# Machine Learning Enhanced User Interfaces for Designing Advanced Knitwear

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**Abstract.** The relationship between visual appearance and structure and technical properties of a knitted fabric is subtle and complex. This is an area that has been traditionally problematic within the knitting sector, understanding between technologists and designers is hindered which limits the possibility of dialogues from which design innovation can emerge. Recently there has been interest from the Human-Computer Interaction (HCI) community to narrow the gap between product design and knitwear. The goal of this article is to show the potential of predictive software design tools for fashion designers who are developing personalized advanced functionalities in textile products. The main research question explored in this article is: "How can designers benefit from intelligent design software for the manufacturing of personalized advanced functionalities in textile products?". In particular we explored how to design interactions and interfaces that use intelligent predictive algorithms through the analysis of a case study, in which several predictive algorithms were compared in the practice of textile designers.

**Keywords:** User Interface · Machine learning · Knitwear

## 1 Introduction

Developments of advanced textile manufacturing techniques—such as 3D body-forming knitwear machinery—allows the production of almost finalized garments, which require little to no further production steps to finalize the garments [17]. Moreover, advanced knitting technology in combination with new materials enable the integration of localized functionalities within a garment on a 'stitch by stitch level', such as moisture management, compression, and abrasion resistance [16]. Knitted constructions provide remarkable diversity and a range of potential end products, however, currently the market is not fully able to absorb and utilize the technological advances [4]. One of the possible reasons for this problem is that the advanced knitting machines require highly skilled programmers and designers with technical understanding. The relationship between


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visual appearance and structure and technical properties of a knitted fabric is subtle and complex [5].

Recently there has been interest from the Human-Computer Interaction (HCI) community to narrow the gap between product design and knitwear. For example, by developing a compiler that can automatically turn assemblies of high-level shape primitives and even 3D models into low-level machine instructions [13,14]. Other research have looked at developing computational parametric tools for digitally designing and industrially producing knitted fabrics, which created a more direct link between design and manufacturability [8]. In the field of Computer Science there have been instances were techniques such as data mining and machine learning were applied to aid the design process of complex garment manufacturing [19]. This led to advantages such as better prediction of parameters, for example fabric elongation [15] and air permeability [12]. Another benefit is enhanced sustainability due to reduction of consumption of textile-related materials, such as fabrics, yarns, dyes, and sewing threads [7]. Better sizing could be achieved by analyzing textile data, leading to improved customer satisfaction [6].

## 2 Case Study

The design process of knitwear garments consists of several sequential steps, requiring multiple translations between different media (such as sketches, patterns and machine code) and between different people (fashion designer, knitwear designer, knitting engineer and machine technician). The final result can only be evaluated by the designer and wearer after the manufacturing. Therefore, the integration of specialized functionalities (such as compression, breathability of the textiles, and areas used for sensing vital signs) require many cycles of product development and manufacturing, for example in the case of smart garments [2]. This leads to a challenge, because in the design process it is often beneficial to be able to have rapid iterations in which potential directions can be explored and evaluated. In the case of knitwear, we have previously attempted to bridge this gap using prototyping techniques such as on-the-body paper prototyping and 3D printing [1]. In this project we hypothesize that knitwear designers can have increased creative freedom when they have direct feedback about the intended functionalities during the design process (without actual manufacturing).

This project focuses exclusively on *functionalities* in knitted garments, more precisely we focus on a specific type of knitting called *circular knitting*. The term 'circular' covers all knitting machines whose needle beds are arranged in circular cylinders and can knit a wide range of fabric structures, garments, hosiery and other articles in a variety of diameters [18]. Circular knitting technology has evolved and enables designers to create sleek bodywear and performance active wear. It allows ready-to-wear three-dimensional (3D) tubular garments to be created directly from yarns without any seams, for example in underwear, swimwear and sportswear [10].

This project aims to predict the functionalities of a manufactured fabric product, without the need of actually producing the product. To this end, one of the most popular and powerful approaches is *machine learning*. Machine learning enables us with the help of computers to predict certain outcomes, or new samples, by "training" mathematical models using example data or past experience [9]. The trained model can generate accurate predictions or decisions without being explicitly programmed to perform the task [3]. Because of its usefulness, machine learning has been widely applied in many domains such as healthcare, fraud detection, personalized recommendation, etc. In this project, we consider multiple machine learning techniques including linear, non-linear, and tree-based models to predict various target variables collected from empirical testing.

## 3 Machine Learning for Knitwear

In this article we will present our exploratory process based on three steps when applying machine learning algorithms: (1) data collection and preparation; (2) model building, evaluating, and selecting; (3) prediction.

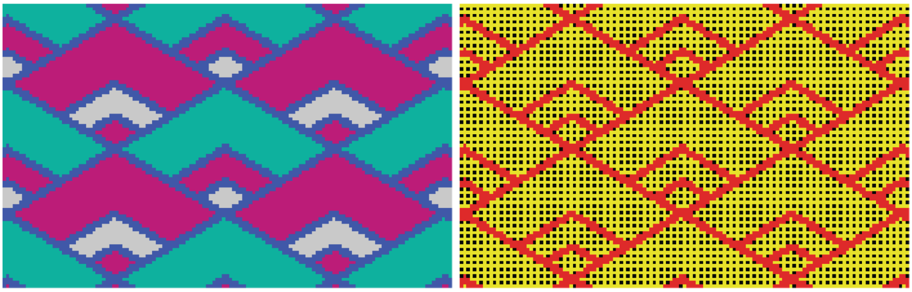

**Fig. 1.** Example of pattern files that represent the knitting machine instructions. The colors on the pattern in the left represent the different material or surfaces as described by the designer. The pattern on the right represents the different knitting structures that the machine has to make (each pixel represents a stitch by the needle).

The main property of circular knitting technology is that all the constructions are restricted by a tubular shape, variations in shape and functionality can be realized by making changes in the materials (the yarns) and structures (the specific knits) within this tube [11]. These variations are normally expressed using patterns which can be converted in machine-readable instructions (Fig. 1 shows an example of these type of patterns). In our data model we express these two parts using predictor variables (the parameters that potentially have an impact on the result) and the target variables (the desired outcomes). In order to simplify the data model for the first try-out of our approach we decided to limit the variation of materials, and instead focus on the combination of different knitting structures. To make variations of the knitting structures we defined three parameters that would serve as the predictor variables: stitch type, stitch structure and tube coverage. As target variables we focused on basic parameters (such as weight and diameter), dynamic parameters (such as unload force and elongation) and performance parameters (such as comfort and energy).

In order to train the machine learning algorithms, it was necessary to create a dataset which the algorithms could use to base the predictions on. Creating this training data consisted from two steps, first it was necessary to create physical samples of fabric with different predictor variable combinations, and secondly, it was necessary to devise a set of testing protocols to evaluate the performance of the target variables within these samples. We used circular knitting machines to knit 36 tubular fabric structures, which cover all the variations of different predictor variables. Figure 2 shows all the physical samples ordered by variation. Finally, testing methods were used to measure the target variable results for each of the fabric structure.

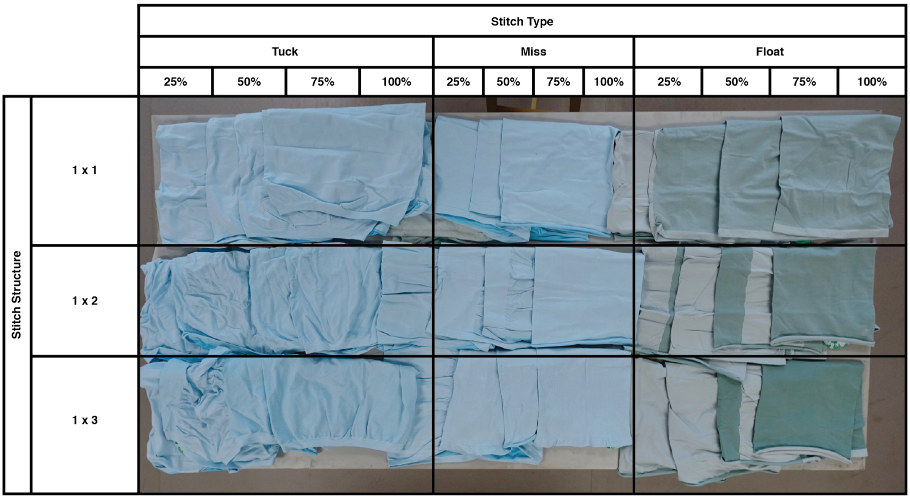


**Fig. 2.** Overview of the 36 samples ordered by variation.

In order to model the relation between the predictors and target variables, we compared a set of eight algorithms. These algorithms can be divided into three groups: linear regression models, non-linear regression models, and tree-based models. We built the eight models and evaluated them in two sets of analysis; first with the data generated from the tests in our own lab, and in a second analysis with the data provided by an external testing lab. Two methods that were used for measuring the effectiveness of the algorithms are *RMSE* (root-mean-square error) and $R^2$ (coefficient of determination). Based on the two analysis, we finally selected six models by eliminating Robust Linear Regression and Elastic Net due to their similar poor performance with Linear Regression.

## 4 Designing the User Interface

The User Interface (UI) design was a process in collaboration with the knitwear designers, who would be eventually using the interface. The design of the interface started by understanding how the predictive capabilities of this tool can play a role in the design process of functional knitwear. We asked our knitwear design partners how their current process looks like, and which tools they used in each step of the process. Summarized this process contains the following steps:

1. Creating the concept based on the visual direction, gathering inspiration for patterns and graphics (for example by manipulating and combining patterns).
2. Creation of a pattern library. Several patterns that can be tested for different knit combinations, and through trial and error achieve the right functionality.
3. Subjective assessment of the visual and functional aspects of the test results, and mapping them on them body.
4. Combining the body mapped patterns into one full garment design.
5. Creation of a square pattern file where both sides are matching (to create a tubular shape).
6. Start engineering process to integrate the design onto a 3D form.

Based on this process our initial aim was to use the tool in the step which normally require iterative testing (Step 2). The tool should offer the designer the possibility to evaluate and explore the changes in functionality, without having to physically knit each sample. This could result in faster explorations, as well as more flexibility in the exploration process. The main starting point for this process is the visual patterns which have already been designed during Step 1. Therefore, the tool should be able to use the visual patterns as input, and allows the designer to make variations of the knitting structures, to determine the values of the functionalities.

Based on the directions set-out in the requirements phase, a mock-up was created. The main interface (Fig. 3 left) consists from the *pattern canvas*, *prediction results panel*, and *pattern samples library*. The pattern canvas loads a vector visual pattern, and separates the different objects in separate layers onto the canvas. The property adjustments panel gives a quick overview of the prediction results for the designed fabric. The pattern samples library panel let the users re-use patterns they have created before. Clicking on one of patterns will load the *pattern design window* (Fig. 3 right). This window allows the designer to change knitting parameters of the pattern, such as stitch type and stitch structure. The window shows a visual representation of how the knitting pattern will look like, as well as an overview of the direct feedback about the predicted functional values (such as breathability, elongation, weight and evaporation, etc.).

The main interface of the tool (Fig. 4) was divided in two main areas. The *pattern design area* shows the representation of the fabric by a rectangle consisting of two areas. A draggable line allows the designer to change the coverage percentage. The knitting type and knitting structure can be adapted by using the dropdown lists. When manipulating the pattern values, the software will calculate the predicted values of the functionalities in real-time, and display them

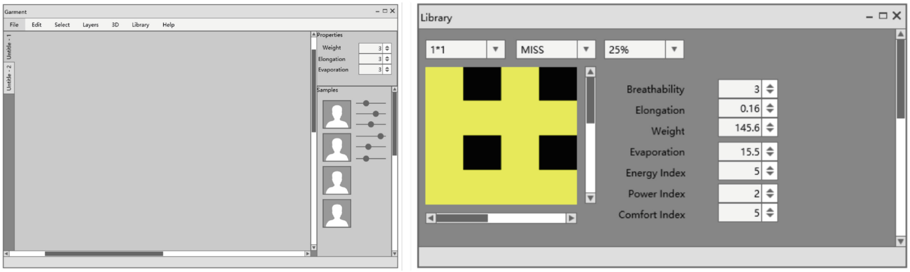


**Fig. 3.** The window on the left shows the proposed main window of the software. The window on the right shows the pattern design window.

in the *predicted values table* on the right side of the interface. The designer has the possibility to switch between different Machine Learning algorithms in order to see how this will change the predicted values of the target variables. The software will also display the reliability score in the form of colored stars which is based on the RMSE and $R^2$ values, this enables the designer to make a decision on the design based on the reliability of the intended functionalities.

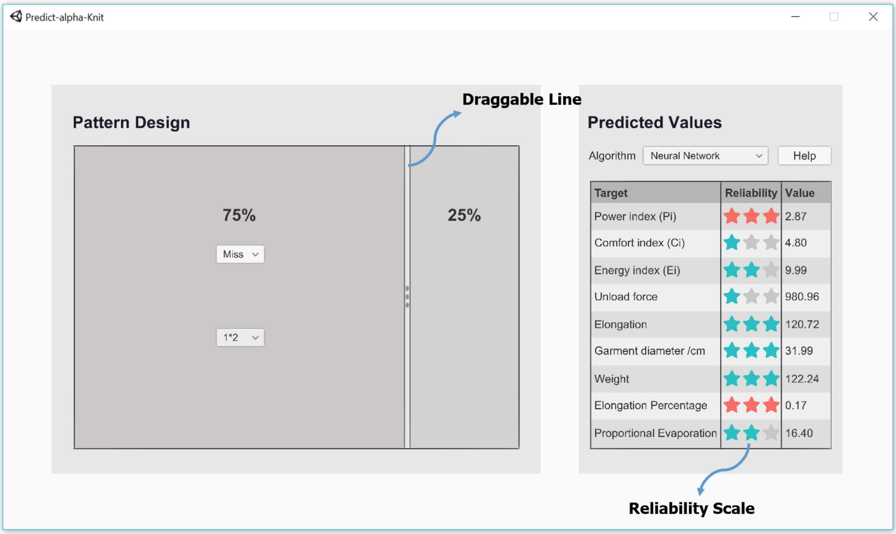


**Fig. 4.** Screenshot of the working prototype.

## 5 Conclusion

One of the challenges of designing the User Interface was to find a balance between how much of the Machine Learning features should be open for manipulation by the designer. In the first mock-up, most of the control parameters were hidden, and the algorithms would just show the target variables and predictor variables. During the process, as we discovered that different algorithms will have some variety in their output, we realized that it could be valuable for the designer to show the different algorithms, and also could give more creative control to the designers to be able to explore the different prediction results.

One of the crucial decisions was to decide how the software could represent the knitting pattern in the software. From the designer's perspective, it was not necessary to directly interact with the technical knitting patterns. Instead, it would be preferred to use a more abstract visual representation that focuses on the visual and functional qualities. However, for the algorithm to work accurately, it is necessary to work with a pattern representation and predictor variables which come as close as possible to the final manufactured fabric. Based on our current exploration we think there is an interesting tension here, where future research can help to find new opportunities.

One of our concerns is related to the process of replacing physical sampling with virtual sampling. By eliminating cycles of iterative physical manufacturing (one of the goals of developing this software), the designer might lose the chance to gain inspiration from manufacturing "accident". On the other hand, new control possibilities and insight for the designer about the algorithms (such as trying different algorithms and models) can also be a new source of creativity, leading to results which would not have been possible with a traditional physical approach.

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