INTELLIGENT WASTE CLASSIFICATION SYSTEM USING CNN

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Abstract *- One of the key environmental issues has been trash management, which has negative consequences on both society's health and the environment's delicate balance. The traditional trash management system can be replaced with a real-time monitoring system thanks to technological advancements, enabling improved waste management. Using a deep learning model, the project's goal is to create a smart trash management system. The pre-trained detection model with photos is used to carry out object detection. With a classification accuracy rating of around 90%, CNN achieves great performance. In this paper, we proposed to use the ResNet algorithm for efficient waste image classification. The ResNet algorithm allows for the training of extremely deep networks without suffering from the vanishing gradient problem,making it highly effective for image classification tasks.*

Keywords: *image classification, deep learning, waste classification, recycling, CNN, ResNet*

I. INTRODUCTION

The management of garbage is a major global concern, and the environment is seriously threatened by the growing volume of waste. A Convolutional Neural Networks (CNN)-powered Intelligent Waste Classification System (IWCS) is one of the creative alternatives offered by modern technology to address this problem. The IWCS idea, its significance in waste management, and how CNNs might be used to improve waste sorting and recycling

procedures are all covered in this project. The process of trash management must begin with waste classification. An environment that is more sustainable and environmentally friendly is made possible by accurate waste sorting, which increases recycling efforts and decreases the amount of waste dumped in landfills. To automatically recognize and classify various waste products, an intelligent waste classification system makes use of deep learning techniques[56]. CNNs are a kind of deep learning model created for tasks requiring image identification. They have a multi-layered design that derives hierarchical features from images and is modeled after the human visual system. They are therefore especially well -suited for jobs requiring picture categorization, such as garbage classification.Automatic recognition and detection of waste from images has become a popular choice to replace manual waste sorting, thanks to the rapid advances in computer vision and artificial intelligence. Many machine learning algorithms have been proposed to improve the *accuracy* of automatic waste classification [12,13,14].

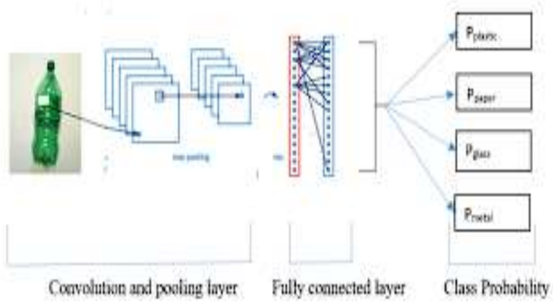

Figure 1. Waste classification using CNN

In recent years however, deep neural networks[15], especially convolutional neural networks (CNN), have proven to be very effective in learning from existing data, achieving remarkable results in image classification[14,16,17,18]. Thus, by taking images of solid waste as input data, CNNs can automatically classify waste into the relevant categories. Figure 1 depicts the waste classification system using CNN layers..[68]ResNet is an invaluable tool in garbage classification and other computer vision applications due to its innovation in managing deep networks and its capacity to capture subtle patterns. You can develop precise and effective waste classification systems that support environmental sustainability by taking advantage of ResNet's advantages.

II. LITERATURE SURVEY

Sujan Poudel and Prakash Poudyal(2022), have pre-trained CNN model such as InceptionV3, InceptionResNetV2, Xception, VGG19, MobileNet, ResNet50 and DenseNet201 and performed fine-tuning on the waste dataset. Among these models, the VGG19 model performed with less accuracy, whereas the InceptionV3 model performed with high learning accuracy.A total of 101, 102, and 95 images have been classified correctly by InceptionResNetV2, DenseNet201, and ResNet50 out of 140 images which means InceptionResNetV2 and DenseNet201 have almost similar performance on testing data but DenseNet201 have better validation accuracy[1].In [2], Adedeji Olugboja, Zenghui Wang(2019),proposed an intelligent waste material classification system, which is developed by using the 50-layer residual net pre-train (ResNet-50) Convolutional Neural Network model which is a machine learning tool and serves as the extractor, and Support Vector Machine (SVM) which is used to classify the waste into different groups/types such as glass, metal, paper, and plastic etc. The proposed system is tested on the trash image dataset which was developed by Gary Thung and Mindy Yang, and is able to achieve an accuracy of 87% on the dataset. The separation process of the waste was faster and intelligent using the proposed waste material classification system without or reducing human involvement. Nonso Nnamoko et al.,(2022) employed two picture resolution sizes (i.e., 225264 and 8045) to examine the performance of a five-layer convolutional neural network in terms of development time, model size, predictive accuracy, and cross-entropy loss in order to evaluate the computational cost issue. They reason that a model trained with lower picture resolution will be more lightweight and/or accurate than one trained with higher image resolution[3]. Nasir, I., & Aziz Al-Talib, G. A. (2023) have studied that the efficiency and accuracy of conventional trash classification techniques are both low. Waste classification is the process of identifying and categorizing different types of waste based on their characteristics[4]. Accurate waste classification is important for a number of reasons, including supporting recycling and other forms of resource recovery, protecting the environment and human health, and reducing the costs of waste management. [5]Haruna Abdu, Mohd Halim Mohd Noor (2022), have reviewed various image classification and object detection models, and their applications in waste detection and classification problems, providing an analysis of waste detection and classification techniques with precise and organized representation and compiling over twenty benchmarked trash datasets. Ali Usman Gondal et al.,(2021) have presented the idea of a real-time smart waste classification model that uses a hybrid approach to classify waste into various classes. Two machine learning models, a multilayer perceptron and multilayer convolutional neural network (ML-CNN), are implemented. The multilayer perceptron is used to provide binary classification, i.e., metal or non-metal waste, and the CNN identifies the class of non-metal waste[6]. [10]Yi Zhao etal., have proposed an intelligent waste classification system based on the improved MobileNetV3-Large. The network model is enabled to classify garbage images through deep separable convolution, inverse residual structure, lightweight attention structure and the hard_ swish activation function.[9]Shuang Wu et al.,(2021) used CNN (convolutional neural network) model to classify garbage images, and the final accuracy is 85.32%. This model is used to assist people with garbage classification, reducing the time and energy needed for the classification and identification, so as to achieve the purpose of promoting garbage classification.[8]Suganda Girsang, A et al.,(2023) conducted research to collect datasets with two categories, namely organic and inorganic, which were divided into three parts, namely training, testing, and validation and used hyperparameter testing, preprocessing to find the best learning outcomes. The models used are MobileNet, VGG16, and Xception.[7]Nguyen Ngoc Bao, Nguyen Ngoc Le Minh (2022) aimed to present the best solution to solve the waste management problem. In the waste management category, sorting by type of garbage is one of the most essential steps. By using a camera, convolutional neural network (CNN), a dataset of various training and testing pictures, detection and classification can occur with the accuracy of 99%. The robotic arm is added to grab the garbage.

III.COMPONENTS OF WASTE CLASSIFICATION

Deep Learning Framework: This concept is employed in CNN's training. The framework typically comprises of a collection of algorithms and tools for optimizing the network's performance during training.
Neural Network: In order to categorize the items in the photos and movies, this network is used. Neurons in the network are normally coupled to one another and are utilized to process input data and produce outputs.

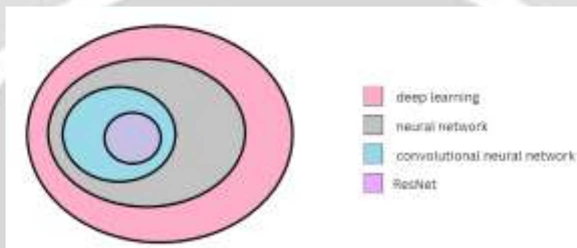

Figure 2. Components of waste classification

Convolutional Neural Network: This network is used to classify the objects in the images and videos. The CNN typically consists of convolutional layers that are used to extract features from the input data and generate an output. This output is then used to classify the objects in the images and videos.
ResNet: The ResNet type of CNN learns a residual mapping from the input data to the intended output based on the idea of residual learning. This enhances the effectiveness of the model and lowers the complexity of deep network training.

IV. METHODOLOGY PROPOSED

Data Collection: A diverse dataset of different waste images are collected. The dataset consisted of different waste images that we are going to classify.Alternatively, custom-collected images can also be used. This involves taking pictures of different types of waste, and then labeling them accordingly. This approach can provide a more accurate and diverse dataset, as it captures the real-world environment. Annotating those waste images using appropriate labels indicating the waste type (eg., plastic, paper, glass,vegetables and fruits waste etc..) as shown in Figure 3.

Figure 3. Different types of wastes used for classification

Preprocessing: Using data augmentation, a collection of strategies for boosting the amount of data by adding slightly changed copies of the original data, to improve the size and quality of the dataset. When training a machine learning or deep neural network model, this is a typical technique used to reduce overfitting[25]. The ImageDataGenerator class offered by the Keras deep learning neural network framework provides the foundation for the augmentation described in this paper [34,58].

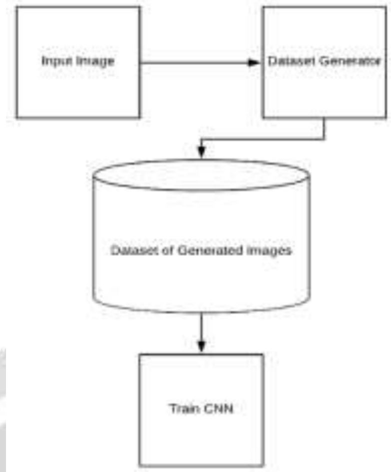

Figure 3. ImageDataGenerator for Data Augmentation

We specifically apply adjustments to the photos (such as image rotation and height and width shift) using the ImageDataGenerator class. Figure 3 depicts how the ImageDataGenerator class of Keras works. We are splitting the dataset into training, validation and testing sets

CNN Architecture: After preprocessing, the next step is to pick a CNN Architecture that goes well with classifying waste images. We have chosen *ResNet (Residual Network)* for classification[39]. Pretrained ResNet model weights from a source like ImageNet have been loaded. In deep learning packages like TensorFlow or PyTorch, these models can be discovered. We added a new classification head that corresponds to the number of garbage categories in our dataset after removing the old classification head (completely connected layers) from the pretrained ResNet model[24]. We employed CNN layers as feature extractors to extract hierarchical and discriminative properties from the garbage images. For multi-class classification, a suitable loss function, such as categorical cross-entropy should be applied and an optimizer such as Adam or SGD is used to adjust the model's weights throughout training[47]. Then, we overlay fully linked layers on top of the CNN and map the extracted features to the final waste classifications.Utilising activation functions (such as ReLU) to expedite training and improve convergence after each fully linked layer.

Training: A big collection of photos labeled with the required objects must be used to train the model after it has been created. It is crucial to remember that the data must be balanced for the ResNet model to correctly learn to distinguish between the various classes. The data must then be fed into the ResNet model once it is ready. This can be carried either in batches or all at once, depending on the size of the dataset[67]. The model must then be trained using an appropriate optimizer, like Adam or SGD. The model's weights are continuously updated during the training phase so that it can learn to recognise the various items in the photos.

Testing and Model Evaluation: The model can then be tested on the testing set to evaluate its accuracy. Various metrics such as precision, recall, and F1 score can be used to measure the performance of the model. By counting the number of images that are correctly categorized, we may evaluate the model's accuracy[65]. Additionally, the model can be tested on unseen data to evaluate its generalization ability. This will show us how well the model works with unobserved data.

Fine-tuning: If necessary, fine tuning can be performed. This will help the model to adapt to the task of classifying wastes.

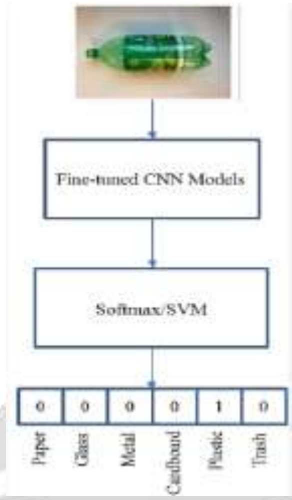

Figure 4. Fine-tuning the constructed model using image data

There are various processes involved in fine-tuning a pre-trained ResNet model for garbage picture categorization. The original model must first be loaded before a new layer with the necessary number of outputs (one for each waste type) is substituted for the final layer.Figure 4 shows how fine tuning is performed using the constructed model. The weights of the pre-trained layers must then be frozen in order to prevent updating of those weights during training[44]. A small subset of the available data must then be used to fine-tune the model in order to prevent overfitting.

V.RESULTS AND DISCUSSIONS

The results of the analysis for the designed framework were shown below, and the same output data had been examined in several ways to get various results.Precision was 88.54%, recall was 87.62%, F1-score was 87.12%, MDR was 12.37%, and FDR was 13.37% for our framed CNN architecture.

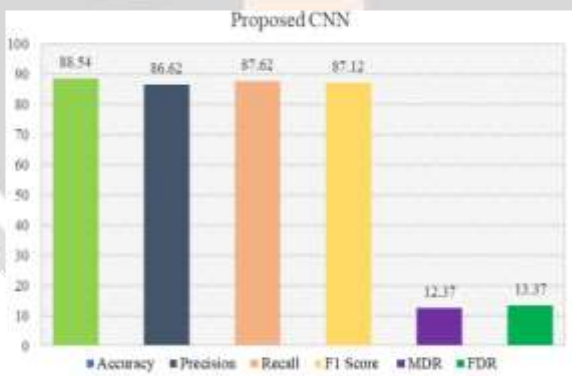

Figure 5. Outcome of the proposed CNN Architecture

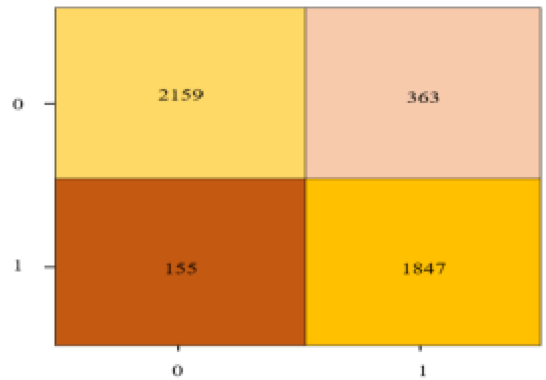

Figure 6. Confusion Matrix for the proposed Architecture

VI. BENEFITS OF WASTE CLASSIFICATION USING CNN

Precision and Accuracy: As CNNs are so good at image recognition tasks, they can accurately and precisely categorize different types of garbage. Complex patterns and traits that are challenging for traditional sorting approaches to identify can be recognized by them. Due to this high level of precision, contamination is reduced and recycling rates are raised through proper identification and placement in the recycling stream.

Effectiveness and Swiftness: Intelligent trash classification based on CNN is a lightning-fast procedure. In contrast to manual sorting, which can be labor and time-intensive, an IWCS can process waste materials fast, making it a good fit for high-throughput garbage sorting facilities. The system's efficiency and speed improve waste management processes and reduce processing expenses.

Consistency and Reliability: Manual sorting is prone to human mistake, which could result in inconsistent waste classification. On the other hand, CNN-based systems deliver reliable and repeatable results. Once trained, the model's performance remains constant over time, ensuring a trustworthy recycling process.

Environmental Impact: By correctly classifying waste, an IWCS effectively encourages recycling and lessens the amount of trash that is sent to landfills. This immediately aids in lowering the negative environmental effects of discarding trash, protecting natural resources, and minimizing pollution.

Cost-Effectiveness: Although buying hardware and software may be required for the initial deployment of an IWCS, the long-term benefits surpass the immediate costs. The technique streamlines waste sorting operations, lowering labor costs and increasing recycling revenue. By lowering the requirement for landfill management and disposal of trash, better waste management can help lower overall expenditures.

VII. APPLICATIONS OF WASTE CLASSIFICATION SYSTEM USING CNN

Automated Waste Sorting Facilities: The adoption of an Intelligent Garbage Classification System is viable in these facilities. They can swiftly and accurately differentiate between different types of waste, such as plastics, metals, paper, glass, and organic waste. The effectiveness of waste management operations as a whole is increased because of this automation, which increases sorting efficiency and necessitates less physical work.

Recycling Facilities: An IWCS can be very useful in separating recyclables from other sorts of waste at recycling facilities. By recognizing and classifying a number of recyclable items, including PET bottles, aluminum cans, and cardboard, the system helps to maximize recycling efforts and enhances the purity of recovered materials.

Smart Recycling Bins: Intelligent Waste Classification can be incorporated into smart recycling bins that are placed in public areas, businesses, and homes. These bins aid in raising recycling participation and environmental awareness by classifying and separating recyclables from non-recyclable garbage.

Industrial Waste Management: Controlling waste streams in the industrial sector is possible with intelligent waste classification. Many companies produce a variety of waste products, and an IWCS can help detect and separate hazardous and non-hazardous waste to guarantee proper disposal and conformity to environmental regulations.

Campaigns for Education and Public Awareness: IWCS can be used as a tool in campaigns for education and public awareness to enlighten the public about correct waste sorting techniques. By demonstrating garbage classification and emphasizing the importance of recycling, the strategy can raise awareness and encourage proper trash disposal among the general population.

VIII. CONCLUSION

Convolutional Neural Networks (CNNs) were shown to be effective in this study's waste image categorization, highlighting its potential to address the urgent problem of garbage management. CNNs provide a promising way to automate and improve garbage sorting procedures by clearly discriminating between distinct waste kinds. When compared to conventional techniques, the model's capacity to learn detailed features from garbage photos greatly increases accuracy and efficiency. The results highlight the significance of utilizing cutting-edge technologies for environmental sustainability. While this study demonstrates a successful use of CNNs for waste categorization, subsequent research might look into real-time implementation optimisations and broaden the dataset to include a variety of garbage scenarios. At the end of the day, incorporating CNN-based waste categorization systems into waste management infrastructure could revolutionize garbage sorting procedures, promoting cleaner ecosystems and resource-efficient societies.

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