Enhancing Waste Management: Automated Classification of Biodegradable and Non-biodegradable Waste using CNN

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Abstract— **The way trash is managed has a significant impact on both the ecosystem and human health. For effective trash handling, it is necessary to correctly classify garbage into various types, such as biodegradable and non-biodegradable waste. In this paper, CNNs, are very efficient deep-learning algorithms for classifying images. where the technique uses several waste types as data, pre- processes the data, develops the architecture of a CNN model, trains the model, and then assesses the model's performance using accuracy, fl-score, precision, and confusion matrix visualization. The CNN model architecture consists of convolutional, activation, dense, pooling, and fully connected layers. Two nodes are included in the bottom layer, one for biodegradable waste and one for non- biodegradable waste. Waste management companies can better manage their resources by correctly classifying rubbish into biodegradable and non-biodegradable categories to avoid manual waste classification. Additionally, the system can be improved and expanded to categorize other waste types, resulting in waste management techniques that are significantly more efficient and environmentally benign.**

Keywords*— *Waste management, Deep learning, CNN, Biodegradable, Non-biodegradable.

I. INTRODUCTION

Waste is wealth placed in the wrong place [1]. Waste management is crucial for contemporary civilization because the globe produces billions of tons of waste annually [2]. The detrimental effects of waste on the environment and human health can be lessened with the use of efficient waste management techniques [3], [4]. Waste classification, which entails classifying waste into several groups depending on its traits and features, is a crucial component of waste management [5] [6]. Separating biodegradable waste from non-biodegradable waste is crucial because it can influence how quickly waste decomposes and how quickly dangerous compounds are released into the environment. Deep neural network architecture is frequently used in CNN-based waste classification systems to learn to extract and categorize features from waste photos [7] [8]. Numerous research that obtained acceptable accuracy rates in sorting waste into biodegradable and non-biodegradable categories have shown the usefulness of CNN-based waste classification systems [9]. In this paper, we use a supervised strategy to accurately categorize various waste categories that are visible in images (such as metal, paper, plastic, vegetable, food, and so on. To accomplish this, we trained CNN, deep classification networks, to identify waste categories contained in photos from the provided dataset [10] [11].

Traditionally, human workers perform waste classification manually, which can be time-consuming, labor-intensive, and error-prone [5]. However, with the development of computer vision and deep learning techniques, automated waste classification systems based on CNNs have emerged as promising solutions to this problem [11].

There are various ways to classify a nation's level of development. Justifiably, the level of waste management is one method. For several reasons, resource recovery is a key component of solid waste management in developing countries [12]. The process is being formalized and automated as of late. The adoption of intelligent technology is a goal for the present and the future [13]. One of the main problems in Nepali municipalities that needs a long-term solution is the solid waste management [14]. According to the preliminary study and review, most municipalities' waste management procedures, such as collection, transportation, and resource recovery, are ineffective, and nearly all collected waste is eventually dumped at a dump site [12], [14].

In recent years, the amount of waste produced by human activity has been growing tremendously. The World Bank estimates that 2.01 billion tons of municipal solid trash are produced a year, and that number is anticipated to rise to 3.4 billion tons by 2050 [2].

An estimated trash projection for 2017 has been made using baseline data from the 2013 Asian Development Bank report on solid waste management in Nepal. According to the estimated figures, garbage generation in Nepali municipalities averages 3023 tons per day and 0.223 kilograms per person per day.
About 60% of waste is typically decomposable, and 25% of waste is recyclable material including plastic, paper, and metals [12] [15].

The municipalities must deal with issues like a lack of expert assistance, budgetary limitations, the need to wait for government clearance before buying land for planned landfill sites, issues with location selection, and vehement opposition from neighboring villages. The chosen area also has other geographic issues like flooding, low water tables, highly permeable soil, and slope instability. The qualities of the garbage that is produced are influenced by socioeconomic factors like population, economic position, and consumption habits as well as physical elements like height, temperature, rainfall, and humidity [12].

In Nepal and other areas of the world, environmental pollution has been a significant issue because of improper garbage disposal, which is blamed for environmental damage. Even though appropriate waste management is crucial, human error and a lack of effective sorting procedures cause many towns and organizations to struggle with effectively classifying biodegradable and non-biodegradable garbage. garbage management is a considerable difficulty because of the rising worldwide garbage production. Effective waste management depends on accurate trash classification into biodegradable and non-biodegradable groups. Overall, the creation of trash classification systems utilizing CNNs has the ability to resolve a number of difficulties and problems related to effective waste management. Sorting garbage into biodegradable and non-biodegradable groups can be automated. Such systems can aid in reducing human error, increasing waste management efficiency, and promoting a more sustainable environment by automating the process of classifying garbage into biodegradable and non-biodegradable categories.

Therefore, the purpose of this study is to effectively classify garbage using a customized CNN, which can more correctly sort garbage with the aid of these networks, and this improves trash management by moving beyond the basic organic and inorganic labels. This implies that when managing garbage, consider both nature and human health to ensure that both are protected. The traditional division of garbage into organic and inorganic categories ignores the complex reality of waste materials. It is critical to understand that not all organic waste is naturally biodegradable and that some inorganic waste components might pose dangers to the environment and human health. By ignoring the different rates of breakdown and potential toxicity associated with certain materials, this oversimplification prevents efficient waste management. By precisely dividing garbage into biodegradable and non-biodegradable categories, the paper lays the groundwork for developing waste management methods that take into consideration the intricacies of decomposition, protecting both the environment and human health.

II. Related Theory

As a tool for sustainable garbage recycling, Jin, Shoufeng, et al. created Garbage identification and categorization utilizing a new deep learning-based machine vision system. The system achieved an accuracy of 89.26% by extracting characteristics from the garbage photos using a pre-trained model, MobileNetV2 [16]. Similarly, the study of Malik, Meena, et al. used transfer learning with the EfficientNet-B0 model to categorize garbage. They were able to classify images with an accuracy of 85%, demonstrating the potential of deep learning for environmentally friendly garbage management. The results highlight the value of deep learning neural network models and transfer learning for enhancing waste classification systems for the sustainable development [17]. Additionally, Azis, Fatin Amanina, et al. "Waste classification using convolutional neural network." Waste was classified into 6 types using a multilayer CNN named Inception-V3, which has an accuracy of 92.5% [18].In more research on Bobulski, Janusz and Mariusz Kubanek. "Waste classification system using convolutional neural networks and image processing" used 23-layer CNN to categorize plastic garbage into 4 categories with an accuracy of 99.23%, demonstrating remarkable accuracy when utilizing image processing and artificial intelligence [19]. The same goes for S. Altikat, A. Gulbe, A. A. A. G. S., and A. A. A. G. Deep convolutional neural networks are used for “Intelligent solid waste classification”. Algorithms for four- and five-layer deep convolutional neural networks were employed for classification. a five-layer design that achieves a 70% accuracy rate; as the number of layers was reduced, the networks' performance values declined [20].Adedeji, Olugboja, and Wang, Zenghui. "Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network." proposed an intelligent waste material classification system that uses the 50-layer residual net pre-train (ResNet-50) CNN model and Support Vector Machine (SVM) to categorize the waste into different groups/types and achieves an accuracy of 87% [11]. The Trash Net dataset was utilized by Ruiz, Victoria, et al. Their study, "Automatic image- based waste classification, " compared the three CNN architectures, VGG, Inception, and ResNet. Finding the optimum classification outcome from a combination Inception_Resnet model that achieves 88.6% accuracy [21]. Similarly, Srinilta, Chutimet, and Sivakorn Kanharattanachai’s "Municipal Solid Waste Segregation with CNN “trash was divided into four categories using the CNN- based classifiers VGG-16, ResNet-50, Mobile Net V2, and DenseNet-121, including biodegradable trash, recyclable waste, and hazardous waste. The generated ResNet-50 classifier had a 94.86% accuracy rate for classifying trash types [22]."Recyclable Waste Image Recognition Based on Deep Learning," by Zhang, Qiang, et al., intends to increase the accuracy of waste sorting through deep learning by creating a classification model of recyclable waste photographs. The model's image classification accuracy is 95.87% [23].In their study "Recyclable waste classification using computer vision and deep learning," Ramsaran, Nadish, et al. provide a Deep Learning method for classifying waste into 5 categories: plastic, metal, paper, cardboard, and glass. Using pre-existing images, three classifiers—Support Vector Machine (SVM), Sigmoid and SoftMax, and VGG19—are trained using a minimum of 12 variations of the (CNN) algorithm. The SoftMax classifier can achieve an accuracy of about 88% [24]. Girsang, Abba Suganda, et al. "Classification of Organic and Inorganic Waste with Convolutional Neural Network Using Deep Learning." In this study, deep learning models with two classes—organic and inorganic—called Mobile Net, VGG16, and Xception are used where the Mobile Net model's top result has an accuracy of 93.35% [25].

A. Proposed Convolution Neural Network (CNN) Architecture

A form of artificial neural network called a convolutional neural network (CNN) is used most frequently in deep learning to interpret visual imagery [26], [27]. Convolutional layers, which are predominantly found in CNNs, are composed of filters [27]. An input layer, several hidden layers, and an output layer make up the CNN. Convolutional, pooling and completely linked layers are among the interspersed layers that make up the hidden layers. The term "feature maps" refers to the mapping between different levels. Convolutional layers "convolve" the input and pass on to the following layer the resulting information[28]. By minimizing the sample size of a feature map, the pooling layer optimizes the number of parameters the network needs to evaluate, resulting in a pooled feature map. To increase computation efficiency, a pooling layer essentially mixes the features gathered from one convolution layer before sending them to the following. The network's rectified linear unit layer ensures nonlinearity as data moves across it [27], [29]. Neural networks that are fed forward are the Fully Connected Layer. The output from the last pooling or convolutional layer is passed into the fully connected layer, where it is flattened before being applied [27]. Biodegradable and non-biodegradable waste is sorted using a convolutional neural network architecture [18]. As shown in Fig. *1*, we create a convolutional neural network (CNN) based image classifier that, by examining training features, can identify and detect any objects that are biodegradable and nonbiodegradable waste.

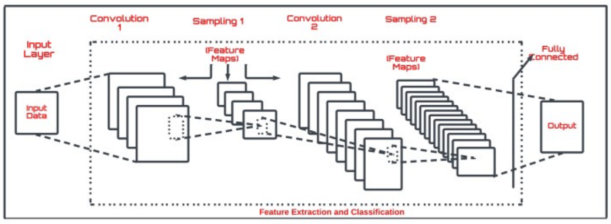

Fig. 1 Proposed CNN Architecture

B. Structure of Research Network

When deciding on the best network structure, several crucial elements must be considered. The input image's size was a crucial factor to start with. The number of calculations increased because of the too-high resolution, which sometimes overloaded the computer unit's memory. On the other hand, inadequate resolution in the input data may have prevented the performance from being as predicted [19]. So, we determined to look for images with a 150x150 pixel resolution. The choice of the CNN network's layer types and the number was another crucial factor [19].

In Fig. 2, the input layer receives the input information, which in this instance is 150*150*3 would be preprocessed waste image data. To extract pertinent characteristics from the input data, the convolutional layer uses a collection of trainable filters. A collection of feature maps is what this layer produces. The activation layer applies a ReLu activation function to the convolutional layer's output to provide nonlinearity to the model. The feature maps that are acquired from the layer of convolution are made reduced dimension by the pooling layer i.e., the max pooling layer that follows. To avoid overfitting and enhance model generalization, we used a dropout layer i.e., dropout (0.25). This aids in lowering the model's computational complexity. The flattened output of the pooling layer is mapped to a group of output nodes by a fully connected layer. These output nodes represent the two types of wastes that the model is attempting to classify, namely biodegradable and non-biodegradable. The output layer creates a probability distribution over the 2 waste classes by applying a SoftMax function to the output of the fully connected layer.

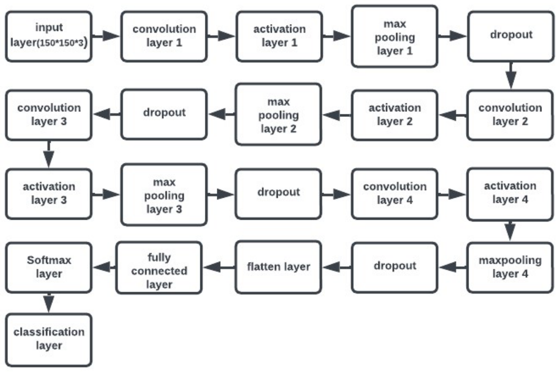

Fig. 2 Structure of Research Network

C. Activity Diagram of Proposed Model

We follow the following procedure as in Fig. *3* with the help of CNN:

1) Data Collection: Waste has been divided into biodegradable and non-biodegradable categories in our datasets. In a similar manner, we have selected objects and gathered images for each group. As a result, there are images of various items in all our datasets.

2) Data preprocessing: Data are preprocessed after collection to ensure that the datasets that will be used for training are standardized i.e., tidy datasets, noiseless datasets, and uniform datasets. Images are resized, noise is removed, and data is normalized.

3) Creating architecture: Following the preprocessing of the datasets, we build the model's architecture by selecting the right amount of convolution layers, activation layers, pooling layers, hidden layers, and other pertinent hyperparameters to ensure that the model can accurately classify different waste types according to their characteristics.

4) Training model: The created model is then trained using the preprocessed data after the model architecture has been designed. The model's biases and weights are adjusted during the training phase to reduce the discrepancy between the expected and actual outputs. Using a training process, which modifies the weights and biases based on the discrepancy between expected and actual results, is accomplished.

5) Testing model: After the model has been trained, it needs to be examined to ensure it hasn't overfit the training data set. This entails testing the model using a different set of data that was not incorporated during training. It can be concluded that the model is generalizing well and is not overfitting if it performs well on the testing data.

6) Obtaining results- At the end, the model is evaluated on its accuracy, loss, and using other performance metrics like F1-score, precision, recall, and drawing confusion matrix.

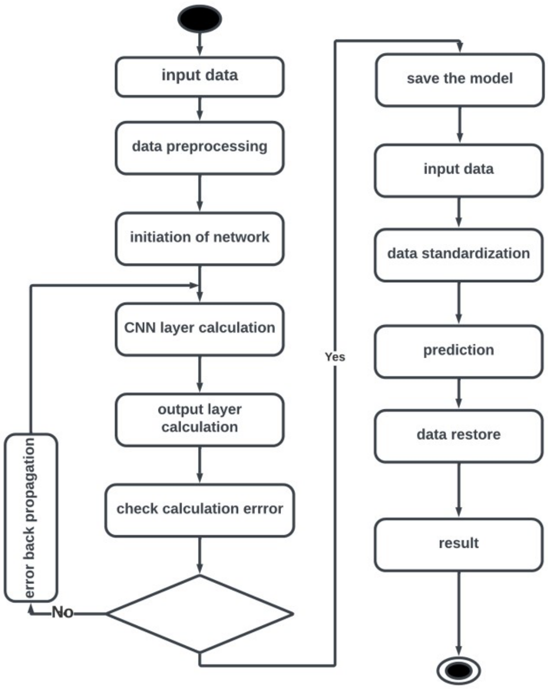

Fig. 3 Activity Diagram of the proposed model

III. Result and Discussion

Using Convolutional Neural Networks (CNN) and datasets from Kaggle, we have created a system that fills the need for categorizing waste into biodegradable and non-biodegradable categories. Before a CNN model was trained on the collected datasets, they were preprocessed and normalized. Metrics like accuracy, loss, confusion matrix, F1 score, precision, and recall were used to assess the model's performance. This section contains an analysis of the experiment's findings.

90% of the dataset was used to train the CNN model, with the remaining 10% being set aside for testing. With a batch size of 16, the Nadam optimizer, and the categorical cross-entropy loss function, the training procedure was carried out over 20 epochs. On the training set, the model had an accuracy of 96.06%, while on the test set, it had an accuracy of 91%.

A. Visualization of Accuracy and Loss

Fig. 4 and Fig. 5, respectively, display the accuracy and loss curves for the training and validation sets. The model performs admirably during the training phase, producing stunning results on the training data. However, when the model is tested using hypothetical data, an unanticipated rise in loss and decrease in accuracy is noted. Hyperparameters are essential in determining how a model behaves and performs. The model may become overfit to the training data if the hyperparameters are not properly tweaked, which prevents it from generalizing to new samples [30]. Overfitting is when a model struggles with novel and varied input during testing because it overly captures the unique patterns and noise present in the training set [31]. The batch size, number of hidden Layers, number of neurons per hidden layer, activation functions, dropout rate, optimizer, activation function in the output layer, filter size, number of filters, pooling loss function, and network design are just a few of the deep learning hyperparameters that influence our model performance. When these hyperparameters are adjusted incorrectly, the model may memorize the training set rather than discover useful patterns. Several factors, including hyperparameter tuning and other deep learning model characteristics, might be blamed for this behavior. However, the model performs well on both sets, with acceptable accuracy and minimal loss, demonstrating that it has mastered the art of accurately classifying waste photos.

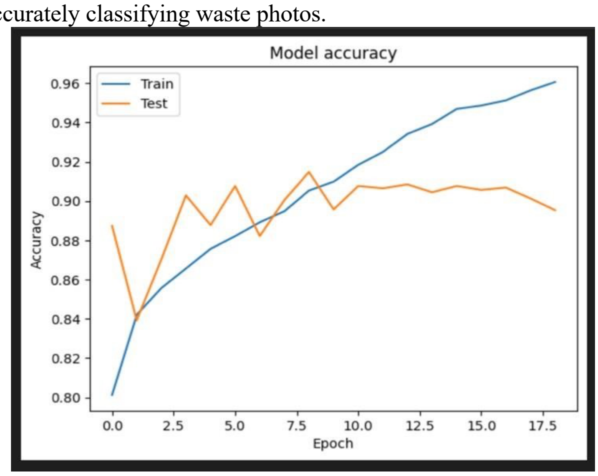

Fig. 4 Epoch vs accuracy

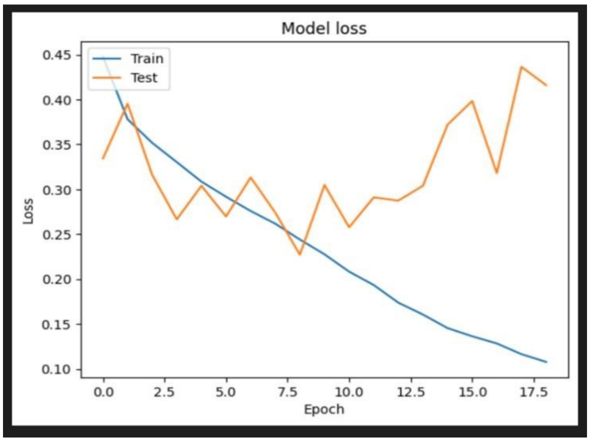

Fig. 5 Epoch vs loss

B. Confusion Report Analysis

TABLE I and TABLE II display the model's confusion matrix and classification report respectively. The model does a good job of classifying waste into biodegradable and non-biodegradable categories. High precision and recall scores for each class show that the model is capable of distinguishing between the two categories of waste.

TABLE I

Confusion Matrix

Predicted value	Actual value	
	1290	111
	103	1009

where,TP=1290, FP=111, FN=103, TN=1009

TABLE II

Classification Report

	precision	recall	F1-score	Support
O	0.93	0.92	0.92	1401
R	0.90	0.91	0.90	1112
Macro avg	0.91	0.91	0.91	2513
Weighted avg	0.91	0.91	0.91	2513
accuracy	0.91	2513		

where, O=bio-degradable, R=non-biodegradable

C. Analysis using Confusion Matrix

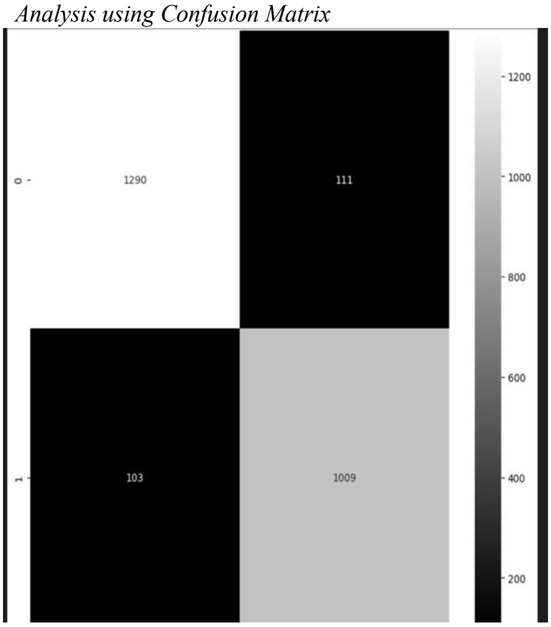

Fig. 6 Confusion Matrix

The model accurately identified 1290 images as belonging to the biodegradable image (predicted class), i.e., they were, in fact, biodegradable images (actual class) and expressed as a True positive value as in Fig. **6**.

The model accurately identified image 1009 as being non-biodegradable (predicted class), i.e., an image that is in fact non-biodegradable (actual class) and represented as a true negative value.

The model misidentified 111 images as a biodegradable picture (predicted class), when in fact it was a non-biodegradable image and was therefore represented as a False Positive value.

The model misclassified 103 images as non-biodegradable, while in fact, it was a biodegradable picture (actual class), and it was displayed as a false negative value.

IV. CONCLUSIONS

This work makes a substantial advancement in waste categorization by addressing the complex interactions between organic and inorganic components, which are naturally present in both bio-degradable and non-biodegradable waste. This nuanced approach acknowledges that not all organic waste falls under the formal definition of "bio" and that not all inorganic materials exactly correspond to "non-bio" categories. This paper has distinguished between bio and non-bio waste categories with noteworthy precision by utilizing the strength of our algorithm. This result highlights Convolutional Neural Networks (CNNs) ability to support efficient waste management procedures. This research demonstrates the necessity for sophisticated trash categorization strategies that consider the complexity of waste materials and provide a technologically driven solution that is in line with environmental sustainability goals. This study addresses an important turning point in waste management where traditional methods of waste collection and manual separation offer problems for effectiveness and public health, notably in places like Nepal. The manual methods expose workers to potentially toxic materials, which adds to their time and labor requirements while also posing health hazards. These difficulties highlight the demand for creative answers that improve waste management procedures. New technologies present a potentially revolutionary path for trash management. The use of Convolutional Neural Networks (CNNs) for waste classification represents a revolutionary change in the precision and effectiveness of waste sorting. CNNs dramatically shorten sorting times by removing the need for physical intervention, minimizing worker health risks, and modernizing waste management procedures.

The paper also has limits and shortcomings. A small collection of garbage photos was used to train the model. Due to a lack of generality, such as when using various datasets or real-world images that aren't represented in the training data, its performance may vary. When presented with photographs of mixed rubbish or waste that is challenging to visually separate, the model may have trouble. The current waste classification system only distinguishes between biodegradable and non- biodegradable trash, although many additional waste kinds could be categorized in the future. More datasets comprising photographs of other types of rubbish, including mixed waste and other real-world images, would help us perform better. Vision Transformer can be used to categorize trash photos accurately, increase model accuracy, and shorten training times. To increase waste management efforts, it can be integrated into mobile apps so that municipalities can classify vast amounts of garbage without doing it manually. Additionally, this document can be expanded to categorize garbage into other different sorts of waste.

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APPENDIX

Home

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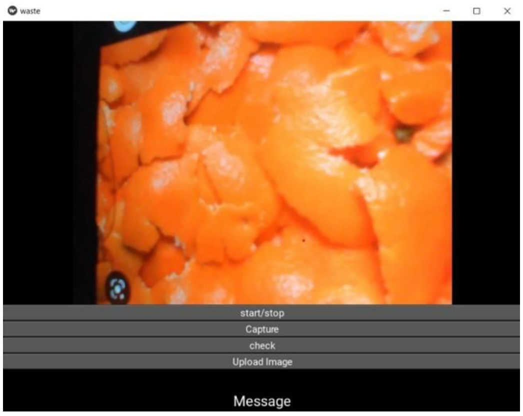

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