EcoSort: A Deep Learning Approach to Waste Segregation and Recycling

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Abstract

Ghana, like many other countries, faces a significant environmental challenge of plastic waste management.

According to the United Nations Development Programme (UNDP), Ghana produces 1.7 million tonnes of plastic waste each year, yet only a small percentage of this waste is recycled. This low recycling rate can be attributed to insufficient investment in the sector by both the government and private sector, as well as limited capacity within the recycling industry. The management of plastic waste in Ghana is a pressing issue that requires action to address its negative impacts on the environment and public health.

PROBLEM IDENTIFICATION

The Kpone community in the Greater Accra Region of Ghana is one of the many communities that suffer from lack of waste management resources.

The problem of lack of segregation of waste in the Kpone community is a significant issue that needs to be addressed. In this community, there is a lack of proper infrastructure and facilities for the segregation of waste, which leads to the mixing of different types of waste. This results in the contamination of recyclable materials, which makes it difficult to properly dispose of or recycle the waste. Additionally, the lack of segregation of waste leads to increased environmental pollution, as mixed waste is often not properly disposed of and ends up in landfills or in the natural environment. This problem has negative impacts on both the local community and the wider environment and needs to be addressed through the implementation of effective waste segregation and management practices.

Furthermore, the lack of segregation of waste in the Kpone community can have negative impacts on public health. When waste is not properly managed and disposed of, it can attract pests and vermin, which can carry diseases and pose a risk to human health. In addition, the presence of mixed waste can create unpleasant odors and unsanitary conditions, which can affect the quality of life for community members. The lack of segregation of waste can also contribute to the overloading of landfills, which can lead to environmental degradation and further negative impacts on the local community and the wider environment. It is therefore important that steps are taken to address this issue and implement effective waste segregation and management practices in the Kpone community.

Images of unsegregated waste in the Kpone community

Proposed Solution

My approach to solve this problem was by creating a convolutional neural network in TensorFlow and using a raspberry pi, camera, motors, bins to segment the waste (plastic and metal waste) into two different bins.

The raspberry pi will be powered via solar energy and the bins will be placed at vantage points in the community. When the waste is dropped in the bin, an ultrasonic sensor detects it and this activates the raspberry pi camera to take a picture of the waste which is then processed to determine the type of waste. The classified waste is then moved into the respect compartment of the bin via motors which enable the movement. The neural network was trained largely on only image data of plastics and metals. I trained the neural network with image data I took pictures of and also gathered from Kaggle.

TOOLS USED FOR THIS PROJECT:

Software

Python **TensorFlow** **Keras**

NumPy **Matplotlib** **OpenCV**

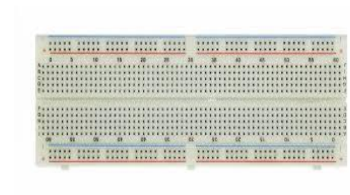
Hardware



Raspberry Pi **Raspberry Pi Camera** **H Bridge Motor Driver**
L298N

Ultrasonic Sensor

Resistors



Breadboard

Servo Motors

Male To Female Jumper Wires

Bins

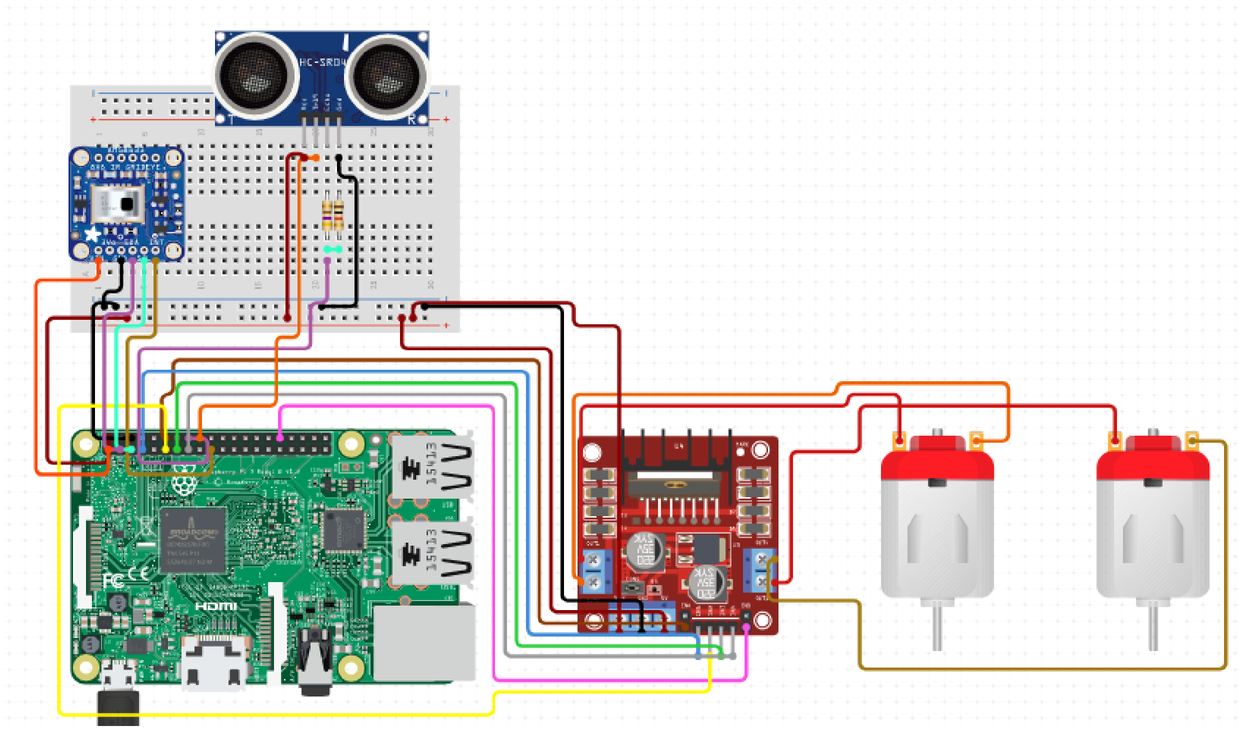
A convolutional neural network (CNN) is a type of artificial neural network specifically designed to process data that has a grid-like structure, such as an image. CNNs are composed of multiple layers of interconnected nodes, which process and analyze the data as it passes through the network. The layers of a CNN typically include:

Convolutional layers: These layers apply a series of filters to the input data, which extract features such as edges, lines, and shapes.

Pooling layers: These layers reduce the size of the data by taking the maximum or average value within a set of adjacent units. This helps to reduce the computational cost and make the network more robust to small variations in the input data.

Fully connected layers: These layers are similar to the layers in a traditional neural network and are used to make predictions or classify the input data based on the features extracted by the convolutional and pooling layers.

Below is my proposed circuit for the description above.



The convolutional neural network (CNN) classifies images of plastic and metal. The images are first read and converted to grayscale arrays. Then they are resized to a fixed size of 32x32 pixels. The training data is created by iterating over the images in the 'plastic' and 'metal' directories and adding each image's array and its corresponding label (0 for plastic and 1 for metal) to a list called training data. The create_training_data function shuffles the list and saves it as a NumPy array. The code then separates the labels and the image data into separate lists, X and y, respectively. The image data is then normalized by dividing by 255.0 to scale the pixel values between 0 and 1.
The code then defines some lists of hyperparameters for the CNN model: dense_layers, layer_sizes, and conv_layers. These lists are used in a loop to create different versions of the CNN model with different numbers of dense layers, layer sizes, and convolutional layers. The model consists of a series of convolutional layers, each followed by an activation function, a max pooling layer, and a dropout

layer. These layers extract features from the input images and reduce their size. The extracted features are then flattened and passed through a series of dense layers, each followed by an activation function, to make the final classification. The model is compiled with the Adam optimization algorithm and the binary cross-entropy loss function and is trained on the training data using a batch size of 32 and 10 epochs. The model's performance is evaluated on the test data and the results are logged using TensorBoard.

I fed the convolutional neural network with image data I took pictures of and collected from kaggle.com

After 100 epochs, I had a loss of 0.0049 and an accuracy of approximately 100%.

```
Epoch 90/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0137 - accuracy: 0.9945 -
val_loss: 1.3225 - val_accuracy: 0.7712
Epoch 91/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0050 - accuracy: 1.0000 -
val_loss: 1.6925 - val_accuracy: 0.7669
Epoch 92/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.1201 - accuracy: 0.9672 -
val_loss: 1.0857 - val_accuracy: 0.7754
Epoch 93/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0567 - accuracy: 0.9836 -
val_loss: 0.9188 - val_accuracy: 0.7839
Epoch 94/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0655 - accuracy: 0.9854 -
val_loss: 0.9379 - val_accuracy: 0.7542
Epoch 95/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0302 - accuracy: 0.9891 -
val_loss: 1.0850 - val_accuracy: 0.7415
Epoch 96/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0187 - accuracy: 0.9872 -
val_loss: 1.1539 - val_accuracy: 0.7712
Epoch 97/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0226 - accuracy: 0.9927 -
val_loss: 1.2159 - val_accuracy: 0.7585
Epoch 98/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0035 - accuracy: 1.0000 -
val_loss: 1.2974 - val_accuracy: 0.7754
Epoch 99/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0057 - accuracy: 0.9982 -
val_loss: 1.2436 - val_accuracy: 0.7881
Epoch 100/100
548/548 [==============================] - 4s 7ms/sample - loss: 0.0049 - accuracy: 1.0000 -
val_loss: 1.2619 - val_accuracy: 0.7754
0.99998486
```

This graph shows how my model performed over the span of 100 epochs which lasted for about 7 minutes.

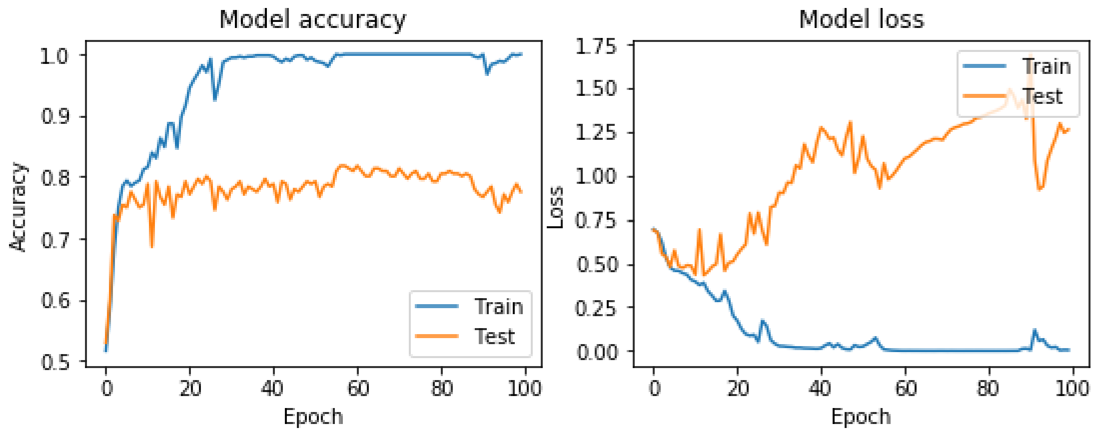


Figure 3.5: Graphs showing the accuracy and loss of my machine learning model over the span of 100 epochs

These were some sample predictions my model made

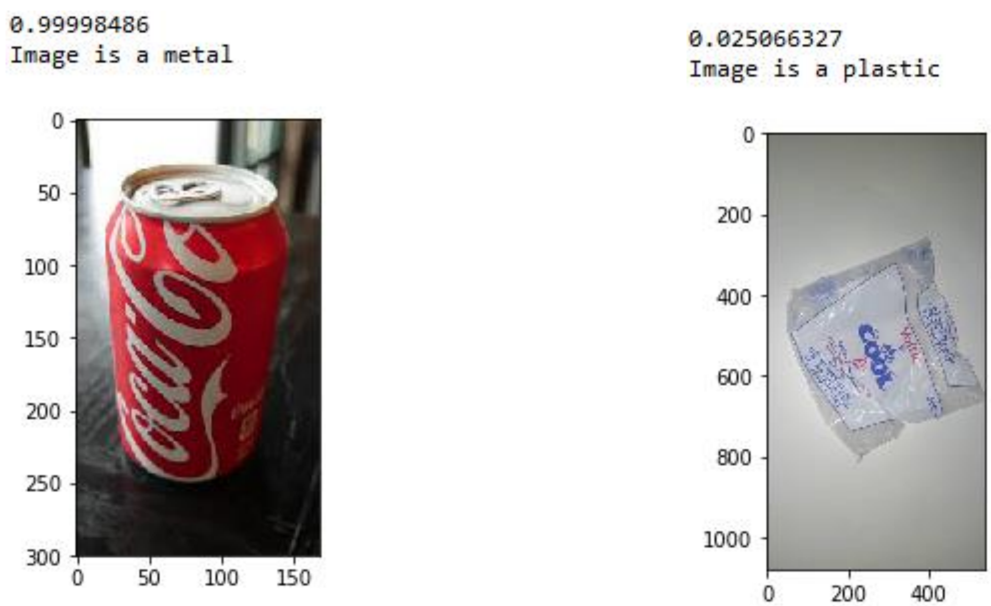
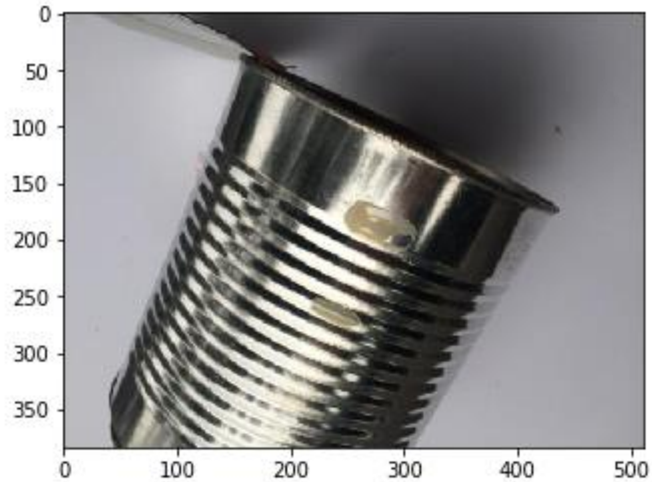
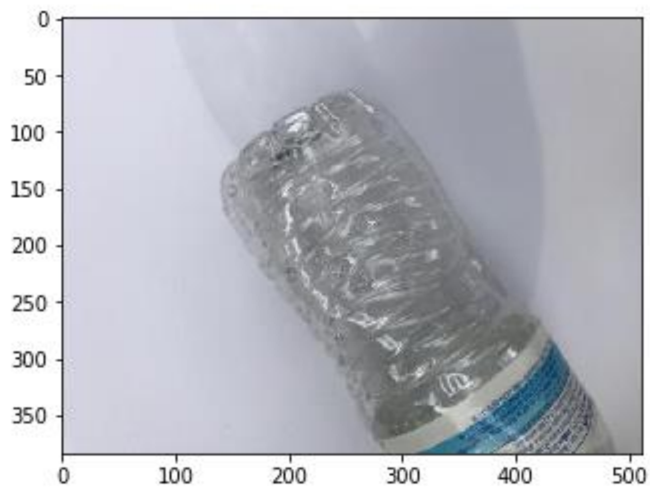


Figure 3.6: Results of my machine learning model

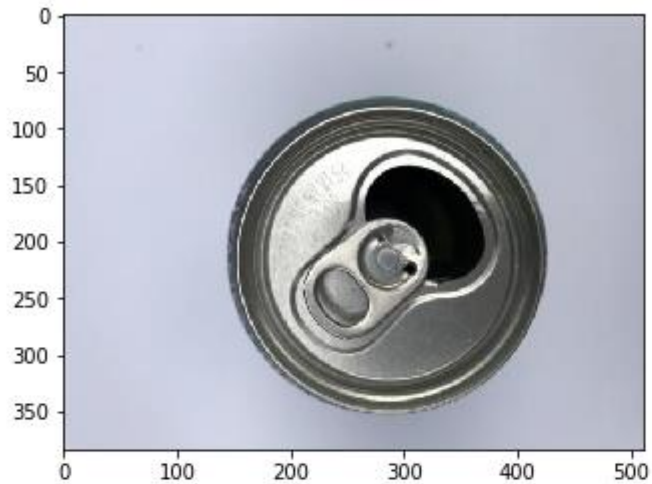
```
0.99999917
Image is a metal
```



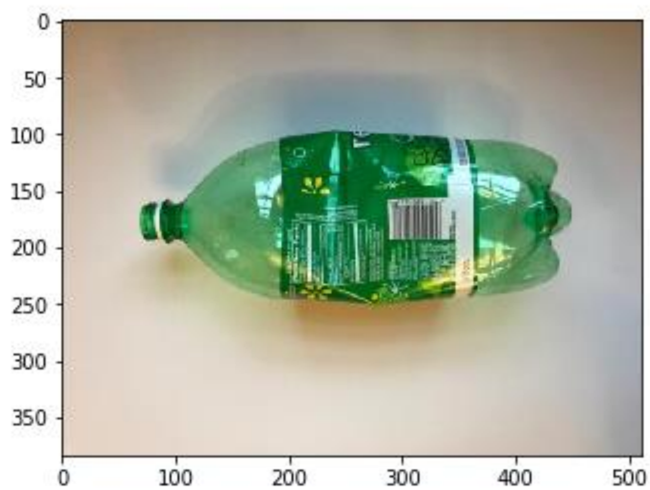

```
0.00432899
Image is a plastic
```



```
1.0
Image is a metal
```



```
0.06737176
Image is a plastic
```



After segregation, it then becomes easier for the waste to be recycled.

CONCLUSION

In conclusion, the use of convolutional neural networks for segregation of waste for recycling in the Kpone community has the potential to greatly improve the efficiency and accuracy of waste segregation efforts.
By using machine learning algorithms to analyze and classify waste items, the system can accurately identify and sort recyclable materials, leading to a more efficient and effective recycling process.
This not only benefits the environment by reducing the amount of waste that ends up in landfills, but it also has the potential to create economic benefits for the community by reducing the cost of waste management and potentially generate revenue through the sale of recycled materials.
Overall, the integration of convolutional neural networks into waste segregation efforts in the Kpone community is a promising step towards a more sustainable and resource-efficient future.

RECOMMENDATION

For the problem of lack of segregation of waste to be properly tackled in the Kpone community, authorities should invest in my idea to place bins equipped with the technologies described to segregate waste which can then be recycled.

REFERENCES

1. https://www.tensorflow.org/tutorials/images/cnn
2. https://towardsdatascience.com/build-your-own-convolution-neural-network-in-5-mins-4217c2cf964f

Final words

As technology and artificial intelligence become increasingly prevalent in our lives, machine learning will continue to be a vital field. From facial recognition to self-driving cars and even the algorithms used by social media networks, machine learning has played a role in many groundbreaking developments. Unfortunately, Africa was left out of the industrial revolution and is now lagging behind in technological progress as well. A lack of skilled individuals in technology and computer science has held back Africa's development in this area.

However, I have a dream for Africa to become a leader in technology and go head-to-head with the technological giants of the world. By accelerating the development of technology in Africa, we can turn it into the Silicon Valley of the world and bring about much-needed progress and prosperity for the continent.