

PREDICTING MATERIAL LIFESPAN: MACHINE LEARNING MODELS FOR DEGRADATION ANALYSIS

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Abstract: This study investigates the use of machine learning models to predict the lifespan of textile materials by analyzing their degradation, particularly for fabrics used in sportswear. The research examines how environmental factors like UV exposure, temperature, and humidity influence material properties over time. Polyester fabrics, chosen for their durability, were subjected to simulated weathering to mimic typical sports conditions. Key properties, including thickness, surface mass, and tensile strength, were measured pre- and post-aging. Machine learning algorithms, such as J48 decision trees and clustering methods, were applied to classify and predict degradation levels, with supervised models showing higher accuracy. These findings suggest that machine learning can effectively support durability predictions, offering valuable insights for material design in the textile industry.

Key words: modeling, material, yarn, machine learning, degradation

1. INTRODUCTION

The aging of textile materials describes the gradual degradation or alteration of their properties over time, driven by various internal and external factors. These changes significantly impact on the lifespan and quality of textiles, making research on material aging crucial for extending the durability of textile products. Generally, natural fibers are more prone to aging than synthetic fibers; for instance, cotton fibers can be damaged by prolonged exposure to sunlight and moisture, resulting in strength loss and discoloration. Conversely, synthetic fibers are typically more resistant to many aging elements and are often preferred for outdoor products, though they degrade over time under certain conditions.

Aging impacts textiles by reducing strength and elasticity, altering texture, and causing color changes. As strength declines, materials lose resistance to stress and may tear more easily. Elastic fibers, like elastane, also lose flexibility over time, leading to material deformation. Textiles may stiffen, and frequent UV exposure often causes discoloration or yellowing. To assess a textile's aging resistance, various tests—such as simulated UV exposure, mechanical wear tests, and chemical exposure—are employed. These assessments can be conducted in laboratories or through real-world exposure, helping to gauge durability under different conditions. Though aging is natural, it can be slowed with proper maintenance and high-quality fibers, allowing for prolonged use and protection of textiles [1].

The primary factors contributing to textile aging include UV radiation, heat, moisture, mechanical stress, and chemical agents, each affecting textiles in distinct ways. Sunlight, particularly UV rays, triggers photooxidation in textile fibers causing fading, discoloration, and weakened mechanical strength, especially in natural fibers like cotton and wool. High temperatures can induce thermal degradation, while humidity may lead to mold or bacteria growth, especially in natural fibers. For instance, wool is notably susceptible to moth damage. Cleaners such as detergents and bleaches can accelerate textile aging. Although synthetic fibers resist these agents better than natural fibers, long-term exposure can still cause degradation. And finally, wearing and friction can lead to fiber wear, microcracks, yarn breakage, and material thinning [2,3].

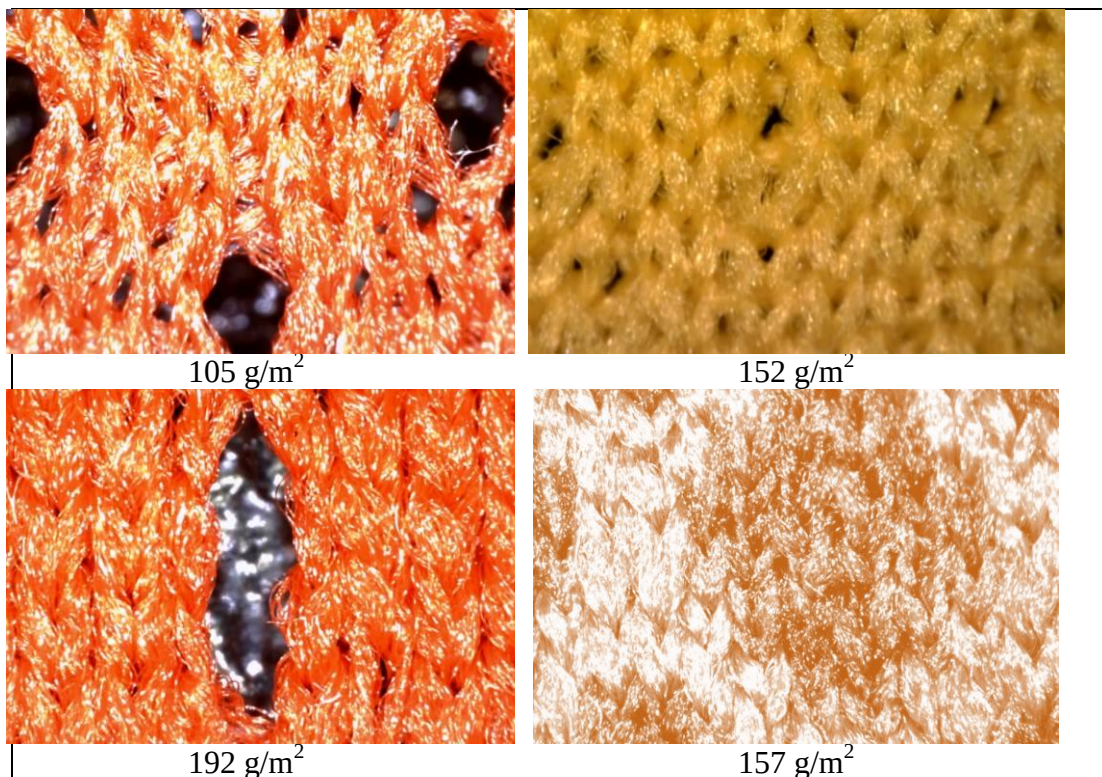
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In sportswear production, the most widely used polyester fiber is polyethylene terephthalate, prized for its elasticity, durability, ease of maintenance, and wear resistance, making it ideal for diverse applications. Its chemical resistance, particularly against acids and cleaning agents, further enhances its suitability for sportswear. Its recyclability is also valued for sustainability. PET offers good UV resistance, although prolonged exposure may degrade its molecular structure. Typical PET fibers exhibit tensile strengths ranging from 30–70 cN/tex, and a breaking elongation between 20–30% [4,5].

Regarding the aging of sportswear materials, there is limited literature on the subject. Previous research has focused on the tactile qualities of fabrics, as well as physical-mechanical properties and their changes due to the exposure of materials to aging under defined environmental conditions [6-11]. The current study aims to build a model for describing and predicting material property changes due to aging.

2. EXPERIMENT

In this study, a selection of knitted materials designed for sportswear production was tested under simulated weathering conditions to mimic typical use by football players. For the experiment was selected a set of materials produced of polyester yarns differing in the structural characteristics (type of knit pattern) and surface mass. Examples of typical materials used are given in Figure 1. In the Figure are images of materials as well as the average surface masses.



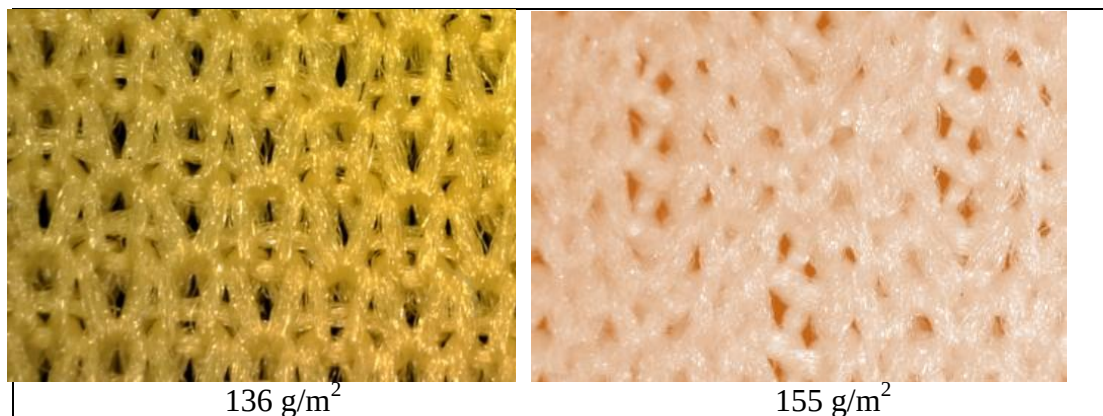
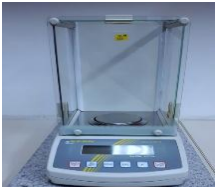


Figure 1 –Typical materials

All materials underwent static outdoor exposure in summer conditions characteristic of the Mediterranean climate, supplemented by the application of artificial sweat. During this period, the average air temperature was 31°C, with a 7.36% variation; the UV index averaged 8, with a 14.49% variation; and the average humidity was 58%, showing a 17.27% variation. Environmental conditions were monitored by the European Meteorological Center using the HRES weather forecast model. A diluted acid sweat solution (pH 5.5) was applied to the fabric samples 15 minutes into each exposure. Following each two-hour simulated training session, the materials were washed at 30°C with phosphate-free detergent and then air-dried. All materials, i.e. unaged and aged, were tested for several physical-mechanical properties including thickness, surface mass, pilling, bursting force, breaking force and elongation at break. The overview of the methods used is presented in Figure 2.

Material property	Testing device	Testing method details
Thickness		Thickness tester Standard used: ISO 5084:1996 - 10 repetitions were made
Surface mass		Analytic scale Standard used: ISO 3801 - specimen size was 100 x 100 mm - scale accuracy +/- 0.001 g
Pilling		Wet and Dry Abrasion Tester Standard used: ISO 12947-3:1998 - abrasion was performed using the standard woven woollen material - number of abrasion cycles: 2500
Bursting force		Bursting tester Standard used: ISO 13938-2 - materials were measured using the 'ball burst test'.

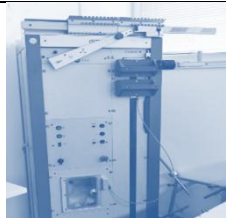
Breaking force and elongation at break		Tensile meter	Standard used: ISO 13934-1 - test specimen with dimensions 200x50 mm were exposed to a constant elongation force
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Figure 1 –Testing methods

3. MACHINE LEARNING AND ALGORITHMS

Machine learning enables computer systems to learn from data without explicit programming. It is based on the theory of pattern recognition and artificial intelligence, developing algorithms that learn and predict from data. It is used in tasks such as email filtering, pattern recognition, text mining, and computer vision, where creating explicit algorithms with good performance is challenging. Classification in machine learning and statistics is the problem of determining which category a new observation belongs to base on a training dataset. It is considered a supervised learning example since the categories are predefined. The unsupervised process is clustering, where data is grouped by similarity. Observations are analyzed through measurable features, which can be of various types. Algorithms performing classification are called classifiers, and the features that explain observations are grouped into a feature vector. Classes are possible categories that the classifier predicts.

Clustering or data grouping organizes objects, so they are more similar within the same group than between different groups. It is a key unsupervised learning technique, revealing natural groupings without needing an output variable prediction. It is applied in data analysis, image processing, bioinformatics, and market segmentation.

3.1. Decision Tree Algorithms

The ID3 decision tree algorithm, developed by Quinlan, uses information gain to select the best attribute at each tree split. The attribute with the highest information gain becomes the test attribute of the node, reducing necessary splits and data mixing. C4.5, also Quinlan's algorithm, is an extension of ID3 and can work with categorical and numerical data, using a similar approach to build decision trees. Essentially, it creates a leaf node when all samples belong to the same class, and when there is insufficient information, it uses expected values. J48 is a Java implementation of the C4.5 algorithm.

3.2. K-means Algorithm

The K-means algorithm is popular for clustering data due to its simplicity and efficiency. Its primary goal is to divide n objects into k clusters, thereby minimizing the distance between individual data points and the center of each cluster. The algorithm begins by randomly selecting k initial centers. Each point is then assigned to the nearest center, after which the centers are updated by averaging the points within each cluster. This process repeats until the centers reach stability and stop changing significantly. The advantages of the K-means algorithm are its simplicity and speed, making it applicable to a variety of clustering problems. However, it also has some limitations. The algorithm requires the pre-selection of k , the number of clusters, and is sensitive to initial conditions and outliers. Additionally, it assumes that clusters are spherical and of similar size.

3.3. Expectation Maximization (EM) Algorithm

The Expectation Maximization (EM) algorithm is used to estimate probability parameters in models that include hidden variables, where direct computation of these parameters proves challenging. It is frequently applied in tasks such as data clustering and in modeling mixture distributions. The EM algorithm operates in two main steps. In the E-step, it calculates the probability that a data point belongs to a particular cluster based on the

current estimates of the parameters. Following this, the M-step updates these parameters to maximize the overall probability of the model. This process iterates, with each cycle bringing the parameters closer to stability.

The EM algorithm offers significant advantages, such as its ability to handle complex models with hidden variables and its flexibility in application across various types of models. However, it also has certain limitations; it may converge to local maxima, which can affect solution quality, and it is computationally demanding, especially for large datasets.

3.4. Learning Vector Quantization (LVQ)

Learning Vector Quantization (LVQ) is a supervised learning technique that uses prototypes for data classification, though it can also be applied to clustering. LVQ works by adjusting prototypes to optimally represent both the data and the classes within it.

The LVQ algorithm involves several key steps. First, the prototypes are initialized, either randomly or according to certain heuristics. For each instance in the dataset, the algorithm identifies the closest prototype, a process known as competition. If the classification is correct, the prototype moves closer to the instance; otherwise, it moves away to refine the classification. This iterative process continues until the prototypes stabilize and no longer require further adjustment.

LVQ has the advantage of being intuitive for both classification and clustering tasks and is particularly effective with data that is not linearly separable. However, it is sensitive to the initial parameters, and determining the optimal number of prototypes can be challenging.

4. RESULTS

The WEKA (Waikato Environment for Knowledge Analysis) program was used to develop a J48 classifier. WEKA is a data mining tool offering various algorithms for data analysis and predictive modeling through a graphical interface. A dataset of 70 instances and 19 attributes was used, containing five classes (A, B1, B2, C1, C2), with each class having 14 samples. Attributes include thickness - D, area mass - m, breaking force in warp direction - Fp1, breaking elongation in warp direction - epsB1, breaking force in weft direction - Fp2, breaking elongation in weft direction - epsB2, breaking force (ball punch) - FB, piling grade - OP, K, WT1, WT2, OMMC, W, VM, VS, TD, KM, NR, HG, and output (result, class). The dataset has five classes (A, B1, B2, C1, and C2). Class A corresponds to non-aged samples, class B1 corresponds to samples after 12 training sessions and sun aging, class B2 corresponds to samples after 24 training sessions and sun aging, class C1 corresponds to samples after 12 training sessions and shade aging, and class C2 corresponds to samples after 24 training sessions and shade aging. The J48 algorithm was compared with the ZeroR model, which simply predicts the most common class (A); however, in this case, all classes are equally represented. J48 is expected to perform better than the ZeroR model as it uses more advanced data analysis.

Detailed results will be shown for the dataset consisting of 70 instances, 19 attributes, and five classes.

Matthew's Correlation Coefficient (MCC) is the correlation coefficient between observed and predicted binary classifications, returning a value between -1 and +1. A coefficient of +1 represents perfect prediction, 0 indicates random prediction, and -1 shows complete disagreement between predictions and observations. The Receiver Operating Characteristic curve (ROC curve) is a graphical plot illustrating the diagnostic ability of a binary classification system as its discrimination threshold varies. The ROC curve is generated by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The area under the ROC curve measures the overall performance of the classifier. PRC Area (Area Under the Precision-Recall Curve) measures a classifier's ability to correctly identify positive instances with high precision and recall, which is especially useful for evaluating performance on imbalanced datasets.

Table 1-The confusion matrix for the J48 algorithm

	Classified as				
	A	B1	B2	C1	C2
A	14	0	0	0	0
B1	0	11	1	2	0
B2	0	1	11	0	2
C1	0	2	0	12	0
C2	0	1	0	3	10

Table 2-Accuracy by class for the J48 algorithm

Class	TP rate	FP rate	Precision	F	MCC	ROC Area	PRC Area
A	1.000	0.000	1.000	1.000	1.000	1.000	1.000
B1	0.786	0.071	0.733	0.759	0.696	0.945	0.813
B2	0.786	0.018	0.917	0.846	0.815	0.980	0.911
C1	0.857	0.089	0.706	0.774	0.716	0.946	0.700
C2	0.714	0.036	0.833	0.769	0.720	0.951	0.796
Weighted average	0.829	0.043	0.838	0.830	0.790	0.965	0.844

The confusion matrix for the J48 algorithm in Table 1 can be interpreted as follows: the number of correctly classified instances is 58 (out of 70) or 82.8571%, while the number of incorrectly classified instances is 12 (out of 70) or 17.1429%. In terms of classes: for class A – 14 cases were correctly classified and 0 incorrectly classified, for class B1 – 11 cases were correctly classified and 3 incorrectly classified, for class B2 – 11 cases were correctly classified and 3 incorrectly classified, for class C1 – 12 cases were correctly classified, and 2 cases were misclassified. and for class C2 – 10 cases were correctly classified, and 4 cases were misclassified. Using the WEKA program, clustering models were created using the K-means, Expectation Maximization (EM), and Learning Vector Quantization (LVQ) algorithms. The dataset contains 70 instances and 19 attributes, divided into five classes (A, B1, B2, C1, C2). The classes refer to material samples under different aging conditions. The algorithms were used to group the materials into classes based on their attributes. The clustering results for each algorithm (K-means, EM, and LVQ) are shown below.

Table 3-Group Distribution for the K-means Algorithm

Groups	Number of examples
A	7 (10%)
B1	13 (19%)
B2	15 (21%)

C1	25 (36%)
C2	10 (14%)

Table 4-Comparison of Groups and Actual Classes for the K-means Algorithm

Groups					
A	B1	B2	C1	C2	Classes
3	1	3	5	2	A
1	3	3	5	2	B1
1	3	3	5	2	B2
1	3	3	5	2	C1
1	3	3	5	2	C2

Table 5-Group Distribution for the Expectation Maximization (EM) Algorithm

Groups	Number of examples
A	10 (14%)
B1	5 (7%)
B2	16 (23%)
C1	25 (36%)
C2	14 (20%)

Table 6-Comparison of Groups and Actual Classes for the Expectation Maximization (EM) Algorithm

Groups					
A	B1	B2	C1	C2	Classes
2	1	3	5	3	A
2	1	3	5	3	B1
2	1	4	5	2	B2
2	1	3	5	3	C1
2	1	3	5	3	C2

Table 7_Group Distribution for Learning Vector Quantization (LVQ)

Groups	Number of examples
A	3 (4%)
B1	23 (33%)
B2	12 (17%)
C1	6 (9%)

C2	26 (37%)
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Table 8-Comparison of Groups and Actual Classes for Learning Vector Quantization (LVQ)

Groups					
A	B1	B2	C1	C2	Classes
3	3	1	1	6	A
0	6	4	1	3	B1
0	4	4	1	5	B2
0	5	1	2	6	C1
0	5	2	1	6	C2

5. CONCLUSION

The classification and clustering results demonstrated variations in accuracy among the algorithms used. K-means, Expectation Maximization (EM), and Learning Vector Quantization (LVQ) were used to group materials based on their attributes into five classes. The highest percentage of incorrect groupings was recorded with the EM algorithm (78.57%), while LVQ had the lowest error rate (70%). All algorithms showed challenges in achieving precise classification due to the data's complexity, suggesting a need for a larger dataset and additional optimizations to improve grouping accuracy.

Classification results using the J48 algorithm showed significantly better accuracy compared to clustering. J48 achieved an accuracy of 82.86%, whereas K-means, EM, and LVQ algorithms had much higher percentages of incorrect groupings, with the EM algorithm at the lowest level of accuracy (78.57% incorrect). This result indicates that J48, as a supervised algorithm, was able to classify data more precisely due to the availability of pre-labeled data (supervised learning), whereas clustering algorithms, which operate without pre-defined classes, had greater difficulty accurately grouping samples. The confusion matrix for J48 also shows that classes A and C1 were the best classified, while class C2 had the highest number of misclassified samples. These results confirm that the J48 decision tree algorithm offers better classification accuracy compared to unsupervised clustering techniques.

The dataset with 70 samples distributed across five classes of 14 samples each presents a specific challenge for classification and clustering. The equal distribution of samples across classes and the relatively small number of instances may limit the algorithms' ability to learn patterns in the data accurately, especially for clustering algorithms that lack access to class labels. For supervised algorithms like J48, such balance among classes aids in even learning of all classes, reflected in high accuracy (82.86%).

The clustering algorithms (K-means, EM, and LVQ) showed poorer results, partly due to the dataset's complexity and the relatively small number of samples. The high rate of incorrect groupings (70% to 78% error) points to the challenge of clustering in datasets with a smaller sample size and similar characteristics across classes. This analysis suggests that a larger dataset or additional parameter optimization could improve clustering results in future research.

This study demonstrates the effectiveness of machine learning models, such as J48, in predicting material degradation under aging conditions. These findings align with recent research highlighting the role of machine learning in addressing material defects and

optimizing textile performance. For instance, studies employing deep learning models like YOLO and GANs have achieved high accuracy in detecting defects and addressing complex patterns of wear, suggesting potential synergies with predictive approaches in material aging [12,13]. Machine learning models, such as LSSVR, have shown great potential in optimizing textile processes, as demonstrated by Pervez et al., who combined Taguchi's design with machine learning to achieve accurate predictions of dyeing outcomes [14]. Recent advances, such as using convolutional neural networks (CNNs) for feature extraction from unlabeled data, offer promising solutions for enhancing model robustness [15].

These comparisons underline the value of this study in advancing material degradation analysis. However, incorporating emerging techniques and addressing sample size limitations could further enhance predictive accuracy and practical applications. A key limitation of this study is the small sample size of 70 instances, which may limit the generalizability and robustness of the results. Larger datasets would reduce the risk of overfitting in supervised models like J48 and improve the reliability of clustering outcomes in unsupervised models. Expanding the dataset with more diverse material samples and exposure conditions would enhance the evaluation of machine learning algorithms. Future research should prioritize larger sample sizes to refine predictive accuracy and explore advanced models like deep learning for better insights into material degradation.

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6. REFERENCES

- [1] Shishoo. R.: Textiles in Sport. 1st ed.; E-Book; Woodhead Publishing Limited: Cambridge. 2005.
- [2] Hayes. S. G.; Venkatraman. P.: Materials and Technology for Sportswear and Performance Apparel. 1st ed. Taylor & Francis Group. 2016.
- [3] Salopek Čubrić. I.: Approach towards design of functional sportswear for improved human performance. Proceedings of the 8th International Ergonomics Conference: ERGONOMICS 2020. 2021. pp. 3-11
- [4] Zhou. R.; Yu. J.; Qin. J.: Comfort properties of modified knitted polyester fabrics. Melliland International . Vol. 20. 2014. pp. 38–41.
- [5] Deopura. B. L.; Alagirusamy. R.; Joshi. M.; Gupta. B.: Polyesters and Polyamides. 1st ed.; Woodhead Publishing Limited. 2008.
- [6] Salopek Čubrić. I.; Potočić Matković. V.M.; Skenderi. Z. Impact of substrate on water vapor resistance of naturally weathered coated fabrics. Textile research journal. 2017. pp. 1541-1553
- [7] Salopek Čubrić. I.; Čubrić. G.; Majumdar. A.: Sensory attributes of knitted fabrics intended for next-to-skin clothing. Journal of Textile Institute. 2023.. pp. 757–762.
- [8] Salopek Čubrić. I.; Čubrić. G.; Perry. P.: Assessment of Knitted Fabric Smoothness and Softness Based on Paired Comparison. Fibers and Polymers. 2019.. pp. 656–667.
- [9] Katić Križmančić. I.; Salopek Čubrić. I.; Potočić Matković. V.M.; Čubrić. G.: Changes in Mechanical Properties of Fabrics Made of Standard and Recycled Polyester Yarns Due to Aging. Polymers. 2023.. pp. 4511.
- [10] Petrov. A.; Salopek Čubrić. I.; Čubrić. G.: Influence of Aging on the Physical Properties of Knitted Polymeric Materials. Polymers. 2024.. pp. 513.
- [11] Salopek Čubrić. I.; Čubrić. G.; Katić Križmančić. I.; Kovačević. M.: Evaluation of

Changes in Polymer Material Properties Due to Aging in Different Environments. *Polymers*. 2022.. pp. 1682. 2022.

- [12] Nasim, M., Mumtaz, R., Ahmad, M., Ali, A.: Fabric Defect Detection in Real World Manufacturing Using Deep Learning, *Information*, Vol. 15, 2024., pp. 476.
- [13] Hu, F., Gong, J., Fu, H., Liu, W.: Fabric Defect Detection Method Using SA-Pix2pix Network and Transfer Learning, *Applied Sciences*, Vol. 14, 2024., pp. 41.
- [14] Pervez, M. N., Yeo, W. S., Lin, L., Xiong, X., Naddeo, V., Cai, Y.: Optimization and prediction of the cotton fabric dyeing process using Taguchi design-integrated machine learning approach, *Scientific Reports*, Vol. 13, 2023., pp. 12363.
- [15] Koulali, I., Eskil, M. T.: Unsupervised textile defect detection using convolutional neural networks, *Applied Soft Computing*, Vol. 113, 2021., pp. 107913.