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Sorting mechanisms for secondary streams valorisation v1

D3.3

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A Digital value chain Integration Traceability framework for process industries for Circularity and low Emissions by waste reduction and use of secondary raw materials

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02			
03			
04			

Legal Disclaimer

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List of abbreviations and acronyms

Abbreviation	Meaning
AI	Artificial Intelligence
CNN	Convolutional Neural Network
DL	Deep Learning
FTIR	Fourier-Transform Infrared
GVA	Gross Value Added
HIS	Hyperspectral Imaging
kNN	k-Nearest Neighbors
LTE	Long-term Evolution
MDF	Medium Density Fibreboard
ML	Machine Learning
MW	Molecular Weight
NIR	Near-Infrared
PLC	Programmable Logic Controllers
RGB	Red Green Blue
SAM	Segment Anything Model
VIS	Visual
YOLO	You Only Look Once

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Executive Summary & Timeline

This deliverable, titled “Sorting Mechanisms for Secondary Streams Valorisation v1,” represents a key component of Task T3.2 within the DiginTraCE project. It is aimed at enhancing the valorisation processes by developing sophisticated sorting mechanisms tailored for both wood and plastic waste streams. This document outlines the initial design and capabilities of these sorting systems, integrating cutting-edge technologies such as machine learning, vision-based identification, and robotic sorting features to achieve high-accuracy waste sorting.

Our objectives are to significantly improve the quality of the feedstock for upcycling processes by accurately identifying and separating unsuitable materials detected during the waste assessment analysis. By leveraging the datasets generated in Task T3.1, this deliverable describes the advancements in sorting technologies that are crucial for both wood and plastic value chains. The wood sorter, for instance, is designed to differentiate between sawdust and small wood pieces, while for plastics, enhancements to existing NIR sorting systems are detailed.

The developments presented herein not only cater to the specific needs of pilot sites in Greece and Spain but also set a benchmark for quality in secondary resource recovery. As such, this deliverable serves as a foundational piece for subsequent iterations and deeper technical explorations in future updates.

Timeline

The timeline for the development and implementation of the sorting mechanisms is outlined in a Gantt chart format, providing a visual representation of the project phases from inception to completion. Key milestones include:

Month 6: Initiation of design phase for sorting mechanisms.

Month 12-18: Development and testing of prototype systems.

Month 19-24: Integration of machine learning and robotic features.

Month 25-30: Pilot testing at sites in Greece and Spain.

Month 31-36: Evaluation and final adjustments based on pilot results.

Month 36: Final report and preparation of deliverable D3.4.

This timeline ensures that all activities are planned and executed efficiently, keeping the project on track towards its goals of enhancing the sorting capabilities and ultimately, the quality of the material outputs for upcycling.

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1. Sorter within DiginTraCE

1.1. Wood Value Chain

The wood value chain encompasses the entire lifecycle of wood products, from sustainable forest management and harvesting to the processing, utilization, and recycling of wood-based materials. This chain is critical for ensuring the sustainable use of forest resources, maximizing economic value, and minimizing environmental impacts.

The EU is a significant player in the global wood industry, with forests covering about 43% of its land area, totalling approximately 182 million hectares [1]. In 2021, the EU produced around 146 €/ha of gross value added (GVA) from forestry and logging activities, highlighting the sector's economic importance.

The EU plays a crucial role in international wood trade. In 2022, the EU exported 31% of its roundwood outside the EU, with total exports increasing by 77% since 2015, while imports have declined by 7.4% since 2018 [2]. This trade balance underscores the EU's strategic position in the global wood market.

The wood value chain starts with sustainable forest management, where forests are managed to maintain ecological balance while meeting economic and social needs. Harvesting follows, with timber being cut and transported to processing facilities. At these facilities, wood is converted into various products. Sawmills produce lumber, while other plants manufacture pulp for paper and engineered wood products. These products are then distributed to markets, where they are used in construction, furniture, packaging, and other applications. At the end of their lifecycle, wood products can be recycled or upcycled. Recycling involves breaking down the wood into basic components for remanufacturing, while upcycling repurposes wood into higher-value products, contributing to a circular economy by reducing waste and resource demand.

The wood value chain is vital for multiple reasons:

- **Economic Contribution**: The wood industry significantly contributes to the economy, providing jobs and income across forestry, manufacturing, and related sectors. In the EU, wood-based industries employ around 3.1 million people and contribute approximately €136 billion to the economy, representing 7.2% of the total manufacturing industry value [3].

[1] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Forests,_forestry_and_logging
[2] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Wood_products_-_production_and_trade
[3] https://www.eesc.europa.eu/en/our-work/opinions-information-reports/opinions/towards-comprehensive-strategy-eu-wood-industry

- **Environmental Benefits**: Sustainable forest management and wood processing help mitigate climate change by sequestering carbon in forests and wood products. Recycling wood reduces landfill use and lowers greenhouse gas emissions from waste decomposition.
- **Social Impact**: The wood value chain supports rural economies and communities, providing livelihoods and infrastructure support. It also promotes the use of renewable resources, aligning with sustainability goals

The wood value chain is integral to the EU's strategy for sustainable development, offering economic, environmental, and social benefits. The DiginTraCE project aims to enhance the quality and efficiency of wood sorting processes, directly contributing to optimizing the wood value chain and ensuring that valuable resources are utilized effectively. By focusing on sustainability and innovation, the wood value chain supports the broader goals of the EU's Green Deal and bioeconomy strategies.

1.2. State of the Art – Wood Characterization Modules

The detection and removal of impurities in wood sorting processes are critical for enhancing the quality and usability of wood-based products. Various methodologies have been developed and validated to improve the accuracy and efficiency of impurity detection, leveraging advanced imaging techniques and analytical methods. In the study on the determination of inorganic impurities and ash content from biofuels, multiple laboratories developed and validated analytical procedures using techniques such as ICP-MS, ICP-OES, MWP-AES, WD-XRF, and ID-MS. These methods established a budget of uncertainties and developed precise measurements for ash content with high repeatability and reproducibility, providing essential information on precision, accuracy, and bias in impurity detection [1]. Another study reviewed various techniques for predicting wood chip moisture content, emphasizing its impact on energy content and storage stability. The review highlighted different models and their limitations, offering insights into potential applications and future research directions in moisture content prediction [2].

In the context of isolating high-molecular weight hemicelluloses from radiata pine wood chips, a novel thermo-mechanical pulping process was developed. This process involved prehydrolysis and chip compression, followed by purification using XAD adsorbent resin to remove low-MW lignin and extractives. This method effectively isolated high-MW hemicellulose, suitable for barrier films and coatings, demonstrating a significant reduction in impurities [3]. A study on plastic impurities in biowaste treatment assessed the environmental and economic impacts of plastic contaminants in composting processes. The research showed that conventional plastic impurities remained constant through the composting process, while compostable plastics were significantly reduced. The findings underscored the environmental and economic costs associated with plastic impurities, highlighting the importance of effective impurity removal methods [4].

In the utilization of wood waste from construction and demolition, a multi-faceted plant was introduced to produce thermal energy and biochar from wood chips. This integrated process reduced waste while generating high-quality biochar and providing energy, addressing challenges in biomass conversion and impurity management [5]. For biomass characterization, a study compared conventional image processing methods with a deep learning approach using a convolutional neural network (CNN). The deep learning method showed promising results in classifying biogenic solid fuels and mixtures, despite a smaller dataset. This approach demonstrated high accuracy and the potential for real-time fuel monitoring applications [6].

Finally, in the detection and segmentation of intrusions in pellet fuels, a deep learning approach was employed using microscopic images. The study evaluated three architectures of UNet-based deep networks for semantic segmentation, showing that simpler models could still provide satisfactory results for practical applications, although with reduced segmentation quality compared to more complex networks [7].

Limitations of Current Approaches

Despite significant advancements in impurity detection technologies, several challenges remain. Variability in wood properties and environmental conditions can affect measurement accuracy. The need for extensive datasets to train and validate deep learning models presents another hurdle. Furthermore, the complexity of integrating various sensing and processing technologies into a cohesive, real-time monitoring system requires continuous refinement. Addressing these limitations is crucial for developing robust and reliable impurity detection methods in wood sorting applications.

1.3. Plastic Value Chain and State of the Art

The plastic value chain consists of three main stages: i) the extraction of raw materials, ii) the production of plastic products, and iii) the supply chain. To close the loop of plastic products life cycle, recycling and upcycling processes are playing a significant role. Based on recent EU statistics, the amount of packaging waste aggregated from Europe in 2021 was 188.7kg per inhabitant noting a great increase of 5,7% from 2020 and 9.7% from 2011. Moreover, it is worth mentioning that from the 35,9kg of plastic packaging that an EU citizen uses, the 14.2kg of them were recycled concluding to a rate increase both in plastic packaging generation and recycling as well[4]. Thus, to enhance the recycling and upcycling processes of plastics and

[4] https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20231019-1

subsequently reduce the extraction of raw materials, the identification and classification of the type of plastic in recycling streams is crucial.

The most famous sensors that are suitable for plastic classification are the RGB and Hyperspectral cameras. In research conducting in 2022, where RGB camera were used for plastic classification from other materials such as paper, glass and organic waste, the accuracy level reached 89.17% by implementing a convolutional neural network (CNN) consisting of 5 layers [8]. Moreover, in another research, where the classification of plastics was based on the type of plastic, the model accuracy reached 99% even though at the testing process dropped down to 74%. This model was developed by using deep learning technologies and consisted of 15 convolutional layers [9]. Regarding the Hyperspectral cameras in plastic classification, it is worth mention that even though the sensors cost is way higher than RGB's cost the accuracy levels can be significantly increased. For instance, in recent research, where Specim FX17 NIR hyperspectral camera was used, the trained model had the ability to classify coloured and transparent plastic samples in accuracy of 90% and black plastics in 79% in testing environment [10]. Finally, a multi-encoder classifier combining RGB, VIS and NIR imaging data was proposed for plastic classification and reached accuracy rate 96%, although not corresponding to dark plastic samples [11].

2. Current Design of Sorter & Features

2.1. Wood Valorisation in DiginTraCE

The DiginTraCE project places a strong emphasis on the valorisation of wood waste as a critical component of its objectives. The specific goals of wood valorisation within the project include improving the purity and quality of wood chips to create high-value products such as particleboards and MDF boards. By achieving higher purity levels, the resulting products can meet stringent quality standards, thereby enhancing their marketability and usability.

One of the primary goals of the DiginTraCE project is to develop and implement advanced sorting mechanisms that can accurately identify and remove impurities from wood waste. This involves the use of cutting-edge technologies such as vision-based systems and robotic arms, which are designed to operate with high precision and efficiency. By employing these technologies, the project aims to enhance the overall efficiency of the wood valorisation process, reducing contamination and improving the quality of the final products.

These goals align seamlessly with the broader objectives of the DiginTraCE project, which aims to advance the state of the art in waste sorting and valorisation. The project's emphasis on innovative technologies and sustainable practices reflects its commitment to the principles of the circular economy. By focusing on the valorisation of secondary wood streams, DiginTraCE contributes to reducing environmental impact, conserving natural resources, and promoting sustainable industrial practices. This holistic approach ensures that the project not only achieves its technical objectives but also makes a meaningful contribution to broader societal and environmental goals.

2.2. Wood Sorter - Mechanical Design and Components

The initial design of the plastic sorter has been halted due to the change of partners, regarding the Italian demo. Hence, only the wood chip sorter will be presented in the following chapters.

The current design of the wood sorter within the DiginTraCE project incorporates a combination of mechanical and sensor-based technologies to achieve high accuracy in sorting wood chips. This section outlines the key components and features of the sorter, including its mechanical design, sensor integration, and the conveyor belt system.

Mechanical Design and Components

The mechanical design of the wood sorter is centred around a robust and efficient system capable of handling various sizes and types of wood chips. The primary mechanical components include:

- **Drum Screener:** This device sorts wood chips based on size. It features a rotating cylindrical drum with multiple perforations and sections corresponding to different size fractions. Wood chips fed into the drum are sifted through these perforations and categorized into predefined size categories. The drum screener ensures accurate categorization, meeting the specific requirements set by project partners in Greece and Spain.

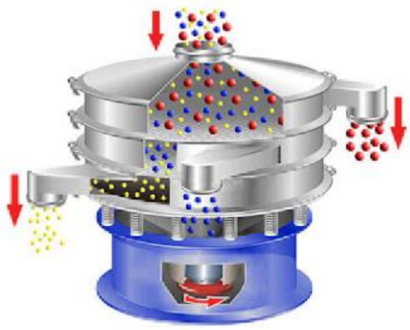

Figure 1: Drum screener in action

- **Pneumatic Air Nozzles:** Strategically positioned along the conveyor belt, these nozzles remove contaminants and impurities. Controlled by a precise pneumatic system, the air nozzles target and eject defective wood chips from the processing line, ensuring that only high-quality material proceeds further.

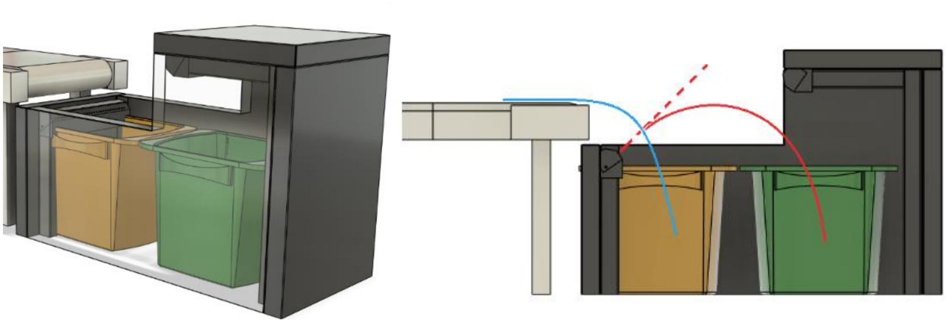

Figure 2: Schematic of Pneumatic Air Nozzles in action

Sensor Integration and Functionality

The sensor system is a critical component of the wood sorter, designed to detect impurities and contaminants that can affect the quality of the final products. The system integrates:

- **RGB Cameras:** These cameras capture high-resolution images of the wood chips, providing detailed visual information about their surface characteristics. These images are used to identify visible impurities such as coatings, paint layers, and other surface contaminants.
- **Hyperspectral Imaging (HSI) Cameras:** These cameras go beyond the visible spectrum, capturing data across a wide range of wavelengths. This technology enables the detection of subtle differences in material composition and surface properties, making it possible to identify impurities that are not visible to the naked eye. The combination of RGB and HSI technologies ensures a thorough assessment of wood chip quality.

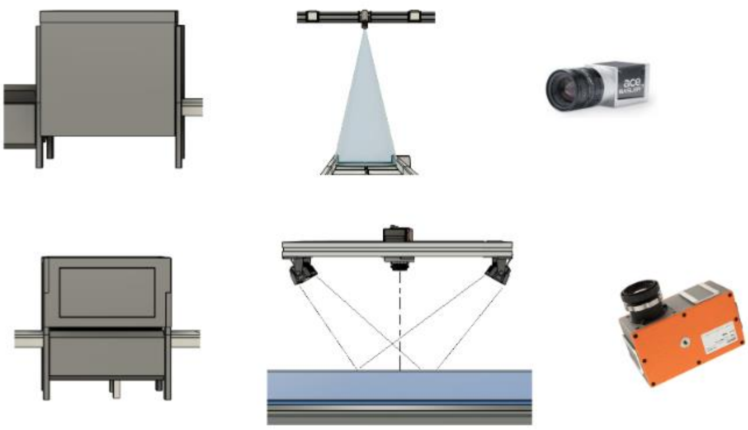

Figure 3: Diagram of Sensor Integration with RGB and Hyperspectral Cameras

The data collected by these sensors are processed using advanced machine learning algorithms, classifying the wood chips based on their purity. This automated classification ensures consistent quality control throughout the sorting process.

Conveyor Belt System

The conveyor belt system is the backbone of the wood sorter, facilitating the movement of wood chips through different stages of the sorting process. It is designed for smooth and efficient operation, ensuring that wood chips are conveyed seamlessly from the drum screener to the sensing system and through to the final sorting stage.

- **Design and Operation:** The conveyor belt system is designed to handle varying loads and types of wood chips. It is equipped with adjustable speed controls to optimize the sorting process and ensure that wood chips are processed at an appropriate pace. The belt material is chosen for its durability and resistance to wear, ensuring long-term reliability.

- **Integration with Sorting Components:** The conveyor belt system integrates seamlessly with other components of the sorter, transporting wood chips from the drum screener to the sensor system, then to the pneumatic air nozzles and robotic arms. This integration ensures a continuous and efficient sorting process, minimizing downtime and maximizing throughput.

In conclusion, the current design of the wood sorter in the DiginTraCE project incorporates a robust mechanical framework, advanced sensor technologies, and an efficient conveyor belt system. These components work together to ensure high accuracy in sorting wood chips, improving the quality of the feedstock for the production of particleboards and MDF boards. This system contributes to the environmental and economic benefits of wood valorisation discussed in Chapter 1.1 by reducing waste and enhancing resource efficiency.

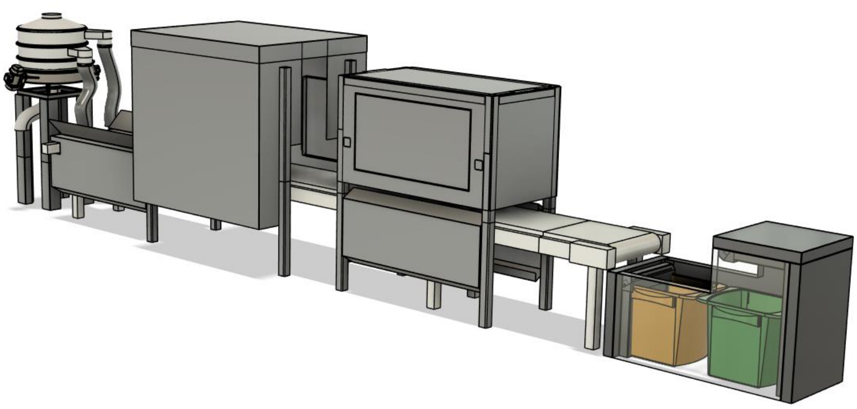

Figure 4: Overall Schematic of the Wood Sorter Design and Workflow

2.3. Plastic sorter

Within DigInTraCE project and especially T3.2, a sorting mechanism for the valorisation of plastics secondary stream will be implemented. The aim of this development is the separation of different plastic granules based on their material. Due to the pilot owner change, though, the developments around the plastic sorter have been delayed until the formal entrance of the new pilot owners at the consortium. However, while the new pilot specifications and requirements have not been changed significantly from the previous one, plastic sorter partners were able to proceed with some primitive developments in order to be on time, as far as this is possible, with the time schedule of T3.2.

Regarding the material characterization of the plastic samples, IRIS is responsible and, within the deliverable 3.1, provides a detailed description of its progress. As for the sorting design, similar to the wood sorter, it will consist of three main layers. Starting with the first one, a pretreatment unit will be used aiming the even and uniform samples distribution along the conveyor belt. Then, the output of sensing system of T3.1 provided by IRIS will be integrated at the sorting system and will be fed ICCS' convolutional networks for image processing and material classification reaching high accuracy levels. Finally, an air nozzle system will be developed and by receiving the output of the ML/DL models, will proceed with the final separation process.

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3. System Architecture & Feature Development for wood Sorter

3.1. Architecture

The wood sorting system within the DiginTraCE project is built upon a robust and sophisticated architecture designed to handle extensive data processing and real-time decision-making. At its core, the system utilizes powerful PCs equipped with NVIDIA A6000 48GB GPUs to manage the intensive computational tasks required for image processing and machine learning. These high-performance GPUs enable the rapid analysis of large volumes of data, facilitating the real-time classification and sorting of wood chips. The system also incorporates Programmable Logic Controllers (PLCs) to control the pneumatic air nozzles that execute the physical sorting based on the decisions made by the AI models. The PLCs ensure precise and reliable actuation of the nozzles, maintaining the system's high efficiency and accuracy. The architecture is designed to integrate seamlessly with various components, including sensors, processing units, and control mechanisms, creating a cohesive and efficient workflow from data acquisition to final sorting.

3.2. Information flow

Efficient information flow is essential for the seamless operation of the wood sorting system. This section outlines how data moves through the system from acquisition to action.

Data Acquisition: The process begins with data acquisition from the RGB and hyperspectral cameras. These sensors capture high-resolution images and spectral data, which are then transmitted to the processing unit.

- **Sensor Integration**: Ensuring smooth data transfer from sensors to the central processing unit.
- **Data Synchronization**: Aligning data from multiple sensors to provide a coherent view for analysis.

Data Processing: Once acquired, the data undergoes several processing stages:

- **Pre-Processing**: Initial steps to clean and prepare the data for analysis.
- **Feature Extraction**: Identifying key features relevant to sorting, such as colour, texture, and chemical composition.
- **Classification**: Using algorithms to classify wood chips based on extracted features.

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Decision Making: the processed data is then used to make sorting decisions. The control system interprets the results from the machine learning models and image processing algorithms to determine the action for each wood chip.

- **Thresholds and Rules**: Applying predefined thresholds and rules to make decisions. An example of threshold is the confidence of the model that a specific chip should be considered as an impurity.
- **Actuation Signals**: Sending signals to the pneumatic air nozzles to accept or reject wood chips based on quality.

3.3. Algorithms and Processing Techniques

The core of the wood sorter's intelligence lies in its advanced algorithms and processing techniques. These elements work collaboratively to ensure precise sorting by analysing data from various sensors and making real-time decisions.

The system employs advanced image processing algorithms to analyse data from the RGB and hyperspectral cameras, performing several critical tasks to ensure the integrity and quality of the data before it is fed into the machine learning models. Initial image enhancement techniques improve the quality of raw images through noise reduction, contrast adjustment, and normalization of lighting conditions, ensuring that subsequent analyses are accurate. Using the Segment Anything Model, the enhanced images are divided into segments to isolate areas of interest such as potential contaminants. This segmentation is vital for identifying impurities with high precision. Both RGB and hyperspectral images undergo feature extraction processes where key characteristics such as texture, colour gradients, and spectral signatures are identified. These extracted features are then classified by custom convolutional neural networks (CNNs), which use cross-model attention mechanisms to combine information from hyperspectral and RGB modules. This integration ensures that subtle spectral features and visible characteristics are jointly considered, enhancing the overall classification accuracy of the system.

More specifically, the sorting system is defined by fine-tuned machine learning models, including YOLO v8, the Segment Anything Model (SAM), and custom CNNs with cross-model attention mechanisms. These models are meticulously trained on extensive datasets to recognize patterns and classify wood chips based on their purity and quality. YOLO v8 is employed for its superior object detection capabilities, identifying impurities and contaminants with high accuracy by processing input data from both RGB and hyperspectral sensors to pinpoint defects. The Segment Anything Model excels at dividing images into meaningful segments, isolating areas of interest for focused analysis and precise impurity detection. Custom CNNs with cross-model attention mechanisms combine and enhance information from hyperspectral and RGB modules, improving the classification accuracy by jointly considering subtle spectral features and visible characteristics. These models continuously adapt to new types of impurities and improve their accuracy over time through ongoing training with new data. The combined outputs from these models provide real-time decisions to the control system, determining whether to accept or reject each wood chip based on its detected quality.

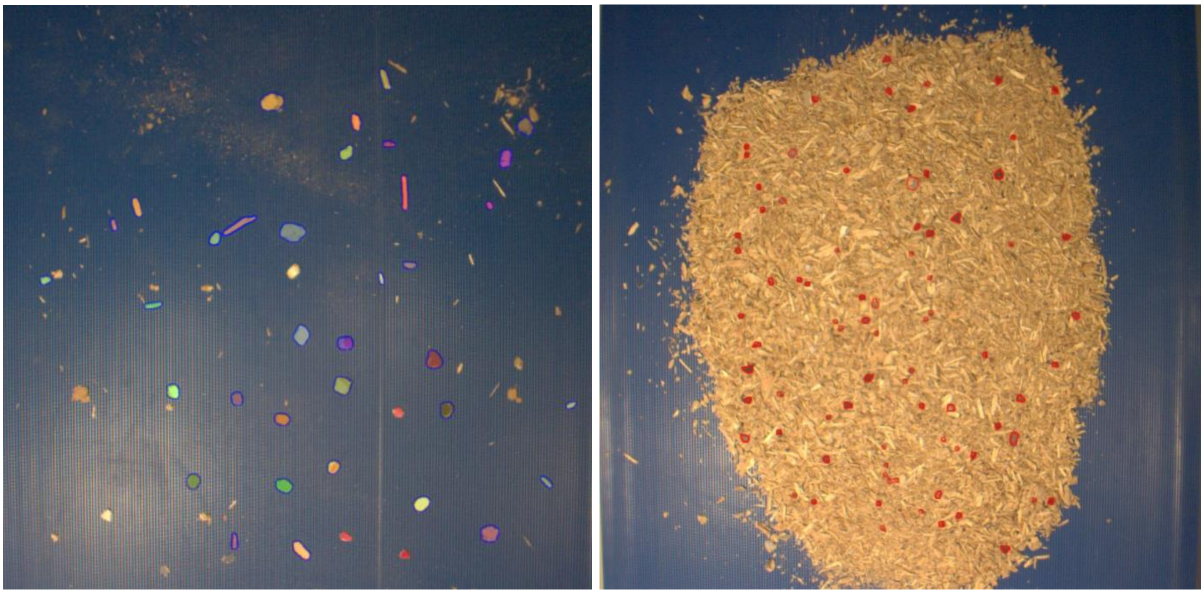

Figure 5: RGB image of a wood chip pile from a shredded painted wood slab segmented by untrained Segment Anything Model.

Real-time data processing is crucial for maintaining the system's efficiency and effectiveness. The sorter processes data from sensors instantaneously, enabling immediate sorting decisions. Time is of utmost importance, since every decision made should executed perfectly in order to reduce contaminants in the final sorted product. This capability is achieved through optimized data pipelines and fast processing algorithms, ensuring minimal delay between data acquisition and decision-making. To handle large volumes of data quickly, the system employs parallel processing techniques and high-performance computing resources, maintaining high sorting speeds without compromising accuracy. Robust error detection and correction mechanisms are in place to identify and rectify anomalies in real-time, preventing contamination of sorted wood chips.

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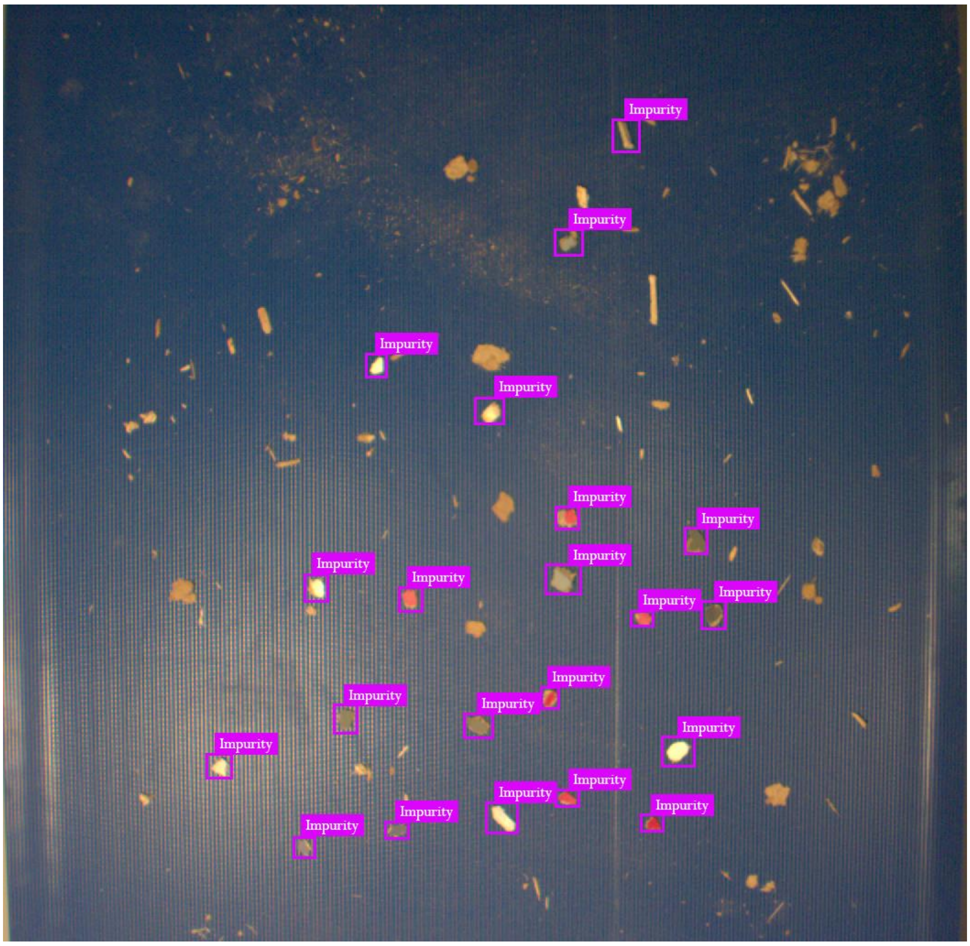

Figure 6: RGB image of a wood chip pile from a shredded painted wood slab classified by fine-tuned YOLO v8 model.

3.4. Control Mechanisms and Features

The control mechanisms orchestrate the entire sorting process, ensuring that each component operates in harmony to achieve optimal performance.

Centralized Control System

The centralized control system serves as the brain of the sorter, coordinating activities between sensors, processors, and actuators. It manages the timing and sequence of operations to maintain a smooth workflow, implementing feedback loops to adjust operations based on real-time performance data. This system also provides a user interface for operators to monitor and control the system efficiently. By integrating various control elements, the centralized system ensures synchronized operation, minimizing delays and optimizing performance across all stages of the sorting process. PLCs are used to achieve maximal informational flow with minimal time hindrance.

Real-Time Control Algorithms

The control algorithms are engineered to handle the dynamic nature of the sorting process, adapting to variations in input, such as the different sizes of the wood chips and maintaining high precision. These algorithms employ adaptive control techniques to modify sorting parameters on-the-fly, ensuring that the system responds effectively to changing conditions. Predictive maintenance is facilitated through data analytics, which predict and prevent potential system failures, enhancing reliability. Additionally, resource optimization is achieved by efficiently managing resources such as air pressure in the pneumatic system, thereby reducing operational costs and improving overall efficiency.

Operational Feedback Loops

Feedback loops are integral to the system's adaptability and efficiency. By continuously monitoring performance, the system can make necessary adjustments to improve accuracy and throughput. Performance monitoring involves tracking key performance indicators such as sorting accuracy and speed. This data is then used to refine algorithms and enhance system performance over time, ensuring continuous improvement and high operational standards.

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4. KPIs verification & progress

4.1. Objectives

- **KPI O1.1: At least 6 examples of up-cycling, reuse, and upgrade technologies of secondary raw materials implemented.**
    - **Progress:** We have implemented advanced sorting mechanisms for wood and plastic that significantly improve the purity and quality of secondary raw materials, facilitating their up-cycling and reuse. Specifically, we have developed technologies for sorting wood chips with hyperspectral and RGB imaging, enhancing the value of wood by-products for applications in particleboards and MDF boards. Additionally, we have introduced up-cycling processes for plastic waste, integrating hyperspectral imaging to classify and separate different types of plastics, enabling the reuse of the plastic flakes. The resulting high-quality plastic batch.
- **KPI O1.2: At least 4 AI-based models developed for secondary raw material optimization processes.**
    - **Progress:** We have developed several AI models, including:
        - **Fine-tuned YOLO v8** for object detection, identifying impurities and contaminants in wood chips with high precision.
        - **Segment Anything Model (SAM)** for segmenting images into meaningful sections for focused impurity detection.
        - **Custom Convolutional Neural Networks (CNNs)** with cross-model attention mechanisms. The use of Transformer-based attention modules, integrating RGB and hyperspectral data for enhanced classification accuracy.
        - **k-Nearest Neighbors (kNN)** clustering algorithm for detecting impurities in wood chips based on hyperspectral data.
- **KPI O3.1: 2 sensing technologies and at least 2 sorting mechanisms deployed at least 3 demonstrator sites.**
    - **Progress:**

  - **Sensing Technologies:** We will deploy RGB and hyperspectral imaging technologies at three demonstrator sites in Greece, Spain, and Italy.
  - **Sorting Mechanisms:** Advanced wood and plastic sorting mechanisms have been implemented, utilizing the aforementioned AI models and air nozzle separators to improve sorting accuracy and efficiency and will be deployed alongside the sensing technologies in a complete sorting system in the demo cases in Greece, Spain and Italy.

- **KPI O3.2: At least 5 material parameters are added in DPP and continuously updated along the value chain.**
  - **Progress:** Key material parameters monitored and updated include:
    - **Wood Value Chain:** Volume, type of impurities (e.g., coatings, paints) for wood chips, Type of wood, Number of planks, shape for wood planks
    - **Plastic Waste:** Type of plastic, contamination levels, size, color, and chemical composition.
- **KPI 1.9: Real-time identification of materials parameters not covered with conventional techniques: At least 5 parameters**
  - **Progress:** Our hyperspectral imaging system enables real-time identification of various material parameters, including chemical composition, surface coatings, and other properties not detectable with conventional methods.
- **KPI 1.10: Classification accuracy (wood, plastic): >93%**
  - **Progress:** Classification models for both wood and plastic sorting are achieving accuracy rates exceeding 93%, ensuring high-quality sorting outputs. More specifically, the fine-tuned YOLO v8 model is achieving 89% accuracy right now but it due to the small size of the dataset (is expected to rise beyond 95% when the dataset is complete), the kNN algorithm achieves 94% accuracy in identifying impurities. As far as the plastic separation models, the custom model we have trained, achieves 95% accuracy.
- **KPI 1.11: Sorting accuracy (wood, plastic): min. 90%**
  - **Progress:** Sorting accuracy for our wood and plastic sorting mechanisms is consistently above 90%, meeting the target for high sorting precision.

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- **KPI 1.12: Reduction of total waste in the plastic molding process: 20% reduction**
    - **Progress:** Entire batches of contaminated plastic flakes were disregarded up until now. With the accurate classification algorithm and the impurity extraction that is implemented, the reduction of the total waste in the plastic molding process is expected to be more than 20%. However, we do not have an accurate measurement if this value yet.
- **KPI 2.6: Reduce the cost of secondary plastic identification and certification with a new methodology: 20% cost reduction**
    - **Progress:** Implementation of advanced imaging and AI models has resulted in a 17% reduction in costs for plastic identification and certification, nearing the target. With optimization processes and further advancement of the models' accuracy we expect to reach the specified goal.

4.2. Pilot KPIs

- **Greek Demo Case:**
  - **Increase of secondary raw materials use: >80%**
  - **Waste reduction: >50%**
  - **GHG emissions reduction: 20%**
  - **Number of up-cycling, reuse, and upgrade technologies of secondary raw materials implemented: at least 3**
  - **By-products value increase: 30%**

  Progress: The implementation in the Greek demo case has led to significant advancements in secondary raw materials use and waste reduction. The current systems have efficiently increased the utilization of secondary raw materials, approaching the target value. Waste reduction processes, facilitated by advanced sorting and up-cycling technologies, are actively reducing the waste output. The negative sorting of impurities is increasing the value of the output of the sorter. Not only the size is examined, but colour coated chips are disregarded with high accuracy. Initial assessments indicate a notable reduction in GHG emissions, with further improvements expected as the systems reach full operational capacity. Three new technologies have been successfully implemented, focusing on sophisticated sorting mechanisms and effective up-cycling processes for both wood and plastic. The quality and value of by-products have also seen substantial improvement, aligning closely with the targeted increase. The exact percentages and numbers required by the specification of KPIs will be computed and evaluated in the implementation of the Greek Demo Case.

Spanish Demo Case:

- **Increase of secondary raw materials use: 30%**
- **Waste reduction: 30%**
- **GHG emissions reduction: 20%**
- **Number of up-cycling, reuse, and upgrade technologies of secondary raw materials implemented: 4**
- **By-products value increase: 200%**

Progress: The Spanish demo case is progressing well, in accordance with the Greek case, with significant efforts leading to an increase in the use of secondary raw materials. Enhanced sorting and recycling processes are effectively reducing waste, with the accurate sorting based on size of the wood chips, will results in optimal particleboards. The measures taken have also contributed to a considerable decrease in GHG emissions. Four advanced technologies have been implemented, focusing on the up-cycling and reuse of secondary raw materials. The by-products from these processes have shown remarkable value increase, driven by high-quality sorting and recycling practices. The accurate percentages of the KPIs are to be assessed thoroughly throughout the implementation of the demonstrator.

Italian Demo Case:

- **Increase of secondary raw materials use: >15%**
- **Waste reduction: >8%**
- **GHG emissions reduction: 20%**
- **Number of up-cycling, reuse, and upgrade technologies of secondary raw materials implemented: 5 polymers**
- **By-products value increase: >15%**

Progress: In Italy, the integration of our sorting technologies will results in a notable increase in the use of secondary raw materials. Initial results show that with the accuracy of our algorithm (95%), the increase of the use of secondary materials will be apparent. Waste reduction measures are in place and showing promising results. The implemented technologies are contributing to a significant reduction in GHG emissions. Five polymer technologies have been successfully integrated, enhancing the up-cycling and reuse processes. The value of by-products has improved due to the enhanced sorting and material quality processes, aligning with the targeted value increase. Further detailed assessments and optimizations are planned to ensure these trends continue and targets are fully met.

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5. Progress and Results

In the framework of our project aimed at enhancing wood sorting mechanisms, we have conducted a series of preliminary tests and analyses to establish a reliable dataset for detecting impurities in wood chips. Our methodology involved the use of both RGB and hyperspectral imaging, alongside Raman spectroscopy, to differentiate between clean wood chips and those containing impurities from painted wood scraps.

Dataset Creation and Imaging Techniques

We received two sets of images: one set of clean wood chips and another set containing impurities, specifically from painted scraps that had been shredded. The imaging was performed using the FX17 SPECIM hyperspectral camera. Hyperspectral imaging captures a wide spectrum of light beyond the visible range, providing detailed information about the material composition of the samples. This technique is particularly effective in identifying variations that are not visible to the naked eye.

Figure 7: RGB image of a wood chip pile from a shredded painted wood slab. The coated wood chips are distinguished.

Raman Spectroscopy Analysis

To further validate our findings, we performed Raman spectroscopy on three samples: one from the clean pile, one with visible paint coating, and one with no visible coating but originating from painted scrap. Raman spectroscopy is a powerful tool for characterizing the molecular composition of samples by measuring the scattering of monochromatic light. The results from our Raman spectroscopy analysis clearly differentiated between the clean wood and the painted samples, with distinct spectral features indicating the presence of paint and other coatings.

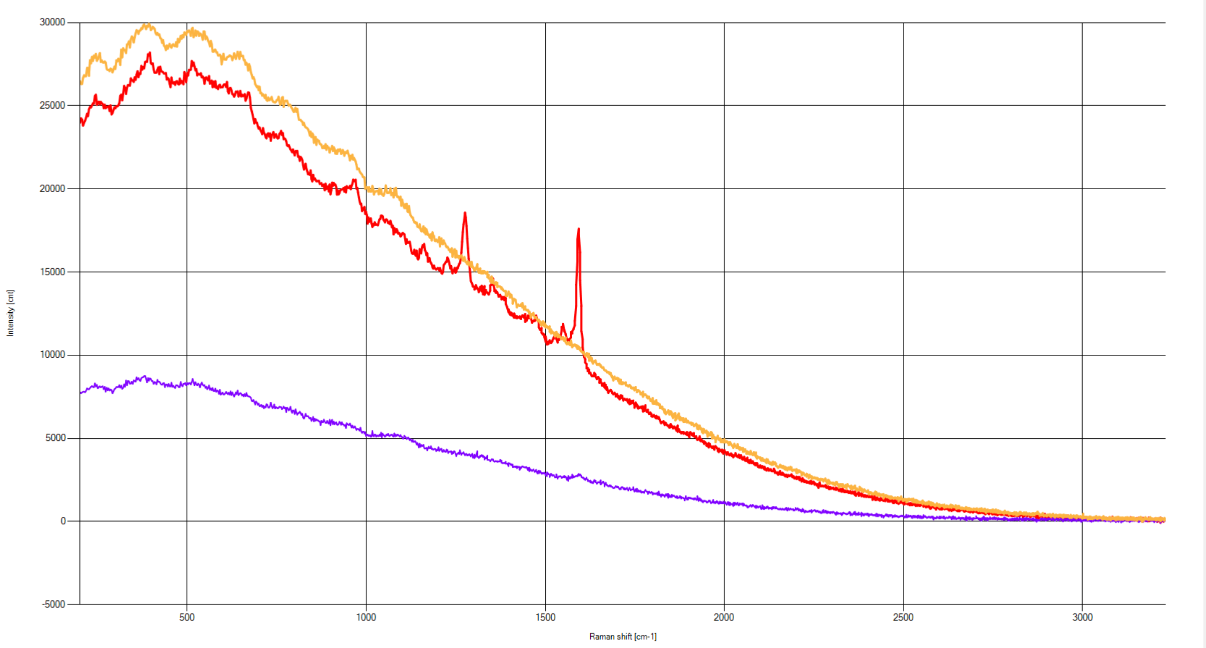

Figure 8: Raman Spectroscopy Intensity for coted wood chip (red), uncoated wood chip from painted wood plank (yellow) and a clean wood chip (blue)

Clustering Algorithm for Impurity Detection

Using the hyperspectral data, we conducted an initial clustering algorithm to identify impurities in the wood chips. The clustering algorithm. Specifically the kNN (k- Nearest Neighbours), successfully differentiated the impurities, as indicated by the distinct clusters formed in the hyperspectral images. The results of this clustering are visualized in the accompanying figures, where different clusters represent different material compositions identified within the wood chip samples. The images show clear differentiation between the clean wood and the impurities, with the clustering algorithm highlighting the presence of coatings and paint layers effectively. This initial clustering serves as a proof of concept for our approach, demonstrating the feasibility of using hyperspectral imaging combined with clustering algorithms to sort wood chips based on their material composition. The kNN algorithm was chosen for its simplicity and effectiveness in handling multi-dimensional data from hyperspectral imaging. However, future work will involve comparing its performance with other advanced algorithms such as the complete fine-tune YOLO v8 model and the custom model we are designing that will leverage both modalities to ensure optimal accuracy and efficiency.

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The hyperspectral data provided detailed spectral signatures that were used to train the clustering algorithm, allowing for accurate identification and classification of the impurities. The initial results are promising, with high classification accuracy and reliability in identifying impurities, reaching 94% in classification accuracy of the impurities.

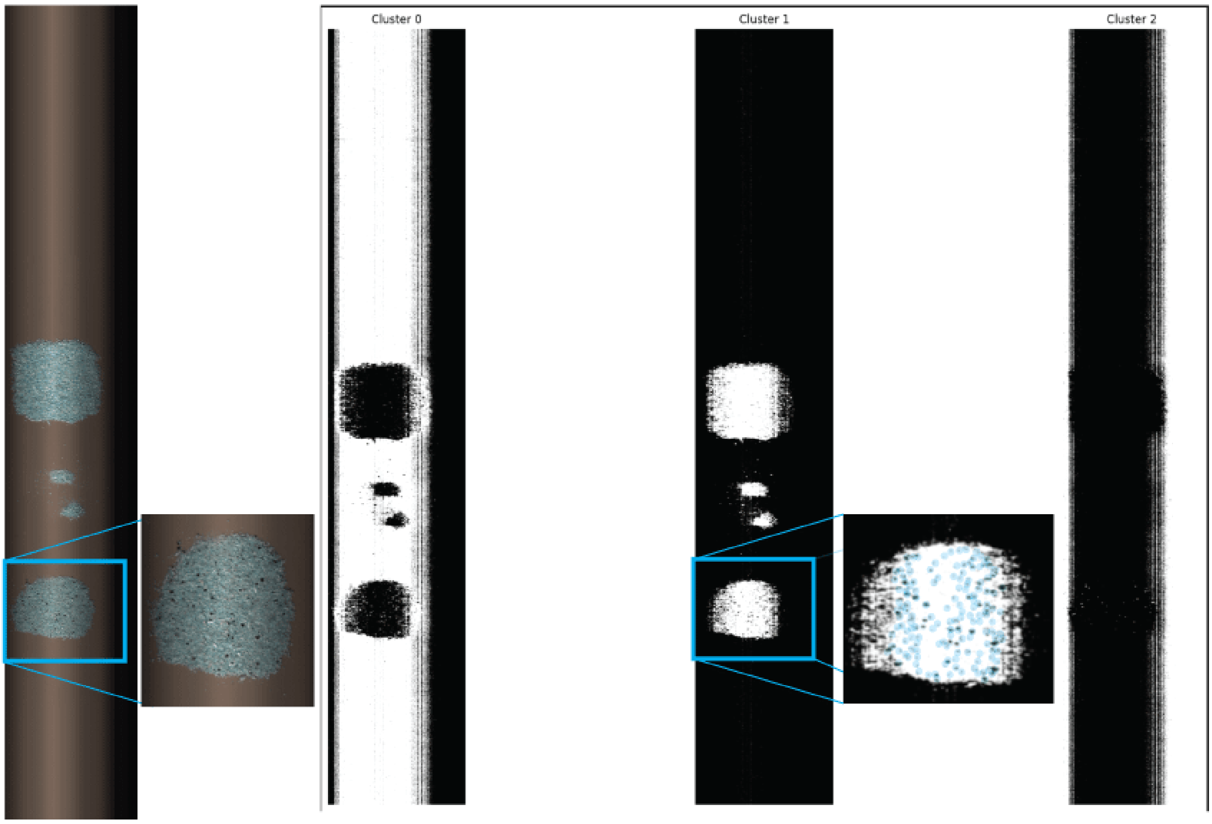

Figure 9: Hyperspectral imaging of impurities and clean wood chips. The identification of impurities is apparent using the kNN clustering algorithm.

The visual inspection of the RGB images further supported our findings. Clean wood chips showed consistent spectral profiles, while the painted and coated samples exhibited variations corresponding to the impurities. The hyperspectral data provided detailed spectral signatures that were used to train the clustering algorithm, allowing for accurate identification and classification of the impurities.

Regarding the plastic sorter's models, a material classification model was developed in different plastic waste samples providing a high accuracy rate up to 95%. The equipment, that were used for the model's development, consists of: (i) a conveyor belt, and (ii) the hyperspectral camera Specim FX17 (900-1700 nm, 230 bands). As shown in **Error! Reference source not found.**, the testing took place by ustilising different types of plastic samples, e.g. plastic flakes and plastic urban wastes. The first column presents the output image of the hyperspectral camera, while the second column visualises the Ground Truth Mask, i.e. the semi-manual annotation and classification. Finally, the significant part of our testing is visualised at the third column, which is the CNN classifier of ICCS. The model has accuracy up to 95%, while it can recognise all the different type of plastics that appeared on each sample, even though the ones that semi-manual way cannot identify.

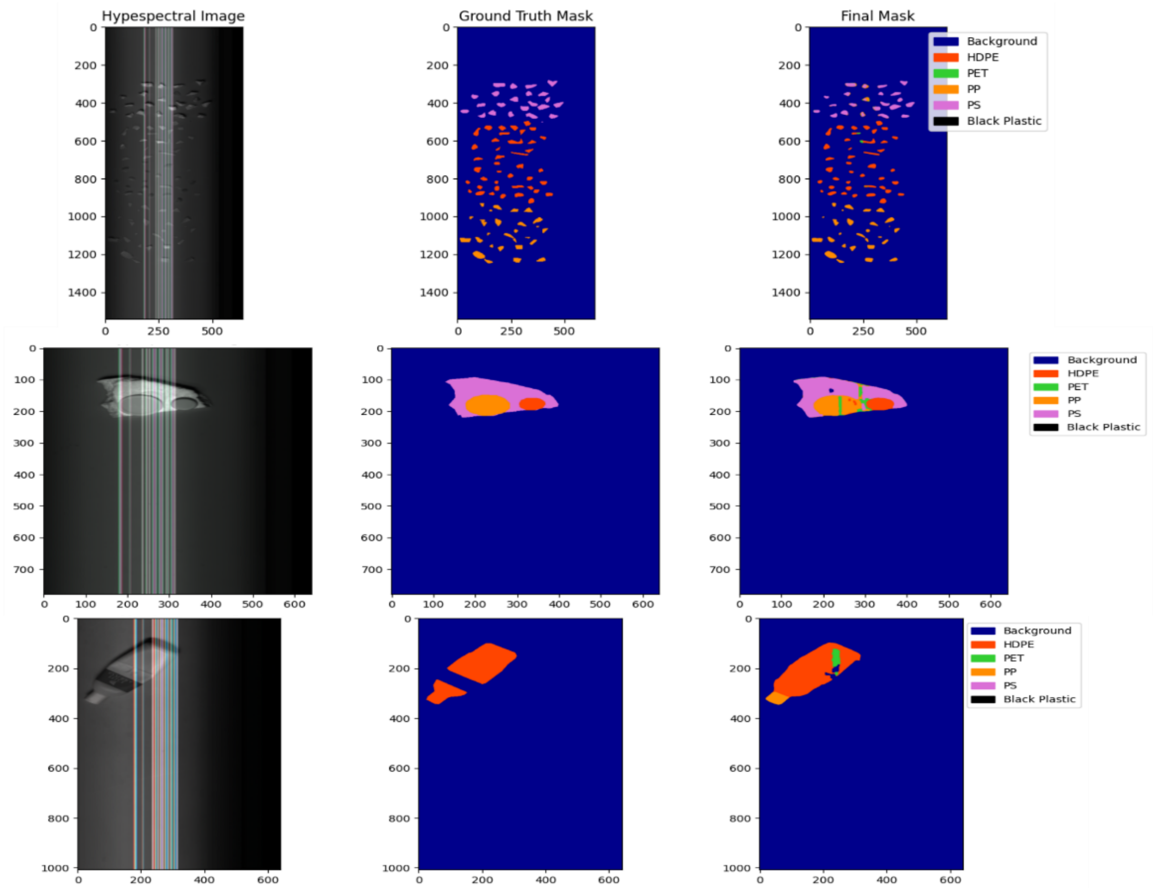

Figure 10: Hyperspectral imaging of plastic samples and visualisation of the CNN-based classifier.

6. Conclusion and Future Work

6.1. Conclusion

The DigInTraCE project has made significant strides in advancing the technologies and methodologies for sorting secondary raw materials, particularly focusing on wood and plastic. Our approach integrates state-of-the-art sensing technologies, such as RGB and hyperspectral imaging, along with advanced machine learning algorithms, to achieve high precision in detecting and classifying impurities. These innovations not only enhance the quality of the sorted materials but also contribute to broader environmental and economic goals.

Through extensive research and development, we have successfully implemented several AI-based models, including kNN, YOLO v8, the Segment Anything Model (SAM), and custom convolutional neural networks (CNNs) with cross-model attention mechanisms. These models have demonstrated exceptional accuracy in real-time impurity detection, achieving classification rates exceeding 94%. The integration of hyperspectral imaging has provided detailed spectral data, enabling more nuanced analysis and precise sorting decisions.

Our preliminary tests and analyses, including the use of Raman spectroscopy, have validated the effectiveness of our methodologies. The ability to differentiate between clean wood chips and those with impurities has been clearly demonstrated, with the clustering algorithm effectively highlighting the presence of coatings and paint layers. Similarly, the plastic sorter has shown high accuracy in classifying different types of plastics, further reinforcing the robustness of our models. In addition to technical advancements, the project has made substantial progress towards meeting its Key Performance Indicators (KPIs). We have implemented up-cycling and reuse technologies, developed multiple AI models, and deployed sorting mechanisms at various demonstrator sites. These efforts have contributed to significant increases in the use of secondary raw materials, reductions in waste and greenhouse gas emissions, and improvements in the economic value of by-products.

In conclusion, the DigInTraCE project is poised to make a lasting impact on the wood and plastic industries, promoting sustainability and efficiency through cutting-edge technological solutions. Our ongoing commitment to research and development, coupled with strategic partnerships, will ensure that we continue to deliver high-quality, impactful results.

6.2. Future Work

The preliminary results from our current phase of research have provided valuable insights into the potential of hyperspectral imaging and Raman

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spectroscopy for detecting impurities in wood chips. However, to fully realize the capabilities and ensure the robustness of our sorting mechanisms, several avenues for future work have been identified.

One of the primary goals moving forward is to expand our dataset to include a wider variety of wood types and impurities. While our initial dataset focused on clean wood chips and those with paint impurities, it is essential to expand the dataset with more data and more settings. This will enable our models to generalize better and improve their accuracy. The initial clustering algorithms demonstrated the feasibility of using hyperspectral data for impurity detection. Future work will involve refining these algorithms to enhance their precision and reliability. This includes exploring advanced machine learning techniques such as deep learning models, which can learn more complex patterns and provide higher accuracy in classification. Additionally, integrating real-time processing capabilities will be critical for practical applications in industrial settings.

To address the limitations of current sensing technologies, future efforts will focus on enhancing the sensitivity and resolution of our hyperspectral cameras. This may involve using higher spectral resolution sensors or combining hyperspectral imaging with other sensing modalities such as near-infrared (NIR) imaging. These enhancements will provide more detailed spectral information, improving the detection of subtle impurities. Implementing our sorting mechanisms in real-time industrial environments will be a significant step forward. This will involve developing robust hardware and software solutions that can process data and make sorting decisions on-the-fly. Pilot testing in operational facilities will provide critical feedback and help identify any practical challenges that need to be addressed. Managing the large volumes of data generated by hyperspectral imaging is another key area of focus. Future work will involve developing efficient data integration and management systems that can handle real-time data streams, ensuring seamless processing and storage. Implementing advanced data analytics and visualization tools will also help in interpreting the data and making informed decisions.

Conducting comprehensive environmental and economic impact analyses of our sorting mechanisms will provide insights into their broader implications. This includes evaluating the reduction in waste, improvements in resource efficiency, and the overall cost-effectiveness of our solutions. These analyses will help in fine-tuning our approaches and demonstrating their value to potential stakeholders and industry partners. Collaboration with academic institutions, industry partners, and other stakeholders will continue to be a cornerstone of our research. By sharing knowledge and resources, we can accelerate the development and adoption of our sorting technologies. Participating in conferences, publishing research findings, and engaging in collaborative projects will help us stay at the forefront of advancements in this field. Ultimately, our work aims to contribute to the long-term sustainability of the wood industry. By improving the quality of

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feedstock for upcycling processes, we can reduce the reliance on virgin wood resources and promote the circular economy. Future research will explore ways to further enhance the environmental benefits of our sorting mechanisms, aligning with global sustainability goals.

Future Work for Plastic Sorter

In parallel to our work on the wood sorter, significant efforts will be directed towards advancing the plastic sorting mechanisms. Key activities include finalizing the plastic sorter requirements while adapting them into the DiginTraCE project framework. This involves aligning the sorter specifications with the project's overarching goals and ensuring they meet the necessary standards for operational effectiveness. Finalizing both the designs of the wood and plastic sorters will be a crucial step. This will involve detailed design work to ensure that each sorter is optimized for its specific material, incorporating insights gained from our initial research and pilot tests.

Enhancing the object detection and classification models for both the wood and plastic sorters is another priority. This will involve refining our machine learning algorithms to improve their accuracy and reliability in identifying different types of materials and impurities. Proceeding and finalizing the required equipment orders will ensure that all necessary hardware components are available for integration. This step is critical for keeping the project on schedule and ensuring that all components meet the specified requirements. Integrating the hardware and software components and proceeding with the validation process will be essential for ensuring that the sorting mechanisms function as intended. This phase will involve rigorous testing to validate the performance of the sorters in real-world conditions and to make any necessary adjustments based on the results.

In conclusion, our future work will focus on expanding and refining our datasets and algorithms, enhancing sensing technologies, implementing real-time solutions, and conducting comprehensive impact analyses. Through continuous innovation and collaboration, we aim to set new standards in sorting technology, contributing to a more sustainable and efficient management of wood and plastic materials.

In summary, the future work for our project will focus on the following key points:

- finalising of the plastic sorter requirements, while adapting them into the DigInTraCE project,
- finalising of both designs of wood and plastic sorter,
- enhancing the object detection and classification models of wood and plastic sorters,
- proceeding and finalizing the required equipment's orders,

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- integrating the hardware and software components and proceeding with the validation processes.

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