Applications of various convolutional neural networks for sorting different types of waste

Shelkova Darya,
Bauman Moscow State Technical University
Russia, Moscow
daryashelkova0@gmail.com

Abstract

With the development of artificial intelligence, we have new opportunities to preserve the environment. One such opportunity is more efficient waste sorting. By using machine learning algorithms and sensor technologies, we can automate the process of waste sorting and reduce the number of errors. But not only technology can help us become more environmentally responsible. The Internet provides us with access to information on how to correctly sort waste and which materials can be recycled. In this article, we will explore how the use of the Internet can help us become more environmentally conscious and reduce the negative impact of our activities on nature.

***K*eywords** Garbage sorting · Neural networks · VGG · Resnet50 · Googlenet

1 Introduction

Waste sorting is crucial for achieving a more sustainable future, as it reduces the amount of waste sent to landfills and promotes the recovery of valuable resources. The use of convolutional neural networks in waste sorting can improve its accuracy and efficiency, making it a more effective solution for waste management. According to a study by the European Commission [1], advanced technologies like AI can increase the purity of sorted waste by up to 95%, leading to higher recycling rates and reduced environmental impact. By promoting waste sorting and investing in advanced technologies, we can create a circular economy that benefits both the environment and the economy.

Additionally, waste sorting has been shown to have significant economic benefits. According to a report by the Ellen MacArthur Foundation [2], a circular economy that includes waste sorting and recycling could generate 700 billion dollars in economic benefits globally by 2025. This includes cost savings from reduced waste disposal and the creation of new business opportunities and jobs in the recycling industry.

Governments around the world are recognizing the importance of waste sorting and implementing policies to promote it. For example, in the European Union, the Waste Framework Directive [1] sets out a hierarchy of waste management options, with waste prevention and recycling at the top. Many countries have also introduced extended producer responsibility schemes, where manufacturers are responsible for the disposal of their products at the end of their life cycle.

Overall, waste sorting is a critical component of a sustainable future. By investing in advanced technologies and promoting active participation from individuals and communities, we can create a circular economy that benefits both the environment and the economy.

2 Features of the selected convolutional neural networks

2.1 ResNet50

Features of the network ResNet50 due to which it was chosen to complete the task:

- Skip connections to mitigate the vanishing gradient problem and improve training quality.

- Use of 1x1 convolutions to reduce network parameters and computational complexity.
- Use of 3x3 convolutions and max pooling to reduce image dimensionality and extract features.
- Batch normalization for stabilizing feature distributions and accelerating training.
- ReLU activation function for faster training and reduced vanishing gradient effect.
- Data augmentation to improve training quality and prevent overfitting.
- Use of the Adam optimization algorithm for fast and efficient network training.

The ResNet50 network can be chosen for image classification because of its deep architecture with 50 layers, residual connections that allow for better gradient flow and easier training, and state-of-the-art performance on various image classification benchmarks.[3]

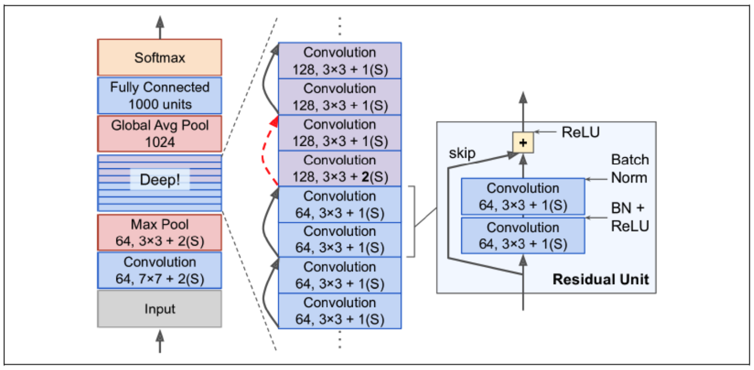

Figure 1: Resnet50 network architecture.

2.2 VGG

Features of the network VGG due to which it was chosen to complete the task:

- Deep architecture with up to 19 layers
- Small 3x3 convolutional filters
- Ability to learn complex features and patterns
- Simple and uniform structure.

VGG network can be chosen for image classification due to its deep architecture [4]

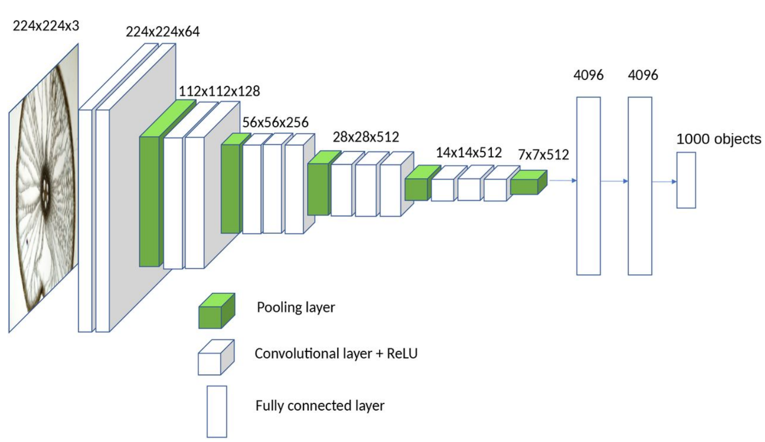

Figure 2: VGG network architecture.

2.3 GoogLeNet

Features of the network GoogLeNet due to which it was chosen to complete the task:

- Inception modules: GoogLeNet uses inception modules which are designed to efficiently capture features at different spatial scales.
- Deep architecture: The network has 22 layers, making it deeper than previous models.
- Global average pooling: Instead of using fully connected layers, GoogLeNet uses global average pooling which reduces the number of parameters and helps prevent overfitting.
- Auxiliary classifiers: The network has two auxiliary classifiers that help with training and improve performance.
- State-of-the-art performance: GoogLeNet achieved state-of-the-art performance on the ImageNet Large Scale Visual Recognition Challenge in 2014.

GoogLeNet is a good choice for image classification due to its use of inception modules, deep architecture, global average pooling, auxiliary classifiers. [5]

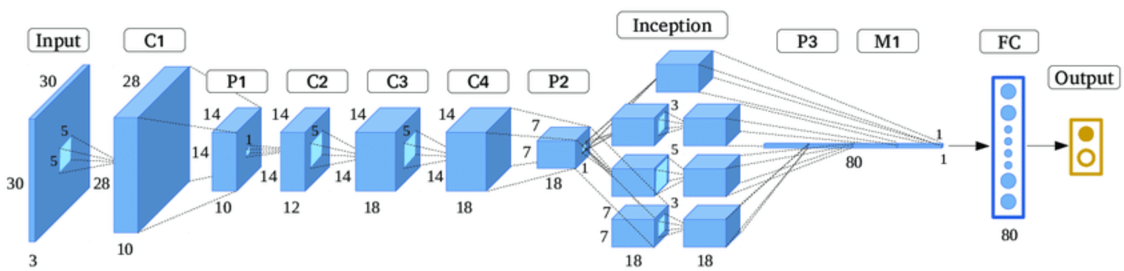

Figure 3: GoogLeNet network architecture.

3 Related Work

4 Methods

To conduct the study, a publicly available (from open sources) Garbage Classification garbage imagery dataset was taken from the Kaggle website. This dataset contains an image section of 5 garbage types.

4.1 Classify photos of garbage

To classify photos of garbage using the network, follow these steps:

1. Collect a dataset of images of garbage in various forms and conditions.
2. Preprocess the images by resizing them to a standard size and normalizing the pixel values.
3. Split the dataset into training, validation, and testing sets.
4. Load the model and its pre-trained weights.
5. Add a new fully connected layer to the model for classification.
6. Train the model using the training set and validate it using the validation set.
7. Fine-tune the model by adjusting the hyperparameters and optimizing the loss function.
8. Test the model on the testing set and evaluate its accuracy and performance.
9. Use the model to classify new images of garbage by feeding them into the trained network and interpreting the output probabilities as the likelihood of each class.

4.2 Accuracy obtained using the network Resnet50

Like any other deep learning model, the accuracy of ResNet50 depends on the specific task it is applied to, as well as the quality of the data it is trained on.

Overall, however, ResNet50 is considered one of the most accurate models for image classification. For example, on the ImageNet dataset, which contains more than 1 million images from 1000 different classes, ResNet50 shows an accuracy of around 75-80

In addition, ResNet50 also performs well in other computer vision tasks such as object detection and image segmentation. In general, the use of ResNet50 can significantly increase the accuracy of the model and improve its ability to recognize and classify images. Resnet50 accuracy was 96% at 5 epochs.

4.3 Accuracy obtained using the network VGG

The accuracy of using VGG in image classification also depends on the specific task and data quality. However, like ResNet50, VGG is considered to be a very accurate model for image classification.

On the ImageNet dataset, VGG demonstrates an accuracy of around 70-75%, which is also a high indicator. In addition, VGG also performs well in other computer vision tasks such as object detection and image segmentation.

In general, the use of VGG can significantly increase the accuracy of a model and improve its ability to recognize and classify images. However, ResNet50 performed better than VGG in my study. VGG accuracy was 85% at 8 epochs.

4.4 Accuracy obtained using the network GoogLeNet

The accuracy of using GoogLeNet in image classification also depends on the specific task and the quality of the data. However, like VGG and ResNet50, GoogLeNet is considered to be a very accurate model for image classification.

On the ImageNet dataset, GoogLeNet, like VGG, demonstrates an accuracy in the region of 70-75%. In addition, GoogLeNet also performs well in other classification tasks. In my study, GoogLeNet showed greater accuracy than VGG, but less than ResNet50 VGG accuracy was 89% at 7 epochs.

5 Graphs

5.1 Graphs of accuracy versus number of epochs

Below are the graphs for each Convolutional Neural Network

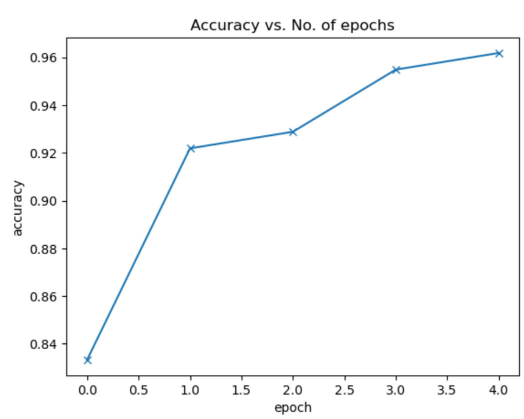

Figure 4: Resnet50 accuracy.

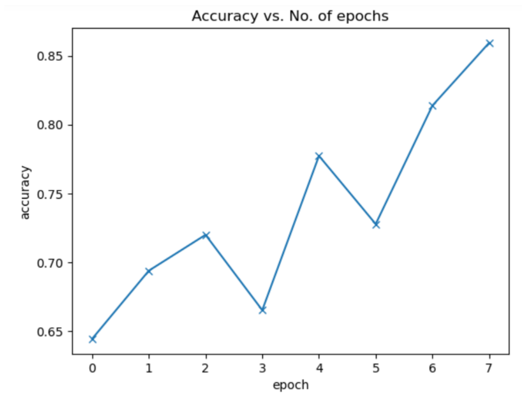

Figure 5: VGG accuracy.

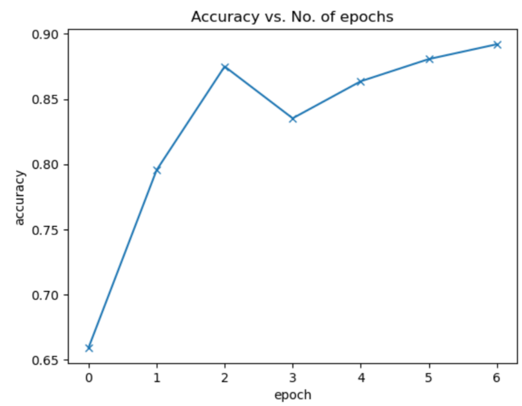

Figure 6: GoogLeNet accuracy.

5.2 Graphs of accuracy versus number of epochs

Below are the dependences of the losses of the training set and validation set on the number of epochs for each Convolutional Neural Network

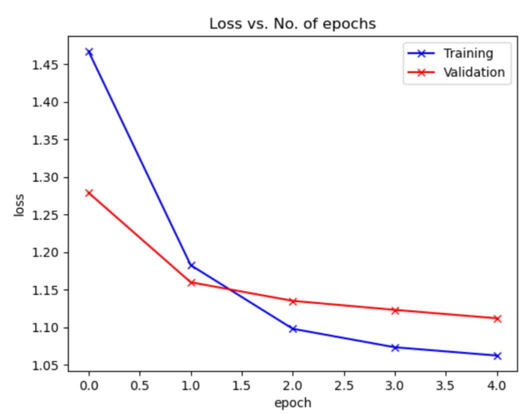

Figure 7: Resnet50 accuracy.

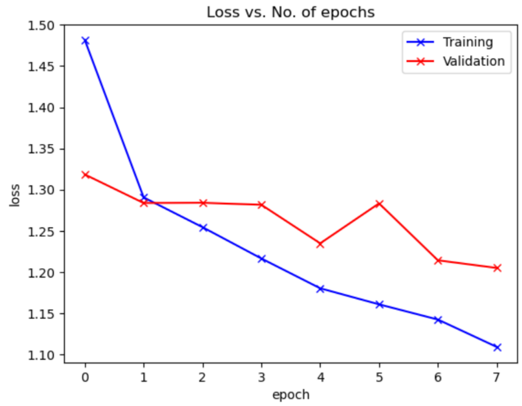

Figure 8: VGG accuracy.

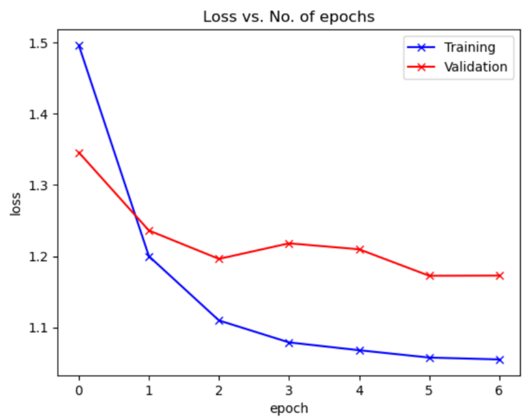

Figure 9: GoogLeNet accuracy.

6 Comparison of all obtained results

The solution of the project described in this article is presented on the open source platform GitHub in the public repository at the link:

`https://github.com/Nuzuret/OgoDZ`

References

[1] Regulation of the european parliament and of the council. *Official Journal of the European Union*, (20/1), 2022.

[2] World Economic Forum. *Ellen MacArthur Foundation and McKinsey Company, The New Plastics Economy: Rethinking the Future of Plastics*, 120:24–44, 2016.

[3] Zhangshangjie Ge Hongbo Mu Dawei Qi Ruolei Zhang, Yijun Zhu and Haiming Ni. Transfer Learning for Leaf Small Dataset Using Improved ResNet50 Network with Mixed Activation Functions. *Forests*, 2072(13):40–47, 2022.

[4] Andrew Zisserman Karen Simonyan. Very deep convolutional networks for large-scale image recognition. *Visual Geometry Group, Department of Engineering Science, University of Oxford*, 14, 2015.

[5] Yangqing Jia Pierre Sermanet Scott Reed Dragomir Anguelov Dumitru Erhan Vincent Vanhoucke Andrew Rabinovich MChristian Szegedy, Wei Liu. Going Deeper with Convolutions. *CVF*, 2015.