PREDICTIVE MODELLING OF KNIT FABRIC SHRINKAGE USING ARTIFICIAL NEURAL NETWORKS

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The dimensional shrinkage of knitted fabrics has been extensively investigated; however, existing predictive models remain limited in their ability to accurately estimate shrinkage solely from fabric properties. This study reports on the development of an Artificial Neural Network (ANN) model specifically designed to predict the dimensional shrinkage of single-jersey knitted fabrics composed of 100% cotton and polyester–elastane blends. The model integrates parameters from the knitting, pre-setting, and finishing stages, thereby providing a comprehensive framework for prediction. The training dataset was systematically compiled through controlled experimental trials on a range of knitted fabric samples, ensuring consistency and reliability of input variables.The model was trained using twenty-three input variables, including yarn count, loop shape factor, tightness factor, stitch density, course density, wale density, machine settings, and areal density. These inputs were chosen based on their known influence on shrinkage, as identified in previous literature and empirical observations. The ANN model was trained on experimental data and validated using samples not used for testing, demonstrating high prediction accuracy and a strong correlation between actual and predicted shrinkage values. The ANN was built using TensorFlow-Keras with a feed-forward backpropagation architecture, and its performance was evaluated using statistical measures, including correlation coefficients between the observed and predicted values, mean square error, mean absolute error, and mean absolute percentage error. This study demonstrates the superiority of ANN over conventional predictive models in both accuracy and scalability. Once trained, the ANN model can rapidly estimate fabric shrinkage using known input parameters, enabling proactive quality control at the production planning stage. This approach reduces reliance on physical sampling and post-compacting shrinkage testing, conserving time and material resources. The results establish ANN as a robust and practical solution to the persistent challenge of predicting shrinkage in knitted fabrics. By integrating machine learning with empirical textile knowledge, the textile industry can advance toward predictive manufacturing, improved productivity, and enhanced product performance. Furthermore, the proposed framework can be extended to incorporate parameters such as finishing and thermal treatments, and to forecast shrinkage in other knitted structures, including rib and interlock. Future research may also explore hybrid models combining ANN with fuzzy logic or genetic algorithms to strengthen predictive capability.

Keywords: fabric shrinkage, artificial neural networks, machine learning in textiles, knitted fabrics, dimensional stability

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INTRODUCTION

In the textile and apparel industry, dimensional stability, especially shrinkage, is a key quality factor affecting fabric performance and garment usability. Knitted stretch fabrics, known for their comfort and elasticity, are particularly prone to shrinkage due to their looped structure and the complexity introduced by blended fibres like cotton and elastane (Choi & Ashdown, 2000). Traditional shrinkage prediction methods are often time-consuming, costly, and reactive (Unal et. al., 2012). This study addresses these challenges by using Artificial Neural Networks (ANNs), a machine-learning approach capable of analysing complex, nonlinear relationships among multiple fabric and process parameters. ANNs have already proven useful in various textile applications, including defect detection, quality assessment, and process optimisation. (Sentthil Kumar & Dhinakaran 2015; Elkateb, 2022)

The research focuses on predicting shrinkage in two types of single jersey knitted stretch fabrics after finishing. Initially, input parameters relevant to shrinkage behaviour were carefully selected. These include measurable properties of the raw fabric and known process variables from the knitting and finishing stages (Pannu et al., 2020). The fabrics were then produced under controlled conditions, and dimensional measurements were recorded before finishing. Subsequently, standard finishing treatments were applied, and the dimensional changes were measured once again. This dataset was used to train the ANN model to predict post-finishing shrinkage based on the original fabric parameters.

The aim is to develop a reliable, data-driven predictive tool that allows manufacturers to anticipate shrinkage early in production, enabling proactive quality control and supporting smarter, more sustainable textile manufacturing aligned with Industry 4.0 principles (Kyzymchuk & Melnyk, 2018).

METHODOLOGY

Test and Measurement Plan

The overall research framework was organised systematically to ensure reliability and consistency of findings and is illustrated in Figure 1.

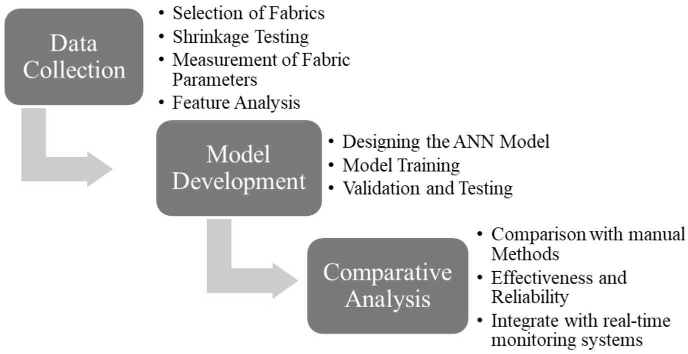


Figure 15: Major steps of research

Fabric Manufacturing and Raw Fabric Measurements

A total of 500 different fabric samples were produced for this study, with their characteristics summarised in Table 1. The production plan was developed to study the influence of elastane addition on fabric dimensional changes. Accordingly, fabrics were manufactured in two distinct types.

Table 8: Types of fabric used for this study

Sample	A	B
Material Type	Haddon	Asbury
Knit Type	Single Jersey, Plain	Single Jersey, Plain
Machine Gauge	36 GG	28 GG
Machine Diameter	30	30
Composition	90% Polyester, 10% Elastane	100% Cotton
Yarn Count	75D / 72F + 22DTex	30 Ne
GSM, g/m^2	155	150
Cuttable Fabric width, cm	147	164

Input parameters

The input parameters relevant to shrinkage behaviour that included measurable properties of the raw fabric and known process variables from the knitting and finishing stages that were selected for the shrinkage prediction through ANN are, Material Code, Yarn Count, Machine No, Machine Type, Quantity (Weight/Length), Width, GSM, & Elongation at knitting stage, GSM, Shrinkage Length & Width at Pre-set stage, Usable Width, GSM, courses and wales per cm after finishing, Stitch Density (S), Tightness Factor (TF), Loop Shape Factor (LSF) and Take-Up Rate (TUR). (Kumar & Sampath, 2012; Unal et. al., 2012)

Shrinkage Measurement

Dimensional changes in both longitudinal and latitudinal directions were measured following TS EN ISO 3759-2009 standards. The fabric is constantly under tension during the process, and the yarn and the fibre would accumulate elongation deformation. After the fabric tension is off the fabric, the elastic deformation would be accumulated (Ahirwar & Behera, 2022). In production, some fabrics (such as fabrics with better elasticity) usually need to be placed for a while (usually 24 hours) after being laid. For this purpose, a 50cm x 50cm panel was taken and laid down in room conditions, and the shrinkage was measured after 24 hours. If the residual shrinkage is more than 1.5%, the fabric is rejected.

Artificial Neural Networks (ANN) and Network Structure

ANNs are helpful in the prediction of different, sometimes very complex phenomena, although they do not explain them (Ahirwar & Behera, 2023; Kumar, 2024). An artificial neural network (ANN) is a mathematical model that is inspired by the structure and functions of the human brain. The human brain is a biological network of neurons, which are specialised biological cells able to transfer and process electrochemical signals. The biological neuron consists of a cell body with a nucleus, axon, dendrites and synapses. The ANN consists of an interconnected group of artificial neurons. There are various types of ANNs of different topologies, neural neutron models as well as algorithms of activation and learning function. In most cases the ANN is an adaptive system that changes its structure based on external or internal information flowing through the network during the learning phase. ANNs are powerful tools for modelling, especially when the underlying data relationships are unknown (Bishop, 2006).
Random initialisation of weights and biases was applied. Weights were updated online during training, meaning they changed continuously with each iteration. A sigmoid activation function was employed due to its ability to produce continuous, non-discrete responses, making it ideal for problems requiring sensitive evaluations. The ANN model was trained for 50 epochs.

Input Layer: The nodes in it are called input units, which encode the instance presented to the network for processing. Accepts the features from the dataset

Hidden Layers: Performs computations using weights, biases, and activation functions. The nodes in it are called hidden units, which are not directly observable and hence hidden. They provide nonlinearities for the network

Output Layer: Generates predictions (shrinkage length and width)
Jupyter notebook demonstrates how to build a machine learning model to predict shrinkage values in fabrics based on various knitting and finishing parameters. By following these steps, you can train a neural network model to make predictions on new, unseen data, provided that the data follows the same structure as the training data.

Neural Network Model in Python

Development of this Artificial Neural Network (ANN) model implemented in Python using a Jupiter Notebook. The development process includes data preparation, model building, training, and evaluation, with each stage designed to ensure robust and reliable prediction outcomes (Tu et al., 2024; Ahirwar & Behera, 2023).

Importing Required Libraries

To begin with, essential Python libraries were imported to facilitate data processing, model building, and evaluation. The pandas library was used for reading and handling structured data, particularly useful for reading CSV files and managing data frames. The numpy library supported numerical computations, enabling efficient array operations during preprocessing. For splitting the dataset into training and testing sets, the train_test_split function from sklearn.model_selection was utilized to ensure the model is evaluated on unseen data, enhancing generalization and preventing overfitting (Brownlee, 2019).
The StandardScaler from sklearn.preprocessing was employed to standardize input features by removing the mean and scaling to unit variance. This is particularly beneficial for neural networks, which are sensitive to feature scales. From the TensorFlow Keras API, Sequential was used to initialize a linear stack of layers for the neural network. The Dense layer, representing a fully connected neural layer, was used to build the architecture. Additionally, the Adam optimizer was chosen for its ability to adjust learning rates during training, helping the model converge efficiently while minimizing the loss function (Brownlee, 2019; Dataquest, 2023).

RESULTS AND CONCLUSION

The establishment of such an expert system needs a large volume of information. The collected 500 samples were split into two parts: 80% samples for the training data set and 20% samples for the testing data set. To supervise the training process, the learning curve concept was used. The training was successful, and the learning curve approached zero. To test the effectiveness of the trained model, a few samples were randomly collected, and the computed responses were compared with the desired responses. The computed responses exactly matched the desired responses, confirming the effectiveness of the system.
Accordingly, the number of hidden layers and cells in the hidden layers, as well as the learning rate and momentum coefficients in the study, were determined based on data frequently encountered in the relevant literature (Elkateb, 2022). In the structured model, the number of neurons of the hidden layer was tested in the range from 1 to 50.

Table 2 exhibits parameters of the structured ANN.

Table 9: Parameters of the structured artificial neural network.

Parameter	Value
Number of Input Parameters	26

Number of Hidden Layers	4
Number of Neurons in the Hidden Layer	[64, 32, 16, 8]
Learning Rate	0.001
Number of Iterations	50
Number of Output Parameters	2
The Most Successful Network Number of Iterations	43
The Most Successful Network RÂ^2 Value	-0.60247

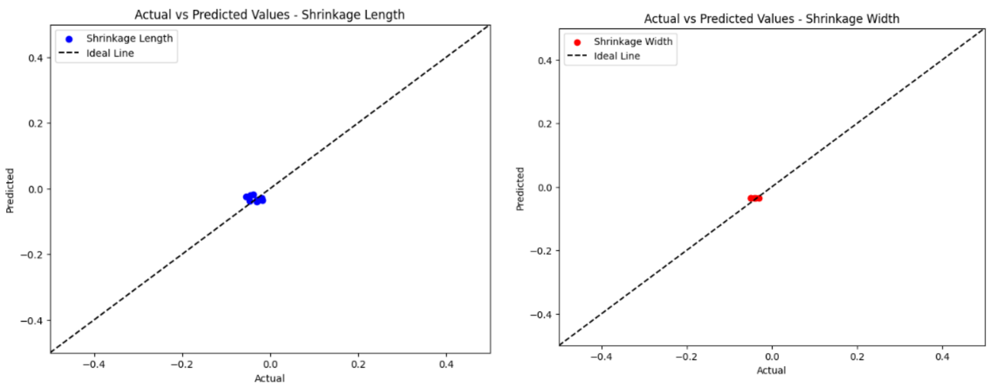
The analysis of prediction quality included a comparison of observed and predicted values of manual shrinkage, as well as values of statistical measures:

Feature Correlation Analysis
A correlation heatmap was constructed to visualize relationships between input features and shrinkage outcomes. Key parameters such as GSM, loop length, machine type, and yarn composition showed moderate to strong correlation with shrinkage behavior, confirming their relevance in predicting dimensional changes. Features with weak correlation were either engineering-related constants or variables with minimal variance across the dataset.

Model Accuracy and Validation
After training, the model's predictions on the testing dataset were evaluated using multiple statistical measures:

- Loss vs Epochs
- MAE vs Epochs
- MSE vs Epochs

Prediction Accuracy Evaluation
Figures 2 compares actual and predicted values for shrinkage in the length and width directions. The values cluster closely around the ideal diagonal line,



indicating a strong linear relationship and high prediction accuracy. The minimal deviation from the line reflects the ANN's ability to replicate real-world shrinkage behavior effectively.
Figure 2: Actual vs Prediction

Such alignment between predicted and actual values confirms that the model has learned the underlying physical relationships between input parameters and fabric dimensional changes.

MAPE Error Analysis

To further evaluate the prediction quality, a MAPE-based comparison was made between actual and predicted shrinkage values for both directions. A summarized table is presented below.

Table 3: MAPE value chart

Actual Length	Predicted Length	Error Length	MAPE Length (%)	Actual Width	Predicted Width	Error Width	MAPE Width (%)
-0.047	-0.03754	-0.00946	20.12621	-0.053	-0.04461	-0.00839	15.82092
-0.019	-0.02847	0.00947	49.84978	-0.046	-0.02471	-0.02129	46.28369
-0.027	-0.03450	0.00750	27.77871	-0.054	-0.03589	-0.01811	33.54059
-0.055	-0.02448	-0.03052	55.49994	-0.055	-0.04338	-0.01162	21.12525
-0.029	-0.03426	0.00526	18.15286	-0.040	-0.04918	0.009182	22.95624
-0.030	-0.03877	0.00877	29.24984	-0.014	-0.03614	0.022135	158.1106
-0.038	-0.01755	-0.02045	53.82415	-0.038	-0.04498	0.006978	18.36345
-0.045	-0.02096	-0.02404	53.41576	-0.053	-0.03247	-0.02053	38.72719
-0.017	-0.03423	0.01723	101.33160	-0.055	-0.03025	-0.02475	44.99217
-0.031	-0.03457	0.00357	11.51285	-0.032	-0.02924	-0.00276	8.638402

These results indicate moderate prediction accuracy, with MAPE values ranging from 8% to 50% depending on the sample. Although certain samples show high percentage errors, the actual error values remain small in absolute terms. These values illustrate acceptable prediction errors within industry tolerances, particularly for mid-range shrinkage values. However, further fine-tuning of model parameters and training data balance could reduce MAPE in edge cases.

In addition to this, working on the development of a real-time shrinkage prediction application, leveraging historical production and measurement data. This application aims to provide instant predictions of shrinkage behaviour in knitted fabrics based on fabric type, construction, and process parameters.

To apply the ANNs successfully, it is necessary to know ANNs, especially in the range of the kind of ANN, its topology, learning algorithm and functions of activation. However, knowledge and the ability to work with the ANN are only the starting point for further investigation. Understanding the phenomenon investigated is equally important for correct work with ANNs and the reliability of results (Park et al., 2000).

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