Comparative Analysis of Transfer and Continual Learning for Vision Based Particle Classification in Plastics Sorting for Recycling

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FFG Forschung wirkt.

ober österreich

Das Land Steiermark

SFG NEUES DENKEN. NEUES FÖRDERN.

https://www.wired.com/story/plastic-waste-packaging/

Context: recAIcle Project

***Re**cycling-oriented **c**ollaborative w**a**ste sort**i**ng by **c**ontinual **le**arning*

FFG AI for Green - Kooperatives F&E Projekt

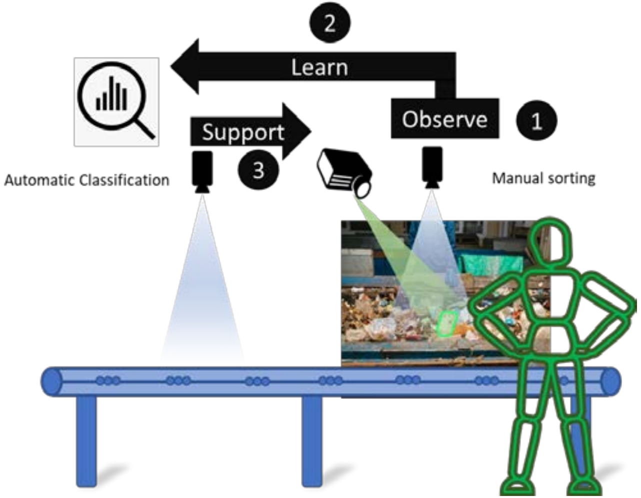
Duration: 01.07.2022 – 30.09.2025 (39 Months)

Partner:

- **Pro2Future GmbH**
- **Montanuniversität Leoben (AVAW)**
- **Siemens Aktiengesellschaft Österreich (DI Graz + T Wien)**

[https://www.youtube.com/watch?v=EvuNJ_yZi3g]

[https://www.youtube.com/watch?v=ok4l3-q-5w4]

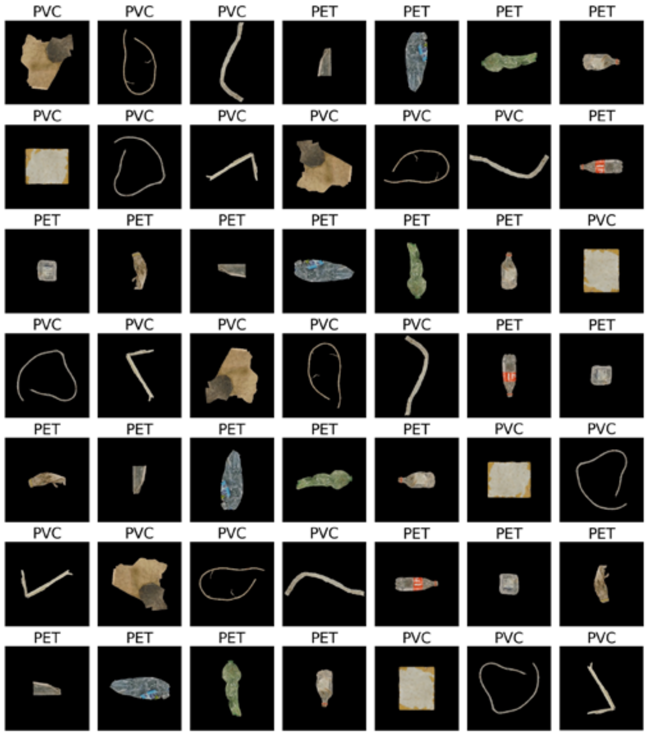


Goal:

AI-based visual assistance for workers in waste sorting plants to improve conditions of work, reduce stress and workload, and increase the sorting quality for better recycling and circular economy.

Problem: How to visually classify different types of plastic waste?

- **Good: Classes are known in advance: PET, PVC, PE, GVK, PS, …**
- **Bad: Waste comes arbitrarily crushed and in all rotations**
- **Bad: Labels + Packages/Bottles + Caps**
- **Bad: Dirt, stains, interleaves and overlaps**
  (in reality! -- not lab conditions)



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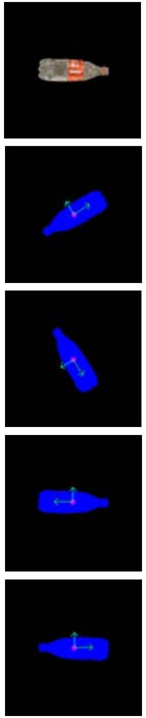

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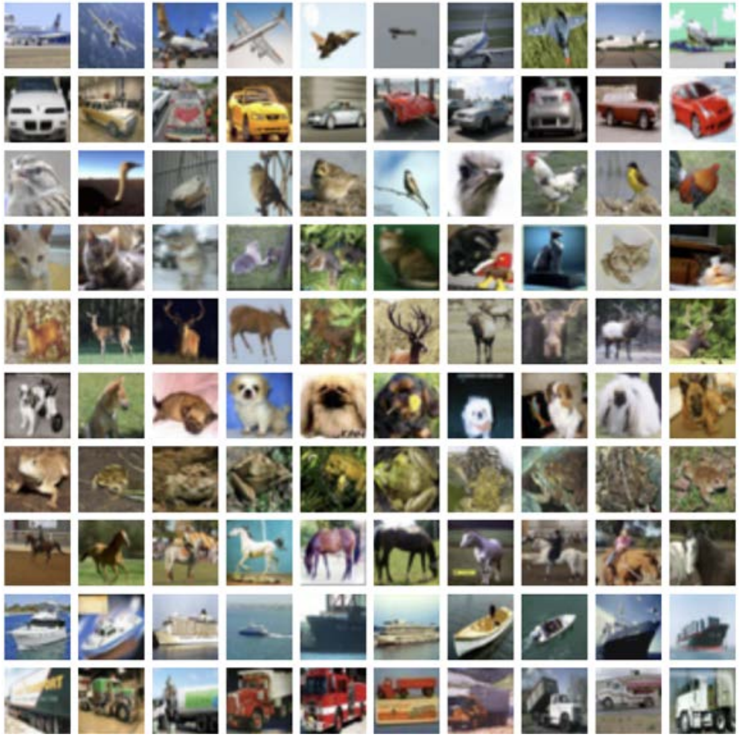
Datasets: CIFAR100, DWRL, Synthetic

CIFAR100 Dataset (60 000 images, 100 classes)



[https://www.cs.toronto.edu/~kriz/cifar.html]

DWRL Dataset (5 classes)

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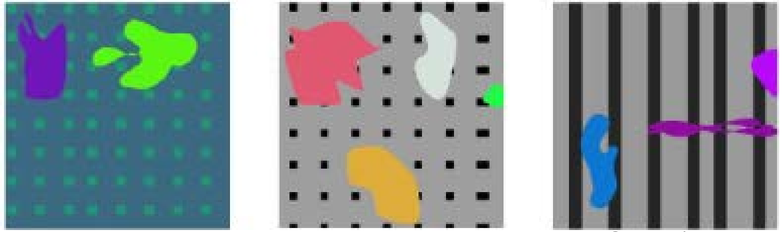
Synthetic Dataset



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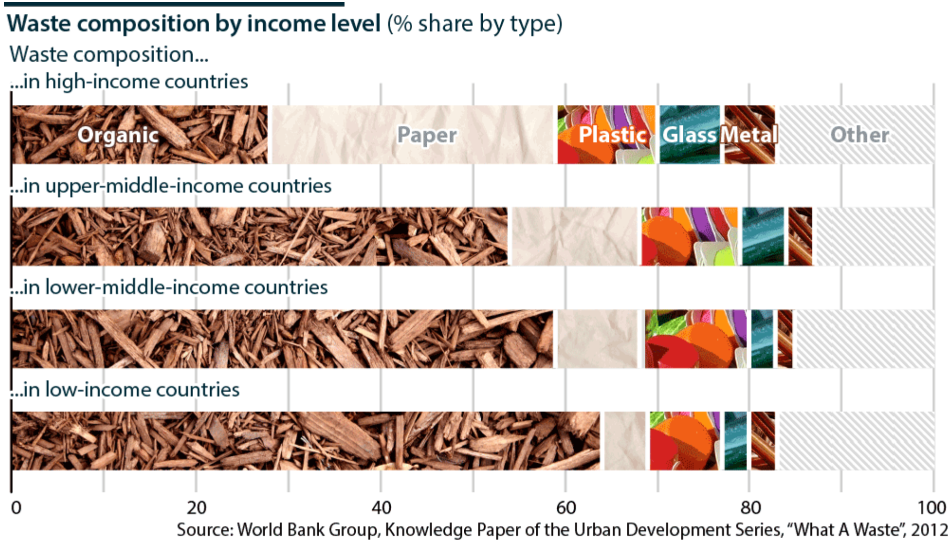
Problem: Local and Seasonal Data Bias

Waste is biased based on location/seasons/events



[https://dailybrief.oxan.com/Analysis/DB236831/Waste-management-is-key-to-sustainable-global-growth]

New waste „emerges“

Christmas

[https://plasticoceans.org/creating-a-more-sustainable-christmas]

Festival

[https://drinkflowater.com/reducing-plastic-waste-at-events-the-role-of-water-refill-stations]

What is better: Transfer Learning or Continual Learning?

Transfer Learning

Use pretrained model and retrain it with all input data from use-cases

„Classical“ models and techniques used (CNN)

- \+ Optimal fit for this training data set
- \- Needs all training data to be known a priori
- \- Problem of Overfitting
- \- Local biases may not be optimally recognized
- \- Retraining is costly (high computing overhead)

Continual Learning

Use pretrained model and fine-tune it iteratively with batches of new input data from use-cases

Special techniques for fine-tuning (EWC, Replay)

- \+ Training data can be added continuously
- \+ Fine-tuning is fast
- \+ Fastly adopts to data biases
- \- Accuracy may be worse in the beginning
- \- Catastrophic Forgetting: Accuracy „may“ decrease

Method: Experimental Setup / Preparing the Training Datasets

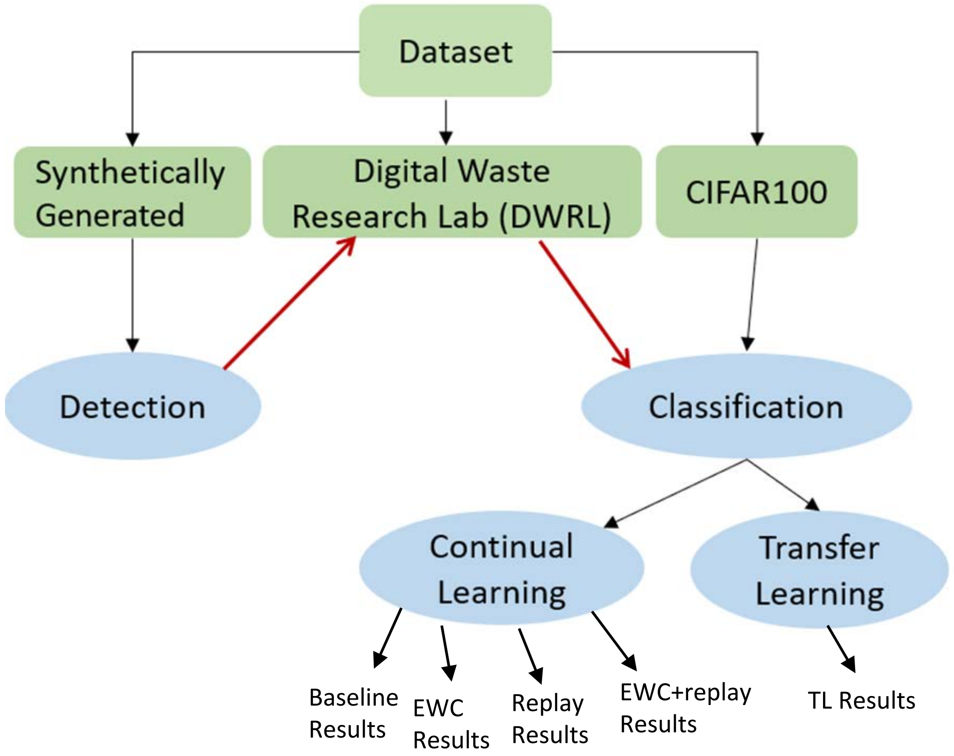
1. **Data Preprocessing**
    1. Synchronize
    2. Split and Crop
    3. Clean up

2. **Object Detection**
    1. Detect Bounding-Boxes / Boundaries
    2. Object Segmentation
    3. Background Segmentation

3. **Object Classification**
    1. Annotate / Tag with Waste Type
    2. Store individual images

4. **Use for Training & Validation**

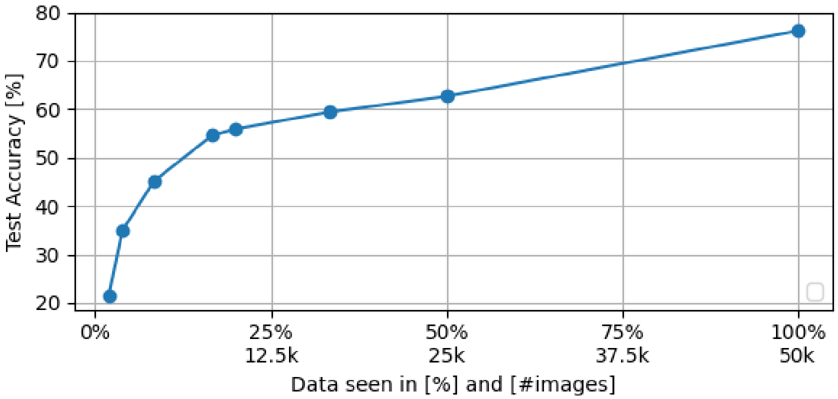
5. **Measured and Compared Accuracy for:**
    - Transfer Learning
    - Continual Learning
        - ✓ Baseline
        - ✓ EWC
        - ✓ Replay
        - ✓ EWC+replay



Object Detection Examples

Results

Results & Evaluation: Transfer Learning on CIFAR-100

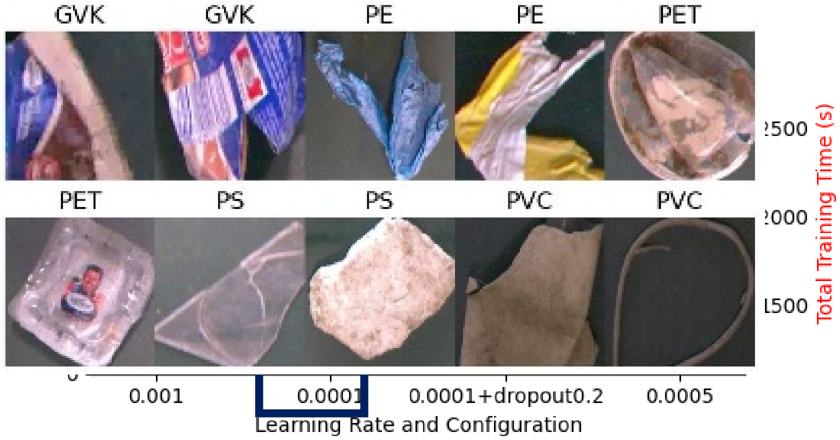


Test accuracy by dataset size

Accuracy:

961 images: 21.36%

50 000 images: 76.17%



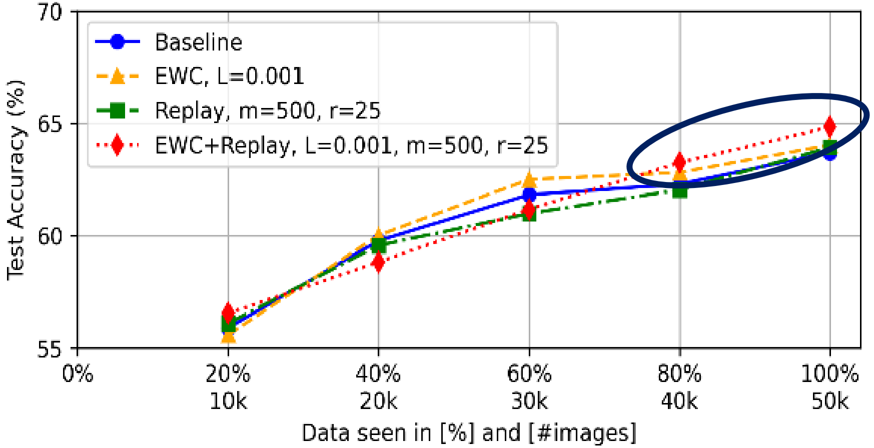
Test accuracy and training time for various learning rates

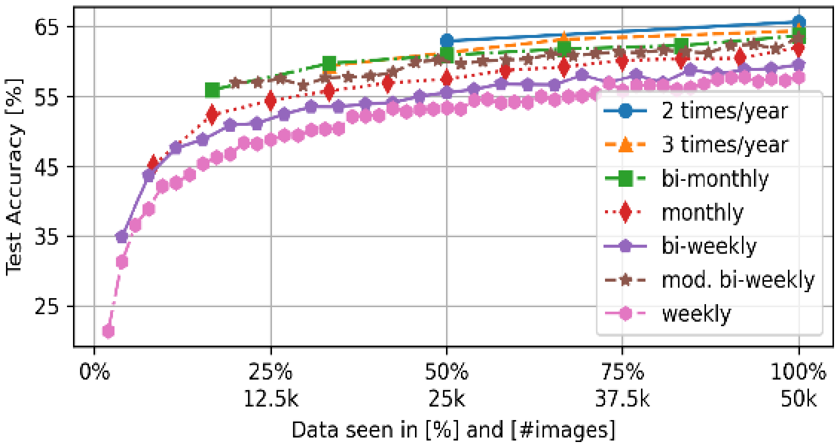
Best Configuration:

LR = 0.0001, no dropout – 13% accuracy gain.

20minutes training time

Results & Evaluation: Continual Learning on CIFAR-100





Accuracy by continual learning strategy

Strategies: Baseline, EWC, Replay, EWC+Replay.

Best Performance:

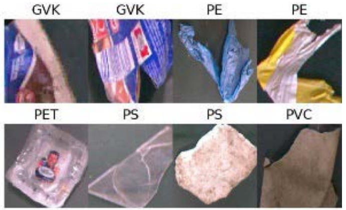
EWC+Replay, 64.83% accuracy (+3% baseline)

Accuracy by batch size and count

Higher Accuracy: Fewer, larger batches (+9%).

Modified Bi-Weekly: Outperforms constant batch size by 4%, achieving 63.44%.

Results & Evaluation: CIFAR 100 vs. DWRL

	Transfer Learning	Continuous Learning
CIFAR 100 	76.17%	65.64%
DWRL 	90%	84%

Conclusion and Outlook

Key Takeaways:

1. **Continual learning starts weaker, but improves over time.**
2. **Continual learning adapts better to changing input streams (adapts to data bias).**
3. **Recommendation: bi-weekly batches and considering replaying upcoming events (e.g. Christmas).**
4. **EWC + replay have higher accuracy in the later stages (much data seen).**

Outlook:

Further techniques have to be evaluated (network expansion, pruning, dynamic architecture search)

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