Advance Machine Learning

Final Project

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1. Introduction

Deep learning revolutionized artificial intelligence by enabling machines to understand, process, and classify complex data with unprecedented accuracy. Deep learning algorithms have excelled at object detection, segmentation, and classification in computer vision. One of the promising applications of deep learning is in waste management, particularly in automating the recycling material classification.

Manual waste sorting is time-inefficient, inconsistent, and prone to human error, with a tendency to cause contamination and lower recycling rates. In this project, we aim to develop an automatic waste sorting system through the use of transfer learning techniques with the EfficientNetB0 model on the publicly available TrashNet dataset. We hope to demonstrate how deep learning can help achieve smarter waste management and foster sustainability.

2. State-of-the-Art Deep Learning Models

The development of deep learning models has significantly enhanced the ability of machines to classify and analyze images. The AlexNet and VGG16 models were the first to revolutionize the field of deep learning by automatically extracting hierarchical features. The models were, nonetheless, marred by problems such as overfitting and the need for high computations.

The ResNet innovation introduced residual connections, which enabled efficient training of extremely deep networks and avoided the vanishing gradient problem. Subsequent to these innovations, EfficientNet introduced a compound scaling approach that scales depth, width, and resolution equally, and they were able to achieve amazing accuracy at minimal computational expense.

Of the recent models, EfficientNetB0 is especially interesting for offering a superior performance-resource trade-off. It is very suitable for real-world applications where resources are computationally constrained, such as in intelligent waste collection systems. Recent advances in Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) have also delivered new ways to enhance classification and data augmentation, although they are more computationally costly.

3. Literature Review of Waste Classification Techniques

3.1 Latest Techniques

Early techniques for waste classification by employing conventional manual image processing algorithms like edge detection and thresholding were inadequate under real-world conditions. The arrival of CNNs enabled automatic hierarchical feature extraction, transforming visual classification.

These models like VGGNet, ResNet, and its later variants EfficientNet, pushed classification accuracy to unprecedented levels. Transfer learning where models pre-trained on large image datasets like ImageNet are fine-tuned using small, domain-specific datasets is now a standard approach, significantly improving the rate of convergence as well as generalization even from limited data.

Some of the contemporary trends involve data augmentation (flip, rotation, zoom, adjust brightness) to simulate variability in the real world and enhance robustness. Researchers are also exploring Vision Transformers for image classification and GANs for synthetically augmenting datasets with images.

3.2 Effectiveness of Deep Learning Techniques

Deep learning models have been very successful in waste classification tasks. Experiments repeatedly indicate that applying transfer learning with EfficientNet models results in faster convergence and improved performance compared to training from scratch.

More sophisticated augmentation techniques further improve model generalization, and hence CNNs are very robust against object orientation variation, lighting variation, and occlusion.

EfficientNetB0, specifically, provides cutting-edge performance with a much reduced parameter size than previous architectures such as VGG or Inception, making it well-suited for real-world deployment scenarios with limited computational capabilities.

3.3 Challenges and Limitations

Even though they have been successful, there are a number of challenges that remain:

Dataset Size and Diversity: TrashNet and other such datasets are quite small, which restricts model generalization to novel environments.

Model Interpretability: CNNs are black-box models, and their predictions are difficult to interpret without additional tools like Grad-CAM.

Real-Time Deployment: Even lightweight models like EfficientNetB0 can be computationally heavy for real-time embedded deployment.

Generalization Issues: Models trained on a specific dataset may do poorly when they encounter new classes of waste, mixed materials, or varying backgrounds.

Addressing these challenges is crucial to translating research success into real-world impact.

4. Industrial Applications of Deep Learning

Deep learning is finding applications in various fields, revolutionizing traditional ways of working. CNNs are being used in civil engineering to detect defects in bridges and buildings. In healthcare, models assist in the detection of diseases at an early stage using medical imaging, tumour detection, lesion detection, and fracture detection. Deep learning is assisted by the transportation sector with autonomous vehicle systems that detect objects, lane markings, and traffic signs. In security and surveillance, facial recognition, activity recognition, and real-time threat detection is being improved using deep learning.

In the waste management industry, AI-based smart bins and automated sorting systems are now being employed to sort waste streams, improve recycling rates, reduce contamination, and support environmental sustainability. Deep learning models like EfficientNetB0 play a key role in enabling accurate and efficient waste sorting in such systems.

5. Dataset and Methodology

5.1 Dataset Overview

The TrashNet dataset was used in this project. The dataset comprises approximately 2,500 labelled images distributed across six classes: cardboard, glass, metal, paper, plastic, and trash. During model training, 2024 images were used for training and 503 images were reserved for validation. All the images were reshaped to 224x224 pixels to match the input requirements of the EfficientNetB0 model.

5.2 Data Pre-processing

Pre-processing of data involved normalizing pixel values to a [0,1] range and applying data augmentation techniques to simulate real-world variability. Data augmentations were performed using random horizontal flips, rotations of up to 30 degrees, and zoom transformations. This was intended to improve model generalization and prevent overfitting.

5.3 Model Design and Training

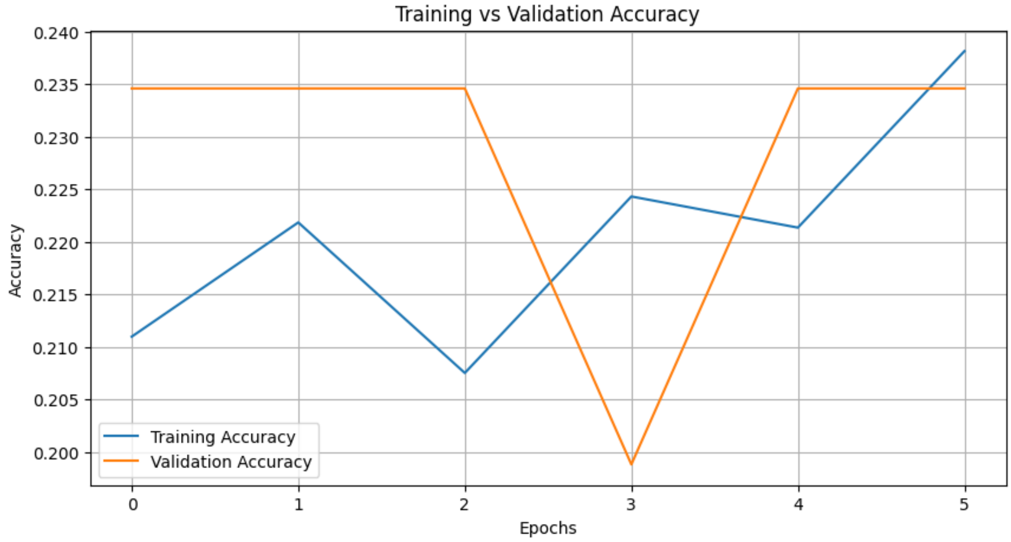
EfficientNetB0 was used as the base model, which was pre-trained on ImageNet. The base layers were frozen initially, and a custom classifier was added on top, including a Global Average Pooling layer, a Dense layer with 128 neurons (ReLU activation), a Dropout layer with a rate of 0.3, and a final Dense output layer with six neurons using softmax activation.
It was trained with the Adam optimizer and categorical cross-entropy loss. It was trained to a maximum of 10 epochs with Early Stopping based on validation loss to avoid overfitting.

6. Evaluation and Results

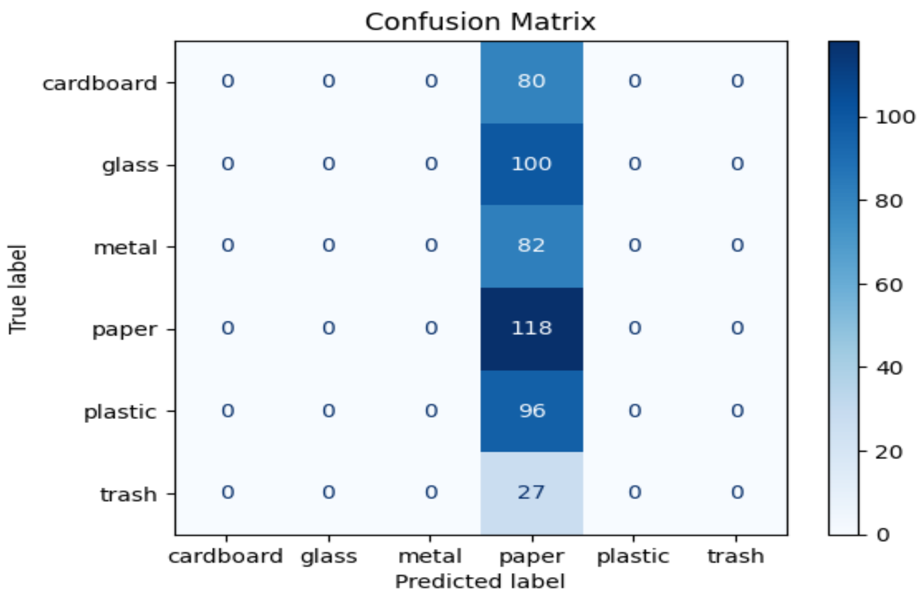
The model concluded with a final validation accuracy of 23.46%. Despite the application of a robust architecture and data augmentation, the model performed poorly in classification for all the classes except paper.
The confusion matrix revealed that classes including cardboard, metal, glass, plastic, and trash were highly confused.
The classification report showed very low precision and recall for most categories, with a macro-averaged F1-score of 0.06 and a weighted F1-score of 0.09.

Training and validation accuracy curves were flat across epochs, indicating severe underfitting, likely due to dataset size limitations and the freezing of pre-trained layers without fine-tuning.

Training vs Validation Accuracy



Plot shows the training and validation accuracy trends over epochs. Both curves remain relatively flat, and there is no significant convergence or improvement, highlighting the model's underfitting due to insufficient learning from the data.



Confusion Matrix presents the confusion matrix for the validation dataset. It is observed that almost all waste categories were misclassified as 'paper'. This reflects the model's inability to distinguish between different waste types and indicates a significant class bias.

7. Limitations of Deep Learning in Waste Classification

Several limitations were identified in this project.

First, the small size and class imbalance of the TrashNet dataset significantly constrained the ability of the model to learn. Second, freezing EfficientNetB0 base layers without selective fine-tuning prevented the model from learning domain-adaptive features. Third, computational needs and inference latency remain challenges for real-time, resource-constrained deployment. Finally, model interpretability remains low without additional explain ability techniques.

8. Future Work

Future work must focus on expanding the dataset with more balanced and diverse samples collected under various conditions. Fine-tuning certain EfficientNetB0 layers can potentially allow the model to capture more task-specific features.
Even more advanced augmentation methods like Auto Augment and brightness/contrast might enhance robustness.

Implementing light-weight architectures like MobileNetV3 or model compression techniques would make it easier to deploy on edge devices.
In addition, the use of object detection methods and the integration of interpretability methods like Grad-CAM would increase real-world applicability potential.

9. Potential Solutions

Various techniques may be used to overcome the above limitations:

- **Fine-tuning Pre-trained Models**: Rather than freezing all the EfficientNetB0 layers, selectively unfreezing deeper layers allows models to learn waste classification tasks more effectively.
- **More Sophisticated Data Augmentation and Synthetic Data Generation**: Techniques including CutMix, AutoAugment, and the use of GANs can enrich training datasets to improve generalization and robustness.
- **Model Optimization**: Pruning, quantization, and knowledge distillation techniques can be employed to compress models to allow them to execute on mobile or edge devices.
- **Explainable AI Integration**: Grad-CAM or LIME needs to be incorporated to increase transparency, user confidence, and compliance with regulations.
- **Expanding and Diversifying Datasets**: Larger real-world datasets collected in varied environments and types of wastes are required to increase model robustness.
- **Moving to Object Detection Frameworks**: Transiting from direct classification to more complex models like YOLOv8 facilitates the detection and classification of numerous waste objects within one image, better mimicking real-world mixed-waste conditions.

By tackling these constraints methodically, deep learning models can further help in building smart waste management systems and eco-friendly city environments.

9. Conclusion

This project investigated the application of deep learning techniques for automated waste material classification using the TrashNet dataset in combination with the EfficientNetB0 architecture. Although the model achieved limited accuracy due to dataset constraints and underfitting challenges, the research offered critical insights into the inherent difficulties of training deep learning models on small, imbalanced datasets.

The outcomes of this study highlight the importance of robust data collection, advanced augmentation strategies, and the fine-tuning of pre-trained networks to unlock better model performance. Furthermore, the integration of explainable AI methods will be essential to enhance model transparency, trust, and practical deployment viability.

Looking ahead, with continued efforts in dataset expansion, model optimization, and the adoption of more sophisticated and efficient architectures, deep learning can play a transformative role in creating intelligent, scalable waste management solutions. Such advancements are pivotal to achieving smarter, greener cities and advancing global sustainability goals through efficient recycling and resource utilization initiatives.

10. References

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