Towards Improved Sustainability in The Textile Lifecycle with Deep Learning

Anonymous Submission

Abstract

The garment industry is one of the world's largest carbon and waste polluters. In the next decade, this industry is expected to produce 150 billion garments per year, while currently recycling about 1%. Garment landfills are growing large enough to be seen from space, while the water consumption and manufacturing side effects threaten both the environment and human health. Creating a circular economy for textiles in hampered by two key challenges – fabric identification and tracking. Without precise automatic fabric identification – scalable recycling measures cannot be put into effect. Without traceability, governments cannot enforce recycling laws and incentives. We propose two solutions to this problem – leveraging low cost hardware and deep learning. Approach A – using microscope fabric images and Convolutional Neural Networks – demonstrates classification accuracy of over 90% for 14 fabric classes. Approach B, marking fabrics with a binary code visible only under UV light and using YOLOv8 object detection to remain effective in the presence of unique fabrics challenges such as creasing, wear and light refraction, demonstrates an mAP of over 0.98, retaining up to 0.93 after wash cycles. We outline a traceability system based on Approach B that can be implemented worldwide at low cost to enable global fabric traceability for a functioning textile circular economy. Finally, we provide three created fabric based datasets for future research.

1.0 Introduction

There are 80-100 billion garments produced globally every year - expected to grow further to 150 billion in the next decade [1]. The garment industry is currently one of the world's largest carbon polluters and waste producers, accounting for over 8% of global climate impact - outpacing both international flights and maritime shipping combined [2]. The number of garments produced every year far outstrips the population growth (the current human population is ~8 billion and expected to grow to ~11 billion in 2100 – while the amount of clothing created during that time is expected to exceed 10 trillion garments [1]). The environmental impact is staggering.

The damage does not end there. As an example, every cotton T-shirt produced consumes more water than a person drinks in over 14 years (5283 gallons - which if an adult drank the recommended one gallon per day - would last over 14 years) (Newell 2023). Entire seas have come close to drying up due to the water consumed for cotton production, while humans lack access to drinking water (see Figure 2 for an example of the Aral Sea, close to drying out due to cotton production)[3]. This disaster occurred as cotton production in nearby farmlands doubled between 1960 and 2000, leading to a shrinking of the sea at an accelerated pace (from 20cm/year in 1961-1970 to 80-90 cm/year in the 1980s) (Mambra, 2022, Micklin 2007). The textile industry recycles less than 1% of its products, shipping (sometimes brand-new clothes) to third world countries where they are dumped into landfills - some so big that they can be seen from space (See Figure 2). These landfills further pollute the environment through chemicals that leak from the clothes to the soil and water. The Atacama landfill, seen in Figure 3 has been designated by the United Nations as an environmental and social emergency for the planet. (Robles 2023).

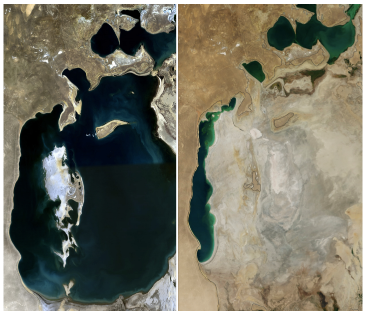


Figure 1: The loss within the Aral Sea caused by nearby cotton production deviating water [4].

---

[1] *17 Most Worrying Textile Waste Statistics & Facts - the Roundup*, theroundup.org/textile-waste-statistics/. Accessed 16 Sept. 2023

[2] "Waste and Pollution." *Clean Clothes Campaign*, 16 Aug. 2021, cleanclothes.org/fashions-problems/waste-and-pollution.

[3] "Fashion & Environment." *SustainYourStyle*, www.sustainyourstyle.org/en/whats-wrong-with-the-fashion-industry#anchor-environmental-impact. Accessed 15 Sept. 2023.

[4] "Cotton." *WWF*, World Wildlife Fund, www.worldwildlife.org/industries/cotton#:~:text=Soil%20Erosion%20and%20Degradation,the%20soil%20in%20many%20areas. Accessed 2 Oct. 2023.

The health impacts of the textile industry are also profound (Islam 2022, Xie 2011). The area around the Aral Sea disaster contains 80% of all throat cancer cases in the world [5]. Those exposed to cotton dust report a 10x increase in Asthma (Mberikunashe 2010). In Brazil - cotton production has caused pesticides to rain down from the sky - threatening the health of everyone nearby [5]. 85% of the population of Uzbekistan has health issues linked to cotton-related pesticides [5].

Figure 2: The Atacama Landfill - taken from [6]

All of these issues demand the creation of a circular economy for textiles and garments. There are many challenges to creating a sustainable circular textile economy. This paper focuses on two critical challenges – automated textile sorting and textile traceability.

Technologies are being rapidly developed to safely dispose of or to reuse textiles - but these methods are very specific to the fabric types. For example - the methods for processing polyester/cotton blends are very different from the methods used for pure cotton or linen (Becker 2022). As such - the sorting process - which is heavily manual today - is becoming the bottleneck in getting discarded textiles to the right disposal method[7]. As noted by the US Department of Commerce, even expensive manual labor cannot correct sort by fiber composition since visual inspection is not sufficient. To further complicate the issue – over 40% of garment labels are incorrect [8], and even correct labeling is designed for the consumer, not circular partners, and are often removed prior to reaching post-consumer stakeholders. Failing sorting - fabrics end up in the landfill. Recycling can deliver many benefits – such as reduced landfill space, reduced use of virgin fibers, reduced consumption of energy and water and reduced demand for dyes [9] . As such – being able to cost effectively sort fabrics at scale for recycling is a key goal. Further support for the criticality of automated sorting can be found in (Schumacher 2022), (NIST 2022) and customer demand in (PWC 2023).

The second challenge is traceability. Governments and countries have already attempted to enforce sustainable practices in the textile industry, and consumers have also indicated a desire to encourage sustainability by purchasing recycled clothes – but both are challenged by the lack of traceability (PWC 2023). Given issues such as fake clothing tags - it is hard to trust companies or enforce pledges. Reliable information is required to measure sustainable processes and improve them [UNECE 2023]. The complexity of the textile lifecycle adds further problems. A garment can change hands 7 to 10 times in the supply chain, each time undergoing some level of alteration” (Zaroff . 2021). Wear and tear can further damage garments mid-lifecycle – putting traceability method at risk. (Schumacher, 2022).

Our paper makes the following contributions:

- We investigate and report on the efficacy of a low-cost sorting method using microscope imagery and convolutional neural network classification. We also create a provide a new dataset for further research.
- We demonstrate a low-cost and ubiquitous fabric marking methodology using off-the-shelf UV inking markers, coupled with an object recognition YOLOv8 model (Ponnusamy 2018) which is trained to read the marks for both sorting and traceability. We also create and provide two new datasets for further research.
- We outline an architecture for a worldwide fabric traceability system utilizing the fabric marking method above.

Our results demonstrate the viability of both fabric identification approaches, with an accuracy of 90.4% for the microscope-based image classification approach, and mAP50 values from 0.93 to 0.98 for the UV marker approach.

The rest of the paper is organized as follows. Section 2 describes related work in fabric sorting/traceability and the challenges therein. Section 3 describes our approach to Fabric Identification. Section 4 describes our experimental results. Section 5 illustrates our proposed fabric traceability

---

https://www.worldwildlife.org/industries/cotton#:~:text=Soil%20Erosion%20and%20Degradation,the%20soil%20in%20many%20areas.

[5] *The World Counts*, www.theworldcounts.com/challenges/clothing/cotton-farming-water-consumption. Accessed 3 Oct. 2023.

[6] “Skyfi’s Satellite Image Confirms Massive Clothes Pile in Chile’s Atacama Desert.” *Commercial High Resolution Satellite Imagery and Video*, www.skyfi.com/blog/skyfis-confirms-massive-clothes-pile-in-chile. Accessed 2 Oct. 2023.

[7] “Robotics to Help Sort and Disassemble Clothing.” *TextileR: Future Textile Industries*, 14 Dec. 2021, research.qut.edu.au/textiler/research/robotics-to-help-sort-and-disassemble-clothing/. Accessed Oct 2 2023

[8] “Clothing Labels: Accurate or Not?” *Insights - Circle Economy*, www.circle-economy.com/resources/clothing-labels-accurate-or-not. Accessed 3 Oct. 2023

[9] “The European Market Potential for Recycled Fashion.” *CBI*, www.cbi.eu/market-information/apparel/recycled-fashion/market-potential. Accessed 2 Oct. 2023.

architecture, and Sections 6 and 7 contain discussions, conclusions and directions for future work.

2.0 Related Work

The current solutions for sorting fabrics are either difficult to scale or prohibitively expensive for realistic broad deployment - particularly in the poor communities where these fabrics often end up. The most advanced sorting automation technology today - Near Infrared Spectroscopy (Zhou, 2019) - is expensive for those machines that can operate at the necessary frequency range. Contacts with several NIR spectroscopy manufacturers revealed price quotes ranging from $65,000 to $100,000 [10]. NIR spectroscopes are also challenging to configure and operate, requiring specialized skills, and do not completely work in an automated setting. For example - very thin fabrics allow NIRS to penetrate through the fabric and result in non-matching recognition. Aging is also known to cause chemical changes, especially in the spectra of cotton, that hamper NIR recognition (Cura, 2021). Additional operations - such as folding, which is challenging to automate - can as such be required to generate sufficient fabric depth.

Beyond clothing tags discussed earlier, solutions being developed for traceability include RFID threads (Nayak 2015) and [11], or specialized threads that contain signaling capabilities (Foy 2023). While having the advantage over tags that identifier removal is not possible, they have other problems. Only the manufacturer can add the identifier - and every garment must weave it in - making it hard for manufacturers to adopt this method and no practical way to add new identifiers along the manufacturing path. Also, only a handful of companies make these threads using proprietary technology - so it will be difficult to standardize it across the massive textile industry. Another approach - printing barcodes on fabric – is challenging because the issues that make barcodes hard to read (Gallo 2009) and [12] are magnified in fabric - where surface textures, creasing and fraying are more common than on paper.

Our approach addresses these issues by investigating sorting/traceability approaches that are low-cost, extensible and effective within the unique challenges posed by fabric. By leveraging the power of convolutional neural networks and object detection algorithms, we combine simple hardware techniques coupled with powerful software methods that can overcome the issues posed by fabrics.

3.0 Approach – Fabric Identification

Our research explores two approaches to fabric identification and then further extends one of the approaches to develop a fabric traceability technique. We evaluate two image-based techniques for automated sorting (Figure 3).

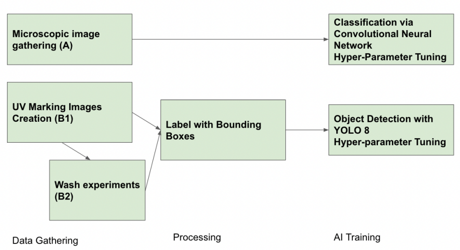


Figure 3: Approaches to Fabric Identification

The first approach (Approach A) tests whether a detailed fabric examination will yield discrimination between fabric types. Images of the fabric gathered via off-the-shelf microscopes and cameras are classified using Convolutional Neural Networks to identify fabric classes. Using commonly available microscopes with 50-100x magnification (Aopick 2023), we assembled a dataset of 840 fabric microscope images in 14 categories of fabrics (specifically Lycra, Crepe, Jersey, Nylon, Satin, Silk, Velvet, Cotton, Cotton-Sateen, Cotton-Linen Blend1, Cotton-Linen Blend 2, Cotton-Silk Blend, Linen and Polyester). The dataset is evenly balanced between all 14 categories. Fabrics are sourced from [13] and [14] and are categorized by the manufacturer provided labels. Figure 4 shows samples of the magnified fabric images. A series of Convolutional Neural Network models are trained using this dataset, and the classification results are measured using standard metrics. Three types of CNN (MobileNetV2, ResNet 50, and ResNet 101 and VGG16) are tested, with an 80/20 training/validation

---

[10] "Malvern Panalytical: Analytical Instrumentation." *Malvern Panalytical | Analytical Instrumentation*, www.malvernpanalytical.com/en/?utm_source=google&utm_medium=cpc&utm_campaign=EN+-+BRAND+-+Search+Ads&utm_term=malvern+panalytical&utm_content=53270491099&gad=1&gclid=CjwKCAjwseSoBhBXEiwA9iZ-txvy5pr1jweunndeaT1WVFhMnVSzx_KdpAOAt-KpX7wxS00VJ8x6JDqxoC8HAQAvD_BwE. Accessed 1 Oct. 2023.

[11] "RFID Thread." *Primo1D*, www.primo1d.com/our-offer/rfid-thread. Accessed 1 Oct. 2023.

[12] Americas, OMRON Automation -. "The Most Common Causes of Unreadable Barcodes." *Automate*, A3 Association for Advancing Automation, www.automate.org/tech-papers/the-most-common-causes-of-unreadable-barcodes#:~:text=The%20most%20common%20causes%20of%20unreadable%20barcodes%20are%20low%20contrast,inconsistency%2C%20and%20damage%20or%20distortion. Accessed 1 Oct. 2023.

[13] "Contrado: Buy or Sell Artist Designs: Print On Demand." *Contrado USA*, www.contrado.com/. Accessed 2 Oct. 2023.

[14] "Custom Fabric Printing." *The Textile District | Custom Fabric Printing | Online Fabric Store*, thetextiledistrict.com/. Accessed 2 Oct. 2023.

split and 5-fold cross validation. Each CNN is hyper-parameter tuned for a range of Learning Rate and Epoch values. Validation Accuracy and Confusion Matrix are reported.

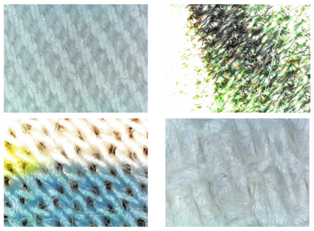


Figure 4: Microscopic images of fabrics

We further experimented with ways to mark the fabric with UV ink such that it cannot be seen by the wearer but is easily visible and readable under blue light (Approach B1). In particular, a code was marked on each fabric via sequence of Xs and Os – focusing on Cotton, Polyester, Blends and Jersey. Through a series of experiments with different easily accessible cheap commercial UV inks, markers and stamps – a dataset was created which had a matrix of X and O markings using custom created stamps (seen on Figure 5). The dataset was manually labeled with bounding boxes using Roboflow 2023 to create 67 images which each had 9-16 individual bounding boxes. We explored the viability of automatically reading these codes under black light via an object detection deep learning algorithm (YOLO 8.8). Fabric is uniquely challenging since different fabrics have different surface and reflectance properties. The dataset was split into 13 validation images which had 131 bounding boxes, and the remainder into the training set – which was augmented via rotation and flip techniques. The training algorithm was hyper-parameter tuned for various Learning Rate and Epoch values – with mAP50 and confusion matrix reported for the validation set.

A second variation (B2) assessed the impact of wash cycles on marker readability. A Cotton-Jersey blend was marked with a 16-symbol code, with images taken after every wash from 1-10 and used to assemble a new dataset, with 20 images for validation, and 105 for training (after augmentation with rotation and flip operations). The same hyper-parameter tuning was used as for B1.

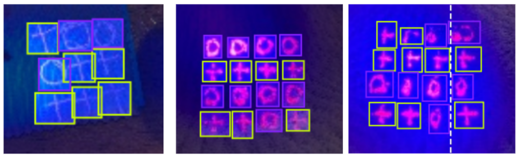
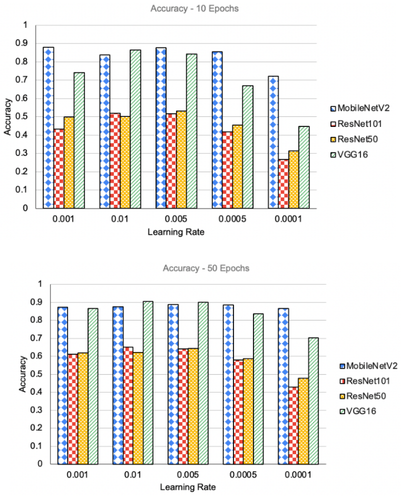


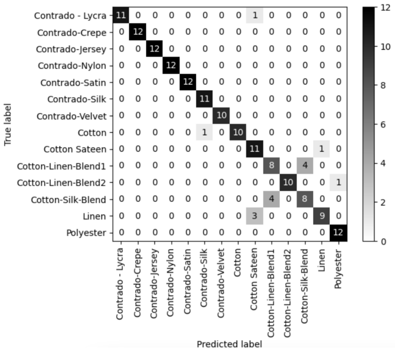
Figure 5 – fabrics marked with circles and crosses, visible under blue light, and marked with bounding boxes for reading by an object detection algorithm.

4.0 Experimental Results

Figures 6(a) and (b) show the results for Approach A. Both MobileNetV2 and VGG16 delivered good results at 50 epochs. The highest accuracy achieved was 90.4% by VGG16 across 5-fold cross-validation. Figure 7 shows a sample confusion matrix for the best performing MobileNetV2 model. While there is some confusion in classification with respect to blends, other categories are well distinguished by the microscopic images.



Figures 6(a) and 7(b) – Accuracy for Experiment A



	Contrado - Lycra	Contrado-Crepe	Contrado-Jersey	Contrado-Nylon	Contrado-Satin	Contrado-Silk	Contrado-Velvet	Cotton	Cotton Sateen	Cotton-Linen-Blend1	Cotton-Linen-Blend2	Cotton-Silk-Blend	Linen	Polyester
Contrado - Lycra	11	0	0	0	0	0	0	0	1	0	0	0	0	0
Contrado-Crepe	0	12	0	0	0	0	0	0	0	0	0	0	0	0
Contrado-Jersey	0	0	12	0	0	0	0	0	0	0	0	0	0	0
Contrado-Nylon	0	0	0	12	0	0	0	0	0	0	0	0	0	0
Contrado-Satin	0	0	0	0	12	0	0	0	0	0	0	0	0	0
Contrado-Silk	0	0	0	0	0	11	0	0	0	0	0	0	0	0
Contrado-Velvet	0	0	0	0	0	0	10	0	0	0	0	0	0	0
Cotton	0	0	0	0	0	1	0	10	0	0	0	0	0	0
Cotton Sateen	0	0	0	0	0	0	0	0	11	0	0	0	1	0
Cotton-Linen-Blend1	0	0	0	0	0	0	0	0	0	8	0	4	0	0
Cotton-Linen-Blend2	0	0	0	0	0	0	0	0	0	0	10	0	0	1
Cotton-Silk-Blend	0	0	0	0	0	0	0	0	0	4	0	8	0	0
Linen	0	0	0	0	0	0	0	0	3	0	0	0	9	0
Polyester	0	0	0	0	0	0	0	0	0	0	0	0	0	12

Figure 7 – Confusion matrix for classification of fabric types via microscopic imagery and CNN.

Figures 8 (a) and 8(b) show the overall and per-class mAP50 for Experiment B1. High levels of mAP were achieved across both classes. mAP values range from 0.89 to 0.98 – with the highest mAP being 0.981. Figure 9(a) and (b) show the results for experiment B2 – which evaluates the ability to read the markers after 1-10 washes. The mAP50 dropped by a few percentage points – with the highest mAP now being 0.938, indicating that the washing process does impact marker readability, but not to a significant extent. Figures 10(a)/(b) and 11(a)/(b) show the confusion matrices and Precision-Recall curves for the best-case results for both experiment B1 and experiment B2 respectively. Both circle and cross markers are well identified – however, a comparison of the two confusion matrices shows a slightly higher level of misclassification as background in experiment B2 – possibly the effect of the marker being less prominent after wash cycles. Figures 12 and 13 show the detailed training results for the best-case hyper-parameter runs for experiments B1 and B2 respectively.

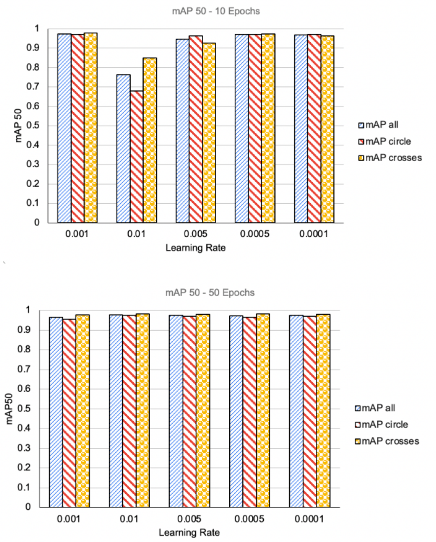


Figure 8(a) and 9(b) – mAP50 for Experiment B1

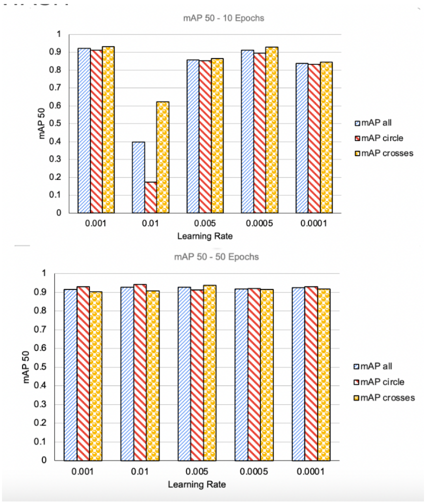


Figure 10(a) and (b) mAP50 for experiment B2 – illustrating the impact of wash cycles.

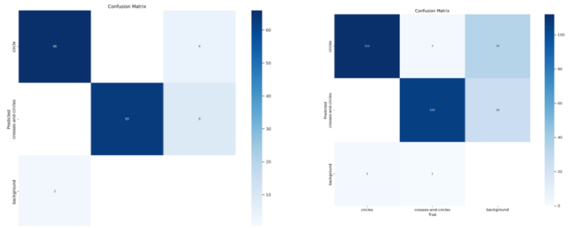


Figure 10(a) and (b) show the confusion matrices for the best-case scenarios for experiment B1 and B2 respectively.

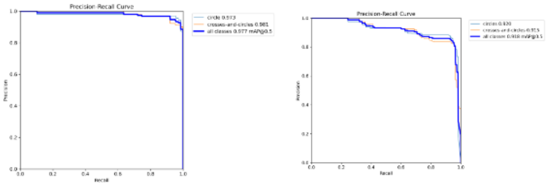


Figure 11(a) and (b) show the Precision-Recall curves for the best-case scenarios for experiments B1 and B2

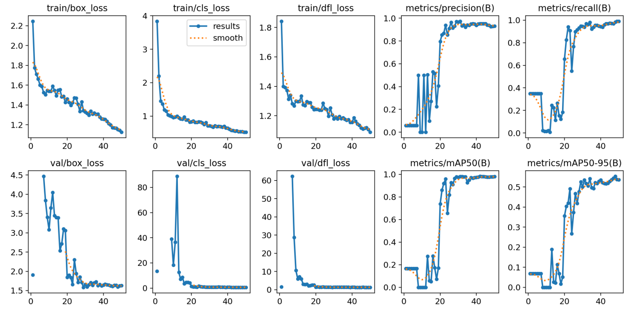


Figure 12 – best training run for Experiment B1

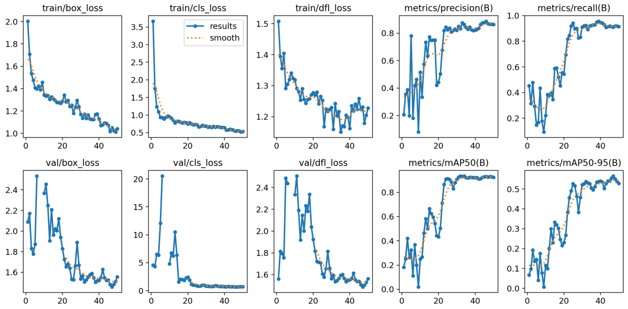


Figure 13 – best training run for experiment B2

5.0 A Traceability System

Experiment B demonstrated the feasibility of a UV ink-based marker system. Unlike Approach A - which is useful for fabric type classification – Approach B can have additional usages in traceability. We illustrate this potential via a strawman design of a traceability system. Figure 13 demonstrates a strawman architecture:

Step 1: Each fabric instance - defined as a manufacturing instance that captures the specific fabric and dyes used to create a textile – is assigned a code. For example – a 90% cotton, 10% polyester with a specific dye – manufactured by entity A – can be assigned a code. While Approach B system can enable codes of virtually any size, it is worth noting the size of codes that are expected to suffice for this process. By encoding each bit as an X (1) or O (0), it is possible to design a fabric code that can accommodate the next 100 years of garment manufacturing. If we assume 150 billion garments per year – and 1000 garments per instance (a conservative assumption), that equates to 150 million instances per year. Over 100 years – 15 billion codes will be required – which can be accommodated in even a 64-bit code with sufficient bits to accommodate ECC algorithms such as LDPC. Our experimentation has determined that a 64-bit code can be stamped onto a fabric within a space of 5 in x 5 in while retaining the readability demonstrated in Section 4.0. If more scale is needed, a larger code can always be created.

Step 2: The codes are issued by a dedicated global entity – similar to how DNS names are assigned [15], leveraging similar techniques for code partitioning and issue across geographies and entities.

Step 3: Codes are stamped by the manufacturer at creation time. At every stage of the fabric lifecycle, the code can be scanned and reported. Codes can also be used to access a public database to retrieve any fabric information necessary for automated sorting.

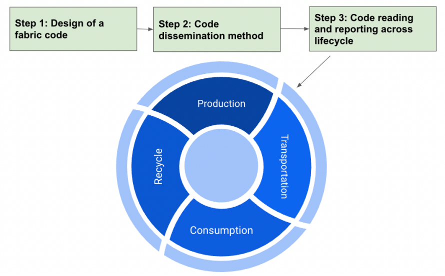


Figure 14 – Strawman Traceability Approach

This type of traceability can also be leveraged by emerging legislation on textile circular economies. For example - the state of California in the United States is attempting to introduce legislation to curb the damaging effects of textiles (Newman 2023). However - this bill is currently stalled till 2024 - as stakeholders struggle with how to implement it cost effectively (Arnold 2023). Similarly, the European Textile Circular Economy Laws (Europe 2023) intend to hold manufacturers accountable for recycling garments, via both fines and incentives. The law also intends to regulate and control export of textile waste to third world countries. In both cases, our traceability approach can enable garment manufacturers to register for unique codes which can then be verified by downstream partners and used by the manufacturer to prove compliance with applicable laws.

6.0 Discussion

Our results demonstrate that deep-learning approaches for fabric classification are viable. While the fabric space is vast, with other fabric types that have not been analyzed in our work – the results indicate promise. The results of Approach A do suggest that further work on blends since Cotton-Linen and Cotton-Silk showed more classification challenges. It is possible that a two-phase classification method can be used – where fabrics showing low classification confidence via cheap methods can then be redirected to more expensive manual or other sorting machines – even such an approach would still deliver substantial value to the recycling process. It is also worth noting that energy-efficient MobileNetV2 (Luo 2020) outperformed far more computationally expensive rivals. Approach B appears to be a good fabric identification and tracking-based technology. Studies have indicated that the average garment is worn 7 times before disposal [15]. A code that can be read after 10 wash cycles can therefore be applicable to a large range of garments.
The lack of broad-spectrum public datasets in this space makes comparative studies difficult. To assist further research, the datasets created in this work will be made available in a public git repository at the time of publication.

7.0 Conclusions and Future Work

Current textile practices pose a major threat to the environment. A sustainable circular textile economy is critical to protect our natural resources. Our research demonstrated low-cost methods that leverage deep learning techniques to automate fabric sorting and traceability. Our future work is to further validate these approaches via an expanded range of fabrics, make our datasets and code publicly available, and complete the implementation of a prototype traceability system for broad use.

---

[15] https://www.techtarget.com/searchnetworking/definition/domain-name-system

[15] https://www.projectcece.com/blog/506/how-many-times-do-we-wear-our-clothes/#:~:text=How%20many%20times%20are%20clothes,seven%20times%20before%20being%20discarded.

References

Arnold & Porter. “California Textile Recycling Legislation Delayed to 2024 - and in Need of Improvement: Advisories.” *Arnold & Porter*, www.arnoldporter.com/en/perspectives/advisories/2023/07/ca-textile-recycling-legis-delayed-to-2024. Accessed 2 Oct. 2023.

Becker, Amrei, et al. “ITA: Current Challenges and Solutions for the Recycling of (Mixed) Synthetic Textiles.” *Www.Textiletechnology.Net*, www.textiletechnology.net, 4 Apr. 2022, www.textiletechnology.net/fibers/trendreports/ita-current-challenges-and-solutions-for-the-recycling-of-mixed-synthetic-textiles-31929.

Cura, Kirsti, et al. “Textile recognition and sorting for recycling at an automated line using near infrared spectroscopy.” *Recycling*, vol. 6, no. 1, 2021, p. 11, https://doi.org/10.3390/recycling6010011.

Foy, Kylie MIT Lincoln Laboratory. “Fiber ‘Barcodes’ Can Make Clothing Labels That Last.” *MIT News | Massachusetts Institute of Technology*, news.mit.edu/2023/fiber-barcodes-can-make-clothing-labels-that-last-0321. Accessed 1 Oct. 2023.

Kleiderly. “How Much Water Is Needed to Make a T-Shirt?” *Kleiderly.*, Kleiderly., 21 Jan. 2021, www.kleiderly.com/our-blog/how-much-water-is-needed-to-make-a-t-shirt.

Luo, Chunjie, et al. “Comparison and Benchmarking of AI Models and Frameworks on Mobile Devices.” *arXiv.Org*, 7 May 2020, arxiv.org/abs/2005.05085.

Mambra, Shamseer. “Aral Sea Disaster: Why One of the Biggest Inland Seas Dried Up?” *Marine Insight*, 25 Aug. 2022, www.marineinsight.com/environment/aral-sea-disaster-why-one-of-the-biggest-inland-seas-dried-up/.

Mberikunashe, Joseph, et al. “Prevalence and Risk Factors for Obstructive Respiratory Conditions among Textile Industry Workers in Zimbabwe, 2006.” *The Pan African Medical Journal*, U.S. National Library of Medicine, 17 July 2010, www.ncbi.nlm.nih.gov/pmc/articles/PMC3063500/.

Micklin, P. (2007). The Aral Sea Disaster. *Annual Review of Earth and Planetary Sciences*, *35*(1), 47–72. https://doi.org/10.1146/annurev.earth.35.031306.140120

Newman, Josh. “California Introduces Act for Responsible Textile Disposal and Reuse.” *Senator Josh Newman*, sd29.senate.ca.gov/news/news/california-introduces-act-responsible-textile-disposal-and-reuse. Accessed 2 Oct. 2023. https://sd29.senate.ca.gov/news/news/california-introduces-act-responsible-textile-disposal-and-reuse

NIST Special Publication 1500-207 Facilitating a Circular Economy for Textiles Workshop Report , nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1500-207.pdf. Accessed 2 Oct. 2023.

NASA. Collage by Producercunningham. - 1989: aral sea 1989 250mFile:Aralsea tmo 2014231 lrg.jpg, Public Domain, https://commons.wikimedia.org/w/index.php?curid=35813435

Ponnusamy, Arun. “Yolo Object Detection with Opencv and Python.” *Medium*, Towards Data Science, 25 Aug. 2018, towardsdatascience.com/yolo-object-detection-with-opencv-and-python-21e50ac599e9.

PricewaterhouseCoopers. “69% of Consumers Hold Back on Non-Essential Spend as Cost of Living Rises; 90% Adopt Cost-Saving Behaviours: PWC Consumer Insights Survey.” *PwC*, www.pwc.com/gx/en/news-room/press-releases/2023/global-consumer-insights-pulse-survey-february-2023.html. Accessed 2 Oct. 2023.

Schumacher, Kelsea A., and Amanda L. Forster. “Textiles in a Circular Economy: An Assessment of the Current Landscape, Challenges, and Opportunities in the United States.” *Frontiers*, Frontiers, 27 Oct. 2022, www.frontiersin.org/articles/10.3389/frsus.2022.1038323/full.

Robles, Tiago. “Pollution: Giant ‘graveyard’ of Clothes in Atacama Desert Can Be Seen from Space.” *Yourweather.Co.Uk | Meteored*, Yourweather.co.uk, 3 July 2023, www.yourweather.co.uk/news/trending/pollution-giant-graveyard-clothes-atacama-desert-seen-from-space-chile.html#:~:text=An%20unsustainable%20problem&text=The%20Atacama%20landfill%20created%20so,generated%20by%20the%20fashion%20industry.

Xie P, Liu X, Liu Z, Li T, Zhong L, Xiang Y. Human health impact of exposure to airborne particulate matter in Pearl River Delta, China. *Water, Air, Soil Pollut*. 2011;215(1-4):349-363.

Zaroff, M. . “The Challenges, Benefits, and Need for a Circular Economy,” in *NIST Workshop: Facilitating a Circular Economy for Textiles*. 2021

Zhou, Jinfeng, et al. “Textile fiber identification using near-infr red spectroscopy and pattern recognition.” *Autex Research Journal*, vol. 19, no. 2, 2019, pp. 201–209, https://doi.org/10.1515/aut-2018-0055.