

Europe faces a growing challenge: over 60 million tons of fibreboard fibreboard waste generated in the last 5 years.

The rapid growth in fibreboard production has caught the European recycling sector off-guard. End-of-life fibreboards currently have no commercially viable recycling methods, creating an urgent need for innovative solutions.



EcoReFibre: A pan-European consortium to build a circular economy for fibreboard

Project Goal

To develop and demonstrate innovative, environmentally sound, and commercially viable recycling technologies for end-of-life fibreboards.

Target Impact

Substitute up to 25% of the virgin fibres currently used in the manufacture of new fibreboard.

Consortium

A strong partnership of 20 leading research institutes, companies, and European associations.

Framework

A project under the Horizon Europe program.



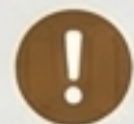
The research foundation is built on a meticulous but laborious manual sorting process.



1. Collection: Samples are gathered from recycling centers.

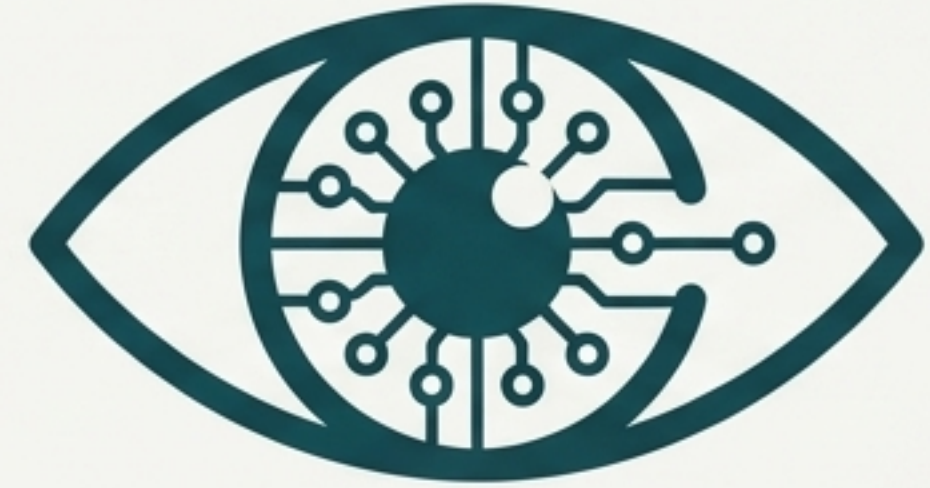
2. Sieving: An electric mesh machine separates particles into four size categories (<4mm, 4-6mm, 6.3-8mm, >8mm).

3. Manual Picking: Each particle is individually visualized and sorted by hand into five categories.



Key Challenge: This process is “time consuming and sometimes tiring,” leading to observed trade-offs between speed and accuracy, especially as worker fatigue sets in.

In response to the manual bottleneck, a personal project was initiated: OSITY.



Optical **S**egmentation and Identification **T**racking with **Y**OLO (OSITY)

Motivation:

To optimize the manual picking process. The limitations of human sorting—fatigue, boredom, and variable accuracy—inspired the exploration of a computer vision solution that is consistent and tireless.

Core Objective:

To develop a proof-of-concept for an AI-driven sorting system capable of identifying and classifying tiny wood particles, aligning with EcoReFibre's goal of creating smart machinery for wood waste.

The model was trained to identify five distinct classes of post-consumer wood particles.



1. Fibreboard Pure (FBP):
Fibreboard without surface finish or adhesives.



2. Fibreboard Coating (FBC): Fibreboard with surface finish like paint or coating.



3. Non-wood (NW):
Includes plastics, metals, or wood containing nails/screws.



4. Wood-based Panels (WBP): Plywood, particleboard, OSB, etc.



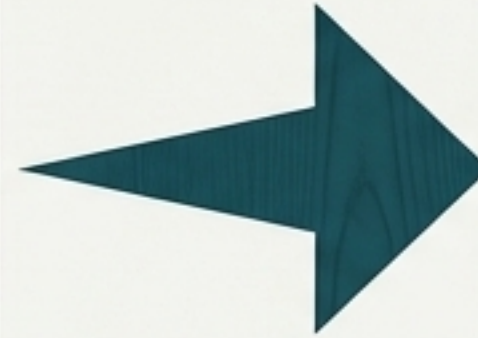
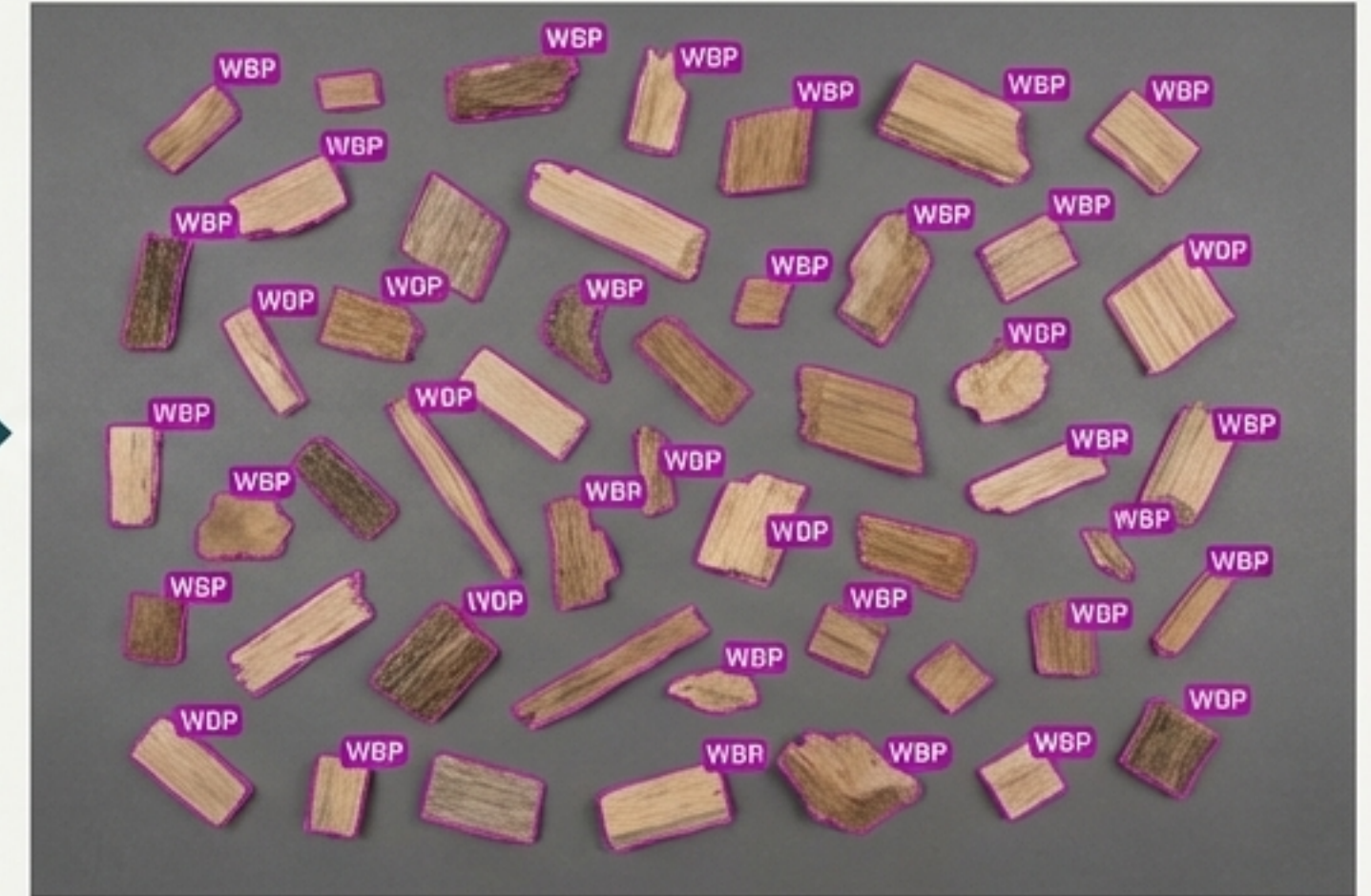
5. Solid Wood (SW):
Wood cut into planks, without adhesives.

A robust dataset was built from 109 high-resolution images, annotated at the pixel level.

Unannotated



Annotated



Source Data

109 original images captured, containing 3,407 individual particle annotations.

Annotation Tool

Roboflow's "Smart Polygon" tool was used for precise instance segmentation, automatically masking each particle. "Label Assist" was later used to accelerate the process.

Data Augmentation

The dataset was expanded to 8,201 total instances across all classes to improve model robustness.

Dataset Split

82% Training, 12% Validation, 6% Testing.

A pre-trained YOLOv11-seg model was fine-tuned over 300 epochs in a cloud environment.

Model Architecture: You Only Look Once v11 (YOLOv11-seg), chosen for its balance of speed and accuracy in real-time detection.

Training Environment: Google Colab, utilizing a Tesla T4 GPU for efficient computation.

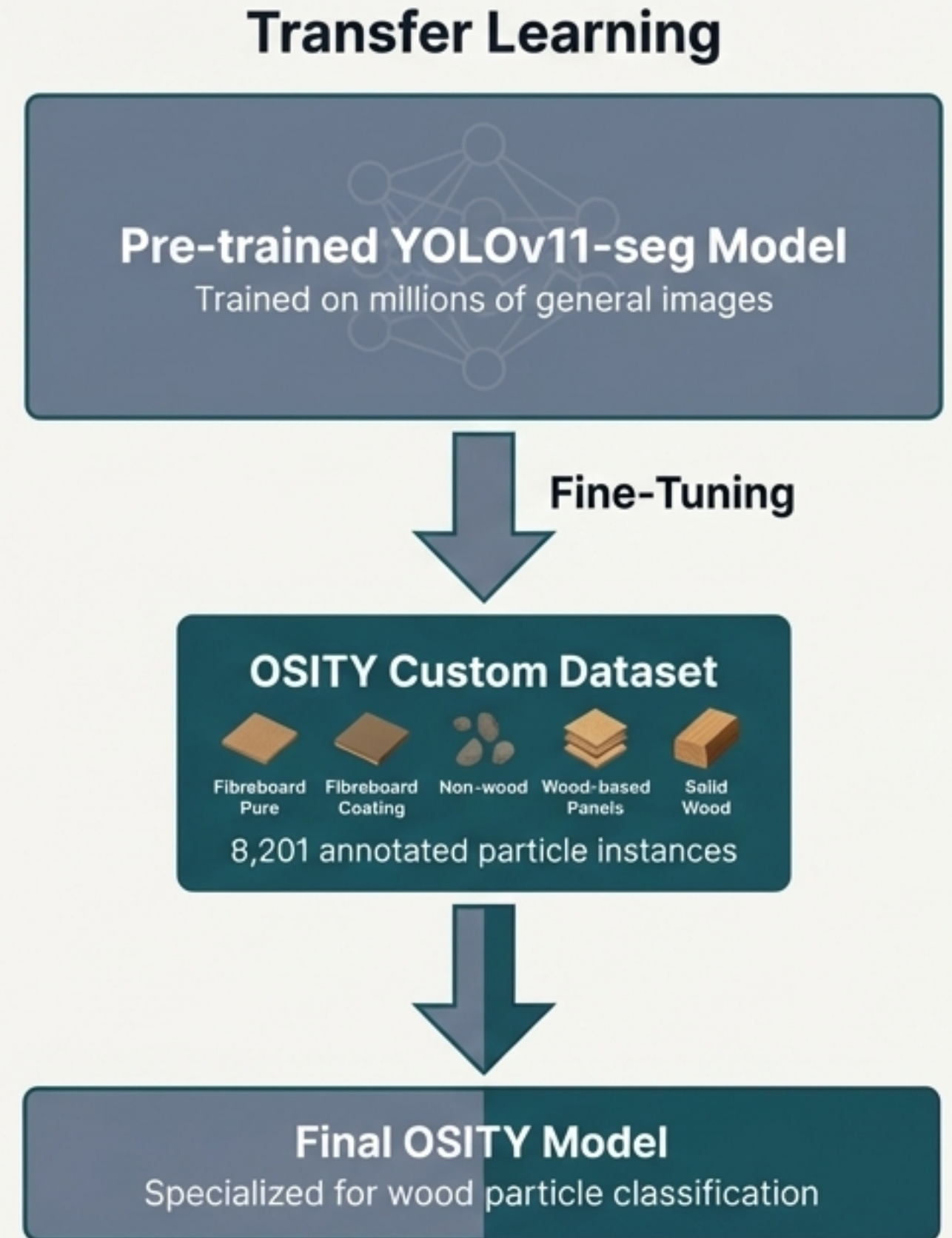
Key Training Parameters:

Epochs: 300 (with early stopping at 269)

Image Size: 640x640 pixels

Batch Size: 4

Primary Evaluation Metric: Mean Average Precision (mAP@0.5), which requires a 50% overlap between the predicted mask and the actual object mask to be considered a correct detection.

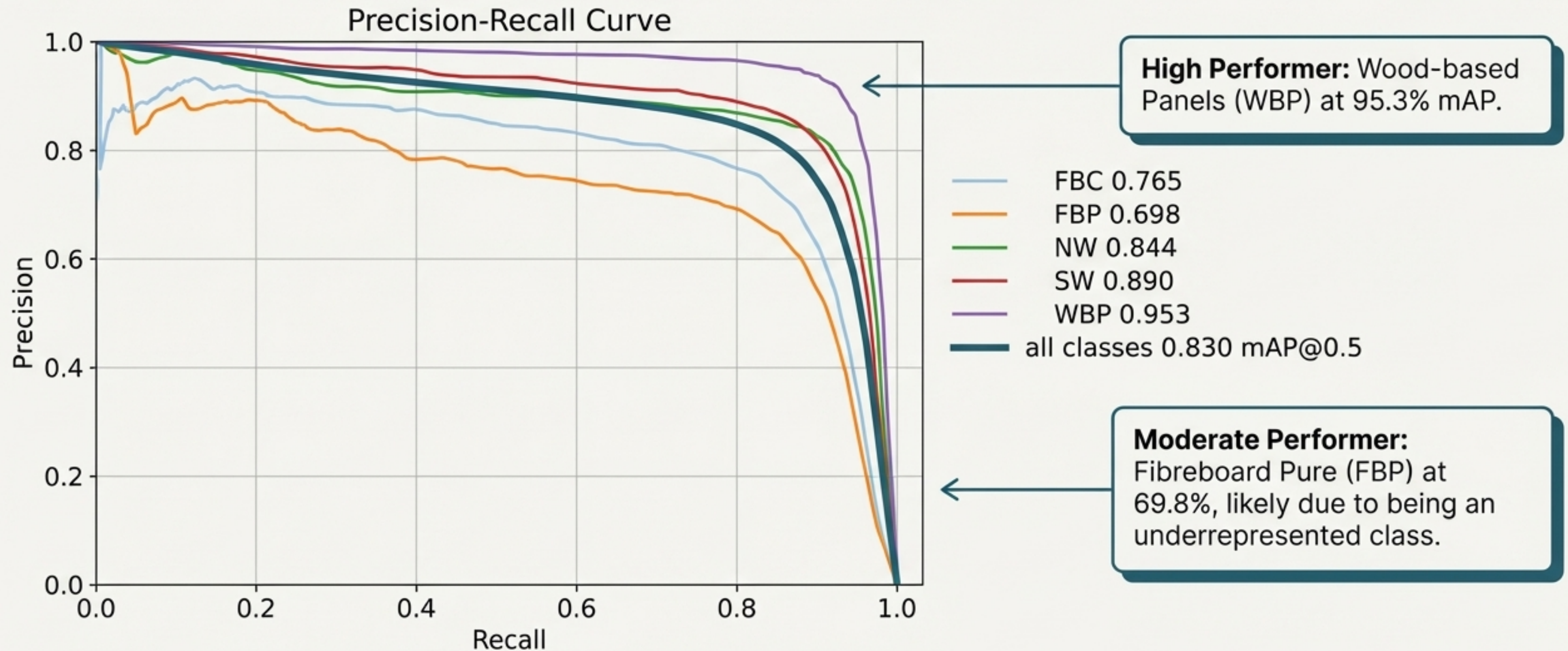


83%

Mean Average Precision (mAP@0.5)

The OSITY model successfully learned to detect and classify post-consumer wood particles with high overall precision on the validation dataset, proving the viability of computer vision for this complex sorting task.

Performance varied by class, with WBP and SW achieving precision over 95% and 89% respectively.



A detailed breakdown of performance metrics reveals strong precision and recall across most classes.

Class	Images	Instances	Mask Precision	Mask Recall	Mask mAP@50	Mask mAP@50-95
all	51	1420	0.82	0.81	0.83	0.69
FBC	27	347	0.82	0.67	0.76	0.70
FBP	21	194	0.67	0.67	0.67	0.58
NW	15	349	0.84	0.93	0.84	0.67
SW	8	226	0.82	0.88	0.90	0.67
WBP	18	304	0.92	0.92	0.95	0.82

Understanding the Metrics

mAP@50: A looser criterion, requiring 50% overlap between predicted and actual object masks for a correct detection.

mAP@50-95: A stricter, more detailed metric, averaging precision across overlap thresholds from 50% to 95%.

The trained OSITY model successfully identifies and classifies particles in new images and video streams.

****Testing Method****: Inference was performed on new images of mixed particles. A test simulating a conveyor belt was also conducted by dragging particles on a sheet under a fixed camera.

****Result****: The model demonstrates strong predictive power, correctly outlining and labeling the majority of particles even in cluttered arrangements.

Cluttered Arrangement



Separated Arrangement



▶ View the model in action at: <https://youtu.be/3RuNQ574XGo>

Acknowledging the challenges provides a clear path for future improvement.



Occlusion: Performance is higher when particles have ~2mm of space; tightly packed objects can be challenging.



Computational Constraints: Use of free-tier platforms limited extensive hyperparameter tuning.



False Positives: The model occasionally misidentified shadows or background elements, suggesting a need for more diverse background data.



Time Frame: The two-month internship allowed for a successful proof of concept, but a production-ready model requires a longer development cycle.



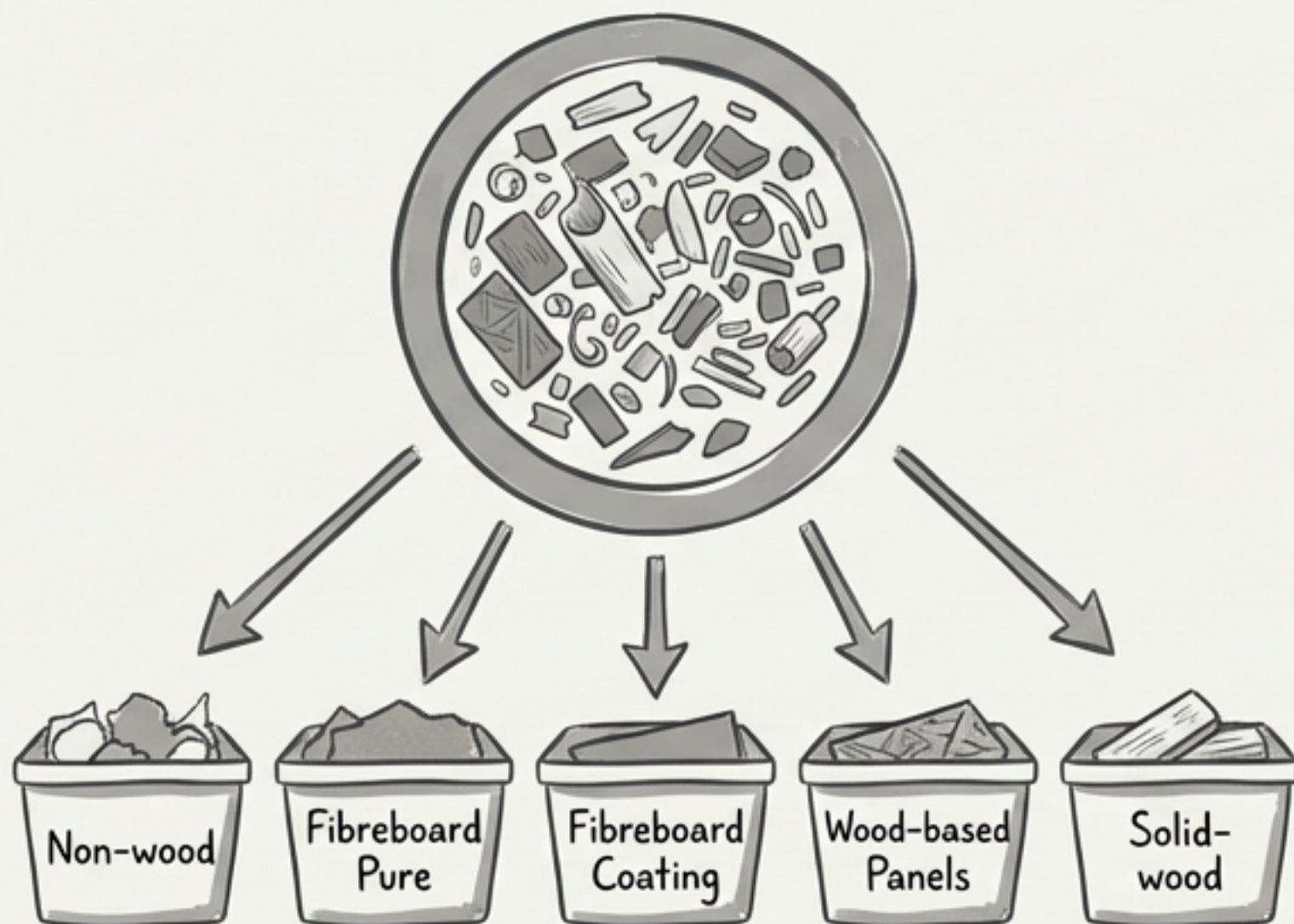
Variable Lighting: Photos were taken at various times of day, which may have introduced inconsistencies in the dataset.

From Manual Labor to Automated Insight

Labor-Intensive & Subjective



Fast & Consistent



Relies on human visualization, subject to fatigue, and trade-offs between speed and accuracy.



The OSITY model provides tireless, objective, and high-precision classification in real-time.

This proof of concept demonstrates that image-based particle recognition is a viable path for the recycling industry.

While the current model achieved 83% mAP, this result establishes a strong foundation. The OSITY project confirms that computer vision, utilizing advanced deep learning architectures, has the potential to replace more complex and manual systems in waste sorting.



Future Outlook:

- Incorporate additional high-quality data.
- Utilize more data processing power for advanced validation.
- Conduct further iterations to move from a prototype to a production-ready model.