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MACHINE LEARNING MODEL FOR PREDICTING DIMENSIONAL STABILITY IN TEXTILE DYEING AND FINISHING PROCESSES

MOUNIKA S[1*], DHARSHINI C[2], MUHAMMED ZAID M[3]

[1,2,3]Department of Textile Technology, Bannari Amman Institute of Technology,
Sathyamangalam – 638 401, Erode District, Tamil Nadu, India

E-mail: *mounikas@bitsathy.ac.in, dharshini.tx22@bitsathy.ac.in,
muhammedzaid.tx22@bitsathy.ac.in

Abstract

Among the textile dyeing and finishing processes, dimensional stability is considered one of the main quality variables. Existing methods for the control of dimensional stability are highly experience-dependent and empirical. The paper explains how the use of machine learning will be able to predict the dimensional stability of the fabric before the finishing process. The type of fabric, yarn count, weave, and density represent the fabric properties; process variables include the dyeing and finishing processes, temperature, pH values, time, tension, and stretch. Finally, metadata is included. The output consists of a dimensional change percentage under standard conditions. A comparative performance analysis of various machine learning classifiers includes XGBoost, LightGBM, CatBoost, Random Forest, and linear regression. Cross-validation and widely used evaluation criteria will be applied: MAE, RMSE, R^2. In this respect, the paper will make sure machine learning is interpretable by using SHAP values and permutation feature importance. The approach will define which factors are significant in changing the dimensional stability of fabrics.The findings indicate the ability to use machine learning to accurately forecast shrink and growth, thereby minimizing guesswork, defects, and inconsistencies within the process. It formulates the best possible implementation plan, starting from the testing phase to the eventual incorporation of the process within the overall quality control system. Therefore, the method will enable predictive process control, promote sustainable manufacturing, and optimize process efficiencies in the textile processing industry.

Keywords**:** *Dimensional stability, Machine learning, Predictive modeling, Process optimization, Sustainability, Textile finishing.*

1. INTRODUCTION

Dimensional stability is the factor that has high priority as a quality attribute of textile dyeing and finishing. Dimensional change, such as shrinkage or extension, of textile fabric has traditionally been dealt with using the trial-and-error approach, involving the use of human observation and inspection carried out after the process has taken place, which may be costly. Even in such scenarios, it is often unreliable and tends to produce waste, rework, and resource waste in general.As an approach to overcome the aforementioned difficulties, the machine learning model has been developed herein with the end-use of predicting the outcome of the dimensional stability as well as other properties associated with the fabric prior to the process of fabric production having been taken into consideration by obtaining the required details with respect to fabric properties and processing requirements.

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Variables such as fiber type, weave pattern, yarn count, fabric density, dye, finish, bath temperature, pH values, processing time, stretching force, fabric extensibility, and multiple layers have been considered in this particular model. There have been additional recordings in the metadata, such as machine numbers, personnel numbers, and time taken for processing.Several machine learning techniques are reviewed: powerful gradient boosting algorithms such as XGBoost, LightGBM, and CatBoost; Random Forest; and simpler linear regression models. Each is trained and tested on carefully labelled production data. Their performance will be evaluated in terms of useful metrics such as mean absolute error, root mean squared error, and R^2 to ensure reliable predictions. In order to make models practical and understandable by engineers on the shop floor, explainability methods (permutation importance and SHAP values) are used to highlight which factors most strongly influence dimensional changes.

There is a clear roadmap outlined that can take the research from the conceptual stage to application. It starts with gathering data for a couple of months, forming synthetic data to verify the system works properly, testing the models on the data they were built upon while passing evaluations, then performing designed experiments upon the data to verify the crucial factors. The model can now be implemented into the “shadow mode” in which it makes predictions without interfering in already existing processes, so performance can be analyzed. Last but not the least, it can be seamlessly integrated into the quality control systems. Adoption of machine learning in dyeing and finishing operations has various advantages. It minimizes time-consuming trials and errors, which cost a great deal to be incurred. Moreover, it will serve to prevent defects and the waste of material, optimize water, energy, and chemicals, and further sustainable manufacturing. Moving from reactive to proactive controls based on data, manufacturers of textiles can ensure size stability and a better environmental sustainability outcome. Ultimately, it means this research looks towards a brighter, smarter, and more efficient future for textile finishing in terms of smarter and more efficient data insights being used to improve product quality and sustainability.

2. LITERATURE SURVEY

Dimensional Stability in Textile Dyeing and Finishing

Dimensional stability is believed to be one among the important qualities in the dyeing and finishing processes of textiles. However, a major cause for the shrinkage in material as well as growth in fabric due to wet processing in textiles may be linked to the swelling in fibers. Along with that, there would be some internal stresses relieved in the wet processing of fabric material too. Chemicals are responsible for fabric growth [1]. Cotton, a natural fiber, is highly prone to dimension variation due to its hydrophilic properties, whilst synthetic fibers are usually more dimension stable in similar processing requirements [2]. Sanforization, resin finishing, heat setting are some of the commonly practiced traditional methods to handle the problem of dimension instability. But these processes require many attempts and optimization of processing variables depending on the fabric structure, thus increasing the cost of production [3]. Small changes in temperatures, the measurements of the pH level, the processing time, or the forces would result in a significant variation of the dimension [4].

Influence of Process Parameters on Dimensional Change

There have been some studies conducted on the impact of dyeing and finishing variables upon the size properties of fabric. Temperature and time of processing stand out as significant variables in aqueous dyeing; these have major effects upon swelling and relaxation of the fibers [5]. For the reactive dyeing of cotton, an alkaline condition helps to swell the fibers and, at times, high shrinkage of the fibers can

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occur if it were not maintained properly [6]. The mechanical variables of fabric tension, overfeed rates, elongation percentages, and the number of layers of fabric during the finishing processes have been found to affect the dimensional stability [7]. Dimensional instability causes dimensional changes. Chemical finishing processes, especially resin finish, enhance dimensional stability by creating cross-links between cellulose fibers, although overuse may impact the texture and strength of the fabric [8]. These studies emphasize the fact that dimensional stability is a function of a complex process wherein the involved parameters interact.

Conventional Quality Control and Its Limitations

Traditional methods for quality control in textile finishing are based much on the experience of the operator, traditional recipes, and inspection after production. Although statistical process control methods are applied to some degree in traditional methods for quality control in textile finishing, they are mostly reactive and based on linear correlations among process variables [9]. Therefore, defects in dimensional stability are mostly detected after processing, which leads to reworking, rejection, and wasting of water, energy, and chemicals [10]. Since there is tremendous pressure regarding efficiency and sustainability within textile manufacturing facilities, in many aspects, traditional approaches have been proven ineffective under the present scenario.

Emergence of Machine Learning in Textile Engineering

Machine learning algorithms have been extensively used in textile engineering to identify complex and non-linear relationships between process variables and quality. Initially, studies were conducted on yarn quality estimation, fabric defect identification, and color matching employing artificial neural networks and decision tree algorithms [11]. Recent studies have successfully explored the use of ensemble learning algorithms like Random Forest, XGBoost, LightGBM, and CatBoost to predict the value of dye uptake, color strength (K/S values), and color difference (DE) from the parameters of dyeing processes [12], [13]. The proposed algorithms displayed greater efficiency and robustness than regression algorithms, reducing laboratory and production waste significantly.

Machine Learning for Dyeing and Finishing Process Optimization

Various researches also involved the application of machine learning to predict the result of dyeing with regards to the shade and fastness properties of the resulting product. Neural network models were also used to predict the CIE Lab* values using concentration, temperature, pH, and time variables to optimize the dye formulation [14]. Moreover, machine learning algorithms were implemented to recognize defects such as patching, streaks, or improper distribution during the process to avoid rejection of the product [15]. Despite this, studies specifically on machine learning for predicting the dimensional stability are extremely limited. The current studies involve no more than a few variables and do not consider machine variables, human variables, or environmental variables, which are extremely relevant when considered in a production setup.

Explainable Machine Learning and Industrial Adoption

For the smooth integration of these models within an industry, the machine learning model needs to be interpretable and trustworthy. The widely used models based on the interpretability of artificial intelligence models are permutation feature importance and SHAP (SHapley Additive exPlanations). These models have been acknowledged in the literature regarding the aspect of model interpretability [16]. These models further help identify the prominent parameters affecting the differences in dimensions, such as density, force, and finishing process, so that process engineers can verify predictions of a model through designed experiments.

Research Gap and Contribution of the Present Study

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Most of the reviewed literature depicted that dimensional stability, though being a highly studied characteristic from the perspective of materials and processing, has not been studied much from a predictive control by machine learning point of view. Further, most studies have focused on postprocess evaluation rather than pre-process prediction; none of these studies were integrated with real-time production data. This paper presents a holistic machine learning framework to predict dimensional stability of fabrics before defects occur, incorporating fabric properties, dyeing and finishing parameters, machine and operator metadata, and environmental conditions. This approach enables predictive process control, reduces trial-and-error, and aids in sustainable textile manufacturing.

3. METHODOLOGY

This study also adopts a data-oriented approach to propose a model of the textile process of dyeing and finishing based on its stability. Contrary to the trial and error method, which often happens before the final processing stage and involves the offline analysis of products created, this approach also aims to achieve the objective of extracting data from the processing of manufacturing. Batches of textile samples processed both in the lab and industrially also present a reality of the process that accurately represents its variability [17].

Data are obtained in terms of different production cycles and are subject to modifications according to material, machine, operator, and environmental changes. Dimensional changes are measured in terms of standardized test procedures described by ISO 5077 or AATCC 135 to ensure the reliability of the dimensions of growth and shrinkage of the obtained data [18].

Data Collection and Experimental Design

Data Sources and Sampling Strategy

The data for production is collected through both continuous, batch dyeing, and finishing processes for a period of one to three months, taking into consideration the variability of the process, which would otherwise be observed. Each data record represents a batch of fabric or a lab sample, which would have been handled in controlled environment settings. Both historical and controlled data help in developing a generic model, as proposed in [18].

These standardized test methods, including ISO 5077 and AATCC 135, are used in the determination of dimensional change when conditioned, according to worldwide adopted standards [19].

Input Features

The input dataset consists of four major feature groups:

- Fabric properties: Type of fibers, yarn count, weave pattern, Picks Per Inch (PPI), areal density (g/m²), porosity.
- Dyeing parameters: dye class, temperature, processing time, pH value.
- Finishing parameters: include finish type, tension, stretching percentage, number of fabric layers treated simultaneously.
- Machine and environment metadata: such as machine ID, operator ID, ambient temperature, and relative humidity.

Adding machine and operator information to the metadata can also assist in identifying hidden variability that is likely not considered in conventional research studies [20].

Target Variable

The target variable is the dimensional change percentage, which represents the shrinkage (negative value) or growth (positive value) as measured after standard conditioning. This continuous variable enables regression modeling, which can be more accurately controlled than other systems of quality classification [21].

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Data Preprocessing and Feature Engineering

Before being used in training the model, preprocessing is done on the dataset. Missing data in a dataset is replaced using median for numeric variables and mode for categorical variables. The outliers created from sensor error and improper recording are eliminated using interquartile range.

The categorical variables “Fiber Type”, “Weave Type”, “Dye Type”, and “Finish Type” are handled through the process of One Hot coding. The numerical attributes are handled through the process of Z-normalization, which enables them to contribute equally during the development of the models, particularly those involving distances [22].

Table I: Machine Learning Model for Predicting Dyeing/Finishing Quality Outcomes

S.No	Outcomes	Variables	Effects
1	Dye shade prediction (CIE lab values)	Dye concentration, temperature, pH, time	Reduces trial & errors, cost & wastes
2	Defect detection	Uneven shade, patchiness, streaks	Avoids rejections & defective materials
3	Dimensional stability	All types of finishing process	Ensures fitness of garment
4	Handfeel / softness	Subjective analysis	Comfortness on wear
5	Dye uptake & fastness	Dye affinity & color fastness	Reduce lab testing cycle
6	Resource optimization	Water, energy, chemical optimization without compromising fabric quality	Sustainable dyeing / finishing
7	Adaptive recipe recommendation	Targeted shade / finish	Automated dye matching system

Some of the featured interactions involve combinations like temperature–time and tension–stretch, so that nonlinear effects observed in textile processes are captured.

Machine Learning Model Development

Model Selection

Several machine learning algorithms based on multiple regression techniques are compared to select the appropriately performing model among the following:

- Linear Regression as a baseline model
- Random Forest Regressor
- XGBoost
- LightGBM
- CatBoost

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The choice of the ensemble learning algorithms depends on their ability to deal with both linear and nonlinear data and their capability to handle mixed data types [12][23].

Training and Validation Strategy

The Stratified sampling method randomly splits the data into subsets used in both testing and training, comprising 80% and 20%, correspondingly. Subsequently, five-fold cross-validation is conducted to enhance the model's generalization capability and thereby avoid overfitting [24].

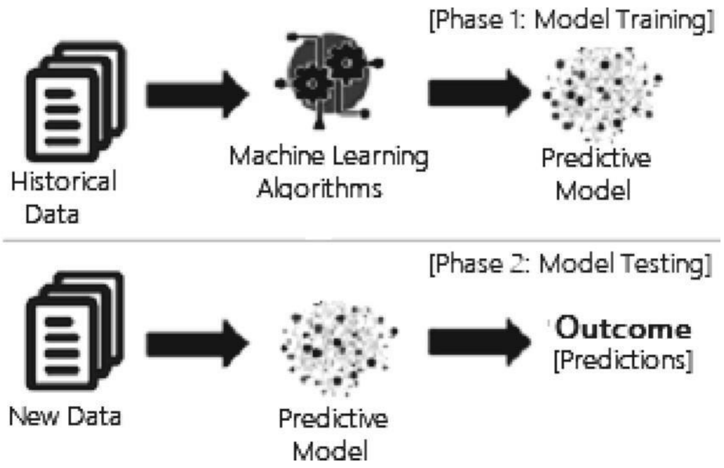

Figure I: Structure of a Machine Learning based Predictive Model

Hyperparameters are optimized for each of the models using techniques such as grid search or randomized search, which can be hyperparameters like tree depth, learning rate, and number of estimators.

Model Evaluation Metrics

To assess model performance, the following multiple regression evaluation metrics are used:

- Mean Absolute Error (MAE) to estimate average error of predictions
- Root Mean Squared Error (RMSE) for discouraging larger errors
- Coefficient of Determination (R^2) measure of goodness of fit

These measures are well used in industrial predictive tasks and give a fair measure of the accuracy and reliability of the task [25].

Model Explainability and Feature Importance

The explainability techniques are, therefore, applied to the best model to ensure practical usability. Feature importance using permutations is carried out to rank input variables in terms of their influence on the prediction accuracy of a model. Computation of SHAP values is also carried out to quantify the contribution of every feature at both global and individual levels of prediction [16].

This step in interpretability helps process engineers to understand the physical significance of model outputs and validate them using DOE, putting data-driven insights into process knowledge, according to [26].

Deployment Strategy and Industrial Integration

A staged deployment approach is advocated to ensure risk containment in the adoption process by industries. At the first stage, a shadow mode is used in which predictions are made without controlling the process [27].

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After validation, the model is then integrated into quality control systems to enable real-time notifications and dynamic recipe suggestions. The integration helps in ensuring continuous improvement and is a factor that ensures sustainable resource utilization by minimizing rework and waste [28].

Ethical, Sustainability, and Data Security Considerations

The proposed framework lays emphasis on responsible AI usage by ensuring data privacy, secure storage, and transparent decision-making. Predictive control reduces excessive chemical usage, water consumption, and energy demand from the viewpoint of sustainability and aligns with global sustainability goals in textile manufacturing [29].

4. RESULT AND DISCUSSION

The machine learning models were assessed based on their capability to predict fabric dimensional change (%) in dyeing and finishing. It was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and an R^2 score. It provides an indication of prediction accuracy as well as dependability in its prediction.

However, ensemble models performed better than the linear regression model. This implies that the dimensional stability of fabric is a function of non-linear relationships between fabric characteristics and processing variables. Tree models are superior in this regard.

Table II: Performance Comparison of Models

Model	MAE (%)	RMSE (%)	R^2 Score
Linear Regression	2.15	2.90	0.62
Random Forest	1.35	1.85	0.82
XGBoost	1.20	1.65	0.86
LightGBM	1.18	1.62	0.87
CatBoost	1.15	1.58	0.88

Indeed, according to Table II, this was confirmed because the lowest prediction error and highest explanatory power were reached by gradient boosting models.

Linear regression had rather limited accuracy, especially for fabrics processed under extreme conditions of temperature, tension, or stretch. In contrast, Random Forest and boosting models provided more stable and accurate predictions; their power was unleashed because such algorithms were able to learn complex relationships between multiple variables. Among the advanced models, CatBoost performed a little better, especially when categorical inputs like fiber type, weave, and finish type were included. That implies that fabric structure and finishing chemistry play an important role in dimensionality stability.

Accordingly, an in-depth analysis of features showed that fabric density, applied tension, processing temperature, and type of finish all significantly influenced dimensional change. Less dense fabrics and those which were stretched more during finishing exhibited greater dimension change, whereas stabilized finishes tended to reduce shrinkage.

The outcomes show that the machine learning approach is capable of accurately predicting the dimensional stability result in textile dyeing and finishing.

The approach tackles the reliance on the trial-and-error approach and the early detection of possible quality problems. The project fully meets the aims by integrating textile engineering expertise and the machine learning approach to develop a feasible quality prediction system. The system allows for better resource utilization.

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Limitations

- The model accuracy depends on the quality and range of available production data; unmeasured factors such as fiber maturity and machine wear may influence results.
- The analysis is limited to specific fabric types and processing conditions, which may restrict direct application to other materials or production setups.
- The model is based on historical data and does not include real-time sensor inputs, limiting its ability to respond to sudden process variations.

5. CONCLUSION

This project demonstrated the effective use of machine learning techniques to predict dimensional stability in textile dyeing and finishing processes. By analyzing fabric properties, processing conditions, and operational factors together, the study showed that dimensional changes such as shrinkage and growth can be accurately predicted before final quality inspection.

The results confirmed that advanced machine learning models outperform traditional linear approaches, as they are better able to capture the complex and nonlinear relationships present in textile finishing operations. Visual evaluations and error analysis further verified that the prediction accuracy achieved is suitable for industrial quality control applications.

An important outcome of this work is the improved understanding of key parameters influencing dimensional stability. Process variables such as applied tension, temperature, and finishing type were found to have a stronger impact than fabric structure alone. This insight can help textile engineers focus on tighter control of critical process conditions to achieve consistent product quality.

Overall, the project highlights the potential of data-driven methods to reduce trial-and-error, minimize rework and material waste, and support more sustainable textile manufacturing. By shifting from reactive inspection to predictive quality control, the proposed approach offers a practical pathway toward smarter and more efficient dyeing and finishing operations.

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