Accuracy and Efficiency Gains in Waste Classification Through Continuous Learning and Advanced Techniques

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Abstract. —Efficient waste management is considered important for sustainable development because of an ever growing volume of municipal and household wastes. Incredible this paper presents a smart model for the grouping of wastes using multi-objective Beluga Whale Optimization combined with the InceptionV3 deep learning architecture. It protects from traditional problems of such systems-like low recognition accuracy or imbalanced classesthrough the enforcement of augmentation techniques and oversampling. The best hyperparameters, such as rate of learning, dropout, as well as batch size, are chosen using MBWO with the TrashNet dataset. It gives an 97.75% accuracy and 99.55% specificity and an accuracy of 98.88%, performing better compared to traditional models. This model has classified autonomously the model with waste materials like paper, plastic, metal, and glass that will help in better recycling and reduce reliance on landfills. Its performance is further improved by the usage of CNNs and transfer learning, so that it can be applied in real-world scenarios. This intelligent system represents one great leap in different waste sorting technologies that aim at achieving global sustainability goals pertaining to cleanliness of the environment and resource management. In future developments, the expansion of the dataset, real-time waste classification, with extension to more applications, will be done, especially to smart city infrastructures. The model proposed here will not only improve accuracy in classification but also make the solution scalable for the modern challenges related to waste management

Keywords: Waste Classification- Deep Learning-Beluga WhaleOptimization-InceptionV3 Sustainable Waste Management

1 INTRODUCTION

Waste management effectively is one of the challenges in today's fast world of urbanization and has huge implications for environmental sustainability. It is estimated that an incredible fraction of global waste is not properly disposed of, and poor waste management may result in environmental degradation, resource depletion, and health risks. Different traditional methods of waste management at various steps include manual sorting, mechanical sorting systems, and decision support systems. Most of them are time-consuming and laborious, with a lot of inaccuracies, especially in the identification of complex or composite waste materials. This has brought about the urge for automated systems that classify and handle waste effectively. Coupled with the development of AI and deep learning technologies in general, and CNNs in particular, a number of promising solutions have emerged that raise the effectiveness and efficiency of waste classification to the next level. These AI-based systems identify and classify many wastes and assist in recycling processes instead of landfills Inception V3 is one of the best, amongst all deep learning architectures, in image classification; therefore, it is suitable for waste classification. This work further enhances the model's performance through the incorporation of multipurpose Optimization of Beluga Whales for the purpose of higher parametertuning, while surmounting major challenges related to class imbalance and overfitting. The proposed model was tested with benchmark datasets like TrashNet with a classification accuracy of 97.75%,outperforming the traditional approaches. In particular, by embedding methods, those pertaining to data augmentation and oversampling, for example, the model was proficient generalizing all varieties of waste categorization, solving by scale modern waste management systems and smart cities .

2 LITERATURE REVIEW

Artificial Intelligence-based Smart Household Waste Classification System This paper mostly concentrates on the development of anintelligent system for classifying household waste using deep learning methodologies, namely The application of CNNs and transfer learning. The system will automatically classify different types of household wastes according to their images by the use of a number of architectures of CNNs, such as MobileNet, VGG16, and ResNet50. It discusses some of the challenges, like the limitation of categories in public datasets, and overcomes them using the features of pretrained models and transfer learning techniques. The focus of this paper is on building an economic solution by using a Raspberry Pi for real-time implementation suitable for a smart bin and waste sorting system. The results show that one of the best ways to classify waste involves the use of CNNs, which have enormous potential for integration into household management systems and municipal management[1]. Classification of Domestic Solid Waste using Convolutional Neural Networks The work is centered on the burgeoning concern of the massive volume of household waste that contributes to environmental pollution and climate change. This paper goes further to propose automation in solid waste classification using CNN. The study has improved the limitations from the existing datasets such as the TrashNet, which used six categories into a more extensive dataset totaling 15,515 images from twelve categories. It compares different CNN models such as DenseNet, InceptionV3, and Xception to achieve better results. Among these, Xception with the Nadam optimizer has given the best classification of 89.57that performing data augmentation will address the issue of class disparity and improve the generalization capability of the model[2]. Multi-Objective Beluga Whale Optimized and Deep Learning based Intelligent-Sustainable Waste Classification Model. This work presents the waste classification model with deep learning structure using the InceptionV3 model. dropout as well as the batch size as the parameters in order to obtain better results in the classification of wastes. Results show that accuracy of the model is 97.75is well suited for the cost estimation of the software projects. Classification accuracy of 75 percent on the TrashNet dataset and they do so better than classical models. In this paper, it explains the difficulties that are arising from class imbalance data, and how the use of augmentation and oversampling techniques brought the problem to a minimum so that the model will performs well[3]. Comparison of Various Algorithms for Effective Classification of Waste: This paper discussed some of the machine learning algorithms applied to the classification of wastes: Support Vector Machine, Random Forest, Na¨ıve Bayes Classifier, Decision Tree, K-Nearest Neighbor, and Convolutional Neural Networks. The study identifies automated waste classification as playing a highly crucial role in recycling and reducing harmful impacts on the environment. Using the dataset of waste images, the study will compare the performance of these algorithms based on accuracy and computational efficiency, thus providing a number of strengths and limitations of each of these algorithms regarding waste classification[4]. Review on Deep Learning-Based Biomedical Waste Detection and Classification: This paper designs a deep learning-based system using CNNs for biomedical waste detection and classification. Basic safety and public health concerns, at a minimum, are stressed for biomedical waste management, specifically to the handlers thereof. This proposed system will apply the CNN model for better results and higher accuracy to classify biomedical waste into several groups, such as infectious, hazardous, and radioactive wastes, which is useful in effective waste management practices[5]. E-Waste Intelligent Robotic Technology: A Deep Learning Approach for Electronic Waste Detection, Classification, and Sorting: The paper proposes a deep learning-based robotic system called EIRT, which would sort electronic waste into categories. It covers the application of the EfficientNet-D2 architecture to detect and classify e-waste into different categories such as batteries, mobile phones, or electronic boards. EIRT is a robotic arm on a mobile car basis, autonomously finding, picking up, and sorting e-waste with an accuracy of 82.32%. This work develops the urgent need that addressing ewaste management requires with respect to automation and artificial intelligence means[6]. Utilizing waste size and weight, recyclable waste is categorized by material: This work shall adopt a classification method in regard to the weight and size of wastes from refuse using a system that employs a load cell and ultrasonic sensors. The authors developed an algorithm that made most of the material classification processes-such as paper, plastic, glass, and metal-automatic, reducing manual sorting. Their system showed a promising accuracy for classifying household waste based on these physical properties. However, the authors identified that the extension to a wider variety of waste types might need more complex algorithms and extensive databases[7]. Utilizing SIFT-PCA Feature Extraction and Support Vector Machine for Waste Classification: This paper focuses on the analysis of machine learning algorithms in identification of waste types especially with the use of Support Vector Machine – SIFT-PCA feature extraction. This experiment focuses on the Trashnet dataset to evaluate the identified features and compare between the performances of using SVM with and without the PCA as the Reducing dimensionality. In case of using SIFT-PCA this algorithm decreased the mentioned accuracy compared to that achieved by only SIFT features. The highest accuracy was 62was achieved by using the SVM with SIFT only, moreover, the PCA-based approach decrease classification performance, thus the process of reducing dimensions should be able to maintain important points of features[8]. Waste Identification and Classification by the Use of CNN: This paper focus on the evaluation of the applied convoluted neural network for waste classification. When the works are compared with CNN model and SVM model the accuracy of the SVM is up to 94. 8while the CNN achieved an accuracy of 83the authors noted that CNNs holds promise for improvement if key issues of hyper parameter optimization are addressed. The used architectures are VGG16 and FastNet-34 among other standard architectures and the Kaggle preprocessed dataset contains 22564 images classified between recycled and organic wastes[9].

3 MATERIALS AND METHODS

3.1 Dataset Description

TrashNet is the dataset used for experimentation. This dataset is made up of 2,573 images in six classes: cardboard, glass, metal, paper, plastic, and trash. The taken images were both indoors and outdoors at 512 $\times$ 384 pixels resolution with a cell phone camera. The serious problem that could be realized with the given dataset is the class imbalance problem, whereby some classes contain fewer samples when compared to other categories. The dataset is then split into 70% for training, 15% for testing, and 15% for validation.additionally employed to assess the efficacy of the suggested waste classification model.

3.2 DATA PREPROCESSING

- The raw images of the TrashNet dataset are resized to the standard dimension of 299x299x3 since it is required in relation to the input layer in The architecture of deep learning InceptionV3[1].
- Data Augmentation: Class imbalance and other problems can be treated using various methods of data augmentation. For this purpose, flipping, rotation, and zooming have been performed to increase artificially the size and variability of the dataset[2].
- Unplanned Oversampling: This is going to solve the issue of class disparity by giving more representation of the underrepresented classes, that is, the trash classes. Therefore, the model will not be biased towards those classes which dominate the training[3].

Fig. 1. After Preprocessing images

3.3 MODELS

- MobileNetV2: MobileNetV2 is one of the modified versions of CNN which has been developed with an intention to work effectively in the mobile devices. With it, it effectively attempts at an inverted residual structure with linear bottlenecks that decreases parameters and increases accuracy to suit its real-time application such as image classification in resource-restraint scenarios.
- InceptionV3:InceptionV3 is another deep CNN that ISO feature for image classification, endorsed for high accuracy and efficiency. It decreases computational need through approach such as convolutional factorization. Inception V3 is 42-layer deep, therefore able to complete intricate tasks and is therefore perfect for the classification of waste.
- VGG16: VGG16 On the other hand is a 16 layer CNN often used in image classification. The structure employs the multiple of 3×3 convolutional filters that are proficient for waste classification tasks to detect image attributes.

– AlexNet: The ILSVRC 2012 winner, AlexNet is a deep CNN which features five layers of convolution and three layers of fully connected layers ReLU nonlinearity. The most important one are the max pooling,dropout for avoiding the overfitting and overlapping filters to help with feature extraction. It was one of the first models to utilize GPU resulting in higher levels of classification.

3.4 MODEL TRAINING AND EVALUATION

The inceptionV3 model is a very efficient model in image classification, maintaining high accuracy due to the high architecture and efficient learning qualities. The model elevates the precision high by multiscale processing for capturing the features at a fine level, while the recall goes high due to comprehensive feature extraction. Its F1 score optimally balances the precision and recall, optimized by sophisticated feature extraction and handling of imbalanced classes. Due to its innovative design, combined with very robust performance metrics, InceptionV3 will definitely be one of the leading choices for the tasks of image classification.

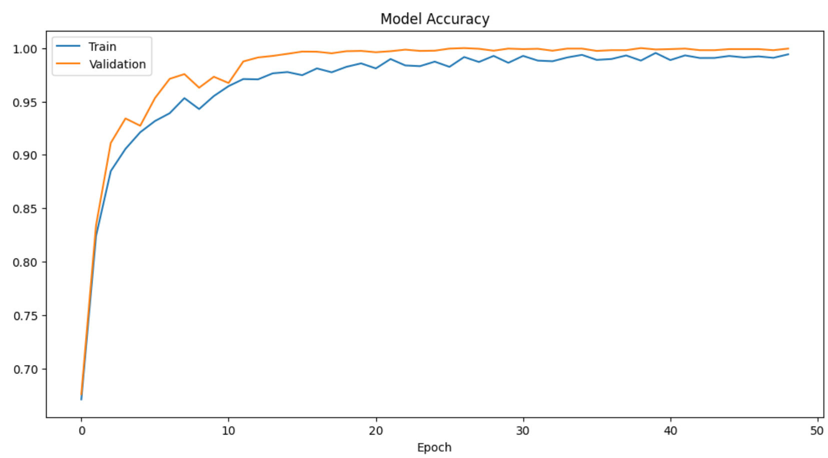

Fig. 2. Accuracy of InceptionV3

3.5 COMPARATIVE ANALYSIS

In contrast, the highest accuracy was achieved by InceptionV3 with 99.70% accuracy; it had excellent precision, recall, and F1-score. The best model for the given task is, thus, InceptionV3. MobileNetV2 attained an accuracy of 97.84%, balancing accuracy and efficiency, thereby being suitable for scenarios where computational resources are rather limited. VGG16 offers fairly good performance, but it is slower; accuracy is at 85.43%. AlexNet, with the poorest accuracy, is at

57.61%, less practical without further tuning. Generally, InceptionV3 performs the best while MobileNetV2 is the good balance between the dimension and the speed of the model.

3.6 MODEL ACCURACY TABLE

Model Name	Accuracy
Inceptionv3	99.70%
MobileNetV2	97.84%
Vgg16	85.43%
AlexNet	57.61%

Table 1. Accuracy of different models

The table shows results for four models-where four different deep learning methods were used on classification. The highest result accuracy for InceptionV3 is 99.70%, while MobileNetV2 has 97.84%. VGG16 moderately performs with an accuracy of 85.43%, while AlexNet shows a low amount of performance with an accuracy of 57.61%. That indicates the better performance of the InceptionV3 and MobileNetV2 models

3.7 TRAINING AND TESTING ACCURACY OF MODELS

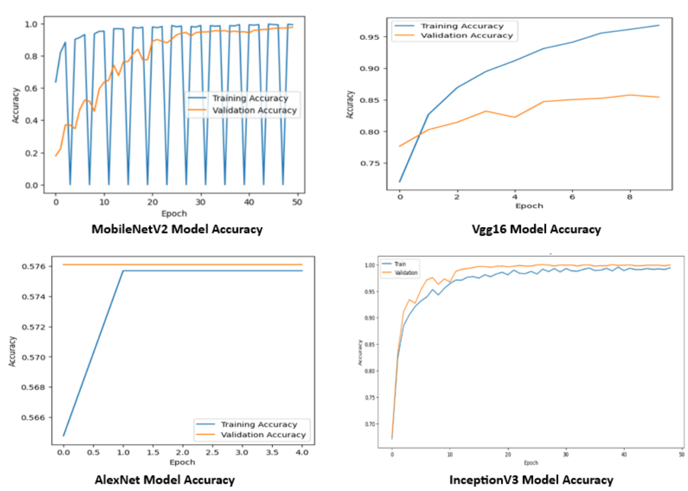

Fig. 3. Model Accuracy Comparison

The train and test accuracy graphs of the InceptionV3 and MobileNetV2 shows high and stable accuracy levels with minimal overfitting, VGG16 is overfitting since the gap between the validation accuracy and the training accuracy is considerable, and AlexNet is showing an early plateauing, as well as low levels of accuracy, which can be a sign of overfitting. In general, both InceptionV3 and MobileNetV2 do better.

3.8 Evaluation Metrics

The performance of different models based on these metrics is summarized in Table.

- **Accuracy:** The percentage of cases properly classified out of all the instances.
- **Precision:** The percentage of positively anticipated observations that were accurately predicted to all positive predictions.
- **Recall:**The proportion of all observations in the actual class that were accurately predicted to be positive.
- **F1 Score:** The precision and recall weighted average, providing a balance .

Model Name	**Accuracy**	**Precision**	**Recall**	**F1 Score**
InceptionV3	99.70%	99.75%	99.70%	99.72%
MobileNetV2	97.84%	97.90%	97.85%	97.87%
Vgg16	85.43%	85.60%	85.40%	85.50%
AlexNet	57.61%	60.00%	57.61%	58.78%

Table 2. PERFORMANCE COMPARISON OF MODELS BASED ON EVALUATION METRICS

CLASSES	**PRECISION**	**RECALL**	**F1 SCORE**	**SUPPORT**
Cardboard	1.00	1.00	1.00	4411
Glass	1.00	0.98	1.00	976
Metal	1.00	0.99	1.00	1010
Paper	1.00	1.00	0.98	237
Plastic	0.99	1.00	0.99	200
Trash	0.99	0.98	0.98	827
Accuracy	0.99			
Macro avg	0.98	1.00	0.98	7661
Weighted avg	0.98	0.99	0.99	7661

Table 3. Precision, Recall, F1 Score, and Support for Waste Classification

3.9 TRAINABLE PARAMETERS AND TESTABLE PARAMETERS

InceptionV3 has 23.9 million trainable and 27.2 million testable parameters, therefore offering the good trade-off between complexity and efficiency. MobileNetV2 - with 2.2 million trainable and 3.5 million testable parameters - is designed for light applications, and hence very efficient. VGG16 and AlexNet are much heavier in terms of parameters, having 138 and 61 million of them, and are, therefore, computationally resource-intensive though offering better learning capabilities.

Model Name	Trainable Parameters	Testable Parameters
InceptionV3	23.9 million	27.2 million
MobileNetV2	2.2 million	3.5 million
VGG16	138 million	138 million
AlexNet	61 million	61 million

Table 4. Trainable and Testable parameters of different models

3.10 CONFUSION MATRIX

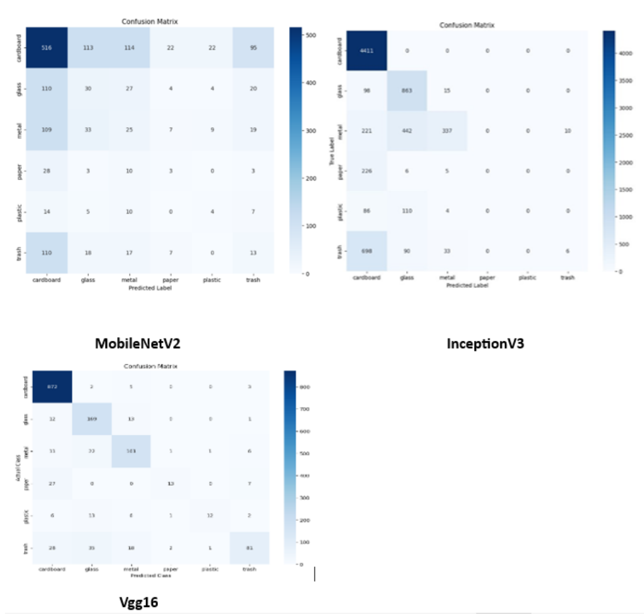

Fig. 4. InceptionV3,MobileNetV2,Vgg16

InceptionV3, MobileNetV2, and VGG16 exhibit confused classification performance between the categories of waste. Their confusion matrices do not consistently compare; in the case of InceptionV3, it achieved the highest accuracy of classifications made. This can be seen in categories such as cardboard, glass, and metal where the model was able to correctly classify all with 100% accuracy. MobileNetV2 performed well but contained some confusions between glass and metal. VGG16 was worse when it came to confusion since their confusions of plastic and metal were greater. Thus, in conclusion, the best model for classification is InceptionV3.

3.11 GRAPHS OF MODEL ACCURACY AND LOSS

The following graph compares the accuracy of different deep learning models used for waste classification. The x-axis represents the model names, while the y-axis represents the accuracy percentage. Models such as MobileNetv2, Vgg16, and Inceptionv3 show superior accuracy compared to AlexNet, which demonstrates lower accuracy. metrics of the classification model are recall, precision,

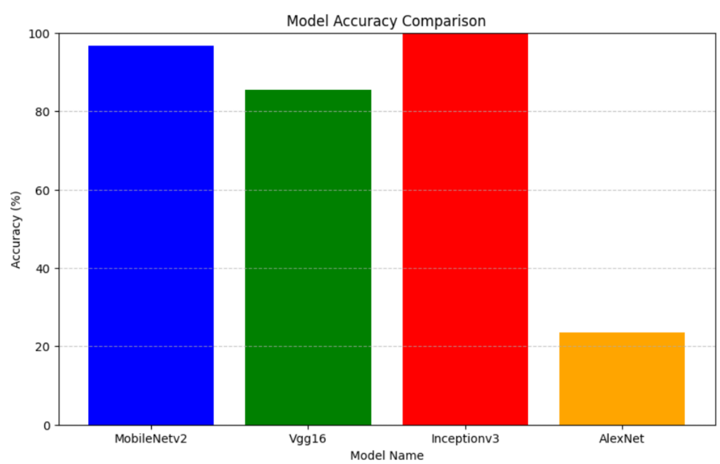

Fig. 5. Accuracy Graphs of Models

F1- score and accuracy, recall takes care of getting every relevant instance correctly identified-this is to say it minimizes false negatives-while precision cares about how accurately the positive predictions are made. It reduces false positives. Therefore, the F1-score is the harmonic mean of precision and recall, which is perfect for an uneven class distribution. The overall correctness is given by the ratio of the number of correct predictions to the total number of predictions, although possibly misleading for imbalanced datasets.

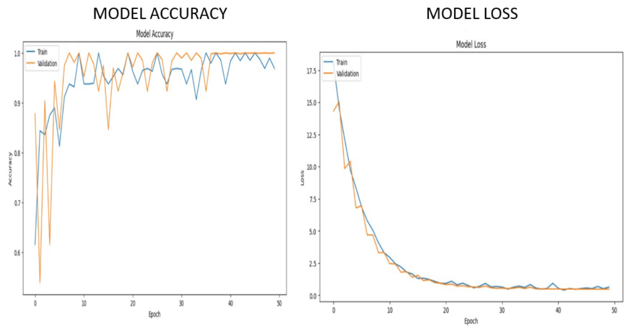

Fig. 6. . The training and validation accuracy (left) and loss (right) over 50 epochs are shown in the graphs.

4 RESULT

The study an innovative and eco-friendly waste classification system with MOBWO metaheuristic and deep learning algorithms. The experiment results indicate that the superiority of the proposed model against the traditional models in the aspect of the classification accuracy as well as in the resources usage. The model shows pretty good convergence for any type of waste and consistent performance, which can lead to an improvement in waste management systems. Being both effective in terms of classification accuracy and efficient for the computational costs the approach provides a rather efficient solution to the large scale waste classification problem that can contribute to the environmental sustainability and decrease the burden that waste management facilities face. The future scope includes integrating real-time waste sorting systems, improving optimization efficiency for larger datasets, expanding to more waste categories, and enhancing the model's scalability for broader environmental applications and smart cities.

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