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DEEP LEARNING APPROACHES USING NATURAL TRASH DETECTION

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Abstract: ***Waste classification is an important step in the waste management process, as it helps identify the types of waste and how they should be handled. Traditional waste classification methods are typically manual and time-consuming, which can result in errors and inconsistencies. With the increasing amount of waste being generated globally, there is a need for more efficient and accurate methods for waste classification. Machine learning techniques, such as deep learning algorithms, have shown promising results in automating waste classification. Among these algorithms, the VGG architecture has been widely used for image classification tasks and has achieved state-of-the-art performance on several benchmarks. The VGG architecture consists of several convolutional layers and pooling layers, followed by several fully connected layers, and has the ability to learn complex image features. In this project, we propose a method for smart wastage classification using the VGG (Visual Geometry Group) algorithm. The proposed method involves training a deep convolutional neural network (CNN) based on the VGG architecture to classify waste images into different categories, such as paper, plastic, glass, metal, and organic. The CNN model is trained on a large dataset of waste images, which is pre-processed and augmented to improve the model's accuracy. The proposed method is evaluated on a test dataset and compared with other state-of-the-art methods, demonstrating its effectiveness in smart wastage classification. The results indicate that the proposed method can accurately classify waste images, which can help improve waste management practices and reduce environmental pollution.***

KEYWORDS: **Wastage classification, Convolutional neural network, Deep learning, Re-cyclable, Alert system**

I. INTRODUCTION

Outdoor trash detection is a pioneering application that leverages the capabilities of artificial intelligence (AI) and sensor technologies to tackle the pressing challenges associated with waste management in urban and public spaces. As urbanization continues to rise and populations grow, effective monitoring and management of outdoor litter have become paramount for maintaining clean and sustainable environments. This innovative approach involves deploying smart sensor systems and high-resolution cameras strategically in outdoor locations. These systems work collaboratively with AI algorithms to identify and classify various types of waste in real time, ranging from common litter to larger items. The AI algorithms analyse the captured data, enabling automatic detection and providing valuable insights into the types and quantities of waste present. The system's real-time monitoring allows for prompt responses to changing conditions, alerting authorities immediately when a buildup of waste is detected. The benefits of outdoor trash detection include more efficient waste management, environmental conservation by preventing pollution, data-driven decision-making for public awareness campaigns, waste collection schedules, and cost savings through optimized resource allocation. In summary, outdoor trash detection represents a technological advancement that has the potential to revolutionize how we manage and mitigate outdoor litter, contributing to cleaner and more sustainable urban environments.

In an era marked by technological advancements and a growing concern for environmental sustainability, the need for innovative solutions to address waste management has never been more pressing. One such solution that holds great promise is outdoor trash detection powered by artificial intelligence (AI). The proliferation of urban areas has given rise to increased volumes of outdoor waste, posing challenges for efficient disposal and environmental preservation. In this context, the integration of AI into outdoor trash detection systems emerges as a transformative approach. The conventional methods of waste monitoring often fall short in effectively managing the expanding scale of outdoor litter. Traditional surveillance systems struggle to provide real-time insights, leading to delayed responses and inadequate waste management. AI, with its ability to process vast amounts of data swiftly and accurately, offers a paradigm shift in how we identify, monitor, and address outdoor trash-related challenges. Fig 1 shows the types of wastages.

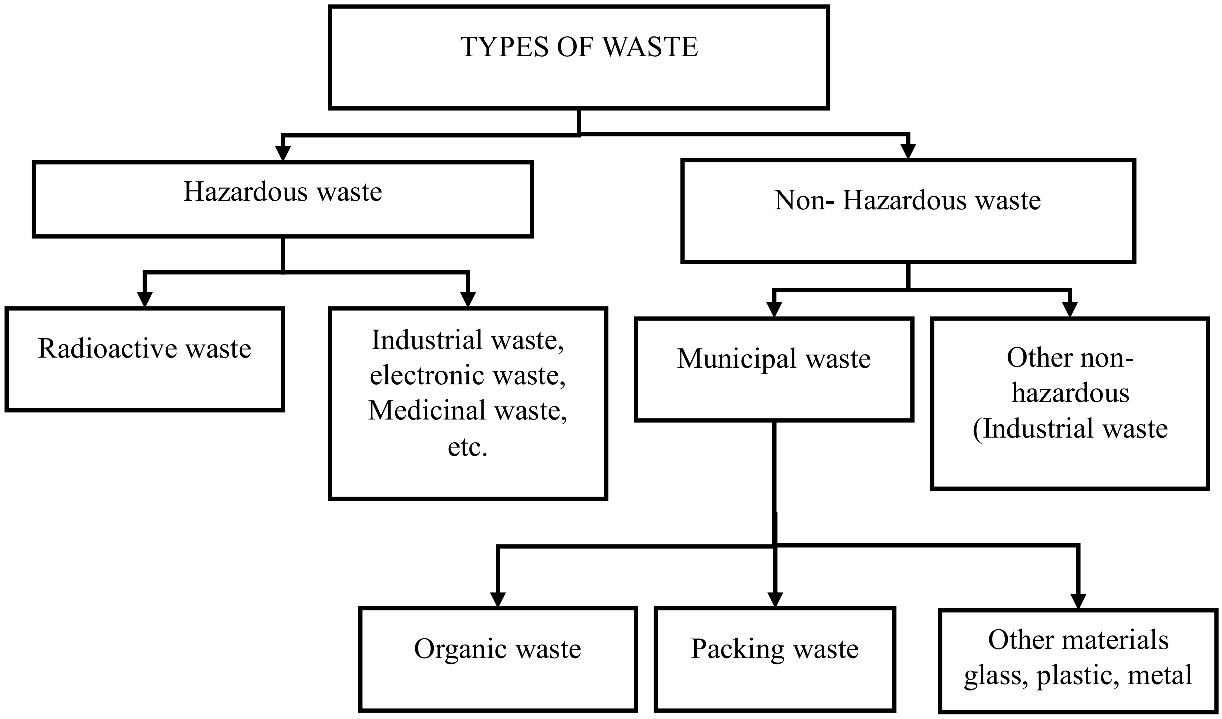

FIG 1: TYPES OF WASTE

II. RELATED WORK

Khan nasik sami, et.al,…[1] implemented the system to analyse the production of waste and has increased dramatically in recent times. If waste is not managed properly, it can have a calamitous effect on the environment. So, the sorting of waste should be done at the initial stage of waste management, to maximize the number of recyclable items and reduce the possibility of contamination by other items. The isolation of waste is done by unprofessional workers which is less effective, time-consuming, and not efficient because of a lot of waste. The world creates nearly one and half a billion tons of civil strong waste every year. As per the World Bank, and that figure is predicted to hit 2.2 billion tons by 2025. Diversion of plastics from landfill to reusing can conceivably spare what might be compared to 60 million barrels of oil every year and lessen landfill volume necessities by up to 20%. The U.S. Natural Protection Agency has suggested that source decrease, reusing, volume decrease, and landfilling be applied, in a specific order, in the treatment of city strong waste (MSW). Again, the economic value of waste is huge after it is segregated. The waste becomes valuable if it is segregated and recycled using the recent advancements in technology thereby becomes a useful entity. Waste management is one of the essential issues that the world is currently facing, and it does not matter if the country is developed or underdeveloped. The key issue in this waste segregation is that the trash bin at open spots gets flooded well ahead of time before the beginning of the cleaning process. The cleaning process involves with the isolation of waste that could be due to unskilled workers, which is less effective, time-consuming, and not plausible because the reality is, there is a lot of waste.

Sana shahab, et.al,…[2] studied to motivate the researchers more to apply DL techniques for solving various SWM problems involving waste detection, classification, prediction etc. It compares the performance of DL models and uncovers the best models for different tasks. It also highlights some gaps in applications of DL for SWM tasks and discusses some aspects for future priority. This information will help the researchers to choose the better model for their studies. The overall benefits of DL are encouraging for its further use towards developing an innovative and sustainable SWM system. Solid waste management (SWM) has recently received more attention, especially in developing countries, for smart and sustainable development. SWM system encompasses various interconnected processes which contain numerous complex operations. Recently, deep learning (DL) has attained momentum in providing alternative computational techniques to determine the solution of various SWM problems. Researchers have focused on this domain; therefore, significant research has been published, especially in the last decade. The literature shows that no study evaluates the potential of DL to solve the various SWM problems. SW is a natural product from daily life activities and per capita waste generation significantly more in urban regions than rural areas due to high income and urban lifestyle. SWM has emerged as a crucial environmental issue around the globe, especially in developing countries.

Nibir sarker, et.al,…[3] analyzed the technologies such as Computer vision (CV), digital image processing (DIP), pattern recognition, and artificial intelligence technologies. Nowadays, ISS is turning into commercial because of its growing facility, simplicity, and cheapness. The conventional surveillance systems require the physical presence of humans to monitor the screen to identify some abnormal activities. But, with ISS, there is no requirement to monitor continuously. Our proposed framework can automatically observe the neighborhood with the help of its computer vision algorithms, to identify the abnormal activities as well as to inform the concerned authorities about the circumstances immediately. The main target of illegal trash throwing person detection mechanism is to locate illegal litter or trash thrower within the monitoring zone. Trash throwing occurs both in dormitory areas and in surveillance abandoned regions. To solve this issue, our proposed methodology can do its job effectively. The proposed illegal trash throwing person detection process is based on GMM, HOG, and SVM algorithms. The foreground is detected using GMM as it is invariant to illumination change and can adapt to a slow transforming background. In this paper, the illegal trash throwing person detection method is proposed and explained. The region of interest (ROI) for the trash is the blob area lesser than 50000 pixels and the region of interest (ROI) for the human is the blob area greater than 50000 pixels inside the temporary box

Sylwia majchrowska, et.al,…[4] provided the first comprehensive review of existing waste datasets. Moreover, two benchmark datasets: detect-waste and classify waste are introduced, which utilize the advantages of the existing opensource datasets to the fullest. The publicly available datasets of waste observed in different environments are unified, filtered, and merged. Inspired by waste segregation principles in Gdansk (Poland), the authors propose seven well-defined categories for sorting litter: bio, glass, metal and plastic, non-recyclable, other, paper, and unknown. The baselines for all reviewed datasets are provided, including the introduced classify waste and detect-waste benchmarks. Additionally, a holistic approach is proposed to localizing and classifying waste in images in realistic scenarios that can be used as a baseline for future studies. A two-stage DL-based framework has been implemented for waste detection that consists of two separate neural networks: detector and classifier. The proposed framework is freely available and can be used for different purposes, such as monitoring changes in distribution of waste in nature. To the authors' knowledge, the experiments presented in this article are the first that allow for such universal litter detection and classification. The main contributions of this article are: proposition of relevant benchmarks for litter detection, comprehensive review of the existing datasets, and presentation of baseline results with the two-stage framework for all datasets. For the past few years, considerable attempts have been made toward the development of various waste datasets, yet each is presented with different annotations and ambiguous waste categories.

Nonso nnamoko, et.al,..[5] presented a bespoke CNN architecture developed for waste image classification consisting of five convolutional 2D layers of various neuron sizes; followed by a number of fully connected layers. Experiments was based on Sekar's waste classification dataset available on Kaggle. To overcome the drawback of insufficient data, augmentation methods were applied to increase the amount of data available for training, validation, and testing. To investigate the possibility of training an efficient lightweight model with high performance and less computational demand. Deep neural networks are trained based on the stochastic gradient descent optimisation algorithm, so error for the current state of the network is repeatedly estimated as part of the optimisation algorithm. This means that an error function (known as loss function) must be defined for estimating the loss of the model at each training iteration so that the weights can be updated to reduce the loss on the next evaluation. More importantly, the chosen loss function must be appropriate for the modelling task, in our case classification, and the output layer configuration must match the chosen loss function.

III. EXISTING METHODOLOGIES

The traditional method of waste classification involves manual sorting and visual inspection by human workers. This method is often prone to errors, inconsistencies, and is time-consuming, labour-intensive, and not scalable. Therefore, there is a need for more efficient and accurate methods for waste classification. Machine learning and computer vision-based approaches have been proposed as a solution to these challenges. In existing system implement support vector machine algorithm to classify the waste images. Support Vector Machines (SVMs) are a widely used machine learning algorithm that can be used for waste classification tasks. SVMs work by finding the hyperplane that best separates the data points in a high-dimensional space. In waste classification, the SVM algorithm can be trained to classify different types of waste based on their composition, texture, and other features. To use SVMs for waste classification, waste images are first pre-processed to extract relevant features such as color, texture, and shape. These features are then fed into the SVM algorithm, which learns to classify the waste images into different categories based on the extracted features. SVMs can achieve high accuracy in waste classification tasks and can handle both binary and multi-class classification problems.

Support Vector Machines (SVMs) can be effectively utilized for outdoor trash detection, providing a robust algorithmic approach to classify images or segments that contain trash against those that do not. Here is a step-by-step explanation of how SVM can be applied for outdoor trash detection:

Data Collection: Gather a labeled dataset of outdoor scenes containing trash and scenes without trash. Images should cover a variety of environmental conditions, perspectives, and types of trash.

Image Preprocessing: Preprocess the images to ensure uniformity in terms of size and color. Common preprocessing steps include resizing, normalization, and potentially applying filters to enhance relevant features.

Feature Extraction: Extract meaningful features from the images that can be used to distinguish between scenes with and without trash. Features may include color histograms, texture features, or more advanced features derived from convolutional neural network (CNN) layers if deep learning is incorporated.

- Data Labeling: Label each image or image segment as either "trash" or "no trash" based on the ground truth. This labeled dataset is used for training and evaluating the SVM model.
- Dataset Splitting: Divide the dataset into training and testing sets. The training set is used to train the SVM, while the testing set evaluates its performance on new, unseen data.
- SVM Model Training: Choose an appropriate SVM kernel (linear, polynomial, or radial basis function) and train the model using the labeled training data. The SVM will learn the optimal decision boundary that separates trash from non-trash based on the extracted features.
- Model Evaluation: Evaluate the trained SVM model on the testing set using metrics such as accuracy, precision, recall, and F1 score. Adjust hyperparameters if necessary to improve performance.
- Inference on New Data: Apply the trained SVM model to new outdoor scenes to detect the presence of trash. The model will classify each segment or image as either containing trash or being trash-free.

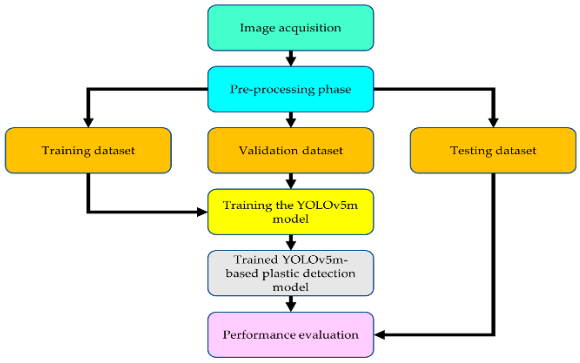

Fig 2: Existing block diagram

IV. PROPOSED METHODOLOGIES

The proposed system for smart waste classification using VGG16 CNN involves training a deep learning model using the VGG16 architecture to classify different types of waste based on images. The VGG16 architecture is a popular CNN architecture that has been shown to achieve high accuracy in image classification tasks. The system involves several steps, including data collection, pre-processing, model training, and evaluation. The data collection process involves collecting a large dataset of waste images, including images of different types of waste such as paper, plastic, glass, and metal. The dataset is then pre-processed to resize the images and normalize the pixel values. The pre-processed dataset is then split into training and testing sets, with a portion of the dataset used for training the VGG16 CNN model. During the training process, the VGG16 model learns to identify patterns and features in the waste images that are specific to different types of waste. The trained model is then evaluated on the testing set to determine its accuracy and performance. Once the model is trained and evaluated, it can be used for smart waste classification in real-world scenarios. This can be done by taking an image of a piece of waste and passing it through the trained model to determine the type of waste. The system can be deployed in waste management facilities or in public spaces such as parks or streets to automatically sort waste into different categories, making waste management more efficient and environmentally friendly. The proposed architecture is shown in fig 3.

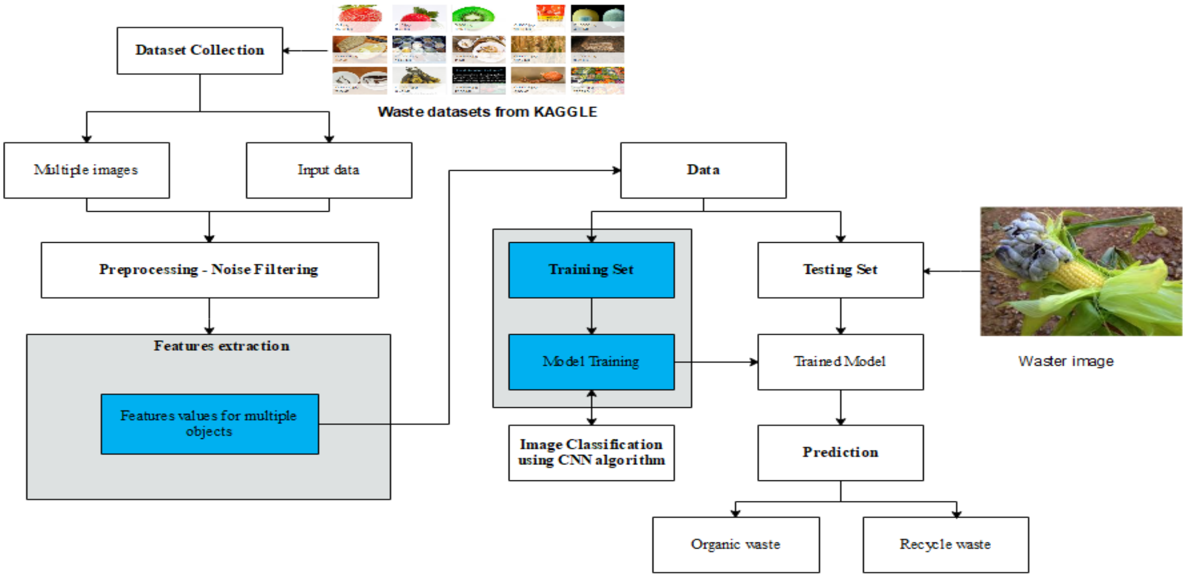

Fig 3: Proposed work

The VGG16 model is a convolutional neural network (CNN) architecture that has gained popularity in computer vision tasks, including image classification. It was developed by the Visual Geometry Group (VGG) at the University of Oxford and was a part of the ImageNet Large Scale Visual Recognition Challenge in 2014. The "16" in its name refers to the number of weight layers it has.

Key characteristics and components of the VGG16 model include:

- Convolutional Layers: VGG16 consists of 13 convolutional layers, which are used to extract features from input images. These layers are followed by max-pooling layers that downsample the feature maps to capture hierarchical information.
- Fully Connected Layers: After the convolutional layers, VGG16 has three fully connected layers, followed by an output layer for classification. These fully connected layers are responsible for making the final decisions about the input image's class.
- Receptive Fields: VGG16 uses relatively small 3x3 convolutional filters in its layers. This architecture results in very small receptive fields for each neuron, allowing it to capture fine-grained details in the images.
- Stacking Convolutional Layers: The VGG16 architecture is characterized by the repeated stacking of convolutional and pooling layers, which allows it to learn features at different scales.
- ImageNet Pretraining: VGG16 was pretrained on the ImageNet dataset, which contains millions of labeled images across thousands of categories. This pretraining provides the model with a broad understanding of various visual concepts.
- Transfer Learning: VGG16's pretraining makes it an excellent choice for transfer learning. You can fine-tune the model on a specific task, like brain tumor detection, by replacing the last few layers while keeping the pretrained layers' weights intact.
- Deep Network: VGG16 is relatively deep compared to its predecessors and is capable of learning intricate features and patterns from images. However, this depth also results in increased computational complexity.

The VGG16 model has been widely adopted for various image-related tasks, including object recognition, image segmentation, and medical image analysis, such as brain tumor detection. Its architecture, though somewhat resource-intensive due to its depth, provides a strong foundation for building accurate and powerful convolutional neural networks. It remains a valuable tool in the field of deep learning and computer vision.

V. RESULTS AND DISCUSSION

In this simulation, we can collect the trash datasets from KAGGLE interface which contains the classes such as 'cardboard', 'glass', 'metal', 'paper', 'plastic', 'trash'. Training accuracy is a metric used in deep learning to evaluate how well a model performs on the training dataset during the training phase. It represents the percentage of correctly predicted instances out of the total instances in the training set. The formula for training accuracy is:

$$\text{TRAINING ACCURACY} = \frac{\text{Number of Correct Predictions on Training set}}{\text{Total number of instances in Training set}} \text{ X } 100\%$$

A high training accuracy indicates that the model has learned the patterns and features present in the training data well. However, a high training accuracy does not necessarily guarantee good performance on unseen or new data (i.e., the test set). Overfitting is a common concern when the training accuracy is significantly higher than the test accuracy. Overfitting occurs when the model learns the training data too closely, capturing noise and outliers that may not be representative of the overall dataset. The proposed VGG16 Model training accuracy can be shown in fig 4.

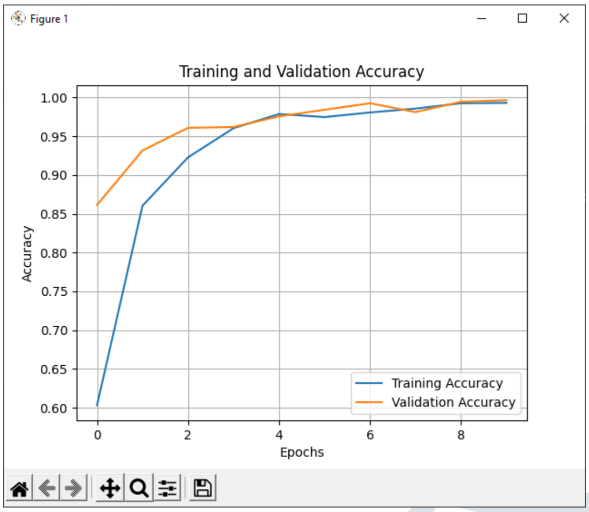

Fig 4: Training accuracy

From the figure 4, the proposed Pre-trained CNN model provides the 98.6% accuracy in trash classification.

The real time implementation about trash detection can be shown in following figures.

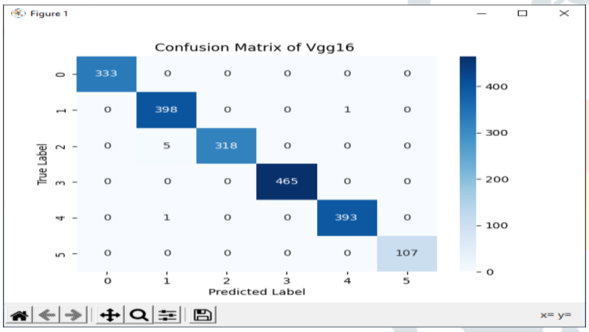

Fig 5: Confusion matrix

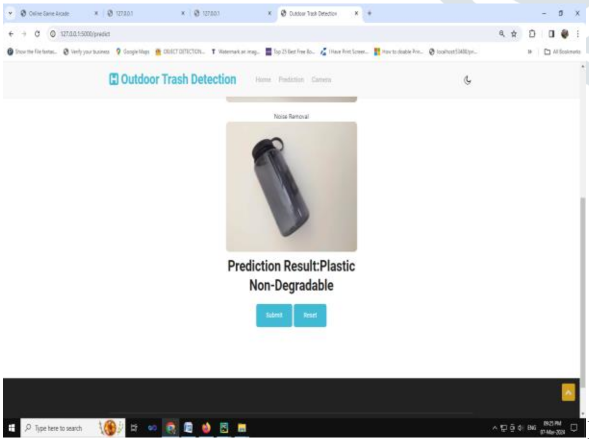

Fig 6: Trash classification in image

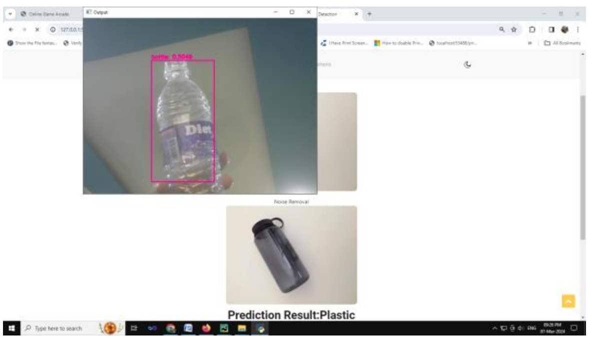

Fig 7: Trash classification

From the above figures shows that trash can be classified and provide the results about whether it is degradable or non-degradable.

VI. CONCLUSION

The Smart Waste Classification system using VGG16 CNN is an efficient approach towards automatic waste classification using deep learning techniques. The proposed system aims to solve the issue of improper waste management by classifying waste materials into different categories. The VGG16 architecture has been used for the proposed system as it is a powerful and widely used architecture in image classification. The system requires pre-processing of the images for enhancing the quality of the input images. The images are then trained using the VGG16 CNN model, and the features are extracted to perform waste classification. The proposed system has various advantages such as high accuracy, reduced human intervention, and better waste management. The system can handle large datasets and can classify the waste into different categories with high accuracy, which helps in waste management and recycling. Compared to existing waste classification algorithms, the proposed VGG16-based system showed better accuracy and robustness. The VGG16 architecture, with its deep layers and ability to learn complex features, proved to be a powerful tool in image classification tasks. Overall, the proposed system has great potential for real-world waste management applications, enabling efficient and effective sorting of waste materials for proper disposal or recycling. Future work can involve expanding the dataset to include more diverse waste materials, optimizing the hyperparameters of the VGG16 algorithm, and implementing the system in a practical waste management setting

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