

Machine Learning–Based Identification of Textile Composition from NIR Spectroscopy for Automated Sorting

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Abstract—The growing volume and complexity of post-consumer textile waste make accurate material identification increasingly important for automated sorting and high-value recycling. This study investigates whether near-infrared (NIR) spectroscopy combined with machine learning can classify recycling-relevant textile compositions and detect elastane. A dataset of 181 textile samples is collected from certified suppliers and measured in the 900–1700 nm range using a benchtop NIR spectrophotometer. Spectral, ratio-based, and wavelet-based features are extracted, after which feature selection and supervised classification are applied for composition identification, while a 1D convolutional neural network is developed for binary elastane detection. The best composition classification model, based on Weighted KNN, achieved an accuracy of 91.7%, showing that common mono-materials and blends can be distinguished reliably. The elastane detection model achieved an overall accuracy of 92.6%, with class-specific accuracies of 83.3% for elastane-present samples and 95.2% for elastane-absent samples. These results show that NIR spectroscopy combined with machine learning is a promising approach for automated textile sorting and for improving material recovery in circular textile recycling.

Index Terms—Near-infrared spectroscopy, textile sorting, machine learning

I. INTRODUCTION

A. Textile production and circular economy

Global textile production has doubled since 2000, with over 100 billion garments produced annually, equating to roughly 12–15 items per person worldwide [1]. Driven by rising wealth and fast fashion, textile consumption is projected to reach 105 million tonnes by 2030. Consumers now purchase 60% more clothing than in 2000, while keeping garments for only half as long, which contributes to increasing textile waste [2], [3]. Annual fibre production reached a record 124 million tonnes in 2023, more than doubling since 2000, and is projected to approach 160 million tonnes by 2030. Synthetic fibres account for around 67–74% of total output, with polyester alone representing 57–59%. Cotton follows at around 20%, while the remainder consists of other natural and cellulosic fibres [4], [5], [6]. Textiles are often made from fibre blends to achieve desirable material properties. For example, polyester-cotton blends combine durability with comfort, polyester-elastane blends provide stretch, viscose improves drape, polyamide contributes strength, and wool adds insulation [7]. Although these blends improve garment performance, they also make sorting and recycling

more difficult. Different fibre types often require different recycling processes, while fiber composition information is frequently incomplete, unclear, or unavailable. As a result, mixed textile streams are difficult to separate accurately and are often directed toward low-value incineration rather than material recovery [8]. This creates a major bottleneck in the textile circular economy, where effective post-consumer sorting is essential for enabling high-value recycling. SORTED is a collaboration of 15 partners working on a circular textile chain in the Northern Netherlands, covering collection, sorting, reuse, and recycling [9]. For context, the whole circular loop is shown in Figure 1.

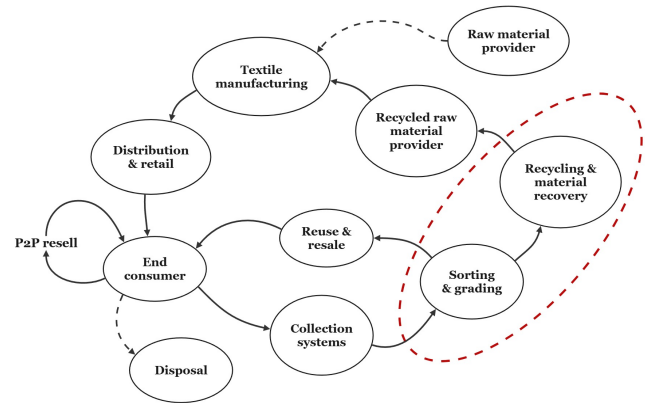


Fig. 1: Schematic overview of the textile circular loop. Solid arrows represent internal circular flows, whereas dotted arrows indicate inflows to and outflows from the system. The dotted red oval highlights the scope of this research.

B. Sympany sorting station

Sympany is a Dutch textile sorting facility which handles second-hand textiles for resale or recycling and currently processes approximately 5 truckloads per week [10]. This is expected to rise to 25 trucks per week by 2030 due to, among other things, the influx of low-quality fast fashion from platforms such as Temu and Shein [11], [12]. At Sympany, trucks deliver bags containing mixed clothing, which are initially screened for gross contaminants such as non-textile items and excess moisture. Rejected bags enter the residual waste stream. Accepted bags are unpacked and divided into two streams.

Reuse stream ($\sim 90\%$): Garments suitable for resale are graded as vintage (high-value, excellent condition), A-quality (near-new), B-quality (minor wear or dirt), or C-quality (repairable defects such as holes) [13].

Recycling stream ($\sim 10\%$ currently, projected to 50% by 2030): Non-reusable textiles are directed to downcycling applications, such as insulation or wiping cloths, or to fibre regeneration, although most currently end up being incinerated due to uncertain compositions [14].

The absence of composition labels on many garments can prevent vintage resale and makes recycling-oriented sorting largely dependent on worker experience, which limits both accuracy and scalability. Sensor-based automation is therefore aimed primarily at this stream, in order to handle future throughput while improving classification reliability. The process flow of Sympany is depicted in Figure 2.

C. Recycling stream

Recycled textiles generally follow three main pathways: incineration for energy recovery (the most common route, $\sim 70\text{--}90\%$ of output), downcycling into non-garment products such as insulation or automotive felts ($\sim 10\%$), or fiber-to-fiber regeneration ($< 5\%$) [15], [16], [17]. Sorting stations maximize profitability by selling compositionally certified bales, which are essential for recyclers to forecast yields and match feedstocks to suitable recycling processes [18], [19]. These processes include mechanical shredding for relatively clean cotton or wool streams, and chemical depolymerization for polyester. Undetected contaminants such as elastane, even at levels of 2–5%, can severely disrupt recycling operations by jamming shredders, clogging filters, and contaminating the output fibres, often rendering entire batches unusable [20], [21].

D. NIR sortability

NIR-based sorting is a non-destructive detection method that can automate garment identification at sorting stations. Sorting with NIR sensors is already common practice in several industries, such as plastics sorting and the food industry [22], [23]. For textiles, however, this approach is still not yet widely used [24]. Both a conventional NIR spectrometer and a hyperspectral NIR device are possible options for this purpose. These systems are not just non-destructive but also fast compared to other non-destructive methods such as microscopic analysis. A suitable NIR sensor for textile sorting should at minimum cover the 900–1700 nm range, because this spectral band is already used in industrial textile hyperspectral systems to distinguish common fibres and blends such as cotton, polyester, polyamide, viscose, wool, acrylic, and elastane [25]. A candidate for industrial application is the Specim FX17, which combines this wavelength range with a spectral resolution of about 8 nm, 224 bands, and a signal-to-noise ratio of 1000:1, providing sufficient detail and robustness for textile identification under practical conditions. It is also fast enough for conveyor-based sorting, with up to 670 full frames per second and much higher speeds when only selected bands are used.

E. Aim and research question

Although NIR-based sorting is well established in sectors such as plastics recycling, its application to automated textile sorting is still relatively limited and remains in an early stage of development. This study should therefore be viewed as an initial proof-of-concept that helps establish a foundation for further research within the SORTED project and at the University of Groningen. Rather than presenting a final industrial solution, this work aims to identify a feasible first framework for textile classification using NIR spectroscopy and machine learning.

Research Questions:

- Main-RQ: Can NIR spectroscopy with supervised machine learning classify post-consumer textiles into recycling-relevant categories?
- Sub-Q1: Which algorithms in classical ML, and which preprocessing/feature strategies maximize accuracy for identifying recycling-relevant categories?
- Sub-Q2: How well does a binary classification 1D-CNN model detect low-level elastane (1–20%)?

II. LITERATURE REVIEW

A. Fiber notations and fabric structures

1) *Fibres*: Numerous fiber types are employed in textile manufacturing, with cotton and polyester dominating by weight percentage. While precise global statistics are not known, polycotton blends are estimated to constitute 25–30% of casual apparel garments. Many garments incorporate additional materials, such as elastane (also known as spandex or Lycra), which is required in minimal quantities, typically 3–8% per yarn, equating to $\sim 1\text{--}2\%$ of total fabric weight, yet appears in approximately 40% of garments among the roughly 100 billion garments produced annually.

Common fiber notations include: Cotton (CO), polyester (PE), viscose (VI), elastane (EA), Wool (WO), linen (LI), silk (SE), and hemp (CA).

2) *Common woven and knitted structures*: Garments are produced via two primary construction methods: weaving and knitting. Weaving interlaces warp and weft yarns orthogonally on a loom, while knitting forms interlocking loops using needles, enabling horizontal and vertical stretch without the need for elastane. Plain weaves dominate shirting ($\sim 70\%$ market share), twill prevails in pants and outerwear, and knits are very common in T-shirts, sweatshirts, sportswear, underwear, hosiery, and casual dresses. Table I summarizes common woven and knitted structures.

3) *Material composition*: Materials are categorized by fiber composition as follows: There is *mono-material* fabric where all fibers are identical throughout the yarns and garment (e.g., 100% cotton). There is *blended* fabric which has multiple fibers intimately mixed within individual yarns prior to textile formation (e.g., 65/35 polyester-cotton). There is also *interwoven* fabric which has distinct mono-material yarns combined (e.g., polyester warp, cotton weft). This, however, is very rare in apparel.

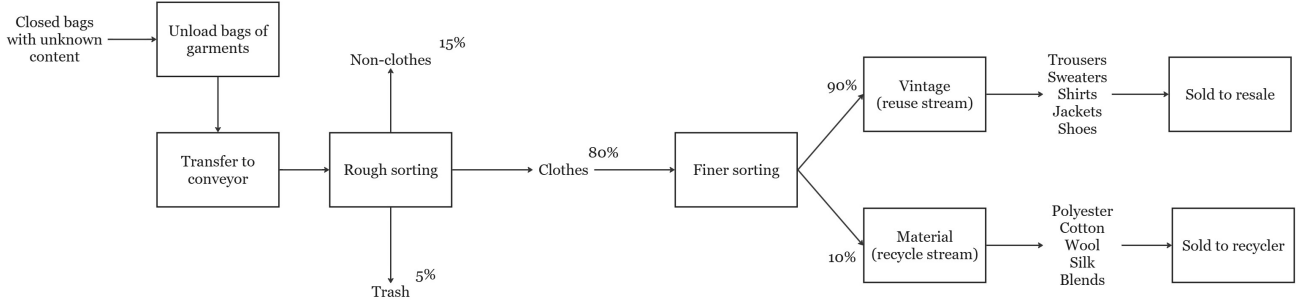


Fig. 2: Sympany's sorting workflow, including separation into reuse and recycling streams

Type	Characteristics	Uses
Woven		
Plain weave	Warp/weft 1×1	Base shirts, muslin
Poplin	Fine warp, thick weft (2:1)	Dress shirts
Broadcloth	Tight, balanced	Formal shirts
Oxford	2×2 basket	Button-downs
Twill (2/1)	Diagonal ribs	Pants, jackets
Denim	Heavy cotton twill	Jeans
Gabardine	Steep, fine twill	Trousers, suits
Chino	Lightweight twill	Casual pants
Satin	Long floats, lustrous	Evening wear
Knitted		
Jersey	Smooth face, textured back	T-shirts, basics
Rib	Alternating knit/purl	Cuffs, collars
Interlock	Double jersey	Base layers, dresses
French terry	Smooth face, uncut loops	Hoodies, sweatpants
Fleece	Brushed terry pile	Insulated loungewear

TABLE I: Common woven and knitted structures in apparel.

4) *Garment homogeneity*: Garments are categorized as homogeneous (uniform composition) or non-homogeneous (varying by zone or layer), excluding non-textile elements (e.g., zippers, buttons). We undertake this into four sub-categories. There is *homogeneous mono-material* which consists of 100% single fiber, and is per definition always homogeneous (e.g., cotton T-shirt). There is also *homogeneous blended* which has a consistent blend throughout (e.g., polycotton sweater). Next there is *non-homogeneous panelled* where discrete panels differ (e.g., polycotton body with elastane waistband: wool sweater and cotton elbow patches). Lastly, we have *non-homogeneous layered* which can be either multi-layer (e.g., cotton shell with polyester fill with lining) or single-layer plated (e.g., polyester face/cotton back found in fleece or performance knits).

B. Recycling stream

Table II groups the main textile recycling routes according to the materials they can process and the outputs they can recover. Mechanical recycling is the simplest route and works best when the feedstock is relatively uniform, but it usually shortens the fibres, resulting in lower-value outputs such as insulation, or wiping cloths [19]. Thermomechanical recycling is mainly relevant for polyester, because the polymer can be melted and repro-

cessed into fibres or pellets [27]. Cellulosic textiles such as cotton, linen, and viscose can also be chemically dissolved or hydrolysed, producing either regenerated cellulose for new fibres or sugars such as glucose for chemical or biological conversion [28]. Polyester can be chemically depolymerised back into monomers, which is the route that most closely resembles true closed-loop recycling [29]. For blends, the main challenge is to separate the different fibre types cleanly enough for each fraction to be directed into its appropriate recycling pathway, which is where selective hydrolysis or enzymatic separation becomes important [30].

C. NIR-based sorting

As mentioned, NIR spectroscopy has become a standard technique for high-speed sorting in plastics recycling facilities. It operates in the near-infrared region, generally between about 700 and 2500 nm, and can identify common polymers such as PE, HDPE, PP, and PVC by detecting differences in overtone and combination bands associated mainly with C–H, O–H, and N–H vibrations [31]. Similar systems are also used in food quality applications, for example to detect bruising or moisture-related changes in agricultural products [32].

Although NIR is not yet widely used for textile sorting, it is receiving increasing attention in research pilots and early commercial developments for distinguishing natural fibres, such as cotton and wool, from synthetic materials [33]. Textile identification benefits from wavelength regions in which characteristic absorption features of the constituent fibres are present. Cellulose-based fibres such as cotton and viscose show strong O–H-related absorption bands around 1400 nm and 1900 nm, while polyester and other polymers exhibit characteristic features in the longer-wavelength NIR/SWIR region [34], [35]. Elastane, as a polyurethane-based fibre, is associated with urethane-related absorption features around 1700–1730 nm [34].

D. Pure wavelength fingerprints for reference

Every textile fibre produces a characteristic NIR “fingerprint” arising from molecular vibrations, mainly O–H, C–H, and N–H overtone and combination bands [36]. Compared with fields such as plastics and food analysis, the literature on NIR spectra of textile fibres is more limited, although several key references are available. A detailed overview of characteristic wavelengths is given in Table

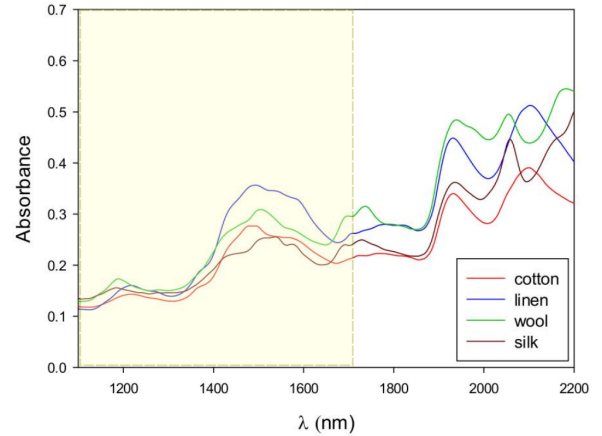
TABLE II: Overview of textile recycling processes, inputs, outputs, and applications

Recycling process	Relevant inputs	Main output(s)	Typical use of outputs
Mechanical recycling	Cotton, linen, wool, some polyester-rich textiles, and some low-complexity blends	Shortened fibers, recycled yarn, nonwovens	New yarns, insulation, stuffing, wiping cloths, felts [19], [26]
Thermomechanical recycling	Mostly polyester and polyester-rich textiles	Reprocessed polyester fibers or pellets	New synthetic fibers, filling materials [27]
Cellulose regeneration	Cotton, linen, viscose, other cellulosic textiles	Regenerated cellulose pulp or regenerated fibers	Lyocell- or viscose-type fibers, new cellulosic products [28]
Enzymatic cellulose hydrolysis	Cotton, linen, cellulosic blends	Glucose, cellulose-derived sugars	Fermentation feedstock, bioplastics, chemicals [29]
Polyester depolymerization by glycolysis	Polyester, polyester-rich blends, polycotton after separation	BHET or related PET monomers/intermediates	New polyester fibers and PET products [29]
Blend separation by selective hydrolysis	Polycotton, poly-linen	Cotton or linen-derived glucose/cellulose plus polyester residue or monomers	New cellulose-based materials plus recycled polyester [30]
Enzymatic separation of protein/cellulose blends	Wool-cotton, wool-polyester blends	Wool hydrolysate, amino acids or peptides, plus cotton or polyester fraction	Fertilizers, additives, feedstock, and recycled fiber streams [29], [30]

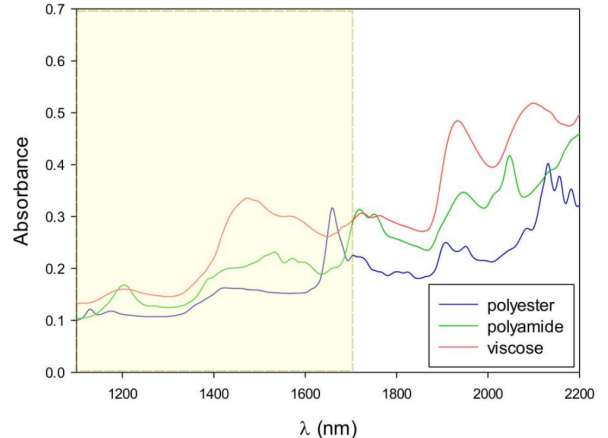
III. Reference spectra are shown in Figure 3. These spectra can be used to validate the measured data by comparing overall spectral shape and characteristic absorption regions, and they also help guide feature selection by indicating the most relevant wavelength regions for analysis.

TABLE III: Characteristic NIR wavelengths of common textile fibers and their likely chemical origins.

Material	Characteristic wavelengths / ranges	Bond or chemical origin
Cotton	1355, 1416, 1470, 1605 nm [37]; also ~1942 and ~2100 nm outside the shorter NIR window [38]	Mostly cellulose bands; dominated by O–H and C–H overtone/combination absorptions [39]
Polyester (PE)	1120–1150 nm, ~1185 nm, 1645–1680 nm; practical points near 1648 and 1660 nm [37]	Mainly C–O and C–H overtone absorptions from polyester structure [37]
Linen (flax)	show distinctions at ~1726–1730 nm, 1766 nm, ~1942 nm, ~2100 nm, 2312 nm, 2345–2350 nm [40]	Cellulose-based fiber; O–H and C–H are important, with flax-specific effects from wax, lignin, and surface chemistry [40]
Viscose	~925 nm, 1355 nm, 1416 nm, 1450 nm, 1470 nm, 1550 nm, 1605 nm; sometimes ~1690 nm [37], [41]	Regenerated cellulose; mainly O–H and C–H overtone/combination bands [41]
Wool	1120–1160 nm, 1170 nm, 1405 nm, 1485 nm, 1680 nm, 1713 nm, 2170 nm [34], [37]	Protein fiber; bands linked to N–H, amide, C=O, and some C–H vibrations in keratin [42]
Silk	Best-supported feature at 1713 nm; within 900–1700 nm, useful region is 1450–1550 nm, with supporting use of ~1552 nm and ~1650–1700 nm [43]	Protein fiber; mainly amide and N–H overtone/combination behavior, plus some C–H contributions [43]
Elastane	Practical diagnostic wavelengths at ~1200 nm, ~1400 nm, and ~1700 nm [44]	No clean peak-by-peak assignment reported here; likely related to polyurethane-specific NIR absorption differences [37]



(a) Spectra for reference for cotton, linen, wool, and silk



(b) Spectra for reference of polyester, polyamide, and viscose

Fig. 3: Combined NIR literature spectra for textile fibers. The Highlighted area denotes the spectral window used in this study [36].

III. MATERIALS AND METHODS

A. Collecting textile samples

The sample set used in this study is designed to provide broad coverage of the principal textile composition classes relevant to sorting and recycling, while also ensuring sufficient data for model training. Approximately 20 samples are targeted for the 100% cotton and 100% polyester classes, while around 10 samples are targeted for each of the blended polycotton categories, namely cotton-rich, mid-blend, and polyester-rich. For wool-rich samples, around 20 samples are targeted, and around 10 samples are included for both viscose-blend and linen-blend categories. Elastane is treated as a separate label, and therefore around 40 samples across different material classes are considered necessary for proper binary classification training. These categories are defined according to typical fibre composition ranges, such as 65–97% cotton for cotton-rich materials, 36–64% cotton/polyester for mid-blends, and 1–20% elastane for elastane-containing samples.

The samples are sourced from certified wholesalers rather than Sympany’s sorting station. Although Sympany can provide ample textiles, such samples exhibit two key limitations: (1) surface contamination from wear, detergents, and moisture, which may alter NIR spectra; and (2) inaccurate or incomplete composition labels due to heterogeneous garment construction (e.g., polyester accents remaining unlabeled on primarily cotton garments) and inconsistent regulatory compliance across global manufacturing standards. Such real-world samples remain essential for future model validation, but they are less suitable for initial training, which requires ground-truth spectral references.

Wholesaler samples are selected based on three strict criteria: (1) compositional homogeneity; (2) known material composition; and (3) coverage of the target classes, with a minimum of 10 samples per class to ensure adequate supervised learning.

Samples are indexed in a digital table recording colour, weave, material composition, assigned class, sample number, supplier, item code, and size. Additional fields included supplier links, purchase price, and post-scan notes on irregularities for future verification. Physical samples are stored in 10×15 cm photo album pages. Oversized samples are cut to fit, and thick samples are stored separately. Cross-contamination is minimized by using individual plastic sleeves, although the spectral impact of trace fibres is expected to remain negligible given the resolution limits of the NIR measurements.

Each sample is assigned both a primary composition category and a binary elastane presence label. Elastane content is not treated as a primary determinant in the composition-based classification. Instead, samples are categorized based on the proportion of the non-elastane fibres. When elastane is present, its proportion is disregarded for category assignment, provided that the remaining fibre composition satisfied the specified thresholds. Consequently, textiles containing elastane could still be labeled as “pure” if the dominant fibre met the purity criterion.

For example, a fabric composed of 94% cotton and 6% elastane is classified as “cotton pure”.

B. Collecting spectra data

NIR spectra are acquired using a JASCO V-570 spectrophotometer. This NIR sensor captures absorbance intensity in the range of 900–1700 nm with a resolution of 2 nm. Samples are placed on a certified Spectralon™ (PTFE) reference tile, while a 50 W halogen lamp provided uniform illumination at 45° incidence. Background spectra of the reference tile are first recorded for normalization. Next, the samples are placed between the sensor and the reference tile, after which measurements are taken. The resulting spectra were exported as ASCII (.txt) files using the naming convention `SNNN_composition_color_construction`, for example `S078_60cotton-40polyester_brown-white_jersey`. If the colour is not specified, it is assigned by visual inspection. If the weave or knit type is not specified or is unknown, it is labeled as “UNK”.

To identify characteristic wavelengths, the mono-material spectra are examined, meaning samples that contained only one material and no elastane. To improve peak visibility, the first derivative of the spectra is used during spectral interpretation.

C. Defining categories for classification

The categories used in this study are defined as an initial, practical grouping based on the main textile recycling streams currently available. Rather than representing a standardized industry sorting system, they are designed to reflect the material combinations most relevant to recycling feasibility, such as pure cellulose fibres, pure polyester, protein-based fibres, and common blends such as polycotton or polyester-containing viscose. Because textile recycling is still a developing field, such sorting categories are not yet fully established or universally agreed upon. This classification should therefore be regarded as a first attempt to link textile composition to realistic recycling pathways. The precise criteria used to assign the defined categories are given in Table IV.

D. Feature gathering

1) Wavelengths extraction:

2) *Wavelength extraction:* Each spectrum is represented using three complementary feature sets: the smoothed raw spectral intensity, the first-order derivative, and the second-order derivative. First, the measured wavelength-intensity data are smoothed using a Savitzky–Golay filter in order to reduce noise while preserving the underlying spectral shape and absorption features. In general, the smoothed signal can be written as

$$\tilde{y}(\lambda_i) = \sum_{j=-m}^m c_j y(\lambda_{i+j}),$$

where $y(\lambda_i)$ is the measured intensity at wavelength λ_i , c_j are the Savitzky–Golay filter coefficients, and $\tilde{y}(\lambda_i)$ is the smoothed intensity.

The first derivative is then computed to capture changes in slope across the spectrum:

$$\frac{d\tilde{y}}{d\lambda} \approx \frac{\tilde{y}(\lambda_{i+1}) - \tilde{y}(\lambda_{i-1})}{2\Delta\lambda},$$

where $\Delta\lambda$ is the wavelength step size. The second derivative is subsequently calculated to emphasize curvature and improve the visibility of overlapping or subtle bands:

$$\frac{d^2\tilde{y}}{d\lambda^2} \approx \frac{\tilde{y}(\lambda_{i+1}) - 2\tilde{y}(\lambda_i) + \tilde{y}(\lambda_{i-1}))}{(\Delta\lambda)^2}.$$

This resulted in a total of 1203 extracted features per sample.

3) *Wavelength ratios*: In addition to the full spectral features, a reduced set of ratio-based features is extracted from selected wavelength regions. These ratios are chosen on the basis of the characteristic near-infrared absorption bands discussed in the literature review, where specific wavelength regions are identified as being sensitive to differences in textile fibre composition. The aim of this approach is to obtain a compact set of physically interpretable features that emphasized relative intensity differences between relevant spectral bands.

As in the previous preprocessing step, the spectra are first restricted to the wavelength range of 900–1700 nm, smoothed using a Savitzky–Golay filter, and transformed into first- and second-order derivatives. Ratios are then calculated between selected wavelengths. For two wavelength intervals A and B , a ratio feature is defined as

$$R_{A/B} = \frac{\bar{y}_A}{\bar{y}_B},$$

where $\bar{y}_A$ and $\bar{y}_B$ are the mean spectral values within the numerator and denominator windows, respectively. By expressing one region relative to another, the ratio features reduced the influence of absolute intensity variation and instead emphasized relative spectral behaviour, which can be more robust to changes in colour and moisture levels.

The various ratios resulted in 286 features per sample. Compared with the full wavelength-based feature set, this representation is more compact while still retaining information from the most relevant spectral regions identified in the literature.

4) *Wavelets*: A third feature extraction approach is based on wavelet analysis of the preprocessed spectra. As in the previous methods, the spectra are first restricted to the wavelength range of 900–1700 nm and smoothed using a Savitzky–Golay filter. Wavelet analysis is then applied to the smoothed spectra in order to capture localized spectral patterns at different scales, rather than using only the raw intensity values or their derivatives.

More specifically, a continuous wavelet transform with the Mexican hat wavelet is used. This transform decomposes the spectral signal into coefficients that describe how strongly a wavelet-shaped pattern is present at a given wavelength and scale. In this study, three scales are considered, allowing the method to capture spectral structures

of different widths. Several wavelength windows are then selected around relevant absorption regions, and within each window the wavelet coefficients are summarized into numerical descriptors.

For each combination of wavelength window and scale, three summary measures are extracted: the wavelet energy, the maximum absolute coefficient, and the wavelength position at which this maximum occurred. In simplified form, the wavelet energy within a window can be written as

$$E = \sum_{i \in W} |c_i|^2,$$

where c_i denotes the wavelet coefficient at wavelength position i within the selected window W . The maximum coefficient is defined as

$$M = \max_{i \in W} |c_i|,$$

and the location feature corresponded to the wavelength at which this maximum occurred. In this way, each spectral region is no longer represented by a curve, but by a small set of numeric values describing the strength and position of local spectral patterns.

The final wavelet-based representation therefore consisted only of numeric descriptors that could be used directly as input features for machine learning models. Rather than providing the full spectral signal, the method compressed each relevant wavelength interval into a limited number of descriptors that summarized local behaviour. In total, 468 wavelet features are gathered.

All extracted features are combined into one large table, with the individual samples as rows and the predictors as columns. In total, each sample is represented by 1957 features.

E. Machine learning

1) *Supervised classification learning*: This study employs supervised learning exclusively, using labeled spectra with known compositions to train predictive models. Unlike unsupervised methods, which identify patterns in unlabeled data, supervised approaches directly map spectral inputs to verified fibre categories. This approach has previously been applied in NIR-based textile classification, for example by Riba [36], who reported high classification accuracies for both pure materials and blends.

Because textile compositions vary continuously, regression could in principle be used to predict exact fibre percentages, such as 65% cotton. However, preliminary testing showed that regression performed poorly with the available dataset, likely because the data did not provide sufficiently dense coverage across the full 0–100% composition range for all material types. For this reason, classification is chosen instead, assigning samples to discrete composition categories as defined in Table IV. These categories are intended to reflect the main textile groupings relevant to practical sorting and recycling. Elastane presence is handled separately through a parallel binary classification

task (elastane present/elastane absent), allowing elastane detection across all composition classes. A summary of the complete training pipeline is given below.

Preparing data:

- 1) Load ASCII .txt files exported from the JASCO V-570 spectrophotometer
- 2) Subtract the PTFE reference spectrum for baseline correction
- 3) Apply Savitzky--Golay smoothing (2nd-order polynomial, 5-point window)
- 4) Compute wavelength-based features per sample: smoothed raw absorbance, 1st derivative, and 2nd derivative
- 5) Compute wavelength-ratio features from selected diagnostically relevant spectral regions
- 6) Compute wavelet-based features using a continuous wavelet transform (Mexican hat wavelet), summarized by energy, maximum coefficient, and peak location across selected windows
- 7) Label each sample with its primary composition class according to Table IV and assign binary elastane label
- 8) Assemble the final feature table: 181 samples $\times$ 1957 features, alongside categorical labels

Composition Identification:

- 1) Rank composition-discriminating features using Kruskal--Wallis
- 2) Compare feature rankings with ANOVA and Chi-square for consistency
- 3) Screen classical ML models in MATLAB Classification Learner, including KNN, decision trees, SVMs, logistic regression, and ensemble methods
- 4) Evaluate models across different numbers of top-ranked features, between 10 and 1900
- 5) In parallel, evaluate PCA-based models using the minimum number of principal components needed to explain 95% of the variance
- 6) Select the best-performing model under the optimal feature or PCA dimensionality

Elastane Detection:

- 1) Retain only raw, 1st-derivative, and 2nd-derivative spectral features within the elastane-relevant range of 1040--1700 nm
- 2) Normalize the input features and split the dataset into fixed training, validation, and test sets

- 3) Train a 1D-CNN using repeated runs with different random seeds while keeping the data split fixed
- 4) Perform a full-factorial grid search over dropout-rate pairs and class-weight settings for the elastane-present and elastane-absent classes
- 5) Evaluate each configuration using validation performance to assess both accuracy and training stability
- 6) Select the optimal hyperparameter configuration and export the final binary elastane detection model

2) *Composition identification*: To determine whether textile materials can be differentiated, MATLAB's Classification Learner is used [45]. First, feature importance is assessed using several built-in ranking methods, including MRMR, Chi-square, ANOVA, and the Kruskal--Wallis algorithm. The Kruskal--Wallis test is used as the primary ranking method. This is a non-parametric test that determines whether a feature differs significantly across multiple classes. Unlike one-way ANOVA, it does not assume normally distributed data, because it operates on the ranks of the observations rather than on their raw values. This makes it well suited to machine-learning datasets in which features may be skewed, noisy, or influenced by outliers. NIR datasets often contain small or uneven sample groups, repeated resampling results, and measurements that are not well described by a Gaussian distribution. Under such conditions, ANOVA may give misleading inference because it relies on group means and distributional assumptions, whereas Kruskal--Wallis compares rank distributions instead [46], [47].

For a given feature, all observations from the k classes are pooled and ranked from 1 to N , where

$$N = \sum_{i=1}^k n_i,$$

and n_i is the number of samples in class i . Let R_i denote the sum of ranks for class i . The Kruskal--Wallis test statistic is then computed as

$$H = \frac{12}{N(N+1)} \sum_{i=1}^k \frac{R_i^2}{n_i} - 3(N+1).$$

A larger value of H indicates greater differences between the classes for that feature. Under the null hypothesis that all classes follow the same distribution, H approximately follows a chi-squared distribution with $k - 1$ degrees of freedom.

Each feature is tested independently, and features with the largest H -values or smallest p -values are considered the most discriminative. This makes the method particularly useful as an initial screening step for identifying informative features before training a classification model. Models are constructed using either the original predictor features or a PCA-transformed representation of the data.

For the PCA-based configuration, the minimum number of principal components required to explain 95% of the variance in the predictor set is retained and used as input to the classifier.

Classification models are developed in MATLAB using labeled data and are evaluated with 50-fold cross-validation because the dataset is relatively small. In this procedure, the dataset is divided into fifty folds. In each round, 49 folds are used for training and the remaining fold is used for validation. Multiple algorithms are evaluated in MATLAB's Classification Learner, including KNN, Random Forest, decision trees, and SVMs. All models are compared based on cross-validated accuracy after shuffling the dataset.

As a preliminary step, the same framework is first applied to a mono-material dataset containing samples without elastane. For both the mono-material and category-based classification tasks, model performance is evaluated using the top-ranked features from the Kruskal–Wallis procedure, while PCA-based alternatives are assessed in parallel for comparison.

3) *Elastane detection*: In parallel, a one-dimensional convolutional neural network (1D-CNN) is used for binary elastane detection. This 1D-CNN model is implemented in MATLAB [48]. Its pseudocode can be seen in Appendix I. A 1D-CNN is a deep learning model designed for sequential data, and it is commonly applied to spectral classification tasks because it can learn local patterns along ordered spectral inputs [49]. For this model, the dataset is divided into training, validation, and test subsets. The training set is used to fit the model, the validation set is used during training to monitor performance and tune the model, and the test set is reserved for the final evaluation of predictive performance. The validation set is chosen to reflect the class distribution of the full dataset, with 4 of the 16 samples belonging to the elastane-present class. The model uses only the first category of features within the elastane-relevant wavelength range of 1040–1700 nm: raw intensities, first-order wavelength intensities, and second-order wavelength intensities. Because these features remain ordered along the wavelength domain, a 1D-CNN can still learn local relationships between neighbouring features.

For an input feature vector

$$\mathbf{x} = [x_1, x_2, \dots, x_n],$$

a convolutional filter of length m slides along the sequence and computes

$$y_i = \sum_{j=1}^m w_j x_{i+j-1} + b,$$

where w_j are the filter weights and b is a bias term. In this way, the model identifies combinations of nearby features that are characteristic of the target classes.

To determine the most suitable hyperparameter configuration, a grid search is conducted [50]. Grid search is a standard hyperparameter optimization method in which all predefined combinations of candidate values are evaluated systematically in order to identify the setting that yields the

best predictive performance. In this study, the procedure is used primarily as a hyperparameter optimization step, although it also provides insight into the stability of model performance across repeated runs.

The hyperparameter optimization is implemented as a full-factorial 6×6 grid search, resulting in 36 model configurations. Six dropout-rate pairs are tested for the two dropout layers of the 1D-CNN: (0.10, 0.05), (0.15, 0.10), (0.20, 0.15), (0.25, 0.15), (0.30, 0.20), and (0.40, 0.25). These are combined with six class-weight settings for the classification layer: (1.0, 1.0), (1.5, 1.0), (2.0, 1.0), (2.5, 1.0), (3.0, 1.0), and (4.0, 1.0), where the first value corresponds to the “Elastane present” class and the second to the “Elastane absent” class. This full-factorial design makes it possible to assess both the individual and combined effects of the selected hyperparameters on model performance.

To ensure a fair comparison between hyperparameter settings, the train/validation/test split and the associated preprocessing are fixed in advance. The dataset is partitioned once using a fixed random seed, after which normalization parameters are estimated exclusively from the training subset and then applied to the validation and test subsets. For each hyperparameter configuration, the network is subsequently trained repeatedly using different random seeds for the training stage only, while the data split remains constant. In this way, stochastic effects inherent to neural network training, such as random weight initialization, mini-batch ordering, and dropout, can be assessed separately from variation caused by changes in the train, validation, and test sets.

Model performance is evaluated using both overall accuracy and false negative rate, with particular emphasis placed on the false negative rate. In the present application, false negatives are considered more critical than false positives, because it is preferable for some garments without elastane to be incorrectly sorted into the elastane bin than for garments containing elastane to be mistakenly mixed with the pure-fibre stream, where they may compromise downstream recycling quality.

F. Validation of results

G. Model validation

Feature ranking is validated by comparing model performance obtained with the selected number of features against models using both fewer and more features. In addition, the highest-ranked features identified by the Kruskal–Wallis method are compared with those obtained using ANOVA and Chi-square in order to assess whether the most important features are consistent across ranking methods.

For the classical machine-learning models, performance is evaluated using cross-validation. PCA-based and feature-based models are compared to evaluate whether dimensionality reduction improves or reduces classification performance. Because the dataset is relatively small, 50-fold cross-validation is used throughout the main analysis. The

predictions from these runs are used to construct confusion matrices and to assess classification accuracy. In addition,

For the 1D-CNN, the data are split into training, validation, and test sets. The training set is used for model fitting, the validation set is used for hyperparameter selection and monitoring during training, and the test set is reserved for final performance evaluation. To assess the stability of the model, repeated training runs are performed using different random seeds. In this way, the effect of stochastic variation during network training can be evaluated separately from the chosen model configuration.

IV. RESULTS AND DISCUSSION

A. Data gathering

Samples with varying compositions are sourced from three certified suppliers, covering pure textiles, polycotton blends, wool variants, and a range of elastane-containing materials [51], [52], [53]. An index of all samples can be seen in Appendix II. The compositions are labeled for machine learning according to the definitions provided in the description column of Table IV, which also presents the full distribution across the defined categories. Samples specifying alpaca hair are categorized as containing wool. Materials outside the scope of this study are classified as “other” when present above 2%. These samples are included to evaluate whether they could be distinguished from the predefined categories.

It should be noted that the categories “Wool-rich PE”, “Wool-rich cotton”, and “Viscose cotton” contained no samples in this study. Furthermore, sample S087 had a total material percentage of 101%. Despite this, it is still labeled and included for machine learning. In addition, 25 samples could not be assigned to one of the predefined composition categories based on the available description, or contained materials outside the scope of this study. These samples are still retained for elastane detection.

B. Spectra analysis

As shown in Table IV, a total of 181 measurements are obtained. A compound graph of all measured sample spectra is provided in Appendix III. When examining the absorbance spectra of pure cotton in Figure 10, the overall spectral shape appears highly consistent across samples of the same material. A similar pattern is also observed in the literature (Fig. 3a) [36], [37]. Differences in absorbance intensity can likely be attributed to the dyes used in the fabrics. Darker colours generally absorb more infrared light, whereas lighter colours reflect more, therefore, darker materials are expected to produce higher absorbance values.

When the mono-material samples are compared side by side in Figure 11, wool shows several distinct peaks, although greater variation is visible at the lower wavelengths. This variation may be explained by differences in the protein-based structure of wool, which can vary between sheep breeds or between different animal sources [34], [42]. Although the overall chemical composition remains broadly similar, additional factors such as natural oils and

surface structure may also influence the spectra. Furthermore, linen shows a clearly distinct spectrum compared with cotton, which is consistent with literature describing flax-specific spectral effects related to wax, lignin, and surface chemistry [40].

When examining the different polycotton spectra in Figure 12, a clear gradual transition can be observed from pure cotton to pure polyester samples. The intermediate blends show spectral characteristics that lie between those of pure cotton and pure polyester, indicating a progressive change in composition, which is in agreement with previous NIR-based studies on textile blends [37].

When comparing cotton with cotton containing elastane in Figure 13, only small differences can be observed between the spectra. This suggests that the addition of elastane produces relatively subtle spectral changes, making the distinction between these materials challenging, which is consistent with literature indicating that elastane detection often depends on weak or distributed spectral differences rather than one dominant visible feature in the measured range [37], [44].

TABLE IV: Textile dataset labeling scheme. Each sample is assigned (i) one primary composition category based on the proportion of non-elastane fibers, and (ii) a binary elastane label indicating the presence or absence of elastane. Elastane content is not considered in the composition thresholds: e.g., a sample with 94% cotton and 6% elastane is classified as “cotton pure” while also labeled as “elastane present”.

(a) Material composition categories		
Category	#	Description
Cotton pure	54	$\geq 98\%$ Cotton, $< 2\%$ others
Cotton-rich polycotton	8	65–97% Cotton, 3–35% PE
Mid-blend polycotton	13	36–64% Cotton/PE
PE-rich polycotton	6	65–97% PE, 3–35% Cotton
PE pure	21	$\geq 98\%$ PE, $< 2\%$ others
Wool pure	22	$\geq 98\%$ Wool, $< 2\%$ others
Wool-rich PE	0	50–97% Wool, rest PE
Wool-rich cotton	0	50–97% Wool, rest cotton
Viscose pure	3	$\geq 98\%$ Viscose, $< 2\%$ others
Viscose PE	9	20–97% Viscose, rest PE
Viscose cotton	0	20–97% Viscose, rest cotton
Silk blend	8	40–100% Silk, rest others
Linen blend	12	40–100% Linen, rest others
Other	25	Undefined category based on description OR includes $\geq 2\%$ other materials (e.g., polyamide, hemp, lyocell)
(b) Binary elastane label		
Label	#	Description
Elastane present	39	Any percentage of elastane
Elastane absent	142	No elastane

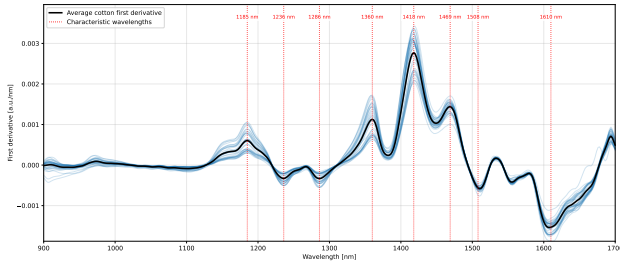


Fig. 4: Averaged first-derivative spectrum of 100% cotton with characteristic wavelengths at 1185, 1236, 1286, 1360, 1418, 1469, 1508, and 1610 nm.

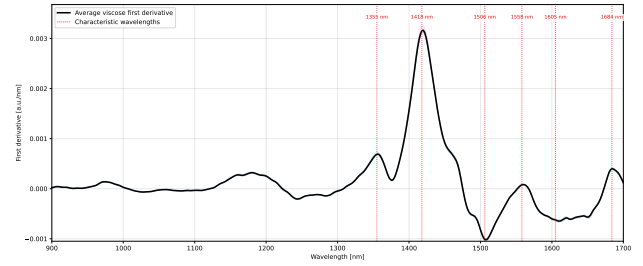


Fig. 8: Averaged first-derivative spectrum of 100% viscose with characteristic wavelengths at 1355, 1418, 1506, 1558, 1605, and 1684 nm.

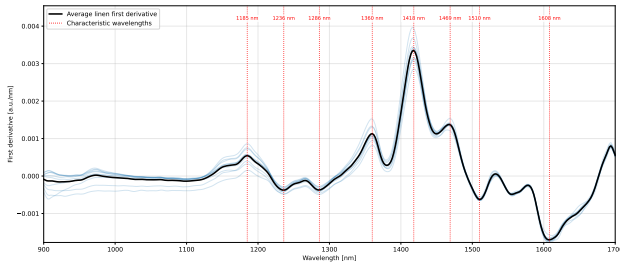


Fig. 5: Averaged first-derivative spectrum of 100% linen with characteristic wavelengths at 1185, 1236, 1286, 1360, 1418, 1469, 1510, and 1608 nm.

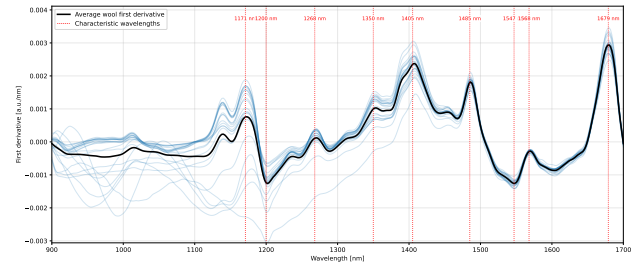


Fig. 9: Averaged first-derivative spectrum of 100% wool with characteristic wavelengths at 1171, 1200, 1268, 1350, 1405, 1485, 1547, 1568, and 1679 nm.

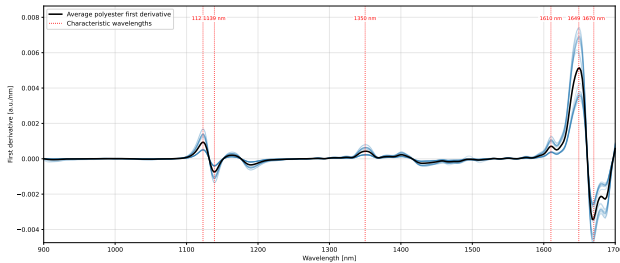


Fig. 6: Averaged first-derivative spectrum of 100% polyester with characteristic wavelengths at 1123, 1139, 1350, 1610, 1649, and 1670 nm.

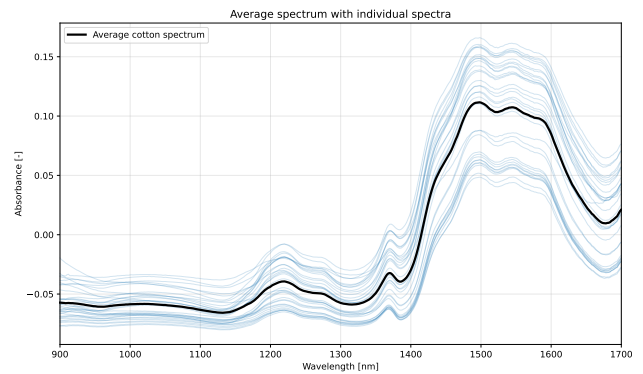


Fig. 10: Mean absorbance spectrum of cotton, with the individual sample spectra shown in light blue.

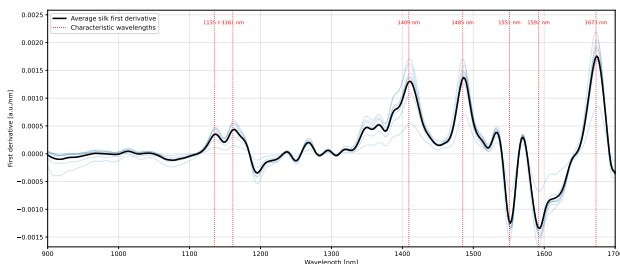


Fig. 7: Averaged first-derivative spectrum of 100% silk with characteristic wavelengths at 1135, 1161, 1409, 1485, 1551, 1592, and 1673 nm.

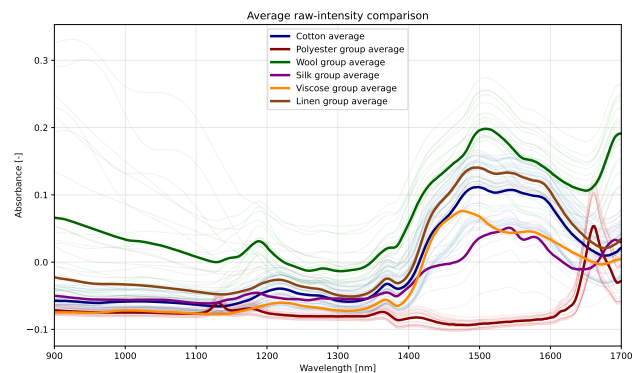


Fig. 11: Mean absorbance spectra for six mono-materials, with lighter lines indicating individual sample measurements.

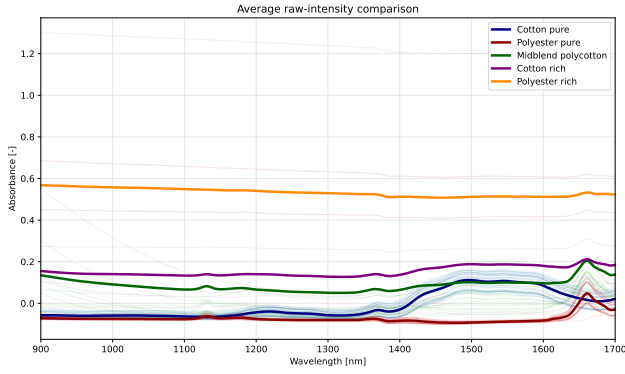


Fig. 12: Absorbance spectra of various polycotton categories. The bold lines represent the average spectra, and the lighter lines show the individual sample spectra.

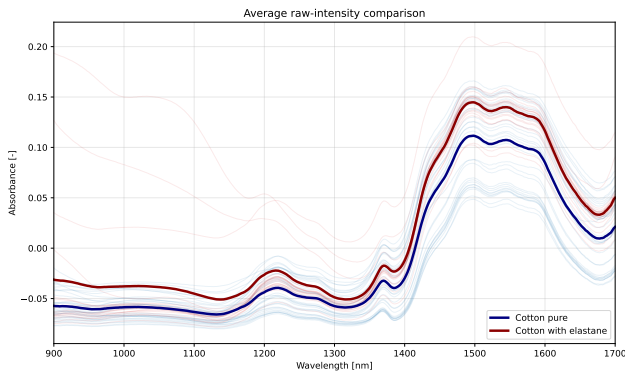


Fig. 13: Absorbance spectra of cotton and cotton containing elastane. The bold lines represent the average spectra, and the lighter lines show the individual sample spectra.

C. Feature selection

Three complementary feature types are evaluated: (1) spectral features from the raw, first-, and second-order signals; (2) ratios between selected wavelengths; and (3) wavelet-based features. Analysis showed that the most discriminative information is concentrated in a limited number of spectral regions rather than being spread uniformly across the full wavelength range. The strongest concentrations are found in the 1450–1529 nm, 1530–1589 nm, 1590–1649 nm, and 1650–1700 nm regions. In particular, wavelengths around 1490 nm, 1526 nm, 1590–1635 nm, and 1663–1684 nm appeared repeatedly across derivative, ratio, and window-based wavelet features, indicating that these regions contain the most relevant spectral variation for classification. This is consistent with the literature, in which important absorption features for cellulose-based fibres, protein-based fibres, polyester, and elastane are also reported in the 1400–1700 nm region [34], [37], [41], [42], [44].

To determine the optimal number of features, multiple tests are performed using subsets ranging from 5 to 1900 features with varying increments. For each subset, the highest classification accuracy is considered in order to assess how many features gave the best performance. It is found that using either fewer or more features reduced

performance. The best-performing range lay between 25 and 250 features, as shown in Figure 14. This behaviour is in line with the general purpose of feature selection, where too few variables may discard useful information, while too many may introduce redundancy or reduce classifier efficiency [46], [47].

In addition, ANOVA and Chi-square are also evaluated for feature ranking. Comparison of all three ranking methods showed that 67 features appeared in the top 175 across all algorithms. The full feature rankings are provided in Appendix IV.

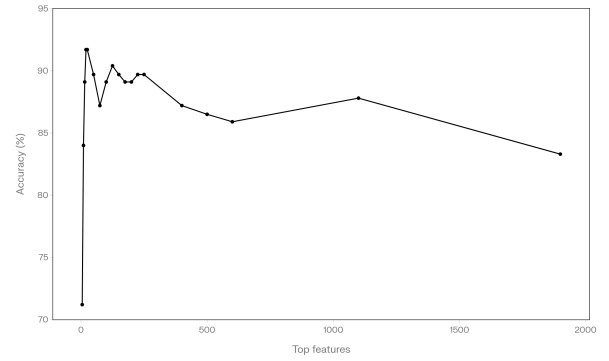


Fig. 14: Classification performance for different numbers of selected top features

D. Composition classification

1) *Mono-material classification:* As a preliminary test, classification is first performed on the mono-material dataset, which consisted of samples without elastane. PCA is evaluated across different parameter settings, but consistently underperformed compared with using the selected features directly. Using the top 175 features ranked by the Kruskal–Wallis method, the Weighted KNN algorithm achieved an accuracy of 99.0%. The scatter plot in Figure 15 shows substantial overlap between cotton and linen when only a limited feature view is considered. Nevertheless, the confusion matrix in Figure 16 shows that these materials could still be distinguished clearly when multiple features are considered simultaneously. This is a notable result, because it suggests that even though cotton and linen appear spectrally similar by visual inspection, the model is still able to capture subtle differences across the full feature set, which is consistent with previous studies showing that cellulose-based fibres can exhibit only subtle spectral differences while still remaining distinguishable through spectroscopic analysis and multivariate methods [54], [55]. Only one misclassification occurred, in which a wool sample is classified as silk, which is understandable given that both are animal-based fibres with protein-based spectral characteristics in the near-infrared region [34], [42], [43].

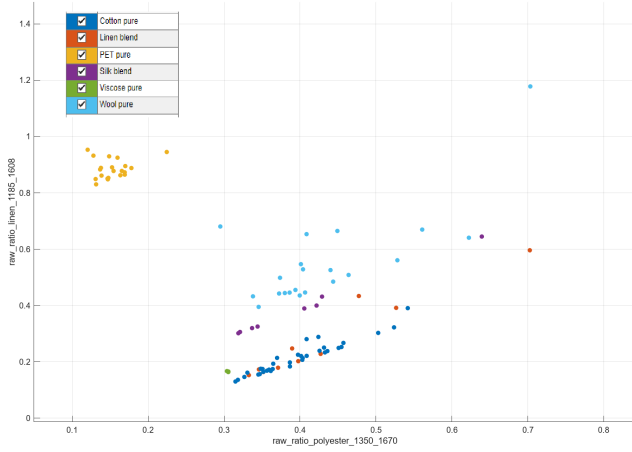


Fig. 15: Scatter plot of the mono-material samples using the ratio feature between 1185 nm and 1608 nm on the x-axis and the ratio feature between 1350 nm and 1670 nm on the y-axis.

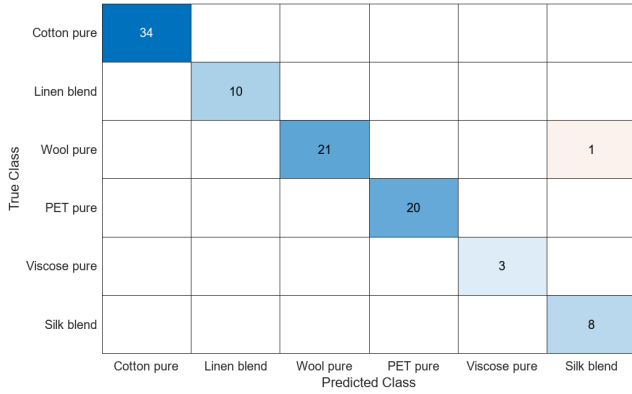


Fig. 16: Confusion matrix mono materials of Weighted KNN model with performance of 99.0%

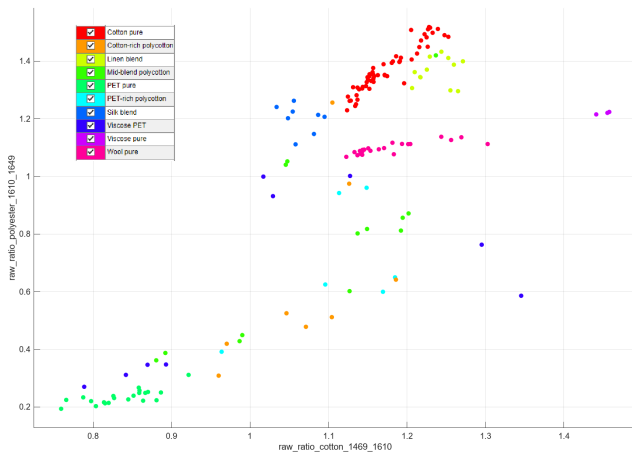


Fig. 17: Scatter plot of the mono-material samples using feature 1 on the x-axis and feature 2 on the y-axis.

2) *Category classification:* The samples are labeled according to their category, while categories containing no samples and the “Other” category are excluded from the

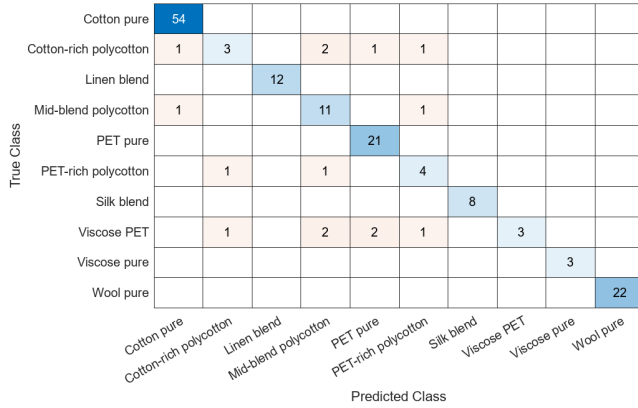
analysis. The scatter plot in Figure 17 shows a clear degree of separation between broad categories, and also indicates gradual separation between categories that are more similar in composition. Across all experiments, feature-based models consistently outperformed PCA-based models. In addition, KNN classifiers consistently achieved higher performance than alternatives such as decision trees and SVMs. As shown in Figure 18, the classifier achieved stable performance across repeated 50-fold validation, with only minor variation between runs. The confusion matrices confirm that the strongest performance is obtained for the pure-material classes. Most misclassifications occurred between neighbouring polycotton categories, which is expected because these classes lie close to one another in composition and form gradual spectral transitions between cotton-rich and polyester-rich materials [36], [37].

E. Elastane detection

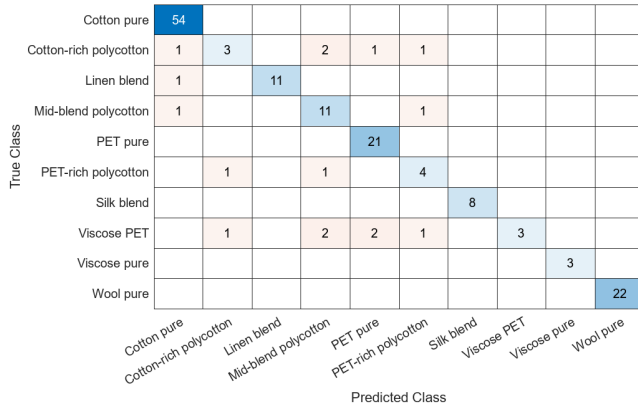
A total of 36 different hyperparameter combinations are evaluated, with each configuration repeated thirty times to calculate confidence intervals. A summary of these results is provided in Appendix V. The results indicate that the most suitable parameter setting, when prioritizing a low false negative percentage while maintaining strong overall classification performance, is Combination 12 (Dropout1 = 0.15, Weight_ElastanePresent = 4.0). This configuration achieved a mean false negative percentage of 16.39% with a 95% confidence interval of 15.10% to 17.68%, while still reaching a mean overall accuracy of 89.94% with a 95% confidence interval of 89.05% to 90.82%, suggesting a favourable balance between minimizing missed elastane-present samples and preserving robust predictive performance. The achieved elastane detection performance is noteworthy, because the most characteristic elastane-related absorption bands are commonly associated with the longer-wavelength NIR/SWIR region around and above 1700 nm [34], [44]. However, previous work has shown that even low elastane contents can be identified using NIR-based classification methods, indicating that successful detection may rely on distributed multivariate spectral information rather than on one isolated diagnostic band [37], [44]. In this context, the present results suggest that the 1040–1700 nm range still contains sufficient indirect or weak elastane-related information for reliable binary classification.

Although Combination 30 (Dropout1 = 0.30, Weight_ElastanePresent = 4.0) yielded the lowest false negative percentage overall at 16.11%, its mean overall accuracy is substantially lower at 85.74%, which weakens its practical usefulness when both sensitivity to the positive class and general model performance are considered important. By contrast, Combination 14 (Dropout1 = 0.20, Weight_ElastanePresent = 1.5) produced the highest mean overall accuracy at 91.11%, but this came with a noticeably higher false negative percentage of 19.72%, indicating a less desirable trade-off when reducing missed positive cases is a key objective. This pattern reflects the broader trade-off between maximizing

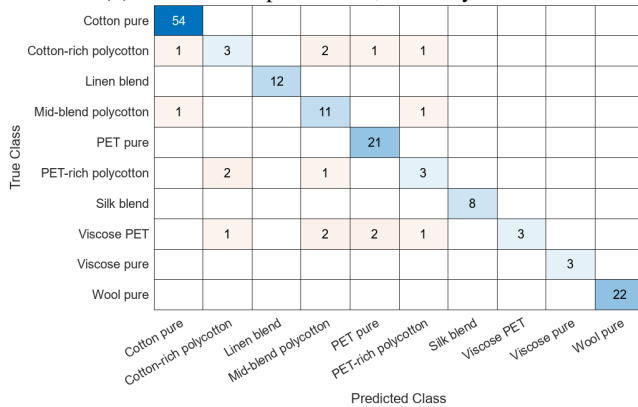
overall accuracy and minimizing false negatives, which is particularly relevant in textile sorting because elastane contamination can reduce the suitability of textile streams for high-value recycling processes [19].



(a) Shuffled sample order 1, accuracy 90.4%.

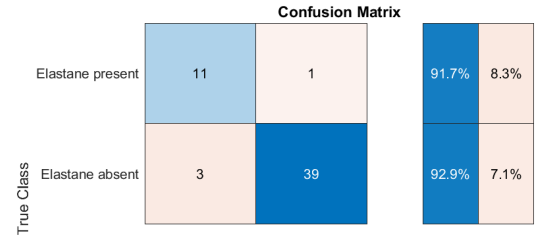


(b) Shuffled sample order 2, accuracy 89.7%.

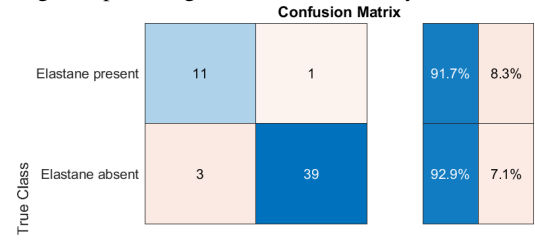


(c) Shuffled sample order 3, accuracy 89.7%.

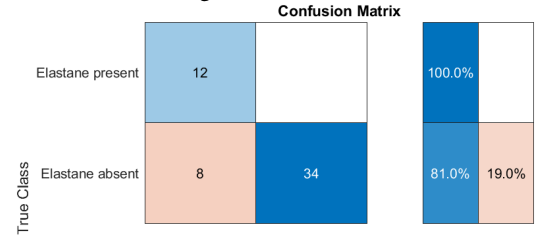
Fig. 18: Confusion matrices of the composition classification model for three repeated 50-fold validation runs with shuffled data. The results are highly consistent across runs, with overall accuracies between 89.7% and 90.4%.



(a) Combination 12: balanced trade-off between false negative percentage and overall accuracy.



(b) Combination 14: highest overall accuracy among the evaluated configurations.



(c) Combination 30: lowest false negative percentage, but with reduced overall accuracy.

Fig. 19: Confusion matrices for the three best-performing model configurations, illustrating the trade-off between minimizing false negatives and maintaining strong overall classification accuracy.

The three strongest model configurations show distinct but complementary performance profiles, as shown in Figure 19. Combination 12 (Dropout1 = 0.15, Weight_ElastanePresent = 4.0; Figure 19a) provided the best overall balance, combining a low mean false negative percentage with strong overall accuracy, and the corresponding confusion matrix shows 11 correctly iden-

tified elastane-present samples, only 1 false negative, and 39 correctly classified elastane-absent samples. Combination 14 (Dropout1 = 0.20, Weight_ElastanePresent = 1.5. Figure 19b) achieved the highest mean overall accuracy among the tested settings, although the confusion matrix suggests a somewhat higher false negative tendency than Combination 12. By contrast, Combination 30 (Dropout1 = 0.30, Weight_ElastanePresent = 4.0. Figure 19c) yielded the lowest false negative percentage, correctly identifying all 12 elastane-present samples in the illustrated run, but this is accompanied by more false positives and a lower overall accuracy, indicating a stronger bias toward detecting elastane presence. These results highlight the trade-off between maximizing overall accuracy and minimizing missed elastane-positive cases, with Combination 12 representing the most balanced compromise among the best-performing configurations.

As Combination 14 achieved the highest overall accuracy among the evaluated configurations, its training progress is included in Appendix VI to provide additional insight into the convergence behaviour of the model during training. To further examine model stability, Combination 14 is repeated 20 times, and the false-negative samples obtained across these runs are aggregated. Their frequencies are presented in Table V. Although certain samples appeared repeatedly as false negatives, no consistent relationship is observed between misclassification frequency and elastane percentage. For instance, samples containing 2%, 3%, 4%, and 5% elastane all appeared among the more frequently misclassified cases, indicating that misclassification cannot be explained by elastane concentration alone.

TABLE V: False-negative frequency across 20 runs for combination 14

Sample	False negatives (out of 20 runs)	Elastane (%)
S093	8	2
S117	8	2
S064	7	3
S113	7	5
S091	6	4
S011	5	1
S087	5	5
S035	4	4
S046	4	4
S052	4	2
S058	4	2
S070	4	3
S114	4	3
S043	3	4
S059	3	2
S190	3	4
S039	2	4
S056	2	3
S071	2	4
S057	1	3
S118	1	5

V. CONCLUSION

This study investigated whether near-infrared (NIR) spectroscopy combined with machine learning can be used to classify textile compositions relevant to recycling and to detect elastane as a separate binary label. Using NIR

spectra measured in the 900–1700 nm range from 181 textile samples, the results showed that this approach can successfully distinguish between key mono-materials and common blends, while also identifying elastane with good performance. For composition classification, the best-performing model achieved an accuracy of 91.7%, demonstrating that recycling-relevant textile categories can be recognized with high reliability from spectral data. For elastane detection, the 1D-CNN model achieved an overall accuracy of 92.6%, with class-specific accuracies of 83.3% for elastane-present samples and 95.2% for elastane-absent samples. These results indicate that even subtle elastane-related spectral differences can be detected within the measured wavelength range. The results further showed that feature-based classical machine-learning models outperformed PCA-based approaches, with KNN models giving the strongest results for composition classification. Important discriminatory information is concentrated in specific wavelength regions rather than across the entire spectrum, which supports the use of targeted feature extraction and feature selection for textile identification. In addition, the mono-material classification results showed that materials with visually similar spectra, such as cotton and linen, could still be distinguished accurately when multiple spectral features are considered simultaneously.

Together, these findings show that NIR spectroscopy can capture sufficient compositional information for practical textile classification, even when some spectral differences are subtle. The dataset is relatively limited in size, several categories contained few or no samples, and the measurements are obtained from certified wholesaler samples rather than true post-consumer textiles from the sorting stream. Nevertheless, the present study provides a strong first basis for further research within the SORTED project and the University of Groningen, and shows that NIR spectroscopy combined with machine learning is a promising route toward automated textile sorting for circular recycling applications.

VI. FUTURE WORK

Although the 900–1700 nm range used in this study already proved sufficient for discrimination between several common textile classes, particularly cotton-rich and polyester-rich materials, future work could investigate whether extending the spectral range further into the SWIR region improves classification performance. This may be especially relevant for more compositionally similar fibres and blends, for which the spectral differences within the shorter NIR range are relatively subtle. In particular, elastane-related absorption features are often associated with the longer-wavelength region around and above 1700 nm, suggesting that broader spectral coverage may further improve elastane detection and reduce false negatives [34], [37], [44]. A wider wavelength range may also support better separation of difficult classes such as wool, viscose, and other blended or structurally similar textiles [33], [35].

A second important direction for future work is the

use of hyperspectral imaging instead of single-point spectroscopy. Whereas the present study relies on point-based spectral measurements under controlled laboratory conditions, hyperspectral systems can capture both spectral and spatial information across the textile surface. This would be particularly valuable for non-homogeneous garments, layered materials, printed fabrics, or textiles with local contamination, where composition may vary across different parts of the item. In addition, hyperspectral imaging is more directly aligned with conveyor-based industrial sorting, because it enables rapid scanning of complete garments rather than isolated measurement points [25], [33].

Future research should also expand the dataset with a larger number of samples and a broader range of real post-consumer textiles. The current dataset provides a strong foundation for model development, but industrial application will require validation on more heterogeneous garments that may also include wear, moisture, dyes, prints, missing labels [36], [37]. In this way, future studies can move from proof-of-concept classification toward a more robust and practically deployable textile sorting system.

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REFERENCES

- [1] UniformMarket, *Global apparel industry statistics (2025)*, Accessed: March 8, 2026, 2025.
- [2] Rawshot.ai, *Global clothing production statistics - report 2026*, Accessed: March 8, 2026, 2026.
- [3] W. R. Institute. "By the numbers: The economic, social and environmental impacts of "fast fashion"." Accessed: March 8, 2026, World Resources Institute, Accessed: Mar. 8, 2026. [Online]. Available: <https://www.wri.org/insights/numbers-economic-social-and-environmental-impacts-fast-fashion>.
- [4] Textile Exchange, *Global fiber production reached an all-time high of 124 million tonnes in 2023, according to textile exchange's materials market report*, Accessed: March 8, 2026, Textile Exchange, 2024.
- [5] Textile Exchange, "Materials market report 2025," Textile Exchange, Tech. Rep., Sep. 2025, Accessed: March 8, 2026.
- [6] Statista. "Global textile fiber market share by type 2023." Accessed: March 8, 2026. Synthetic fibers: 67%; Polyester: 57%, Statista, Accessed: Mar. 8, 2026. [Online]. Available: <https://www.statista.com/statistics/1250812/global-fiber-production-share-type/>.
- [7] Merchize. "Cotton polyester blend explained: Pros, cons, applications." Accessed: March 8, 2026, Merchize, Accessed: Mar. 8, 2026. [Online]. Available: <https://merchize.com/cotton-polyester-blend/>.
- [8] E. Andini, P. Bhalode, E. Gantert, S. Sadula, and D. G. Vlachos, "Chemical recycling of mixed textile waste," *Science Advances*, vol. 10, no. 27, eado6827, 2024.
- [9] SORTED. "Sorted." Homepage. Accessed: April 15, 2026, Accessed: Apr. 15, 2026. [Online]. Available: <https://www.sorted.nl/en/>.
- [10] Sympany. "Wie we zijn." Accessed: April 15, 2026, Sympany, Accessed: Apr. 15, 2026. [Online]. Available: <https://www.sympany.nl/wie-we-zijn/>.
- [11] Sorted. "Together we built the textile chain of the future." Accessed: March 10, 2026, Sorted, Accessed: Mar. 10, 2026. [Online]. Available: <https://www.sorted.nl/en/partners/sympany>.
- [12] N. T. staff. "Temu, shein killing the market for dutch second-hand clothing." Accessed: March 10, 2026, Accessed: Mar. 10, 2026. [Online]. Available: <https://nltimes.nl/2024/09/02/temu-shein-killing-market-dutch-second-hand-clothing>.
- [13] Sympany. "Sympany lca-berekening deel 3." Accessed: March 14, 2026, Sympany, Accessed: Mar. 14, 2026. [Online]. Available: <https://>

- www.sympany.nl/nieuws/sympany-lca-berekening-deel-3/.
- [14] Sorted. "Circular textile chain: Why sorting is necessary." Interview with Charles Graft (Sympany) and Sven Jurgens (Ecoras). Accessed: March 20, 2026, Sorted, Accessed: Mar. 20, 2026. [Online]. Available: <https://www.sorted.nl/en/news/circular-textile-chain-why-sorting-is-necessary>.
- [15] Fanterco. "From textile to textile: How fiber-to-fiber recycling is reshaping the circular textile economy." Accessed: March 17, 2026, Fanterco, Accessed: Mar. 17, 2026. [Online]. Available: <https://fanterco.com/from-textile-to-textile-how-fiber-to-fiber-recycling-is-reshaping-the-circular-textile-economy/>.
- [16] Sustainability Directory. "Fibre-to-fibre recycling." Accessed: March 15, 2026, Sustainability Directory, Accessed: Mar. 15, 2026. [Online]. Available: <https://fashion.sustainability-directory.com/term/fibre-to-fibre-recycling/>.
- [17] International Fiber Journal. "Scaling fiber-to-fiber recycling facing formidable challenges." Accessed: March 14, 2026, Accessed: Mar. 14, 2026. [Online]. Available: <https://www.fiberjournal.com/scaling-fiber-to-fiber-recycling-facing-formidable-challenges/>.
- [18] A. Lehmann Enevoldsen. "From textile waste to value: Why detailed sorting for recycling matters." By New-Retex. Accessed: March 14, 2026, STREP Project, Accessed: Mar. 14, 2026. [Online]. Available: <https://strepproject.eu/from-textile-waste-to-value-why-detailed-sorting-for-recycling-matters-newretex/>.
- [19] M. Dahlbom and A. Martvall, "Maturity of fibre-to-fibre recycling in europe: Assessment of recycling companies in europe," IVL Swedish Environmental Research Institute, Tech. Rep. C874, Jan. 2025, Funded by Formas. Accessed: March 14, 2026.
- [20] Wrenbys. "Why elastane is the biggest hidden plastic problem in fashion." Accessed: March 15, 2026, Wrenbys, Accessed: Mar. 15, 2026. [Online]. Available: <https://wrenbys.com/blogs/be-iconic/why-elastane-is-the-biggest-hidden-plastic-problem-in-fashion>.
- [21] TU Wien. "Elastane recycling: Stretching the lifespan of textiles." Reports TU Wien study in Resources, Conservation & Recycling. Accessed: March 14, 2026, Phys.org, Accessed: Mar. 14, 2026. [Online]. Available: <https://phys.org/news/2023-12-elastane-recycling-lifespan-textiles.html>.
- [22] Solid Scanner. "Nir spectroscopy for plastic sorting and polymer identification." Accessed: April 15, 2026, Accessed: Apr. 15, 2026. [Online]. Available: <https://solidscanner.com/basics-and-limitations-of-nirs-and-how-it-is-used-in-plastic-recycling/>.
- [23] C. A. T. Dos Santos, M. Lopo, R. N. Páscoa, and J. A. Lopes, "A review on the applications of portable near-infrared spectrometers in the agro-food industry," *Applied spectroscopy*, vol. 67, no. 11, pp. 1215–1233, 2013.
- [24] H. Wedin et al., "Can automated nir technology be a way to improve the sorting quality of textile waste," *Environmental Science, Materials Science, Engineering; Research Institutes of Sweden: Gothenburg, Sweden*, 2017.
- [25] Specim. "Smarter textile sorting solutions with hyperspectral imaging." Accessed: April 15, 2026, Specim, Accessed: Apr. 15, 2026. [Online]. Available: <https://www.specim.com/hyperspectral-imaging-applications/textile-sorting/>.
- [26] M. Christis, B. Stubbe, P. Colignon, M. Hinzmann, and A. Sachdeva, "Study on the technical, regulatory, economic and environmental effectiveness of textile fibres recycling," Ecologic Institute, Final Report, Nov. 2021, Accessed 2026-04-21.
- [27] A. Stanton. "How does textile recycling work?" Accessed 2026-04-21. [Online]. Available: <https://www.thegoodtrade.com/features/textile-recycling-process/>.
- [28] SORTED. "Recell group." Accessed 2026-04-21. [Online]. Available: <https://www.sorted.nl/en/partners/recell-group>.
- [29] U. N. Ndagano, L. Cahill, C. Smullen, J. Gaughran, and S. M. Kelleher, "The current state-of-the-art of the processes involved in the chemical recycling of textile waste," *Molecules*, vol. 30, no. 2, p. 299, 2025.
- [30] M. Seifali Abbas-Abadi et al., "Advancing textile waste recycling: Challenges and opportunities across polymer and non-polymer fiber types," *Polymers*, vol. 17, no. 5, p. 628, 2025.
- [31] H. Chesshir. "Nir plastic sorting & its impact on packaging." Accessed: March 14, 2026, Paramount Global, Accessed: Mar. 14, 2026. [Online]. Available: <https://www.paramountglobal.com/knowledge/nir-plastic-sorting/>.
- [32] Felix Instruments. "In-line application of vis-nir spectroscopy for produce sorting." Accessed: March 14, 2026, Felix Instruments Applied Food Science, Accessed: Mar. 14, 2026. [Online]. Available: <https://felixinstruments.com/blog/in-line-application-of-vis-nir-spectroscopy-for-produce-sorting/>.
- [33] Ocean Optics. "Identifying textiles with extended-range ft-nir spectroscopy." Accessed: March 14, 2026, Ocean Insight, Accessed: Mar. 14, 2026. [On-

- line]. Available: <https://www.oceanoptics.com/blog/identifying-textiles-with-extended-range-ft-nir-spectroscopy/>.
- [34] Metrohm, "Analysis of textile using near-infrared spectroscopy," Metrohm, Tech. Rep. AB-413, 2011, Application Bulletin AB-413_{1EN}. Accessed: March 14, 2026.
- [35] Monospektra. "Identifying textiles with extended-range ft-nir spectroscopy." Accessed: March 16, 2026, Monospektra, Accessed: Mar. 16, 2026. [Online]. Available: <https://www.monospektra.com/identifying-textiles-with-extended-range-ft-nir-spectroscopy/>.
- [36] J.-R. Riba, R. Cantero, P. Riba-Mosoll, and R. Puig, "Post-consumer textile waste classification through near-infrared spectroscopy, using an advanced deep learning approach," *Polymers*, vol. 14, no. 12, p. 2475, 2022.
- [37] A. Becker, A. Datko, N. Kroell, B. Küppers, K. Greiff, and T. Gries, "Near-infrared-based sortability of polyester-containing textile waste," *Resources, Conservation and Recycling*, vol. 206, p. 107577, 2024.
- [38] H. Diu. "Textile recycling with nir spectroscopy." Accessed: March 28, 2026, INTINS, Accessed: Mar. 28, 2026. [Online]. Available: <https://intins.vn/blogs/news/textile-recycling-with-nir-spectroscopy>.
- [39] LabRulez. "Quantification of cotton content in textiles by near-infrared spectroscopy." Applications page for Metrohm Instrumentation item AN-NIR-118, accessed March 28, 2026, Accessed: Mar. 28, 2026. [Online]. Available: <https://gcms.labrulez.com/paper/26464>.
- [40] M. Sohn, F. E. Barton, D. E. Akin, and W. H. Morrison, "A new approach for estimating purity of processed flax fibre by nir spectroscopy," *Journal of near infrared spectroscopy*, vol. 12, no. 4, pp. 259–262, 2004.
- [41] J. Huang and C. Yu, "Fiber content determination of linen/viscose blends using nir spectroscopy," *BioResources*, vol. 15, no. 2, p. 3006, 2020.
- [42] Y. Zhu, L. Chen, X. Chen, J. Chen, and H. Zhang, "Near-infrared spectroscopy identification method of cashmere and wool fibers based on an optimized wavelength selection algorithm," *Heliyon*, vol. 10, no. 14, 2024.
- [43] V. Prajzler, K. Min, S. Kim, and P. Nekvindova, "The investigation of the waveguiding properties of silk fibroin from the visible to near-infrared spectrum," *Materials*, vol. 11, no. 1, p. 112, 2018.
- [44] E. Mahlamäki, I. Schlapp-Hackl, T. Koralage, M. Hummel, and M. Mäkelä, "Spectral imaging and a one-class classifier for detecting elastane in cotton fabrics," *Analyst*, vol. 150, no. 11, pp. 2295–2301, 2025.
- [45] MathWorks. "Classification learner app." Accessed 2026-04-21. [Online]. Available: <https://nl.mathworks.com/help/stats/classificationlearner-app.html>.
- [46] S. Ali Khan, A. Hussain, A. Basit, and S. Akram, "Kruskal-wallis-based computationally efficient feature selection for face recognition," *The Scientific World Journal*, vol. 2014, no. 1, p. 672630, 2014.
- [47] M. A. Jamil and S. Khanam, "Influence of one-way anova and kruskal-wallis based feature ranking on the performance of ml classifiers for bearing fault diagnosis," *Journal of Vibration Engineering & Technologies*, vol. 12, no. 3, pp. 3101–3132, 2024.
- [48] MathWorks. "Convolution1dlayer - 1-d convolutional layer - matlab." Accessed: April 21, 2026, Accessed: Apr. 21, 2026. [Online]. Available: <https://nl.mathworks.com/help/deeplearning/ref/nnet.cnn.layer.convolution1dlayer.html>.
- [49] X. Chen et al., "Probing 1d convolutional neural network adapted to near-infrared spectroscopy for efficient classification of mixed fish," *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 279, p. 121350, 2022.
- [50] APXML. "Hyperparameter search strategies." Accessed: April 21, 2026, Accessed: Apr. 21, 2026. [Online]. Available: <https://apxml.com/courses/applied-data-science/chapter-3-building-tuning-predictive-models/hyperparameter-tuning-search>.
- [51] Ecological Textiles. "Ecological textiles," Accessed: Apr. 22, 2026. [Online]. Available: <https://www.ecologicaltextiles.com/>.
- [52] Actiefstoffen. "Actiefstoffen - uw stoffen verkoop," Accessed: Apr. 22, 2026. [Online]. Available: <https://www.actiefstoffen.nl/>.
- [53] Budgetstoffen.nl. "Budgetstoffen: Stoffenwinkel — shop online stoffen én furnituren," Accessed: Apr. 22, 2026. [Online]. Available: <https://www.budgetstoffen.nl/>.
- [54] K. Saito, T. Yamagata, M. Kanno, N. Yoshimura, and M. Takayanagi, "Discrimination of cellulose fabrics using infrared spectroscopy and newly developed discriminant analysis," *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 257, p. 119772, 2021.
- [55] X. Geng, J. Gui, X. Liu, L. Zhou, J. Zhu, et al., "Study of specificity of mid-infrared spectra of cotton and linen fabric," *Journal of Infrared*, vol. 36, no. 9, pp. 30–34, 2015.

APPENDIX I

PSEUDOCODE OF THE 1D-CNN ELASTANE DETECTION PIPELINE

Algorithm 1 Generic pipeline for binary classification using a 1D-CNN

Require: Input dataset containing feature variables and class labels

Ensure: Trained model, class predictions, and evaluation metrics

- 1: Define the class labels, selected feature subset, validation-set size, hyperparameter values, and random seeds
 - 2: Load the dataset
 - 3: Identify the target label variable
 - 4: **if** the target label variable is not available **then**
 - 5: Stop and report an error
 - 6: **end if**
 - 7: Convert the target labels into a consistent categorical representation
 - 8: **if** invalid or undefined labels are present **then**
 - 9: Stop and report an error
 - 10: **end if**
 - 11: Select the numerical predictor variables
 - 12: Remove the target variable from the predictors
 - 13: Extract the desired feature subset
 - 14: Initialize the random number generator for the data split
 - 15: Partition the dataset into training-validation data and test data
 - 16: Shuffle the training-validation indices
 - 17: Select a class-balanced validation subset
 - 18: Assign the remaining samples to the training set
 - 19: Extract the training, validation, and test feature matrices and label vectors
 - 20: Enforce a consistent class order across all label vectors
 - 21: Compute normalization parameters from the training set only
 - 22: Apply the same normalization to the validation and test sets
 - 23: Convert the input data to the format required by the neural network implementation
 - 24: Determine the class order used by the training labels
 - 25: Assign class weights according to the selected hyperparameter setting
 - 26: Reinitialize the random number generator for model training
 - 27: Define the 1D-CNN architecture:
 - input layer
 - first 1D convolution block
 - activation and regularization
 - second 1D convolution block
 - activation and regularization
 - pooling layer
 - fully connected output layer
 - softmax and classification layer
 - 28: Define the training options, including optimizer, learning rate, number of epochs, mini-batch size, validation strategy, and execution environment
 - 29: Train the 1D-CNN model on the training set
 - 30: Use the trained model to predict the labels of the test set
 - 31: Compute the performance metrics, for example:
 - accuracy
 - precision
 - recall
 - F1-score
 - specificity
 - confusion matrix
 - 32: Store the predicted labels, class probabilities, and misclassification indicators
 - 33: Save the trained model, preprocessing parameters, and evaluation results
-

APPENDIX II

SAMPLE REGISTER

TABLE VI: Overview of textile samples, labels, elastane status, suppliers, and material compositions used in the dataset.

Sample ID	Item code	Composition	Elastane	Material composition	Color	Structure	Supplier	Link	Unit price	Amount	Notes	File name
S001	ET_Fullset	Cotton pure	Elastane absent	100% cotton	natural-white	poplin	ecologicaltextile\$ink	-	10x15 cm	-		S001_100cotton_natural-white_poplin
S002	ET_Fullset	Cotton pure	Elastane absent	100% cotton	navy	batist	ecologicaltextile\$ink	-	10x15 cm	-		S002_100cotton_navy_batist
S003	ET_Fullset	Cotton pure	Elastane absent	100% cotton	white-blue	poplin	ecologicaltextile\$ink	-	10x15 cm	-		S003_100cotton_white-blue_poplin
S004	ET_Fullset	Wool pure	Elastane absent	100% wool	brown	UNK	ecologicaltextile\$ink	-	10x15 cm	-		S004_100wool_brown_UNK
S005	ET_Fullset	Other	Elastane absent	70% cotton, 30% hemp	navy	sweat-unbrushed	ecologicaltextile\$ink	-	10x15 cm	-		S005_70cotton-30hemp_navy_sweat-unbrushed
S006	ET_Fullset	Other	Elastane absent	100% hemp	beige	gauze	ecologicaltextile\$ink	-	10x15 cm	-		S006_100hemp_beige_gauze
S007	ET_Fullset	Linen blend	Elastane absent	100% linen	lightblue	twill	ecologicaltextile\$ink	-	10x15 cm	-		S007_100linen_lightblue_twill
S008	ET_Fullset	Other	Elastane absent	100% hemp	beige	UNK	ecologicaltextile\$ink	-	10x15 cm	-		S008_100hemp_beige_UNK
S009	ET_Fullset	Cotton pure	Elastane absent	100% cotton	ochre	waffleweave	ecologicaltextile\$ink	-	10x15 cm	-		S009_100cotton_ochre_waffleweave
S010	ET_Fullset	Cotton pure	Elastane absent	100% cotton	offwhite	crepe	ecologicaltextile\$ink	-	10x15 cm	-		S010_100cotton_offwhite_crepe
S011	ET_Fullset	Cotton pure	Elastane present	99% cotton, 1% elastane	offwhite	weave	ecologicaltextile\$ink	-	10x15 cm	-		S011_99cotton-1elastane_offwhite_weave
S012	ET_Fullset	Other	Elastane absent	60% cotton, 40% tencel	chambray	UNK	ecologicaltextile\$ink	-	10x15 cm	-		S012_60cotton-40lyocell_chambray_UNK
S013	ET_Fullset	Cotton pure	Elastane absent	100% cotton	offwhite	weave	ecologicaltextile\$ink	-	10x15 cm	-		S013_100cotton_offwhite_weave
S014	ET_Fullset	Cotton pure	Elastane absent	100% cotton	chambray	UNK	ecologicaltextile\$ink	-	10x15 cm	-		S014_100cotton_chambray_UNK
S015	ET_Fullset	Cotton pure	Elastane absent	100% cotton	indigo-chambray	UNK	ecologicaltextile\$ink	-	10x15 cm	-		S015_100cotton_indigo-chambray_UNK
S016	ET_Fullset	Cotton pure	Elastane absent	100% cotton	black	sweat-brushed	ecologicaltextile\$ink	-	10x15 cm	-		S016_100cotton_black_sweat-brushed
S017	ET_Fullset	Cotton pure	Elastane absent	100% cotton	offwhite	sweat-brushed	ecologicaltextile\$ink	-	10x15 cm	-		S017_100cotton_offwhite_sweat-brushed
S018	ET_Fullset	Cotton pure	Elastane absent	100% cotton	dotted-blue	UNK	ecologicaltextile\$ink	-	10x15 cm	-		S018_100cotton_dotted-blue_UNK
S019	ET_Fullset	Cotton pure	Elastane absent	100% cotton	darkblue	herringbone-weave	ecologicaltextile\$ink	-	10x15 cm	-		S019_100cotton_darkblue_herringbone-weave
S020	ET_Fullset	Other	Elastane absent	88% wool, 12% polylactide	white	quilted-batist	ecologicaltextile\$ink	-	10x15 cm	-		S020_88wool-12polylactide_white_quilted-batist
S021	ET_Fullset	Cotton pure	Elastane absent	100% cotton	black	poplin	ecologicaltextile\$ink	-	10x15 cm	-		S021_100cotton_black_poplin
S022	ET_Fullset	Cotton pure	Elastane absent	100% cotton	black-onyx	batist	ecologicaltextile\$ink	-	10x15 cm	-		S022_100cotton_black-onyx_batist
S023	ET_Fullset	Cotton pure	Elastane absent	100% cotton	natural-white	heavy-canvas	ecologicaltextile\$ink	-	10x15 cm	-		S023_100cotton_natural-white_heavy-canvas
S024	ET_Fullset	Cotton pure	Elastane absent	100% cotton	offwhite	heavycanvas	ecologicaltextile\$ink	-	10x15 cm	-		S024_100cotton_offwhite_heavycanvas
S025	ET_Fullset	Cotton pure	Elastane absent	100% cotton	saxonyblue	batist	ecologicaltextile\$ink	-	10x15 cm	-		S025_100cotton_saxonyblue_batist
S026	ET_Fullset	Cotton pure	Elastane absent	100% cotton	starlightblue	batist	ecologicaltextile\$ink	-	10x15 cm	-		S026_100cotton_starlightblue_batist
S027	ET_Fullset	Cotton pure	Elastane absent	100% cotton	olivine	batist	ecologicaltextile\$ink	-	10x15 cm	-		S027_100cotton_olivine_batist
S028	ET_Fullset	Cotton pure	Elastane absent	100% cotton	maroon	batist	ecologicaltextile\$ink	-	10x15 cm	-		S028_100cotton_maroon_batist
S029	ET_Fullset	Cotton pure	Elastane absent	100% cotton	barelypink	batist	ecologicaltextile\$ink	-	10x15 cm	-		S029_100cotton_barelypink_batist
S030	ET_Fullset	Cotton pure	Elastane absent	100% cotton	natural-white	batist	ecologicaltextile\$ink	-	10x15 cm	-		S030_100cotton_natural-white_batist
S031	ET_Fullset	Cotton pure	Elastane absent	100% cotton	burntsienna	batist	ecologicaltextile\$ink	-	10x15 cm	-		S031_100cotton_burntsienna_batist
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Sample ID	Item code	Composition	Elastane	Material composition	Color	Structure	Supplier	Link	Unit price	Amount	Notes	File name
S060	BS-JSS-138 Mid-blend polycotton	Elastane present	59% polyester, 33% cotton, 8% elastane	blue	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S060_59polyester- 33cotton- 8elastane.blue_UNK
S061	BS-KPR-KA-02	Cotton-rich polycotton	Elastane absent	65% cotton, 35% polyester	white	UNK	budgetstoffen	link	0,50	8x8 cm	–	S061_65cotton- 35polyester.white_UNK
S062	BS-KPR-KA-05 Cotton-rich polycotton	Elastane absent	65% cotton, 35% polyester	lightblue	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S062_65cotton- 35polyester.lightblue_UNK
S063	BS-KPR-KA-47 Cotton-rich polycotton	Elastane absent	65% cotton, 35% polyester	ochre	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S063_65cotton- 35polyester.ochre_UNK
S064	BS-KPR-STR- KA-01 Cotton pure	Elastane present	97% cotton, 3% elastane	UNK	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S064_97cotton- 3elastane_UNK
S065	BS-KTRU-51	Cotton pure	Elastane present	95% cotton, 5% elastane	fuchsiaroze	UNK	budgetstoffen	link	0,50	8x8 cm	–	S065_95cotton- 5elastane.fuchsiaroze_UNK
S066	BS-SUE-31 PET pure	Elastane absent	100% polyester	mossgreen	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S066_100polyester-mossgreen_UNK
S067	BS-SUE-38 PET pure	Elastane absent	100% polyester	oldpink	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S067_100polyester-oldpink_UNK
S068	BS-VDP-69	PET pure	Elastane absent	100% polyester	taupe	UNK	budgetstoffen	link	0,50	8x8 cm	–	S068_100polyester-taupe_UNK
S069	P-BIO-KAU-48 Cotton pure	Elastane absent	100% cotton	orange	interlocked	UNK	budgetstoffen	link	0,50	8x8 cm	–	S069_100cotton.orange_interlocked
S070	P-CS-10	Viscose PET	Elastane present	72% polyester, 25% viscose, 3% elastane	flower-on- offwhite	UNK	budgetstoffen	link	0,50	8x8 cm	–	S070_72polyester- 25viscose- 3elastane.flower-on- offwhite_UNK
S071	P-DIA-JER-11 Viscose PET	Elastane present	60% viscose, 36% polyester, 4% elastane	cassis	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S071_60viscose- 36polyester.cassis_UNK
S072	P-JOG-STR-04- 01 Cotton-rich polycotton	Elastane present	72% cotton, 25% polyester, 3% elastane	lightgrey	joggingrib	UNK	budgetstoffen	link	0,50	8x8 cm	–	S072_72cotton- 25polyester- 3elastane.lightgrey_joggingrib
S073	P-KA-RUI-193- 08489	Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	lightgrey- whitestripes	UNK	budgetstoffen	link	0,50	8x8 cm	Blousestof	S073_60cotton- 40polyester.lightgrey- whitestripes_UNK
S074	P-KA-RUI-31567 Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	ruitjes-pink	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S074_60cotton- 40polyester.ruitjes- pink_UNK
S075	P-KA-RUI-33967 Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	deeeppurple	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S075_60cotton- 40polyester.deeeppurple_UNK
S076	P-KA-RUI-34052 Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	ruitje-lila	UNK	UNK	budgetstoffen	link	0,50	8x8 cm	–	S076_60cotton- 40polyester.ruitje- lila_UNK
S077	P-KA-RUI-34061	Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	navyblue-white	UNK	budgetstoffen	link	0,50	8x8 cm	Blousestof	S077_60cotton- 40polyester.navyblue- white_UNK
S078	P-SWM-2-02	Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	brown-white	UNK	budgetstoffen	link	0,50	8x8 cm	–	S078_60cotton- 40polyester.brown- white_UNK
S079	P-SWM-2-03	Mid-blend polycotton	Elastane absent	60% cotton, 40% polyester	darkred-white	UNK	budgetstoffen	link	0,50	8x8 cm	–	S079_60cotton- 40polyester.darkred- white_UNK

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Sample ID	Item code	Composition	Elastane	Material composition	Color	Structure	Supplier	Link	Unit price	Amount	Notes	File name
S107	1111.0270-10	Mid-blend polycotton	Elastane absent	50% cotton, 50% polyester	white	UNK	actiefstoffen	link	1,00	2x4 cm	–	S107_50cotton-50polyester_white.UNK
S108	1111.0270-21	Mid-blend polycotton	Elastane absent	50% cotton, 50% polyester	anthracite	UNK	actiefstoffen	link	1,00	2x4 cm	–	S108_50cotton-50polyester_anthracite.UNK
S109	1011.0020-34	Cotton-rich polycotton	Elastane absent	70% katoen, 30% polyester	applegreen	twill weave	actiefstoffen	link	1,00	2x4 cm	–	S109_70cotton-30polyester_applegreen_twillweave
S110	2011.0082-72	PET pure	Elastane absent	100% polyester	silvergrey	UNK	actiefstoffen	link	1,00	2x4 cm	–	S110_100polyester_silvergrey.UNK
S111	2011.0082-41	PET pure	Elastane absent	100% polyester	lightblue	UNK	actiefstoffen	link	1,00	2x4 cm	–	S111_100polyester_lightblue.UNK
S112	2011.0082-63	PET pure	Elastane absent	100% polyester	darkred	UNK	actiefstoffen	link	1,00	2x4 cm	–	S112_100polyester_darkred.UNK
S113	8181.1908-25	Viscose PET	Elastane present	65% viscose, 30% polyester, 5% elastane	antracite	UNK	actiefstoffen	link	1,00	2x4 cm	–	S113_65viscose-30polyester-5elastane_antracite.UNK
S114	7121.1894-71	Viscose PET	Elastane present	67% viscose, 30% polyester, 3% elastane	lightgrey	UNK	actiefstoffen	link	1,00	2x4 cm	–	S114_67viscose-30polyester-3elastane_lightgrey.UNK
S115	1121.1979-21	Cotton pure	Elastane present	92% cotton, 8% elastane	black	UNK	actiefstoffen	link	1,00	2x4 cm	–	S115_92cotton-8elastane_black.UNK
S116	7111.3334-11	Viscose PET	Elastane absent	55% viscose, 45% polyester	white	UNK	actiefstoffen	link	1,00	2x4 cm	–	S116_55viscose-45polyester_white.UNK
S117	7121.3348-61	Viscose PET	Elastane present	48% viscose, 50% polyester, 2% elastane	pink	UNK	actiefstoffen	link	1,00	2x4 cm	–	S117_48viscose-50polyester-2elastane_pink.UNK
S118	7121.1749-71	Viscose PET	Elastane present	78% viscose, 17% polyester, 5% elastane	grey-whitestripes	UNK	actiefstoffen	link	1,00	2x4 cm	–	S118_78viscose-17polyester-5elastane_grey-whitestripes.UNK
S119	2111.0089-20	PET pure	Elastane absent	100% polyester	black	UNK	actiefstoffen	link	1,00	2x4 cm	–	S119_100polyester_black.UNK
S120	2111.0089-41	PET pure	Elastane absent	100% polyester	navyblue	UNK	actiefstoffen	link	1,00	2x4 cm	–	S120_100polyester_navyblue.UNK
S121	2111.0089-42	PET pure	Elastane absent	100% polyester	royalblue	UNK	actiefstoffen	link	1,00	2x4 cm	–	S121_100polyester_royalblue.UNK
S122	2111.0089-60	PET pure	Elastane absent	100% polyester	red	UNK	actiefstoffen	link	1,00	2x4 cm	–	S122_100polyester_red.UNK
S123	2111.0089-30	PET pure	Elastane absent	100% polyester	green	UNK	actiefstoffen	link	1,00	2x4 cm	–	S123_100polyester_green.UNK
S124	2111.0089-31	PET pure	Elastane absent	100% polyester	lightgreen	UNK	actiefstoffen	link	1,00	2x4 cm	–	S124_100polyester_lightgreen.UNK
S125	2111.0089-10	PET pure	Elastane absent	100% polyester	white	UNK	actiefstoffen	link	1,00	2x4 cm	–	S125_100polyester_white.UNK
S126	2011.0082-31	PET pure	Elastane absent	100% polyester	applegreen	UNK	actiefstoffen	link	1,00	2x4 cm	–	S126_100polyester_applegreen.UNK
S127	2011.0082-94	PET pure	Elastane absent	100% polyester	lilac	UNK	actiefstoffen	link	1,00	2x4 cm	–	S127_100polyester_lilac.UNK
S128	2011.0082-62	PET pure	Elastane absent	100% polyester	cardinalred	UNK	actiefstoffen	link	1,00	2x4 cm	–	S128_100polyester_cardinalred.UNK
S129	ET_Fullset	Other	Elastane absent	67% cotton, 33% linen	anthracite	panama-weave	ecologicaltextiles	link	-	10x15 cm	–	S129_67cotton-33linen_anthracite_panama-weave
S130	ET_Fullset	Other	Elastane absent	67% cotton, 33% linen	alloy	panama-weave	ecologicaltextiles	link	-	10x15 cm	–	S130_67cotton-33linen_alloy_panama-weave
S131	ET_Fullset	Other	Elastane absent	67% cotton, 33% linen	black	panama-weave	ecologicaltextiles	link	-	10x15 cm	–	S131_67cotton-33linen_black_panama-weave
S132	ET_Fullset	Other	Elastane absent	67% cotton, 33% linen	bluemirage	panama-weave	ecologicaltextiles	link	-	10x15 cm	–	S132_67cotton-33linen_bluemirage_panama-weave
S133	ET_Fullset	Other	Elastane absent	67% cotton, 33% linen	mossstone	panama-weave	ecologicaltextiles	link	-	10x15 cm	–	S133_67cotton-33linen_mossstone_panama-weave
S134	ET_Fullset	Other	Elastane absent	67% cotton, 33% linen	feathergrey	panama-weave	ecologicaltextiles	link	-	10x15 cm	–	S134_67cotton-33linen_feathergrey_panama-weave

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Sample ID	Item code	Composition	Elastane	Material composition	Color	Structure	Supplier	Link	Unit price	Amount	Notes	File name
S135	ET_Fullset	Cotton pure	Elastane absent	100% cotton	natural-white	gabardine	ecologicaltextilesink		-	10x15 cm	-	S135_100cotton_natural-white_gabardine
S136	ET_Fullset	Cotton pure	Elastane absent	100% cotton	organic-white	UNK	ecologicaltextilesink		-	10x15 cm	-	S136_100cotton_organic-white_UNK
S137	ET_Fullset	Wool pure	Elastane absent	100% wool	lightbrown	doublefaceboiled-knit	ecologicaltextilesink		-	10x15 cm	-	S137_100wool_lightbrown_doublefaceboiled-knit
S138	ET_Fullset	Wool pure	Elastane absent	100% wool	boiledgrey	interlock	ecologicaltextilesink		-	10x15 cm	-	S138_100wool_boiledgrey_interlock
S139	ET_Fullset	Wool pure	Elastane absent	100% wool	red	interlockfelted-knit	ecologicaltextilesink		-	10x15 cm	-	S139_100wool_red_interlockfelted-knit
S140	ET_Fullset	Wool pure	Elastane absent	100% wool	sand	boiled-knit	ecologicaltextilesink		-	10x15 cm	-	S140_100wool_sand_boiled-knit
S141	ET_Fullset	Wool pure	Elastane absent	100% wool	mulberry	jersey	ecologicaltextilesink		-	10x15 cm	-	S141_100wool_mulberry_jersey
S142	ET_Fullset	Wool pure	Elastane absent	100% wool	black	gabardine	ecologicaltextilesink		-	10x15 cm	-	S142_100wool_black_gabardine
S143	ET_Fullset	Wool pure	Elastane absent	100% wool	brown	boiled-knit	ecologicaltextilesink		-	10x15 cm	-	S143_100wool_brown_boiled-knit
S144	ET_Fullset	Wool pure	Elastane absent	100% wool	navy	gabardine	ecologicaltextilesink		-	10x15 cm	-	S144_100wool_navy_gabardine
S145	ET_Fullset	Silk blend	Elastane absent	100% silk	ochre	jersey	ecologicaltextilesink		-	10x15 cm	-	S145_100silk_ochre_jersey
S146	ET_Fullset	Silk blend	Elastane absent	100% silk	rubia	jersey	ecologicaltextilesink		-	10x15 cm	-	S146_100silk_rubia_jersey
S147	ET_Fullset	Silk blend	Elastane absent	100% silk	white	jersey	ecologicaltextilesink		-	10x15 cm	-	S147_100silk_white_jersey
S148	ET_Fullset	Silk blend	Elastane absent	100% silk	pink	UNK	ecologicaltextilesink		-	10x15 cm	-	S148_100silk_pink_UNK
S149	ET_Fullset	Silk blend	Elastane absent	100% silk	black	jersey	ecologicaltextilesink		-	10x15 cm	-	S149_100silk_black_jersey
S150	ET_Fullset	Silk blend	Elastane absent	100% silk	turquoise	UNK	ecologicaltextilesink		-	10x15 cm	-	S150_100silk_turquoise_UNK
S151	ET_Fullset	Other	Elastane absent	84% cotton, 16% silk	white	UNK	ecologicaltextilesink		-	10x15 cm	-	S151_84cotton-16silk_white_UNK
S152	ET_Fullset	Silk blend	Elastane absent	100% silk	offwhite	satin	ecologicaltextilesink		-	10x15 cm	-	S152_100silk_offwhite_satin
S156	ET_Fullset	Silk blend	Elastane absent	100% silk	offwhite	satin	ecologicaltextilesink		-	10x15 cm	-	S156_100silk_offwhite_satin
S157	ET_Fullset	Linen blend	Elastane absent	100% linen	natural-brown	twill	ecologicaltextilesink		-	10x15 cm	-	S157_100linen_natural-brown_twill
S158	ET_Fullset	Linen blend	Elastane absent	100% linen	white	UNK	ecologicaltextilesink		-	10x15 cm	-	S158_100linen_white_UNK
S159	ET_Fullset	Linen blend	Elastane absent	100% linen	white	UNK	ecologicaltextilesink		-	10x15 cm	-	S159_100linen_white_UNK
S160	ET_Fullset	Linen blend	Elastane absent	100% linen	oyster	UNK	ecologicaltextilesink		-	10x15 cm	-	S160_100linen_oyster_UNK
S161	ET_Fullset	Linen blend	Elastane absent	100% linen	black	UNK	ecologicaltextilesink		-	10x15 cm	-	S161_100linen_black_UNK
S162	ET_Fullset	Linen blend	Elastane absent	100% linen	grey	UNK	ecologicaltextilesink		-	10x15 cm	-	S162_100linen_grey_UNK
S163	ET_Fullset	Linen blend	Elastane absent	100% linen	anthracite	UNK	ecologicaltextilesink		-	10x15 cm	-	S163_100linen_anthracite_UNK
S164	ET_Fullset	Linen blend	Elastane absent	100% linen	silver	UNK	ecologicaltextilesink		-	10x15 cm	-	S164_100linen_silver_UNK
S165	ET_Fullset	Linen blend	Elastane absent	100% linen	grey	UNK	ecologicaltextilesink		-	10x15 cm	-	S165_100linen_grey_UNK
S166	ET_Fullset	Cotton pure	Elastane present	96% cotton, 4% elastane	phantomgrey	UNK	ecologicaltextilesink		-	10x15 cm	-	S166_96cotton-4elastane_phantomgrey_UNK
S167	ET_Fullset	Wool pure	Elastane absent	100% wool	natural-white	jersey	ecologicaltextilesink		-	10x15 cm	-	S167_100wool_natural-white_jersey
S168	ET_Fullset	Wool pure	Elastane absent	100% wool	licorice	jersey	ecologicaltextilesink		-	10x15 cm	-	S168_100wool_licorice_jersey
S169	ET_Fullset	Wool pure	Elastane absent	100% wool	natural-white	UNK	ecologicaltextilesink		-	10x15 cm	-	S169_100wool_natural-white_UNK
S170	ET_Fullset	Other	Elastane absent	85% cotton, 15% linen	blue-striped	poplin	ecologicaltextilesink		-	10x15 cm	-	S170_85cotton-15linen_blue-striped_poplin
S171	ET_Fullset	Wool pure	Elastane absent	100% wool	natural-white	UNK	ecologicaltextilesink		-	10x15 cm	-	S171_100wool_natural-white_UNK
S173	ET_Fullset	Wool pure	Elastane absent	100% wool	indigo	UNK	ecologicaltextilesink		-	10x15 cm	-	S173_100wool_indigo_UNK
S174	ET_Fullset	Cotton pure	Elastane absent	100% cotton	natural-white	UNK	ecologicaltextilesink		-	10x15 cm	-	S174_100cotton_natural-white_UNK
S175	ET_Fullset	Wool pure	Elastane absent	100% wool	lightbrown	duffelmelange	ecologicaltextilesink		-	10x15 cm	-	S175_100wool_lightbrown_duffelmelange
S176	ET_Fullset	Wool pure	Elastane absent	100% wool	grey	UNK	ecologicaltextilesink		-	10x15 cm	-	S176_100wool_grey_UNK

Continued on next page

Sample ID	Item code	Composition	Elastane	Material composition	Color	Structure	Supplier	Link	Unit price	Amount	Notes	File name
S177	ET.Fullset	Wool pure	Elastane absent	100% wool	darkgrey	UNK	ecologicaltextile	link	-	10x15 cm	–	S177_100wool_darkgrey_UNK
S178	ET.Fullset	Wool pure	Elastane absent	100% wool	darkbrown	UNK	ecologicaltextile	link	-	10x15 cm	–	S178_100wool_darkbrown_UNK
S179	ET.Fullset	Wool pure	Elastane absent	100% wool	merlot	UNK	ecologicaltextile	link	-	10x15 cm	–	S179_100wool_merlot_UNK
S180	ET.Fullset	Wool pure	Elastane absent	100% wool	grey	UNK	ecologicaltextile	link	-	10x15 cm	–	S180_100wool_grey_UNK
S181	ET.Fullset	Wool pure	Elastane absent	100% wool	black	twill	ecologicaltextile	link	-	10x15 cm	–	S181_100wool_black_twill
S182	ET.Fullset	Linen blend	Elastane absent	57% linen, 43% wool	chocowhite	UNK	ecologicaltextile	link	-	10x15 cm	–	S182_57linen-43wool_chocowhite_UNK
S183	ET.Fullset	Linen blend	Elastane absent	57% linen, 43% wool	bluewhite	wovencheck	ecologicaltextile	link	-	10x15 cm	–	S183_57linen-43wool_bluewhite_wovencheck
S184	ET.Fullset	Wool pure	Elastane absent	100% wool	honey	heavyploeden	ecologicaltextile	link	-	10x15 cm	–	S184_100wool_honey_heavyploeden
S189	ET.Fullset	Cotton pure	Elastane present	96% cotton, 4% elastane	opticalwhite	UNK	ecologicaltextile	link	-	10x15 cm	–	S189_96cotton-4elastane_opticalwhite_UNK
S190	ET.Fullset	Cotton pure	Elastane present	96% cotton, 4% elastane	black	rib-knit	ecologicaltextile	link	-	10x15 cm	–	S190_96cotton-4elastane_black_rib-knit
S191	ET.Fullset	Cotton pure	Elastane present	95% cotton, 5% elastane	black	interlock	ecologicaltextile	link	-	10x15 cm	–	S191_95cotton-5elastane_black_interlock

APPENDIX III

OVERLAY OF ALL MEASURED NIR SPECTRA

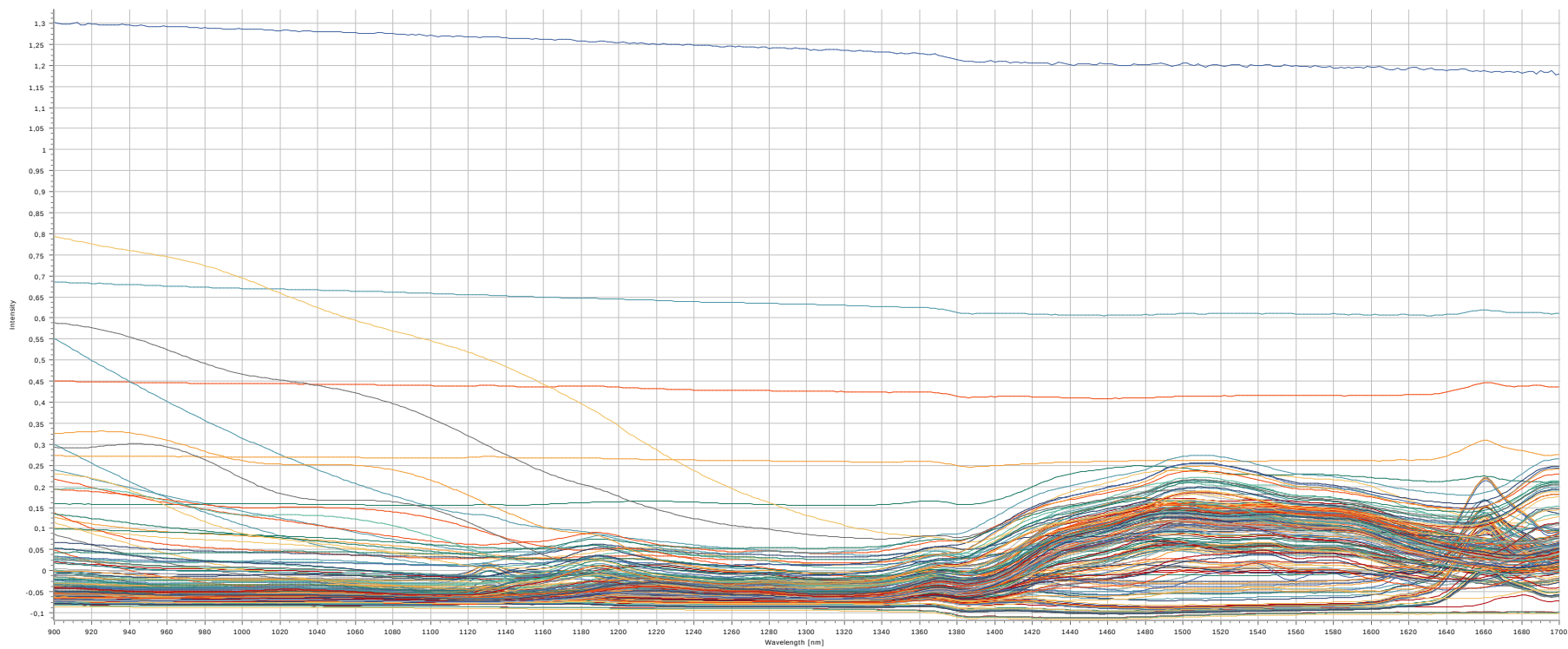


Fig. 20: Overlay of all measured NIR absorbance spectra for the textile samples included in this study.

APPENDIX IV TOP 175 FEATURES IDENTIFIED ACROSS FEATURE-RANKING ALGORITHMS

Chi2	Anova	Kruskal–Wallis	Overlapping features
der1.1566	smooth_wav_argmax.c1679.s2.1667.1685	d2_wav_argmax.c1693.s4.1687.1700	d1_wav_argmax.c1649.s2.1635.1663
der1.1564	der1.1552	smooth_wav_argmax.c1608.s4.1590.1626	der1.1564
der1.1570	der1.1554	smooth_wav_argmax.c1608.s3.1590.1626	der1.1568
der1.1556	smooth_wav_argmax.c1608.s2.1590.1626	der1.1480	der1.1558
der1_ratio_silk.1551.1673	der1.1558	der1.1562	
der1.1572	der1.1548	der1.1566	der1.1482
der1.1560	der1.1546	der1.1560	
der1.1558	der1.1560	der1.1568	der1.1484
der1_ratio_wool.1568.1679	der1.1544	der1.1570	
der1_ratio_wool.1485.1679	der1.1542	der1.1572	der1.1486
d1_wav_argmax.c1558.s4.1536.1580	der1.1562	d1_wav_argmax.c1649.s3.1635.1663	der1.1546
der1.1540	d1_wav_argmax.c1649.s4.1635.1663	der1.1488	der1.1558
smooth_wav_argmax.c1558.s4.1536.1580	der1.1564	der1.1574	der1.1490
der1.1548	der2.1522	d1_wav_argmax.c1679.s4.1667.1685	smooth_wav_argmax.c1235.s4.1213.1257
der1.1536	der1.1490	der1.1492	der1.1552
der2.1520	der1.1486	der1_ratio_viscose.1506.1684	der2.1524
der1.1576	der1.1494	raw_ratio_polyester.1610.1649	der1.1534
der1.1488	smooth_wav_argmax.c1180.s3.1160.1200	der1.1566	der1.1484
der1.1496	smooth_wav_argmax.c1180.s4.1160.1200	der2.1526	der1.1544
der1.1550	der2.1518	der2.1510	der1.1498
der1.1488	smooth_wav_energy.c1508.s4.1490.1526	der1.1482	
der1.1544	smooth_wav_energy.c1508.s3.1490.1526	d1_wav_argmax.c1649.s2.1635.1663	der1.1522
smooth_wav_argmax.c1235.s3.1213.1257	der1.1532	der2.1498	
der1.1528	smooth_wav_energy.c1508.s2.1490.1526	der1.1492	der1.1524
der1.1554	der2.1528	der2.1508	
der1.1574	der2.1516	raw_ratio_polyester.1610.1649	der1.1528
raw_ratio_viscose.1418.1684	der1.1530	der1.1546	
der1.1522	der2.1514	der2.1512	der1.1530
der1.1530	der2.1362	smooth_wav_energy.c1358.s4.1333.1383	d2_wav_argmax.c1235.s4.1213.1257
der2.1510	der1.1542	der1.1532	der1.1484
der2.1512	smooth_wav_energy.c1358.s3.1333.1383	der1.1482	d1_wav_energy.c1467.s4.1449.1485
raw_ratio_silk.1551.1673	der1.1534	raw_ratio_linen.1469.1510	smooth_wav_argmax.c1608.s3.1590.1626
smooth_wav_energy.c1358.s2.1333.1383	raw_ratio_silk.1592.1673	der2.1530	der2.1500
der1.1536	smooth_wav_argmax.c1508.s2.1490.1526	der2.1364	der1.1480
d1_wav_argmax.c1558.s3.1536.1580	der1.1568	der1.1494	der1.1538
der1_ratio_silk.1485.1592	smooth_wav_meanabs.c1508.s3.1490.1526	der1.1472	
smooth_wav_argmax.c1417.s4.1395.1439	smooth_wav_meanabs.c1508.s2.1490.1526	der1.1548	der1.1540
der1.1520	smooth_wav_meanabs.c1508.s4.1490.1526	der2.1504	
der1.1486	smooth_wav_argmax.c1608.s2.1590.1626	der1.1540	der1.1542
der1.1492	der2.1360	der1.1536	
d1_wav_argmax.c1235.s3.1213.1257	der2.1366	der1.1496	der1.1544
d1_wav_argmax.c1235.s4.1213.1257	smooth_wav_argmax.c1608.s4.1590.1626	raw_ratio_silk.1592.1673	der1.1556
d2_wav_max.c1508.s4.1490.1526	der1.1474	der1.1546	raw_ratio_silk.1551.1673
der2.1358	raw_ratio_wool.1547.1679	der1_ratio_linen.1469.1510	der1.1528
der1.1538	der1.1548	d2_wav_argmax.c1235.s3.1213.1257	der2.1508
smooth_wav_argmax.c1649.s4.1635.1663	der2.1386	d1_wav_energy.c1467.s3.1449.1485	der1.1550
der1.1550	der1_ratio_wool.1405.1568	d2_wav_max.c1417.s4.1395.1439	der2.1506
der1_ratio_cotton.1469.1508	der2.1356	smooth_wav_energy.c1508.s3.1490.1526	der1.1552
d2_wav_max.c1608.s3.1590.1626	d2_wav_meanabs.c1508.s4.1490.1526	der2.1502	
raw_ratio_cotton.1469.1508	der2.1354	raw_ratio_polyester.1610.1670	der1.1554
der1.1490	der2.1368	der1.1532	der1.1556
der1.1532	der1.1492	raw_ratio_silk.1485.1673	
smooth_wav_energy.c1508.s3.1490.1526	der1.1494	der1.1478	der1.1558
der2.1384	der1.1490	smooth_wav_energy.c1508.s4.1490.1526	
der1.1538	der2.1552	der1.1534	der1.1560
raw_ratio_viscose.1558.1684	d2_wav_energy.c1417.s3.1395.1439	der1.1618	
der1_ratio_wool.1171.1350	der2.1532	der2.1374	der1.1562
der1.1576	der1.1488	der1.1616	smooth_wav_argmax.c1558.s3.1536.1580
der2.1510	der1.1496	smooth_wav_meanabs.c1508.s3.1490.1526	der1_ratio_linen.1185.1510
der2.1554	d1_wav_max.c1558.s4.1536.1580	der1.1564	der1.1570
der1.1672	der2.1634	der1.1542	der1.1526
smooth_wav_energy.c1508.s2.1490.1526	der1.1566	der1_ratio_silk.1409.1551	der1.1556
der1.1620	raw_ratio_wool.1568.1679	der1.1670	der1.1612
der1.1568	d1_wav_argmax.c1649.s2.1635.1663	der1.1486	der1.1570
der2.1496	d2_wav_max.c1508.s3.1490.1526	smooth_wav_meanabs.c1508.s4.1490.1526	
smooth_wav_argmax.c1235.s2.1213.1257	der1.1498	der1.1530	der1.1572
der2.1498	der2.1506	der1.1470	
der1.1494	d2_wav_meanabs.c1508.s3.1490.1526	der1.1552	der1.1574
der1.1636	d2_wav_max.c1417.s3.1395.1439	der1.1614	
der1.1534	der2.1350	der1.1610	der1.1576
der2.1530	der1.1484	der1.1422	
der1_ratio_cotton.1508.1610	d1_wav_energy.c1467.s2.1449.1485	der1.1476	der1.1578
d1_wav_argmax.c1358.s3.1333.1383	d2_wav_energy.c1417.s4.1395.1439	der1.1624	
d2_wav_meanabs.c1508.s4.1490.1526	der2.1504	der1.1632	
der2.1388	der1.1500	der1.1626	der1_ratio_viscose.1506.1684
der1.1638	smooth_wav_max.c1508.s2.1490.1526	der1.1630	
der1_ratio_silk.1485.1673	der1.1482	smooth_wav_meanabs.c1508.s2.1490.1526	der2.1498
der1_ratio_viscose.1605.1684	der2.1560	raw_ratio_polyester.1649.1670	der2.1636
der2.1370	der1.1608	der2.1502	der1_ratio_cotton.1236.1610
d2_wav_energy.c1508.s4.1490.1526	der2.1634	der2.1672	der2.1352
raw_ratio_wool.1568.1679	der2.1508	d1_wav_max.c1608.s3.1590.1626	der2.1634
smooth_wav_meanabs.c1358.s4.1333.1383	raw_ratio_polyester.1610.1670	smooth_wav_max.c1508.s3.1490.1526	der1.1628
der2.1510	raw_ratio_wool.1547.1679	der1.1502	der2.1636
smooth_wav_energy.c1508.s2.1490.1526	der1.1572	der2.1514	der2.1512
d2_wav_energy.c1508.s4.1490.1526	der1.1480	der2.1372	
der2.1512	d1_wav_meanabs.c1467.s4.1449.1485	smooth_wav_argmax.c1693.s4.1687.1700	der2.1514
der1_ratio_cotton.1418.1508	der1.1524	der1.1528	
d2_wav_argmax.c1285.s4.1263.1307	raw_ratio_polyester.1649.1670	smooth_wav_meanabs.c1358.s3.1333.1383	der2.1520
der1_ratio_linen.1236.1608	der1.1674	d1_wav_argmax.c1608.s2.1590.1626	der2.1634
smooth_wav_max.c1508.s4.1490.1526	der1_ratio_polyester.1610.1649	der2.1636	der1_ratio_polyester.1610.1649
smooth_wav_meanabs.c1358.s4.1333.1383	der1.1606	raw_ratio_silk.1409.1673	der2.1500
der1.1636	raw_ratio_cotton.1469.1508	der1.1634	der2.1240
raw_ratio_viscose.1418.1684	der2.1680	smooth_wav_meanabs.c1358.s3.1333.1383	der1.1638
raw_ratio_linen.1469.1510	der2.1678	der1.1504	raw_ratio_viscose.1506.1684
der2.1676	der2.1632	der1.1554	raw_ratio_polyester.1610.1649
d1_wav_energy.c1608.s4.1590.1626	der2.1242	raw_ratio_viscose.1558.1684	der1.1496
der2.1348	der1.1578	raw_ratio_polyester.1610.1670	der2.1382
der1.1478	der1.1524	der1.1536	der2.1244
smooth_wav_meanabs.c1358.s2.1333.1383	raw_ratio_silk.1485.1673	der1.1642	der2.1238
d1_wav_argmax.c1608.s3.1590.1626	der1_ratio_wool.1547.1679	d1_wav_max.c1558.s4.1536.1580	der2.1496
raw_ratio_silk.1551.1673	der2.1682	d1_wav_argmax.c1679.s3.1667.1685	der1.1496
smooth_wav_argmax.c1608.s4.1590.1626	der2.1502	der2.1520	raw_ratio_wool.1485.1679
der2.1502	smooth_wav_meanabs.c1358.s2.1333.1383	der2.1376	raw_ratio_silk.1592.1673
der2.1508	d1_wav_meanabs.c1467.s3.1449.1485	smooth_wav_argmax.c1235.s4.1213.1257	raw_ratio_viscose.1418.1684
der2.1356	d2_wav_energy.c1508.s3.1490.1526	der2.1384	
der2.1674	der2.1236	der2.1494	raw_ratio_viscose.1558.1684
der1.1540	der1.1668	smooth_wav_max.c1508.s2.1490.1526	d1_wav_argmax.c1358.s2.1333.1383
der1.1574	der1.1526	raw_ratio_wool.1485.1679	d1_wav_energy.c1608.s3.1590.1626
smooth_wav_argmax.c1693.s3.1687.1700	der1.1640	der1_ratio_cotton.1469.1610	der2.1498
der2.1386	raw_ratio_wool.1547.1679	der1_ratio_viscose.1418.1605	der1.1476
der1.1498	der1.1640	der2.1556	der1.1604
raw_ratio_wool.1568.1679	der1.1472	der1.1506	smooth_wav_max.c1508.s3.1490.1526
der2.1686	d2_wav_energy.c1417.s2.1395.1439	der1.1602	smooth_wav_argmax.c1608.s2.1590.1626
der1.1524	der2.1372	der1.1656	
der2.1684	der2.1246	der1_ratio_viscose.1506.1684	
der2.1532	raw_ratio_polyester.1610.1670	der1.1594	smooth_wav_argmax.c1608.s4.1590.1626
d2_wav_max.c1608.s2.1590.1626	der2.1346	der1.1522	smooth_wav_energy.c1508.s2.1490.1526
der2.1534	d1_wav_argmax.c1649.s4.1635.1663	smooth_wav_argmax.c1693.s3.1687.1700	d2_wav_max.c1608.s4.1590.1626
raw_ratio_polyester.1610.1649	der1.1642	smooth_wav_energy.c1508.s3.1490.1526	der2.1670
der1_ratio_viscose.1506.1684	der1.1458	der2.1528	d1_wav_meanabs.c1467.s2.1449.1485
der1.1596	smooth_wav_energy.c1508.s4.1490.1526	smooth_wav_argmax.c1508.s3.1490.1526	der1.1474
d1_wav_argmax.c1679.s3.1667.1685	d1_wav_argmax.c1358.s4.1333.1383	der2.1234	der2.1670
smooth_wav_max.c1508.s3.1490.1526	der1.1578	der1.1576	der2.1672
d1_wav_max.c1608.s2.1590.1626	d2_wav_energy.c1467.s4.1449.1485	raw_ratio_viscose.1605.1684	der1.1498
der1.1522	der1.1600	der2.1648	d1_wav_argmax.c1679.s4.1667.1685
der1.1592	der1.1680	d1_wav_argmax.c1649.s3.1635.1663	smooth_wav_max.c1508.s4.1490.1526
d2_wav_max.c1417.s4.1395.1439	der1.1676	der2.1668	
d1_wav_energy.c1608.s2.1590.1626	raw_ratio_silk.1592.1673	der1.1598	
d1_wav_argmax.c1180.s4.1160.1200	der2.1534	der2.1600	
der2.1688	d1_wav_max.c1508.s3.1490.1526	der2.1648	
smooth_wav_energy.c1508.s4.1490.1526	raw_ratio_viscose.1605.1684	der2.1674	
der2.1178	smooth_wav_energy.c1358.s4.1333.1383	der2.1666	
der1.1518	d2_wav_max.c1417.s2.1395.1439	der1.1668	
raw_ratio_wool.1485.1679	der1.1508	d1_wav_max.c1508.s3.1490.1526	der1_ratio_wool.1350.1568

Chi2	Anova	Kruskal-Wallis	Overlapping features
der2.1636	smooth_wav_argmax.c1235.s3.1213.1257	smooth_wav_argmax.c1508.s4.1490.1526	der1.1472
der1.1468	der1.1452	der2.1558	der2.1388
der1_ratio_viscose.1506.1558	d1_wav_max.c1508.s4.1490.1526	der2.1382	
smooth_wav_argmax.c1608.s2.1590.1626	der2.1248	der2.1676	
smooth_wav_argmax.c1180.s2.1160.1200	raw_ratio_silk.1551.1673	der2.1664	
d1_wav_argmax.c1180.s3.1160.1200	der1.1578	der1.1644	
der1.1480	smooth_wav_energy.c1358.s3.1333.1383	der1_ratio_viscose.1605.1684	d2_wav_meanabs.c1508.s3.1490.1526
der2.1562	d1_wav_argmax.c1235.s4.1213.1257	der1_ratio_linen.1418.1608	smooth_wav_argmax.c1649.s4.1635.1663
d1_wav_max.c1558.s3.1536.1580	raw_ratio_viscose.1506.1684	raw_ratio_linen.1469.1510	raw_ratio_linen.1469.1510
der2.1692	raw_ratio_wool.1568.1679	der2.1678	
der2.1520	raw_ratio_cotton.1469.1508	der2.1680	
d1_wav_max.c1508.s2.1490.1526	der2.1232	der1.1590	
smooth_wav_max.c1508.s3.1490.1526	raw_ratio_silk.1485.1673	der2.1516	
der2.1170	raw_ratio_wool.1547.1679	der1.1454	
der1.1676	smooth_wav_energy.c1358.s2.1333.1383	der2.1682	
der2.1694	d2_wav_meanabs.c1467.s4.1449.1485	der1.1586	
der2.1690	der2.1374	raw_ratio_cotton.1469.1508	
der1.1470	der2.1518	smooth_wav_argmax.c1135.s2.1115.1155	der1.1434
der1.1588	der2.1514	der2.1584	d1_wav_max.c1508.s2.1490.1526
raw_ratio_wool.1547.1568	d2_wav_argmax.c1649.s4.1635.1663	der2.1608	der2.1684
raw_ratio_silk.1485.1673	raw_ratio_viscose.1558.1684	der2.1662	
der2.1640	d1_wav_argmax.c1649.s2.1635.1663	d1.1452	
der2.1614	der1.1580	der2.1686	
der1_ratio_silk.1485.1551	raw_ratio_wool.1485.1679	der1.1460	
d1_wav_meanabs.c1608.s2.1590.1626	raw_ratio_viscose.1418.1684	der2.1638	
d1_wav_argmax.c1135.s3.1115.1155	d2_wav_argmax.c1649.s3.1635.1663	der2.1606	

APPENDIX V

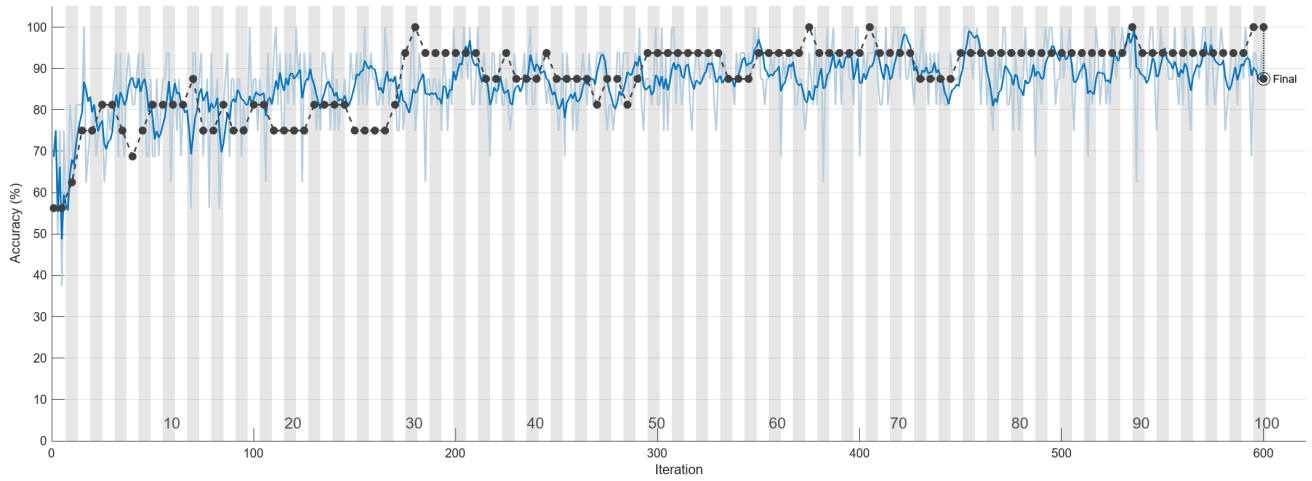
HYPERPARAMETER COMPARISON FOR ELASTANE DETECTION



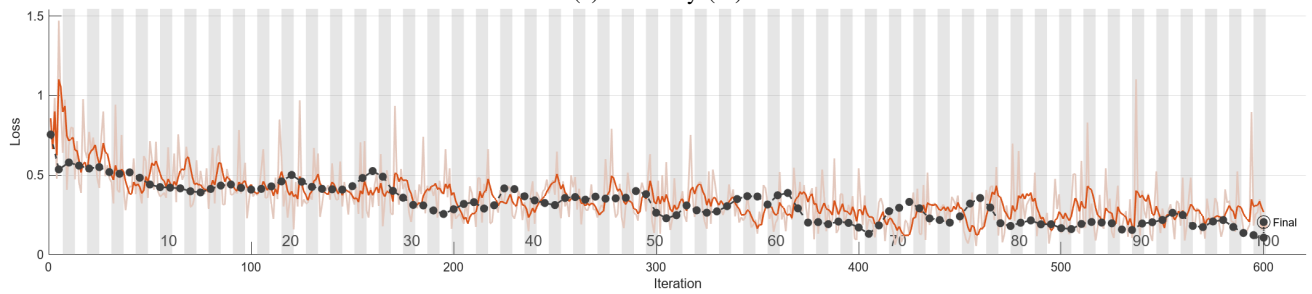
Fig. 21: 6 × 6 grid of classification results for the tested hyperparameter combinations, where rows correspond to the first dropout rate, and columns correspond to the elastane-presence class weight. Each combinations shows the performance of the false negative rate in percentage (FN %) where lower is better, and the overall accuracy in percentage (Acc %) where higher is better.

APPENDIX VI

TRAINING PROGRESS OF THE SELECTED 1D-CNN ELASTANE DETECTION MODEL



(a) Accuracy (%)



(b) Loss

Fig. 22: Training progress of binary elastane detection 1D CNN model of combination 14 (dropout rate = 0.2 - 0.15 and classweight = 1.5 - 1.0)