product development process. Mass manufacturing uses markers, which are created from accurate patterns to guide the cutting of fabric, which is then stitched into garments. Inaccurate patterns result in ill-fitting garments and problems such as product returns [2]. Thus, it is necessary to create patterns with accurate size and fit.

Current research is focused on using technologies such as CAD and 3D body scanning to develop automated solutions for patternmaking. Many of such attempts focus on converting 3D body scan-based designs into 2D patterns [3], [4]. Data driven modeling has also been used for this purpose [5]. However, most of the research has not incorporated the fabric stretch properties of knit fabrics that influence pattern development. The recent research has focused on applying machine learning techniques to automate garment pattern creation [6]. Such methods suggested that data-driven approaches are gaining prominence in research on automating the apparel production process.

This research aims to examine the impact of fabric stretch characteristics on garment fit and to develop predictive models for accurately determining pattern shapes as fabric stretch values vary. The key objectives of this research study were: (1) To review existing data driven approaches in automated pattern making (2) To create CAD patterns according to different body measurements and fabric stretch values to prepare the data set, (3) To develop a machine learning based approach to predict garment patterns under the body measurements and stretch values, (4) To validate the developed patterns using digital fit experiments. The findings of this study will benefit apparel designers, patternmakers and garment manufacturers by improving efficiency and accuracy of pattern generation for stretch fabrics. Additionally, further improvements of this approach will guide towards mass customization and automated apparel product development.

2. Literature Review

2.1. Traditional Patternmaking Methods in Apparel Manufacturing

Patternmaking transforms 2D fabrics into 3D garments which fits to the complex shapes and dimensions of the human figure. There are two main methods in traditional patternmaking: fabric draping and pattern drafting [7].

Fabric draping is a tactile method that involves modeling fabric on a selected dress form to achieve the desired garment shape. Draping is an art that requires skill; therefore, it is challenging to automate [8]. Thus, it is mainly used in the couture designs tailor made into unique consumer segment [9]. On the contrary, pattern drafting is based on mathematical principles which systemize the geometrical connections between lengthwise, widthwise and girth wise measurements. Pattern measurements are calculated using body measurements of an individual or from an average figure developed based on size surveys [8], [9]. As the current apparel market demands accurate sizing, style variations and fast production, most manufacturers opt for pattern drafting [9].

The techniques of general pattern drafting mainly depend on the silhouette and fabric choice. In the case of non-stretch fabrics such as woven fabrics, darts and dart equivalents may be used to achieve proper fit and body shape. This method is termed “form pattern cutting” [9]. The darts are used to reduce unwanted fullness in the garment, and they convert flat fabrics fit to the curves of the human figure [7], [10]. Patternmaking with stretch fabrics typically does not include darts for shaping. Instead, it is achieved through pattern making techniques and the stretch of fabrics. This is defined as “flat pattern cutting”. The flat pattern cutting is widely used due to the rise in popularity of leisurewear garments which require knitted easy fit garments [9].

2.2. Applying Fabric Stretch in Pattern Drafting, Fit and Garment Construction

Several manual pattern drafting methods are established for generating patterns for stretch fabrications. Each method classifies fabrics into different levels of stretch. The stretch of the fabric can be determined using stretch gauges and thereafter the fabrics can be classified into different categories based upon the obtained stretch factors. Stretch factor is maximum percentage that a fabric will stretch [11]. For example, Armstrong [10] classifies stretch fabrics into four categories as follows: stable knit (widthwise stretch factor of 18%), moderate stretch knit (widthwise stretch factor between 18% to 25%), stretchy knit (widthwise stretch factor of 50%, lengthwise stretch factor between 18% to 50%), and super-stretch knit (both widthwise and lengthwise stretch factor of 100%). According to the classification, pattern blocks are modified lengthwise and widthwise to accommodate the required level of stretch [10], [12] or new patterns are developed with reductions in pattern measurements [11], [13]. Aldrich [9] has introduced a new method of pattern drafting for stretch fabrics considering minimal stretch and maximum stretch. In that method, she has created patterns focusing on maximum stretch for fine ribbed jersey or Lycra fabrics, with added ease allowances for low stretch fabrics. For example, in her close-fitting body blocks, the quarter bust measurement reduction for maximum stretch fabrics is 3 cm, whereas the reduction is 1 cm for less stretch fabrics. When using knitted jersey fabrics, the fabric can stretch to fit the body. Especially in the case of close fitted garments, the pattern blocks are made to be smaller than the body measurements. The fabric used should be able to compensate for the difference by stretching [9].

2.3. Machine Learning approach in pattern construction

Initially, patternmaking was solely performed manually using paper templates. With the introduction of CAD systems, pattern drafting and production patterns are developed mostly using computerized 2D CAD software. Using 3D CAD simulations, garment fit, and appearance can be evaluated without making physical samples [8]. As Artificial Intelligence (AI) methods continue to develop in design and development, there is a growing

demand for automated patterns; however, such pattern generations should ensure accurate garment fit.

New approaches for customizable patternmaking involve the creation of digital avatars and sketching the seam lines on them, finally extracting 2D flat patterns from them [8]. The garment pattern construction is significantly transforming due to integration of Machine Learning (ML) technologies. Traditional patternmaking methods, heavily dependent on manual measurements and individual skill levels, are often time-consuming, susceptible to error, and impractical in generating comprehensive anthropometric databases and rapidly adapting to diverse body shapes [14]. Furthermore, conventional CAD systems often require expert knowledge and involve manual modifications. They generally do not incorporate AI-based automation for creating highly personalized designs, making them less accessible and more expensive for small businesses and independent designers [15]. Machine Learning offers powerful solutions to these challenges by automating complex tasks, predicting crucial measurements, reconstructing garment structures from digital inputs, and embedding expert knowledge into design systems [6], [16], [17].

2.3.1 Precise prediction of anthropometric data:

Addressing the inefficiency and inaccuracies of manual anthropometric data collection, AI-driven approaches using Back-Propagation Artificial Neural Networks (BP-ANN) have been effectively applied to estimate key body measurements for garment patternmaking, particularly for women's upper tops [16]. Commonly accessible anthropometric data: Height (HT), Bust Circumference (BC), Waist Circumference (WC), and Total Shoulder Width (TSW) was chosen as independent data and accurately predicted 19 other anthropometric variables that are difficult to obtain via manual methods. Comparatively, the BP-ANN model showed superior predictive accuracy compared to the Linear Regression (LR) models demonstrating a strong correlation coefficient ($R \approx 0.99$) [16]. Even though certain measurements, including shoulder tilt angles and abdominal circumference, remain challenging due to individual variability or factors like body fat percentage, BP-ANN model offers notable benefits such as high efficiency, outstanding accuracy and reduced time consumption [16].

2.3.2 AI-Assisted Pattern Construction Tools:

These systems convert scans into an Ideal Construction Body (ICB) model, which accurately reflects individual body shapes with adjustable offsets for garment layers and fit preferences [6]. AI models, including those inspired by NeuralTailor, use 3D body scanning data and predict garment piece count, shapes, and configurations, which are then flattened into 2D patterns via CAD algorithms with minimal distortion. Virtual simulations enable fit evaluation before production, reducing reliance on expert patternmakers and physical prototypes. Such systems enhance accessibility, support diverse garment styles and desired fit, and improve efficiency and sustainability by minimizing material waste [6].

2.3.3 Knowledge-Supported Garment Pattern Design:

Patternmaking is a knowledge intensive process, and reliance on experienced personnel introduces risks related to turnover and quality inconsistency [17]. The proposed fuzzy logic-ANN approach predicts pattern parameters

by considering garment style, fabric properties, and fit preferences, using inputs such as body dimensions. This hybrid approach predicts and controls garment pattern parameters by considering factors such as garment styles, fabric properties, and desired fitting degrees (e.g., loose, neutral, tight). Inputs typically include feature body dimensions (e.g., stature, waist girth, hip girth), while outputs are key pattern parameters (e.g., pants length, crotch length, knee length, waist girth, hip girth, crotch girth, knee girth) [17]. The model has demonstrated superior performance (lower Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE)) compared to traditional models like Linear Regression, BP ANN, and RBF ANN. This model has shown better accuracy and fitting ease compared to traditional methods, supporting mass customization and enabling non-experts to produce quality patterns [17]. Even though they used two stretch-knit fabrics in the investigation, the effect of fabric stretch was not analysed.

Collectively, these applications highlight the growth of data-driven approaches in automating, refining, and personalizing garment pattern construction. The primary data sources include 3D body scans and synthetic garment pattern datasets, which provide the detailed annotations necessary for training advanced ML models [16], [17]. Despite substantial progress, ongoing research focuses on addressing data limitations for complex garments, improving robustness to real-world scanning noise, automating entire workflows, and enhancing model generalization and customization capabilities [17]. Even though some studies have considered fabric properties while pattern creation [17], fabric stretch is not thoroughly examined despite its notable influence on garment fit. Our primary focus is to investigate how the fabric stretch influence on garment fit and predict the correct pattern shapes with the change of the fabric stretch.

2.4. Digital fit validation of stretch garments

When evaluating the fit and appearance of a garment, special attention should be directed towards critical regions such as the shoulder angle, armhole, sleeve crown, bust, and neckline [18]. An essential aspect of this evaluation is the analysis of the pressure exerted by the garment on the body. Such pressure is generated through the design parameters of the garment and through the changes in body motions [19]. Consequently, it is necessary to establish acceptable pressure values.

Previous studies on body pressure analysis indicate that the acceptable pressure values depend on the textile material properties, individual body characteristics and specific location on them [19]. Pressure sensitivity is influenced by factors like warmth, weight, softness, and stiffness of the fabric [20]. Different body areas react differently to pressure, and individual tolerances vary. For instance, 3.0 kPa pressure may be perceived as uncomfortable at the neck yet be acceptable around the waist or iliac bone. In general, joints and bony areas can endure higher pressures. Research findings suggest that the acceptable overall garment pressure range should range between 1.37 to 5.90 kPa. Specifically, the pressure around the bust region typically ranges from 0.50 to 3.90 kPa, while pressure at the waist ranges from 0.20 to 6.40 kPa. Pressures above 4.00 kPa at the waist have the potential to be harmful [21]. Figure 1 shows acceptable possible pressure ranges (expressed in g/cm²) for different body landmarks.

In the context of digital garment fit validation, software such as Browzwear VStitcher utilizes a colour coded pressure map as shown in Figure 2 and is used to visualize the tightness of the garments [22]. Using such tools, it is possible to identify whether the garment pressure is within acceptable levels and verify the digital fit easily. Overall, garment pressure comfort must be carefully designed to ensure it meets ergonomic standards and accommodates individual differences in sensitivity and acceptability.

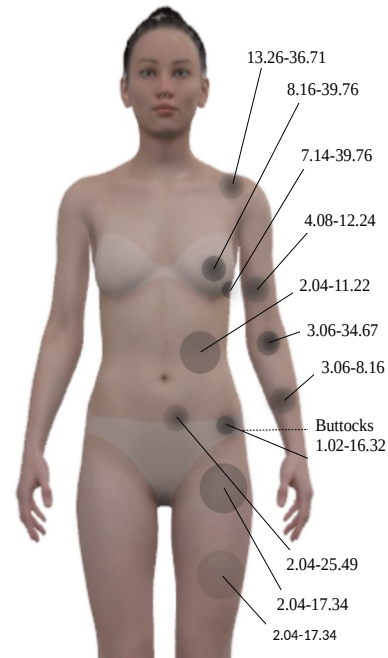


Figure 1: Acceptable Pressure values for body landmarks (g/cm²)

3. Materials and Methods

Balasooriya et al. [2] followed a mathematical approach of using multiple linear regression to predict pattern measurements with the change of the parameters: standard body measurements and fabric stretch values. The current study further explored the above approach considering the possibility of generating the required patterns automatically using a machine learning based approach when given the size and fabric stretch values as inputs. Initially, existing data driven approaches in automated patternmaking were reviewed. Then, data set was prepared by creating patterns according to different sizes and fabric stretch values. Next, a machine learning based approach was developed to predict the garment patterns under varying size and stretch conditions. Finally, the developed patterns were validated using digital fit experiments.

McKinney et al. [23] highlighted key distinctions among existing patternmaking systems, including the body measurements, the amount of ease [24], drafting techniques, and the nature of line connections between the points. Among the available systems, Aldrich's method [9] was chosen due to the availability of a dedicated pattern for stretch fabrics that extend to the hip level, along with its satisfactory digital fit. Then patterns were created according to ASTM D5585-21 [25] size chart. In Aldrich's method [9], pattern drafting for stretch fabrics considers both minimal and maximum stretch levels. Slopers are drafted for high stretch fabrics, mentioning the extra ease needed for fabrics with lower stretch. Therefore, Aldrich's close fitting body blocks for high stretch

fabrics are considered to create patterns for “maximum stretch values”.

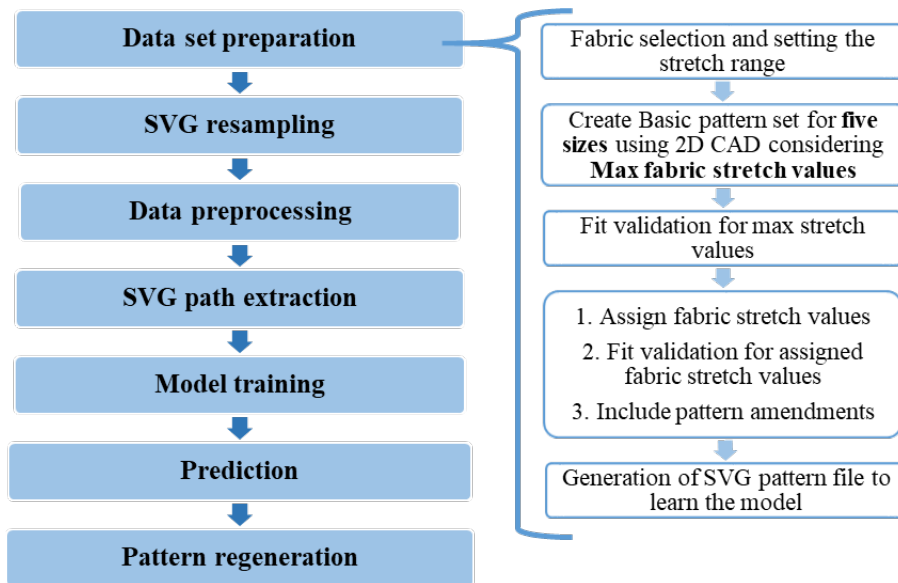
Next, fabrics were selected to identify the stretch values according to the fabric stretch variations and garment category. Five single jersey fabrics with varying elastane percentages were selected. Elastane incorporates stretch into fabric, enables the contour fit and recovers well after stretching [26]. As polyester is popular in the activewear industry due to its durability and affordability [26], fabrics consisting of polyester and elastane are chosen. The elastane percentage varied from 10% to 18% with a step of 2%. They were analyzed using the Browzwear fabric analyzer, and digital fabrics were input to Browzwear VStitcher software. Fabric parameters of selected fabrics were tabulated as shown in Table 1.

Table 1: Fabric parameters and stretch values

Fabric Reference	Actual Fabric Weight (gsm)	Digital Fabric Weight (gsm)	Browzwear Fabric Analyser	
			Lengthwise Stretch Value (N/m)	Widthwise Stretch Value (N/m)
Fabric A	168.68	155.33	77.55	63.91
Fabric B	165.93	155.33	69.53	66.32
Fabric C	164.03	155.33	78.01	62.14
Fabric D	206.54	185	55.27	60.97
Fabric E	277.18	230	208.61	118.43

Browzwear defines stretch values in Newtons per meter (N/m), representing the force required per unit length to extend a fabric to twice its original length by stretching [27]. As a result, fabrics with higher stretchability exhibit lower N/m values. Therefore, the term “maximum stretch values” in this text refers to 50 N/m for lengthwise stretch and 60 N/m for widthwise stretch. Accordingly, the digital stretch values were defined as a lengthwise range from 50 N/m to 242 N/m in 64 N/m increments, and a widthwise range from 60 N/m to 140 N/m in 20 N/m increments. Initial patterns were developed for sizes from size 8 to 16 using 2D CAD, for the “maximum stretch values”. These patterns were tested for digital fit using Browzwear VStitcher. Next, the fabric stretch values are assigned according to the chosen intervals, and corresponding modifications were noted after evaluating the fit using Browzwear VStitcher.

Previously, multiple linear regression was used to predict pattern measurements according to the fabric stretch



values and standard body measurements [2]. Building on this approach, the current study extends the use of multiple linear regression to model the Cartesian coordinates of pattern outlines based on size and fabric stretch values. The machine learning workflow of pattern generation includes several sequential stages as shown in Figure 3: SVG resampling, data preprocessing, SVG path extraction, model training, prediction and pattern regeneration.

Figure 3: Machine Learning Workflow of the Pattern Generation

As the next step, Scalable Vector Graphics (SVG) files for the patterns were obtained using Seamly2D software. To ensure consistent data representation across garment pattern inputs, each SVG file was processed through a resampling procedure to equalize the number of coordinate points across all pattern outlines. This method divides the total path length within a SVG file into equal segments and retrieves the corresponding points along the path, producing a consistent number of coordinate points for each pattern. Resampled coordinates were stored as Cartesian coordinates and SVG attributes were also stored to retain the spatial context of the resampled shapes. Next, the resampled patterns were exported back into new SVG files using the resampled coordinate points and preserved SVG attributes. The number of points in every pattern was equalized by using the maximum available number of points. Cartesian point values for the pattern outlines were extracted.

The objective of this study was to develop a machine learning based approach to predict garment patterns under varying size and stretch conditions. Initially, file names of specific SVG files obtained from a Command Separated Value (CSV) file. Each pattern represented a unique combination of garment size and stretch values. The dataset was structured with fields such as size, widthwise stretch (w_stretch), and lengthwise stretch (l_stretch). After that path data and spatial data are extracted from SVG files and stored. The extracted 'd' path strings were parsed using regular expressions to isolate coordinate pairs, which were then converted from strings to floating-point numbers and stored as NumPy arrays. The parsed coordinates were visualized using Matplotlib

to verify the shape and smoothness of the resampled pattern.

To model the relationship between the input variables (size, w_stretch, and l_stretch) and the output coordinates, a multiple linear regression approach was adopted. A custom SVGLinearRegressor class was implemented to integrate this process. For each coordinate point (x, y), a separate regression model was trained using scikit-learn, resulting in a pair of models per point. This enabled independent prediction of x and y values for new input combinations.

After training, the model was capable of predicting the entire shape of a garment pattern for any given combination of size and stretch parameters (within the trained range). The predicted coordinates were visualized using Matplotlib to verify the shape and smoothness of the generated pattern. Furthermore, these predicted coordinates were used to regenerate new SVG files. To validate the consistency across sizes, the model was used to generate patterns for sizes 8, 10, 12, 14, and 16 at specific stretch values. An interactive function was also implemented to automate the prediction and generation process based on user-defined stretch inputs. Here, the Python code was capable of generating patterns of a full-size set for user-defined w_stretch and l_stretch values. Using these models, patterns of full-size set were generated using the stretch values of previously selected fabrics. Using the obtained patterns, corresponding size set of garments were digitally created for all fabrics and evaluated the fit using Browzwear VStitcher.

4. Results and discussion

In a previous study, the pattern measurements were calculated using multiple linear regression models, considering them as dependent variables, using the corresponding standard body measurement, widthwise stretch (N/m), and Lengthwise stretch (N/m) as the three independent variables [2]. As suggested by this study, pattern dimensions can be modeled using multiple linear regression. A similar execution was used to model Cartesian points using body measurements, widthwise and lengthwise stretch.

4.1. Resampling SVG files

Initially, the path of each pattern was obtained using svgpathtools python library and length of the path is divided into chosen resolution (approximate resolution = 1, equals to one point per unit length) to obtain the maximum points within a pattern. The SVG resampling process successfully standardized all the patterns to a uniform number of coordinate points. A total of 60 SVG files were processed, including 20 pattern files each for the front, back, and sleeve components. For a resolution of 1, the front patterns exhibited the highest number of points, with a maximum of 9264, followed by the back and sleeve patterns, which had maximum point counts of 8950 and 8679, respectively.

Visual inspection of the resampled SVGs ensured the overall shape accuracy was preserved well as shown in Figure 4. The geometric characteristics and contours of the original patterns were retained with minimal distortion, and the points were evenly distributed along the pattern path effectively capturing curved and straight-

line segments.

4.2. Linear Regression Models

Building on these standardized SVG files, multiple linear regression models were developed to predict the



Cartesian coordinates of pattern outlines using garment size, widthwise stretch, and lengthwise stretch as input features. The models were trained on the resampled coordinate data, where each coordinate pair was treated as a target variable and learned independently. Model predictions were visualized for stretch conditions of fabric A (widthwise = 63.91 N/m, lengthwise = 77.55 N/m) across all sizes and resulting plot showed smooth, continuous pattern shapes with clear variation between the sizes as per Figure 5.

Figure 4: Resampled SVGs for size 12 ($w_stretch = 60$ N/m, $l_stretch = 50$ N/m)

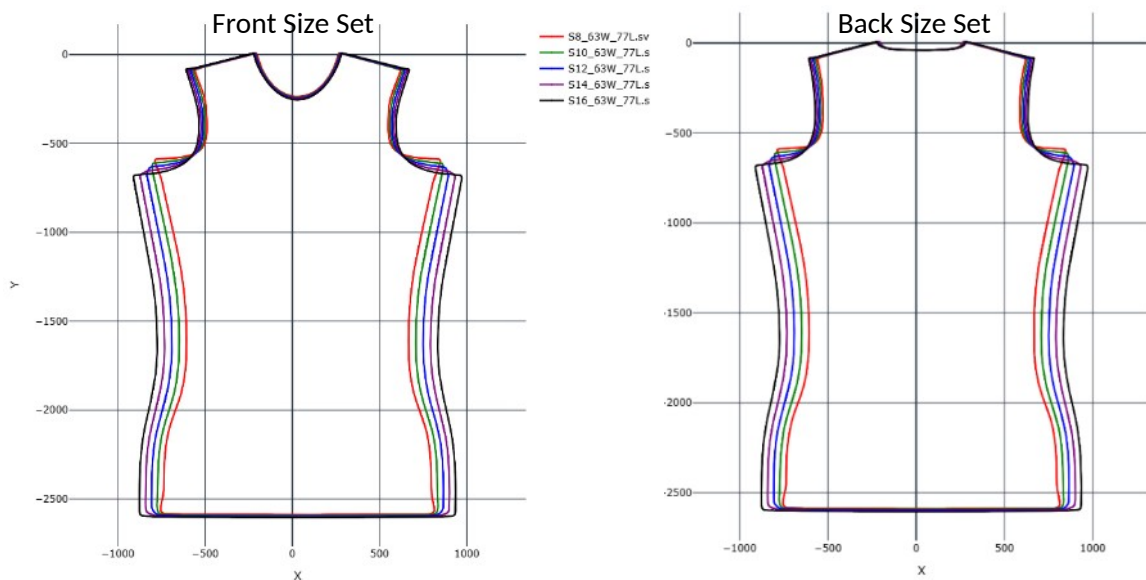


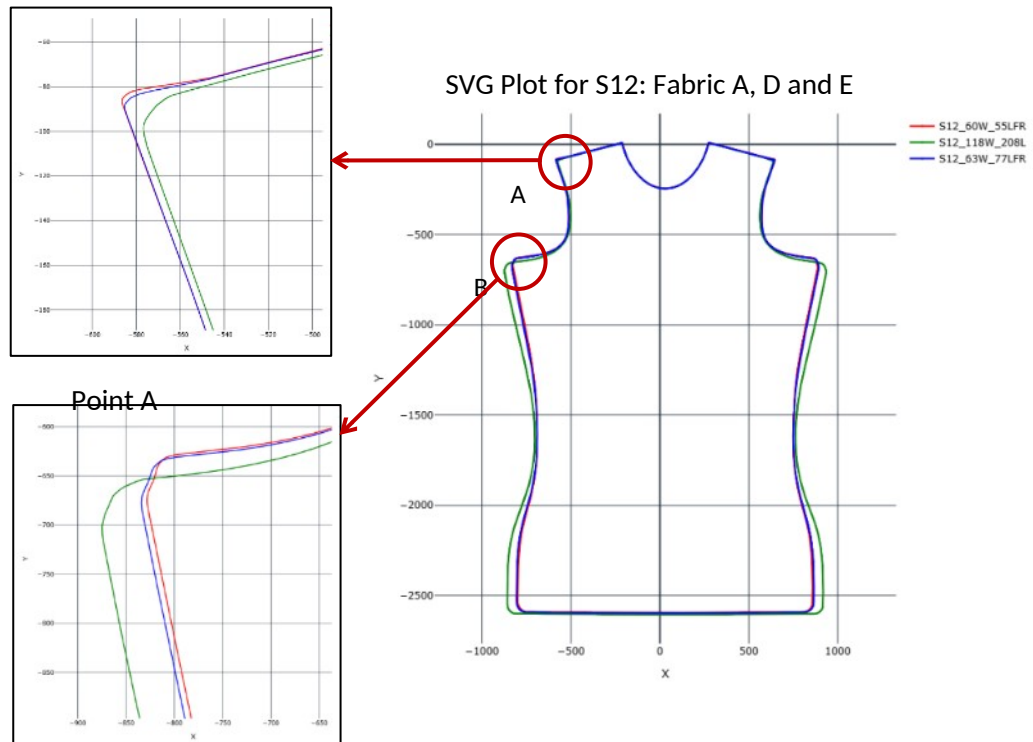
Figure 5: Plot of Size set of patterns for Fabric A

However, despite the continuous pattern shapes, a limitation was observed in the accurate prediction of corner points such as neckline corners, shoulder tips and sleeve tips. These corner points of a predicted pattern appeared rounded and smoothed out as shown in Figure 6. One primary reason for this would be having a limited number of data points for corner points as this model only uses 20 different patterns for one size, which proved

insufficient to capture the sudden directional change in geometry occurring at corner points. Therefore, manual selection of corner points is required to be done during the digital garment creation process.

4.3. Digital Fit of Garments

Using these models, patterns were predicted for all selected fabrics, and corresponding garments for all sizes were digitally created and evaluated. The digital fitting results indicated acceptable pressure distribution and realistic draping behavior, validating the accuracy of the predicted patterns. Figures 7, 8, and 9 show the digital fit



of the size 12 for fabrics A, D and E. By the visual inspection of the pressure maps, digitally fitted garments showcase pressure values within the acceptable pressure ranges as shown in Table 2.

Figure 6: Rounded and smoothed out corner points of predicted pattern

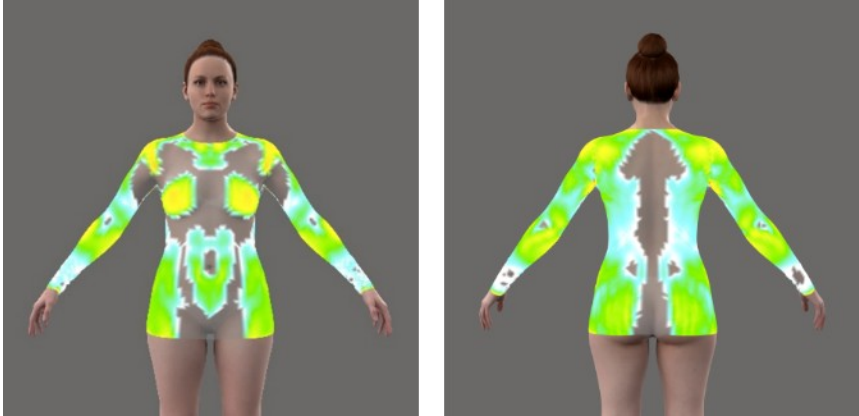
Table 2: Comparison of pressure values of digital fit images

Point of Measure	Acceptable Pressure values (g/cm ²)	Pressure values obtained from pressure map for Size 12 pattern (g/cm ²)		
		Fabric A	Fabric D	Fabric E
Shoulder	13.26 – 36.71	5 – 10	5 – 10	5 – 20
Armhole	13.26 – 36.71	5 – 20	5 – 20	5 – 20
Sleeve crown	4.08 – 12.24	5 – 10	5 – 10	5 – 20
Bust	8.16 – 39.76	5 – 10	5 – 10	5 – 20
Neckline	1.63 – 49.05	5 – 10	5 – 10	5 – 10
Waist	2.04 – 11.22	0.3 – 1	0.3 – 1	0.3 – 2

Hip	2.04 – 17.34	2 – 5	2 – 5	2 – 10
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Despite generating the full-size set using this method, the correlation between different sizes does not require further discourse since linear regression models for each size are trained separately.

Overall, linear regression-based coordinate prediction offers a practical and computationally efficient framework for integrating fabric stretch into patternmaking with data-driven garment simulation. Additionally, the model’s



ability to generate new patterns quickly from numerical inputs demonstrates its potential for scalable and automated pattern generation in the apparel industry.

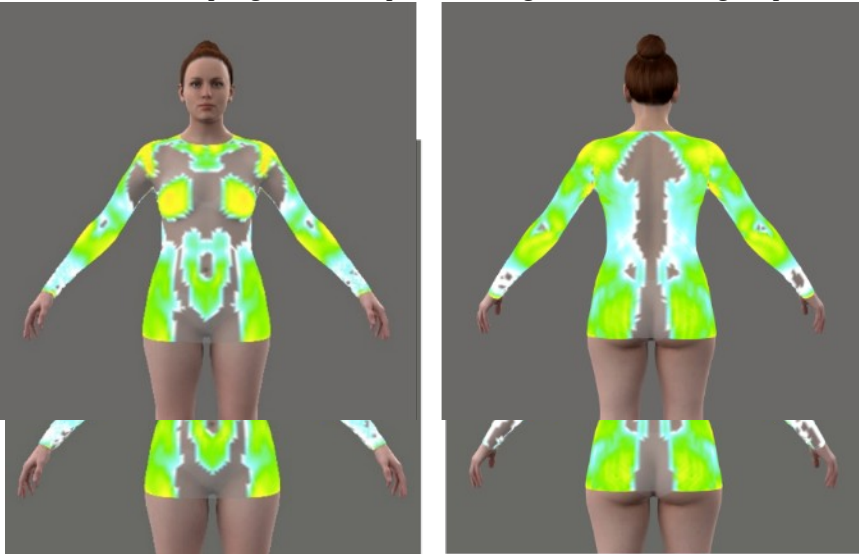
Figure 7: Digital Fit of Size 12 garment using Fabric A

Figure 8: Digital Fit of Size 12 garment using Fabric D

Figure 9: Digital Fit of Size 12 garment using Fabric E

5. Conclusion

This study developed a machine learning based approach to automatically generate garment patterns for women’s upper body garments based on size and fabric stretch values. The process integrated CAD pattern creation, SVG coordinate resampling, and multiple linear regression modelling to predict complete pattern



outlines under varying stretch values. Initially, pattern size set was created for “maximum stretch values” were created and digitally fitted. Then, fabric stretch values were adjusted using Browzwear Vstitcher software and obtained the optimally fitted patterns for equal intervals within the selected stretch range. SVG files for optimal patterns were obtained, resampled and cartesian coordinates for each pattern point were obtained using Python. Next, multiple linear regression was used to create models for each cartesian point. Although the resultant patterns had smooth continuous shapes, the corner points of the neckline, shoulder end, and sleeve ends were not accurately achieved. However, this may be resolved by opting for a higher sample size to train the model.

The fit validation of the created patterns managed to achieve the required fit and appearance, which indicates that the trained regression models can accurately reproduce garment patterns across multiple sizes and stretch values, maintaining shape consistency and fit quality. Overall, the successful implementation of this approach enhances the precision, efficiency, and adaptability of data driven approaches to garment pattern development. This research provides a valuable contribution to the evolving field of AI in garment manufacturing, providing key insights for computer scientists and apparel practitioners.

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