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Classification of waste images using deep learning technique

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Abstract: Waste management is a complex and dynamic issue that demands creative and visionary solutions that exploit the potential offered by recent technological advances. Our research investigates the application of machine learning and deep learning in image recognition and categorization within the waste spectrum. We trained a Convolutional Neural Network (CNN) model on a massive dataset of pictures depicting organics, among others, typically generated as recyclables. We aim to develop a classification model for organic and recyclable waste that leverages transfer learning to classify them with high accuracy. This study aims to lay the foundation for future systems that will recycle automatically while improving waste recycling processes, hence reducing environmental impacts. The goal of our research was to create an image classification model that could differentiate photos between organic and recyclable waste by designing a classifier using the VGG16 architecture. Our study utilized the VGG16 model, based on Convolutional Neural Networks (CNNs), to achieve a precision score of 0.96 for organic and 0.88 for recyclable. This indicates that our model effectively reduces incorrect predictions for non-categorized items. The model achieved a high recall rate of 0.97 on pictures of recyclable garbage, indicating that it could identify most "Recyclable" examples properly. Moreover, these results highlight the VGG16 architecture's effectiveness in categorizing trash types, indicating potential room for improvement in recognizing "Organic" garbage images by the model, particularly in terms of recall.

Keywords: Waste images, deep learning technique, VGG16 architecture, neural networks, confusion matrix.

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1. Introduction

Workers dealing with waste disposal often sustain injuries resulting from negligence or other associated hazards, such as falling objects. Given that the fatality rate remains at its highest level, it is evident that waste recycling is among the most perilous jobs individuals can engage in Chitale et al. (2020).

The classification of waste is a topic to which careful consideration should be given, as well as a matter of intellectual insight. The environment and health are at great peril due to poor waste control practices (Chavan et al., 2018).

Landfills are under strain due to an ever-increasing volume of waste. Similarly, water bodies are becoming polluted by this waste, which in turn poses a threat to ecosystems (Ankit et al., 2021).

Poor sorting methods exacerbate the issue, as some disposable waste ends up in dumpsites and vice versa. There is a significant need for automatic separation of rubbish in order to help manage waste effectively. Humans typically sort waste by hand in traditional ways that are prone to inaccuracies and limited productivity. Furthermore, moving waste streams comprise multiple components, including materials and contaminants, which complicates the existing system (Lofrano & Brown, 2010).

Deep learning methods seem to be a promising way to bypass the above constraints. This research explores the potential of deep learning for sorting out garbage pictures. Particularly, the Convolutional Neural Networks (CNNs), among other deep learning techniques, have also shown remarkable abilities in recognizing and categorizing images. Our objective is to develop a robust system that will be able to classify waste items from images automatically and accurately, powered by deep learning. This will be an addition to already existing systems designed for smarter and more efficient waste management (Sharma et al., 2018).

A sorting efficiency can be significantly improved with the use of an automated classification that is accurate, which minimizes human error, and recycling processes can be optimized. The successful application of this technology could contribute to reducing environmental pollution levels and better utilization of resources.

2. Literature review

Researchers have made significant inroads in using deep learning to classify garbage. This is because Convolutional Neural Networks (CNNs) stand out as the most reliable architectural design in this respect, as they can effectively extract characteristics from images.

The study (Zhang et al., 2021) focuses on enhancing the accuracy of waste sorting through the implementation of deep learning for intelligent classification. A model that includes a residual network's self-monitoring module aims to automatically extract different features of waste. The study introduces the Waste Classification Model that is based on image recognition and, in particular, the Classification of Waste for Recyclability model (CTR).

This module is constructed from a ResNet18 structure, with the aim of sorting out various waste types for recycling. The training process for the module involved using the PyTorch deep learning framework. Experimental results show a high image classification accuracy of 95.87%.

Plastic waste management challenges prompt the development of automated sorting methods using image processing and deep learning. Techniques like optical sorting and spectral imaging are explored for waste segregation. The study (Bobulski et al., 2021) proposed a system that utilizes Convolutional Neural Networks for plastic waste classification. The proposed system focuses on using a microcomputer with image processing capabilities to identify different types of plastic waste. It also uses a classifier based on CNNs and deep learning for object classification. Various numbers of layers were tried, representing stacking convolutional layers and max pooling layers. Experimental results show the effectiveness of a 15-layer network over a 23-layer network in waste sorting accuracy.

The study (Majchrowska et al., 2022) provides a critical analysis of waste datasets and deep learning-based waste detection approaches. Various object detection techniques and architectures are discussed, including EfficientNet and EfficientDet. The proposed framework consists of two separate neural networks: a detector and a classifier. The detector is trained to locate regions with waste, while the classifier is used to determine the type of waste present.

The procedure is broken down into two stages, where litter localization and litter classification are done. We applied the EfficientNetB2 model to these experiments with varying batch sizes, and then calculated the average classification time for each object scale. Using this approach, the two-stage system can handle so many objects in a second, allowing for INT8 quantization to enhance it further if needed.

The study (Alsubaei et al., 2022) introduces a Deep Learning-Based Small Object Detection and Classification Model for Garbage Waste Management in Smart Cities and IoT Environment. This technique is termed DLSODC-GWM, which adopts an arithmetic optimization algorithm and a functional link neural network for object detection and classification procedures.

This document discusses the design of IRD for waste classification, AOA-based hyperparameter tuning, performance validation using benchmark datasets, the FLNN-based object classification module, and comparative analysis with recent methods, with an emphasis on the superior outcomes produced by the DLSODC-GWM approach.

The study (Altikat et al., 2021) addresses the issue of smart solid waste categorization using Deep Convolutional Neural Networks (DCNNs). The significance of recycling garbage for the sake of protecting the environment and making profits is examined here. Images of paper, glass, plastic, and organic waste were sorted using machine learning strategies.

The results showed that organic waste classification accuracy exceeded that of plastic waste classification. Different neural networks driven by deep convolutional technology were used, and a classification rate of 70% was achieved by a deep architecture with five layers.

In the study (Azis et al., 2020), the Inception-V3 model has been used to achieve a good classification performance of 92.5%. A Convolutional Neural Network (CNN) was proposed for classifying common waste such as cardboard, glass, metal, paper, and plastic.

The Inception-V3 architecture provides the model foundation for this waste sorting system because it serves as the classifying machine. This system selects the Inception-V3 model because it strikes a balance between accuracy and the amount of computer work it requires, making it feasible for a mobile and economical processor such as a Raspberry Pi 3B.

3. Convolutional neural networks

The Convolutional Neural Networks (CNN) are a special kind of feed-forward neural networks, which is inspired by the way we humans see things. These networks address various computer vision and artificial intelligence problems, and they are likely the solution (LeCun et al., 2015).

One of the initial CNNs that transformed deep learning was named LeNeT, and it was mainly implemented for tasks related to character recognition (LeCun et al., 2010).

In recent years, CNNs have gained significant importance. As ResNet (He et al., 2016) and DenseNet (Huang et al., 2017) are the latest hand-designed CNNs that have achieved great success in pattern recognition. Subsequently, multiple algorithms have been proposed to design CNN structures depending on whether pre-processing or post-processing of the CNN structure is required.

Figure 1 shows an example of the structure of a CNN network, which typically consists of several distinct layers, each of which has a distinct function. These layers of CNNs are classified into four layers, which are (Khan et al., 2020):

3.1. Convolutional layer

It is the backbone of the CNN, and its name comes from the mathematical folding or convolution process, where the feature map that reflects the weights of each filter's response to a particular pattern in the image is the output of this process. Additionally, the filter weights are automatically calculated during the network training process (Khan et al., 2020). Figure 2 shows an example of the convolution process, assuming that the input image's size is 4×3. The convolution kernel's size is 2×2, so the convolution kernel is overlaid on top of the input image, and the numerical product is calculated between the numbers in the same location in the kernel and the inputs.

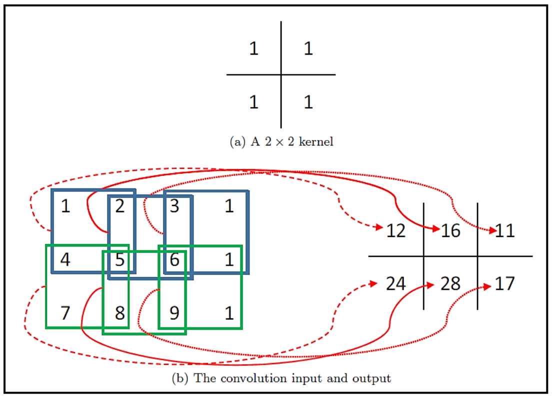

Figure 2. An example of the convolution process.

The feature map consists of several channels, the dimensions of which are related to the input matrix dimensions (considering that the input of these networks is a collection of images), and the dimensions of the filter (considering that some parameters must be specified before the network training process such as the filters' number and size, network structure, etc.) in addition to the factors listed below:

- Stride, which is the number of elements by which the filter is moved after each operation.
- Padding, which is the process of zero padding, to add zeros around the edges of the input image matrix, helping the filter process the edges of the image more effectively. The zero-padding operation helps control the size of the feature maps generated by convolution. It is usually used to make the output size of the convolutional layer (feature map size) equal to the input size.

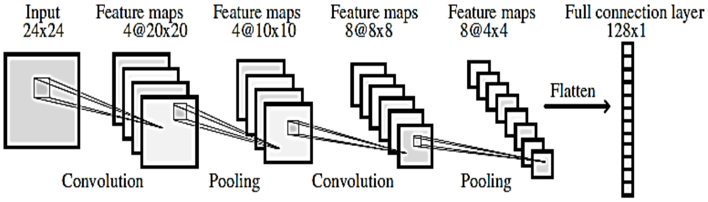

Figure 1. An example of the structure of a CNN.

3.2. Activation layer:

After the convolution process is completed, the feature map is inserted into the activation layer, where the activation function is applied to each neuron, which is equivalent to an element of the feature map. The most important activation function used in this type of network is the ReLU function, which has proven its effectiveness compared to other functions.

3.3. Pooling layer:

This layer is not required to be present in the network's design; instead, if it does exist, it is placed after each convolutional layer. It aims to make the feature map smaller (reduce its size) by reducing each size-specific group of input neurons down to a single one, a small window within the network design defines this size. The reduction is achieved in multiple ways, with max-pooling being the most significant, where every window is matched with the element representing its highest value (Lee et al., 2016).

The output of the pooling process is a feature map that has a similar depth but different widths and heights. Therefore, the pooling process has many benefits, the most prominent of which are:

- Reducing the dimensions of the feature map and the number of computation variables and computations in the network.
- Making the network resistant to minor shifts or distortions of the input matrix.
- Figure 3 shows an example of the max-pooling process, where the matrix on the left represents the feature map (input of the pooling layer) and the matrix on the right is the output of the pooling process through a 2×2 window with a step of 2.

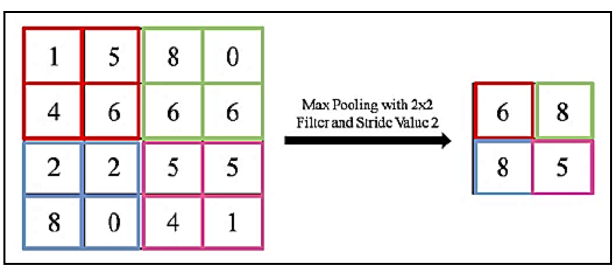

Figure 3. An example of the max-pooling process.

3.4. Fully connected layer:

This layer, the last in the CNN, is of the multi-layer perceptron type, where neurons are fully connected to all nodes in the previous layer, and the final step in the classification process is taken. Its input is a vector formed from the feature map after the pooling process, and its output is a vector that expresses the row (class) to which the feature map belongs (Mirjalili, 2019).

4. Methodology

In this research, we address the problem of image classification using a dataset that contains a small number of image samples, which include images of organic waste and recyclable waste. The goal is to achieve a robust model capable of performing classification despite the small number of samples in the dataset.

The proposed methodology is based on building a model to classify types of waste into organic waste and recyclable waste. The proposed model incorporates transfer learning technology, leveraging the pre-trained VGG16 model and incorporating a set of CNN layers to achieve the proposed architecture, which yields the highest classification accuracy. Figure 4 shows the general structure of our proposed methodology.

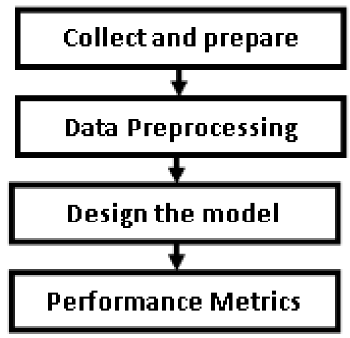

Figure 4. The general structure of our proposed methodology.

4.1. Collect and prepare data:

We used a dataset that includes 25,077 images og organic and recyclable waste obtained via the Kaggle Machine Learning and Data Science Community. The dataset contains two folders: the first for the training and the second for the testing. Each folder contains two subfolders: one containing images of organic waste and the other containing images of recyclable waste.

4.2. Data preprocessing:

This stage involves a set of image processing operations that are applied to the images within the dataset. These operations are used to augment the image data, subtly diversifying the training dataset by applying different transformations to the images. The goal is to improve the model's generalization and strength. Below, we explain the preprocessing operations we applied to the images:

- Rescale: This process rescales pixel values to a range between 0 and 1 by dividing each pixel value by 255. This process helps the deep learning model converge faster.
- Rotation: In this stage, a group of images of the same image is generated after rotating the image randomly at

a specific angle. The maximum rotation angle is set to 40 degrees.

- Change the dimensions of the image: During this process, the width and height of the image are randomly altered by a small percentage of the total. In our work, we limited this change so that it does not exceed 20% of each image's dimensions.
- Shear range: At this stage, image cropping is performed. The maximum shear intensity was limited to not exceed 20% of the image size.
- Zoom range: At this stage, the image is randomly enlarged by a factor of up to 20%.
- Horizontal flip: At this stage, the images are randomly flipped horizontally.
- Fill mode: At this stage, the strategy used to fill newly created pixels that may appear after rotation or transformation is determined. We used the value of the nearest pixel to fill the empty space.

In general, these augmentation techniques aim to expose the model to a variety of transformations that mimic real-world scenarios, making it more robust and better able to handle different shapes of input data during training.

4.3. Design the model

In this research, a model was developed to classify waste images using deep learning techniques. The Keras library in the Python programming language was used to design the proposed model.

The proposed model is an implementation of the VGG16 (Visual Geometry Group 16) model, which is a DCNN architecture designed for image classification. It was introduced by the Visual Engineering Group at the University of Oxford and has become one of the prominent models in the field. The number "16" in VGG16 indicates the total number of layers in the model (Sapijaszko & Mikhael, 2018). The VGG16 model has a uniform and straightforward structure, yet it is relatively deep and contains a large number of variables, which can make training and using the model computationally expensive. Figure 5 shows the VGG16 architecture.

The VGG16 architecture consists of the following:

- Input layer: Default input size: (224, 224, 3) for a color image.
- Convolutional blocks: The architecture consists of multiple convolutional blocks, each containing a set of convolutional layers followed by max-pooling layers. Convolutional layers use small (3x3) receptive fields. Max-pooling layers use a window (2x2).
- Fully connected layers (Dense): After several convolutional blocks, the architecture ends with fully connected layers. Fully connected layers contain a large number of neurons, resulting in a large number of parameters.
- Activation function: ReLU (Rectified Linear Unit) is used as the activation function throughout the network, except for the output layer.
- Output layer: The output layer contains several units equal to the number of classes in the classification task. For binary classification, it usually uses a single neuron with a sigmoid activation function. For multi-class classification, it uses as many neurons as there are classes, with a softmax activation function.
- The VGG16 model was used because it extracts features using a small kernel size, and is therefore suitable for datasets containing a small number of images. The VGG16 model involves using ImageNet weights in the fine-tuning process to avoid overfitting because the amount of image samples is small.

To utilize the VGG16 pretrained model, it is necessary to specify `weights='imagenet'` to access the model trained on the ImageNet dataset. Setting `include_top=False` is crucial to prevent downloading the fully connected layers of the pretrained model. Since the pretrained model's classifier encompasses more than two classes, and our goal is to classify images into only two classes, we must integrate our classifier. Following the extraction of low-level image features like edges, lines, and blobs by the convolutional layers of the pretrained model, the fully connected layers then categorizes these features into the two specified categories. The following Figure 6 shows the model design.

The architecture shown in Figure 6 illustrates the VGG16 model. To derive feature vectors from the VGG16 model, the weights of the five convolutional blocks are frozen and made untrainable in order to preserve the values of the model weights, and the output generated by the VGG16 model is fed into a new classifier which consists of a flatten layer and two fully connected dense layers, each followed by a maximum pooling layer. The last layer, the output layer, is a dense layer with the sigmoid activation function, as the classification is binary.

4.4. Performance metrics:

In this research, a model was developed to classify waste images using deep learning techniques. The Keras library in the Python programming language was used to design the proposed model.

K-fold cross-validation is a widely used resampling technique for assessing model performance. It involves dividing the dataset into k subsets. The model is then trained on k-1 of these subsets and tested on the remaining one (Mirjalili, 2019). In the field of machine learning, the confusion matrix (CM), sometimes referred to as an error matrix (Nowakowski & Pamuła, 2020), is a tabular representation used to represent a model's performance, especially in supervised learning (Ramsurrun et al., 2021). Figure 7 illustrates the layout of the CM.

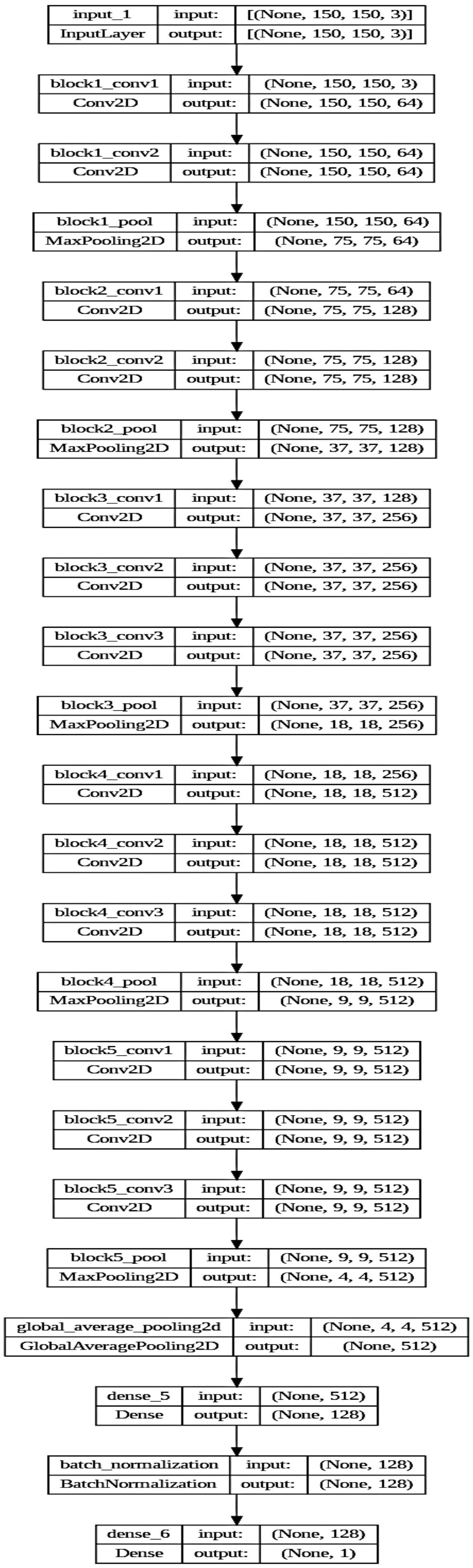

Figure 5. VGG16 architecture.

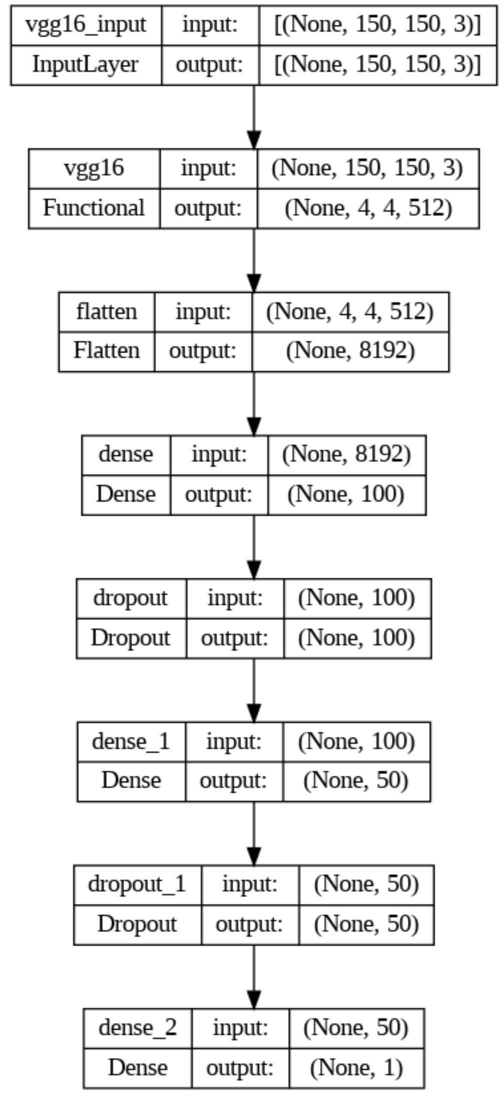

Figure 6. The design of the proposed model.

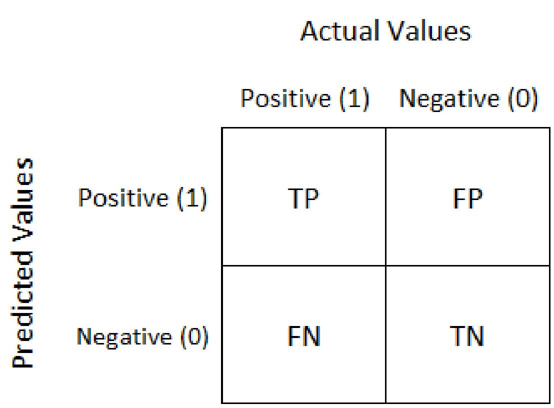

Figure 7. Confusion matrix architecture.

- TP (True Positive): When the model correctly predicts a positive outcome.
- TN (True Negative): When the model correctly predicts a negative outcome.
- FP (False Positive): When the model incorrectly predicts a positive outcome.
- FN (False Negative): When the model incorrectly predicts a negative outcome.

These parameters are used to calculate key performance metrics such as recall, precision, and accuracy.

$$Recall = \frac{TP}{TP + FN} \quad (1)$$

The above equation can be discovered as "Measures the proportion of actual positives that are correctly identified by the model" (Roth et al., 2022).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

The above equation can be discovered as "Measures the proportion of correct positive predictions" (MacEachern & Forkert, 2021) .

The accuracy reflects the overall correctness of the model by measuring the proportion of correct predictions (both positives and negatives) out of all predictions. (Fu et al., 2019). The equation is given as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

The F1-Score is a metric that combines precision and recall, providing a balanced evaluation of a model's overall performance. The formula is as follows:

$$F1\_Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

5. Results and discussions

A getting-to-know-you curve serves as a visible representation that tracks the evolution of a specific metric for the duration of the schooling system of a system studying model. These graphs provide a mathematical example of how knowledge is gained, commonly showcasing time or schooling iterations on the x-axis and performance or error on the y-axis.

The significance of studying curves lies in their capability to monitor a model's progress throughout schooling, facilitating the detection of issues and adjustments to improve predictive accuracy. One common example is the plot of loss over time, in which loss signifies the version's blunders and suggests its increasing efficacy. A lower loss indicates a development in the model's performance.

Another typically used getting-to-know curve is the accuracy curve, which, just like loss, reflects the version's performance. Higher values on these curves denote higher model overall performance. Training loss gauges how well the version fits the schooling statistics, while validation loss assesses its capability to generalize to unseen records.

There are various forms of learning curves, including optimization learning curves, which focus on metrics that aid in optimizing the model's parameters (such as loss), and performance learning curves, which center on metrics used to evaluate and select the model (including accuracy). Figure 8 illustrates the accuracy and loss curves for both the education and validation phases.

In Figure 8, it is evident that our version has made outstanding strides in intelligence. Initially, during the early epochs, there are substantial improvements in both schooling and validation performance, marked by a considerable decrease in loss and an uptick in accuracy. By the third epoch, the validation accuracy starts to decline, indicating that the model is nearing its peak performance on the validation dataset. Throughout training, the model achieved a peak accuracy of 96% on the education records and 94% on the validation records. Our next step involves evaluating the consequences of using the proposed model to examine statistics. Figure 9 shows the CM results.

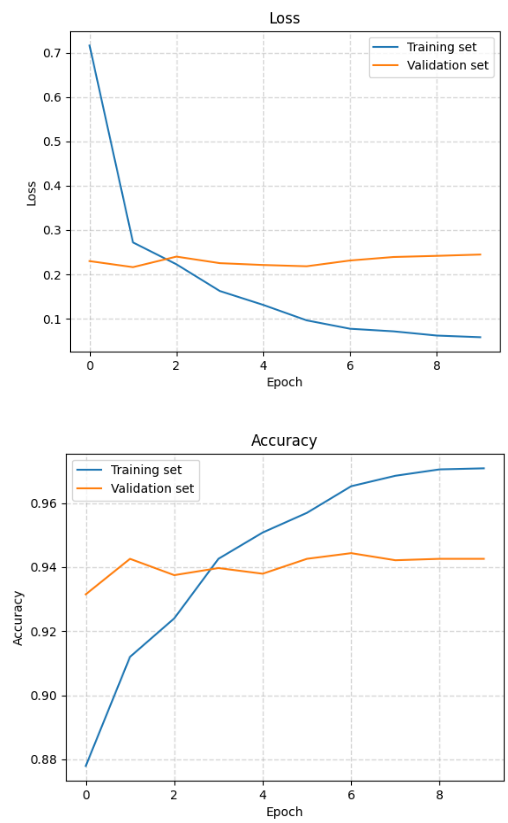

Figure 8. Accuracy and loss curves for both the training and validation processes.

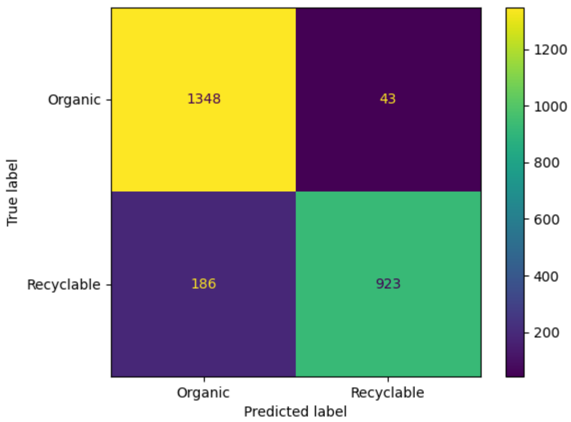

Figure 9. CM results.

The confusion matrix results show that the model correctly classified 1,384 samples as “Organic” and 923 samples as “Recyclable”. However, the model misclassified 43 “Organic” samples as “Recyclable” and incorrectly labeled 186 “Recyclable” samples as “Organic”. The actual accuracy achieved is approximately 91%. However, by applying Equation (3) to calculate accuracy based on the values in the confusion matrix in Figure 9, it is as follows:

$$\text{Accuracy} = \frac{1348 + 923}{1348 + 923 + 43 + 186} = 0.9084 = 90.84\% \approx 91\%$$

We note from Table 1 that the precision for the “Organic” class is 0.96, indicating that ninety-six % of the times anticipated as “Organic” are in reality “Organic”. Similarly, for the “Recyclable” elegance, the precision is 0.88, meaning that 88% of the time anticipated as “Recyclable” are certainly “Recyclable”. High precision indicates that the model makes few fake high-quality predictions, which is essential in scenarios where false positives incur significant costs.

Table 1. The values of Precision, Recall, and F1-Score for each category.

	Precision	Recall	F1-score	Accuracy
Organic	0.96	0.83	0.89	91%
Recyclable	0.88	0.97	0.92	

The model's accuracy is underscored by using excessive precision in each training. The recall for the “Organic” magnificence is 0.83, indicating that 83% of 'Organic' instances are effectively identified. Similarly, the keep in mind for the “Recyclable”elegance is 0.97, implying that approximately 97% of “Recyclable” instances are correctly categorized, that is, about 97 out of every 100 examples.

The model demonstrates high performance in terms of the “Recyclable” magnificence, indicating its proficiency in determining “Recyclable” instances by efficiently recognizing high-quality samples. However, it demonstrates a low recall for the “Organic” class, suggesting room for improvement in detecting “Organic” samples.

In the “Organic” magnificence, the F1-rating is 0.89, signifying a good balance between precision and consideration, while in the “Recyclable” elegance, the F1-rating is 0.92, indicating more balanced overall performance. The model's F1-rankings reveal an equitable distribution of precision, which is consistent for both instructions.

A comparison is made between the proposed model and several other studies on the same topic regarding performance. Table 2 presents the obtained results for reference.

Table 2. Performance comparison of the proposed model with a group of previous studies.

Ref.	Technique	Performance
Altikat et al. (2021)	DCNN	70%
Gundupalli et al. (2017)	Thermal Imaging Techniques	85%
Nowakowski and Pamuła (2020)	R-CNN	90%
Ramsurrun et al. (2021)	VGG19	88%
(Faria et al. (2021)	VGG16	88.42%
Proposed model	VGG16	91%

Comparing different studies is challenging because the VGG16-based model proposed in this study outperforms the VGG16 model suggested by Faria et al. (2021) and other methods in Table 3, achieving an accuracy of approximately 91%.

The key difference between our proposed model and the VGG16 model presented in Faria et al. (2021) lies in the preprocessing operations we performed on the images, which aimed to enhance the accuracy achieved in Faria et al. (2021).

Note: Both RGB and BGR have three color channels: red, green, and blue. However, the order in which those channels are stored in the image file can differ. RGB is commonly used in image editing and display applications, where the order is red, green, and blue. On the other hand, BGR is often used in image processing applications, where the order is blue, green, and red."

The superiority in performance indicates how well this new method can be implemented in garbage sorting projects, making it very useful for waste management systems. Furthermore, it makes the VGG16 architecture one of the strongest choices among citation methods for this task specifically.

Table 3. VGG16-based model.

Reference Faria et al. (2021)	Proposed Model
20-degree rotation	40-degree rotation
horizontal flip=True	horizontal flip=True
vertical flip=True	vertical flip=True
0.1 width shift	0.2 width shift
0.1 height shift	0.2 height shift
Not Used	Shear range=0.2
Not Used	Zoom range=0.2
Not Used	Convert input images from RGB to BGR before entering them into the model
Not Used	Rescale: This process is used to rescale pixel values to a range between 0 and 1 by dividing each pixel value by 255

Note: Both RGB and BGR have three color channels: red, green, and blue. However, the order in which those channels are stored in the image file can differ. RGB is commonly used in image editing and display applications, where the order is red, green, and blue. On the other hand, BGR is often used in image processing applications, where the order is blue, green, and red."

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6. Conclusions

Addressing the complexities of waste management necessitates a range of progressive techniques that leverage the capacity offered by contemporary technological advances. In this study, we utilized the VGG16 architecture to develop a model designed explicitly for distinguishing between "Organic" and "Recyclable" waste images.

The version achieved an accuracy of 96% for "Organic" waste and 88% for "Recyclable" waste, leveraging the capabilities of convolutional neural networks in the VGG16 framework to make accurate high-quality predictions.

Notably, the version achieved a high recognition rate of 97% for images labeled "Recyclable" waste, demonstrating its ability to identify the majority of "Recyclable" items accurately. With an overall accuracy of 91%, the proposed version outperformed all previously referenced methodologies.

Comparative evaluation with specialized strategies like thermal imaging and region-based convolutional neural networks (R-CNN) revealed that the VGG16 structure exhibited competitive overall performance in waste categorization tasks, demonstrating comparable effectiveness.

Future model upgrades should incorporate research into experimenting with diverse model hyperparameters, architectural modifications, and optimization strategies to enhance the version's performance, particularly in the context of "Organic" waste gadgets. Additionally, exploring ensemble education techniques, which entail combining a couple of fashions or architectures, may bolster type precision and stability, mitigating the risk of overfitting and enhancing generalizability on new data.

Conflict of interest

The authors have no conflict of interest to declare.

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