Advanced Research Journal
Volume 6, Number 1, 2025, 35-51
DOI: 10.71350/3062192558
ISSN: 3062-1925

Article

Predictive modeling of tearing strength in laser-engraved denim garments using Multiple Linear Regression

Ashikur Rahaman[1], Elias Khalil [2], Md. Hamid Miah[3], Sabbir Ahmed[4], Arman Hossen[1], Srity Khatun[3]

[1]Department of Yarn Engineering, Tangail Textile Engineering College, Tangail, Bangladesh
[2]Department of Wet Process Engineering, Tangail Textile Engineering College, Tangail, Bangladesh
[3]Department of Fabric Engineering, Tangail Textile Engineering College, Tangail, Bangladesh
[4]Department of Apparel Engineering, Tangail Textile Engineering College, Tangail, Bangladesh

Abstract

This study presents the development of a Multiple Linear Regression (MLR) model to predict the tearing strength of laser-engraved denim garments in both the warp and weft directions, based on key input parameters: Dot Per Inch (DPI) and pixel time. The model achieved excellent predictive accuracy, with R^2 values of 0.9967 for the warp direction and 0.9911 for the weft direction, indicating that over 99% of the variability in tearing strength was explained by the model. The Pearson correlation coefficients (0.9983 for warp, 0.9956 for weft) and Spearman's rank correlation coefficients (1 for warp, 0.9833 for weft) further confirm the strength of the relationship between the predicted and actual values. The Mean Absolute Percentage Error (MAEP) values of 0.8783% (warp) and 1.6837% (weft) demonstrate the model's high accuracy, with significantly lower errors compared to previous fuzzy logic model. Residual analysis confirmed the assumptions of normality, homoscedasticity, and independence, validating the model's reliability. The MLR model provides a robust tool for optimizing laser engraving parameters in denim manufacturing, reducing the need for trial-and-error testing and ensuring consistent product quality.

Article History
Received 13.02.2025
Accepted 16.05.2025

Keywords
Laser-engraving on denim, Tearing strength, Multiple Linear Regression (MLR), Dot Per Inch (DPI), Pixel time

Introduction

Denim is a heavy cotton twill fabric, typically dyed with indigo, that is widely used in the production of jeans and other garments (Bilisik & Demiryurek, 2011). Its distinctive weave, which creates diagonal ribbing, provides both durability and flexibility, making it suitable for a variety of clothing items, including workwear and casual apparel (Lord & Mohamed, 1982). Over time, denim has become a key component of global fashion, known for its ability to develop a unique patina with wear, adding to its appeal. Modern innovations in denim, such as laser engraving, continue to expand its versatility and aesthetic possibilities (Khalil, 2015).

Laser engraving on denim garments has gained popularity as a modern alternative to traditional denim distressing techniques, such as sandblasting and acid washing, offering more precision and design flexibility (Nayak & Padhye, 2016). This technology utilizes focused

Corresponding Author Elias Khalil Tangail Textile Engineering College, Department of Wet Process Engineering, Tangail, Bangladesh

laser beams to create intricate patterns, textures, and fading effects without physical contact with the fabric, resulting in cleaner, crisper designs (Kan, 2014). One of the significant advantages of laser engraving is its ability to produce high-quality, permanent marks with reduced environmental impact, as it eliminates the need for toxic chemicals and water (Kan et al., 2010). The process also allows for real-time control of laser power, ensuring that the fabric is not damaged, such as by unwanted charring or excessive fading (Jucienė et al., 2014). As laser technology continues to evolve, it presents an exciting opportunity for the fashion industry to achieve sustainable, customized, and innovative denim designs.

The effect of dots per inch (DPI) and pixel time (μs) on various properties of denim garments has been a subject of recent research, particularly in the context of laser engraving technology. DPI, which refers to the resolution of the laser engraving process, directly influences the precision and clarity of the designs etched on the denim fabric. Higher DPI values tend to result in more detailed and finer engravings, which can enhance the aesthetic appeal of the garment but may also impact the fabric's strength and texture. On the other hand, Pixel Time controls the exposure time of the laser beam, influencing the depth and intensity of the engraved patterns. Longer Pixel Time can lead to more pronounced fading and deeper engravings, which could potentially weaken the fabric if overexposed (Kan et al., 2010; Nayak & Padhye, 2016).

The combination of DPI and Pixel Time affect multiple fabric properties, including tear strength, color fading, and fabric durability. For instance, higher DPI coupled with excessive Pixel Time can cause a reduction in fabric integrity, particularly in terms of tear strength, as the laser removes more material from the surface (Kan, 2014). Moreover, the laser process, when optimized, can achieve a balance between aesthetic enhancements and the preservation of fabric strength, making it a more sustainable option compared to traditional distressing methods like sandblasting (Ortiz-Morales et al., 2003). These laser settings also influence the appearance of fading—a key characteristic of denim fashion—by allowing precise control over the extent and pattern of the fading. Sarkar et al. studied the effect of CO_2 laser engraving on 100% cotton denim, focusing on dots per inch (DPI) and pixel time. The results showed that higher DPI and longer Pixel Time significantly reduced fabric weight, tearing strength, and crease recovery angle, with tearing strength decreasing by up to 66% (Sarkar et al., 2015). While the laser treatment enhanced aesthetics, it also weakened the fabric, making it softer and more prone to creasing. The study highlights the need for balancing laser intensity to maintain fabric durability while achieving the desired design effects (Sarkar et al., 2015). The optimal laser parameters, including DPI and Pixel Time, depend on the specific application and the desired effect on the garment's properties. Researchers have noted that understanding the interplay between these parameters is crucial for manufacturers to avoid compromising fabric performance while achieving the desired visual effects (Sarkar et al., 2022).

A prediction model for tearing strength is necessary to accurately forecast fabric performance under stress, ensuring product quality and durability in textile manufacturing. It helps manufacturers optimize production processes, reduce material waste, and enhance the design of fabrics for specific applications, ultimately improving cost-efficiency and product reliability.

Eltayib et al. developed a multiple linear regression model to predict fabric tear strength based on yarn count, yarn tensile strength, and fabric linear density. The study analyzed nine fabric samples, revealing significant correlations between these variables and tear strength in both the warp and weft directions, providing valuable insights for fabric optimization in industrial applications (Eltayib et al., 2016).Gültekin et al. applied the Decision Tree Regression method to predict the tear strength of woven fabrics, utilizing factors such as weave type, fabric density, filament fineness, and weave direction. Their model demonstrated strong predictive accuracy with an R^2 value of 0.97, highlighting the potential of machine learning for improving quality control in textile manufacturing (Gültekin et al., 2021). The study by Ahirwar and Behera focuses on predicting the tear strength of bed sheet fabric using a machine learning-based artificial neural network (ANN). The research developed a novel algorithm that takes fabric parameters as input and predicts the warp and weft tear strength as output. Among various algorithms tested, the XGBoost model (Extreme Gradient Boosting) provided the best results, with training accuracy of 99.99%. The model's potential to predict fabric tear strength accurately could be highly beneficial for textile industries, optimizing production and reducing costs (Ahirwar & Behera, 2024). Bilisik and Demiryurek analyzed the tensile and tear properties of abraded denim fabrics with different structural patterns using statistical and artificial neural network (ANN) models. The study explored the impact of abrasion cycles on the mechanical properties of traditional and newly developed denim fabrics. The results indicated that abrasion cycles generally decrease tensile and tear strengths for all fabric types. However, ANN models outperformed regression models, providing more accurate predictions of fabric properties, with high correlation coefficients and low Mean Absolute Percent Errors (MAPE) (Bilisik & Demiryurek, 2011). Kotb et al. investigated factors influencing the tearing strength of pile fabrics produced on face-to-face looms with dobby devices. Using fractional factorial experiments, the study identified significant factors such as the type and count of weft yarns, weft density, ground structure, and tension on ground yarns, which strongly affect tearing strength. The results revealed that polyester weft yarns and higher weft yarn counts generally decreased tearing strength in the warp direction but increased it in the weft direction. Additionally, pile shape and shifting of pile designation had lesser impacts on tear strength. Regression models developed from these findings provide valuable insights for designing fabrics with improved tearing strength.

While Sarkar et al. (2022) developed a fuzzy logic-based model to predict the tearing strength of laser-engraved denim garments, their model primarily focused on using complex fuzzy logic to relate laser parameters such as Dots Per Inch (DPI) and Pixel Time (PT) to fabric tearing strength in both warp and weft directions. Although their model provided valuable insights, the complexity of the fuzzy logic approach may limit its accessibility and practical application for certain textile manufacturers. Furthermore, while fuzzy logic showed promising results, there is limited research comparing it to simpler predictive methods, particularly in the context of laser-engraved denim. This leaves a gap in understanding whether simpler regression techniques, such as Multiple Linear Regression (MLR), could offer equal or superior predictive accuracy while being more straightforward to implement and interpret. Additionally, existing studies, including that of Sarkar et al. (2022), have not sufficiently explored or validated the use of MLR for predicting tearing strength in laser-engraved denim. Furthermore, while Sarkar et al. (2022) focused on predicting the tearing strength using fuzzy logic, they did not consider the potential of MLR to deliver better prediction accuracy. Finally, no prior research has comprehensively modeled both the warp and weft tearing strength using MLR, creating an opportunity to bridge this gap.

This research seeks to fill this gap by using Multiple Linear Regression (MLR) to predict the tearing strength of laser-engraved denim garments, utilizing the same input parameters (DPI and Pixel Time) as Sarkar et al. (2022). Given that MLR has been shown to provide better prediction accuracy compared to fuzzy logic, this study will evaluate MLR's performance against the fuzzy logic-based model from Sarkar et al., highlighting the advantages of MLR in terms of both predictive power and simplicity. By directly comparing these two methods, this study will contribute valuable insights into the effectiveness of simpler regression-based models for denim garments tearing strength prediction. This approach will offer a more efficient, accurate, and accessible tool for manufacturers in the textile industry, providing a new and improved model for predicting tearing strength in laser-engraved denim garments.

Methodology

Data Source

The data used in this study were obtained, with permission, from a research paper by Sarkar, Al Faruque, and Khalil (Sarkar et al., 2022). The dataset, which includes two laser engraving parameters—Dots Per Inch (DPI) and Pixel Time (PT)—along with the corresponding tearing strength values measured in both the warp and weft directions, is shown in **Table 1.**

Table 1. The dataset includes two laser engraving parameters—Dots Per Inch (DPI) and Pixel Time (PT)—along with the corresponding tearing strength values measured in both the warp and weft directions (Sarkar et al., 2022) .

Sl	Input parameters		Output parameters	
	Dot Per Inch	Pixel Time (μs)	Tearing Strength - Warp Way (lb)	Tearing Strength - Weft Way (lb)
1	15	100	6.90	7.21
2	15	150	5.81	6.40
3	15	200	5.10	5.30
4	20	100	5.79	5.90
5	20	150	4.98	5.36
6	20	200	4.12	4.30
7	25	100	4.88	5.15
8	25	150	3.97	4.10
9	25	200	3.20	3.30

Data Preprocessing and Feature Scaling

To prepare the data for the modeling process, the DPI and Pixel Time (PT) features were standardized using the StandardScaler from the scikit-learn library. Standardization ensures that both features have a mean of 0 and a standard deviation of 1, which improves the performance and accuracy of the regression model by preventing features with larger scales from dominating the model.

Multiple Linear Regression (MLR) Model

The MLR model was used to predict the tearing strength in both the warp and weft directions. The MLR model is represented by the equation 1:

$$\hat{y}_i = \hat{m}_1 x_{1i} + \hat{m}_2 x_{2i} + \cdots + \hat{m}_k x_{ki} + \hat{c} \qquad (1)$$

where:

- $\hat{y}_i$ represents the predicted value of tearing strength for the i-th observation,
- $x_{1i}, x_{2i}, \ldots, x_{ki}$ are the predictor values for the i-th sample,
- $\hat{m}_1, \hat{m}_2, \ldots \ldots \ldots, \hat{m}_k$ are the estimated coefficients corresponding to each predictor, and
- $\hat{c}$ is the intercept.

To estimate the model parameters, the least squares method was applied. The objective is to minimize the sum of squared residuals between the observed and predicted values of tearing strength. The objective function is expressed as:

$$\xi = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad \ldots\ldots(2)$$

Substituting the model equation for $\hat{y}_i$, the objective function becomes:

$$\xi = \sum_{i=1}^{n} (y_i - \hat{m}_1 x_{1i} - \hat{m}_2 x_{2i} - \cdots - \hat{m}_k x_{ki} - \hat{c})^2 \quad \ldots\ldots(3)$$

To minimize the objective function, the partial derivatives of ξ with respect to the coefficients $\hat{m}_1, \hat{m}_2, \ldots, \hat{m}_k$, and the intercept $\hat{c}$ are computed. The partial derivatives are as follows:

$$\frac{\partial \xi}{\partial \hat{c}} = -2 \sum_{i=1}^{n} (y_i - \hat{m}_1 x_{1i} - \hat{m}_2 x_{2i} - \cdots - \hat{m}_k x_{ki} - \hat{c}) \quad \ldots\ldots(4)$$

$$\frac{\partial \xi}{\partial \hat{m}_1} = -2 \sum_{i=1}^{n} (y_i - \hat{m}_1 x_{1i} - \hat{m}_2 x_{2i} - \cdots - \hat{m}_k x_{ki} - \hat{c}) x_{1i} \quad \ldots\ldots(5)$$

$$\frac{\partial \xi}{\partial \hat{m}_2} = -2 \sum_{n}^{i=1} (y_i - \hat{m}_1 x_{1i} - \hat{m}_2 x_{2i} - \cdots - \hat{m}_k x_{ki} - \hat{c}) x_{2i} \quad \ldots\ldots(6)$$

.

.

$$\frac{\partial \xi}{\partial \hat{m}_k} = -2 \sum_{i=1}^{n} (y_i - \hat{m}_1 x_{1i} - \hat{m}_2 x_{2i} - \cdots - \hat{m}_k x_{ki} - \hat{c}) x_{ki} \quad \ldots\ldots(7)$$

To obtain the values of the coefficients $\hat{m}_1, \hat{m}_2, \ldots, \hat{m}_k$, and the intercept $\hat{c}$, the partial derivatives are set to zero. This results in the normal equations, which are a system of linear equations that can be solved for the unknowns:

$$\sum_{i=1}^{n} y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i} + \hat{m}_2 \sum_{i=1}^{n} x_{2i} + \cdots \hat{m}_k \sum_{i=1}^{n} x_{ki} + n\hat{c} \quad \ldots\ldots(8)$$

$$\sum_{i=1}^{n} x_{1i} y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i}^2 + \hat{m}_2 \sum_{i=1}^{n} x_{1i} x_{2i} + \cdots \hat{m}_k \sum_{i=1}^{n} x_{1i} x_{ki} + \hat{c} \sum_{i=1}^{n} x_{1i} \quad \ldots\ldots(9)$$

$$\sum_{i=1}^{n} x_{2i}y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i}x_{2i} + \hat{m}_2 \sum_{i=1}^{n} x_{2i}^2 + \cdots \hat{m}_k \sum_{i=1}^{n} x_{2i}x_{ki} + \hat{c} \sum_{i=1}^{n} x_{2i} \qquad \ldots\ldots\ldots(10)$$

.

.

$$\sum_{i=1}^{n} x_{ki}y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i}x_{ki} + \hat{m}_2 \sum_{i=1}^{n} x_{2i}x_{ki} + \cdots \hat{m}_k \sum_{i=1}^{n} x_{ki}^2 + \hat{c} \sum_{i=1}^{n} x_{ki} \qquad \ldots\ldots\ldots(11)$$

For two independent variables,

$$\hat{y}_i = \hat{m}_1 x_{1i} + \hat{m}_2 x_{2i} + \hat{c} \qquad \ldots\ldots\ldots(12)$$

The resulting normal equations are

$$\sum_{i=1}^{n} y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i} + \hat{m}_2 \sum_{i=1}^{n} x_{2i} + n\hat{c} \qquad \ldots\ldots\ldots(13)$$

$$\sum_{i=1}^{n} x_{1i}y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i}^2 + \hat{m}_2 \sum_{i=1}^{n} x_{1i}x_{2i} + \hat{c} \sum_{i=1}^{n} x_{1i} \qquad \ldots\ldots\ldots(14)$$

$$\sum_{i=1}^{n} x_{2i}y_i = \hat{m}_1 \sum_{i=1}^{n} x_{1i}x_{2i} + \hat{m}_2 \sum_{i=1}^{n} x_{2i}^2 + \hat{c} \sum_{i=1}^{n} x_{2i} \qquad \ldots\ldots\ldots(15)$$

Software Implementation

The regression analysis and model evaluation were implemented using Python programming language, utilizing libraries, pandas for data manipulation, scikit-learn for regression modeling, and NumPy for mathematical operations. The StandardScaler from scikit-learn was used for standardizing the features before fitting the regression model.

Model Evaluation Metrics

To assess the performance of the Multiple Linear Regression (MLR) model, several evaluation metrics were employed. R^2 (Coefficient of Determination) was used to determine the proportion of variance between the observed data and predicted data found from the model. The Pearson Correlation Coefficient (R) was calculated to measure the linear correlation between the observed and predicted values. The Mean Absolute Error Percentage (MAEP) quantifies the magnitude of error as a percentage of the actual values, while Mean Squared Error (MSE) and its square root, Root Mean Squared Error (RMSE), provide insights into the overall error and the magnitude of the error in the same units as the target variable. Percent Bias (PBIAS) evaluates whether the model tends to overestimate or underestimate the observed values. The Standard Error of Estimate (SEE) indicates the degree to which the model fits the data, and the Explained Variance Score measures the proportion of variance explained by the model. Additionally, Adjusted R^2 provides an adjusted version of R^2 that accounts for the number of predictors in the model. Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE) were also used to assess the model's predictive skill, considering factors variance, correlation, and bias. Spearman's Rank Correlation Coefficient (ϱ) measures the strength and direction of the monotonic relationship between the observed and predicted values. These metrics were computed to evaluate the accuracy, reliability, and robustness of the model's predictions. Mathematical equations of the above matrices are shown below:

1. Coefficient of Determination, $R^2 = 1 - \frac{\sum\left(y_{\text{true}} - y_{\text{pred}}\right)^2}{\sum(y_{\text{true}} - \bar{y})^2}$……………………………..……..(16)

   Where, y_{true} represents actual or observed values, y_{pred} is the predicted values from the regression model and $\bar{y}$ is the mean of the actual values.

2. Pearson Correlation Coefficient, $R = \frac{\sum(y_{\text{true}} - \bar{y}) \cdot \left(y_{\text{pred}} - \overline{y_{\text{pred}}}\right)}{\sqrt{\sum(y_{\text{true}} - \bar{y})^2 \cdot \sum\left(y_{\text{pred}} - \overline{y_{\text{pred}}}\right)^2}}$ ……………….………..(17)

   Where , n is the number of observations and $\overline{y_{\text{pred}}}$ is the mean of the predicted values.

3. Mean Squared Error, $(MSE) = \frac{1}{n}\sum\left(y_{\text{true}} - y_{\text{pred}}\right)^2$…………………………….………….…..(18)

4. Root Mean Squared Error, $(RMSE) = \sqrt{\frac{1}{n}\sum\left(y_{\text{true}} - y_{\text{pred}}\right)^2}$…………………….………..(19)

5. Percentage Bias, $(PBIAS) = \frac{\sum\left(y_{\text{true}} - y_{\text{pred}}\right)}{\sum y_{\text{true}}} \times 100$…………………………..……….……..(20)

6. Nash-Sutcliffe Efficiency, $(NSE) = 1 - \frac{\sum\left(y_{\text{true}} - y_{\text{pred}}\right)^2}{\sum(y_{\text{true}} - \bar{y})^2}$………………………………..……(21)

7. Adjusted $R^2 = 1 - \left(\frac{1 - R^2}{n - 1}\right) \times (n - p - 1)$…………………………………..…….……(22)

   Where n is the number of observations and p is the number of predictors.

8. Mean Absolute Percentage Error, $(MAPE) = \frac{1}{n}\sum\left|\frac{y_{\text{true}} - y_{\text{pred}}}{y_{\text{true}}}\right| \times 100$…………..……….(23)

9. Mean Squared Logarithmic Error, $(MSLE) = \frac{1}{n}\sum\left(\log(1 + y_{\text{true}}) - \log(1 + y_{\text{pred}})\right)^2$……(24)

10. Standard Error of the Estimate, $(SEE) = \sqrt{\frac{1}{n-2}\sum\left(y_{\text{true}} - y_{\text{pred}}\right)^2}$……………..…………..(25)

11. Explained Variance Score $= 1 - \frac{\text{Var}\left(y_{\text{true}} - y_{\text{pred}}\right)}{\text{Var}(y_{\text{true}})}$…………………………..………..…….(26)

    Here, 'Var' represents variance function, which computes the variance of the data.

12. Kling-Gupta Efficiency, $KGE = 1 - \sqrt{(r - 1)^2 + \left(\frac{\sigma_{\text{pred}}}{\sigma_{\text{true}}} - 1\right)^2 + \left(\frac{\mu_{\text{pred}}}{\mu_{\text{true}}} - 1\right)^2}$ ……………..(27)

    Where:

    - r is the correlation coefficient between the predicted and observed values.
    - σ_{pred} is the standard deviation of the predicted values.
    - σ_{true} is the standard deviation of the actual values.
    - μ_{pred} is the mean of the predicted values.
    - μ_{true} is the mean of the actual values.

13. Spearman's Rank Correlation, $\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}$…………………….…………………….(28)

    Where:

    - d_i is the difference between the ranks of the paired data points
    - $\sum d_i^2$ is the sum of the squared rank differences.

Results and Discussion

Development and Prediction of MLR model

The developed Multiple Linear Regression (MLR) models for predicting the tearing strength of laser-engraved denim garments in the warp and weft directions are represented by the equation (29) to (30).

$$Y_1 = 11.387 - (0.192 \times x_1) - (0.01767 \times x_2) \quad (29)$$

$$Y_2 = 12.144 - (0.212 \times x_1) - (0.01787 \times x_2) \quad (30)$$

Here,

- Y_1 is the Tearing strength in warp way (lb)
- Y_2 is the Tearing strength in weft way (lb)
- x_1 is Dot Per Inch and
- x_2 is Pixel Time (μs)

Both models indicate a negative impact of DPI and pixel time on tearing strength. In the warp direction, an increase in DPI decreases strength by 0.192 lb, and in the weft direction, DPI reduces strength by 0.212 lb. Pixel time reduces strength similarly in both directions, with a decrease of 0.01767 lb for warp and 0.01787 lb for weft. These results underscore the importance of controlling laser parameters to optimize fabric durability.

The table 2 presents the actual and MLR-predicted values of tearing strength in both the warp and weft directions, along with the absolute prediction errors for various combinations of Dot Per Inch (DPI) and pixel time. The results show that the MLR model provides relatively accurate predictions for both warp and weft tearing strength, with absolute errors generally remaining below 4%. This indicates that the MLR model has a high degree of predictive accuracy, demonstrating its potential for practical use in predicting tearing strength based on laser engraving parameters.

Table 2. Prediction of tearing strength by MLR Model.

Sl	Dot Per Inch	Pixel Time (μs)	Tearing Strength-Warp Way			Tearing Strength-Weft Way		
			Actual Value (N)	MLR Predicted Value (N)	Absolute Error (%)	Actual Value (N)	MLR Predicted Value (N)	Absolute Error (%)
1.	15	100	6.9	6.79	1.5862	7.21	7.18	0.45
2.	15	150	5.81	5.93	2.1037	6.40	6.28	1.81
3.	15	200	5.1	5.07	0.512	5.30	5.39	1.72
4.	20	100	5.79	5.83	0.7004	5.90	6.12	3.69
5.	20	150	4.98	4.97	0.1562	5.36	5.22	2.53
6.	20	200	4.12	4.11	0.1483	4.30	4.33	0.72
7.	25	100	4.88	4.87	0.1935	5.15	5.06	1.79
8.	25	150	3.97	4.01	1.0635	4.10	4.16	1.57
9.	25	200	3.2	3.15	1.441	3.30	3.27	0.88

The **Figure 1** illustrates the sensitivity of tearing strength to variations in the input parameters, Dot Per Inch (DPI) and Pixel Time, for both warp and weft directions. In figure 1(a), the sensitivity of tearing strength in the warp direction to changes in DPI and pixel time is shown, where both input parameters exhibit a linear relationship with tearing strength. Similarly, figure 1(b) displays the sensitivity of tearing strength in the weft direction, with a similar trend observed. The graphs demonstrate that tearing strength decreases as both DPI and pixel time increase, highlighting the negative correlation between these inputs and fabric durability in both directions. This sensitivity analysis underscores the importance of optimizing DPI and pixel time during the laser engraving process to control the tearing strength of denim garments.

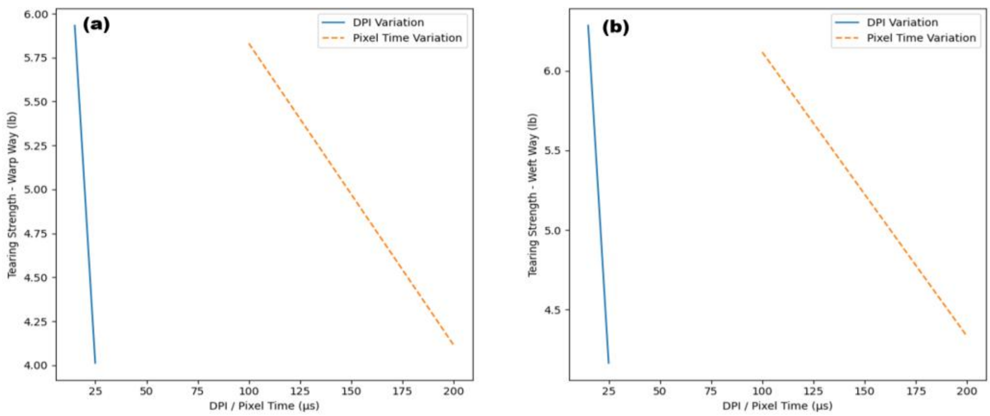

Figure 1. Sensitivity of tearing strength to variations in the input parameters, Dot Per Inch (DPI) and Pixel Time, (a) warp way (b) weft way

Figure 2 presents the 3D surface and contour plots for tearing strength in the warp direction, showing the sensitivity to variations in Dot Per Inch (DPI) and pixel time. Figure 2(a) displays the 3D surface plot, where it is evident that tearing strength decreases as both DPI and pixel time increase. The surface shows a smooth downward slope, indicating a consistent reduction in strength with higher values of both input parameters. Figure 2(b) complements this by showing the contour plot, which visually reinforces the negative relationship between DPI, pixel time, and tearing strength. The contour lines gradually move from yellow (higher strength) to purple (lower strength), demonstrating how tearing strength in the warp direction declines as DPI and pixel time rise. These visualizations clearly illustrate the negative sensitivity of warp way tearing strength to these input variables.

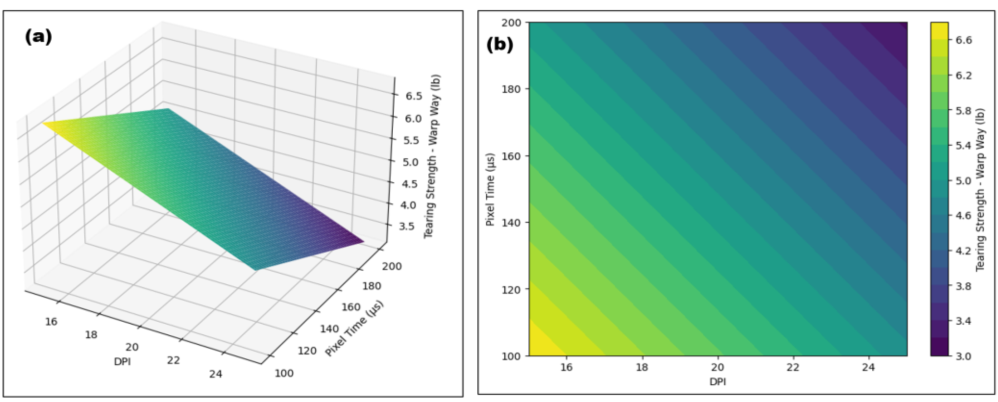

Figure 2. (a) 3D surface and (b) contour plots for tearing strength in the warp direction

Figure 3(a) and 3(b) presents a similar representation for the weft direction, highlighting the same trend of decreasing tearing strength with higher DPI and pixel time. These visualizations underscore the sensitivity of tearing strength to these two input parameters, emphasizing the negative correlation between both DPI and pixel time with fabric durability in both warp and weft directions.

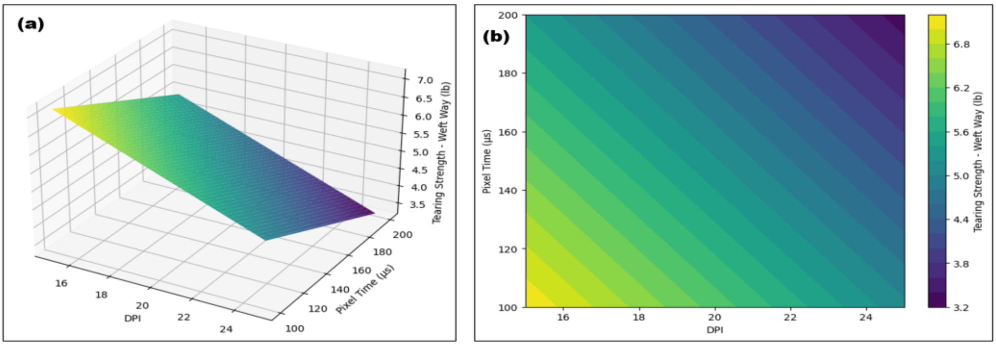

Figure 3. (a) 3D surface and (b) contour plots for tearing strength in the weft direction

Figure 4 presents the correlation matrix heatmap, which shows the relationships between Dot Per Inch (DPI), pixel time, and the tearing strength in both the warp and weft directions. The matrix reveals that DPI and pixel time are uncorrelated with each other (correlation of 0.00). Both DPI and pixel time exhibit a moderate negative correlation with tearing strength in the warp (−0.74 and −0.67, respectively) and weft (−0.76 and −0.64, respectively) directions, indicating that as DPI and pixel time increase, the tearing strength in both directions decreases. Additionally, the high positive correlation (0.99) between the warp and weft tearing strengths suggests that the two directions are similarly affected by the input parameters. This heatmap effectively confirms the negative impact of increasing DPI and pixel time on the tearing strength of the fabric in both warp and weft directions.

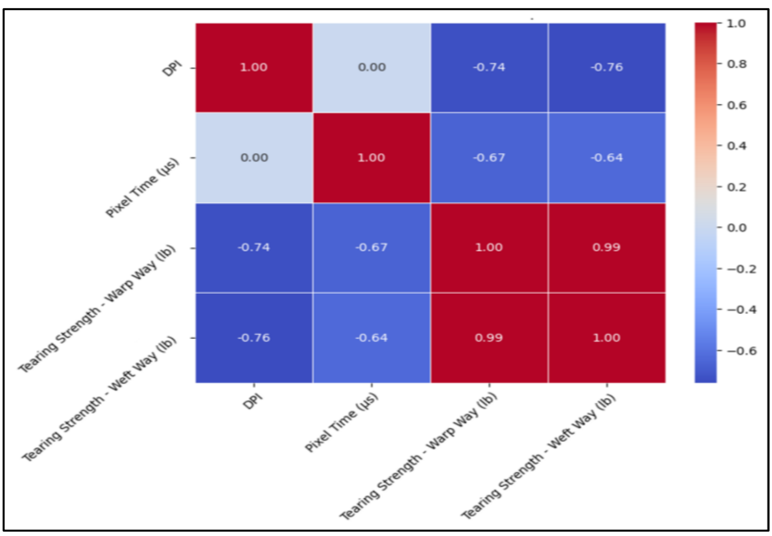

Figure 4. The correlation matrix heatmap, which shows the relationships between Dot Per Inch (DPI), pixel time, and the tearing strength

Statistical Analysis and Validation of Developed Model

Tables 3 and 4 display the parameters of the MLR model for both the warp and weft directions. For the warp way (Table 3), the intercept is 11.3872, with a coefficient of -0.1920 for Dot Per Inch (DPI) and -0.0172 for pixel time. The t-statistics for all parameters are significantly high, with the intercept having a value of 73.8599, and DPI and pixel time having values of -31.5462 and -28.2054, respectively. These high values suggest that all parameters are statistically significant, and their p-values are extremely small (less than 10^{-10}), indicating strong evidence against the null hypothesis. The 95% confidence intervals for the coefficients of DPI and pixel time do not include zero, further confirming their statistical significance. The results show that both DPI and pixel time have a negative impact on tearing strength in the warp direction. For the weft way (Table 4), the intercept is 12.1444, with coefficients of -0.2120 for DPI and -0.0179 for pixel time. Similar to the warp direction, all parameters exhibit significant t-statistics, with the intercept being 44.8249, and DPI and pixel time having values of -19.8213 and -16.7047, respectively. The p-values are also very small, confirming that all parameters are statistically significant. The 95% confidence intervals for DPI and pixel time in the weft way also exclude zero, reinforcing their relevance in the model. The negative coefficients for both DPI and pixel time suggest that, like in the warp direction, increasing these parameters results in a decrease in tearing strength in the weft direction. These results emphasize the consistent effect of DPI and pixel time on tearing strength across both warp and weft directions.

Table 3. Parameters of the MLR model (Warp way)

Model parameter	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	11.3872	0.1542	73.8599	4.15×10^{-10}	11.0100	11.7645
Dot Per Inch	-0.1920	0.0061	-31.5462	6.74×10^{-08}	-0.2069	-0.1771
Pixel Time	-0.0172	0.0006	-28.2054	1.31×10^{-07}	-0.0187	-0.0157

Table 4. Parameters of the MLR model (Weft way)

Model parameter	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	12.1444	0.2709	44.8249	8.26×10^{-09}	11.4815	12.8074
Dot Per Inch	-0.2120	0.0107	-19.8213	1.07×10^{-06}	-0.2382	-0.1858
Pixel Time	-0.0179	0.0011	-16.7047	2.94×10^{-06}	-0.0205	-0.0152

Figure 5 displays a scatter plot with a strong linear relationship between the actual and predicted tearing strength in the warp direction, as indicated by the R^2 value of 0.9967. This suggests that the MLR model explains approximately 99.67% of the variability in the data, with a near-perfect correlation between the actual and predicted values. Figure 6 also shows the predicted vs. actual values for the warp direction with an R^2 value of 0.9911. Although slightly lower than the previous plot, this still indicates an excellent fit, where 99.11% of the variability in the actual tearing strength is captured by the MLR model. The points are tightly clustered along the fitted line, demonstrating high predictive accuracy. Both figures confirm the reliability and high performance of the MLR model for predicting tearing strength in the warp direction, with minimal deviation between the actual and predicted values.

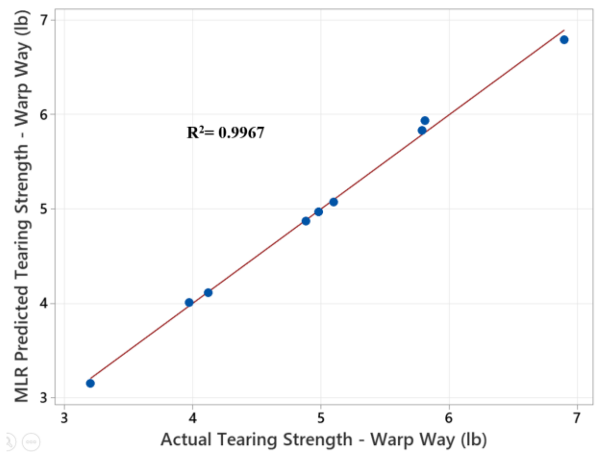

Figure 5. Correlation between actual and predicted values of Tearing Strength (warp way)

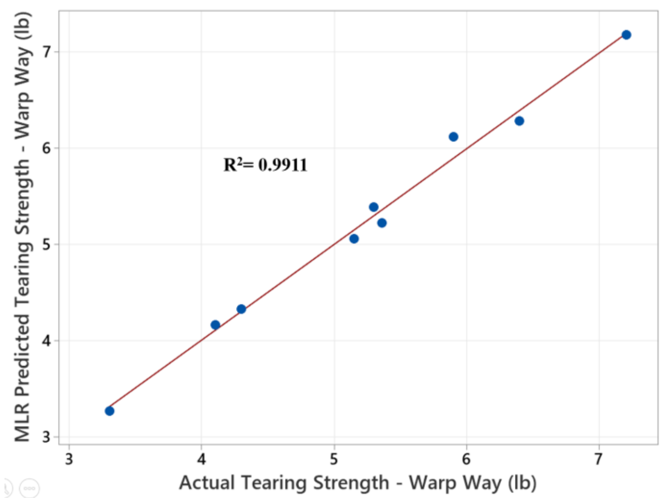

Figure 6. Correlation between actual and predicted values of Tearing Strength (weft way)

The evaluation metrics for the Multiple Linear Regression (MLR) model in predicting tearing strength for both warp and weft directions demonstrate excellent performance that shown in Table 5. The model shows high R^2 values of 0.9967 for the warp and 0.9911 for the weft, indicating that the model explains over 99% of the variability in the data for both directions. The Pearson correlation coefficients (0.9983 for warp and 0.9956 for weft) further confirm a strong linear relationship between the predicted and actual values. Additionally, the Spearman's rank correlation of 1 for the warp and 0.9833 for the weft suggests perfect and near-perfect rank ordering of the predictions. The model also exhibits very low Mean Absolute Percentage Error (MAEP), with values of 0.8783% for the warp and 1.6837% for the weft, and minimal Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), demonstrating precise predictions. Other metrics, such as the Percentage Bias (PBIAS) near zero, Standard Error of the Estimate (SEE), and Adjusted R^2, indicate no significant bias and minimal error in the model's predictions. The model also performs exceptionally in the Nash-Sutcliffe

Efficiency (NSE) and Kling-Gupta Efficiency (KGE) metrics, with values above 0.99 for both warp and weft, further confirming its accuracy and reliability. These results highlight the robustness and high predictive capability of the MLR model in forecasting the tearing strength of laser-engraved denim garments.

Table 5. Evaluation metrics for the Multiple Linear Regression (MLR) model

Sl	Evaluation Matrices	Warp Way	Weft Way
1.	Coefficient of Determination (R^2)	0.9967	0.9911
2.	Pearson Correlation Coefficient (R)	0.9983	0.9956
3.	Spearman's rank correlation coefficient (ϱ)	1	0.9833
4.	Mean Absolute Percentage Error (MAEP)	0.8783	1.6837
5.	Mean Squared Error (MSE)	0.0037	0.0114
6.	Root Mean Squared Error (RMSE)	0.0609	0.1070
7.	Mean Squared Logarithmic Error (MSLE)	0.00008489	0.00026275
8.	Percentage Bias (PBIAS)	-0.000000002235	0.000000002127
9.	Standard Error of the Estimate (SEE)	0.0690	0.1213
10.	Explained Variance Score	0.9967	0.9911
11.	Adjusted R^2	0.9962	0.9899
12.	Nash-Sutcliffe Efficiency (NSE)	0.9967	0.9911
13.	Kling-Gupta Efficiency (KGE)	0.9976	0.9937

Figure 7 and Figure 8 show the comparison between the experimental values and MLR predicted values for tearing strength in the warp and weft directions, respectively.

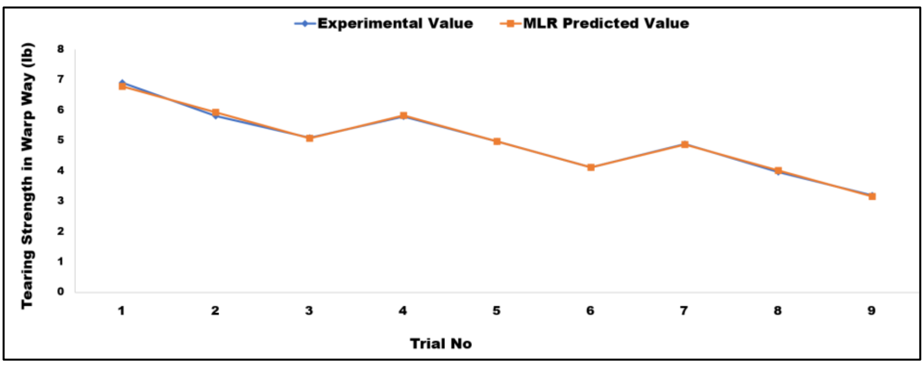

Figure 7. Comparison between the experimental values and MLR predicted values with line diagram for tearing strength in the warp directions

In Figure 7, the plot for the warp direction demonstrates that the predicted values closely follow the experimental data across all trials, with the predicted values (represented by the orange line) aligning almost perfectly with the experimental values (represented by the blue line). This indicates a high degree of accuracy in the MLR model's predictions for the warp way, confirming the model's reliability. Similarly, Figure 8 shows the comparison for the weft direction, where the predicted values also closely match the experimental values, although some small deviations are present. The overall consistency between the experimental and predicted values in both figures highlights the robustness of the MLR model in accurately predicting tearing strength for both warp and weft directions.

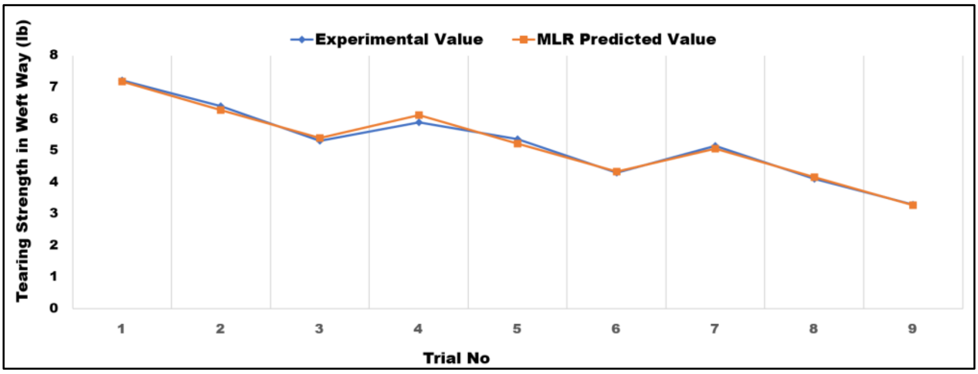

Figure 8. Comparison between the experimental values and MLR predicted values with line diagram for tearing strength in the weft directions

Figure 9 and Figure 10 show the residual plots for the MLR model's predicted tearing strength in both the warp and weft directions, respectively. In Figure 9, for the warp direction, the normal probability plot shows that the residuals are approximately normally distributed, as the points lie closely along the reference line.

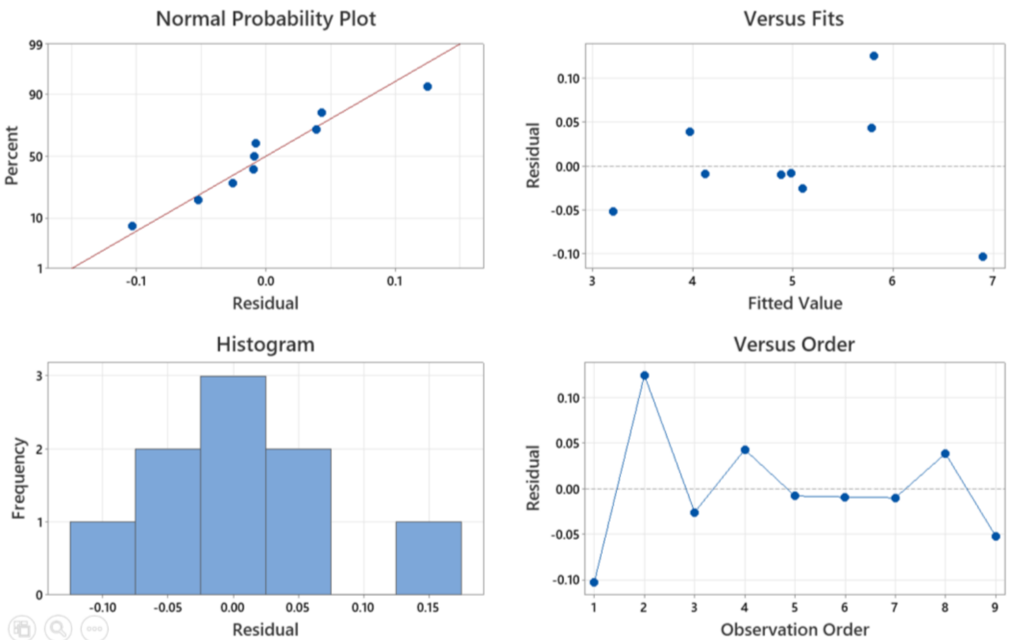

Figure 9. Residual plots for the MLR model (warp way)

This indicates that the assumption of normality for the residuals is met. The versus fits plot shows no clear patterns, suggesting that the model's errors are randomly distributed, which is an indication of homoscedasticity (constant variance of residuals). The histogram confirms that the residuals are mostly centered around zero, further supporting the model's accuracy. The versus order plot shows some minor fluctuations, but overall, there is no systematic pattern, which suggests that the errors do not depend on the observation order.

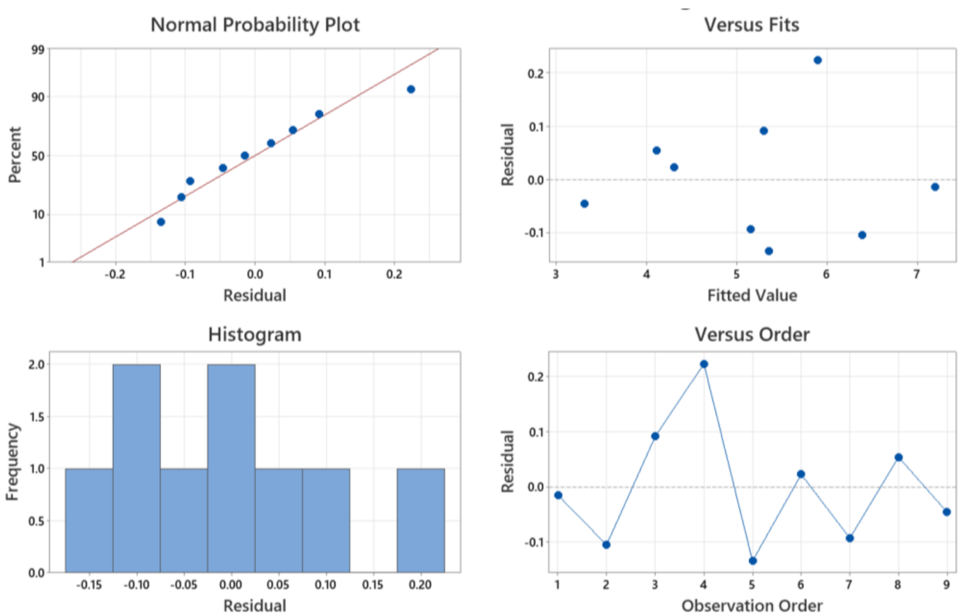

Figure 10. Residual plots for the MLR model (weft way)

In Figure 10, the residual analysis for the weft direction follows a similar pattern. The normal probability plot indicates that the residuals are approximately normally distributed, though the points deviate slightly from the reference line at both ends. The versus fits plot shows no significant pattern in the residuals, indicating that the model is well-behaved with respect to variance homogeneity. The histogram for the residuals shows a roughly symmetric distribution around zero, suggesting no substantial bias in the model's predictions. The versus order plot reveals some slight variation, but there are no significant trends, confirming that the residuals are independent of the order of the observations. Overall, both residual plots demonstrate that the MLR model is reliable and adheres to the necessary assumptions for accurate predictions.

Comparison with Previous Study

When comparing the MLR model with the fuzzy logic model by Sarker et al., the MLR model shows superior predictive performance. The R^2 values for the MLR model are significantly higher, with 0.9967 for the warp and 0.9911 for the weft directions, compared to 0.9819 and 0.9770 for the fuzzy logic model, indicating that the MLR model explains a greater proportion of the variability in tearing strength. The Mean Absolute Error Percentage (MAEP) is also lower for the MLR model, with 0.8783% for the warp and 1.6837% for the weft, compared to 3.3414% and 3.5262% in the fuzzy logic model, signifying more accurate predictions. Furthermore, the Pearson correlation coefficients (R) for the MLR model are higher (0.9983 for warp and 0.9956 for weft) than those for the fuzzy logic model (0.9909 for warp and 0.9885 for weft), reflecting a stronger linear relationship between predicted and actual values. These results indicate that the MLR model provides more reliable and accurate predictions of tearing strength compared to the previously developed fuzzy logic model [10].

Conclusion

This study successfully developed a Multiple Linear Regression (MLR) model for predicting the tearing strength of laser-engraved denim garments in both the warp and weft directions, based on key input parameters: Dot Per Inch (DPI) and pixel time. The model demonstrated exceptional accuracy, with R^2 values of 0.9967 for the warp direction and 0.9911 for the weft direction, indicating that the model explains over 99% of the variability in the data. The performance metrics, such as Pearson correlation coefficients (0.9983 for warp, 0.9956 for weft) and Spearman's rank correlation coefficients (1 for warp, 0.9833 for weft), also confirm the strong linear relationship between the predicted and actual values. Additional evaluation metrics, including Mean Absolute Percentage Error (MAEP), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), further support the model's high predictive accuracy and low error rates.

The residual analysis showed that the model adheres to necessary assumptions such as normality, homoscedasticity, and independence of residuals, confirming its reliability. The practical implications of the MLR model are significant, offering a tool for optimizing laser engraving parameters to ensure consistent and high-quality denim products. The model can help manufacturers achieve more efficient production by minimizing trial-and-error testing and guiding real-time adjustments. However, the linearity assumption in MLR remains a limitation, and future research could explore more advanced models, such as non-linear techniques, for even greater prediction accuracy. Additionally, expanding the dataset to incorporate more variables, such as fabric type and laser power, could further improve the model's generalizability. Overall, the MLR model provides a robust, reliable method for predicting tearing strength in laser-engraved denim garments and optimizing the manufacturing process.

Limitations, Future Work, and Practical Implications

While the MLR model performed well, its primary limitation lies in the assumption of linearity, which may not effectively capture complex, nonlinear relationships between input parameters and tearing strength. Future research could investigate nonlinear modeling approaches, such as support vector machines or neural networks, to improve predictive accuracy. Expanding the dataset to include a wider range of laser engraving parameters and additional influencing factors—such as fabric type and laser power—could enhance the model's generalizability. Furthermore, validating the model on diverse denim samples and integrating real-time production data would increase its robustness and adaptability.

This study's findings offer practical benefits for the textile industry, particularly in optimizing laser engraving settings to achieve consistent tearing strength. The MLR model can support real-time adjustments to DPI and pixel time, reducing reliance on trial-and-error testing and improving overall product quality. It also contributes to fabric design optimization and minimizes material waste. By leveraging the model, manufacturers can enhance production efficiency, ensure consistent outcomes, and better adapt to varying fabric types.

Declarations

Competing interests: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Publisher's note: Advanced Research Journal remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Orcid ID

Elias Khalil https://orcid.org/0000-0001-7856-0866

References

Ahirwar, M., & Behera, B. (2024). Prediction of tear strength of bed sheet fabric using machine learning based artificial neural network. *The Journal of the Textile Institute*, *115*(1), 22-28.

Bilisik, K., & Demiryurek, O. (2011). Analysis and tensile-tear properties of abraded denim fabrics depending on pattern relations using statistical and artificial neural network models. *Fibers and Polymers*, *12*, 422-430.

Eltayib, H. E., Ali, A. H., & Ishag, I. A. (2016). The prediction of tear strength of plain weave fabric using linear regression models. *International Journal of Advanced Engineering Research and Science*, *3*(11), 236921.

Gültekin, E., Kaynak, H. K., & Çelik, H. (2021). Decision tree regression method application for prediction of woven fabrics tear strength. Proceedings of the 3rd International Conference of Materials and Engineering Technology,

Jucienė, M., Urbelis, V., Juchnevičienė, Ž., & Čepukonė, L. (2014). The effect of laser technological parameters on the color and structure of denim fabric. *Textile Research Journal*, *84*(6), 662-670.

Kan, C.-w. (2014). CO2 laser treatment as a clean process for treating denim fabric. *Journal of Cleaner Production*, *66*, 624-631.

Kan, C. W., Yuen, C., & Cheng, C. (2010). Technical study of the effect of CO2 laser surface engraving on the colour properties of denim fabric. *Coloration Technology*, *126*(6), 365-371.

Khalil, E. (2015). Sustainable and ecological finishing technology for denim jeans. *AASCIT Communication*, *2*(5), 159-163.

Lord, P. R., & Mohamed, M. H. (1982). *Weaving: Conversion of yarn to fabric* (Vol. 12). Woodhead Publishing.

Nayak, R., & Padhye, R. (2016). The use of laser in garment manufacturing: an overview. *Fashion and textiles*, *3*, 1-16.

Ortiz-Morales, M. n., Poterasu, M., Acosta-Ortiz, S. E., Compean, I., & Hernandez-Alvarado, M. R. (2003). A comparison between characteristics of various laser-based denim fading processes. *Optics and Lasers in Engineering*, *39*(1), 15-24.

Sarkar, J., Al Faruque, M. A., & Khalil, E. (2022). Predicting the tearing strength of laser engraved denim garments using a fuzzy logic approach. *Heliyon*, *8*(1).

Sarkar, J., Khalil, E., & Rahman, A. (2015). Technical study of the effect of CO2 laser surface engraving on the physical properties of denim fabric. International Conference on Mechanical Industrial and Materials Engineering (ICMIME), RUET.