DEVELOPING CNN-AUGMENTED MODELS TO PREDICT CIELAB OUTCOMES POST-BLEACHING OF DENIM GARMENTS

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ABSTRACT

Denim garment production demands efficient design processes to minimize waste, costs, and production delays. Bleaching, among other finishing processes, holds paramount importance due to its numerous variables and substantial impact on product value. Artificial neural networks have great potential to achieve superior performance in anticipating various process outcomes. Their parameterized structure effectively captures non-linear relationships between input features. This study aims to effectively predict fabric outcomes by developing an artificial neural network (ANN) model supported by convolutional neural networks (CNN) to provide additional features derived from raw and semi-processed fabric images. The study represents a comparison of CNN powered models with a common predictive ANN as base model. Competing models incorporate various process variables and fabric properties, such as dying number and elasticity to predict changes in denim CIELab properties after bleaching. The process features of the model are the number of bleaching cycles, total process time, and concentration of sodium hypochlorite (representing the total amount of chemical used). The mean absolute percentage error is used as the performance measure between predictions and desired outputs. This research plays a significant role in enhancing agility in denim production by providing businesses with more efficient approaches to digitized denim bleaching and Research and Development processes in the textile industry.

KEYWORDS

Denim; Bleaching; Effect; Artificial neural networks.

INTRODUCTION

Denim goes through various manufacturing processes that involve many variables, from fabric production to garment creation. The traditional denim processing begins with cotton fiber selection and dyeing the threads with indigo. Then, the denim fabric is woven using specific techniques [5]. After the garment is made, finishing processes are applied to achieve the desired aesthetic and comfort. These processes include techniques such as enzymatic washing, which can be optimized for fading color, comfort, and durability [6].

The bleaching effect is the process of removing or lightening the indigo from the surface of denim fabric. Typically, a strong oxidative bleach, such as sodium hypochlorite (NaOCl), potassium permanganate ($KMnO_4$), or hydrogen peroxide (H_2O_2), is used, and the bleaching process can be done with or without the addition of stones [7]. This process is labor-intensive, reliant on skilled workers, and considered as costly. Given the significance of bleaching, the importance of digitizing both bleaching-oriented production and related processes becomes apparent. By implementing decision support systems and associated predictive models, digitizing these processes will offer businesses a more agile and efficient approach. Efficiency improvements are crucially needed in the denim garment industry, particularly for businesses where labor, waste, and energy are significant costs.

The use of artificial neural networks (ANNs) in predicting the effects of processes applied to fabrics is encountered in studies. Farooq et al. employ an ANN system to predict the phenomenon of color change for different colors and shade percentages [8]. Mandal et al. model the relationships between measured fabric properties (such as thickness, weight, fabric count) and thermal protective performance and thermo-physiological comfort performance using an ANN to analyze garment performance [9]. Elkateb includes a study on

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predicting output properties of woven fabrics with ANNs across different characteristics [10].

Anomaly detection on textile textures using "Variational Autoencoders" can be cited as an example of the use of images in textiles. In this application, the reconstructed images are compared with the original images, and the calculated reconstruction error is directly used to compute the anomaly score [11]. Another study used deep learning methods to approximately determine input parameters in laser texturing. Different combinations of laser parameters were selected to perform laser fading experiments on denim fabrics using laser technology in data generation, and denim image datasets with various laser fading effects were obtained. The trained convolutional neural network-based (CNN) prediction model produced an approximate parameter group based on the fading image and showed good performance with low prediction error according to the validation dataset [12].

In this study, the proposed CNN prediction models will equip businesses with an agile and thus more efficient approach to digitized denim bleaching in the denim garment industry. Proposed models have been developed to forecast the color properties of denim garments. To the best knowledge, this is the first study to predict color values using fabric images on deep learning models.

EXPERIMENTAL SETUP

This study aims to predict the possible changes in the physical properties of the denim garment after the sodium hypochlorite bleaching process, depending on the process variables and fabric properties to prevent production-related fabric defects. The basic steps of this effort are outlined in the following subsections: first, the material and its structure are described. Second, the data collection process and modeling details are presented, including explanations of the methods employed and the evaluation techniques use.

Materials

Prediction models have been developed based on collected data to forecast the "CIELab" color properties of denim garments. The CIELab color space, also known as L*a*b represents color using three parameters: L* for perceived lightness, and a* and b* for the four primary colors perceived by human vision: red, green, blue, and yellow. The models are built using 1,200 data points gathered from a full factorial design involving 1,200 experiments. The experiments focused on denim fabric type, process time, sodium hypochlorite concentration, and the replicate cycle of bleaching. The sodium hypochlorite bleaching process was conducted with two replicates. Three levels of process time were tested: 3, 5, and 7 minutes. Additionally, four concentration levels of bleach were selected: 2,000, 3,000, 4,000, and 5,000 ml. The bleaching cycle indicates how many times the same bleaching process is replicated to reach the desired visual effect.

50 different types of denim fabric are selected and four variables that can affect the color in the bleaching process have been included in the controlled experimental design. In addition, the constructional fabric properties as yarn count, weaving pattern and density, the CIELab values of raw and semi-processed fabric are accepted as inputs of the models. The semi-processing stage refers to intermediate steps in the bleaching process that prepare the denim for a final, controlled whitening or fading effect. In that stage a controlled amount of hydrogen peroxide is applied to the denim fabric and acts as a mild bleaching agent.

Methods

ANNs, ranging from simple computational units to complex architectures, are a heavily researched area in deep learning. Known for their versatility, strength, and scalability, ANNs excel at handling large-scale, highly intricate machine learning challenges. Their applications span from classifying billions of images to enabling advanced speech recognition systems [1]. ANNs also serve as powerful tools for predicting the outcomes of the processes handled in this research.

With techniques like stochastic gradient descent, ANNs can converge, although the solution may not necessarily reach the global optimum due to the presence of multiple local minima [2]. Additionally, while other machine learning methods require manually engineered features to be fed into the model as input, ANNs can extract useful features from the data without requiring an additional effort, thanks to the mechanism of weight updates [3]. However, when dealing with non-structural data types like image data, fully connected layers struggle to represent important features effectively. For example, even a small 100x100-sized image contains 10,000 inputs, and even if the first hidden layer has a high number of neurons, like 1,000, it may not capture a significant portion of the information [1]. As a result, a specialized structure known as a convolutional layer, commonly referred to as convolutional neural networks (CNNs), is necessary and has consistently delivered successful outcomes.

The convolution is the process of sliding filters of certain sizes, such as 3x3 or 5x5, over the 3-dimensional input data, stopping at every possible position to extract the 3-dimensional patch of environmental features. This patch corresponds to the region covered by the filter at that position. The process starts from the top-left corner of the data and continues towards the bottom-right corner. The weights of the filter are element-wise multiplied with the values in the patch, and the results are summed

Table 1. Input-Output configuration of models.

Attributes			ANN	CNN1	CNN2
INPUTS	Fabric Properties	Type of Dyeing	✓	✓	✓
		Elasticity	✓	✓	✓
		Onz/yd^2	✓	✓	✓
		Yarn Count	✓	✓	✓
		Density	✓	✓	✓
		Type of Weaving	✓	✓	✓
		CIELab (Raw Fabric)	✓	✓	✓
		CIELab (Semi-processed Fabric)	✓	✓	✓
	Process Features	The Number of Bleaching	✓	✓	✓
		The Bleaching Process Time	✓	✓	✓
		Sodium Hypochlorite Concentration	✓	✓	✓
	Image Features	Raw Fabric Images		✓	
		Semi-processed Fabric Images			✓
OUTPUTS	Color Properties of Processed Product	CIELab L*	✓	✓	✓
		CIELab a*	✓	✓	✓
		CIELab b*	✓	✓	✓

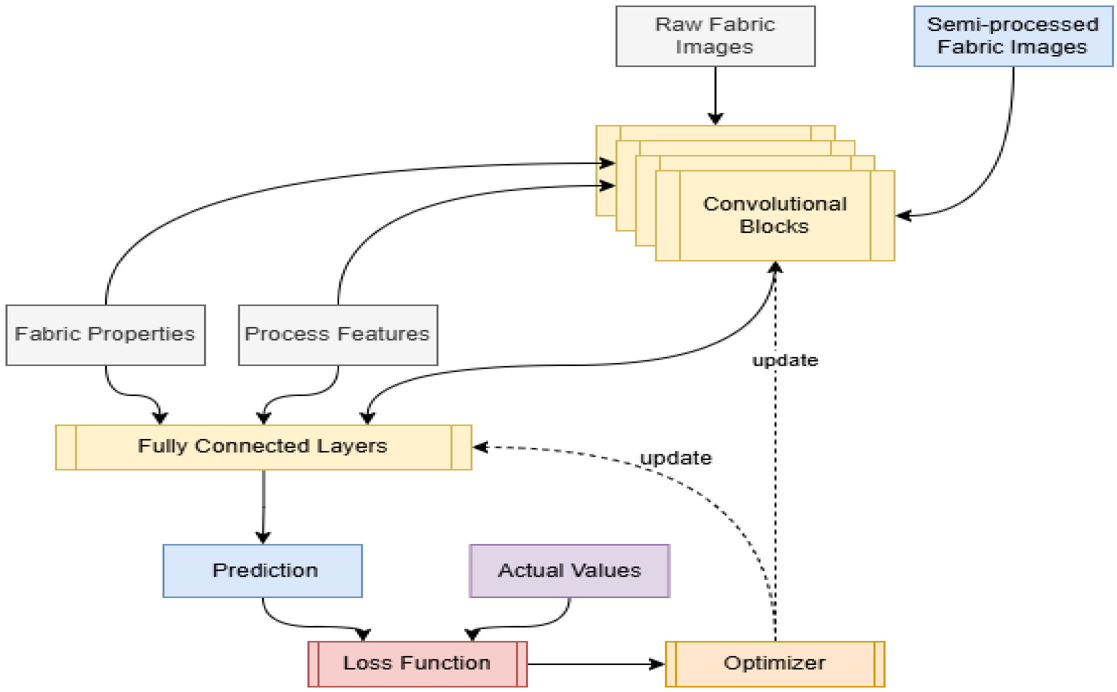

Figure 1. Proposed modeling schema.

to produce a single value. This operation is applied to all positions where the filter is placed [4].

The architectural design of models used in this study is illustrated in Figure 1. Convolutional blocks represent convolution operation over image data. Other types of data are diffused multiple times in following layers. An algorithm called backpropagation will be used to update the weights backward based on the values calculated forward for each neuron [3]. The backpropagation algorithm will search for the parameter set that minimizes errors in this way.

Data diffusion in Figure 1 involves propagating image data across convolutional layers to capture visual features, while feature data (fabric features and process features) are directly concatenated with features extracted from images before passing through fully connected layers. This integration allows the model to leverage both types of information (visual and non-visual) simultaneously for better predictions.

The loss function measures the difference between the predicted values and the actual values. This helps in quantifying how well the model is performing. The optimizer updates the parameters of the model to minimize the loss, iterating through the network to improve predictions over time. It receives feedback from the loss function and adjusts the weights in both the convolutional and fully connected layers accordingly.

RESULTS AND DISCUSSION

A straightforward cross-validation method was employed to evaluate the approach. For each model, the dataset was randomly split five times into a 90/10 ratio. In each split, the first portion (90%) was used for training, while the second portion (10%) was used for prediction. Models' performance was assessed using the mean absolute percentage error (MAPE) as the evaluation metric. MAPE measures the average of absolute percentage errors between actual values and predicted values. It's especially useful for understanding how far predictions deviate from actual results on average, in terms of percentage.

The models were initially trained for 500 epochs. Throughout the training, the loss values were monitored to determine when the models reached a relative plateau. Since the training loss of the ANN model was observed to still be decreasing, it was trained for an additional 500 epochs to allow for a fairer comparison. At the end of each epoch, a performance metric was calculated on the validation dataset, which was kept separate from the training process. Figure 2-4 shows the progression of training and validation values over the first 500 epochs.show a rapid decrease in training loss early on, which then stabilizes, indicating effective initial learning.

Validation MAPE fluctuates more than training MAPE in all models, which is typical due to validation data variability. CNN2 seems to achieve the relatively stable and consistent performance for prediction of three properties.

Table 2 represents the average validation performance of three model types.

CNN2 performs best overall, achieving the lowest prediction values for all three color parameters (L*, a*, and b*), suggesting it provides the most accurate predictions. CNN1 is the second-best model, with relatively low prediction values, though slightly higher than CNN2, indicating it still performs well across parameters.

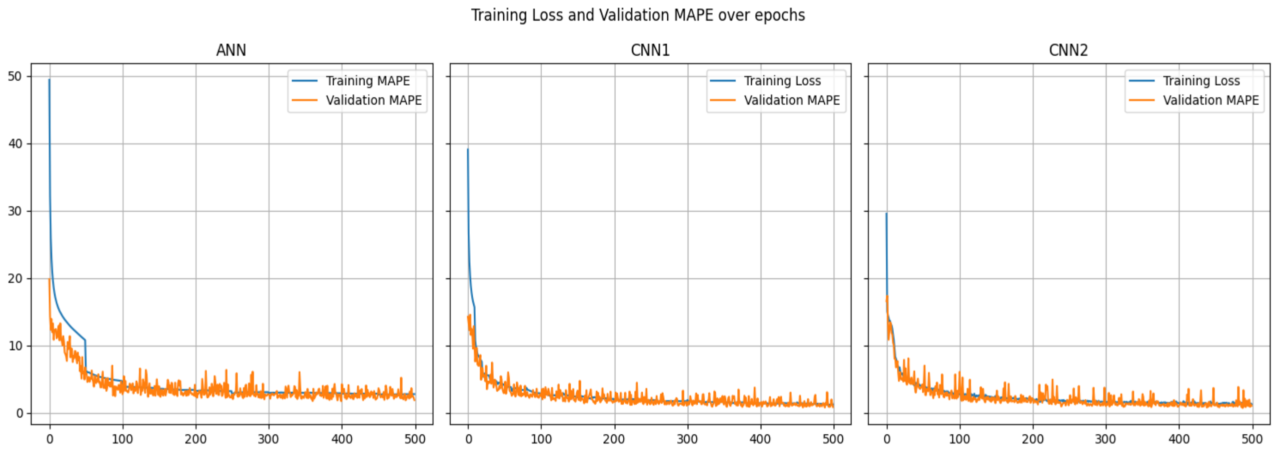

Figure 2. Tracking epochs for L* values.

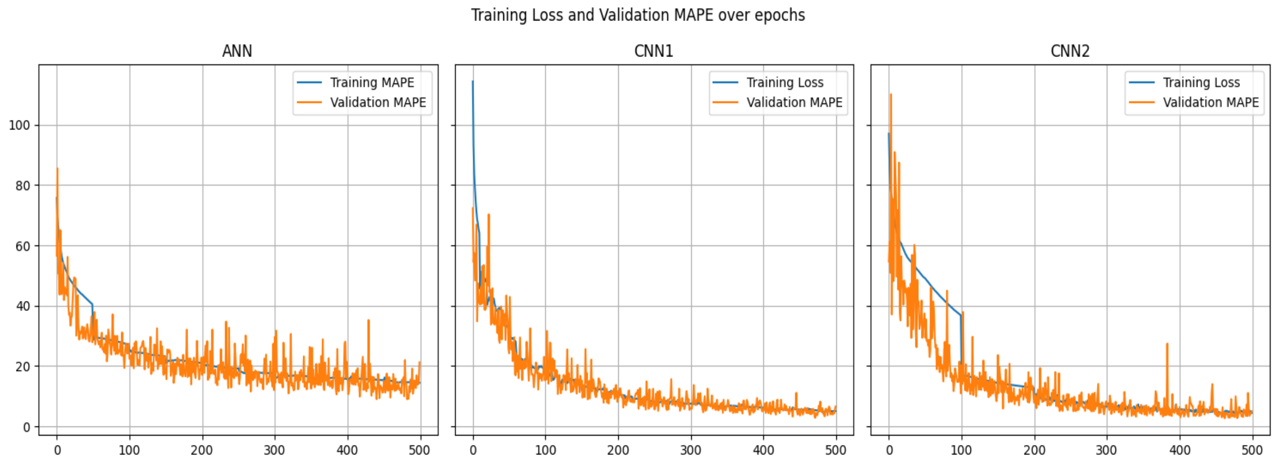

Figure 3. Tracking epochs for a* values.

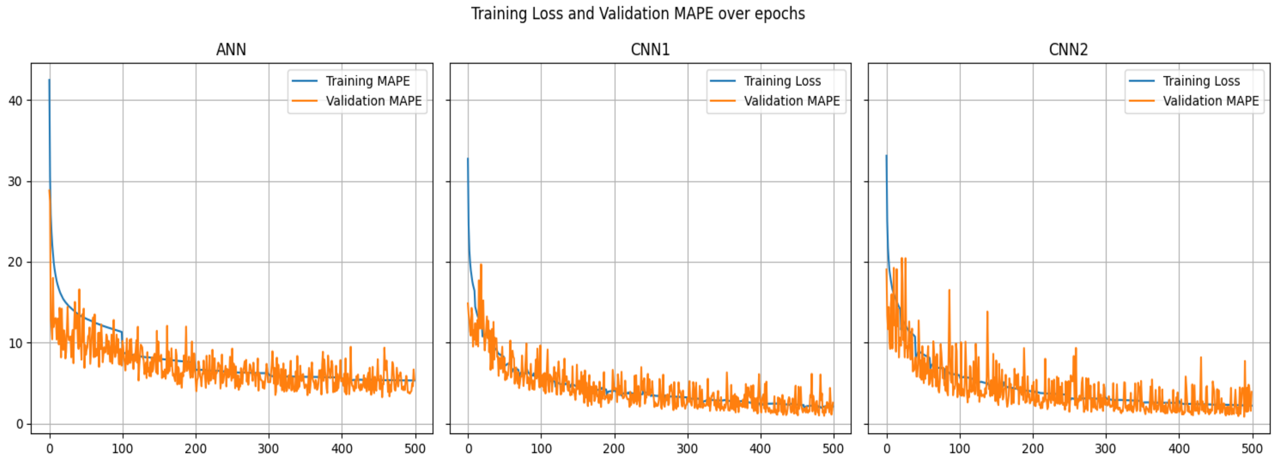

Figure 4. Tracking epochs for b* values.

Table 2. Average prediction error for color parameters (Lower values indicate better performance).

Predicted Value	ANN	CNN1	CNN2
L*	2.04	1.04	1.05
a*	7.56	6.55	4.97
b*	2.78	2.60	2.26

CONCLUSIONS

In this research study, the prediction of outcomes of bleaching process used in ground effecting of denim garments was examined. It has been established that both the dataset utilized and the augmented models employed for predictions have a significant impact on the accuracy of the forecasts. It is concluded that a factory employing these models will be able to forecast process outcomes effectively, minimizing the risk of any losses.

The fact that images of semi-processed fabrics perform better due to being closer to the final product is an expected situation. The results have shown this trend as well. Furthermore, it is an important finding that including images in similar prediction models in denim manufacturing could enhance prediction performance.

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