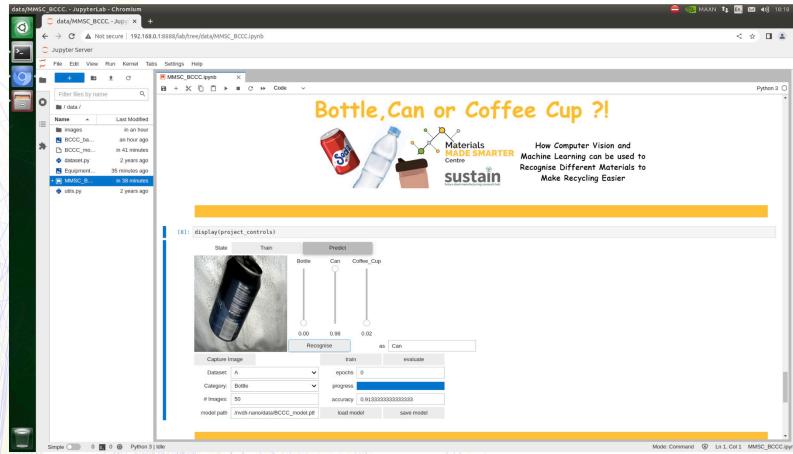


## 04 Training for Different Materials



By using an existing **transferred model**, already trained to recognise general **features** in an image, only the **final layer** of the network needs to be re-trained on the specific task required.

In this demonstration the final layer is trained to recognise the difference between a **bottle**, **can** or **coffee cup**; initially using 50 images of examples of each object. On pressing the **Recognise** button, the system makes a prediction of the likelihood that the image it sees belongs to each category from its training data, and the most likely category is used as the identification. Here you can investigate how well the identification works, **re-train** on other examples of the objects and learn how to improve the **performance** by including more **training images** or more **training epochs**. Or, if you delve into the Python code, you can even try using different transfer models!

**Instructions** on how to use the demonstration and **glossary** of the highlighted **technical terms** are available at Discover Materials by scanning the QR code on the front...

# Bottle, Can or Coffee Cup ?!



How Computer Vision and Machine Learning  
can be used to Recognise Different  
Materials to Make Recycling Easier



## Introduction

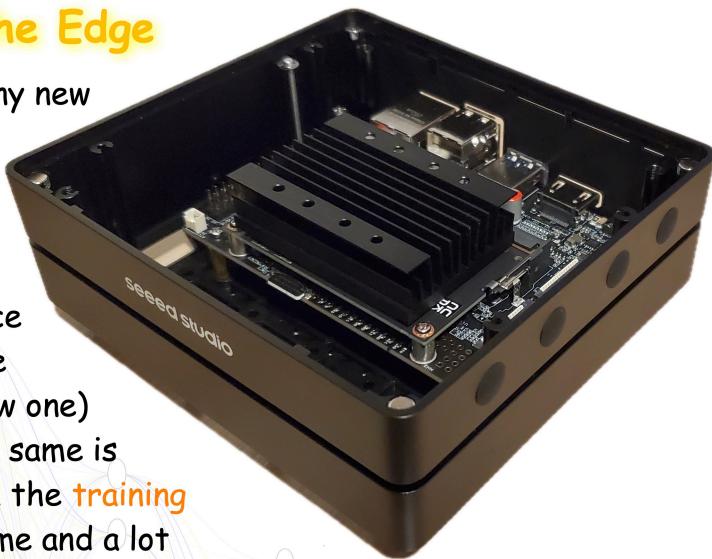
In the past, the sorting of materials for recycling has been performed by people - who observe the objects as they pass by on a very fast-moving conveyor belt, and make quick decisions about which bin to push the objects into. This is a very tiring and unpleasant job, if you have ever tried to watch the nearby scenery go past whilst travelling in a car, bus or train then you can imagine how tiring and damaging to the eyes this work is. As the amount of recycling increases, the speed it must be processed at increases, and soon no human will be able to cope.

This is exactly the type of work **Machine Learning** and **Computer Vision** can help with. This project also demonstrates how, with modern advances in hardware, the task no longer requires large expensive computer systems and can be performed by modest, low-powered, **edge-computing** devices which are cheap enough to enable hundreds of independent **smart sensors**, close to the action, each performing a specific task. This project is divided into four sections. Further information about each section can be found by scanning the QR code...



## 01 Computing on the Edge

The process of learning any new skill, like riding a bike, takes a lot of time and effort, but once your brain has learnt all the tiny corrections-to-balance that it needs, you can ride any bike (even a brand-new one) almost straight away. The same is true when **machines learn**, the **training** of a model takes a long time and a lot of computing power, but once trained, the process of **prediction**, or **inference**, takes much less effort and can be performed in **real-time** with only a relatively modest computing platform.



## 02 Working with Limited Resources

When using computing platforms with limited resources it is common to have multiple units and dedicate one task to each unit.



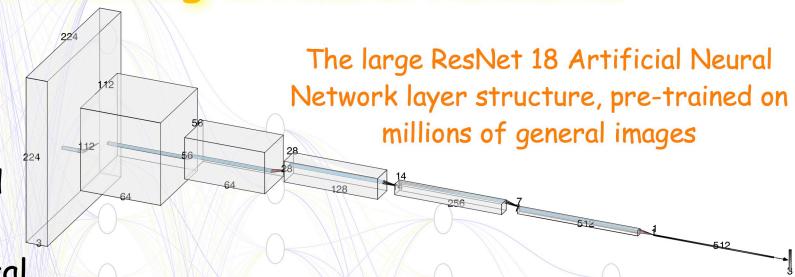
By pairing multiple units together many tasks can be completed at the same time. This technique is used even for the **multi-core** processors of an expensive smartphone or the many **nodes** that make up the large supercomputers in today's **High Performance Computing** data-centres. Sharing the task into many smaller parts, which can be carried

This demonstration is built on two NVIDIA Jetson Nano 2GB based Seeed Studio reComputer J1010s each with an Arm Cortex A57 CPU and NVIDIA Maxwell GPU

out at the same time as each other (in parallel) makes the whole process much faster. Like having many different people, with different specialist skills, work on setting up a concert, instead of just the musician. The key is managing the communication and timing between the different components and communicating only the limited information that is necessary.

## 03 Machine Learning & Neural Networks

The human brain is a web of ~ 86 billion interconnected **neurons** which collect electrical impulse signals of different **weights**, or importance, and send on a signal only once a sufficient **bias** charge has been reached.



The large ResNet 18 Artificial Neural Network layer structure, pre-trained on millions of general images

Artificial versions of these neural networks were first developed in the 1940s, but it is only in the last decade that computers have become powerful enough to simulate the millions of neurons needed to make them useful. The networks are trained by **optimising**, over thousands of examples, the billions of **weight** and **bias** values in a process called **back-propagation** so that particular **inputs** map correctly through the network to chosen learnt **outputs**. Much of the heavy work of training for computer vision problems can be short-cut by **transfer learning** - using large general-purpose models such as **ResNet 18**, that have already been trained on millions of images, to first extract the general **features** of objects in an image.

Further information on each section and a **glossary** of the **highlighted technical terms** are available at Discover Materials by scanning the QR code...



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