

Using Class Activation Maps on Deep Neural Networks to Localise Waste Classifications

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Almost 40% of waste ends up in landfills instead of being recycled



Waste mismanagement is an effect of our decreasing sense of duty



The objective of this study is to alleviate the moral role of waste separation via waste detection



This can be achieved through an automated system such as artificial intelligence (AI)

Introduction



Is it possible for an AI system to be considered as accurate in classifying waste?



Is an AI system able to infer its results efficiently?



Is it possible to utilise specialised techniques such as weak supervision to integrate detection functionality?

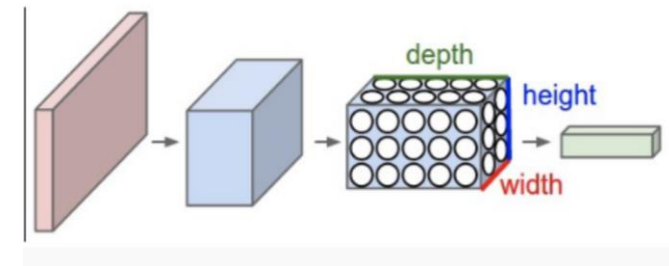
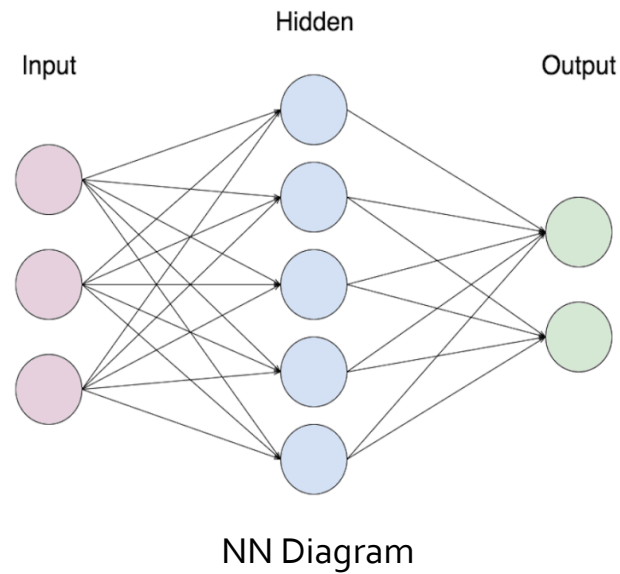
Research Questions

Theory

Machine Learning (ML)
Neural Network (NN)

Deep Learning (DL)
Convolutional Neural
Network (CNN)

Supervision
Supervised Learning
Weakly Supervised
Learning



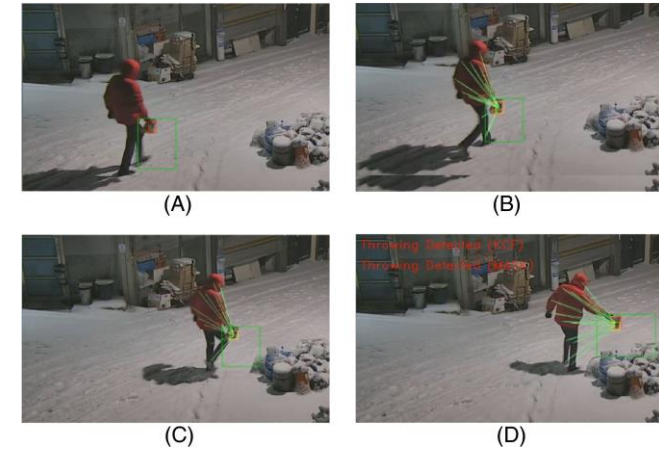
CNN Diagram

Related Works

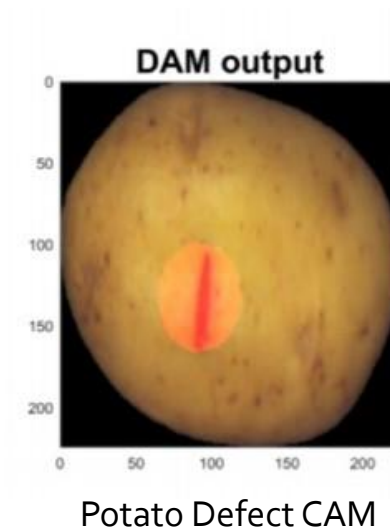
Studies that test deep neural network (DNN) models such as VGG, ResNet, MobileNet and DenseNet on waste classification use cases

Studies that attempt to create viable AI applications for waste management, such as illegal dumping detection and garbage pile marking

Other studies that test possibly useful techniques such as class activation maps (CAM) for weak supervision



Illegal Dumping Detection

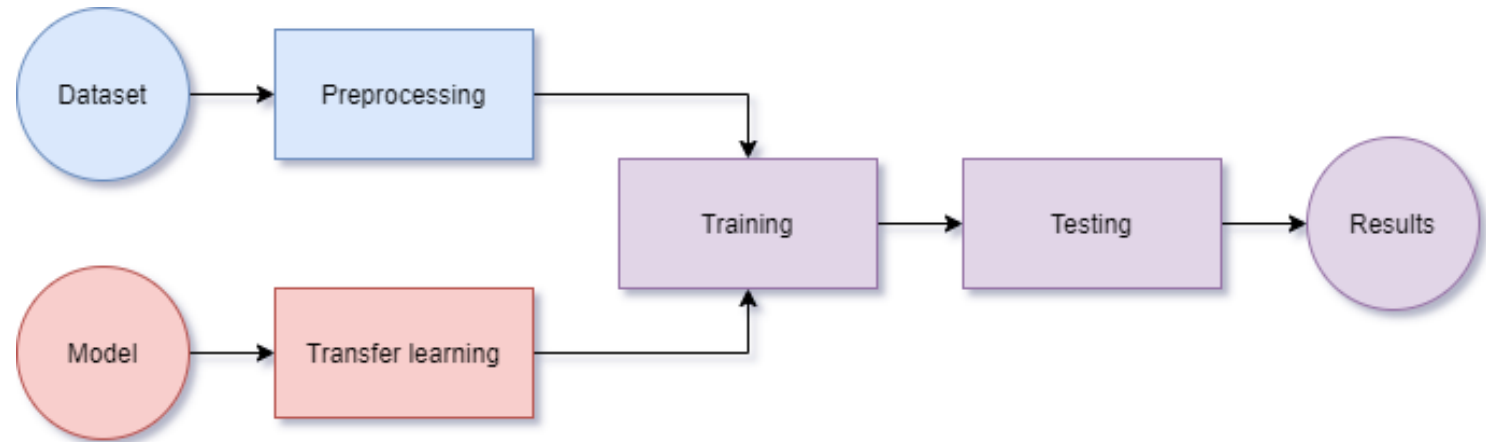


Pipeline

A pipeline inspired from previous studies was created

This was done to streamline the development process

It was also done to allow the existence of multiple configurations which give rise to multiple results





Datasets

TrashNet

Materials in Context
(MINC)



Models

VGG16

ResNet50V2

MobileNetV2

DenseNet121



Fine-tuning

Classifier only

Low-level

High-level

Full re-training



Other techniques

CAMs

Image augmentation

Data splitting

Multiple Configurations

Dataset

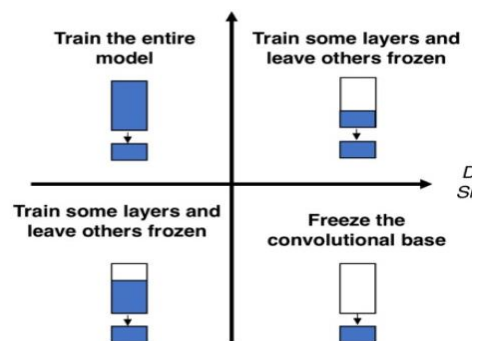
Split into subsets
Pre-process images



TrashNet sample

Model

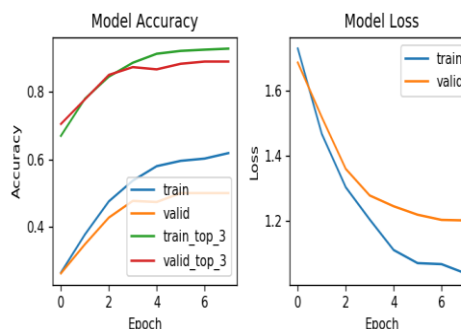
Load weights
Apply sensible fine-tuning



Size-similarity matrix

Train

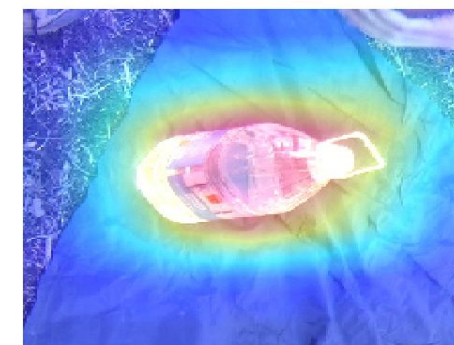
Use stochastic gradient descent (SGD)
Multiple callbacks



Training sample

Test

Process predictions
Create bounding box
CAMs
Generate metrics



MINC CAM sample

Proposed Method

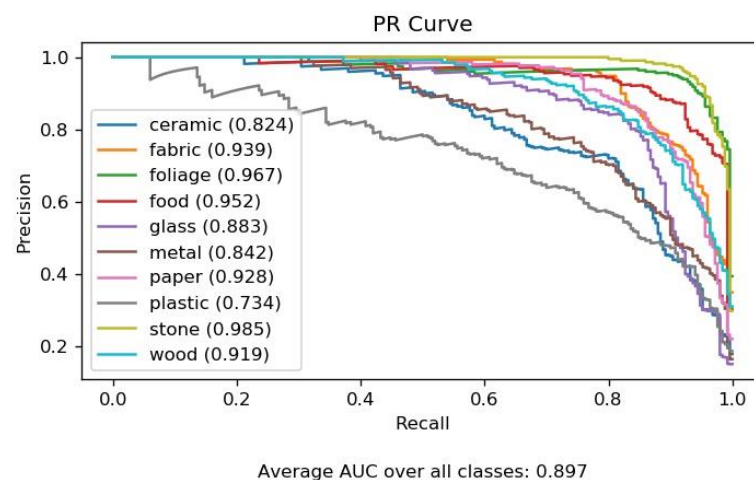
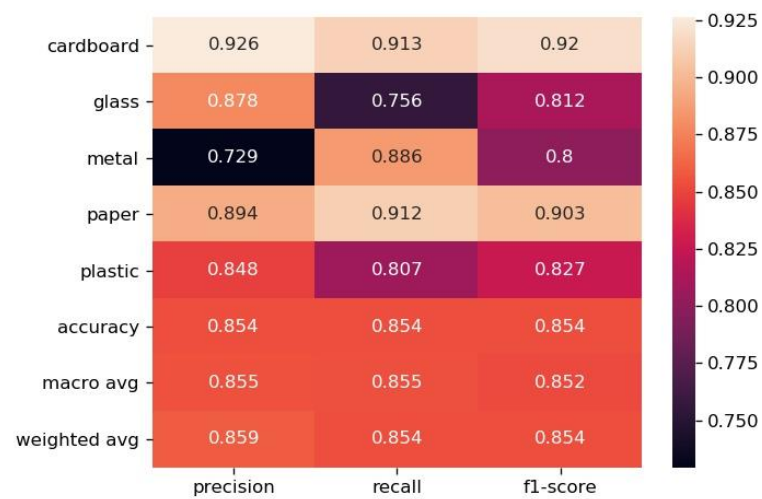
The metrics used were:

F1-score

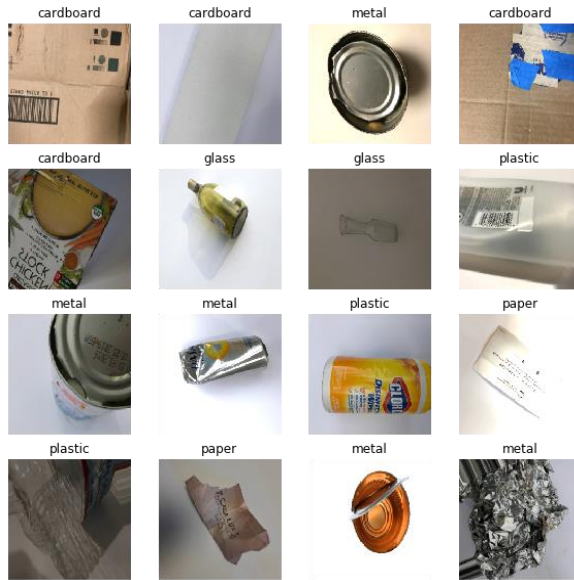
PR-AUC score



Previous studies made use of accuracy, which is not predictive

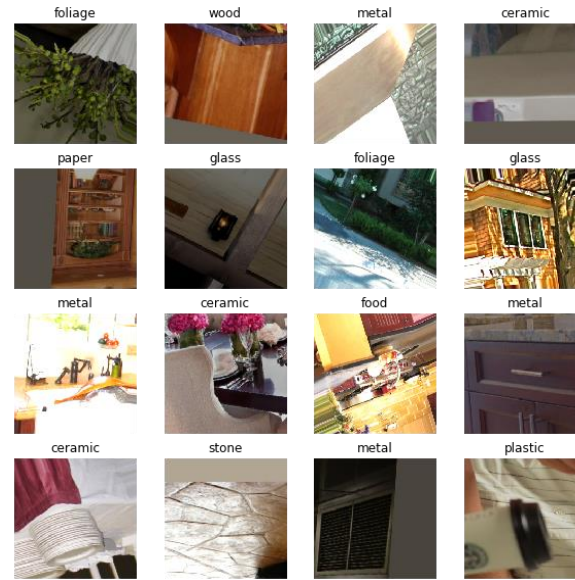


Accuracy Metrics



TrashNet

The **low-level fine-tuned VGG16** model proved to be the most accurate with an **F1-score of 85.4%** and a **PR-AUC score of 93.3%**



MINC

The **fully re-trained DenseNet121** model gained the highest accuracy, by providing an **F1-score of 82.3%** and a **PR-AUC score of 89.7%**

Accuracy Results

Efficiency Metrics

The metrics used were:

Average prediction and
localisation time

Model weights file size



Not many previous studies used this
method



MobileNetV2 proved to be the most efficient algorithm



It gained over 10 frames per second (FPS) in speed



While maintaining under 10 megabytes (Mb) in size



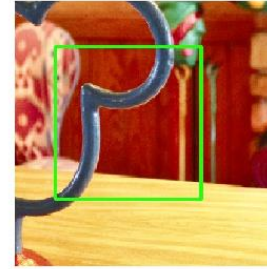
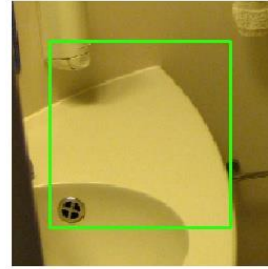
Despite not being the most accurate, it provided an F1-score of around 77% when fully re-trained on MINC



If efficiency is a priority and a large dataset is available, MobileNetV2 is a solid choice

Efficiency Results

Localisation Metrics



Survey Bounding Box Samples

No ground truth bounding boxes existed for localisation

A survey was created to use a human benchmark as an evaluation method

15 images were chosen from the best models to represent each category from both datasets

Localisation Results

The low-level fine-tuned VGG16 trained on TrashNet obtained **83.2%** localisation accuracy

While the re-trained DenseNet121 MINC model gained **68.5%** localisation accuracy

Furthermore, it was found that the participants were confused with MINC, which is why it gained such a lower score

Considering that no ground truth was available, both models provided positive results



It can be safely said that the objective was reached as accuracy, efficiency and localisation results proved to be positive



Improvements include applying more thorough fine-tuning methods and attempting techniques such as k-fold cross validation



Future work could also be undertaken by integrating video functionality and migrating the prototype to an embedded system

Results Review

Research Paper



Since more work is planned on being done, a research paper was made



This was done as to prepare the study for SAMI 2021



This will provide a medium for the improvements and further work to be implemented

The End