Received: 30 September 2023 | **Revised:** 22 November 2023 | **Accepted:** 22 November 2023 | **ISSN:** 2236-210X

Alumni.in

Iberoamerican Journal of
Competitive Intelligence
Revista de Inteligência Competitiva

ARTICLE REVIEW

MACHINE LEARNING ALGORITHMS FOR SLOW FASHION CONSUMER PREDICTION: THEORETICAL AND MANAGERIAL IMPLICATIONS

ALGORITMOS DE APRENDIZAGEM DE MÁQUINA PARA PREVISÃO DE CONSUMIDORES SLOW FASHION: IMPLICAÇÕES TEÓRICAS E GERENCIAIS

[1] Ítalo José de Medeiros Dantas
Universidade Feevale (Feevale), Rio Grande do Sul, Brasil.
https://orcid.org/0000-0003-0710-6142.

[2] Marcelo Curth
Universidade Feevale (Feevale), Rio Grande do Sul, Brasil.
https://orcid.org/0000-0002-9361-8373.

Corresponding Author:
Ítalo José de Medeiros Dantas
E-mail:
italodantasdesign@hotmail.com

Editora chefe
Profa. Dra. Eliana Severo
Alumni.In Editors

How to cite this article:

Dantas, Ítalo J. de M., & Curth, M. (2023). Algoritmos de Aprendizagem de Máquina Para Previsão de Consumidores Slow Fashion: Implicações Teóricas e Gerenciais. Revista Inteligência Competitiva, 13, e0439.
https://doi.org/10.24883/IberoamericanIC.v13i.439

ABSTRACT

Purpose: To compare, propose, and discuss the implications of five machine learning algorithms for predicting Slow fashion consumer profiles.
Methodology/approach: We use the Python programming language to build the models with scikit-learn libraries. We tested the potential of five algorithms to correct classifier Slow fashion consumers: I) extremely randomized trees, II) random forest, III) support vector machine, IV) gradient boosting Tree, and V) naïve bayes.
Originality/Relevance: This paper's originality lies in its combination of sustainability concerns, consumer behavior analysis, and machine learning techniques. It addresses a critical issue in the fashion industry and offers practical implications that can be beneficial for companies seeking to align their practices with Slow fashion principles. This interdisciplinary approach makes it a relevant contribution to both academia and industry.
Key findings: The performance metrics revealed satisfactory values for all algorithms. Nevertheless, the support vector machine presents a better precision (96%) on the dataset for Slow fashion consumer profiling, while random forest performs the worst (87%).
Theoretical/methodological contributions: We understood that the model can be helpful for companies that wish to adopt more targeted and practical approaches in the context of Slow fashion, allowing them to make more informed and strategic decisions. Therefore, these insights can guide future research in optimizing machine learning applications for consumer behavior analysis and provide valuable guidance for fashion marketers seeking to enhance their targeting and engagement strategies.

Keywords: Sustainability, Consumer Classification, Machine Learning, Environmental Awareness, Strategic Decision-making.

RESUMO

Objetivo: Comparar, propor e discutir as implicações de cinco algoritmos de aprendizado de máquina para prever perfis de consumidores de moda lenta.
Metodologia/abordagem: Utilizamos a linguagem de programação Python para construir os modelos com bibliotecas scikit-learn. Testamos o potencial de cinco algoritmos para classificar corretamente os consumidores de moda lenta: I) árvores extremamente aleatorizadas, II) floresta aleatória, III) máquina de vetores de suporte, IV) impulsionamento de gradiente, e V) bayes ingênuo.
Originalidade/Relevância: A originalidade deste artigo reside na combinação de preocupações relacionadas a sustentabilidade na Moda, análise do comportamento do consumidor e técnicas de aprendizado de máquina. Aborda uma questão crítica na indústria da moda e oferece implicações práticas que podem ser benéficas para empresas que procuram alinhar as suas práticas com os princípios do Slow fashion. Esta abordagem interdisciplinar torna-o uma contribuição relevante tanto para a academia como para a indústria.
Principais conclusões: As métricas de desempenho revelaram valores satisfatórios para todos os algoritmos. No entanto, o *Support Vector Machine* apresentou melhor precisão (96%) no conjunto de dados para perfil do consumidor Slow Fashion, enquanto a *Random Forest* apresentou o pior desempenho (87%).
Contribuições teóricas/metodológicas: Entendemos que o modelo pode ser útil para empresas que desejam adotar abordagens mais direcionadas e práticas no contexto do Slow fashion, permitindo-lhes tomar decisões mais informadas e estratégicas. Portanto, esses insights podem orientar pesquisas futuras na otimização de aplicativos de aprendizado de máquina para análise do comportamento do consumidor e fornecer orientações valiosas para profissionais de marketing de moda que buscam aprimorar suas estratégias de segmentação e engajamento.

Palavras-chave: Sustentabilidade, Classificação de Consumidores, Aprendizado de Máquina, Consciência Ambiental, Tomada de Decisão Estratégica.

1 INTRODUCTION

The surge in fashion consumption has led to a rapid escalation in production rates, driven by the need to cater to market demands swiftly. Consequently, this has necessitated the intensified utilization of natural resources and human labor (Niinimäki *et al.*, 2020; Los *et al.*, 2021). Notably, the fashion industry stands out as one of the most unsustainable sectors globally, marked by extensive water consumption in denim production (Niinimäki *et al.*, 2020; Los *et al.*, 2021), the release of synthetic microfibers into oceans, and greenhouse gas emissions (Amaral *et al.*, 2019), among other critical concerns. This paradigm has given rise to the concept of "Fast fashion" (Solino *et al.*, 2015), associated with environmental harm (Niinimäki *et al.*, 2020) and the exploitative use of labor akin to modern-day slavery in garment production (Veronese; Laste, 2022). However, in the past two decades, fashion consumers have grown increasingly aware of Fast fashion's environmental and social repercussions. Consequently, they have begun seeking more ethical and sustainable alternatives (Müller, 2016; Breve; Gonzaga; Mendes, 2018).

Emerging as a deliberate alternative to the Fast fashion model of consumption and production, Slow fashion has evolved into a movement that promotes a more sustainable approach to thinking, consuming, and producing fashion, embracing a comprehensive perspective encompassing not only the environmental aspect but also social and economic considerations (Solino; Teixeira; Dantas, 2020). As Kate Fletcher (2010), the research behind the term "Slow fashion" articulates, the ethos of slowness invites us to contemplate transformative shifts within the fashion industry. It challenges the prevailing emphasis on economic growth, fundamental values, and worldviews that shape the fashion realm, all to nurture a more profound and genuinely enriched society. Consequently, Slow fashion stands as a movement that critically questions the conventions of mass production and rapid consumption of fashion products.

While the Slow fashion movement presents an appealing perspective at first glance, it is essential to acknowledge that some authors have raised concerns regarding its implications within the fashion production and consumption landscape. In their comprehensive systematic literature review, Solino, Teixeira, and Dantas (2020) shed light on adverse attributes associated with the movement. They emphasize issues such as the high cost of Slow fashion products, noting that "The high perceived cost is related to the fact that the pieces tend to use expensive raw materials, due to their durability, quality, and artisanal aspects, or also as a result of paying a fair price to the labor involved in the process." Additionally, they address concerns about the rustic appearance of Slow fashion products, the limited annual production of fashion collections, and the heightened seasonality of consumption. In this context, it becomes imperative to delineate consumption profiles that reflect specific characteristics influencing image construction and the interests of the consumer demographic. This endeavor aids producers in formulating effective business strategies.

Consumption profiles emerge as a viable strategy for stakeholders committed to promoting Slow fashion consumption. It provides insights into how different groups manifest interest in various dimensions of the movement, enabling the tailoring of strategies for enhanced productivity and heightened consumption of Slow fashion products. As articulated by Solomon (2016, p. 220), the insights derived from the definition of consumer profiles "can offer very useful information for advertising creatives who must communicate something about the product. [...] this insight improves your ability to 'talk' to this consumer." Consequently, understanding, and delineating consumer interests and perspectives facilitates the creation of visually appealing, ergonomically sound, and emotionally resonant products, thereby increasing the likelihood of market success (Lobach, 2001; Baxter, 2011). In Slow fashion, consumption profiles are discerned through a metric called "Consumer Orientation to Slow fashion," comprising five key variables: equity, localism, exclusivity, functionality, and authenticity (Jung; Jin, 2014).

With this in mind, we understand that there is a broad focus on the application of machine learning to predict trends or propose recommendation systems (Chakraborty; Hoque; Kabir, 2020; Zhao; Li; Sun, 2021; Han; Kim; Ahn, 2022), leaving a gap in the application of models aimed at classifying consumer preferences and consumer profiling (Kand; Yoo, 2007; Chakraborty *et al.*, 2021; Jhoti; Sulthana, 2021). Therefore, this paper aims to compare, propose, and discuss the effectiveness of five machine learning algorithms in predicting the classification of Slow fashion consumer clusters. The main contributions of this research are:

[1] We are proposing models for classifying Slow fashion consumers in an automated manner based on different machine-learning algorithms.
[2] Comparison of five machine learning algorithms, demonstrating the applicability of the support vector machine to support the construction of Slow fashion consumer classification software.
[3] Demonstrate the potential application of machine learning for consumer profiling in the Fashion area.

We organized this paper as follows: In addition to this first section, which is dedicated to an introductory contextualization, section 2 presents the theoretical subsidies that support the construction of the model, both from the perspective of Slow fashion and the machine learning dimensions adopted. Section 3 presents the methodological approach of the work. Section 4 presents the results of practical research regarding the potential of each algorithm introduced in this study. Section 5, in turn, discusses the theoretical and managerial impacts of the models developed. Section 6 finally demonstrates the study's conclusions and possible future research.

2 THEORETICAL FRAMEWORK

The theoretical subsidies that support the propositions made in this article will be presented in this topic. Initially, we explored the Slow fashion consumption orientation scale. We then get into the specific characteristics of the machine learning algorithms experimented with in this study.

2.1 *"Consumer Orientation to Slow fashion"* scale and the characterization of Slow fashion consumption profiles in Brazil

Slow fashion, also called "sustainable fashion" when considering its principles, has gained significant prominence within the fashion industry and society (Fletcher, 2010). In this context, numerous studies and researchers have contributed diverse perspectives to the discourse surrounding Slow fashion (Fletcher; Grose, 2012; Fabri; Rodrigues, 2015; Berlin, 2016; Silva, 2018; Pinto, 2021). These studies underscore that Slow fashion represents a paradigm shift toward a more sustainable and ethically grounded approach in the fashion industry. This transformation encompasses economic, environmental, and social dimensions, setting it apart from the prevailing Fast fashion model.

From an economic standpoint, Slow fashion champions local production and artisanal craftsmanship, fostering job creation and bolstering local economies (Ertekin; Atik, 2015). By prioritizing durable and high-quality garments, consumers can reduce the need for frequent purchases, potentially leading to long-term financial savings (Štefko; Steffek, 2018). Moreover, Slow fashion promotes conscious consumption, encouraging individuals to support local brands and products, thereby fortifying the production chain (Jung; Jin, 2014).

In environmental terms, Berlin (2016) highlights Slow fashion's significant contribution to waste reduction and the preservation of natural resources. Emphasizing the longevity and quality of clothing, this ethos counteracts the culture of rapid disposal, combating the cycle of mass production and excessive textile waste generation. Additionally, Slow fashion endorses sustainable practices such as using organic, recycled, or environmentally friendly materials and promotes recycling and customization techniques like upcycling (Berlim, 2016).

From a social perspective, Fletcher, and Grose (2012), Fabri and Rodrigues (2015), and Pinto (2021) contend that Slow fashion strives for transparency and equity throughout the entire production chain. This commitment extends to ensuring fair working conditions for everyone involved in the textile industry, from the farmers cultivating raw materials to the sewers crafting the garments. The emphasis on local labor also contributes to community strengthening, sustainable development, and social inclusivity. Furthermore, Slow fashion embraces diversity, representation, and inclusivity, aiming to challenge the stereotypes and beauty standards imposed by the conventional fashion industry.

Sojin Jung and Byoungho Jin (2014) investigated the dimensions shaping Slow fashion consumption and explored how these variables could be translated into a psychometric scale that measures individuals' interactions with the movement. The authors (2014) emphasize that Equity, Authenticity, Functionality, Localism, and Exclusivity within Slow fashion explicitly articulate the relationship between each dimension and environmental and social sustainability. Consequently, Jung and Jin (2014) are credited with synthesizing the concept and defining the dimensions of the Slow fashion movement.

Termed the "Consumer Orientation to Slow fashion" (COSF), the scale developed by Jung (2014) encompasses five observed variables: equity, authenticity, functionality, localism, and exclusivity. Conceptually, these variables encompass: a) equity, reflecting consumers' perspectives on the fair compensation of all participants in the production chain; b) authenticity, emphasizing the appreciation of artisanal and traditional techniques; c) functionality, addressing the maximization of a product's practical potential; d) localism, exploring the preference for locally produced items over imported ones; e) exclusivity, relating to the desire for unique and distinctive products (Jung; Jin, 2014). Grounded in these dimensions and their respective latent variables, the authors devised a scale-based instrument capable of measuring consumers' inclination toward Slow fashion products and constructing consumption profiles based on these proclivities.

Following the development and validation of this measurement instrument, subsequent studies have focused on delineating consumption profiles for Slow fashion products worldwide. The first such endeavor was undertaken by Jung and Jin (2016) in the United States, where they surveyed 221 fashion consumers and identified four distinct profiles: high involvement, conventional, exclusivity-oriented, and low involvement. According to the authors (2016, p. 418), "the consumer profiles derived in this study will facilitate the implementation of sophisticated and targeted marketing, offering comprehensive marketing insights [...] and guiding marketers in promoting Slow fashion brands." Each of these delineated profiles exhibits a specific relationship with the dimensions of Slow fashion consumption as observed in the COSF scale.

In Brazil, a similar study was initially conducted in Ceará by Sobreira, Silva, and Romero (2020). They surveyed 461 clothing consumers exclusively from Ceará using the COSF scale, revealing three potential consumption profiles: *high orientation*, functionality-oriented, and *averse to exclusivity*. Interestingly, variations were observed in the Brazilian profiles compared to their North American counterparts. According to Sobreira, Silva, and Romero (2020, p. 122), the implications of their research encompass "information that can contribute to marketing planning and efficient brand positioning targeted at these potential consumers. In this sense, Slow fashion retailers in Ceará can leverage the factors associated with different profiles." Consequently, brands and designers can shape their marketing strategies based on the insights and characteristics of each consumer profile.

Subsequently, the COSF scale was again employed, this time in the Northeast region of Brazil, specifically in Rio Grande do Norte, in the study conducted by Solino *et al.* (2022). This study surveyed 414 individuals from Brazil, identifying three profiles: *averse to exclusivity*, *high orientation*, and low orientation towards Slow fashion. The results closely resembled those observed in previous studies, with the first profile aligning with the findings of Sobreira, Silva, and Romero (2020), while the latter two corresponded to the profiles identified by Jung and Jin (2016). Within the context of this investigation, the subsequent sections emphasize the concepts and descriptions of each delineated profile (Table 1) to comprehend their characteristics and interrelationships.

Iberoamerican Journal of Competitive Intelligence
Revista de Inteligência Competitiva
Alumni.in

Table 1 – Orientation profiles for Slow fashion consumption in Brazil

Profile	Characteristics
Averse to exclusivity	This group has a medium orientation average in all other three dimensions, with a lesser focus on authenticity; however, it presents an exceptional refusal when consumption involves rare, limited-edition pieces that few people have (exclusivity). It is also worth noticing a slightly lesser tendency towards authenticity, demonstrating that this group does not care much about handcrafted or traditional sewing techniques.
High orientation	This group comprises people with a higher orientation towards consuming Slow fashion products, with a high average in all dimensions studied. There is also a greater focus on authenticity; however, unlike the previous one, there is a positive attitude towards handmade clothes and handcrafted products. Therefore, they present a lesser orientation towards exclusivity, although this was the only cluster with a positive average for this dimension.
Low orientation	It comprises people with little orientation to all Slow fashion product consumption dimensions. The authenticity dimension is highlighted as having a more positive relationship with this group, demonstrating that, despite the resistance to consumption, its components tend to be more interested when there is a context of traditional techniques and crafts. On the other hand, like the other clusters, the dimension of exclusivity was the one with the lowest level of orientation.

Source: Solino *et al.* (2020)

2.2 Machine learning algorithms and the application in fashion consumer profiling

Machine learning represents a fundamental discipline in the era of artificial intelligence. It is a computational approach that aims to enable computer systems to learn from data and past experiences, allowing them to make decisions, make predictions, or perform specific tasks without being programmed for each situation (Mahesh, 2020). This field encompasses several essential concepts and attributes that shape its understanding and application. (Stuart; Norvig, 2009; Mohri; Rostamizadeh; Tawalkar, 2012; El Naqa; Murphy, 2015).

At its core, machine learning is based on algorithms and mathematical models that allow systems to identify patterns and trends in data. One of the fundamental pillars is the division into two main types of learning: supervised and unsupervised. In supervised learning, the model is trained on labeled data, where each example has a label or desired output, aiming to learn how to map inputs to outputs. In unsupervised learning, the model explores data without labels, identifying intrinsic patterns, structures, or groups without guidance from known outputs. The research conducted in this study is a supervised machine-learning model. (Stuart; Norvig, 2009; Mohri; Rostamizadeh; Tawalkar, 2012; Alloghani et al., 2019; Rajoub, 2020; Sohail; Arif, 2020).

Nevertheless, success in machine learning also depends on crucial attributes, including feature selection and engineering, model evaluation, hyperparameter optimization, and ethical considerations such as privacy and fairness. (Stuart; Norvig, 2009; Mohri; Rostamizadeh; Tawalkar, 2012; Zhou, 2016). Thus, machine learning represents a dynamic and constantly evolving field, with applications that extend from virtual assistants (Rawassizadeh et al., 2019) to medical diagnostics (Shehab et al., 2022) and autonomous vehicles (Lian et al., 2020; Bachute; Subhedar, 2021).

Furthermore, machine learning concepts and algorithms are also applied in fashion, ranging from issues of identifying design attributes in clothes (Shajini; Ramanan, 2022) to color classification in Fashion shows (Han; Kim; Ahn, 2022) and information system planning for recommending fashion products on websites or advertisements (Jo et al., 2020; Yang; 2022). However, we understand there is a gap in research into the preferences, desires, and perceptions of Fashion consumers regarding product categories, referred to in this work as "consumer profiling."

In the following subsections, we conceptualize the machine learning algorithms we implement in this investigation.

2.2.1 Machine Learning algorithms

In the context of machine learning models, an algorithm is a sequence of instructions or rules that guide the process of training and operating a model (Gurevich, 2012). Machine learning algorithms are essential for extracting patterns and valuable information from data (Bonaccorso, 2018). They define how a model should adjust its parameters based on training examples to perform specific tasks such as classification, regression, or clustering (Bonaccorso, 2018). Choosing the appropriate algorithm is crucial, as it directly impacts the performance and effectiveness of the model, influencing its ability to generalize to unseen data and make autonomous decisions (Bonaccorso, 2018). Next, we present the conceptual definition of the algorithms used in this research.

First, Extreme Randomized Trees (Extra-Trees) is an ensemble learning method used in machine learning and data analysis. They belong to the family of decision tree-based algorithms, like Random Forests and Gradient Boosting Trees. What sets Extra-Trees apart is their extreme level of randomness during the tree construction process. In Extra-Trees, the algorithm builds multiple decision trees by selecting random subsets of features and random thresholds for each split in the Tree. Unlike traditional decision trees that seek the best split based on some criterion, such as Gini impurity or entropy, Extra-Trees select splits randomly without any optimization. This extreme level of randomness has several advantages. It reduces overfitting, making Extra-Trees less prone to capturing noise in the data. It also significantly speeds up the training process because no time is spent searching for the best splits. Despite their inherent randomness, Extra-Trees perform remarkably well on many datasets, especially in ensemble methods. They are robust, easy to use, and can handle classification and regression tasks effectively. Extra trees are valuable in the machine learning toolkit, offering a trade-off between model simplicity and predictive performance. (Geurts; Ernst; Wehenkel, 2006; Cheng *et al.*, 2021).

Second, Random Forest is a versatile and robust machine learning algorithm widely used for classification and regression tasks. It belongs to the ensemble learning family, a powerful technique that combines multiple base models to make more accurate predictions. What sets Random Forest apart is its ability to mitigate overfitting, handle high-dimensional data, and provide valuable insights into feature importance. Random Forest operates by constructing many decision trees during the training phase. Each Tree is built using a random subset of the available data, and for each split in the Tree, only a random subset of features is considered. This randomness introduces diversity among the trees, forming the “forest.” During predictions, each tree “votes” on the outcome, and the majority decision is taken as the final prediction for classification tasks or the average for regression tasks. The ensemble nature of Random Forest results in better generalization performance, making it less prone to overfitting compared to a single decision tree. Additionally, Random Forest provides a built-in mechanism to assess feature importance, allowing users to identify which features contribute the most to the model’s predictions. (Cutler; Cutler; Steven, 2012; Zhou, 2016; Speiser *et al.*, 2019).

Third, the Support Vector Machine (SVM) is a machine learning algorithm primarily used for classification tasks, but it can also be applied to regression and outlier detection. SVMs are particularly popular for their ability to handle both linearly and non-linearly separable data by finding an optimal decision boundary or hyperplane that maximizes the margin between different classes. This margin represents the distance between the hyperplane and the nearest data points of each class, making SVMs robust to noisy data and effective in scenarios with complex decision boundaries. One of the critical strengths of SVM is its capacity to generalize well, even in high-dimensional spaces, making it suitable for a wide range of applications, including image classification, text categorization, and bioinformatics. SVMs work by transforming the input data into a higher-dimensional space using a mathematical technique known as the kernel trick. This transformation enables SVM to find a hyperplane that can separate data points effectively, even when they are not linearly separable in the original feature space. SVMs also allow for fine-tuning through the choice of kernel functions, such as linear, polynomial, radial basis function (RBF), and sigmoid, which can adapt to the specific characteristics of the data. These characteristics and their solid theoretical foundation make SVMs popular for many machine learning practitioners, especially when dealing with complex classification problems. (Mammone; Turchi; Cristianini, 2009; Zhou, 2016; Cervantes *et al.*, 2020).

Fourth, Gradient Boosting Trees (GBT) is an ensemble learning technique widely used for classification and regression tasks in machine learning. GBT is particularly notable for its exceptional predictive accuracy and ability to capture complex relationships within data. It works by sequentially constructing an ensemble of decision trees, where each Tree aims to correct the errors made by the previous ones. This iterative process involves fitting a new tree to the residuals or errors of the previous models. GBT gradually improves its predictive performance through this step-by-step refinement, making it highly effective in various domains, such as finance, healthcare, and natural language processing. One of the critical advantages of GBT is its capability to handle structured and unstructured data effectively. It can automatically capture non-linear relationships, feature interactions, and complex patterns, making it suitable for real-world applications. Additionally, GBT provides a flexible framework for hyperparameter tuning, allowing users to fine-tune model parameters and control the trade-off between model complexity and predictive accuracy. The interpretability of GBT models varies depending on the depth and complexity of the individual trees within the ensemble. While simpler GBT models can offer insights into feature importance, more complex ensembles may be less interpretable but can achieve higher predictive performance. Overall, Gradient Boosting Trees is a versatile and robust algorithm in the

Iberoamerican Journal of Competitive Intelligence
Revista de Inteligência Competitiva
Alumni.in

machine learning toolkit, often yielding state-of-the-art results in various predictive modeling tasks. (Natekin; Knoll, 2013; Ayyadevara, 2018; Bentéjac; Csörgő; Martínez-Muñoz, 2021).

Lastly, Naïve Bayes is a probabilistic classification algorithm widely used in machine learning and natural language processing tasks. It is based on Bayes' theorem, a fundamental probability theory theorem. The "naïve" in its name comes from the assumption of independence among features, meaning that it assumes that all features are conditionally independent given the class label. While this assumption is often too simplistic for complex real-world data, Naïve Bayes can surprisingly perform well in many practical applications. One of the critical advantages of Naïve Bayes is its computational efficiency and simplicity. It is relatively easy to implement and can handle high-dimensional data efficiently, making it a popular choice for tasks like text classification (spam detection, sentiment analysis), document categorization, and e-mail filtering. Despite its simplicity and the independence assumption, Naïve Bayes often provides competitive or state-of-the-art performance in these applications. Another benefit is that Naïve Bayes provides interpretable results, as it can show which features are most influential in making a classification decision. While its assumptions might not hold in every scenario, Naïve Bayes serves as a valuable tool in situations where its simplicity and speed are advantageous and where the feature independence assumption is a reasonable approximation (Webb *et al.*, 2010; Langarizadeh; Moghbeli, 2016; Zhou, 2016; Berrar, 2019).

3 MATERIALS AND METHODS

This topic will explain the methodological procedures of the study, ranging from the database used for training and testing the model to the definition of the performance metrics that will be used to understand accuracy and precision.

3.1 Dataset: Slow fashion profiles

In this paper, we employ supervised machine learning models using Python on Google Colab as a tool. Therefore, the definition of group labeling is assumed before the machine learning process. In this machine learning model, we use the database Solino *et al.* (2022) provided, which comprises 414 data from Slow fashion consumers in Brazil. The authors employed K-Means to cluster the data into three consumption profiles: 1) *Averse to exclusivity* (*n = 141*); 2) *High orientation* (*n = 160*); 3) Low orientation to Slow fashion (*n = 113*) – for more in-depth information about the consumption profiles, check out section 2.1. In this sense, we used the same data and clusters proposed by the authors (Solino *et al.*, 2022) for training and testing the models (Figure 1).

	FI1	FI2	FI3	FI4	FI5	FI6	Equi1	Equi2	Equi3	Auten1	...	Excl3	PI1	PI2	WPPP1	WPPP2	WPPP3	WPPP4	WPPP5	WPPP6	Clusters
0	4	4	4	4	4	4	4	4	4	4	...	1	3	4	4	3	3	3	4	4	1
1	4	3	3	2	2	3	4	3	5	5	...	3	4	4	3	3	3	3	4	3	1
2	4	3	3	3	4	4	5	4	4	3	...	3	4	4	3	3	3	3	3	3	1
3	4	2	2	1	2	2	3	3	4	2	...	2	2	4	4	1	2	3	4	4	1
4	4	3	3	3	3	3	1	3	4	4	...	3	3	4	3	2	3	4	3	3	1

5 rows × 27 columns

Figure 1. Dataset head
Source: Prepared by the authors, 2023

3.2 Data Preprocessing

We divided the model into "X" for the 26 classifying variables that make up the database, referring to the dimensions of involvement with Fashion (6 variables), equity (3 variables), authenticity (3 variables), localism (3 variables), exclusivity (3 variables), purchase intention (2 variables) and the willing to pay higher prices for Slow fashion products (6 variables) (Solino *et al.*, 2022). The cluster's labels comprise the "Y" dimension (*n = 3*). Then, using *train_test_split* from the *sklearn.model_selection* library, we randomly divided the database between training and testing, using a 70/30 ratio:

- x_train.shape = (289, 26).
- x_test.shape = (125, 26).

3.3 Performance Metrics

To evaluate the proposed machine learning models, we used the results from accuracy, precision, recall, and f1-score (Figure 2). We use *classification_report* from *sklearn.metrics* library to generate performance metrics. Therefore, we use a confusion matrix to visualize the prediction model results. Finally, we compared them and defined which presented the best performance.

$$\boldsymbol{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\boldsymbol{Precision} = \frac{TP}{TP+FP}$$

$$\boldsymbol{Recall\,(Sensivity)} = \frac{TP}{TP+FN}$$

$$\boldsymbol{F1\ score} = 2\ x\ \frac{(PrecisionxRecall)}{(Precision+Recall)}$$

Figure 2. Performance metrics.
Source: Güler and Polat, 2022.

4 RESULTS

In this research, we compare the performance of five machine learning models on the classification of Slow fashion consumers based on pre-existent k-means clustering labels. We can see the results for the performance metrics in Figure 3.

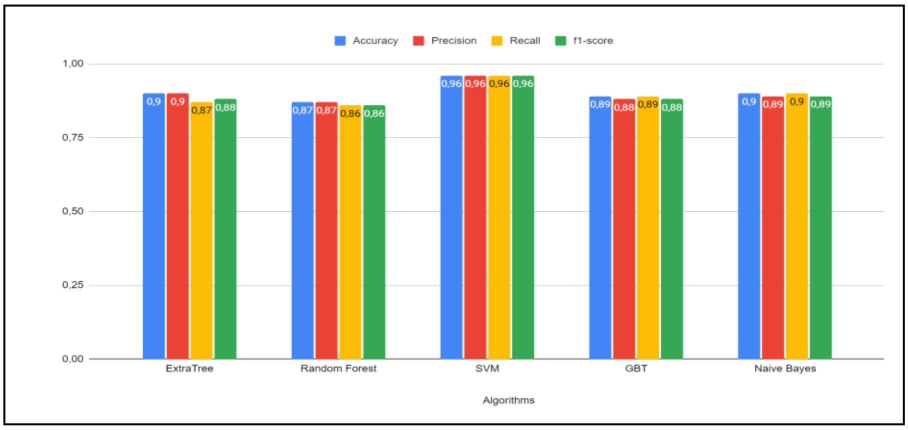

Figure 3. Performance metrics of the five machine learning algorithms
Source: Prepared by the authors, 2023

The five algorithms present a satisfactory result for all the performance metrics. However, we can observe that SVM presented a better overall performance than the other models. Nevertheless, Extra Tree excelled in metrics, especially model accuracy, and precision. Random Forest performed the worst.

For visual comparison, we employ confusion matrices (Figures 4 and 5).

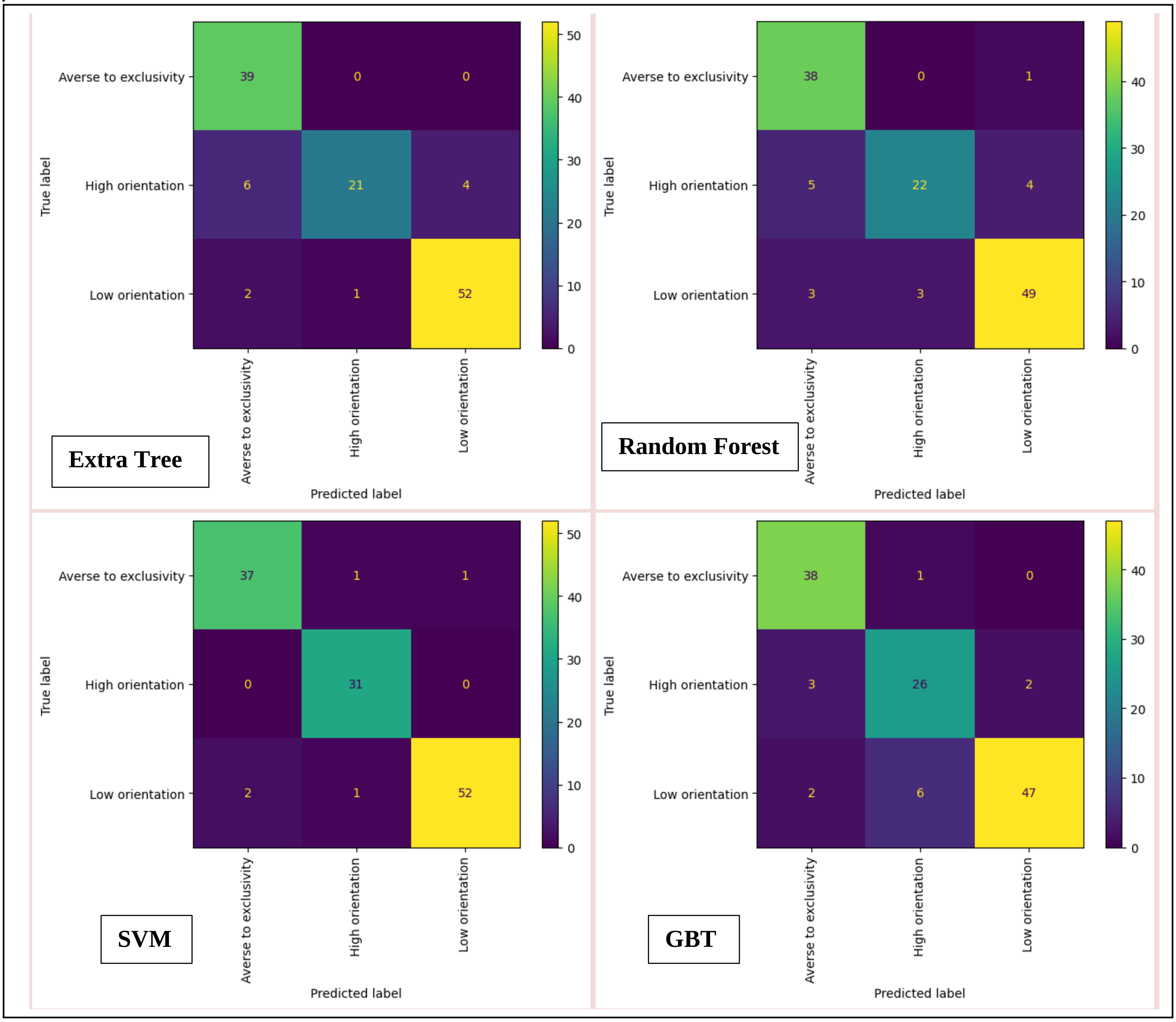

Figure 4. Confusion matrix to Extra Tree, Random Forest, SVM and GBT
Source: Prepared by the authors, 2023

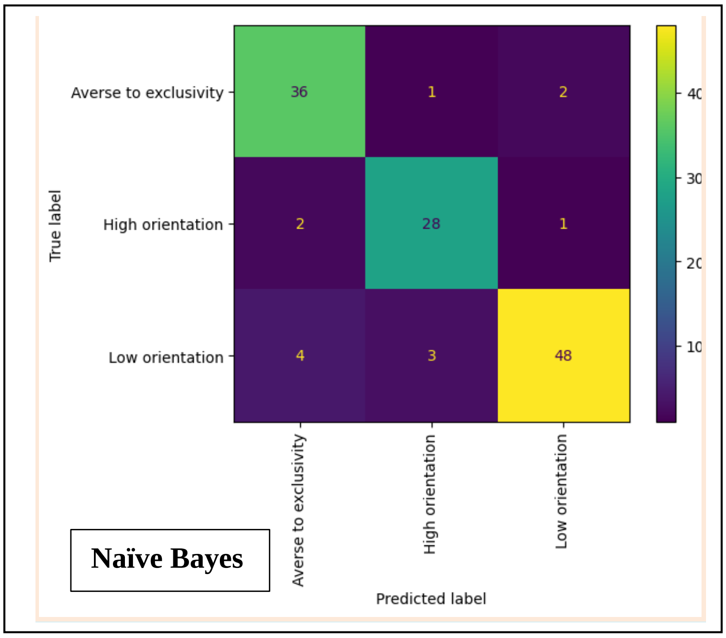

Figure 5. Confusion matrix to Naïve Bayes
Source: Prepared by the authors, 2023

Analysis of algorithm performance metrics reveals valuable information about how each model behaves in classifying different consumer profiles. When considering applying these results in an organization prone to Slow fashion, evaluating how these metrics can impact business decisions and marketing strategies is essential. Therefore, the confusion matrices revealed a satisfactory general result for all algorithms but some severe errors regarding classifying consumers from the "*high orientation*" profile with "*low orientation*." When classifying profiles with such equidistant characteristics, it is necessary to refine the model and the data to avoid confusion. The *"averse to exclusivity"* profile was the one that presented the best classification metric in all algorithms.

Extra Tree correctly classified all consumers in the "*averse to exclusivity*" profile but mislabeled ten consumers in the "*high orientation*" profile. Random Forest correctly classified all consumers in the "*averse to exclusivity*" profile, confusing only one with "*low orientation."* However, it incorrectly classified nine consumers in the "*high orientation*" profile and six in the "*low orientation*" profile. SVM presented the best result, correctly classifying all consumers in the "*high orientation*" group and mislabeling only two in the "*averse to exclusivity*" profile and three in the "*low orientation*" profile. The fact that SVM presents the best overall performance may indicate that it is a solid choice for identifying consumers with preferences aligned with slow fashion. The SVM's ability to correctly classify all consumers into the "high orientation" group suggests consistent effectiveness in this area. This could be crucial for a slow fashion organization, where understanding and adequately serving consumers highly oriented towards this lifestyle is essential.

GBT and Naive Bayes presented similar results, with a satisfactory classification for the "*averse to exclusivity*" profile, some errors for the "*high orientation*" groups, and significant errors for the "*low orientation*" profile. Considering the practical application of these results in a Slow fashion organization, the following strategies can be considered: (i) emphasis on consumers "averse to exclusivity," (ii) improvement of the SVM model, and (iii) continuous evaluation of the data that configure the model.

5 THEORETICAL AND MANAGERIAL IMPLICATIONS

The findings of this study on machine learning algorithms for predicting Slow fashion consumer clusters hold several important theoretical and managerial implications for both the field of fashion marketing and the broader application of machine learning techniques in consumer behavior analysis. Firstly, the superior performance of the SVM algorithm highlights the significance of choosing appropriate models when dealing with complex consumer profiling. The emphasis on maximizing the margin between different clusters in SVM might be particularly effective in deciphering subtle differences in Slow fashion consumer behavior, shedding light on the potential for more nuanced marketing strategies. (Abe, 2010; Yang; Su, 2012).

Secondly, the success of the Extra Tree algorithm, especially in terms of accuracy and precision, underscores the importance of considering ensemble learning methods in consumer prediction tasks. Extra Tree's ability to handle this complex classification problem demonstrates the potential benefits of leveraging ensemble techniques to boost the predictive power of models. (Zhang; Ma, 2012; Whalen; Pandey, 2013). The success of Extra Tree can be attributed to its ability to introduce additional randomness in the tree-building process, thereby promoting diversity among individual trees in the ensemble. This diversity contributes to a more robust and accurate predictive model, as each Tree captures different aspects of the underlying patterns in the data. By aggregating the predictions of multiple trees, Extra Tree achieves a powerful result surpassing individual models' limitations (Zhang; Ma, 2012; Whalen; Pandey, 2013). Moreover, the demonstrated proficiency of Extra Tree in accurately classifying consumers across various profiles suggests that ensemble methods, with their capacity to mitigate the impact of noisy or irrelevant features, can be particularly advantageous in scenarios where data exhibits complexities and subtle distinctions between classes (Chen et al., 2018).

Thirdly, the subpar performance of the Random Forest algorithm suggests that not all machine learning algorithms are equally suited for consumer profiling in Slow fashion. These findings emphasize the necessity of selecting algorithms tailored to the specific characteristics of the dataset and consumer behavior patterns, focusing on the need for a more customized approach in machine learning applications. (Murphy, 2012; Fernández-Delgado *et al.*, 2014). As highlighted by Murphy (2012) and Fernández-Delgado et al. (2014), the significance of algorithm selection cannot be overstated. Machine learning models are not one-size-fits-all solutions, and the suitability of an algorithm depends on the nature of the data and the inherent complexities of the problem at hand (Sokol; Flach, 2020; Morse *et al.*, 2021). A tailored and thoughtful approach to algorithm selection becomes imperative in consumer profiling for Slow fashion, where several factors may influence preferences, behaviors, and purchasing decisions.

Furthermore, the observed confusion in classifying consumers with equidistant characteristics, such as those with *"high orientation"* and *"low orientation,"* underscores the importance of data refinement and feature engineering. To reduce these misclassifications, researchers and practitioners should pay close attention to data preprocessing and feature selection and consider domain-specific knowledge to improve model accuracy. (Provost; Fawcett, 2013; Zheng; Casari, 2018).

Nevertheless, for the market and intra-organizational implications, this research reveals the potential for adopting machine intelligence methods to increase the effectiveness of product and marketing strategies (Chen, Hoyle, and Wsssenaar, 2013) aimed at sustainable consumption (Tseng, Chiu, and Liang, 2018) and Slow fashion and its potential customers. Therefore, we understand that the model can be helpful for companies that wish to adopt more targeted and practical approaches (Chen, Hoyle, and Wsssenaar, 2013) in the context of sustainability (Tseng, Chiu, and Liang, 2018), allowing them to make more informed and strategic decisions. Subsequently, these findings can serve as a foundation for future research to optimize machine learning applications to analyze consumer behavior. Additionally, they offer valuable insights for fashion marketers seeking to enhance their targeting and engagement strategies.

Lastly, the consistent success in classifying the *"averse to exclusivity"* profile across all algorithms suggests that this consumer group exhibits distinct and easily identifiable behavior patterns. This implies that marketing strategies catering to this segment may benefit from a more straightforward approach than other consumer groups. Understanding the uniqueness of this profile can help fashion brands tailor their messaging and product offerings more effectively. (Zahay; Griffin, 2010; Fares, Lebbar and Sbihi, 2019).

6 CONCLUSIONS

Fast fashion and user-centered design influenced the creation of a broad demand and consumption production chain, requiring creators to use the information and data used as project inputs effectively. There is a growing movement focused on sustainable fashion called Slow fashion. This context led to the proposition of consumption profiles, which reflect the main characteristics of this group based on variables such as equity, authenticity, localism, and exclusivity, among others. Therefore, this paper aims to compare five machine learning algorithms for classifying Slow fashion consumers.

The results show that the support vector machine and extra Tree presented better performance metrics than the other algorithm. Meanwhile, Random Forest delivered inferior results. We were able to adequately classify the *"averse to exclusivity"* profile in all algorithms, but there was inconsistency between the *"high orientation"* and *"low orientation"* profiles. This study highlights the potential use of consumer classification and prediction software to broaden the investigation scope regarding the production and consumption of Slow fashion. We recognized that this model could prove valuable for businesses seeking to implement more precise and efficient strategies within the Slow fashion realm, enabling them to make well-informed and strategic choices.

In conclusion, this study's theoretical and managerial implications highlight the critical importance of algorithm selection, ensemble techniques, data refinement, and recognizing distinct consumer profiles in Slow fashion. These insights can guide future research in optimizing machine learning applications for consumer behavior analysis and provide valuable guidance for fashion marketers seeking to enhance their targeting and engagement strategies.

Despite the contributions provided by this study, it is important to acknowledge several limitations that may impact the generalizability and applicability of the findings. The study might have been limited by the size and diversity of the sample used for training and testing the machine learning algorithms. A more extensive and diverse dataset would enhance the robustness and generalizability of the models. Second, consumer behaviors are often influenced by cultural and geographic factors. The study may not fully capture the nuances of Slow fashion consumption across different cultural or geographic contexts, limiting its generalizability to a broader audience. Third, the success of machine learning models in classification tasks is closely tied to selecting relevant features. The study might have limitations if important variables influencing Slow fashion consumption were not included.

Therefore, for future research, we suggest expanding the scope of the research, inserting new variables and a greater diversity of data, and afterward, proposing a web application that uses the machine learning models developed to test the validity of the information with consumers, designers, and practitioners.

REFERENCES

Abe, S. (2010). *Support Vector Machines for Pattern Classification: Advances in Pattern Recognition.* Springer, London. (https://doi.org/10.1007/978-1-84996-098-4).

Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A.J. (2020). A Systematic Review on Supervised and Unsupervised Machine Learning Algorithms for Data Science. In: Berry, M., Mohamed, A., Yap, B. (eds) *Supervised and Unsupervised Learning for Data Science. Unsupervised and Semi-Supervised Learning.* Springer, Cham (https://doi.org/10.1007/978-3-030-22475-2_1).

Amaral, W. A. N., et al. (2019). Moda circular no Brasil. Esalq/USP.

Ayyadevara, V.K. (2018). Gradient Boosting Machine. In: *Pro Machine Learning Algorithms.* Apress, Berkeley, CA. (https://doi.org/10.1007/978-1-4842-3564-5).

Bachute, M. R., & Subhedar, J. M. (2021). Autonomous driving architectures: insights of machine learning and deep learning algorithms. *Machine Learning with Applications*, 6, 100164. (https://doi.org/10.1016/j.mlwa.2021.100164).

Baxter, M. (2011). Projeto de produto: guia prático para o design de novos produtos. Blucher.

Bentéjac, C., Csörgő, A., & Martínez-Muñoz, G. (2021). A comparative analysis of gradient boosting algorithms. *Artificial Intelligence Review*, 54, 1937-1967. (https://doi.org/10.1007/s10462-020-09896-5).

Berlim, L. (2016). Moda e sustentabilidade: uma reflexão necessária. Estação das Letras e Cores.

Berrar, D. (2018). Bayes' theorem and naive Bayes classifier. Encyclopedia of bioinformatics and computational biology: *ABC of bioinformatics*, 403, 412. (https://doi.org/10.1016/B978-0-12-809633-8.20473-1).

Breve, D. G., Gonzaga, L. S., & Mendes, F. D. (2018). Sustentabilidade como uma Tendência no Mercado da Moda. ModaPalavra e-periódico, 11(22), 311-331. (https://doi.org/10.5965/1982615x11222018311).

Bonaccorso, G. (2018). *Machine Learning Algorithms: Popular algorithms for data science and machine learning*. Packt Publishing Ltd.

Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges, and trends. *Neurocomputing*, 408, 189-215. (https://doi.org/10.1016/j.neucom.2019.10.118).

Cheng, H., Shi, Y., Wu, L., Guo, Y., & Xiong, N. (2021). An intelligent scheme for big data recovery in Internet of Things based on multi-attribute assistance and extremely randomized trees. *Information Sciences*, 557, 66-83. (https://doi.org/10.1016/j.ins.2020.12.041).

Chen, K., Guan, D., Yuan, W., Li, B., Khattak, A.M., & Alfandi, O. (2018). A Novel Feature Selection-Based Sequential Ensemble Learning Method for Class Noise Detection in High-Dimensional Data. In: Gan, G., Li, B., Li, X., Wang, S. (eds) *Advanced Data Mining and Applications*. ADMA 2018. Lecture Notes in Computer Science(), vol 11323. Springer, Cham. https://doi.org/10.1007/978-3-030-05090-0_5.

Chen, W., Hoyle, C., & Wassenaar, H.J. (2013). Fundamentals of Analytical Techniques for Modeling Consumer Preferences and Choices. In: *Decision-Based Design*. Springer, London. https://doi.org/10.1007/978-1-4471-4036-8_3.

Cutler, A., Cutler, D.R., Stevens, J.R. (2012). Random Forests. In: Zhang, C., Ma, Y. (eds) *Ensemble Machine Learning*. Springer, New York, NY. (https://doi.org/10.1007/978-1-4419-9326-7_5).

El Naqa, I., & Murphy, M.J. (2015). What Is Machine Learning? In: El Naqa, I., Li, R., Murphy, M. (eds) *Machine Learning in Radiation Oncology*. Springer, Cham. (https://doi.org/10.1007/978-3-319-18305-3_1).

Ertekin, Z. O., & Atik, D. (2015). Sustainable Markets: Motivating Factors, Barriers, and Remedies for Mobilization of Slow fashion. *Journal of Macromarketing*, 31(1), 53-69. (https://doi.org/10.1177/0276146714535932).

Fabri, H. P., & Rodrigues, L. V. (2015). Slow fashion: perspectivas para um futuro sustentável. In Colóquio de Moda, 11

Fares, N., Lebbar, M., Sbihi, N. (2019). *A Customer Profiling' Machine Learning Approach, for In-store Sales in Fast Fashion. In:* Ezziyyani, M. (eds) Advanced Intelligent Systems for Sustainable Development (AI2SD'2018). AI2SD 2018. Advances in Intelligent Systems and Computing, vol 915. Springer, Cham. (https://doi.org/10.1007/978-3-030-11928-7_53).

Fernández-Delgado *et al.* (2014). Do we Need Hundreds of Classifiers to Solve Real World Classification Problems? *Journal of Machine Learning Research*, 15(2014), 3133-3181.

Fletcher, K. (2010). Slow fashion: An Invitation for Systems Change. *Fashion Practice - The Journal of Design, Creative Process & the Fashion Industry*, 2, 259-265. (https://doi.org/10.2752/175693810X12774625387594).

Fletcher, K., & Grose, L. (2012). Moda e sustentabilidade: design para a mudança. Senac.

Geurts, P., Ernst, D. & Wehenkel, L. (2006). Extremely randomized trees. *Mach. Learn.*, 63, 3–42. (https://doi.org/10.1007/s10994-006-6226-1).

Gurevich, Y. (2012). What Is an Algorithm?. In: Bieliková, M., Friedrich, G., Gottlob, G., Katzenbeisser, S., Turán, G. (eds) SOFSEM 2012: Theory and Practice of Computer Science. SOFSEM 2012. *Lecture Notes in Computer Science*, vol 7147. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-27660-6_3.

Güler, O., & Polat, K. (2022). Classification Performance of Deep Transfer Learning Methods for Pneumonia Detection from Chest X-Ray Images. *Journal of Artificial Intelligence and Systems*, 4, 107-126.

Jung, S., & Jin, B. (2014). A theoretical investigation of Slow fashion: sustainable future of the apparel industry. *International Journal of Consumer Studies*, 38(5), 510-519. (https://doi.org/10.1111/ijcs.12127).

Jung, S., & Jin, B. (2016). From quantity to quality: understanding Slow fashion consumers for sustainability and consumer education. *International Journal of Consumer Studies*, 40(4), 410-421. (https://doi.org/10.1111/ijcs.12276).

Langarizadeh, M., & Moghbeli, F. (2016). Applying naive bayesian networks to disease prediction: a systematic review. *Acta Informatica Medica*, 24(5), 364. (https:// doi.org/10.5455/aim.2016.24.364-369).

Lian, Y., Zhang, G., Lee, J., & Huang, H. (2020). Review on big data applications in safety research of intelligent transportation systems and connected/automated vehicles. *Accident Analysis & Prevention*, 146, 105711. (https://doi.org/10.1016/j.aap.2020.105711).

Löbach, B. (2001). *Design Industrial*. Edgard Blücher.

Los, V. A., et al. (2021). Um estudo de caso sobre os impactos ambientais na produção do jeans em uma empresa de Jaraguá do Sul (SC). *Revista Poliedro*, 5(5), 82–102. (https://doi.org/10.15536/2594-4398.2021.v5.n5.pp.082-102.2651).

M. Mohri, A. Rostamizadeh and A. Talwalkar, *Foundations of Machine Learning*, Cambridge, MA, USA:MIT Press, 2012.

Mahesh, B. (2020). Machine Learning Algorithms - A Review. *International Journal of Science and Research*, 9(1), 381-386. (https://doi.org/10.21275/ART20203995).

Mammone, A., Turchi, M., & Cristianini, N. (2009). Support vector machines. *Wiley Interdisciplinary Reviews: Computational Statistics*, 1(3), 283-289. (https://doi.org/10.1002/wics.49).

Müller, M. C. (2016). *Moda sustentável, consumo consciente e comunicação:* estudo de casos no Rio Grande do Sul. Dissertação (Mestrado) - Universidade Fernando Pessoa.

Murphy, K. P. (2012). *Machine Learning: A Probabilistic Perspective*. The MIT Press.

Morse, L., Teodorescu, M.H.M., & Awwad, Y. et al. (2022). Do the Ends Justify the Means? Variation in the Distributive and Procedural Fairness of Machine Learning Algorithms. *J Bus Ethics* 181, 1083–1095. https://doi.org/10.1007/s10551-021-04939-5

Natekin, A., & Knoll, A. (2013). Gradient boosting machines, a tutorial. *Frontiers in neurorobotics*, 7, 21. (https://doi.org/10.3389/fnbot.2013.00021).

Niinimäki, K., et al. (2020). The environmental price of Fast fashion. *Nature Reviews Earth & Environment*, 1, 189–200. (https://doi.org/10.1038/s43017-020-0054-x).

Pinto, Liliane Araújo. (2021). *Consumo Slow fashion e Bem-estar: influência da espiritualidade, da gratidão e do materialismo.* João Pessoa.

Provost, F., Fawcett, T. (2013). *Data Science for Business*. O'Reilly Media, California.

Rajoub, B. (2020). Supervised and unsupervised learning. In *Biomedical Signal Processing and Artificial Intelligence in Healthcare* (pp. 51-89). Academic Press. (https://doi.org/10.1016/B978-0-12-818946-7.00003-2).

Rawassizadeh, R., Sen, T., Kim, S.J. *et al.* (2019). Manifestation of virtual assistants and robots into daily life: vision and challenges. *CCF Trans. Pervasive Comp. Interact.* 1, 163–174. (https://doi.org/10.1007/s42486-019-00014-1).

Shehab, M., Abualigah, L., Shambour, Q., Abu-Hashem, M. A., Shambour, M. K. Y., Alsalibi, A. I., & Gandomi, A. H. (2022). Machine learning in medical applications: A review of state-of-the-art methods. *Computers in Biology and Medicine*, 145, 105458. (https://doi.org/10.1016/j.compbiomed.2022.105458).

Sobreira, E. M. C., Silva, C. R. M., & Romero, C. B. A. (2020). Slow profile: estudo das orientações ao consumo de Slow fashion. *Internext - Revista Eletrônica de Negócios Internacionais*, 15(3), 103-127. (https://doi.org/10.18568/internext.v15i3.589).

Sohail, A., & Arif, F. (2020). Supervised and unsupervised algorithms for bioinformatics and data science. *Progress in biophysics and molecular biology*, 151, 14-22. (https://doi.org/10.1016/j.pbiomolbio.2019.11.012).

Sokol, K., & Flach, P. (2020). One Explanation Does Not Fit All. *Künstl Intell*, 34, 235–250 (2020). https://doi.org/10.1007/s13218-020-00637-y.

Solino, L. J. S., Dantas, Í. J. M., Teixeira, B. M. L., Alves, I. T. P., & Medeiros, A. L. P. (2021). *Slow profile potiguar:* perfis de orientação ao consumo Slow fashion no Rio Grande do Norte. In: Anais do 3º Encontro Científico de Pesquisa em Design de Moda, Passos.

Solino, L. J. S., González, M. O. A., Siqueira, M. E. M., & Nascimento, W. A. (2015). Fast-fashion: uma revisão bibliográfica sistemática e agenda de pesquisa. *Revista Produção Online*, 15(3), 1021–1041. (https://doi.org/10.14488/1676-1901.v15i3.1947).

Solino, L. J. S., Teixeira, B. M. L., & Dantas, Í. J. M. (2020). The sustainability in fashion: a systematic literature review on Slow fashion. *International Journal for Innovation Education and Research*, 8(10), 164–202. (https://doi.org/10.31686/ijier.vol8.iss10.2670).

Solino, L.J.S., De Medeiros Dantas, Í.J., De Lima Teixeira, B.M., Alves, I.T.P., De Medeiros, A.L.P. (2023). Research on the Potential of the Consumption of Slow fashion Products in Brazil. In: Broega, A.C., Cunha, J., Carvalho, H., Providência, B. (eds) *Advances in Fashion and Design Research*. CIMODE 2022. Springer, Cham. (https://doi.org/10.1007/978-3-031-16773-7_50).

Solomon, M. R., et al. (2016). *Consumer Behavior: A European Perspective* (5th ed.). Pearson.

Speiser, J. L., Miller, M. E., Tooze, J., & Ip, E. (2019). A comparison of random forest variable selection methods for classification prediction modeling. *Expert systems with applications*, 134, 93-101. (https://doi.org/10.1016/j.eswa.2019.05.028).

Štefko, R., & Steffek, V. (2018). Key Issues in Slow Fashion: Current Challenges and Future Perspectives. *Sustainmability*, 10(7), p. 2270. (https://doi.org/10.3390/su10072270).

Stuart, R., & Norvig, P. *Artificial Intelligence: A Modern Approach*, Upper Saddle River, NJ, USA:Prentice-Hall, 2009.

Tseng, M. L., Chiu, A. S., & Liang, D. (2018). Sustainable consumption and production in business decision-making models. *Resources, Conservation and Recycling*, 128, 118-121.

Veronese, O., & Laste, A. (2022). O trabalho escravo e Fast fashion: o flerte da indústria da moda com a servidão. *Revista Direito e Justiça: Reflexões Sociojurídicas*, 22(43), 171-185.

Whales, S., & Pandey, G. (2013). *A Comparative Analysis of Ensemble Classifiers: Case Studies in Genomics. In:* IEEE 13th International Conference on Data Mining. Dallas, IEEE.

Webb, G. I., Keogh, E., & Miikkulainen, R. (2010). Naïve Bayes. *Encyclopedia of machine learning*, 15(1), 713-714. (https://doi.org/10.1007/978-0-387-30164-8_576).

Yang, Z., & Su, X. Customer Behavior Clustering Using SVM. *Physics Procedia*, v. 33, p. 1489-1496, 2012. (https://doi.org/10.1016/j.phpro.2012.05.243).

Zahay, D., & Griffin, A. (2010). Marketing strategy selection, marketing metrics, and firm performance. *Journal of Business & Industrial Marketing*, 25(2), 84-93. (https://doi.org/10.1108/08858621011017714).

Zhang, C., & Ma, Y. (.2014). *Ensemble Machine Learning: Methods and Applications*. Springer New York, NY. (https://doi.org/10.1007/978-1-4419-9326-7).

Zheng, A. and Casari, A. (2018) *Feature Engineering for Machine Learning: Principles and techniques for Data Scientists*. O'Reilly Media, Inc., Sebastopol.

Zhou, Z. (2021). *Machine Learning*. Singapore: Springer Nature. (https://doi.org/10.1007/978-981-15-1967-3).