DEVELOPING CONVOLUTIONAL NEURAL NETWORKS (CNNS) FOR WASTE CLASSIFICATION SYSTEM (WCS)

Leveraging CNN, MobileNetV2, and ResNet50 to Automate and Enhance Recycling Accuracy

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ABSTRACT

We built an AI vision system that automatically identifies waste types from photos with **97% accuracy** — outperforming manual sorting. Using advanced deep learning, our solution classifies trash into 10 categories in seconds, offering a scalable way to reduce recycling contamination and advance circular economy goals.

MOTIVATION & IMPACT

Current Waste Crisis

- Global municipal waste growing - projected 70% increase by 2050 (Kaza et al., 2018)
- Ireland: **3.13 million** tonnes municipal waste in 2023 (EPA)
- Current recycling rate: **42%** **vs** EU target: **65%** by 2035
- 15-20% contamination in recycling bins

Economic Impact Today

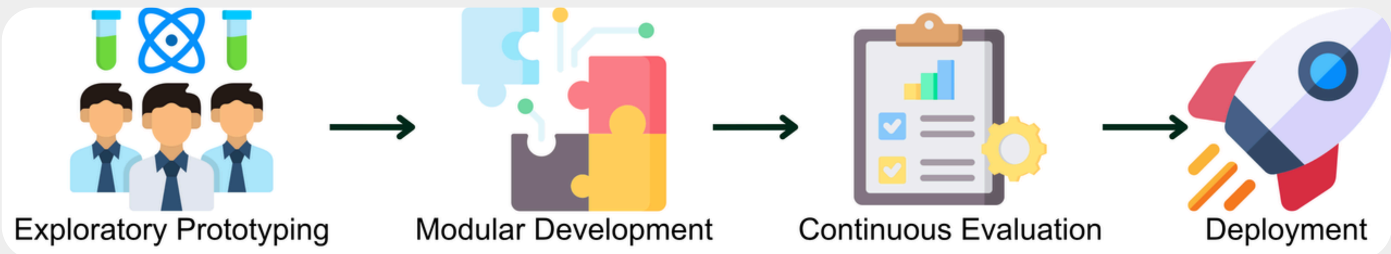
- €25-30 million annual misclassification costs
- Significant value loss from contaminated recyclables

Our Solution

AI-powered waste classification to enhance sorting accuracy and support circular economy goals

DEVELOPMENT APPROACH

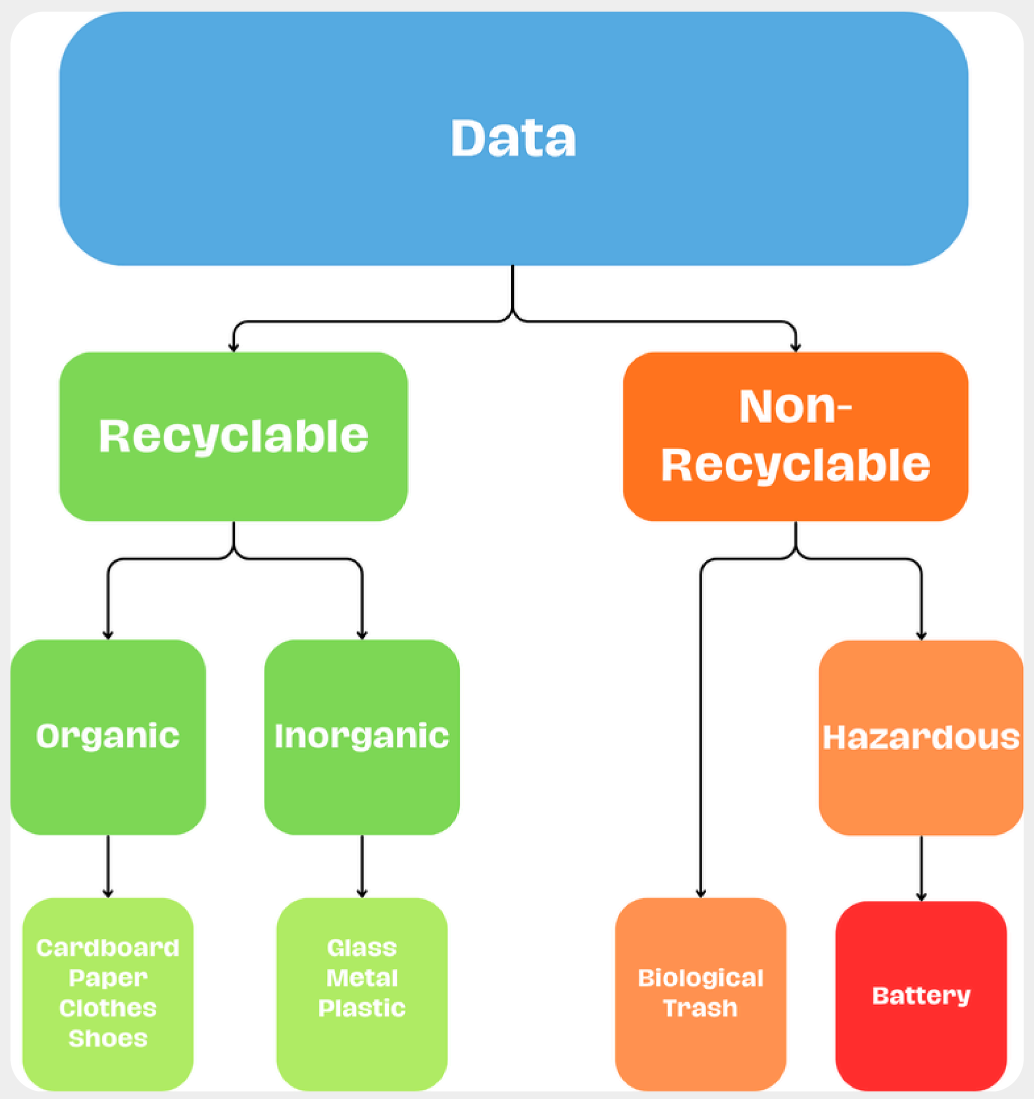
Our development followed an iterative agile-inspired process, structured into four progressive milestones:



Phase Progression:

- **Exploratory Prototyping** - Built baseline CNN & validated core concept
- **Modular Development** - Parallel development of 3 AI models & web interface
- **Continuous Evaluation** - Rigorous testing & user feedback integration
- **Deployment** - Full system integration & performance optimization

DATA OVERVIEW

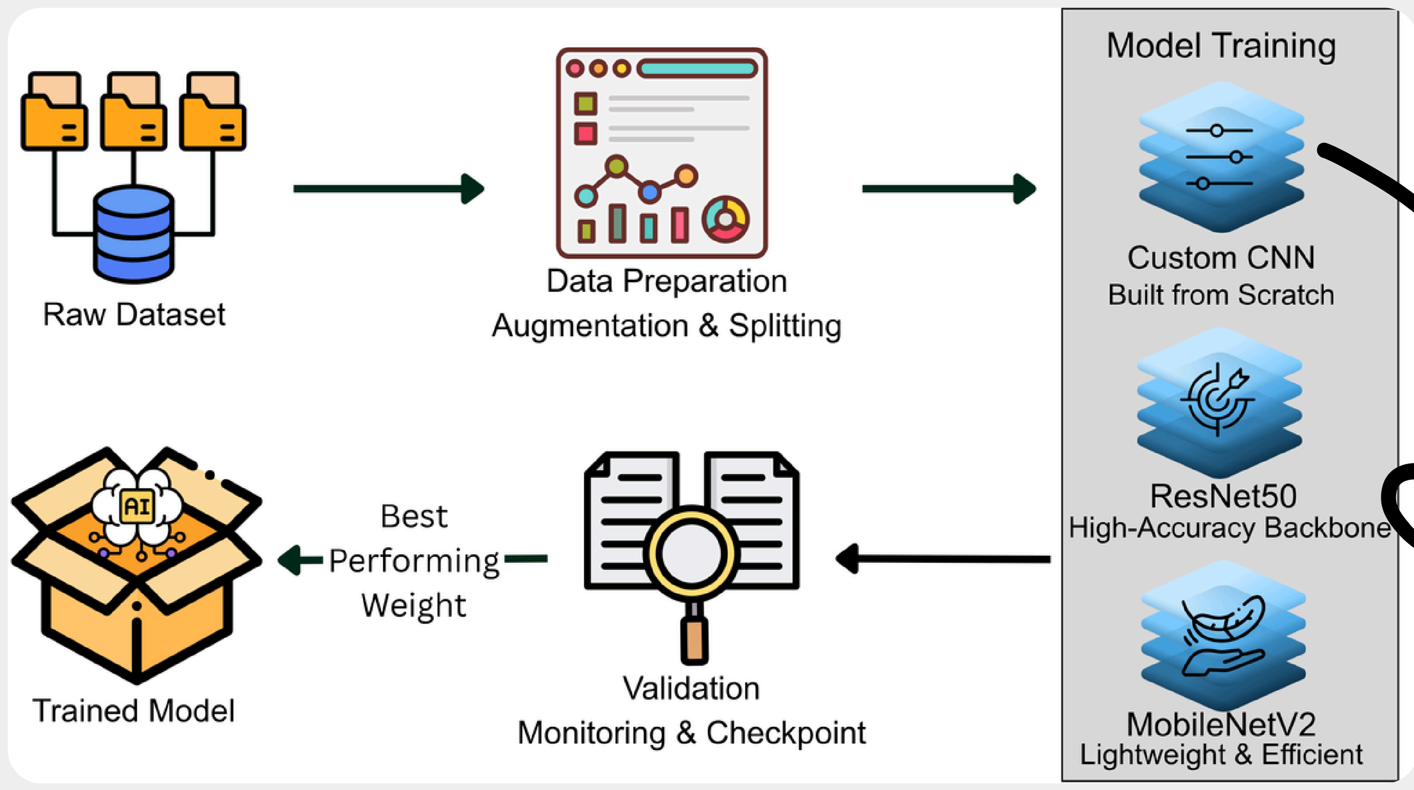


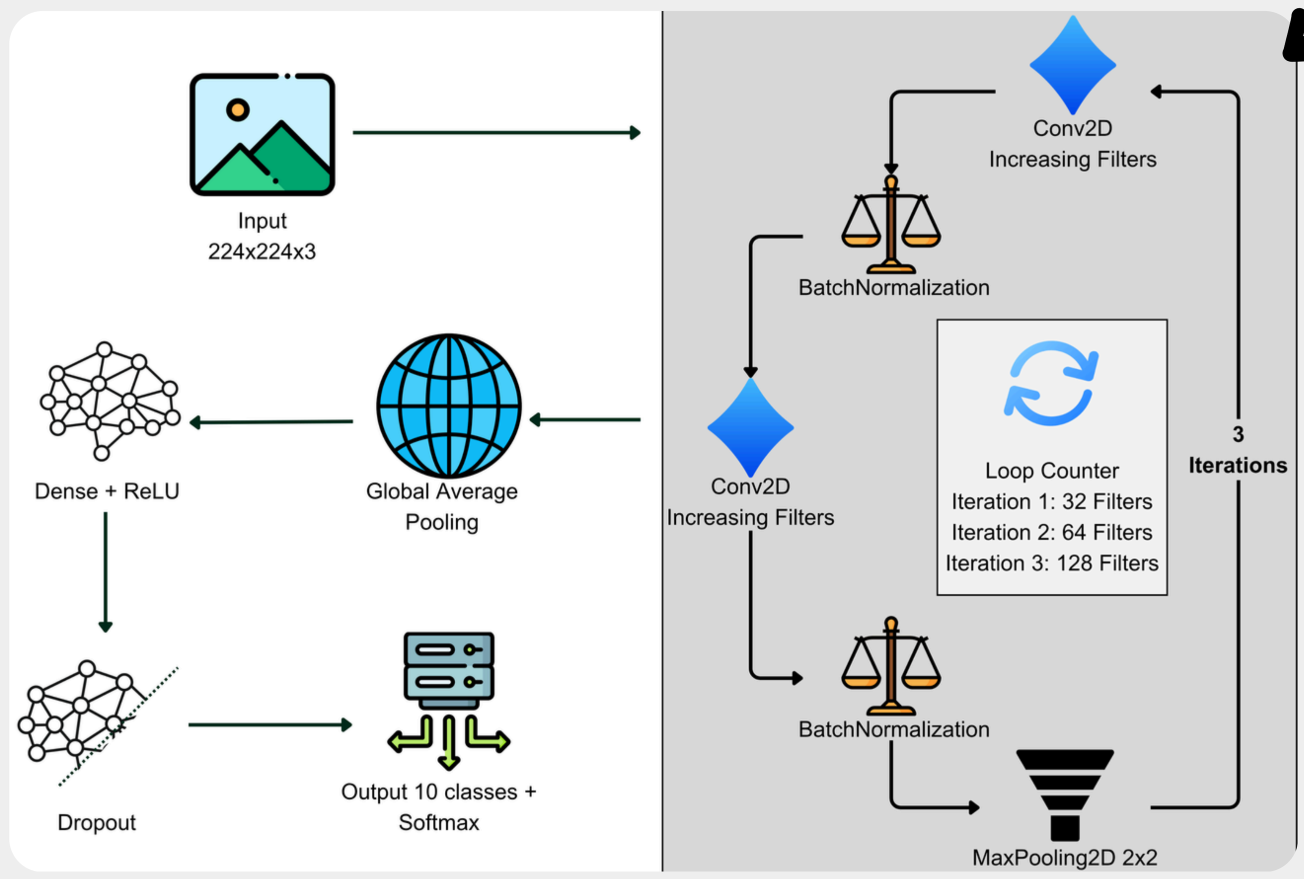
Dataset Statistics:

- Total Images: 19,762
- Data Split: 80% Training, 15% Validation, 5% Testing

MODEL ARCHITECTURE & TRAINING

Our model development followed a systematic workflow:





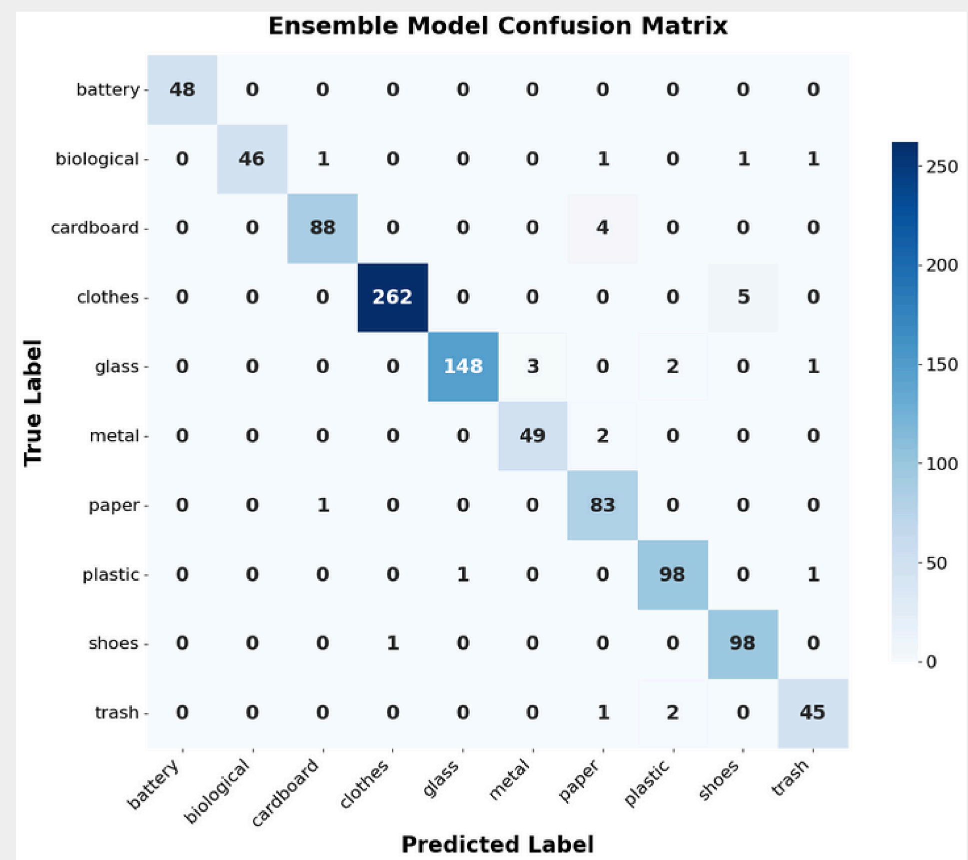
- Conv2D: Feature extraction using 32-128 filters
- BatchNormalization: Stabilizes training by normalizing outputs
- MaxPooling2D: Reduces image size while keeping key features
- Filter Progression: Learns simple edges to complex patterns (32→64→128) using hierarchical feature learning principles (Heaton et al., 2017)
- Global Average Pooling: Summarizes features into fixed vectors
- Dense: Makes classification decisions
- Dropout: Prevents overfitting by disabling 40% of neurons

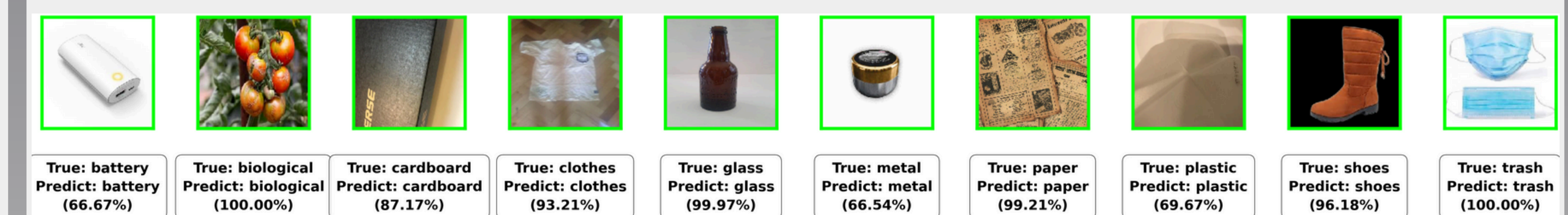
Architecture inspired by breakthrough CNN designs for image classification (Krizhevsky et al., 2012)

RESULTS & EVALUATION

In the evaluation phase, we assessed our ensemble model using confusion matrix analysis and confidence scoring across 10 waste categories. The confusion matrix reveals precise classification with strong diagonal performance and minimal cross-category errors.

Key Insights: Our evaluation shows strong and consistent classification across diverse waste categories, with transparent confidence scoring supporting real-world decision-making.





CONCLUSION

Key Achievements

- ResNet50 achieved the highest accuracy of 97% on the test set
- Real-Time Web Application with user-friendly interface
- Robust Performance across 10 waste categories
- Proven Viability of AI for waste classification tasks

Future Enhancements

- Background Removal for complex image handling
- Mobile Deployment for broader accessibility
- Dataset Expansion with real-world scenarios
- Real-Time Optimization for embedded systems

REFERENCES

Kaza, S. et al. (2018). What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050. Washington DC: The World Bank. https://doi.org/10.1596/978-1-4648-1329-0

Heaton, Jeffrey. (2017). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning: The MIT Press, 2016, 800 pp, ISBN: 0262035618. Genetic Programming and Evolvable Machines. 19. 10.1007/s10710-017-9314-z.

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

For full demo, please open on desktop. Scan the QR code to get the link