International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 01 | January - 2023 Impact Factor: 7.185 ISSN: 2582-3930

WASTE CLASSIFICATION USING RESNET-152

Vijay Gadre[1], Sanika Sashte[2], Apoorva Sarnaik[3]

[1,3]*Student, Dept. of Electronics and Telecommunication Engineering, PICT, Maharashtra, India*
[2]*Student, Dept. of Electronics and Telecommunication Engineering, AISSMS-COE, Maharashtra, India*

---***---

Abstract - Waste classification is the process of identifying and separating different types of waste materials based on their characteristics, such as composition, size, and shape. Accurate waste classification is important for efficient waste management and resource recovery, as it allows for the proper disposal or reuse of waste materials. One method for automated waste classification is the use of deep learning algorithms, such as the ResNet-152 model. ResNet-152 is a convolutional neural network (CNN) that has been trained on a large dataset of images and is able to classify objects in images with high accuracy. By applying ResNet-152 to images of waste materials, it is possible to classify the materials into different categories, such as paper, plastic, or metal. This can be done in real-time using computer vision techniques and can significantly improve the efficiency and accuracy of waste classification processes. However, the success of waste classification using ResNet-152 or other CNNs depends on the quality and diversity of the training data, as well as the availability of computational resources and infrastructure.

Key Words: Computer Vision, Deep Learning, Transfer Learning, ResNet-152, Waste Management.

1. INTRODUCTION

The accumulation of non-recyclable waste in landfills is a significant threat to our lifestyle and health. It can cause a range of negative impacts, including disease transmission through vectors, destruction of natural ecosystems, soil and water contamination, and disruptions to the food chain leading to increased illnesses. If we do not take action to prevent it, the accumulation of waste and its lengthy period of biodegradation will have a substantial impact on our lives shortly.

There are three main reasons why the accumulation of trash has become a more serious concern in recent decades. The first is the lack of recyclable products in the market, despite the existence of more sustainable and environmentally friendly options. The second is overpopulation, which leads to complex logistics challenges in managing trash generation and an increase in the percentage of recyclable products ending up in landfills or the ocean. The third reason is a lack of societal participation in issues such as climate change.

The global population produces between 7 and 9 billion tonnes of waste per year, of which 70% is mismanaged and ends up in landfills, causing pollution and health risks such as ocean microplastics. Municipal Solid Waste (MSW) comprises around 2 billion tonnes of urban waste per year, with approximately 33% not being properly handled. This equates to an average of 0.7 kilograms of garbage per person per day. It is predicted that MSW will increase to 3.4 billion tonnes by 2050 due to the rising world population and the need for natural resources used for industry and civilization.

A fully implemented circular deep transfer learning economy model, which aims to reduce waste and pollution, recycle goods and materials, and renew nature, could be a solution to the accumulation problem and other issues such as climate change and supply shortages. However, it is challenging to implement due to technological, engineering, and logistical constraints.

Developing technologies, such as machine learning, are beginning to change our perceptions and responses to environmental issues. Machine learning, a branch of artificial intelligence that allows machines to learn complex tasks through data and advanced algorithms, can automate a wide range of jobs related to sustainability and the circular economy. These tasks include predicting data trends to improve air quality, identifying patterns in data related to global warming, classifying different types of garbage materials for better waste treatment, and predicting energy or product demand to prevent natural resource waste. Machine learning can also be used to develop novel materials with enhanced efficiency and recyclability.

2. LITERATURE SURVEY

There has been a significant amount of research on the use of machine learning for waste classification, with many studies focusing on the use of convolutional neural networks (CNNs) for this task.

Transfer learning is a technique in machine learning that involves using knowledge or features learned from one task to improve the performance of a different, but related task. It has been widely used in various applications, including waste classification.

In a study published in the journal, "Waste Management"[1], ResNet-50 was used to classify various types of household waste, including paper, plastic, metal, and glass, based on images of the waste. The model was able to achieve an accuracy of 91.6% on the classification task.

In "Transfer learning for waste classification using convolutional neural networks"[2][5], the authors applied transfer learning to the problem of waste classification using CNNs. They used a pre-trained CNN model, called AlexNet, and fine-tuned it on a dataset of waste images. The authors found that the fine-tuned model achieved an accuracy of 94.61%.

In "Waste classification using transfer learning and deep neural networks"[3][6], the authors applied transfer learning to the problem of waste classification using deep neural networks (DNNs). They used a pre-trained DNN model, called ResNet-50, and fine-tuned it on a dataset of waste images. The authors found that the fine-tuned model achieved an accuracy of 94.86%.

Overall, the literature suggests that deep transfer learning is an effective way for waste classification tasks, particularly when it comes to classifying different types of households, construction and demolition, and plastic waste. By using pre-trained models, researchers were able to achieve high accuracy with a relatively small dataset, reducing the need for large amounts of annotated data and the computational resources required to train a model from scratch. However, it is important to note that the performance of the model may vary depending on the specific types of waste being classified and the quality of the training data.

3. DESCRIPTION OF ARCHITECTURE

3.1 RESNET-152 ARCHITECTURE

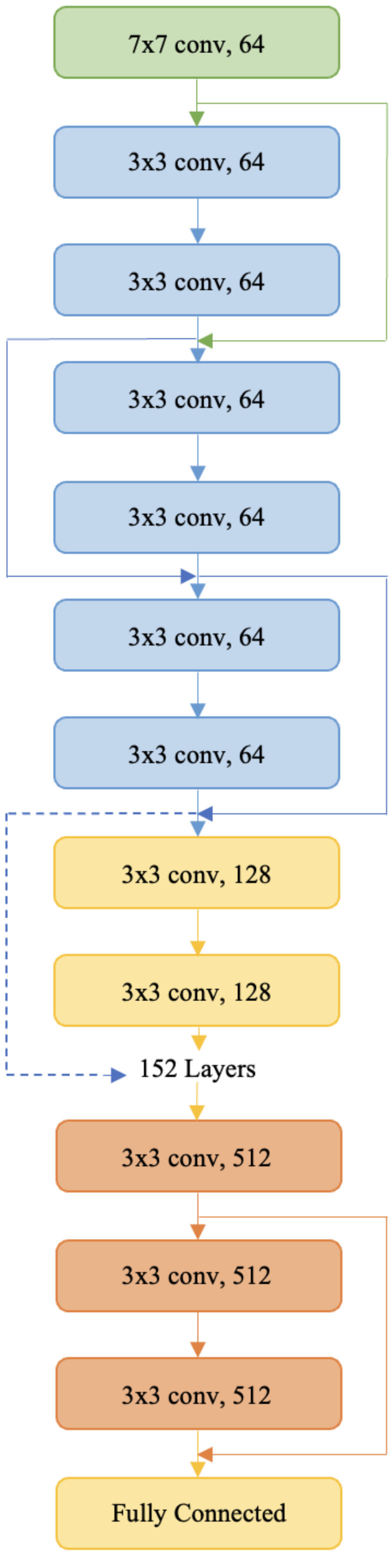

Fig – 1: ResNet-152 Architecture

ResNet-152 is a deep convolutional neural network (CNN) architecture that was developed by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015. It is a 152-layer network that was trained on the ImageNet dataset, which consists of over 1.2 million images and 1000 classes.

The architecture of ResNet-152 is based on the concept of residual learning, which involves adding short-cut connections to the network that bypass one or more layers of the network. This allows the network to learn residual functions instead of the original functions, which makes it easier to train deep networks and helps to prevent the problem of vanishing gradients.

ResNet-152 consists of a series of convolutional, batch normalization, and Rectified Linear Unit (ReLU) activation layers, followed by a series of residual blocks.

Each residual block consists of two convolutional layers with batch normalization and ReLU activation, followed by a short-cut connection that bypasses the convolutional layers and adds the input to the output of the block.

The network also includes a global average pooling layer and a fully connected layer for classification.

Overall, ResNet-152 is a very deep and complex network that has achieved state-of-the-art results on a variety of image classification tasks. It has also been widely used as a base network for transfer learning, where it is trained on a new dataset and fine-tuned for a specific task.

3.2 CNN ARCHITECTURE

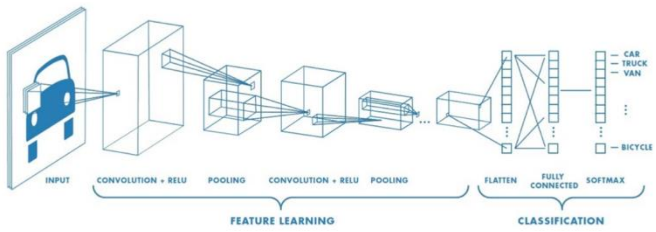

Fig – 2: Convolutional Neural Network Architecture

A convolutional neural network (CNN) is a type of neural network that is specifically designed for image classification and segmentation tasks. It consists of multiple layers of interconnected neurons, with each layer responsible for learning a different level of abstraction of the input image.

The first layer of a CNN typically consists of several convolutional filters, which are responsible for extracting features from the input image.

These filters are followed by one or more pooling layers, which down-sample the output of the convolutional layers and help to reduce the size of the network.

The final layers of a CNN are typically fully connected layers, which use the output of the convolutional and pooling layers to make a prediction about the input image.

In the context of waste classification, a CNN can be trained to recognize different types of waste (e.g., plastic, paper, metal) by analyzing the features extracted from the input images by the convolutional layers.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 01 | January - 2023 Impact Factor: 7.185 ISSN: 2582-3930

4. IMPLEMENTATION AND RESULTS

4.1 OUTLINE OF WASTE CLASSIFICATION

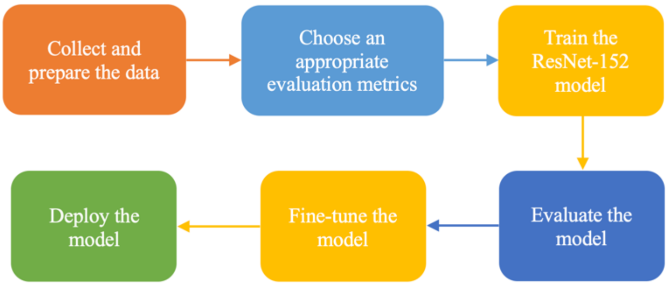

Fig – 3: Outline of Waste Classification

A general outline of the steps involved in implementing a waste classification system using the ResNet-152 architecture:

1. Collect and prepare the data: This includes gathering a dataset of images of different types of waste and preprocessing the data to prepare it for training a machine learning model.
2. Choose an appropriate evaluation metric: Depending on the specific goals of the waste classification system, we may want to use different evaluation metrics to assess our model's performance. Some common options include accuracy, precision, and recall.
3. Train the model: This involves using the prepared data to train a ResNet-152 model to classify images of waste into different categories. This typically involves setting hyperparameters, such as the learning rate and the batch size, and using an optimizer to minimize the loss function.
4. Evaluate the model: After training the model, it is essential to evaluate its performance on a separate dataset to assess its generalizability. This can be done using the chosen evaluation metric.
5. Fine-tune the model: If the performance of the model is not satisfactory, we may need to fine-tune the model by adjusting its hyperparameters, adding or removing layers, or using different data augmentation techniques.
6. Deploy the model: Once the model has been trained and fine-tuned, it can be deployed to classify real-world images of waste.

4.2 PSEUDOCODE

The following pseudocode outlines the general steps involved in implementing waste classification using the ResNet-152 architecture:

1. Initialize the ResNet-152 model and define the required hyperparameters (e.g., learning rate, batch size, etc.).
2. Load the training and test datasets, which should consist of images of different types of waste and their corresponding labels.
3. Preprocess the data by applying necessary transformations (e.g., resizing, normalization) to the images.
4. Define the loss function and optimizer to be used for training.
5. Train the model by iterating over the training dataset and computing the loss and gradients using the loss function and optimizer. Update the model parameters using the gradients.
6. After training, evaluate the model's performance on the test dataset.
7. Use the trained model to classify new images of waste by passing them through the model and predicting the labels.

4.3 RESULTS

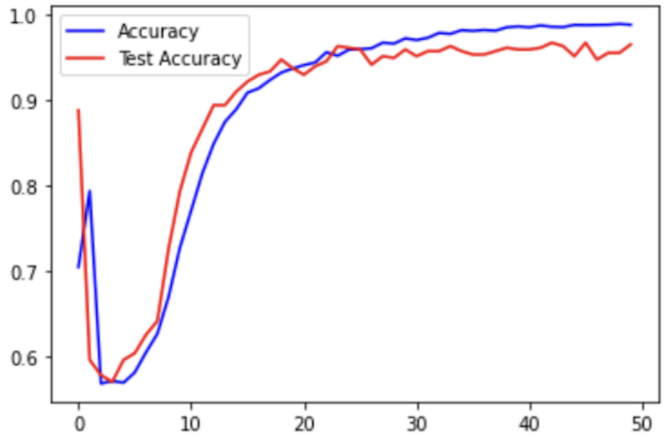

Fig – 4: Model Accuracy

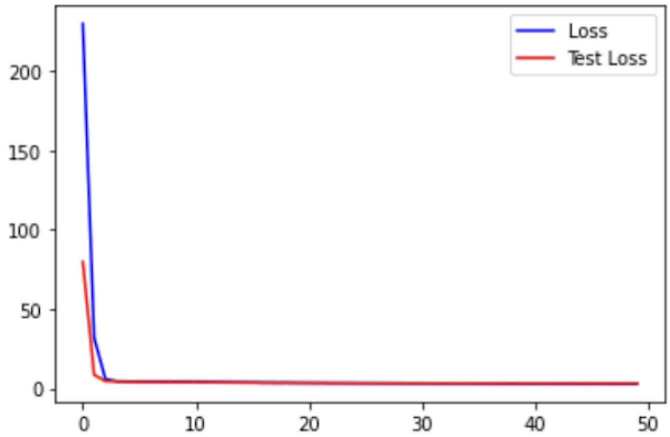

Fig – 5: Model Loss

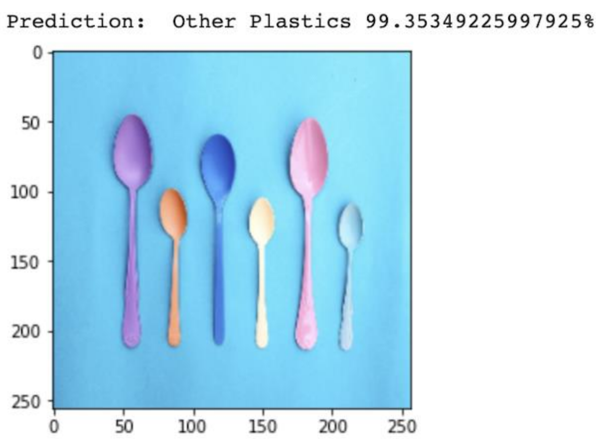

Fig – 6: Model Testing

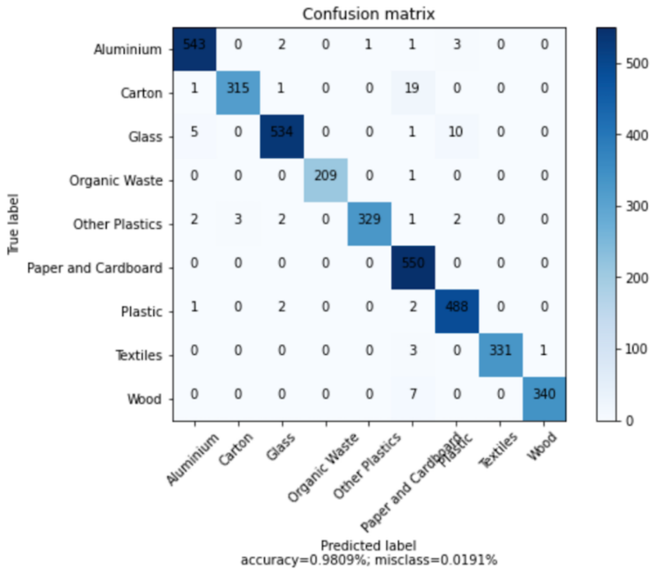

Fig – 7: Confusion Matrix

5. CONCLUSIONS

The use of ResNet for waste classification has shown promising results in accurately identifying and discriminating different types of waste materials. The use of deep learning and transfer learning techniques, particularly through the implementation of the ResNet-152 architecture, has demonstrated the ability to achieve high levels of classification accuracy on various waste datasets. Additionally, the use of ResNet has the potential to improve the efficiency and performance of waste treatment plants, contributing to the overall goal of transitioning to a more sustainable and circular economy. However, further research is needed to optimize the performance of ResNet in waste classification, as well as to evaluate its potential in other applications related to waste management and the environment.

ACKNOWLEDGEMENT

We would like to express our gratitude to all the individuals and organizations that contributed to the successful completion of this research. We would like to thank our supervisor, colleagues, and friends for their valuable guidance and support throughout the research process. We would also like to acknowledge the contributions of the participants who generously gave their time and effort to participate in this study. Finally, we would like to extend our appreciation to all the online resources and libraries that provided us with the necessary information and materials for this research.

REFERENCES

[1] "Waste Management", International Journal of Integrated Waste Management, Science and Technology.

[2] "Waste Classification using Transfer Learning with Convolutional Neural Networks", K Srivatsan, Surender Dhiman, Anuj Jain IOPSCIENCE Conference 2021.

[3] "A Novel Framework for Trash Classification using Deep Transfer Learning", Anh H. Vo, Le Hoang Son, Minh Thanh Vo, Tuong Le IEEE 2019.

[4] "Resources, Conservation, and Recycling", JOURNAL.

[5] "A combination model based on transfer learning for waste classification", Guang-Li Huang, Jing He, Zenglin Xu, Guangyan Huang, WILEY ONLINE LIBRARY, 2021.

[6] "Waste image classification based on transfer learning and convolutional neural network", Zhang Q, Yang Q, Zhang X, Bao Q, Su J, Liu X, EPUB, 2021.

BIOGRAPHIES

Vijay Gadre is a deep learning engineer with expertise in designing and implementing machine learning models using deep neural networks and has a strong background in computer science and mathematics, and is skilled in programming languages such as Python and R.

Sanika Sashte is Electronics and telecommunication engineer with an interest in full-stack development and has expertise in frontend development and has a background in C, and C++ for developing embedded system applications.

Apoorva Sarnaik is a data scientist with expertise in frontend/UI technologies and has a strong background in computer science and mathematics and is skilled in programming languages such as Python and Java.