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WASTE CLASSIFICATION USING EFFICIENT NEURAL NETWORKS AND WEB APPLICATION

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Abstract

The integration of convolutional neural networks and modern web applications can significantly improve the efficiency of recycling processes. Accurate, rapid identification and separation of waste of various types reduces contamination by marking a process essential to the efficiency of the recycling industry. In this study, a modern approach for classifying recyclable waste using deep-learning techniques based on convolutional neural networks and integrated into a web application developed using ReactJS is presented. Leveraging the features of advanced deep-learning models and modern web interfaces, the present study aims to make a substantial contribution to the field of efficient waste management and environmental protection. Neural network architectures, trained and evaluated on a carefully annotated dataset, demonstrated very good accuracy values outperforming classical state-of-the-art models. Integrating these models with modern web technologies built a web application with an intuitive user interface for real-time classification of waste types, providing immediate feedback. In the same framework, implementations with web technologies also provide educational resources regarding recycling practices and the impact of waste on the environment. The impact on the environment is considerable because the development of such established technologies can reduce the amount of waste managed improperly, improving the recycling rate. Future research can explore optimizing the models and techniques presented in these studies, expanding the dataset, and developing the application to support good sustainability practices.

Key words*: waste management, convolutional neural networks, deep learning, web application, reacts.*

INTRODUCTION

The path to sustainability and a cleaner future is closely linked to modern and effective waste management practices. Pollution and waste management are major challenges of modern society. The lack of attention in waste management brings critical problems that can affect the environment in which we live and the activities we carry out due to various factors (Guo & Chen, 2022).

Rapid growth in global consumption and population has led to massive accumulations of waste. They can negatively affect public health and the environment in which we live (Bian et al., 2022). The problems of waste management and recycling can be represented by the increase in the amount of waste, the inefficiency of recycling systems through sorting and problematic practices and finally pollution of various forms (Lu et al., 2020). In the absence of effective systems, large amounts of waste end up in landfills and ecosystems, causing substantial damage (Lin et al., 2022; Boldeanu et al., 2023).

On the other hand, recycling is an important component of waste management, but it faces numerous challenges and limitations. A major problem in this context is the incorrect classification of waste. In principle, these errors in recycling processes can affect the efficiency of recycling systems by contaminating the materials that want to be processed, an example being the contamination of plastic and metals through the accidental and erroneous introduction of non-recyclable lots (Qiao et al., 2023; Long et al., 2024).

Waste management, efficient recycling and pollution are areas that can successfully leverage the advanced features of deep learning to solve problems (Zhang et al., 2021).

In recent years, a trend and important research directions have been observed that want to solve these problems through various automatic methods (Alrayes et al., 2023). Deep learning techniques, especially those based on the use of convolutional neural networks (CNN), offer complete solutions in the task of classifying digital images and have applicability in waste management processes (Lubura et al., 2022).

The process of classifying waste using CNN uses models trained on vast datasets capable of classifying images into specific waste categories such as organic or recyclable, or specific types of metal, plastic, paper, or glass (Sarswat et al., 2024). Throughout studies, such a process involves several steps: collecting data and organizing it into various categories, preprocessing the data, training the models, evaluating the models, and adjusting them (Pitakaso et al., 2024).

The present work aims to implement some convolutional neural network models by creating automatic waste classification systems, in various categories. The systems have been optimized and modified accordingly to extract the details required for superior waste classification performance. Apart from the introduction, the present paper is organized into several sections. A section of materials and methods is introduced to present the methodologies approached in the present research focused on waste classification. Furthermore, an experimental results section presents the obtained performances and discussions based on the implementations. Finally, the paper ends with a conclusion section, presenting a clear summary of the present research.

MATERIALS AND METHODS

The present section notes the methodologies addressed in the waste classification research - the dataset used, the convolutional neural networks implemented, and an overview of the hardware and software area.

As part of the waste classification-oriented research a representative dataset consisting of RGB digital images was used, noting an important part in the training of image classification models.

The dataset used totals 2400 images divided into three parts for training (70% - 1680 images), validation (20% - 480 images) and testing (10% - 240 images). Each part of the dataset illustrates various types of recyclable waste in various poses and scenarios used to train and evaluate convolutional neural network (CNN)-based digital image classification architectures. For the present case, various augmentation techniques were also implemented to increase and diversify the dataset. These included color and geometric transformations: brightness adjustment, contrast adjustment, saturation adjustment, noise addition, blur, rotation, translation, scaling, shearing, horizontal and vertical flipping, cropping. Transformations of this type are essential in image augmentation processes, contributing to the diversification and robustness of the data set. Thanks to these techniques training CNN models can have robust examples to improve performance and generalization, ultimately able to handle the variations and complexity attached to images in real contexts (Pitakaso et al., 2024; Tian et al., 2024). Representative images of the dataset are attached in Figure 1, as well as representative images of the augmentation processes in Figure 2. Using image resizing the size of the input images of the architectures used was 224 x 224 px.

Figure 1. Example images from the dataset

Figure 2. Example images from the augmented dataset

Commonly used for image classification tasks, convolutional neural networks are complex architectures capable of automatically analyzing and capturing essential visual features. Typically, these CNN structures include convolutional, pooling, and complexly connected layers. Essential convolutional structures apply various filters to extract important features such as edges and textures, while generating feature maps that bring to the fore essential features of images and objects in these images, such as waste. Over the years several types of architectures have been developed and heavily optimized to better extract these features. As part of the present study, several CNN architectures were implemented and modified to create robust classification systems as part of the waste management domain. Transfer learning and fine-tuning techniques were used to optimize the proposed models, leveraging pre-trained weights.

DenseNet 201 (Huang et al., 2016) is the first model used for this work. The architecture consists of many stars and is designed to streamline the flow of information. Unlike traditional neural architectures, DenseNet connects each layer in a feed-forward manner with dense connections, where each layer has as input the full feature maps of the previous layers. This approach allows the structure to reuse features, adjust the gradient problem, and use efficient parameters. DenseNet201 is a deep variant that excels in classification tasks in various applications and can be successfully assigned to the waste management area.

Another model used for the present study, VGG19, is a state-of-the-art deep network with 19 layers (Simonyan & Zisserman, 2014). The architecture presents a simple and uniform structure that facilitates the extraction of features from digital images based on convolutional layers (3 x 3), pooling layers and fully connected layers. Such a structure is appreciated for its simplicity and efficiency, although it is based on a large number of parameters but involves significant memory and calculation requirements. A batch normalization structure was implemented in this model.

A model that proved a balance between accuracy and computational efficiency, Xception (Chollet, 2016), represents another approach in the present study. The model is described as an extreme structure of the classic Inception model, implementing depth-separable convolutions (in two stages - spatial convolutions and channel convolutions). These implementations aim to reduce the number of parameters but improve performance with a reduced computational footprint.

Another model used, ConvNext Base, is a convolutional neural network inspired by Vision Transformer (VIT) architectures (Liu et al., 2022). Optimizations to this architecture include large kernel convolutional blocks, hierarchical structures, and Layer Normalization instead of Batch Normalization. At the same time, the gradient vanishing problem and the flow are managed by layering and skip connections. Finally, the ConvNext design demonstrates performance comparable to VIT models, but which preserves the simplicity and efficiency of classical CNN structures.

MNasNet (Tan et al., 2022). is a deep neural network architecture developed for remarkable efficiency and performance among mobile devices. The architecture features a NAS - Neural Architecture Search approach to generate optimal architectures with a balance between complexity and computing resources. The model also features convolutional layers with efficient kernels and inverted moving blocks attached to reduce dimensions and inference times, ideal for computer vision tasks and real-time applications.

A custom system was used to highlight the hardware and software that was the basis of the experiments of the present study. It includes an operating system based on Win 11 Pro, an Intel Core i7-14700HX CPU, 32GB RAM, 1TB SSD and a dedicated NVIDIA GeForce RTX 4070 8GB video card with CUDA support, useful in developing deep learning solutions.

The chosen programming language was Python v3.9, integrating the PyTorch framework, flexible in the implementation and optimization of the chosen architectures.

RESULTS AND DISCUSSIONS

Simple features and complex textures can be extracted as part of waste classification using CNN, demonstrating outstanding performance. Table 1 shows the obtained performances around the accuracy metric and based on images from the test dataset. These images were not seen during the initial training and evaluation process and represent a solid point of testing the architectures using new data.

Table 1. The performances obtained in the case of the classification models

Model	Accuracy	Inference time (ms)
DenseNet201	93.40%	613
ConvNext Base	98.34%	687
Xception	97.38%	553
MNasNet100	90.84%	510
VGG19	94.77%	521

Notable performances were observed in the case of the implemented classification models, noting in some cases points for future development and optimization, based on the graphs of the loss and accuracy functions, from the training and validation side. Figures 3 to 7 show these details, where good convergence and slight fluctuations or differences in the performance of certain models are noted.

The execution time was noted by using a function that takes 5 random images from the test dataset and uses the best saved weights for each model to generate predictions based on these images. The inference times obtained for each model are in the range of 500 - 700ms, Table 1, which marks a fairly good performance on this classification task.

The best accuracy metrics exceed key values of 97% demonstrating superior classification ability for the presented architectures. At the same time, high performance can be observed in the case of the new state-of-the-art models Xception or ConvNext, superior to classic ones such as DenseNet or VGG. However, in the case of DenseNet, the architecture continues to demonstrate superior performance, and this is due to the complex architecture, capable of extracting essential information using densely connected modules.

The same can be noted in the case of VGG where the well-optimized architecture manages to capture essential details in the classification process. Slightly lower performance can be seen in lightweight architectures where the need for optimization must be higher, with architectures risking losing key details as information is passed and analyzed within layers and structures, in the case of MNasNet.

Table 1 and the illustrated functions highlight key metrics for the classification task: accuracy, loss, and inference time. At their core, each model represents deep, widely used architectures adapted in the present case to waste classification tasks.

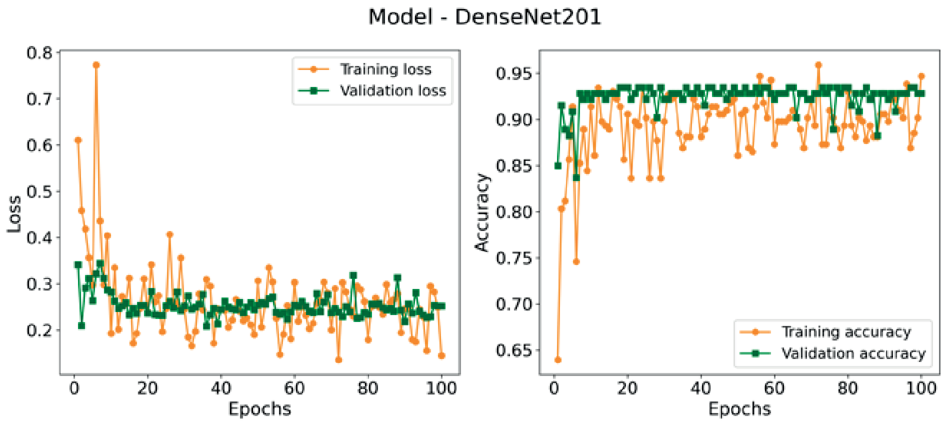

Figure 3. Training and validation performance of DenseNet201 model

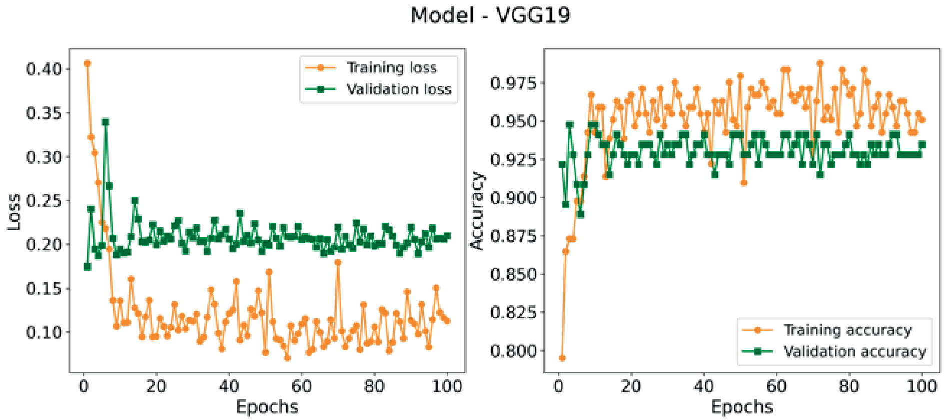

Figure 4. Training and validation performance of VGG19 model

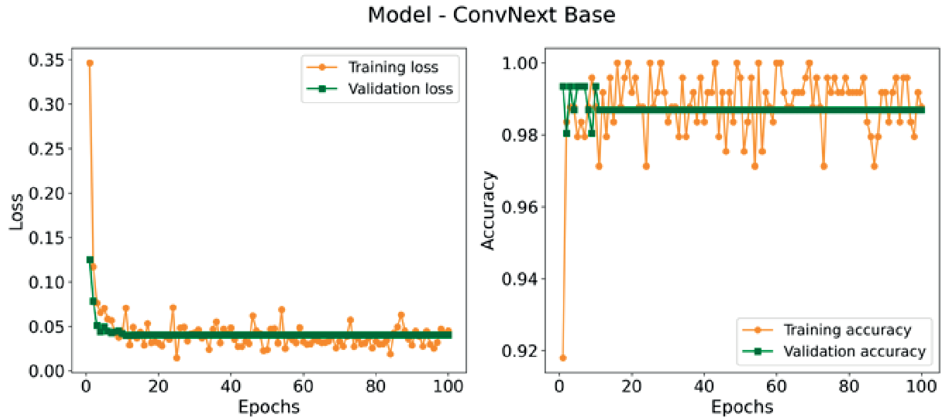

Figure 5. Training and validation performance of ConvNext Base model

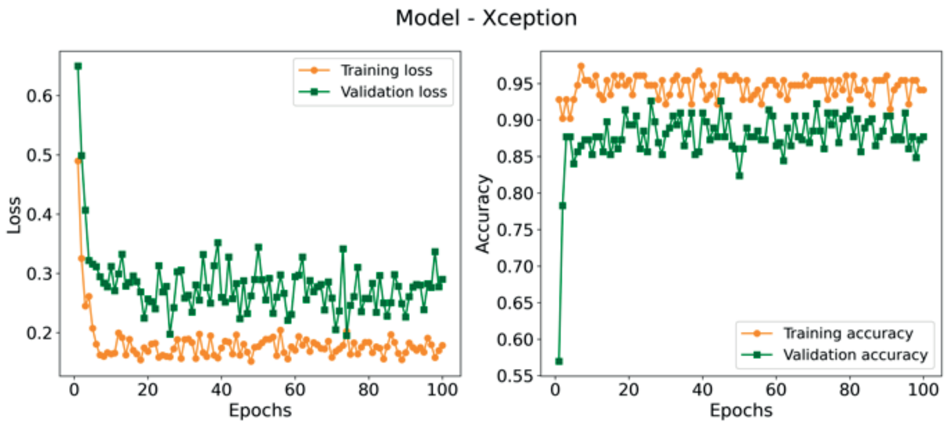

Figure 6. Training and validation performance of Xception model

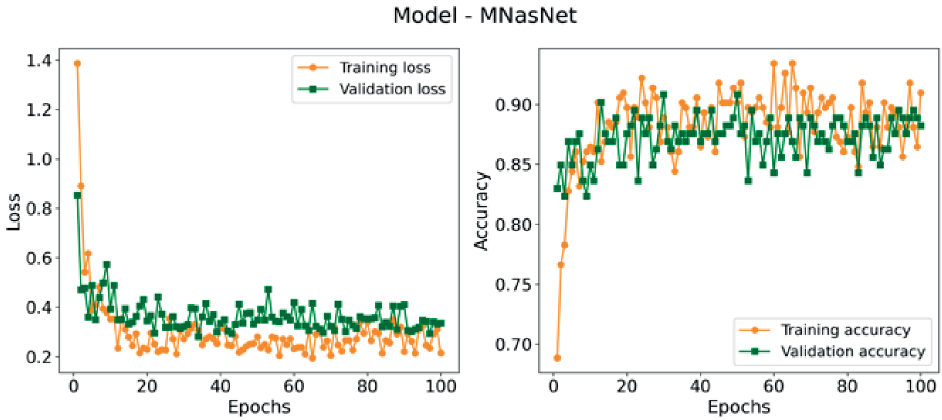

Figure 7. Training and validation performance of MNasNet model

The first model noted, DenseNet201, shows good accuracy with a slightly high inference time. The density of connections and the attached complexity can contribute to a relatively high uptime compared to other better optimized models. The second model, ConvNext Base, describes the best accuracy, but with an equally high inference time due to the associated complexity. The implementation of Layer Normalization modules and large kernels actively contribute to this high performance. Xception shows a slight drop in accuracy compared to ConvNext, but with better inference time due to the reduced complexity associated with using depth-separable convolutions. Designed for efficiency, MNasNet exhibits the shortest inference time, being the fastest in the list of proposed models. This may be due to effective layering in the model architecture. Although the accuracy is lower, the model is an acceptable compromise when developing it for real-time applications on resource-constrained devices. According to the experiments, VGG19 achieves remarkable accuracy being another fast model on the inference side. Although it is an older model, the VGG19 remains competitive due to its simple and deep architecture.

Consequently, choosing the right model depends on the context and application resources where the implementation is needed. In the same context, there must be a focus on accuracy vs inference time, as each model analyzed is suitable for different tasks and different usage scenarios, offering various advantages or limitations.

To complete the present study a web application. was developed to test the proposed models, using the best weights saved after the training process. In this sense, the web application contains a module that can receive as input a digital image and using the exported weights can automatically generate a prediction in the task of waste classification.

The Javascript language and the React.js framework represented the established web technologies to implement the web application, along with the onnx-runtime-web tool to manage the export of classification models in onnx format, image tensors, attached for the proposed web technologies. Figure 8 illustrates the web application interface as well as an attached prediction example. A web application of this type proves to be a useful tool, with availability, that can capitalize on the characteristics of classification models that can be further integrated as modules of an automatic detection system, performance-oriented and at the same time accessible to users.

The development of the web application was based on the creation of JavaScript and React.js components that consider the characteristics of such a waste classification-oriented web application - web interface modules defined by React components, the basis of this framework. In relation to the classification techniques, the images that can be uploaded and sent to generate predictions go through a processing step so that

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the format is known to the classification module, exported in the chosen format.

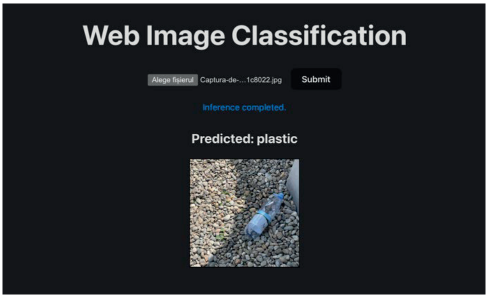

Figure 8. Web application interface

CONCLUSIONS

This study presented a modern method of integrating convolutional neural network architectures with a React.js web application to support the automated waste classification task. Benchmarking of the implemented CNN models revealed notable performance for classification tasks, highlighting strengths and weaknesses for each model, tracking metrics such as accuracy on a test dataset and operation (inference) time. The best models, Xception and ConvNext, demonstrated accuracy values of over 97 and 98%, respectively, which indicates the effectiveness of deep learning techniques adapted as innovative solutions in the field of waste management. However, the observed limitations pave the way for new research and optimization solutions to tune the architectures in achieving maximum performance with reduced inference times. At the same time, it was noted the way to implement such solutions in real-time identification systems and on platforms with limited resources - web applications, mobile hardware.

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