Least Square Support Vector Regression-Based Model for Whiteness Index of Cotton Fabric Prediction

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Research Article

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Abstract

The textile bleaching process uses a hydrogen peroxide (H_2O_2) solution in alkali pH associated with high temperature is the commonly used bleaching procedure in cotton fabric manufacture. The purpose of the bleaching process is to remove the natural colour from cotton to obtain a permanent white colour before dyeing or shape matching. Normally, the visual ratings of whiteness on the cotton are measured by the whiteness index (WI). Notice that lesser research study is focusing on chemical predictive modelling of the WI of cotton fabric than its experimental study. Predictive analytics using predictive modelling can forecast the outcomes that can lead to better-informed cotton quality assurance and control decisions. Up to date, limited study applying least square support vector regression (LSSVR) based model in the textile domain. Hence, the present study was aimed to develop the LSSVR-based model, namely multi-output LSSVR (MLSSVR) using bleaching process variables to predict the WI of cotton. The predictive accuracy of the MLSSVR model is measured by root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2), and its results are compared with other regression models including partial least square regression, predictive fuzzy model, locally weighted partial least square regression and locally weighted kernel partial least square regression. The results indicate that the MLSSVR model performed better than other models in predicting the WI as it has 60% to 1209% lower values of RMSE and MAE as well as it provided the highest R^2 values which are up to 0.9985.

Keywords: Prediction, whiteness index, cotton, least square support vector regression, textile bleaching.

Introduction

Cotton is widely used to make various fabrics such as garments, bedding, curtains, and carpets (Wang et al. 2018). Hence, Cotton is an important textile fibre in the textile industry. It is about 25 million tons of cotton produced annually around the world in which it is used to make about 50% of the clothes (Ahmad et al. 2021). Cotton fabric is popular because it has advantages including softness, biodegradability, comfort, hypoallergenic, breathability, and less toxic (being a natural fibre) (Xie et al. 2013). However, similar to other natural fibres, cotton fibre contains natural pigments that cause it to have a yellowish-brown colour (Oliveira et al. 2018). Also, this naturally coloured cotton fibre may result from natural environmental factors like soil, dust, smoke, dirt, insects, and other particles. Moreover, the yellowish-brown of cotton is visually associated with soiling or the lack of cleanliness and it is an attribute that must be removed.

Cotton fabric bleaching is chemical oxidation used to remove the yellowish-brown colouration from cotton by damaging the colourant that resulted in the discolouration (Oliveira et al. 2018). In other words, the bleaching process is responsible for eliminating the colouring materials from the cotton fibre to have a pure white appearance. A white appearance of the fabric is desirable as it gives the impression of clean and pure, thus higher whiteness is a preferable colour for a white fabric (Jung and Sato 2013). Hence, the degree of whiteness of cotton fabric is the main requirement of bleaching. Besides, the bleaching process is done to get rid of potentially hazardous contaminants such as bacteria, molds, and fungi from the cotton fabrics by using strong reducing or oxidizing agents (Gültekin 2016).

Hydrogen peroxide (H_2O_2) is one of the commonly used bleaching agents that oxidise the colouring matter to discolour fabrics (Oliveira et al. 2018). H_2O_2 is preferable as it is gentler and less toxic than chlorine bleach (Bajpai 2007). Additionally, optical brighteners can be added to the bleaching process to increase whiteness levels (Oliveira et al. 2018). After the bleaching process, the whiteness index (WI) that indicates the degree of whiteness on the cotton is measured as it

relates to a white fabric's colour quality. Whiteness is defined in colorimetric terms as a colour with the highest luminosity, no hue, and no saturation. The WI is calculated from the data computed by colorimetric instruments such as colourimeter and spectrophotometer. The higher the WI value, the greater the whiteness degree of the measured cotton (Topalovic et al. 2007). If the preferred white fabric has a high reflectance, then the ideal reflectance for textile materials should approach 100 (Ferdush et al.).

The WI value of the bleached cotton fabric is perpendicular to the time duration of the bleaching process and the amount of H_2O_2 (Haque and Islam 2015). Contrastingly, the bursting strength of the cotton fabric is fallen with the longer time durations of the bleaching process and the increase of H_2O_2 concentration. On the other hand, the higher temperature can improve the rate of bleaching and shorten the processing time (Abdul and Narendra 2013). Therefore, a colorimetric analysis is usually conducted to assess and investigate the bleaching procedure on the cotton samples. Artificial neural networks and adaptive neuroinference systems have been used as prediction models in the textile domain. However, these models require many data for model parameters optimisation, and they have computational time burdens. Later, a fuzzy predictive model had been developed and studied by Haque et al. (2018) using a fuzzy logic designer app in MATLAB to predict the WI of cotton using the bleaching process parameters that are nonlinear. Nevertheless, this fuzzy model is unable to predict the WI for the bleaching process parameters that are not within the ranges of the input data. It does not have the capability of machine learning models such as least square support vector regression (LSSVR).

Machine learning models including LSSVR-based models can learn information directly from data and understand their performance across a wide range of inputs (Wexler et al. 2019). LSSVR-based model exhibits good predictability to forecast the desired output variable, especially for nonlinear data. Hence, it has grabbed more attention and interest from researchers in many different areas these years (Moosavi et al. 2021; Xu et al. 2013; Zhang and Wang 2021). But it

was found that minimal research is conducted using the LSSVR-based model on colour relevant studies including WI prediction. Thus, in this study, an effective LSSVR-based model, namely multi-output LSSVR (MLSSVR) is developed using the bleaching process variables to estimate the WI of bleached cotton. Then, the accuracy of LSSVR is evaluated by calculating the coefficient of determination (R^2), root mean square error (RMSE), and absolute mean error (MAE). Additionally, its results are compared with partial least square regression (PLSR), predictive fuzzy model, locally weighted partial least square regression (LW-PLSR), and locally weighted kernel partial least square regression (LW-KPLSR) models.

Materials and methods

This section explains the bleaching process, post-treatment of cotton fabric, and WI measurement. Then, it is followed by the MLSSVR model development, regression models parameters setting, and accuracy of the predictive performance measurement. Lastly, computer hardware and software configuration specifications are illustrated.

Bleaching process of cotton fabric and whiteness index

In this study, the collected experimental data was taken from Haque et al. (2018), and Haque and Islam (2015). In their studies, single jersey cotton knitted fabric of 130 grams per cubic centimeter was used as the fabric samples and a 12.5 g of fabric sample with a 1:10 material liquor ratio was treated in each bleaching time. The commercial-grade chemicals used in the bleaching process are H_2O_2 with three different concentrations (1.8 g/L, 2 g/L, and 2.2 g/L) as the bleaching agent, 2 g/L of sodium hydroxide as caustic soda as the alkali for the bleaching process, and 1 g/L of kappazon H53 peroxide stabilizer as H_2O_2 stabilizing action. For each H_2O_2 concentration, the bleaching process was operated at six individual temperatures (T) (78 ºC, 83 ºC, 88 ºC, 93 ºC, 98 ºC, 103 ºC, and 108 ºC) and four different times (t) (20 mins, 30 mins, 40 mins, and 50 mins). Then, the

bleached fabric samples were hot washed at 70 ºC, cold washed at 27 ºC, squeezed by hand, and dried at 70 ºC for 30 mins. Lastly, the WI for each bleached fabric sample was measured using a reflectance spectrophotometer (datacolor 650). Figure 1 shows a flowchart explaining the bleaching operations, post-treatment of fabric samples, and colour measurement.

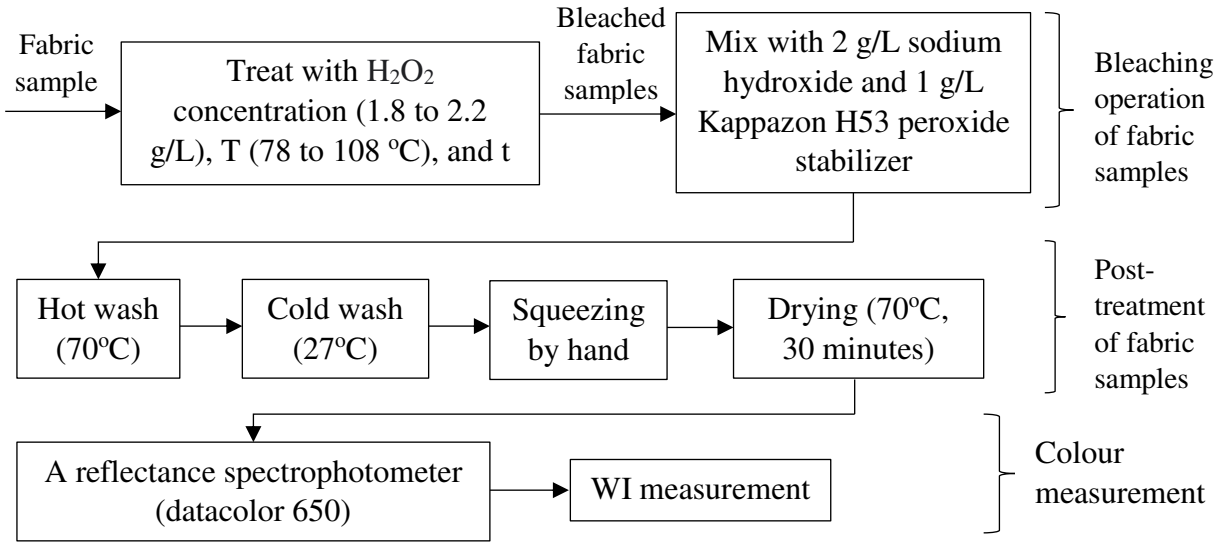


Fig. 1 Flowchart explaining the bleaching operations, post-treatment of fabric samples and colour measurement

Commission on Illumination (CIE) WI is one of the widely used colour measurement methods for computing a WI to measure the degree of whiteness of bleached cotton fabric (Xu et al. 2015). This CIE WI generally refers to measurements made under D65 illumination, which is a standard representation of outdoor daylight. The CIE WI under CIE 1964 10º standard observer can be represented by the Eq. 1 (Haque et al. 2018; Jafari and Amirshahi 2008).

$$WI = Y_L + 800(x_n - x_c) + 1700(y_n - y_c) \quad (1)$$

where Y_L is the lightness, whereas x_c and y_c are chromaticity coordinates of the bleached cotton fabric samples. x_n and y_n are chromaticity coordinates of the illuminant. Moreover, the CIE WI has a constraint as shown in Eq. 2 (Jafari and Amirshahi 2008).

$$40 < WI < (5Y_L - 280) \quad (2)$$

Multi-output Least square support vector regression model development

In this study, LSSVR model is developed from the bleaching process parameters to predict the WI of cotton fabrics. LSSVR model is a nonlinear prediction model that derives the support vector machine (SVM) theory (Liu and Yoo 2016). Different from the SVM, LSSVR gives a better solution for the reduction of the computational burden where a set of linear equations in a dual space is utilised. In this study, a MLSSVR model was adopted from Xu et al. (2013). Due to the multi-output setting in this MLSSVR, it becomes a more efficient training model. The idea of MLSSVR comes from the multi-output case done by An et al. (2009). It is letting $Y = [y_{i,j}] \in \Re^{l \times m}$ where $y_{i,j}$ is the (*i,j*)-th of an output, $\Re$ is the set of real numbers, and $l \times m$ is the order of a matrix. With a given total number of data sets, N_T, i.e., $\{(x_i, y^i)\}_{i=1}^{l}$ where $x_i \in \Re^d$ and $y^i \in \Re^m$ are the input vector and output vector, respectively. And the multi-output regression has an objective to estimate an output vector $y \in \Re^m$ from a given input vector $x \in \Re^d$ where this regression problem can be built as learning a mapping from $\Re^d$ to $\Re^m$. Multi-output regression solves the problem by searching the weighed value vector, $W = (w_1, w_2, ..., w_m) \in \Re^{n_h \times m}$ and a threshold value, $b = (b_1, b_2, ..., b_m)^T \in \Re^m$ that minimises the following objective function with constraints (Eqs. 3 and 4):

$$\min_{W \in \Re^{m \times n_h}, b \in \Re^m} \Im(W, \Xi) = \frac{1}{2} trace(W^T W) + \gamma \frac{1}{2} trace(\Xi^T \Xi), \quad (3)$$

$$s.t. \;\; Y = Z^T W + repmat(b^T, l, 1) + \Xi, \quad (4)$$

where γ is a positive real regularised parameter, $\xi = (\xi_1, \xi_2, ..., \xi_l)^T \in \Re^l$ is a vector containing slack variables, $Z = (\varphi(x_1), \varphi(x_2), ..., \varphi(x_l)) \in \Re^{n_h \times l}, \varphi : \Re^d \to \Re^{n_h}$ is a mapping to some high

or even unlimited/ infinite dimensional Hilbert space or feature space via the nonlinear mapping function φ with n_h dimensions, and $\Xi = (\xi_1, \xi_2, ..., \xi_m) \in \Re_+^{l \times m}$ is a $l \times m$ matrix consisting of slack variables with $\Re_+$ the subset of positive ones.

It can be said that the solution to the regression problem shown in Eqs. 3 and 4 disconnects between the different output variables and only need to use Cholesky decomposition, conjugate gradient, or single value decomposition, etc. to compute a single inverse matrix once that is shared by all the vectors $w_i (\forall_i \in \mathrm{N}_m)$. Unlike the single-output case, its solution to the regression problem needs to be solved multiple times. Hence, the multi-output regression is much more efficient than the single-output regression.

According to Xu et al. (2013), to formulate the intuition of Hierarchical Bayes, all $w_i \in \Re^{n_h} (i \in \mathrm{N}_m)$ is assumed to be written as $w_i = w_0 + v_i$, where the vectors $v_i \in \Re^{n_h} (i \in \mathrm{N}_m)$ are small when the different outputs are same to each other, otherwise the mean vector $w_0 \in \Re^{n_h}$ are small. It can be said that w_0 takes the information of the commonality and $v_i (i \in \mathrm{N}_m)$ brings the information of the specialty. $w_0 \in \Re^{n_h}$, $V = (v_1, v_2, ..., v_m) \in \Re^{n_h \times m}$, and $b = (b_1, b_2, ..., b_m)^T \in \Re^m$ are solved spontaneously to minimise the below objective function with constraints (Eqs. 5 and 6):

$$\min_{w_0 \in \Re^{n_h}, V \in \Re^{n_h}, b \in \Re^m} \Im(w_0, V, \Xi) = \frac{1}{2} w_0^T w_0 + \frac{1}{2} \frac{\lambda}{m} trace(V^T V) + \gamma \frac{1}{2} trace(\Xi^T \Xi), \tag{5}$$

$$s.t. \quad Y = Z^T W + repmat(b^T, l, 1) + \Xi, \tag{6}$$

where $\Xi = (\xi_1, \xi_2, ..., \xi_m) \in \Re^{l \times m}$, $W = (w_0 + v_1, w_0 + v_2, ..., w_0 + v_m) \in \Re^{n_h \times m}$, $\lambda, \gamma \in \Re_+$ are two positive real regularised parameters, and $Z = (\varphi(x_1), \varphi(x_2), ..., \varphi(x_l)) \in \Re^{n_h \times l}$.

The Lagrangian function for the problem shown in Eqs. 5 and 6 is defined as (Eq. 7):

$$\lambda(w_0, V, b, \Xi, A) = \Im(w_0, V, \Xi) - trace(A^T (Z^T W + repmat(b^T, l, 1) + \Xi - Y)), \tag{7}$$

where $A = (\alpha_1, \alpha_2, ..., \alpha_m) \in \Re^{l \times m}$ is a matrix containing of Lagrange multipliers. The Karush-Kuhn-Tucker conditions for optimality result the below set of linear equations (Eq. 8):

$$\begin{cases} \frac{\partial \lambda}{\partial w_0} = 0 \Rightarrow w_0 = \sum_{i=1}^{m} Z\alpha_i, \\ \frac{\partial \lambda}{\partial V} = 0 \Rightarrow V = \frac{m}{\lambda} ZA, \\ \frac{\partial \lambda}{\partial b} = 0 \Rightarrow A^T 1_l = 0_l, \\ \frac{\partial \lambda}{\partial \Xi} = 0 \Rightarrow A = \gamma \Xi, \\ \frac{\partial \lambda}{\partial A} = 0 \Rightarrow Z^T W + repmat(b^T, l, 1) + \Xi - Y = 0_{l \times m} \end{cases} \tag{8}$$

From Eq. 8, the mean vector, w_0 is a linear combination of $v_1, v_2, ..., v_m$. As mentioned earlier since $\forall_i \in \mathrm{N}_m$, so w_i is assumed to be $w_i = w_0 + v_i$ in which w_i is also a linear combination of $v_1, v_2, ..., v_m$. Hence, the following objective function (Eqs. 9 and 10) can obtain an equivalent optimisation problem with constraints including only the V, and b.

$$\min_{V \in \Re^{n_h}, b \in \Re^m} \Im(V, \Xi) = \frac{1}{2} \frac{\lambda^2}{m^2} V 1_m 1_m^T V^T + \frac{1}{2} \frac{\lambda}{m} trace(V^T V) + \gamma \frac{1}{2} trace(\Xi^T \Xi), \tag{9}$$

$$s.t. \quad Y = Z^T V + repmat(\frac{\lambda}{m} Z^T V 1_m, 1, m) + repmat(b^T, l, 1) + \Xi \tag{10}$$

From Eq. 9, MLSSVR figures out a trade-off between small size vectors for every output, $trace(V^T V)$, and nearness of all vectors to the mean vector, $V 1_m 1_m^T V^T$. Like the standard LSSVR, W and Ξ are discharged to get the below linear system (Eq. 11).

$$\begin{bmatrix} 0_{ml \times m} & P^T \\ P & H \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0_m \\ y \end{bmatrix} \tag{11}$$

where $P = \overbrace{blockdiag(1_l, 1_l, ..., 1_l)}^{m} \in \Re^{ml \times m}$, $H = \Omega + \gamma^{-1} I_{ml} + \left(\frac{m}{\lambda}\right) Q \in \Re^{ml \times ml}$,

$\Omega = repmat(K, m, m) \in \Re^{ml \times ml}$, $Q = \overbrace{blockdiag(K, K, ...K)}^{m} \in \Re^{ml \times ml}$, and $K = Z^T Z \in \Re^{l \times l}$ are definite matrices while $\alpha = (\alpha_1^T, \alpha_2^T, ..., \alpha_m^T)^T \in \Re^{ml}$ and $y = (y_1^T, y_2^T, ..., y_m^T) \in \Re^{ml}$ are vectors. Hence, the linear system shown in the Eq. 11 has $(l+1) \times m$ equations.

Then, the solution of Eq. 11 can be written in term of $\alpha^* = (\alpha_1^{*T}, \alpha_2^{*T}, ..., \alpha_m^{*T})^T$ and b^*. Hence, the respective decision function for the multiple output is (Eq. 12).

$$f(x) = \varphi(x)^T W^* + b^{*T} = \varphi(x)^T repmat(w_0^*, 1, m) + \varphi(x)^T V^* + b^{*T} = \varphi(x)^T repmat(\sum_{il}^{m} Z\alpha_{il}^*, 1, m) + \frac{m}{\lambda} \varphi(x)^T ZA^* + b^{*T} = repmat(\sum_{il=1}^{m} \sum_{j=1}^{l} \alpha_{il,j}^* \mathrm{K}(x, x_j), 1, m) + \frac{m}{\lambda} \sum_{j=1}^{l} \alpha^{j*} \mathrm{K}(x, x_j) + b^{*T} \tag{12}$$

Same as the conventional LSSVR, the linear system of MLSSVR as displayed in Eq. 11 is not positive define, hence solving Eq. 11 instantly is hard. But it can be reconstructed into the below linear system (Eq. 13):

$$\begin{bmatrix} S & 0_{ml \times ml} \\ 0_{m \times m} & H \end{bmatrix} \begin{bmatrix} b \\ H^{-1} Pb + \alpha \end{bmatrix} = \begin{bmatrix} P^T H^{-1} y \\ y \end{bmatrix}, \tag{13}$$

with $S = P^T H^{-1} P \in \Re^{m \times m}$. Notice that it is easy to display S that is a positive definite matrix. Then, this new linear system as shown in Eq. 13 can be solved using the below steps:

Step 1: Solve η, and ν from $H\eta = P$ and $H\nu = y$;

Step 2: Compute $S = P^T \eta$;

Step 3: Obtain the solution: $b = S^{-1} \eta^T y, \alpha = \nu - \eta b$.

Thus, in MLSSVR, the solution of the training procedure can be obtained by solving two sets of linear equations with the same positive definite coefficient matrix $H \in \Re^{ml \times ml}$ and the inverse matrix of $S \in \Re_{+}^{m \times m}$ can be computed easily (Xu et al. 2013).

In this study, the radial basis function (RBF) kernel function adopted from Keerthi and Lin (2003) as shown in Eq. 14 is used in the MLSSVR.

$$k(x, z) = \exp(-p\|x - z\|^2), p > 0 \tag{14}$$

where p is the positive hyperparameter of RBF kernel function. Moreover, all the tuning parameters in MLSSVP including γ, λ, and p are tuned and optimised using leave-one-out (LOO) procedure to obtain the average relative error, δ as shown in Eq. 15 (Xu et al. 2013).

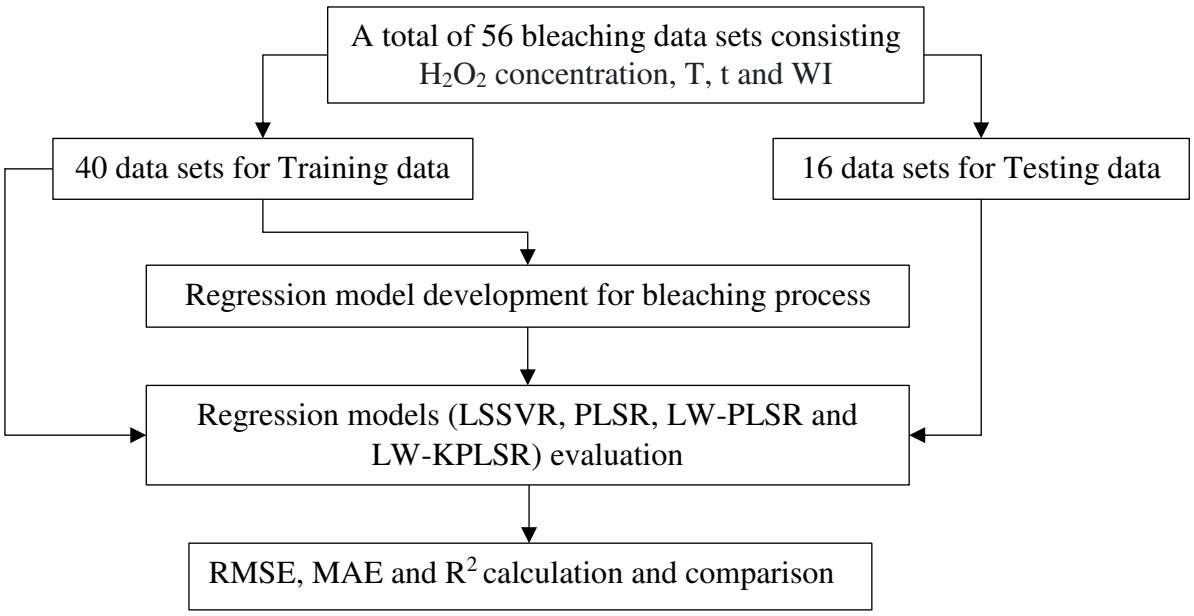
$$\delta = \frac{1}{l}\sum_{i=1}^{l} \frac{\left|Y_i - \hat{Y}_i\right|}{Y_i} \tag{15}$$

whereby Y_i shows the actual output, and $\hat{Y}_i$ shows the predicted output.

Regression models parameters setting

A total of 56 bleaching data sets which consists of H_2O_2 concentration, temperature, time of bleaching, and the WI of the cotton fabric were adopted from Haque et al. (2018). In this study, H_2O_2 concentration, T and t are served as the input variables for the regression models including MLSSVR, PLSR, LW-PLSR and LW-KPLSR models while the WI of the bleached cotton fabric is denoted as the output variable. These datasets are imported into MATLAB software, and they are split into 40 data sets are training data utilised to develop the regression models and 16 data sets are used as testing data for validation purposes. Moreover, training data are also employed to evaluate the performance of the MLSSVR, PLSR, LW-PLSR and LW-KPLSR models. Then, RMSE, MAE, and R^2 for all regression models are determined and compared. Figure 2 shows a flow chart explaining the framework of the regression models for the bleaching process.

247 N_T, N_1, N_2, and latent variable (LV) represent the total numbers of data sets, numbers of training
248 data sets, numbers of testing data sets, and number of LV, respectively. In this study, LV is set as
249 1, and the kernel parameter (b_k) for LW-KPLSR is set as 1 as well as the value of phi in the LW-
250 PLSR and LW-KPLSR are fixed at 0.1 (Yeo et al. 2017). Besides, some parameters for MLSSVR
251 model which are, γ, λ, and p were tuned using LOO technique to get the optimal results. The
252 summarised parameters setting for MLSSVR, PLSR, LW-PLSR and LW-KPLSR models are
253 displayed in Table 1.



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255 **Fig. 2** Framework of regression models for the bleaching process

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257 **Table 1** Values used for the regression models

Parameters	N_T	N_1	N_2	**LV**	**phi**	b_k	γ	λ	**p**
Values	56	40	16	1	0.1	1	15	10	3

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259 Accuracy of the predictive performance measurement

260 In this study, the performance of the prediction models is evaluated using RMSE, MAE, R^2 and
261 prediction error (PE). Both RMSE and MAE are goodness-of-fit indicators that

describe differences in observed and predicted values (Harmel et al. 2010). RMSE as shown in Eq. 16 is the square root of the total of the squared differences between the actual and expected output. Thus, a lower RMSE implies better accuracy and predictive performance (Hocaoğlu et al. 2008).

$$RMSE = \sqrt{\frac{\sum_i \left(Y_i - \hat{Y}_i\right)^2}{n}} \tag{16}$$

whereby n shows the number of samples.

MAE calculates the average absolute difference between the actual and predicted output value. The formula to calculate MAE is displayed in Eq. 17:

$$MAE = \frac{1}{n}\sum_{1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{17}$$

As can be seen from Eq. 18, R^2 is obtained by comparing the total of the squared errors to the total of the squared deviations about its mean. R^2 uses to measure the goodness of fit between real and predicted variables and its ranges is from 0 to 1 (Jaeger et al. 2017).

$$R^2 = 1 - \frac{\sum_i \left(Y_i - \hat{Y}_i\right)^2}{\sum_i \left(Y_i - \bar{Y}\right)^2} \tag{18}$$

whereby $\bar{Y}$ represents the mean value of the actual output.

Additionally, PE in percentage can be calculated using the below well-known equation such as Eq. 19 (Guang et al. 1995).

$$PE = \left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| \times 100\% \tag{19}$$

Computer hardware and software configuration specifications

In this study, all simulation works were performed on the same computer and software system to ensure the consistency of the results from all regression models. The hardware and software configuration specifications of the used Asus ZenBook UX305 laptop are Window 10 (64 bit);

The Central processing unit (CPU): 2.20 GHz Intel core M3-6Y30, CPU processor, 4.0 GB of Random-access memory and 128GB Solid state drive storage. And the software used is MATLAB version R2021a.

Results and discussion

As mentioned earlier, an LSSVR-based model that is called MLSSVR is developed using the bleaching process parameters, and these parameters including H_2O_2 concentrations, T, t, and WI of cotton fabric samples are nonlinear. The higher the value of WI indicates the greater the degree of whiteness of the cotton fabric. Whiter cotton fabric is desired before it is dyed, printed or other wet-treatments (Ferreira et al. 2019; Kabir et al. 2014). Many studies have reported that WI of cotton fabric can be increased by H_2O_2 concentrations and T (Abdul and Narendra 2013; Ferdush et al.). Nevertheless, the high concentrations of H_2O_2 could break up the unsaturated bonds, like C=C, and then decreases the bursting strength of cotton fabric (Ferdush et al. ; Haque and Islam 2015; Tang et al. 2016). Hence, the optimum bleaching process parameters are required to determine the effectiveness of the bleaching process to produce a targeted cotton fabric whiteness. The predictive modelling techniques including the MLSSVR model can be used to estimate the outcome or the results of the bleached cotton fabric such as its WI using the bleaching process parameters. Initially, a fuzzy predictive model was constructed by Haque et al. (2018) for a bleaching process using a MATLAB app that is called a fuzzy logic designer. However, this method is unable to predict beyond the range of the input data. Hence, in this study, an MLSVVR was developed using the bleaching process parameters to overcome the limitations of this fuzzy method. Moreover, other regression models including PLSR, LW-PLSR and LW-KPLSR models were also built using the same process parameters. All results from these regression models are summarised in Table 2 for comparison purpose. In Table 2, the results for fuzzy method were adopted from Haque et al. (2018).

308 **Table 2** Comparison of results from MLSSVR, fuzzy method, PLSR, LW-PLSR and LW-KPLSR models

Results	MLSSVR	Fuzzy method*	PE (%)	PLSR	PE (%)	LW-PLSR	PE (%)	LW-KPLSR	PE (%)
Kernel function	RBF	-	-	-	-	-	-	Log kernel	-
$RMSE_1$	**0.1606**	0.7373	359	2.1014	1209	0.3335	108	0.4755	196
MAE_1	**0.1126**	0.6133	445	1.5981	1320	0.2560	127	0.4088	263
R^2_1	**0.9985**	0.9673	3	0.6469	35	0.9934	1	0.9863	1
$RMSE_2$	**0.3339**	0.5358	60	1.2194	265	0.8122	143	0.6714	101
MAE_2	**0.2388**	0.4781	234	1.0427	337	0.7101	197	0.5861	145
R^2_2	**0.9829**	0.9549	3	0.8357	15	0.9103	7	0.9334	5

309 *Results for fuzzy method were taken from Haque et al. (2018).

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From Table 2, $RMSE_1$, MAE_1, and R^2_1 are the RMSE, MAE and R^2 for training data whereas $RMSE_2$, MAE_2, and R^2_2 are the RMSE, MAE and R^2 for testing data. Among these regression models, MLSSVR with RBF kernel function provided the best predictive performance. On the other hand, PLSR which is a linear model gave the worse results as PLSR is unable to cope with the nonlinear process data from bleaching process [30]. As compared with PLSR, MLSSVR has lowered 265% to 1320% of all RMSE and MAE values as well as 15% to 35% higher values of all R^2. Additionally, as compared to fuzzy method, MLSSVR obtained 60% to 445% lower RMSE and MAE values and 3% higher R^2 values. The fuzzy method involves membership function, fuzzy logic operators, and if-then rules. There are three conceptual components such as a rule case that include a selection of fuzzy rules, a database which explains the membership functions used in the fuzzy rules, and a reasoning mechanism that shows the inference way upon the rules to derive an output (Brevern et al. 2009; Kovac et al. 2013). From Table 2, for testing data set, fuzzy method performed better than PLSR, LW-PLSR, and LW-KPLSR in which the $RMSE_2$ and MAE_2 for fuzzy method are lower and its R^2_2 values are higher. However, the overall results show that this fuzzy method worked poorer than MLSSVR. This may be due to the helps of LOO in the MLSSVR to determine the optimal tuning parameters and the RBF kernel function that helps to map the original data into a high dimensional space for better prediction. For both LW-PLSR and LW-KPLSR, notice that MLSSVR demonstrated 101% to 263% lower RMSE and MAE values and 1% to 7% higher R^2 values. On the other hand, LW-PLSR and LW-KPLSR gave better results than fuzzy method for the training data set where their $RMSE_1$ and MAE_1 are lower and R^2_1 are higher. This may be due to the presence of locally weighted algorithm in the LW-PLSR and LW-KPLSR which improves their predictive performance for the training data. From Figures 3 and 4, it is obvious that the outputs for training data and testing data from MLSSVR are closer to the actual data as compared to other models. Moreover, from Figure 5 which illustrates the correlation between the actual and predicted values of output from MLSSVR for testing data, all the data

points are closed to the line. In general, the results show that MLSSVR copes much better than the rest of the methods. Hence, it can conclude that MLSSVR is an effective method to predict the WI using the bleaching process parameters.

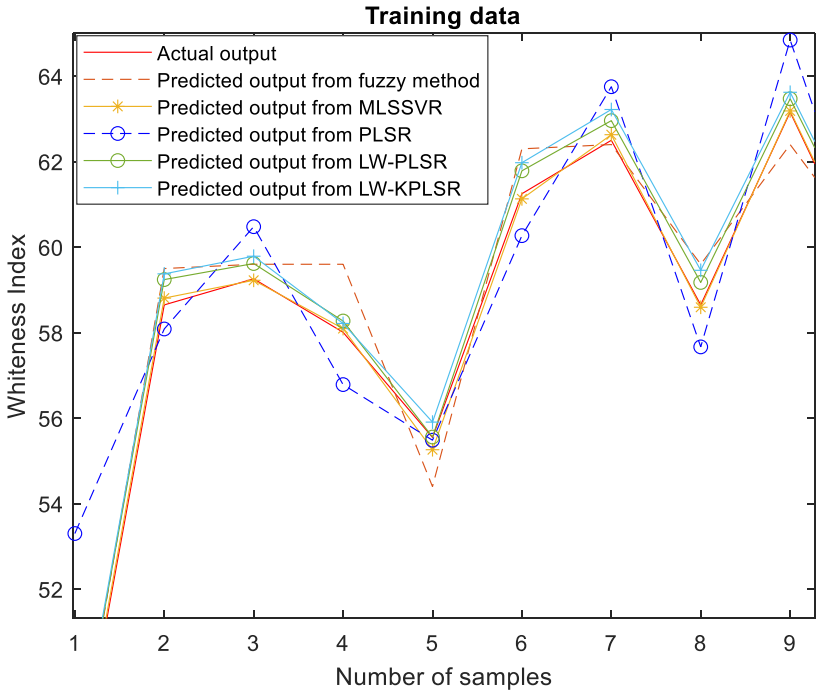

Fig. 3 Comparison of the predicted output values from regression models for training data

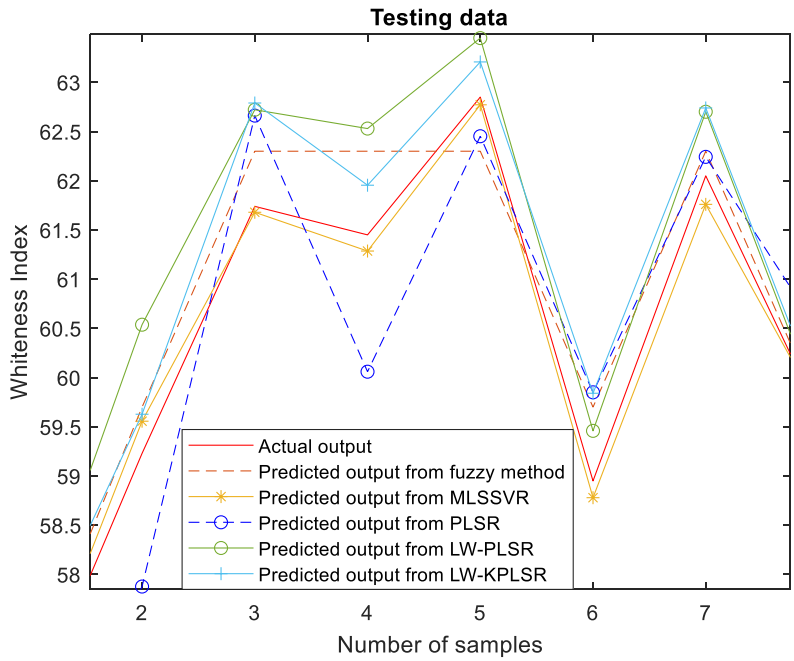

Fig. 4 Comparison of the predicted output values from regression models for testing data

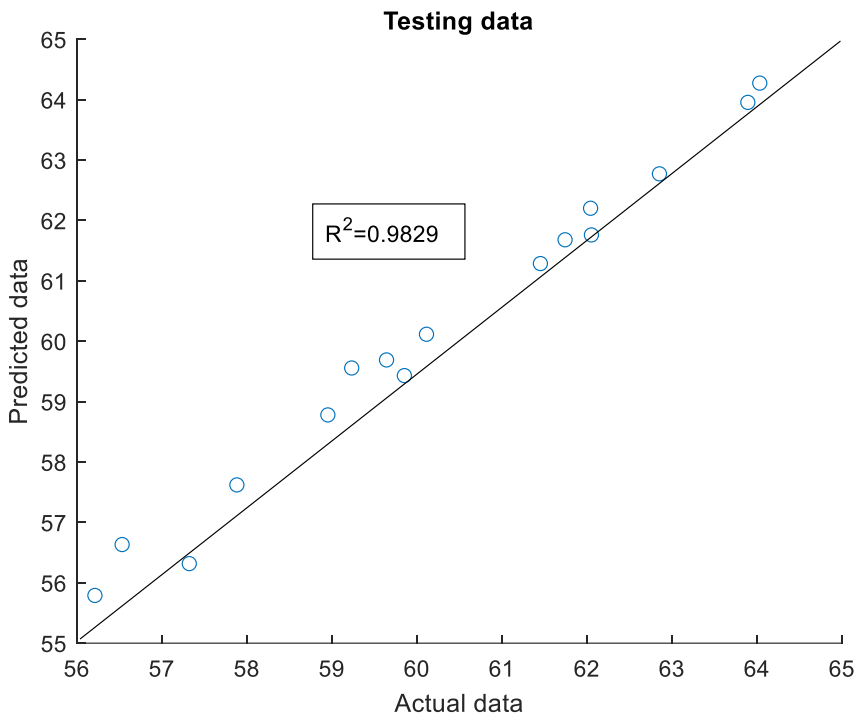

Fig. 5 Correlation between the actual and predicted values of output from MLSSVR for testing data

Conclusions

In the current study, a LSSVR-based model, namely MLSSVR was developed using the bleaching process parameters like H_2O_2 concentrations, T, and t to predict the WI of the cotton fabric. It is important to determine the optimal bleaching process parameters to achieve the highest WI values of the cotton fabrics. Hence, the predictive modelling including MLSSVR plays an essential role to meet the targeted quality of cotton fabrics in the textile manufacturing processes. By contract with fuzzy method, PLSR, LW-PLSR and LW-KPLSR, the developed MLSSVR was outperformed where its RMSE and MAE values were improved by 60% to 1209% and its R^2 values are the highest that are up till 0.9985. These results denote that MLSSVR model is a potential predictive model for the bleaching process in the textile domain. In future studies, the inclusion of locally weighted algorithm in the MLSSVR model could be expected to enhance its predictive outcomes.

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Conflicts of interest/Competing interests

The author has no conflicts of interest to declare. The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Authors' contributions

The author discussed the results and contributed to the final manuscript.

Ethics approval

This research program does not involve testing to be done on humans or animals. It also does not involve any potentially dangerous equipment and hazardous substance of any kind. Therefore, no ethical issue will be expected in this research project.

Compliance with ethical standards

No animal studies or human participants involvement in the study, hence this research project is compliance with ethical standards.

Abbreviations

A	A matrix consisting Lagrange multipliers
b	A threshold value
b_k	Kernel parameter for locally weighted kernel partial least square
CIE	Commission on Illumination
CPU	Central processing unit (CPU)
H, P, Q, K, Ω, 0, S	A definite matrix
H_2O_2	Hydroxide peroxide
LSSVR	Least squares support vector regression
LOO	Leave-one-out
LW-KPLSR	Locally weighted Kernel partial least square regression
LW-PLSR	Locally weighted partial least square regression
LV	Latent variable
MAE	Mean absolute error
p	A positive hyperparameter of radial basis function kernel function
PE	Prediction error
PLSR	Partial least square regression
MLSSVR	Multi-output least square support vector regression
N_T	Total number of data sets
N_1	Number of training data sets
N_2	Number of testing data sets
R^2	R-squared or the coefficient of determination
RBF	Radial basis function
RMSE	Root mean square error
SVM	Support vector machine
T	Temperature of bleaching process
t	Time of bleaching process
V, v_i	A vector in multi-output least square support vector regression
WI	Whiteness index
W	Weighed value vector
x_i, x	Input vector
x_c and y_c	Chromaticity coordinates of the bleached cotton fabric samples
x_n and y_n	Chromaticity coordinates of the illuminant
y^i, y, Y	Output vector
Y_L	Lightness
Z	A mapping to some high or even unlimited/ infinite dimensional Hilbert space or feature space via the nonlinear mapping function φ with n_h dimensions
γ, λ	Two positive real regularised parameters in the multi-output least square support vector regression
$\varphi(x)$	A nonlinear mapping function
ξ	A vector containing slack variables
Ξ	A matrix consisting of slack variables with an order of $l \times m$
α	A vector consisting of Lagrange multipliers
λ	The Lagrangian function

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