Enabling circular and sustainable clothing in your wardrobe*

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Abstract. Today's e-commerce landscape is consumer-centric, and among them, the fashion industry wields substantial influence. The fashion industry in a way shapes and dictates many societal norms but is also a significant contributor towards environmental pollution. Heightened awareness among consumers regarding the social and ecological consequences of their purchases has pushed the demand for sustainable and ethical fashion options. Yet, the scarcity of easily accessible and reliable information on product sustainability creates an intention-behavior gap. To address this challenge, a new framework is needed that can leverage domain expertise to discern sustainable products and facilitate consumer access to them. In response, our research lab endeavors, through this paper, to devise a content-based sustainability-focused recommendation algorithm for 'esprit.com,' a leading apparel retailer. Our approach extends the work of Satinet and Fouss [17], utilizing supervised machine learning to extrapolate findings from life cycle assessment studies, thereby enabling the evaluation of clothing product sustainability with limited online retailer data. Leveraging a dataset comprising clothing product life cycle attributes and corresponding environmental impact data, we trained a recommendation system employing three supervised machine learning algorithms. Notably, the random forest algorithm emerged as the most effective, with an average accuracy of 82 percent. The resultant recommendation system stands poised to benefit consumers with sustainable product suggestions, thus cultivating informed and responsible shopping behaviors.

Keywords: Recommendation System · Content based filtering · Sustainable fashion.

1 Introduction

As per [8], up to 100 billion garments are produced by the fashion industry every year. At the current rate, global clothing sales would reach 160 million tons by 2050. Today, we own more clothes than we used to in the past, and we wear them less. Fifteen years ago, our wardrobes were simpler and more sustainable. But today, we find ourselves buying 60 percent more clothing than before, only to discard each item after wearing it 50 percent as often. This means, as much

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as 92 million tons of clothing ends up in landfills and only 20 percent of textiles are collected for reuse or recycling globally. Reference [8] suggests that almost 60 percent of all clothing material is actually plastic. Textile production generates 42 million tons of plastic waste per year, making it the second-highest plastic waste producer after the packaging industry. Nylon, acrylic, and polyester clothes are just a few examples of these synthetic fibers that have become so ubiquitous in our wardrobes. Every time a synthetic garment is washed, it releases tiny plastic microfibers into the water and close to 500,000 tons of microfibers end up in the ocean every year. Apart from this the fashion industry is the second-largest consumer of water and accounts for around ten percent of carbon emissions globally [1],[8], [9], [10].

1.1 Sustainability

It is imperative to understand and define 'sustainability' in order to identify sustainable products. If a textile product negatively impacts people's health or the environment during its production, use and disposal, shouldn't it just be taken of shelf and substituted with a safer and more sustainable alternative? Or should brands and regulators provide consumers with information about product sustainability so that they can make an informed choice? [11]However, this rarely happens in execution. This leaves consumers unaware of what product to choose to avoid potential health or environmental risks. To improve the situation, the UN-Environment and ITC 2017 Guidelines for Providing Product Sustainability Information (Guidelines) were developed in the frame of the Consumer Information Programme (CISCP) of the One Planet Network with the aim of empowering consumers to make informed purchasing decisions that will minimize adverse impacts on people and the environment. Such information contributes to sustainable consumption that includes the purchase, use and disposal of consumer products [11]. Acording to The UN Alliance for Sustainable Fashion (please refer [12]), Sustainability encompasses social issues, such as improvements in working conditions and remuneration for workers, as well as environmental ones, including the reduction of the industry's waste stream, and decreases in water pollution and contributions to greenhouse gas emissions. Our work tries to focus on environmental issues rather than social ones.

1.2 Life Cycle Assessment (LCA)

LCA is an instrument to assess the potential environmental impacts and resources used throughout a product's life cycle, that is, from raw material acquisition, through production and use stages, to waste management [13]. As per [36], Life cycle assessment (LCA) has established itself as part of the sustainability toolkit of the private sector, informing environmental decision-making and improving environmental performance. As per [14], when conducting an LCA in the fashion and textile industry, it is crucial to consider a wide range of environmental indicators to gain a comprehensive understanding of the product's overall environmental impact. These indicators represent different potential environmental impacts throughout the product's life cycle, for example, global warming, acidification, eutrophication, ozone depletion, harm to ecosystems and humans, land use, water consumption, and more. According to [14], the two

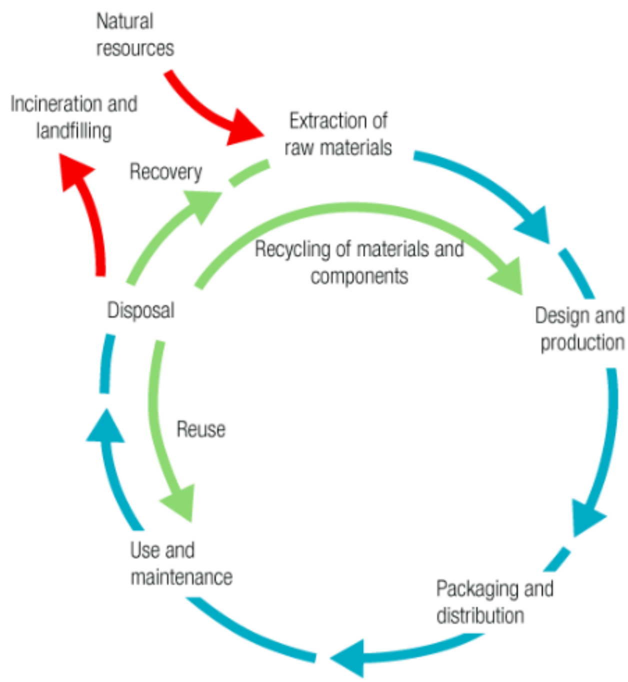


Fig. 1: A typical lifecycle of a product over which LCA is relevant. Refer [13]

prominent LCA boundary models for fashion and textiles are 'Cradle-to-Grave' and 'Cradle-to-Gate'. 'Cradle-to-Grave' model assesses impacts from the beginning (raw material extraction or 'cradle') to the end (disposal or 'grave') of a fashion product's life cycle (Refer Fig.1). In order to get a holistic view of environmental impacts, when developing sustainability strategies, making product development decisions, or communicating the total environmental footprint to stakeholders, it is better to use the 'Cradle-to-Grave' model. Further, [14] clarifies that, in order to conduct this assessment, data pertaining to the following questions need to be obtained: What are the materials used for the product? Where are the materials produced? What chemicals are used in the supply chain? What processes does the product go through such as spinning, weaving/knitting, bleaching, dyeing, finishing, etc? How the product is transported and how long are the distances? What happens to the product when it becomes waste? While collecting the data pertaining to textile products Satinet, C.; Fouss [17] has focussed on this aspect of LCA and this dataset is also the base of our current work.

1.3 Supervised Machine Learning

The task of recommending sustainable clothing options to a customer begins with identifying sustainable products. This can be pictured as a classification problem where, based on the environmental impact we categorize the available products into different levels of sustainability [17]. Hence, in the current work, we first applied supervised machine learning techniques on a classification problem to categorize textile products based on their environmental impact. Classification is a supervised learning technique since it categorizes data from prior information. The class of each testing instance is decided by combining the features and finding patterns common to each class from the training data. Classification is done in two phases. First, a classification algorithm is applied on the training data set and then the extracted model is validated against a labeled test data set to measure the model performance and accuracy. [42]

1.4 Recommender Systems

As per [43], Recommender systems are software tools and techniques providing suggestions for items to be of use to a user. These suggestions are intended to support the users in various decision-making processes, such as what items to buy, what music to listen, or what news to read. The development of recommender systems is a multi-disciplinary effort that involves experts from various fields such as artificial intelligence, human-computer interaction, data mining, statistics, decision support systems, marketing, and consumer behavior. [43].

2 Related Work

The fashion Industry and its supply chain operations are always under global scrutiny due to its significant contribution to environmental pollution. Niinimäki et. al. [18] identify that the current business logic in the fashion sector is based on ever-increasing production and sales, fast manufacturing, low product quality, and short product life cycles, all of which lead to unsustainable consumption, fast material throughput, substantial waste, and vast environmental impacts. However, no experimental study is conducted to measure the impact of change in processes by the authors. One of the earlier studies on Life Cycle Assessment (LCA) was done by Weerasinghe et. al. [23] where they developed a color code-based environmental labeling (EL) scheme based on Product Life Cycle Assessment (LCA). Cruz et. al [19] reviewed the state-of-the-art literature on digital solutions for engaging the end-consumers in the Circular Economy of the Textile and Clothing Value Chain and organized the solutions into Social and Sustainable Marketing, Recommender systems, Non-gamified Applications, and Gamified Applications. They observed that recommender systems that take into account the sustainability of the garments can facilitate consumer engagement, both for new and second-hand garments. Tomkins et. al [37] conducted research work that could be considered as an initial step towards developing a sustainable recommender system. They identified that the lack of easily accessible and credible information on product sustainability leads to the intention-behavior gap and proposed a model using a flexible probabilistic framework that uses domain knowledge to identify sustainable products and customers and thereby predict customer purchases. In their study, Spillo et. al. [38] compared 18 popular recommendation algorithms in terms of both performance metrics (i.e., accuracy and diversity of the recommendations) as well as in terms of energy consumption and carbon footprint on three different datasets. Their experiments showed that the choice of the optimal recommendation algorithm requires a thorough analysis since more sophisticated algorithms often lead to tiny improvements but with an exponential increase of carbon emissions. Satinet and Fouss [17] developed a model that could easily and quickly assess the environmental sustainability of clothing products with the limited data available to online retailers. They also contributed by providing a dataset that could be used for further research on the sustainability of clothing products. In their review about fashions recommendation systems models and methods, Chakraborty et. al [2], identified that the selection of an effective and accurate filtering technique is crucial for developing a successful recommendation system. According to them, in general recommendations, user satisfaction is not observed and there is an inherent scarcity of negative feedback and there should be more novel research on developing recommendation models by combining sentiment analysis with user images to provide intelligent and social-network-based hyper-personalized recommendations. Nguyen, H.T. et al. (2014) [3] designed and implemented fashion recommendations by analyzing implicit feedback from users in an app. As per their research alternating least-squares with weighted λ-regularization (ALSWR) when combined with price and popularity, provided better results. However, the algorithm has to deal with the 'cold-start' problem and assumes that generated implicit scores represent users' preferences well. Hwangbo, H. and Kim, Y. [20], in their work, tried to improve recommendation systems' performance by considering item sessions and attribute session information. The authors combined various Attribute Session Based Recommenders (ASBRs) with feature-weighted schemes, resulting in superior performance over pure Item Session Based Recommender (ISBR) and conventional CFR. This allows the recommenders of cold-start items to users without a loss of performance. Wei et. al [4] proposed two recommendation models to solve the Complete Cold Start (CCS) and Incomplete Cold Start (ICS) problems for new items, which are based on a framework of tightly coupled Collaborative Filtering (CF) approach and deep learning neural network. From their experiments, the impact of including the time and item content information is very large on the performance of the recommendation system. L. Yu-Chu et. al [39] developed a clothing recommendation system based on a Bayesian network that recommends clothing combinations from a user's wardrobe that is particularly suitable to a user based on the user's personal preference, history of clothing items, and the user's evaluations of previous system recommendations. The system however could face cold-start problems, and performance could downgrade when more parameters (such as sustainability-related) are taken into account. Zhou et. al (2021) [5] developed a machine learning approach that makes personalized fashion recommendations based on aesthetic and descriptive features of fashion products. The model extracts and learns aesthetic and descriptive features from product descriptions and images in a combined neural network model which improves the quality of the recommendations made to users. However, sustainability-related features may be difficult to extract from images or titles and usually need more descriptive/textual data. Bellini. P. et. al.[21] developed a recommendation system for fashion retail shops, based on a multi-clustering approach of items and users' profiles in online and on physical stores. The algorithm collects and uses data regarding customers' behavior and interactions with items from physical stores by RFID technology. This may not be within the scope of our current study as complex architecture is required for the same. Naham A-Z et. al.[22] proposed an improved fashion RecSys by detecting gender and retrieving object similarity from the query images, to recommend the most relevant products. The system uses a query image to extract data and then recommend similar products. However in the context of our research lab, this model may not be suitable for online fashion, as recommendations are based on search queries, past purchases, and browsing patterns etc., Lin et. al. (2023) [24] proposed a machine learning method that can discover signals of sustainability from online interactions, like reviews and product descriptions. Researchers trained an LLM to predict the sustainability score of products using labeled data from public resources. However, this approach could be challenging due to the non-availability of high-quality ground truth sustainability labels and the presence of noisy online data. Cacheda et. al. [26] compare various collaborative filtering algorithms under diverse conditions and propose a simple yet effective tendencies-based algorithm that demonstrates competitive precision and computational efficiency. Dong, Min et al. [27] proposed a novel designer-oriented recommender system that combines professional design knowledge with user preferences to enhance personalized fashion design. The system dynamically adjusts based on designer evaluations and provides virtual product demonstrations for enhanced user feedback. Shankar et al. [28] developed a recommender system that bridges the gap between designer expertise and user preferences by leveraging professional design knowledge with user feedback and technological advancements. Lu, Ping et al. [29] proposed a Product Recommendation System using Deep Learning to address the challenges of personalized recommendations in the dynamic e-commerce landscape. The system utilizes a DNN double tower recommendation algorithm, incorporating user and item embeddings, advanced feature engineering, and a combination of classic and deep learning techniques. It is developed using Python, TensorFlow, and a high-performance GPU, and employs a big data lambda approach with Golang and gRPC microservices. Atina et al. [40] proposed a Clothing Product Selection Recommendation System addressing the challenges of product selection and providing a personalized experience for both admins and customers. The system's implementation is aligned with the Rapid Application Development (RAD) methodology, enabling a rapid and efficient process. J. Yu et al. [41] proposed the "Fluctuation Method", which measures user preference fluctuations across four different periods and incorporates these values into traditional collaborative filtering to create a more dynamic and personalized recommendation system. Stalidis et al. [31] outlined that recommendation systems should balance accuracy and serendipity, consider contextual factors, foster trust and transparency, leverage holistic user data, and utilize advanced neural network techniques. It also envisions the development of more intelligent recommendation systems that integrate marketing insights and cater to smaller enterprises with flexible solutions. Pulukool et al. [32] proposed using advanced computer models, including the Random Forest model, to predict global hailstorms by considering a few critical input features to improve accuracy and generalizability. Seo et al. [6] put forth an approach to incorporate environmental considerations into product development using an ANN-based LCA model that estimates environmental impact based on identified product attributes and categorized groups, and a product classification system using a decision tree algorithm. In their research, Koyamparambath. A et. al [25] use AI techniques to predict the environmental performance of a product or service to assist LCA practitioners and verifiers. Even though the authors' focus is on the construction industry, this method could be generalized and extended to fashion recommendations by suitably adopting the LCA in the fashion industry. A sustainability score could be developed and can be combined with a content-based filtering technique for effective recommendation. Considering the potential of this method, we have decided to work on our research lab by improving and/or modifying this method.

3 Methods

The task of recommending sustainable clothing options to a customer begins with identifying sustainable products. This can be pictured as a classification problem where in, based on the environmental impact we categorize the available products into different levels of sustainability.

3.1 Dataset and Pre-Processing

Reference [17] assembled a dataset of clothing products with their life cycle characteristics and corresponding known total environmental impact, to be used by future research works in the area of sustainability. The dataset contains a representative sample of clothing products with complete data on product attributes and corresponding environmental impact. The dataset contains LCAs conducted for 75 products of Netherlands based company "MUD Jeans", which were shared by the company themselves to researchers [17]. It also contains LCA results of 45 clothing products which were freely available in the database of The International EPD System. In addition to this, the researchers Satinet, C.; Fouss, F [17] included data for 27 other products from studies provided by different researchers and organizations. Finally, using the Python 'BeautifulSoup' library, researchers Satinet, C.; Fouss, F [17] extracted 159 and 830 clothing products, respectively—with their attributes and environmental impact from the e-commerce site “Reformation” and a second popular online retailer. The attributes in the dataset are so selected such that they have logical and statistical links to environmental impact data and are also accessible to online retailers. The main criteria used for selecting product attributes to form the original dataset are their relationship to various factors impacting the environment (e.g., energy consumption, garment recyclability, etc.) and their accessibility to online retailers [17]. The textile industry supply chain starts with the production of fibers and the spinning process is done to produce yarn. Then, through the process of knitting or weaving fabrics are manufactured from yarns. Before the final garment is manufactured, it undergoes steps like bleaching, dyeing, cutting, sewing, and adding trims. The garments are then shipped to central distribution centers which are then shipped across the globe to reach the smaller retailers. At the end of a Garment's useful life, they are incinerated, transported to landfills or developing countries, and only a few are recycled. As inferred from [18], at each of the above-mentioned stages in its supply chain, a garment has an adverse impact on the environment. According to [33] and [34], most of the life cycle impacts of apparel products occur in the production phase and then in the use phase. Due to carbon emissions, energy and water consumption, chemicals, microplastics, and waste, textile production is regarded as resource-intensive and gives rise to substantial environmental impacts. As inferred from [35] and [17] these environmental impacts are determined generally by the following aspects namely garment and raw material type, the manufacturing processes, by where the garment is produced, and how it is transported, how the garment should be taken care of prior to disposal, and the product's end-of-life. The dataset assembled by [17] and that is used as a basis for the current study is based on previously conducted LCA studies. It contains clothing products as observations and their life cycle characteristics as independent input variables or features. Based on the LCA method, the corresponding total 'Environmental Impact' is the dependent output variable. The original data set assembled by the researchers Satinet, C.; Fouss [17] has the following features - (1) Cotton, Organic_cotton, Linen, Hemp, Jute, Other_plant, Silk, Wool, Leather, Camel, Cashmere, Alpaca, Feathers, Other_animal, Polyester, Nylon, Acrylic, Spandex, Elastane, Polyamide, Other_synthetic, Lyocell, Viscose, Acetate, Modal, Rayon, Other_regenerated, Other, Recycled_content and Reused_content show their percentage composition in the cloth type under consideration. (2) Material_label, Chemicals_label, Production_label, Reusability_label and Recyclability_label show whether the particular label is present or not in the cloth type under consideration. (3) Feature Manufacturing_location shows where the cloth was manufactured namely 'Africa', 'America', 'Asia', and 'Europe'. (4) Feature Use_location shows in which location, the particular cloth is being used or sold. The dataset contains clothes that are intended for use in 'Africa', 'Asia', 'Austria', 'Belgium', 'Czechia', 'EU', 'Denmark', 'Finland', 'France', 'Germany', 'Greece', 'Italy', 'Latvia', 'Luxembourg', 'Netherlands', 'Norway', 'Poland', 'Spain', 'Sweden', 'Switzerland', 'UK', 'USA', and 'USA-UK-EU'. (5) Transportation_distance is a feature that shows the distance between the manufacturing place and the place where the product is intended for use, in kilometers. (6) 'Washing_instruction' and 'Drying_instruction' can have the following values respectively - 'Dry Clean', 'Hand Wash', 'Machine wash_cold', 'Machine wash_hot', 'Machine wash_warm' and 'Dry clean', 'Line dry', 'Tumble dry_low', 'Tumble dry_medium'.

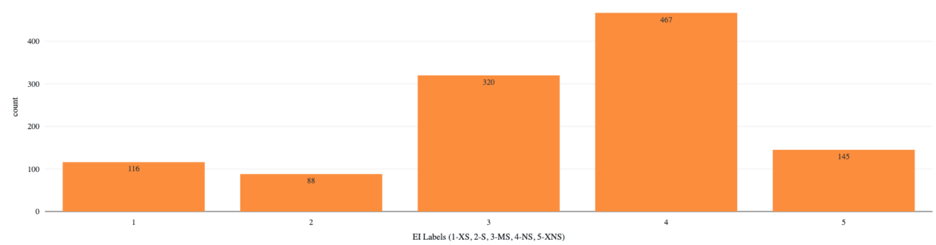


Fig. 2: Distribution of total number of cloth items under each category based on their Environmental Impact (EI) score. Majority of the items are in class 3 (Medium Sustainable) and class 4 (Non Sustainable)

Feature Selection and Feature Engineering Roughly half of all garments contain either cotton or polyester, but it's uncommon for both to be present simultaneously. It is observed that garments with a higher proportion of organic cotton also tend to incorporate more recycled materials. Further, a higher lyocell content often correlates with the presence of responsibly sourced material labels. On the other hand, polyester-rich garments are less likely to feature such labels. Manufacturing of these garments is widespread, and a significant portion originated from Southeast Asia. Approximately four percent of products are certified for controlled chemical usage during production. Garments undergo significant journeys, spanning an average distance of 11,570 km from manufacturing to distribution to end consumers. Washing instructions vary, with 68 percent suitable for machine washing with cold water, 16 percent requiring warm water, and only a minority necessitating hot water, hand washing, or dry cleaning. Line drying is recommended for the majority, while tumble drying at low to medium temperatures is advised for only a small fraction. Notably, washing and drying instructions often correlate, as garments suitable for dry cleaning usually bypass drying, while those washable in warm water can often be tumble-dried. Additionally, 7 percent of products feature end-of-life instructions for recycling or reuse, with reusable products often also featuring recyclability labels.

Pearson Correlation analysis was performed to understand and remove strongly correlated features. When two variables were strongly correlated, we removed

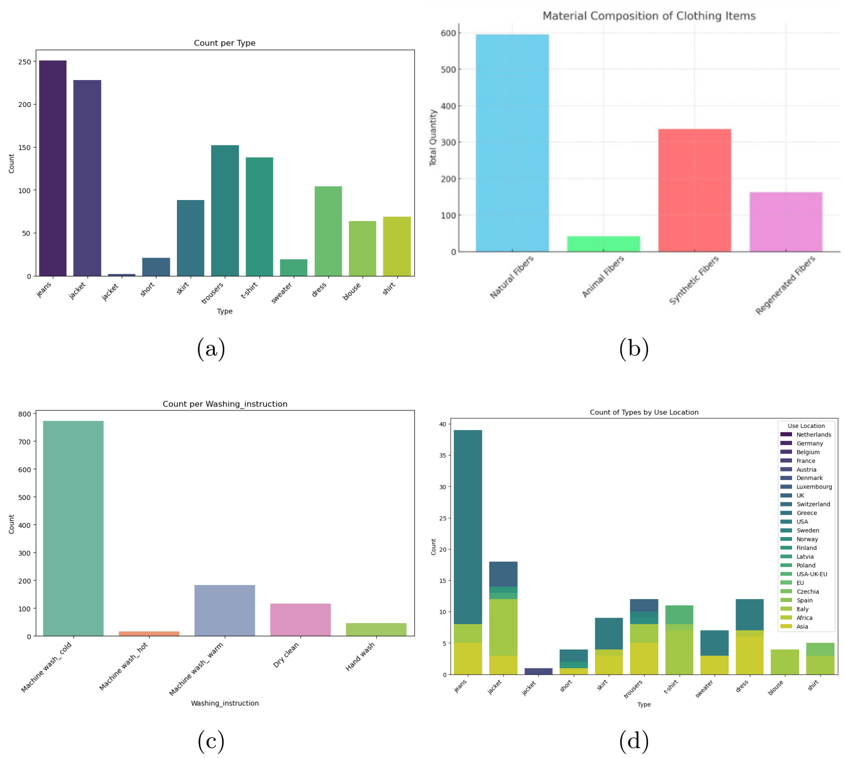


Fig. 3: (a) Distribution of available clothing types. Jeans and Jackets are the most common ones. (b) Material composition of different clothing items. Synthetic fibers are the second most common, emphasizing the need for responsible use and disposal. (c) Washing instructions for various clothing items. (d) Types of clothes and their use location

the feature that initially contained the most missing values. Categorical columns "Drying_instruction", "Manufacturing_location" and "Washing_instruction" were converted (and separated) into numerical columns (with values indicating each category) to better understand feature importance. The features "Alpaca", "Other-animal", "Camel","Other_regenerated","Other_plant" and "Jute" were removed as they were empty. These attributes were added by the original reserachers according to the existing LCA method and available sustainability indeices like Higg MSI [15]. Feature importance was explored using decision tree analysis and we found that certain features like percentage of Organic_cotton, percentage of Cotton, Use location, transportation distance etc have relatively high importance in deciding the product sustainability. Also, due to the sparse nature of the available data set and since the datapoints are limited, the contribution of each feature towards decision making is relatively small and is almost evenly distributed signalling that allmost all features (retained together with transformed) may be necessary for meaningful classification. Had there been more datapoints with less sparse feature-set, the relative importance of features may have changed and dimensionality could have been further reduced. We also performed principal component analysis (PCA), to analyze the possibility of reducing the dimensionality of our data prior to modeling. However, the results showed that more than 29 factors are needed to explain at least 95% of the variance. In view of these results it seemed wise to keep all the features (retained non empty features together with transformed features) unearthed so far, for building and experimenting with our model.

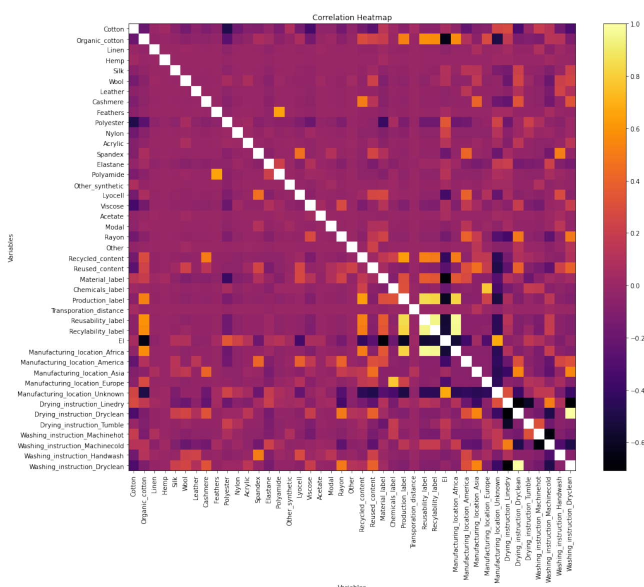


Fig. 4: Feature correlation analysis

As can be seen from the analysis, the majority of data points are in class 3 (Medium Sustainable) and 4 (Non-Sustainable) which may affect the model performance and prediction accuracy. This also points out the fact that the number of sustainable products in the market is currently significantly lower than the number of non-sustainable products. The classification algorithms used in case of class imbalances should be impervious to the scarcity of data in one class compared to the other. According to Chen, Chao, and Liaw, Andy (2004),[47] tree based methods show superior resilience to class imbalances due to their hierarchical nature and the way they split data.

Algorithms The Random Forest algorithm, lauded for its ensemble learning approach that amalgamates the outcomes of numerous decision trees, is particularly adept at navigating the complex, multidimensional data associated with sustainable fashion attributes [44]. This methodology is instrumental in enhancing the predictive accuracy of our system, making it well-suited to tackle the intricate patterns tied to the sustainability aspects of clothing. In parallel, the Decision Tree algorithm, known for its straightforward yet powerful classification capabilities, facilitates the segmentation of our dataset into more manageable subsets, simplifying the analytical process [45]. This algorithm's capacity for clear data visualization and interpretation is invaluable in elucidating the myriad factors that influence a garment's sustainability score. The Gradient Descent algorithm plays a crucial role in optimizing the model's performance. By iteratively minimizing the cost function, it meticulously adjusts the model's parameters to hone its predictive precision [46]. This fine-tuning is particularly essential for calibrating the weights assigned to various features within our dataset, thus sharpening the model's acuity in detecting subtle distinctions in the sustainability attributes of fashion items.

4 Results

4.1 Construction of Models and Pipelines

In this section, we detail the construction of the Random Forest classifier and Gradient Boosted Tree classifier using Spark, specifically within the Databricks environment. The Random Forest and Gradient Boosted Tree algorithms are powerful ensemble learning methods that combine multiple decision trees to improve predictive accuracy and mitigate overfitting. Leveraging Spark's distributed computing capabilities (within the Databricks environment), we aimed to develop a robust classification model which can then be developed into a recommendation system. We utilised Spark's MLlib (Machine Learning Library), which is a robust toolset available within the Databricks environment, offering a wide array of machine learning utilities for scalable and distributed data processing.

First, the categorical variables are encoded using 'StringIndexer' to convert them into a numerical format suitable for tree-based machine learning algorithms. This encoding facilitates the processing of categorical features by the

Tree-based classifier. Then the feature vectors are assembled using 'VectorAssembler', which combines numerical and encoded categorical features into a single vector representation. This consolidated format is required so that Spark can enable seamless integration into the classification pipeline.

Pipeline: A pipeline is constructed which consists of multiple stages, each comprising a specific processing or modeling task. As explained above, the 'StringIndexer' stage encodes categorical variables and assigns a unique numerical index to each distinct category. The 'VectorAssembler' stage then assembles these encoded categorical features with numerical features into a single feature vector and prepares the data for model training. The pipeline then incorporates the respective (random forest, gradient boosted tree, or decision tree) 'classifier' stage. This stage is configured with specified hyperparameters and facilitates the training process using the preprocessed data. The creation of such a pipeline would aid in the systematic execution of these steps and will also ensure the reproducibility of results.

According to Dalianis, H. [7], if data is scarce, k-fold cross-validation is carried out by dividing the whole dataset into k folds, and the k-1 folds are used for training, and the remaining 1 fold for evaluation: the folds are switched until all folds are trained and tested on the remaining of the k-1 folds and finally an average is calculated. By partitioning the training dataset into multiple subsets and iteratively training the model on different combinations of these subsets, cross-validation helps in reliably estimating model performance and preventing overfitting.

Hyperparameter Tuning Using HyperOpt: Hyperopt is a popular open-source hyperparameter tuning library[16]. All tuning experiments, along with their hyperparameters and evaluation metrics, are automatically logged to MLflow in Databricks. In our experiment, we used HyperOpt, to systematically search for the optimal set of hyperparameters for our tree-based classifier. We defined a search space comprising of various hyperparameters and an objective function to minimize. The configurations that yield the best model performance are identified by hyperopt. HyperOpt's optimization algorithm (TPE - Tree-structured Parzen Estimator) is employed to iteratively explore the hyperparameter space, updating the search based on past evaluations. Through multiple iterations, HyperOpt converges towards the optimal set of hyperparameters that maximize the model's performance. The search space for hyperparameters, including the number of trees, maximum depth, maximum bins, feature subset strategy, subsampling rate, minimum instances per node, and minimum information gain, is specified using appropriate parameter distributions.

4.2 Accuracy, Precision, Recall, and AUC analysis

Table 1 shows the accuracy, precision, and recall of the 3 machine learning algorithms that we experimented on, over their five folds. We used a weighted

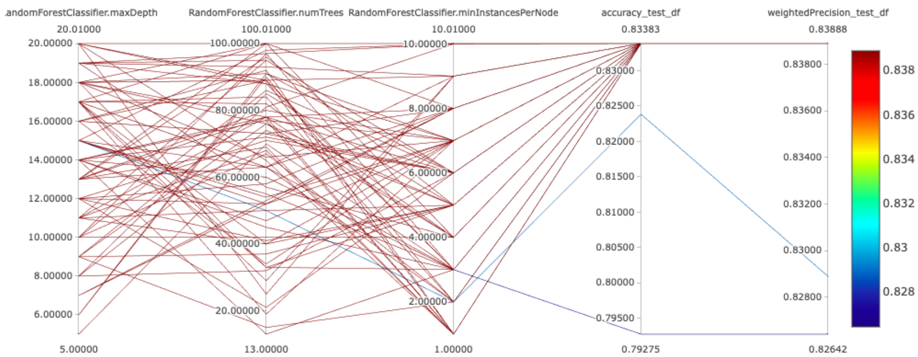


Fig. 5: Parallel coordinates Plot for comparison of 79 runs of 1 HyperOpt Trial (tracked by Databricks MLflow)

Table 1: Accuracy, Weighted average precision and Weighted average recall of 3 algorithms

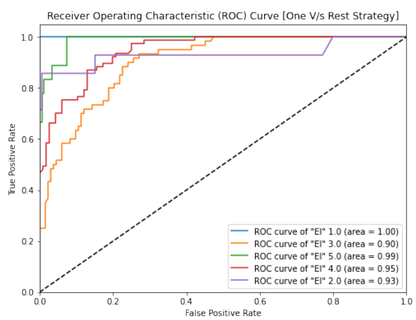
Algorithm	**Accuracy**	**Wt. Avg. precision**	**Wt. Avg. recall**	**F1-score**
Random Forest	82.38	82.89	82.38	82.18
Gr.B-Tree	80.83	80.88	80.83	80.69
Decision Tree	80.83	81.22	80.83	80.81

average for recall and precision and therefore the precision and recall values are close to the accuracy results.

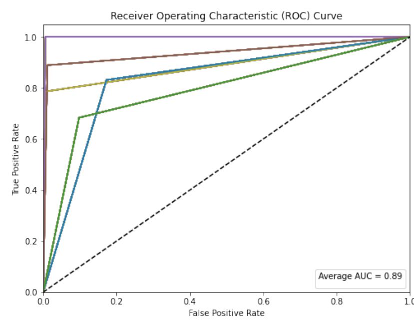
We also employed Receiver Operating Characteristic (ROC) curve analysis and the Area Under the Curve (AUC) metric, which provide insights into the model's ability to discriminate between positive and negative classes. The ROC curve graphically represents the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) across various threshold values. Each point on the ROC curve represents a sensitivity-specificity pair corresponding to a particular threshold. The overall performance of the classifier is quantified by measuring the area under the ROC curve (called AUC). An AUC value close to 1 indicates a model with high discriminatory power, while an AUC value close to 0.5 suggests random classification. In our classification task, we used the 'One-vs-Rest' scheme to compare each class against the rest (assumed as one). A higher AUC value indicates superior discrimination capability, reflecting the model's effectiveness in correctly classifying positive instances while minimizing false positives.

4.3 Building the Recommender System

The recommendation system serves to provide personalized suggestions for sustainable products based on individual preferences and characteristics. Leveraging



(a)



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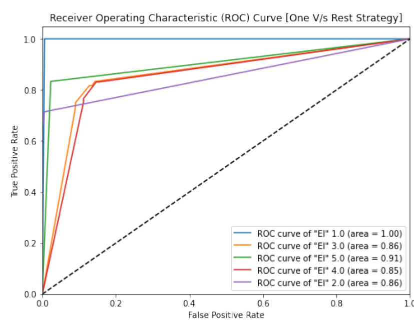

(c)

Fig. 6: Area under the Curve (AUC) of classification model by (a) Random Forest algorithm (b) Gradient Boosted Tree and (c) Decision Tree

the insights gained from our classifier (Random Forest, Gradient Boosted Tree or Decision Tree), we implement a content-based filtering approach to recommend items that align with users' desired clothing type. Unlike collaborative filtering methods that rely on user-item interactions, content-based filtering focuses on the attributes or features of items and matches them with users' preferences. In our context, we leverage the predictions generated by the classifier to identify sustainable products and subsequently recommend them to the users.

- **Generate Predictions**: The trained pipeline model is first utilized to make predictions on the entire dataset of sustainable clothing products (Jackets, Jeans, Shirts, Blouses, etc.). The predictions include probabilities of items belonging to different sustainability labels (categories of XS, S, M, NS, and XNS based on the Environmental Impact, or the EI score), enabling us to identify sustainable clothing products effectively.
- **Filter Sustainable Cloth Types**: We then filter the predictions to extract sustainable cloth types, identified based on their predicted labels. These products are classified as environmentally friendly or sustainable by the model (Random Forest, Gradient Boosted Tree or Decision Tree).
- **Sorting and Ranking**: The filtered sustainable cloth types are then sorted and ranked based on their probability of belonging to the sustainable classes (XS or S). This ranking provides a measure of confidence in the 'Environmental Impact' of each recommended item, allowing users to make informed purchase decisions.

Our recommended system relies solely on the product attributes (mainly composition) and provides targeted suggestions for specific product types, such as jackets, jeans, and shirts, etc.,. By filtering the recommended items based on their types, we ensure that users receive recommendations that are relevant to their immediate needs and preferences in sustainable fashion.

4.4 Recommendation results

The recommended items are presented along with their corresponding probabilities of being environmentally impactful (EI). This approach allows users to make informed purchase choices while promoting sustainable consumption habits. Fig.7 shows the results when the user preferred the cloth type 'Jacket'. The recommendation system identified a selection of jackets that exhibit high probabilities of being environmentally friendly (high EI score or belonging to classes XS (class 1) and S (class 2). These recommendations have a strong likelihood of aligning with sustainable fashion principles. Two separate images in Fig.7 show the recommendation results from the recommender system based on the random forest model and gradient-boosted tree model. While both models prioritize sustainability, their nuanced approaches result in divergent EI score predictions for certain jacket options. For instance, the system based on the Random Forest classifier assigns EI score of 1 to all selected jackets and recommends them to the user. In contrast, the recommender system based on the

ID	Type	probability	EI
4	jacket	[0.0,0.9966265946...	1
35	jacket	[0.0,0.9966265946...	1
37	jacket	[0.0,0.9966265946...	1
120	jacket	[0.0,0.8978765946...	1
82	jacket	[0.0,0.8732565960...	1
83	jacket	[0.0,0.7599232627...	1

ID	Type	EI
4	jacket	1
35	jacket	1
37	jacket	1
82	jacket	1
83	jacket	1
120	jacket	1
86	jacket	2
90	jacket	2
94	jacket	2
96	jacket	2
1068	jacket	2
1073	jacket	2

Fig. 7: Recommendation results by Random Forest model based recommender system (left) and Gradient Boosted Tree based recommender system (right)

Gradient Boosted Tree classifier assigns a mix of EI scores of 1 and 2 to the selected jackets and recommends them, thereby reflecting a broader spectrum of environmental impact considerations. This discrepancy underscores the distinct modeling techniques and decision boundaries employed by the two classifiers in assessing sustainability. While both models aim to promote environmentally friendly choices, their differing methodologies and decision-making processes result in distinct recommendation outcomes.

5 Discussion and Analysis

5.1 Interpretation of Results

Comprehensive Evaluation of Model Performance: The superior performance of the Random Forest model, with an accuracy of 82.38%, reflects its robustness in managing the complexities inherent in the sustainability dataset. This model effectively leverages ensemble learning by combining multiple decision trees to mitigate overfitting and enhance generalization capabilities. The high accuracy indicates a strong alignment between the model predictions and the actual sustainability classifications, underscoring its potential as a reliable tool in guiding consumers towards more sustainable clothing choices.

The weighted precision of 82.89% further demonstrates the model's ability to minimize false positives, which is crucial in maintaining trust in the recommender system. High precision ensures that when a product is recommended as sustainable, it is highly likely to be so, reinforcing the system's credibility.

Despite the Random Forest model's strengths, the relatively lower performance of the Gradient Boosted Tree and Decision Tree models, both with an 80.83% accuracy, suggests areas for improvement. These models, while effective, may be more susceptible to the dataset's nuances, such as its class imbalance and the multifaceted nature of sustainability attributes.

Insights into Classification Challenges: The difficulty in accurately classifying items into the "Medium Sustainable," "Non-Sustainable," and "Extremely Non-Sustainable" categories highlights a critical challenge in the dataset's composition and the models' sensitivity to class imbalance. This suggests that while the models are proficient in identifying clear-cut cases of sustainability, they struggle with more nuanced or borderline cases. Enhancing the models' ability to discern these subtleties is crucial for a more nuanced and accurate recommender system.

5.2 Analysis of Methodological Approaches

Choice and Implementation of Machine Learning Models: The researchs's methodological approach, centered around tree-based machine learning models, is well-justified given their known resilience to class imbalances and their capability to model non-linear relationships without needing extensive pre-processing. The Random Forest model's ensemble approach effectively addresses the variance-bias trade-off, providing a more stable and accurate model by aggregating predictions from multiple decision trees.

The Gradient Boosted Tree model, by focusing on correcting the residuals of prior trees, offers a powerful method for incremental error reduction. However, its performance in this context, comparable to the simpler Decision Tree model, suggests that the incremental gains may not fully compensate for the increased complexity and computational cost, especially given the dataset's specific challenges.

Evaluating the One-vs-Rest Strategy: The application of the One-vs-Rest strategy in handling multiclass classification illuminated the models' capacity to differentiate between various sustainability levels. This approach, by decomposing the multiclass problem into multiple binary classification problems, simplifies the learning task, allowing for more specialized models that can capture the nuances of each sustainability level. However, the effectiveness of this strategy is inherently tied to the quality and balance of the dataset, as well as the inherent capabilities of the underlying binary classifiers.

6 Conclusion and Future Works

The research underscores the complexity of sustainable fashion, highlighting the multifaceted nature of sustainability attributes and the challenge of classifying items across a spectrum of sustainability levels. The effectiveness of the Random Forest model, in particular, demonstrates the viability of using advanced analytics to parse these complexities, offering a glimpse into a future where consumers can make informed choices that align with their values and the planet's well-being.

Our investigation into leveraging machine learning models to aid in the selection of sustainable clothing has yielded promising results, particularly with the Random Forest model showcasing a commendable balance of accuracy and precision. This suggests a significant potential for machine learning to contribute to more environmentally responsible consumer behavior in the fashion industry. The models' capacity to classify clothing items based on sustainability criteria aligns with the urgent need for innovative solutions that address the environmental impact of the fashion sector.

Future Works: Future research should aim to address the limitations identified in the current study, particularly the challenges related to data scarcity, class imbalance, and the nuanced classification of sustainability levels. Efforts to enrich the dataset with more diverse and detailed sustainability attributes could enhance the models' accuracy and reliability. Additionally, exploring techniques to mitigate class imbalance, such as synthetic data generation or advanced sampling methods, could improve model performance, especially in underrepresented categories. The exploration of more sophisticated machine learning models and hybrid approaches could offer new insights and improvements. Techniques such as deep learning, transfer learning, and reinforcement learning could be investigated for their potential to capture complex patterns and relationships within the data. Furthermore, integrating user preference data into hybrid models could enable more personalized and contextually relevant recommendations, aligning sustainability with individual consumer needs and preferences. Future work could also extend beyond the realm of clothing to encompass the broader fashion industry, including accessories, footwear, and other textiles. Investigating the applicability of machine learning models in these areas could provide a more holistic view of sustainable fashion and its potential impact. Additionally, research could explore the integration of these models into real-world applications, such as e-commerce platforms or sustainable fashion apps, to assess their practical effectiveness and user acceptance. The complexity of sustainable fashion necessitates a collaborative and interdisciplinary approach, drawing on expertise from environmental science, data science, fashion design, and consumer behavior. Future research initiatives could benefit from partnerships between academia, industry, and environmental organizations to foster innovation, share knowledge, and drive collective action towards a more sustainable fashion ecosystem.

The research has shown the potential of machine learning to contribute to the sustainable fashion movement, offering insights and methodologies that could pave the way for more responsible consumer choices. The path forward calls for continued research, innovation, and collaboration, with the shared goal of harmonizing fashion with environmental sustainability. By building on the foundations laid by this research, future work can further the development of technologies and strategies that promote a more sustainable and ethical fashion industry, ultimately contributing to the well-being of our planet and society.

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