A Novel Methodology for AI-based Sorting of Post-Consumer Textile Using Spectrophotometer

Megan Robinson[1,*], Saikat Ghosh[2], Parikshit Goswami[2] and Mauro Vallati[1]

[1]School of Computing and Engineering, University of Huddersfield, Huddersfield, HD13DH, United Kingdom.
[2]Technical Textiles Research Centre, School of Arts and Humanities, University of Huddersfield, Huddersfield, HD13DH, United Kingdom.

Abstract

The growth of the textile sector worldwide, coupled with the extensive utilisation of synthetic polymers, is exacerbating challenges related to the global plastic waste problem. To effectively tackle this problem, a crucial aspect during recycling is the accurate identification of the composition of textiles, to allow the most appropriate chemical and mechanical treatments to separate natural fibres from synthetic ones. In this work, we present preliminary results achieved by leveraging machine learning approaches on spectrophotometry information extracted from textile samples to identify cotton and polyester samples.

Keywords

Textile sorting, Machine Learning, Spectrophotometer

1. Introduction

The textile industry has been rapidly expanding over recent years. Thanks to globalisation, clothing can be made at increasingly low prices, thus encouraging a *fast-fashion* mindset in consumers where clothing is considered disposable [2]. The growth in production of the textile industry is posing significant challenges to the environment. Currently the textile industry is responsible for producing 10% of global carbon emissions[1]. Furthermore, over 92 Million tonnes of textile waste are produced each year worldwide, with this expected to grow to 134 Million tonnes by 2030 [3].

Synthetic polymers in textile waste are a major contributor to the global plastic waste problem. As an example, in 2017, 438 Million tonnes of plastic were produced worldwide; 62 Million tonnes were used in the textile industry and 158 Million tonnes in plastic packaging [4]. While plastic packaging has attracted attention and concern for some time, textile waste has only become prominent recently, in part because recycling textile waste is a highly challenging task.

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*Corresponding author.
m.robinson2@hud.ac.uk (M. Robinson); s.ghosh3@hud.ac.uk (S. Ghosh); p.goswami@hud.ac.uk (P. Goswami); m.vallati@hud.ac.uk (M. Vallati)
http://www.mvallati.net (M. Vallati)
0000-0002-4052-1746 (M. Robinson); 0000-0003-1488-409X (P. Goswami); 0000-0002-8429-3570 (M. Vallati)

[1]https://shorturl.at/cEEdS

A 2016 UK survey showed that the destinations of textile waste are landfills 55%, incineration 26% and recycling/reusing 16% [5], with less than 1% textile waste used to generate new raw materials to be used for producing new clothing.

Garment waste is often complex and made up of more than one polymer. This could be exemplified by PET-Cotton t-shirts. Processes to recycle synthetic polymers from textile waste are gaining traction, with growing attention being posed on the use of chemical approaches to remove natural fibres, in order to allow the separation and re-use of the synthetic ones [6]. The automated sorting of the textile waste can play a pivotal role in fostering the recycling of the increasing amount of complex textile waste generated world-wide. Despite some initial work in the field, recycling facilities are still relying on human operators for the sorting process, leading to significant problems associated with cost and accuracy [7, 8]. Manual sorting is laborious, requiring months of training to understand the major and minor difference among the materials for accurate sorting.

As part of the EPSRC UK "Textile waste refinery for the production of recycled plastic, cellulose and dye" project, that looks into prototyping the complete process of recycling plastic from textile waste, we are investigating the use of machine learning techniques to sort post-consumer textiles according to their fibre type automatically. In this preliminary work, we report on the progress made in automatically classifying fabrics made either of cotton or polyester by training AI models on data extracted using spectrophotometric analysis. Spectrophotometry is a method to measure light absorption of a material, and the analysis of a sample can be performed in a matter of seconds, hence making this approach ideal for deployment.

2. Complexity of Textile Sorting

Automated textile sorting is a significant challenge due to the inherent complexity of textiles. Accurate fibre identification is hindered by the differences in physical and chemical properties among various fibres and the presence of fibre blends. In a yarn, different fibre types can be blended together to obtain a required fibrous architecture. Contaminants, such as buttons, zippers, and labels, introduce further complexities, as these elements are of very different material composition and are challenging to be removed. Similarly, garments often comprise of layers of textile fabric, which can be composed of different fibre types. A well-known example of this can come from jackets, with inset pockets, collar, and internal lining often made with fibres and patterns that are different from those of the external surface.

Additionally, there is also to consider colour variations within the same fibre type, while the diverse range of fabric structures impacts material properties. Furthermore, textiles can present varying conditions such as stains, tears, and wear.

When it comes to the development of AI-based solutions for textile sorting, the lack of high-quality, labelled data must also be taken into account. Moreover, there is also to consider the potential of noisy data when it comes to labelling of garment: on the one hand, indicated composition can be inaccurate and, on the other hand, the composition can be non-uniform throughout the different parts of the garment.

Figure 1: The benchtop spectrophotometer utilised in our experiments.

3. Methodology

We rely on features extracted by a benchtop spectrophotometer Datacolor Spectro 1000, shown in Figure 1. It is a precision instrument employed in analytical chemistry to quantitatively determine the concentration of a substance in solution or the absorbance of a solid sample by measuring its light absorption or reflectance spectrum. It operates by illuminating the sample with a polychromatic light source and analysing the intensity of light transmitted through or reflected from the sample as a function of wavelength.

The underlined hypothesis for using the spectrophotometer is that the data collected using this analytical tool could distinguish between natural and synthetic fibres. This is because the even structure of manmade fibres allows for higher reflectance due to their surface geometry compared to the uneven shape of natural fibres. Specular reflection occurs when light is reflected from a smooth surface at a specific angle, while diffuse reflection happens when light is scattered in multiple directions by rough surfaces (see Figure 2 for an example) [9]. The geometry of manmade fibres, which typically have a more uniform and smooth structure, tends to produce greater specular reflection. In contrast, the irregular and uneven geometry of natural fibres results in more diffuse reflection, leading to a different distribution of light [10]. However, reflectance is also a function of the colour of the material analysed, hence the need to consider a wide range of colours in the analysis. Using the considered spectrophotometer, the analysis of a sample requires at most 5 seconds to be completed and is therefore suitable to be used in

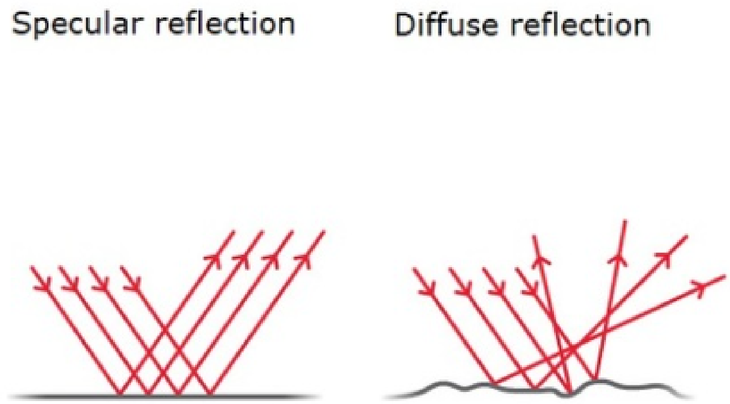

Figure 2: Specular and diffuse reflection.

real-world deployment.

Measuring both specular reflection and gloss is crucial for evaluating the reflectance of natural and manmade fibres because it provides a comprehensive understanding of their optical properties. Specular reflection reveals how light interacts with smooth surfaces, while gloss indicates the overall sheen and surface quality. Understanding these characteristics could be essential for differentiating between manmade and natural fibres during the automatic sorting process using a spectrophotometer, ensuring optimal performance in various settings. With this in mind, from the set of features that can be extracted from the spectrophotometer, we consider in our preliminary analysis a set of 40 features as this is expected to provide useful information on the reflectance nature of the material. The features provide ways to quantify the colour and reflectance characteristics of the sample.

For the following experiments we consider an initial set of 10 textile samples, 6 100% RFD (ready for dyeing) polyester and 4 100% cotton fabric with a combination of bleached and grey (details provided in Table 1). The fabric samples have different weave structures, that differ between samples, and do not include any impurity or contamination. For further analysis, the fabric samples were dyed using disperse and reactive dyes for polyester and cotton respectively on small sections (7cm X 7cm) from the original samples.

For the cotton samples, Reactive Red 01 dye was used, resulting in a total of 8 cotton samples including undyed fabrics. The dyeing process was done using the specific dye amounts (2% omf), 55 gdm^{-3} of NaCl, 5 gdm^{-3} of Na_2CO_3 and 0.5 gdm^{-3} of NaOH with 25:1 liquor ratio at 80°C for 60 minutes. After dyeing, the samples were rinsed in hot water two times for 30 seconds, followed by a cold-water rinse for 30 seconds to remove the unreactive dye. The samples were finally left to hang dry. Some of the cotton samples are shown in Figure 3.

For the polyester, 4 different dyes (Disperse Red 60, Disperse Orange 30, Disperse yellow 114, Disperse Blue 56) were used to prepare 5 different colour (red, orange, yellow, green, blue), resulting in a total of 36 polyester samples. In the case of dyeing PET, a 0.1M (8.2g) solution of

Cotton			Polyester		
Fabric Name	**Weave**	**GSM**	**Fabric Name**	**Weave**	**GSM**
Plain Cotton White	Plain	156	PET Empress White	Plain	74
Denim Cotton Heavy Natural	Twill	394	PET Satin Kent White	Satin	156
Raised Natural Cotton	Plain	250	PET Taffeta White	Plain	65
Cotton Drill Heavy White	Twill	393	PET Suedette Solarno White	Suedette	280
			Recycled PET Venus White	Plain	65
			Recycled PET Satin White	Satin	216

Table 1
Details of the considered fabric samples. GSM indicates the grams per square metre, which refers to the weight of the fabric.

sodium acetate was added to a 0.1M (6.0g) acetic acid solution in a 50:50 mixture ratio, creating a buffer at pH 4.5 in a 1-litre solution. The buffer solution was heated to 60°C and gdm^{-3} of Univadine TOP was added. The specific dye amounts (2% omf) were added to each dye tube, followed by adding the correct amount of buffer solution (10 times fabric weight in ml – approx 80 ml), and the RFD fabric. The dyeing was carried forward for 60 minutes. After dyeing, reduction clearing is done for the removal of unfixed dyes and auxiliaries from the fabric surface being a prerequisite of quality assurance and the ease of subsequent processes. Samples were placed into 400ml of reductive clearing solution (1.5 gdm^{-3} of sodium carbonate 2 gdm^{-3} of sodium dithionite ($Na_2S_2O_4$)) and heated at 65°C for 20 minutes with regular stirring. Once complete, the samples were rinsed in hot water for two times for 30 seconds. Finally, the samples were washed for 10 minutes in 1.5L of soaping solution (1 gdm^{-3} of Ultravon JUN) before being rinsed in hot water for 30 seconds, followed by a cold-water rinse for 30 seconds. The samples were then finally left to hang dry.

It is worth noting that, as a result of the initial samples and of the dyeing processes, the final dataset of samples is imbalanced with a bias towards the polyester class.

For use with machine learning models to distinguish between cotton and polyester, the full collection of measurements was split into separate datasets based on colours. First, we consider a dataset including all the samples. Then, further datasets are created containing the red and white/natural samples together, just the white/natural samples, and just the red samples. This is done to shed some light into how colour and dye affects the classification process. We focus on red colours because they are present in both cotton and polyester samples.

Due to the small number of samples, the datasets are augmented with simulated measurements to provide an idea of the results possible with a larger dataset. Perturbations of between 0 - 5% were applied to each sample. This was repeated four times per sample, creating four new data points per original sample.

We consider four well-known machine learning techniques: logistic regression, random forest (RF), support vector machine (SVM) and K-Nearest Neighbours (KNN), that are tasked with the binary classification of a given sample either as cotton or polyester. Results are presented using cross-validation.

Figure 3: Example of cotton samples in white/natural colour (left) and in red (right).

Data split	Log. reg.	RF	SVM	KNN
All samples	89.77%	85.23%	**93.18%**	89.77%
Red and white	87.5%	85%	87.5%	**97.5%**
White	90%	90%	90%	90%
Red	100%	100%	100%	100%

Table 2
Accuracy results achieved on the different data splits, for the considered machine learning approaches. Best results per data slit are in bold.

4. Preliminary Results

First, we turn our attention to the ability of the trained models to distinguish between cotton and polyester. Results presented in Table 2 show that the considered features can be informative, particularly when used for textiles within the same class of colours. In particular, support vector machines and KNN tend to deliver the best results across all classes, with accuracy results consistently above 90%. While the presented results are promising for all the considered learning techniques, it is worth reminding that the considered set of samples is small, hence it can be the case that results do not generalise well on larger and more variegated benchmarks.

As there are only two colours of cotton samples (red and white/natural) but six polyesters (red, orange, yellow, green, blue, white/natural), it is possible that a model including all data could be biased towards the colour information, and nothing else. In other words, considering the fact that extracted features focus on the characteristics of colours and reflectance, it is plausible that the imbalanced dataset is allowing the learning models to rely only on colour-related characteristics, ignoring the rest of the data. To test this, models trained using only the red and white/natural samples (with augmented data included) were presented with the other coloured polyester samples as a test set. The results are shown in Table 3.

Model	Accuracy
Log. reg.	50%
RF	25%
SVM	41.67%
KNN	29.17%

Table 3
Accuracy results achieved by the considered machine learning models training on red/white samples and tested on coloured polyester samples.

Results presented in Table 3 provide a more concerning figure when it comes to the performance of the trained models. First, results show that the models do not generalise well on previously unseen colours. Second, as the colours on the cotton and polyester samples used in the training are not the same, it can also suggest that models are indeed learning the colour of the sample, rather than a pattern of features that can identify the composition. To rectify the first point, as many colours of sample as possible need to be included in training if they are to be used for predictions at a later stage. This can be complicated in the presence of textiles presenting complex design patterns. An increased size of the data sets would also be beneficial for ensuring that colours are not considered as a valuable indicator of textile fibres by the learning models.

5. Discussion and Conclusion

In this paper we presented the preliminary results of the use of machine learning methods for automatically sorting textile samples by leveraging on data extracted by a spectrophotometer. Spectrophotometry is suitable to analyse textile samples due to its speed and its ability to identify reflectance properties of a material. Based on optical principles, synthetic fibres tend to reflect more light than natural fibres due to their uniform geometry, which facilitates specular reflection. As a result, reflection occurs at specific angles, making this type of analysis particularly advantageous. In the empirical evaluation we trained four well-known machine learning approaches on data sets composed of pure cotton or polyester samples in a limited range of colours, and achieved promising results. However, the limited size of the benchmark and the observed generalisability issues require the use of larger data sets to confirm the usability of the approach in real settings. Future work will also investigate the capabilities of the proposed approach in the presence of blended fibres, where recycling issues are exacerbated.

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