Optimized Waste Classification Using Deep Learning: A Focus on Biodegradable and Non-Biodegradable Materials

ABSTRACT

Waste classification is a crucial task in waste management systems, aimed at improving recycling efficiency and environmental sustainability. This paper presents a convolutional neural network (CNN) based approach for distinguishing between biodegradable and non-biodegradable waste using deep learning techniques. We utilize the cnn architecture, a well-established model known for its success in image classification tasks and adapt it for our specific waste classification problem.

INTRODUCTION

Waste generation has been rising dramatically over the years. One of the reasons for the increase in waste generation would be due to increase in population. The accumulation of waste in urban areas have become a significant concern as it may lead to the pollution of the environment. It might also lead to effecting human health if they are not properly managed. Effective waste management is crucial to mitigate these risks and ensure sustainable urban living.

The reports of the World Bank Data says that the global waste generation is projected to increase from 2.1 billion tons to 3.8 billion tons per year by the end of 2050. This sharp rise in waste generation highlights the urgent need for effective waste management strategies.

In metropolitan cities like Bengaluru, where the local governing body, Bruhat Bengaluru Mahanagara Palike (BBMP), has implemented a rule to segregate wet waste and dry waste before their disposal to facilitate appropriate disposal and recycling.

LITERATURE REVIEW

Deep learning techniques are applied to waste detection and classification, examining various models and evaluating their effectiveness. The survey reviews over twenty trash datasets, discusses current limitations, and provides insights into state-of-the-art models for waste management while highlighting future research opportunities [1].

An intelligent waste classification system is implemented using a pre-trained ResNet-50 CNN for feature extraction and an SVM for classification. The system aims to enhance the manual waste separation process, achieving an 87% accuracy rate on a tested dataset, thus improving efficiency and reducing human involvement [2].

The study focuses on categorizing Municipal Solid Waste (MSW) using deep learning techniques, specifically the EfficientNet-B0 model for image classification. Fine-tuning this model for images from single population regions is proposed to improve classification accuracy and efficiency in waste management [3].

Challenges in waste segregation are addressed by proposing an automated classification system using machine learning and deep learning algorithms. The study compares CNN, SVM, Random Forest, and Decision Tree models, finding CNN to have the highest classification accuracy, making it the most effective for waste sorting [4].

Solid waste management is improved using supervised deep learning techniques to enhance recycling efforts by detecting and classifying waste types. The study contrasts manually engineered models with conventional machine learning algorithms, demonstrating the potential of automated machine learning in smart waste management systems [5].

An improved deep convolutional neural network (DCNN) is proposed for automating the classification of organic and recyclable waste, with a dataset of 25,077 images. The model shows better performance than others like VGG16 and MobileNetV2, achieving a classification accuracy of 93.28% after transfer learning [6].

Various convolutional neural networks, including AlexNet, DenseNet121, and SqueezeNet, are evaluated for waste classification. The study aims to find the most efficient model for accurately categorizing waste, with DenseNet121 performing the best in terms of accuracy and efficiency [7].

The performance of deep learning models such as ResNet50, GoogleNet, InceptionV3, and Xception is compared for waste material classification. Metrics like accuracy, precision, recall, and F1 score highlight ResNet50's high accuracy, demonstrating the potential of advanced deep learning models for improving waste management [8].

Waste classification is explored using Convolutional Neural Networks (CNNs), focusing on transfer learning versus full learning approaches. A custom dataset is utilized, and results indicate that DenseNet121 in transfer learning outperforms other models, achieving the highest accuracy of 95.2% [9].

An automated plastic waste classification system is developed using deep learning and CNNs to improve recycling efficiency. The system sorts various types of plastic, enhancing urban waste management by automating the segregation process, which can be applied to sorting belts or portable devices [10].

Increased waste production is managed using deep learning and neural network algorithms to detect and classify garbage. Models like CNNs, SVMs, and Faster R-CNN are tested, and their effectiveness is evaluated using metrics such as the confusion matrix and ROC curve to improve automated waste management systems [11].

To address global waste production challenges, deep learning techniques are used to improve waste sorting efficiency. The study focuses on classifying organic and inorganic waste, with MobileNet achieving the highest accuracy of 93.35%, demonstrating its effectiveness in separating waste types [12].

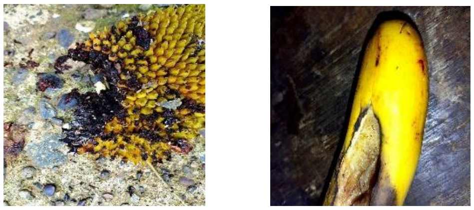
An automated waste segregation system, ConvoWaste, is developed using a Deep Convolutional Neural Network (DCNN) for precise classification and a servo motor-based mechanism for sorting waste. The system supports circular economy principles by promoting recycling and reducing waste, with a high classification accuracy of 98% [13].

Convolutional Neural Networks (CNNs) are used for efficient waste sorting, achieving a high accuracy rate of 98.92% on a test set. The model's accurate identification and sorting of waste materials make it a viable solution for reducing landfill waste and conserving resources [14].

Addressing waste segregation issues in India, an automated classification system using deep learning is developed. Four CNN models are evaluated for their performance in categorizing waste types, with DenseNet169 achieving the highest accuracy, followed by ResNet50, highlighting their effectiveness in recycling processes [15].

DATASET DESCRIPTION

The dataset includes a total of 1,618 images, divided into two primary classes: biodegradable and non-biodegradable which is generated from the website named ‘Roboflow’. This website has multiple datasets through which a few images were used. The real time images of the waste were also collected along with the images used from website. Each class represents a variety of waste items commonly encountered in real-world scenarios. To ensure the robustness and generalizability of the model, the images were sourced from diverse environments, including urban, rural, and industrial settings. This diversity in sourcing helps capture a wide range of visual features, such as different lighting conditions, backgrounds, and object orientations. Additionally, the dataset includes variations in waste item size, color, and texture to better reflect the complexity of real-world waste management tasks. By incorporating these variations, the dataset aims to prepare the model to accurately classify waste items under various conditions, thereby improving its performance in practical applications.



a. Biodegradable Data

b. Non – biodegradable Data

METHODOLOGY

The dataset contains images of different types of biodegradable waste and non-biodegradable waste. Images were pre-processed using image augmentation techniques like resizing the images, RGB conversion and other image augmentation. VGG16 model was chosen for its accuracy. Performance metrics showed high accuracy. Hyperparameters were fine-tuned for optimal performance.

A. About the model

VGG16 is a convolutional neural network architecture that was introduced by the Visual Geometry Group (VGG) at the University of Oxford. It became widely recognized for its performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014, where it achieved significant accuracy. VGG16 is known for its simplicity and effectiveness, relying on a deep architecture with small convolution filters. VGG16 is comprised of a total of 16 layers in which 13 layers are convolutional and 3 layers are fully connected layers.

VGG16, a deep convolutional neural network pre-trained on ImageNet, was chosen due to its effectiveness in feature extraction and high performance in image classification tasks. The pre-trained model provides a robust starting point, leveraging learned features from a large and diverse dataset.

B. Data – preprocessing

The dataset underwent pre-processing steps that involved image augmentation, normalizing the images and the images were resized and stretched to have a dimension of 255x255 to ensure consistency in the model's input. This resizing step standardizes the input size, enabling the model to process images efficiently. Additionally, image normalization is applied by scaling pixel values to the range [0, 1]. This normalization helps in stabilizing the training process and accelerating convergence by ensuring that the input features are on a similar scale.

Each image was carefully inspected to ensure they were free from corruption or irrelevant content that could affect model training. Duplicates were identified and removed to prevent bias in the model's learning process. Additionally, all images were checked for correct labeling, ensuring they accurately represented the biodegradable or non-biodegradable categories. These steps were crucial to maintain the integrity and quality of the dataset, ensuring that the model learns from accurate and representative examples.

C. Data Augmentation

Purpose and Benefits: Data augmentation is a technique used to artificially expand the training dataset by creating modified versions of existing images. This process helps to improve the model’s robustness and generalization by exposing it to a wider range of image variations that it might encounter in real-world scenarios. The primary benefits of data augmentation include:

IMPLEMENTATION

This section outlines the implementation steps taken to develop the waste classification system using Convolutional Neural Networks (CNNs), specifically leveraging the VGG16 architecture. The process includes data collection and preprocessing, model architecture setup, training and evaluation using different evaluation metrics.

The model is loaded with pre-trained weights on the ImageNet dataset. The VGG16 model's convolutional layers were kept frozen to retain the features learned from the ImageNet dataset. This reduces the risk of overfitting when the dataset is small. The ReLU (Rectified Linear Unit) activation function is applied, introducing non-linearity and enabling the model to learn complex patterns. This dense layer acts as a new "brain" of the network, learning specific features relevant to waste classification. The fully connected layers were replaced with a new classifier tailored to the two waste categories. This new classifier consists of a global average pooling layer followed by a dense layer with a SoftMax activation function.

The model's performance was evaluated using accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's classification capabilities. A confusion matrix was also generated to visualize the performance across different classes.

It was carried out in Python using TensorFlow and Keras as the primary deep learning frameworks. Data pre-processing was conducted mainly using OpenCV and NumPy libraries.

RESULTS

A. GRAPHS

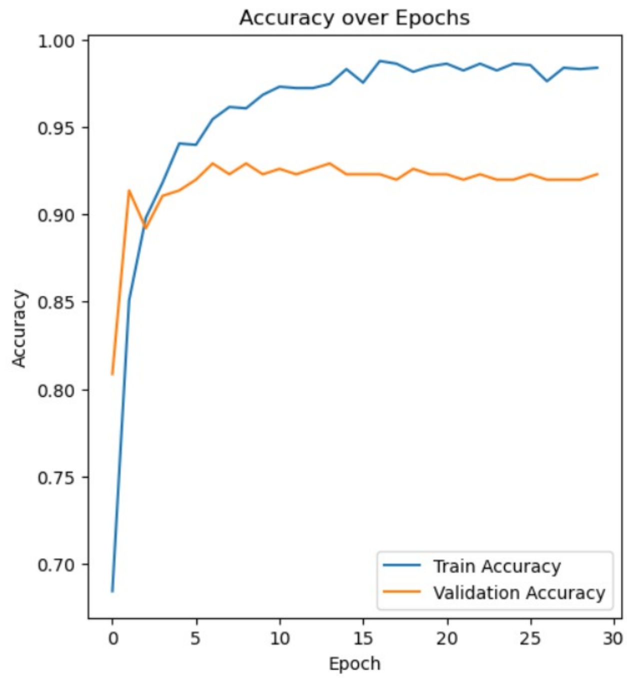


Fig-1. Accuracy over epoch graph

This graph shows the accuracy of a model on both training and validation data across 30 epochs. It demonstrates that the model effectively learns during the initial stages, with both training and validation accuracy improving rapidly within the first five epochs. The training accuracy continues to increase, eventually surpassing 95%, while the validation accuracy stabilizes around 90-93%, indicating good generalization. However, the slight divergence between the training and validation accuracy suggests potential overfitting, as the model continues to improve on the training set without corresponding gains on the validation set. Overall, the model exhibits strong performance and stable optimization throughout the training process.

training data but fails to generalize as effectively to unseen data. Despite this, the relatively low validation loss suggests that the model maintains a reasonable level of generalization.

B. EVALUATION METRICS

To comprehensively evaluate the performance of a classification model, several metrics are utilized. Each metric provides unique insights into different aspects of model performance:

MODEL	CLASS	PRECISION	RECALL	F1-SCORE
VGG16	0	0.96	0.90	0.93

	1	0.90	0.96	0.93
	Accuray			0.93
	Macro Avg			0.93
	Weighted Avg			0.93

The class label named 0 represents the biodegradable waste images and the label named 1

CONCLUSION

The proposed approach demonstrates the effectiveness of using a pre-trained VGG16 model for waste classification. By leveraging transfer learning and fine-tuning, the model achieves high accuracy in distinguishing between biodegradable and non-biodegradable waste. The application of data augmentation, careful tuning of hyperparameters, and thorough evaluation ensure the model's robustness and reliability. Future research may explore additional architectures or incorporate more diverse datasets to further enhance classification performance.

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