Predicting ozone bleaching in denim fabrics with ensemble learning models

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ABSTRACT – REZUMAT

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Ensemble learning models, particularly advanced methods such as LightGBM and CatBoost, were applied to predict and improve the ozone bleaching process of denim fabrics, an eco-friendly alternative to conventional chemical methods that reduces water and energy consumption. Complex interactions among variables, including indigo/cotton ratio, sulphur/cotton ratio, moisture content, pH, temperature, and processing time, hinder consistent bleaching results. Although machine learning has been increasingly used to model textile processes, research specifically focused on predicting and optimising ozone bleaching performance in denim fabrics remains limited. To address this gap, we developed predictive models using six techniques (Random Forest, AdaBoost, GBM, XGBoost, LightGBM, and CatBoost) to estimate ΔEcmc values. The dataset was split into training (80%) and testing (20%) subsets, and model parameters were optimised via GridSearch. LightGBM provided the best fit in terms of explained variance (R^2 = 0.9972) with low test error (RMSE = 0.4214), while CatBoost achieved the best test-set generalisation with the lowest error metrics (RMSE = 0.4168 and MAPE = 4.9138%). These results show that ensemble models effectively capture complex interactions in the bleaching process, thereby reducing trial and error. To enhance applicability, the CatBoost model was coupled with a Genetic Algorithm to identify optimal ozone bleaching conditions across four fabric types (CI, CS, CEI, CES), yielding input settings that minimised ΔEcmc and supporting a sustainable, data-driven production approach.

Keywords: *ozone bleaching, ensemble learning, optimisation, denim fabrics, machine learning, sustainability*

Preconizarea decolorării cauzate de ozon în țesăturile din denim cu ajutorul modelelor de învățare de tip ansamblu

Au fost aplicate modele de învățare de tip ansamblu, în special metode avansate precum LightGBM și CatBoost, pentru a preconiza și a îmbunătăți procesul de decolorare cu ozon a țesăturilor din denim, o alternativă ecologică la metodele chimice convenționale care reduce consumul de apă și energie. Interacțiunile complexe dintre variabile, inclusiv raportul indigo/bumbac, raportul sulf/bumbac, conținutul de umiditate, pH-ul, temperatura și timpul de procesare, împiedică obținerea unor rezultate consistente în ceea ce privește decolorarea. Deși învățarea automată a fost utilizată din ce în ce mai mult pentru modelarea proceselor textile, cercetările axate în mod specific pe preconizarea și optimizarea performanței decolorării cu ozon a țesăturilor din denim rămân limitate. Pentru a remedia această lacună, am dezvoltat modele predictive utilizând șase tehnici (Random Forest, AdaBoost, GBM, XGBoost, LightGBM și CatBoost) pentru a estima valorile ΔEcmc. Setul de date a fost împărțit în subansambluri de antrenare (80%) și de testare (20%), iar parametrii modelului au fost optimizați prin GridSearch. LightGBM a oferit cea mai bună potrivire în ceea ce privește varianța explicată (R^2 = 0,9972) cu o eroare de testare redusă (RMSE = 0,4214), în timp ce CatBoost a obținut cea mai bună generalizare pe setul de testare cu cele mai mici metrici de eroare (RMSE = 0,4168 și MAPE = 4,9138%). Aceste rezultate arată că modelele de tip ansamblu surprind în mod eficient interacțiunile complexe din procesul de albire, reducând astfel procesul de încercare și eroare. Pentru a spori aplicabilitatea, modelul CatBoost a fost combinat cu un algoritm genetic în vederea identificării condițiilor optime de albire cu ozon pentru patru tipuri de țesături (CI, CS, CEI, CES), generând setări de intrare care au redus la minimum valoarea ΔEcmc și susținând o abordare de producție sustenabilă, bazată pe date.

Cuvinte-cheie*: albirea cu ozon, învățarea de tip ansamblu, optimizare, țesături din denim, învățare automată, sustenabilitate*

INTRODUCTION

Ozone bleaching has become a sustainable, cost-effective alternative to conventional methods, reducing water, hazardous chemicals, and energy use while meeting industry sustainability demands. Its reactions proceed via direct oxidation (dominant in acidic media) and indirect/radical pathways catalysed under alkaline conditions [1, 2]. Ozone effectively degrades chromophores in synthetic and natural fibres, enabling colour fading [3–5], and substantially lowers water/chemical consumption versus traditional processes [6, 7]. Yet process outcomes remain sensitive to parameters such as ozone concentration, moisture content, pH, temperature, and exposure time, necessitating careful optimisation [8–9]. Recent finishing innovations target aesthetics and functionality, but conventional fading often incurs high resource use and toxic effluents [10]. By contrast, ozone is an

eco-friendly oxidant that decomposes to O_2, can be applied in gas form, and markedly reduces water use [11–15]. Still, optimising colour fading depends on material properties and process settings (e.g., temperature, time) [16–18]. Consequently, researchers increasingly employ process modelling and machine learning (ML) [19–22]. Prior ML studies in textiles show promise with ANNs (fast learning) [23, 24], SVMs (good generalisation) [25], and Random Forests (variable-interaction insights) [26, 27], spanning applications from defect detection [28] to property prediction [29]; for ozone-related fading on cotton, ANN/SVM/RF have also been effective [30].
However, direct work on predicting and optimising ozone bleaching in denim via ensemble learning remains limited. This study addresses that gap by developing ensemble learning–based predictive models tailored to ozone bleaching conditions in denim fabrics and, further, by integrating a CatBoost model with a Genetic Algorithm to identify parameter sets that minimise ΔEcmc. In doing so, it tackles process variability and advances sustainable, data-driven bleaching practice for the textile industry.

MATERIALS AND METHODS

Fabric samples

For the experiments, samples were taken from four types of denim fabrics: CI fabric 100% cotton fabric dyed with indigo 448 g/m^2, CS fabric: 100% cotton fabric dyed with sulphur, 479 g/m^2, 3/1 Z, CEI fabric 98% cotton–2% elastane fabric dyed with indigo 399 g/m^2, 3/1 Z, and CES fabric: 98% cotton–2% elastane fabric dyed with sulphur, 325 g/m^2, 3/1 Z.

Equipment and devices

A range of specialised equipment and devices was employed to conduct experimental procedures. The Smartex Miracle Ozone Machine was used to generate ozone gas required for the bleaching treatments. At the same time, the Denim Ozone Generator enabled precise regulation and monitoring of ozone levels throughout the bleaching process. Fabric samples were spin-dried before or after bleaching using the YILMAK HG30 Spin Machine, and subsequently dried with the Tolkar Carina 405 Industrial Dryer. For sample preparation, the Vibral Gold Weighing Device was employed to obtain accurate fabric weights. The APERA PH800 pH Meter was used to determine the pH values of the fabric samples. Colour characteristics were assessed using the LABORTEKS X-Rite Ci7800 Spectrophotometer, which measured colour changes and differences, while the Laborteks James Heal Grey Scale was applied to evaluate the colour fastness properties of the fabrics.

Ozone bleaching

Ozone bleaching was conducted on four fabric samples: CI (100% cotton, indigo-dyed), CS (100% cotton, sulphur-dyed), CEI (98% cotton–2% elastane, indigo-dyed), and CES (98% cotton–2% elastane, sulphur-dyed). Different pH levels, temperatures, and moisture conditions were tested, with colour fading observed at varying durations. Ozone concentration was controlled and monitored using the Denim Ozone Generator, with ozone feeding set at 300 g/h. The temperature was adjusted using precision heating devices, and moisture was controlled through various spin-drying levels. The fabric colour was measured using a spectrophotometer, and fast tests were performed to assess dye retention and fabric strength after bleaching.

Experimental design

Selected denim fabrics were evaluated under five different moisture conditions: dry (0% moisture), fully spun (35% moisture), half spun (38% moisture), quarter spun (41% moisture), and no spun (69% moisture). Ozone bleaching experiments were conducted at specific combinations of pH (4, 5, 6, 7, 9), temperature (15°C, 25°C, 35°C, 45°C, 55°C), and ozonation time (ranging from 10 to 80 minutes). However, experimental intervals varied according to fabric types. For example, while some fabrics can be subjected to ozonation for up to 80 minutes, others have a time limit of 40 minutes due to material sensitivity and colour change behaviour. These differences were determined through preliminary experiments. Instead of a full factorial design, a partial factorial sampling strategy specific to the fabric type was adopted in the study, which is highly suitable for industrial use and experimentally applicable. Numerous treatment combinations were evaluated on four different fabric types, with each experimental condition repeated three times to generate reliable data sets. The resulting data were used in advanced modelling and optimisation studies.

Colour measurement

Colour changes were measured with the Ci7800 spectrophotometer in accordance with ASTM E3098 and CIE guidelines. The device, equipped with internal temperature and humidity sensors, recorded conditions during each reading to ensure comprehensive data documentation. Optional UV balancing was used to control fluorescence and optical brighteners, improving measurement reliability in textiles. Integration with NetProfiler and Colour iMatch/Colour iQC software ensured consistent calibration and quality control, while Pantone Digital Colour Libraries provided digital references without the need for physical samples. The Δ*Ecmc* formula measures perceptible colour difference more precisely than the basic CIE76 Δ*E*, as it incorporates weighting factors reflecting human visual sensitivity to lightness, chroma, and hue [31]. Equation (1) presents the Δ*Ecmc* formula:

$$\Delta Ecmc = \left(\frac{\Delta L^*}{l \cdot S_L}\right)^2 + \left(\frac{\Delta C^*}{c \cdot S_C}\right)^2 + \left(\frac{\Delta H^*}{S_H}\right)^2 \quad (1)$$

where ΔL^* is difference in lightness, ΔC^* – difference in chroma (colour saturation), ΔH^* – difference in hue (colour tone), S_L, S_C, S_H – weighting factors that account for the sensitivity of the human eye to lightness (L^*), chroma (C^*), and hue (H^*), l and c – user-defined parameters, often set as $l = 2$ (sensitive to lightness differences) and $c = 1$ (standard chroma differences), depending on the application.

The CMC model is widely adopted in textiles, paints, and printing because it aligns more closely with human perception, providing accurate evaluation of colour differences. In denim bleaching, predicting $\Delta Ecmc$ values is essential for fine-tuning process parameters (moisture, pH, temperature, time) to optimise bleaching while ensuring uniform batch-to-batch colour consistency.

Dataset

The dataset consisted of 415 experimental records with six inputs: indigo/cotton ratio, sulphur/cotton ratio, moisture (%), initial pH, temperature (°C), and processing time (min). Figure 1 illustrates their distributions using box–whisker plots, showing variability, scale, and outliers. This analysis supported preprocessing, confirming dataset suitability and guiding normalisation to ensure consistent feature scaling for model training and validation.

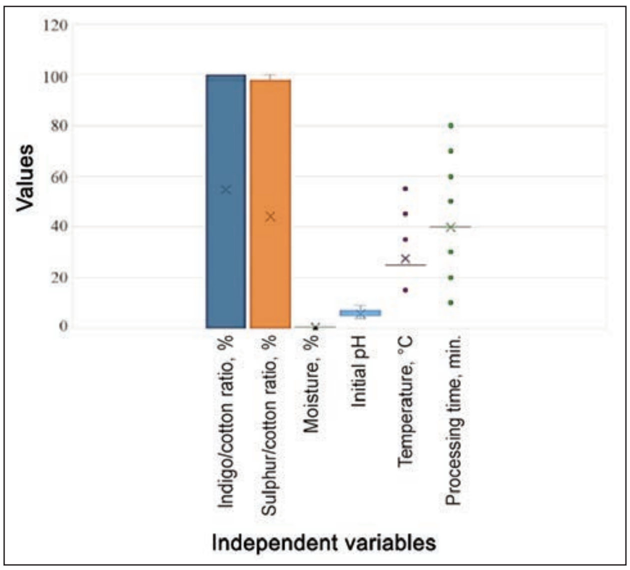

Fig. 1. Distribution of key input variables (indigo/cotton ratio, sulphur/cotton ratio, moisture content, pH, temperature, time) used in the machine learning models, providing insights into data variability and feature range

Data preprocessing

All inputs were z-score standardised (mean=0, SD=1) to avoid scale dominance across mixed units. The data were then split 80/20 into training and test sets for unbiased evaluation. Assumptions: stable environmental/equipment conditions (e.g., temperature, ozone concentration), uniform ozone output (300 g/h), and consistent fabric dyeing/thickness; automated spectrophotometer settings minimised measurement bias. Potential variability from fabric structure, residual chemicals, ambient humidity, and airflow may persist, slightly limiting generalizability beyond the tested conditions.

Hyperparameter optimisation and ensemble algorithms for ΔEcmc prediction

GridSearch was used to systematically explore predefined hyperparameter grids for each model and select configurations that maximised performance on the training/validation data. Six ensemble learners were then employed to capture nonlinear relationships among pH, temperature, moisture, and time: Random Forest Regression reduces variance via bagging and random subspaces [32]; AdaBoost iteratively reweights harder samples to build a strong learner from weak ones [33]; GBM fits residuals stage-wise to minimize a chosen loss [34]; XGBoost accelerates GBM with sparsity-aware learning and parallel block processing for large/sparse data [35]; LightGBM speeds training through histogram binning and high parallel efficiency [36]; and CatBoost uses oblivious trees with native categorical handling (e.g., indigo/cotton, sulphur/cotton ratios) and strong regularization [37]. Assumptions included accurate/consistent spectrophotometer $\Delta Ecmc$ readings and (for modelling convenience) independent inputs; limitations involved RF/GBM interpretability and potential overfitting on small/noisy data, finite GridSearch coverage of the hyperparameter space, and restricted generalizability beyond the studied fabric types and conditions.

Workflow overview

This study followed an integrated workflow to predict and optimise ΔEcmc values in the ozone bleaching of denim fabrics. The steps include data preprocessing, model training, performance evaluation, and optimisation using a Genetic Algorithm. The process begins with data collection and preprocessing, where fabric characteristics and relevant input variables, such as the indigo/cotton ratio, sulphur/cotton ratio, moisture content, pH, temperature, and treatment time, are organised and structured into a dataset. The dataset is then split into training and testing sets. In the model selection phase, ensemble learning algorithms including Random Forest, XGBoost, LightGBM, and CatBoost are implemented. To ensure optimal performance, hyperparameter tuning is carried out using GridSearch. Models are trained on the training set and evaluated using key performance metrics such as *RMSE*, *MAPE*, and R^2. Following model evaluation, the best-performing algorithm, CatBoost, is selected for integration with a Genetic Algorithm (GA). This GA-based optimisation identifies the ideal process conditions that minimise $\Delta Ecmc$ values for different fabric types. The integration of predictive modelling and heuristic optimisation ensures a robust, data-driven approach for enhancing the sustainability and efficiency of the ozone bleaching process.

Statistical evaluation of model performance

Model performance was evaluated using Root Mean Square Error (*RMSE*), Mean Absolute Percentage Error (*MAPE*), Mean Squared Error (*MSE*), and

Coefficient of Determination (R^2). All machine learning models were implemented using Python, with the corresponding code written in Jupyter Notebooks. Libraries such as Scikit-learn, XGBoost, LightGBM and CatBoost were utilised for model development, while data preprocessing and evaluation metrics were executed using Pandas and NumPy.

Optimisation Process with CatBoost-Based Genetic Algorithm

The ozone bleaching parameters were optimised using a Genetic Algorithm (GA) integrated with a CatBoost regression model [38]. The implementation was carried out in Python using the DEAP library [39], considering four continuous variables (moisture %, pH, temperature °C, time min). A population of 200 was evolved for 50 generations with tournament selection, blend crossover, and Gaussian mutation. The fitness function was the $\Delta Ecmc$ predicted by a pre-trained CatBoost model (inputs z-score standardised). To minimise $\Delta Ecmc$, individuals exceeding a set threshold were penalised, following a penalty-based constraint handling strategy [40]. Optimisation was performed per fabric type; the best individuals were ranked by fitness, and the optimal parameter sets were recorded for experimental validation.

RESULTS AND DISCUSSION

This study used ensemble learning to predict $\Delta Ecmc$ in ozone bleaching of denim, with inputs including indigo/cotton and sulphur/cotton ratios, moisture (%), initial pH, temperature (°C), and processing time (min). Six models, Random Forest, AdaBoost, GBM, XGBoost, LightGBM, and CatBoost, were applied to predict bleaching outcomes across different conditions. Hyperparameters (e.g., *n_estimators, learning_rate, max_depth*) were tuned via GridSearch, yielding model configurations tailored to the dataset and process characteristics.

Performance of machine learning algorithms in predicting ΔEcmc values

Six ensemble models (RF, AdaBoost, GBM, XGBoost, LightGBM, and CatBoost) were evaluated based on their ability to predict $\Delta Ecmc$ values. Performance was assessed using Root Mean Square Error (*RMSE*), Mean Absolute Percentage Error (*MAPE*), Mean Squared Error (*MSE*), and R^2. The results, summarised in table 1, show that LightGBM and CatBoost achieved the strongest performance, particularly in terms of generalisation accuracy on the test set.

LightGBM demonstrated strong overall performance, achieving the highest R^2 (0.9972) and low RMSE values (*RMSE_train* = 0.3620; *RMSE_test* = 0.4214), confirming its ability to reliably predict $\Delta Ecmc$ values across bleaching conditions (figure 2). These findings show that LightGBM effectively captured complex nonlinear patterns in ozone bleaching with strong generalisation ($R^2 > 0.995$), outperforming models such as ELM, SVR, and RF reported in [30].

CatBoost also performed strongly (figure 3), achieving the lowest test *RMSE* (0.4168) and lowest *MAPE* (4.9138%), confirming its superior generalisation capability with minimal preprocessing, consistent with [37]. Random Forest fit the training data well ($R^2 = 0.9969$) but showed a higher test *RMSE* (0.4995), suggesting slight overfitting, a limitation also noted in earlier textile studies [29]. AdaBoost delivered balanced results (*RMSE_train* = 0.3686; *RMSE_test* = 0.4303) with reliable generalisation, while GBM and XGBoost showed stable and similar outcomes, with XGBoost slightly ahead on the test set. Overall, LightGBM provided the best fit (highest R^2), whereas CatBoost achieved the best test set generalisation (lowest *RMSE* and *MAPE*). Both models effectively captured nonlinear dynamics and interactions between key variables such as moisture and pH. From a practical standpoint, ensemble models reduce trial and error in experiments and revealed that higher moisture levels and slightly acidic pH values yield better bleaching efficiency in shorter times. Their application supports sustainable process optimisation by lowering chemical and water use, improving control, and reducing environmental impact. These results align with sustainability goals in textile production and highlight the value of integrating AI into bleaching. One key finding was the strong influence of moisture and initial pH, consistent with earlier research. Conversely, RF's weaker test performance despite high training accuracy highlighted the advantage of boosting methods for complex

Table 1

COMPARISON OF MODEL PERFORMANCE ON TRAINING AND TEST SETS

Method/Statistical parameters	Training				Test			
	RMSE	MAPE (%)	MSE	R^2	RMSE	MAPE (%)	MSE	R^2
Random Forest	0.3764	5.2577	0.1417	0.9969	0.4995	5.5497	0.2495	0.9940
AdaBoost	0.3686	5.1546	0.1358	0.9971	0.4303	5.0415	0.1851	0.9955
GBM	0.3640	5.4451	0.1325	0.9971	0.4220	5.1061	0.1781	0.9957
XGBoost	0.3646	5.3991	0.1330	0.9971	0.4254	5.1497	0.1810	0.9956
LightGBM	0.3620	5.0849	0.1311	0.9972	0.4214	4.9570	0.1776	0.9957
CatBoost	0.3645	5.4349	0.1329	0.9971	0.4168	4.9138	0.1737	0.9958

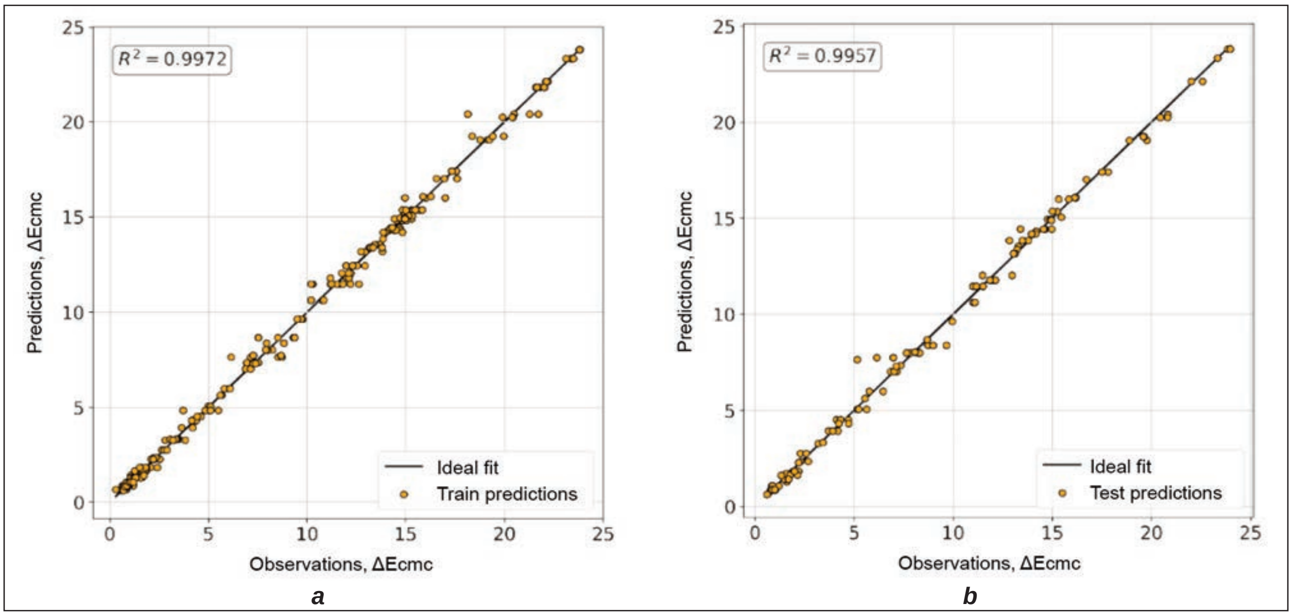

Fig. 2. Predicted vs. observed Δ*Ecmc* using LightGBM for:
a – training; *b* – test, showing strong correlation and low prediction error

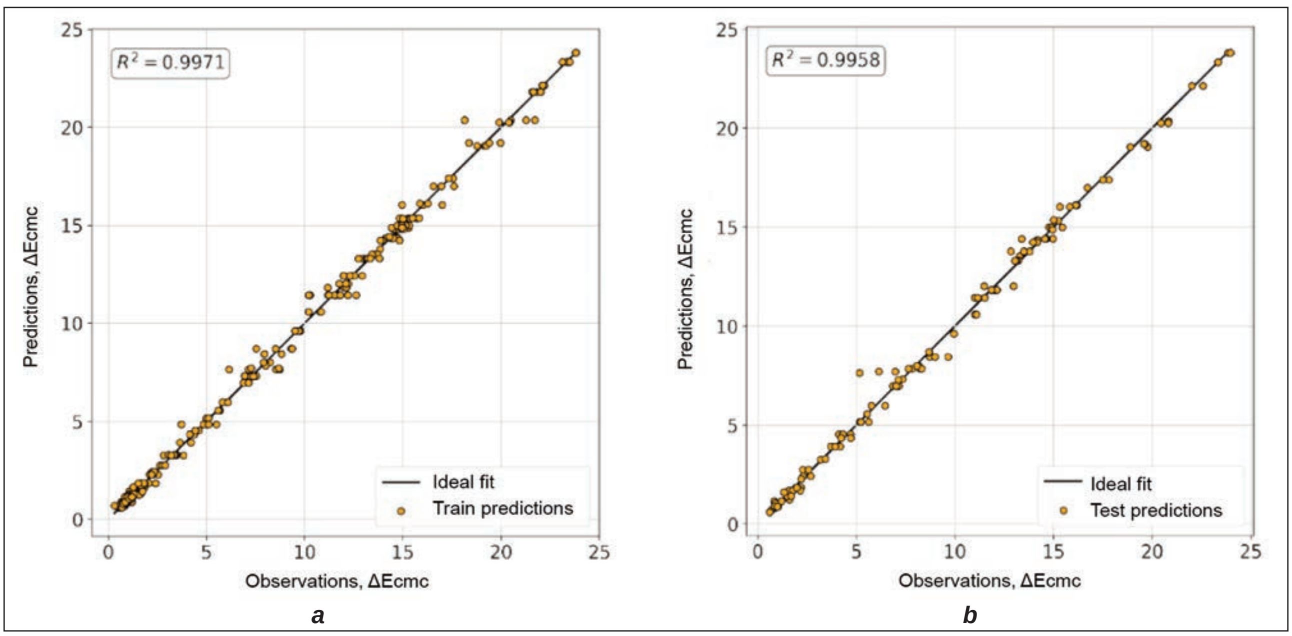

Fig. 3. Predicted vs. observed Δ*Ecmc* using CatBoost for:
a – training; *b* – test, indicating good agreement between predictions and observations

interactions. While promising, limitations (including the focus on specific denim types and controlled laboratory settings) may affect generalizability, pointing to the need for broader datasets and real-world trials in future work.

Optimisation of ozone bleaching conditions using CatBoost and Genetic Algorithm

CatBoost was chosen for GA because it delivered the best test set generalisation (lowest *RMSE* and *MAPE*), which is critical when evaluating new parameter combinations beyond the training data. A CatBoost regression model coupled with a Genetic Algorithm (GA) was used to minimise Δ*Ecmc* by optimising moisture (%), pH, temperature (°C), and time (min) for four denim types (CI, CS, CEI, CES). GA-generated parameter sets were scored by CatBoost, and the best candidates were validated experimentally. Predictions closely matched measurements (*MAPE* < 5%; CI 2.7219%, CEI 3.2063%, CS 4.3370%, CES 4.2410%), confirming the CatBoost–GA framework as a reliable, industry-ready approach for ozone bleaching optimisation.

CONCLUSIONS

Ensemble learning, particularly LightGBM and CatBoost, accurately predicted Δ*Ecmc* in ozone bleaching, with LightGBM achieving the highest R^2 (best fit) and CatBoost delivering the lowest test-set

RMSE and *MAPE* (best generalisation), outperforming alternatives across *RMSE*, *MAPE*, and R^2. Leveraging this predictive strength, the CatBoost–GA framework identified process settings (moisture, pH, temperature, time) that minimised $\Delta Ecmc$ for four fabric types, with experimental validation showing close agreement ($MAPE < 5\%$). These results demonstrate a practical, industry-ready pathway that reduces trial and error, improves process control, and lowers waste, costs, and environmental impact. In contexts where conventional bleaching is resource-intensive, ozone paired with machine learning offers a cleaner and more efficient option. Overall, the approach provides data-driven guidance for sustainable manufacturing. Future work should broaden fabric and dye coverage, include more diverse operating ranges, and deploy real-time, model-based control to enable dynamic decision-making at scale.

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