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EfficientNet-Based Deep Learning Model for Advanced Waste Classification

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Abstract— **One of the main obstacles to recycling systems in developing countries like Bangladesh is waste classification. About 22.4 million tons of garbage are produced in the nation each year, of which 70% is organic waste and 30% is nonorganic. Regarding this unmanaged situation, it is critical to build an autonomous smart garbage sorting system that makes use of intelligent capabilities. Waste classification from waste images is a crucial computer vision problem that must be solved by developing an intelligent system. The accuracy and efficiency of conventional waste classification techniques are not that remarkable. First, a dataset of 5012 waste images is generated from nine distinct classes—including inorganic and organic waste. The goal of the proposed study is to develop an automatic image classifier that can identify objects and determine the kind of waste material in order to increase the efficiency and accuracy of waste categorization processes. Feature extraction from photos is done in this work using pre-trained EfficientNet models (EfficientNet B0, EfficientNet B2, EfficientNet B3, and EfficientNet B4) on ImageNet. This allows the classifier to provide predictions and differentiate the type of garbage from its related category. EfficientNet B0, EfficientNet B2, EfficientNet B3, and EfficientNet B4 models have been employed appropriately for this experimental dataset based on the EfficientNet pre-trained models. Based on the experimental results, it can be seen that EfficientNet B0 and B2 both achieve 93% accuracy through transfer learning. Furthermore, EfficientNet B3 and EfficientNet B4 models surpass earlier image classification methods with 91% classification accuracy.**

Keywords— Waste Classification, Intelligent System, EfficientNet,Image Processing, Recycling Automation, Computer Vision

I. INTRODUCTION

Waste is unusable materials. Waste is that which is discarded after primary use or is worthless, defective and of no use. Some wastes are recyclable which can be used later and some wastes pollute our environment. Waste can be classified into 2 major types of waste that are commonly found as organic and non-organic . Organic wastes are green waste, food waste, food-soiled paper, and so on. Non Organic wastes are Plastic soda bottles, glass, yogurt cups, spoons, cellophane, aluminum cans, plastic bags. The world bank report shows that there are almost 4 billion tons of waste around the world every year and the urban alone contributes a lot to this number, the waste is predicted to increase by 70 percent in the year 2025 [1].Every year, between 30 and 50 million tons of electrical and electronic equipment trash, or "e-waste," are created globally[4]. [1] predicts a large rise in garbage accumulation in less developed nations during the next 25 years. The issue of waste mismanagement will ultimately arise because a sizable portion of the population lacks access to adequate trash disposal services. Just 37% of waste gets collected overall in Bangladesh's largest cities, including Dhaka. The issue of excessive waste in developing nations arises from factors such as urbanization, overpopulation, and inadequate waste treatment infrastructure. Hence, it is necessary to recycle the waste to protect the environment and human beings' health, and we need to separate the waste into different components which can be recycled using different ways.To ensure effective recycling, it is crucial to classify waste before recycling [5].

The current way of waste or garbage segregation as the manual method, whereby someone is employed to separate various objects/materials.A person who separates the waste gets sick due to harmful substances in the waste.Resolving this issue is essential to the health of society. Keeping this in mind, it inspired us to develop an automated system capable of sorting waste. Machine learning and Deep learning as a branch of artificial intelligence provide potential answers; in recent years, they have shown to be adaptable in a variety of fields[6]. And this system can take short time Sort waste, and it will be more accurate in sorting than manual method. With systems in place, separate beneficial waste can still be recycled and converted into energy and fuel to grow the economy[2]. Various research efforts have been employed for the classification of waste images by utilizing machine learning , deep learning approaches and others approaches. A large scale CNN based image-Net is used for visual recognition challenges in waste classification[5]. Since 2012 many different CNN architectures have been developed which have solved many image classification problems [6]. U-Net and VGG16 neural networks are used in the study "Deep Learning Approach for Automatic Micro plastics Counting and Classification[7].For TrashNet garbage classification, CNN, SVM, and DenseNet are used [8]. YOLOv5 is a neural network model used for waste classification accurately[9]. SVM, DT, and KNN algorithms are used in the study using a Kaggle dataset in order to meet certain waste management goals[10].The study uses CNN models such as AlexNet, VGG16, GoogLeNet, and ResNet, on the TrashNet waste dataset for waste classification[11].Although a lot of work has been done by many researchers,there are some shortages and limitations in terms of performance,techniques, and size of the dataset. Additionally, there remains a lot of scope to enhance the waste classification to provide better waste management by applying different techniques on large scale dataset.This study aims to develop a system by utilizing various pretrained deep learning based Efficientnet models with an optimal size of dataset and the proposed system will able to segregate waste efficiently. The major contributions of this study is mentioned as follows:

- Dataset is accommodated with almost 5012 waste images data, collected from various sources by physical effort.
- To ensure the data quality and to make the machine feasible,some image preprocessing techniques are applied.
- Preprocessed data is feeded with selected convolutional neural networks based models and performance of them is evaluated in terms of some performance matrices.
- Finally, the result has been analyzed with a comparative analysis of performance metrics of each EfficientNet model.

This Paper is organized as follows: Section-2 describes literature review with related works. Section-3 presents research methodology. Section-4 introduces the system architecture with the methodology and result analysis is demonstrated in Section-5. presents the conclusion and future work..

II. Literature Review

Waste classification is one of the most prominent topics for the computer vision research domain. Many experts have already worked on this segregation of wastes around the world. Some employed their datasets, while others used publicly accessible or merged datasets to train their classifiers. In this paper, we observed those papers to develop our research work. Nowakowski, Piotr, and Teresa Pamuła. [2] 3480 photos of self-collected data from Zhejiang University's The First Affiliated Hospital are used in the study. Using the ResNeXt model, it attains a remarkable 97.2% accuracy, indicating the usefulness of the model for medical imaging applications in a hospital context. Patel et al.[4] the publication "Garbage Detection Using Advanced Object Detection Techniques" used a variety of models, including YOLOv5M, on a dataset of 500 photos obtained from SpotGarbage GINI and Google photos. YOLOv5M achieved the maximum accuracy, with a Mean Average Precision of 0.613.Lorenzo-Navarro et al .[7] u-Net and VGG16 neural networks are used in the study "Deep Learning Approach for Automatic Microplastics Counting and Classification" to analyze 49 photos of mixed microplastics samples with a 98.11% accuracy rate. Self-collected samples and Deep Medical Waste (Deep MW) are included in the data.Abu-Qdais et al . [8] on a dataset of 5151 photos taken from TrashNet, Local Garbage, and Multiple Objects Local Garbage, the study uses multiple models such as CNN, SVM, and DenseNet 201. CNN's accuracy is 92.7%, and the JONET Model's accuracy on TrashNet is 96.06% and 94.40% overall.Wu et al .[9] the study applies YOLOv5 with a proprietary garbage image dataset and achieves remarkable accuracy. The model achieves an impressive mean Average Precision (mAP) of 99.59% with 682 images at an IoU threshold of 0.52, demonstrating strong object detection performance.Yasin, Elham Tahsin, and Murat Koklu[10] SVM, DT, and KNN algorithms are used in the study using a Kaggle dataset that contains 24,705 photos of solid household garbage that have been divided into recyclable and organic groups. Without feature selection, SVM obtains
96.3% accuracy, Decision Trees 85.8%, and KNN 94.9%, demonstrating their efficacy in garbage classification.Srinilta, Chutimet, and Sivakorn Kanharattanachai. [11] The study uses CNN models such as AlexNet, VGG16, GoogLeNet, and ResNet, using the TrashNet dataset, which consists of 2527 photos divided into 6 types. With a remarkable 97.86% accuracy rate, these models show strong categorization abilities in trash management.Adedeji, Olugboja, and Zenghui Wang .[12] resNet-50 and Support Vector Machine (SVM) methods are applied to a dataset of 1989 self-collected photos. The models perform well in picture categorization, as evidenced by their 87% accuracy rate, which highlights their usefulness for data-driven applications and research. Ahmad, Kashif. [13] a benchmark large-scale dataset for waste classification evaluation is introduced in this research. The work uses 2,527 photos to run deep learning models pre-trained on ImageNet, such as AlexNet, GoogleNet, VggNet, and ResNet. With an accuracy of 3.58%, it shows that there is still a need for better waste sorting techniques.Srivastava, Sunil Kumar, and Rahul Kumar Shrivastava .[14] four categories—Latent Dirichlet Allocation (LDA), machine learning, deep learning, reference relations, and text mining—are used in the paper to organize topic identification algorithms. With a dataset of 112 samples, it uses machine learning to create a model for copper recovery from e-waste; however, accuracy is not made clear.Zhang, Qiang, et al. [15] the 18,911-image NWNUTRASH recyclable garbage picture dataset is used in the paper. It makes use of a number of techniques, including deep learning, machine learning, reference relations, and latent dirichlet allocation (LDA). With an 82% accuracy rate, the study demonstrates efficient trash categorization methods for recycling programs.Abu-Qdais, Hani et al. [16] he research combines internal, secondary, and primary data sources to create an extensive dataset. It operates on a dataset of 5151 photos using CNN and deep learning algorithms, obtaining an accuracy of 94.40%. This strategy improves the effectiveness of picture classification techniques by utilizing a variety of data sources.Altikat, A. A. A. G. S et al.[17] or each form of waste material (paper, glass, plastic, and organic), the paper uses 400 RGB-coded photos that are taken from the outside world. By utilizing CNN, it attains an 83% accuracy rate, showcasing its efficacious waste classification abilities via deep learning on actual environmental data.Shi, Cuiping, et al. [18] the research makes use of the TrashNet collection, which consists of 2527 photos. By utilizing MLH-CNN, it attains 92.6% accuracy. This emphasizes how well the model performs trash classification tasks and shows how useful it could be for waste management and environmental sustainability initiatives.Chen, Zhichao, et al. [19] with a self-constructed dataset of 4256 photos, the research investigates supervised and unsupervised learning methods. The research highlights the effectiveness of these models in picture classification tasks, demonstrating their potential in a variety of applications, with an amazing accuracy of 97.9%.Ramesh Kumar, et al .[20] utilizing the 2,527-image TrashNet dataset, the research makes use of a deep convolutional neural

network. By using advanced neural network approaches to address waste management difficulties, the research attempts to improve waste classification methods, with reported accuracies of 39.56% and 42.46%.Susanth, G. Sai, et al.[21] the study uses CNN models such as ResNet50, DenseNet169, VGG16, and AlexNet using a mix of raw data and photos from Google. The models demonstrate their efficacy in garbage classification tasks with 92.6% and 94.9% accuracy on a dataset of 4,163 photos.Panwar, Harsh, et al. [22] the research makes use of the AquaTrash dataset, which consists of 2527 photos, although it doesn't say which model or technique was used. The research probably concentrates on garbage classification or related tasks utilizing this dataset, with the goal of supporting environmental conservation efforts, even though the accuracy is not stated.Srivastava et al.[23] uses CNN,ResNet-50, MobileNet V2 and DenseNet-121 on 9,200 images and their obtained accuracy is 95.36%-98.72%.

III. METHODOLOGY

This study aimed to quickly and efficiently identify West classification categories using machine learning. Our primary data was first gathered, and it was then preprocessed. We used techniques for training, testing, and verifying the dataset after preprocessing. Finally, we used this dataset and our methodologies to determine the accuracy. Four different kinds of approaches were employed: EfficientNet B0, B2, B3, and B4.

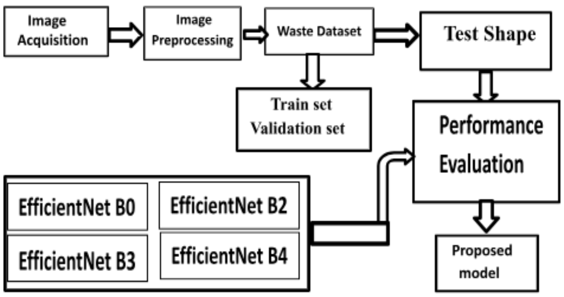


Fig. 1: Methodological Diagram for waste classification.

A. Dataset Description

Images of waste that were gathered were analyzed for this study. Total 5012 pictures were acquired. These pictures show several kinds of waste, and they are all unique from one another. It is believed that this dataset is all raw data. There are 9 types of data in our dataset 'Food-and-fruits', 'Glass-West', 'Metal', 'Paper', 'Plastic', 'Polythene', 'Textile', 'plant-andwoods', 'vegetable, and other miscellaneous trash were among the numerous waste types that is divided into categories. Fig 3. Represents the sample dataset. Both training and validation images have been used. In our dataset there are 4010 files for training and 1002 files for validation. Use these images to evaluate the method of EfficientNet. WE use four types of methods: EfficientNet B0, EfficientNet B2, EfficientNet B3, EfficientNet B4. Using this dataset to find out the classification of waste.

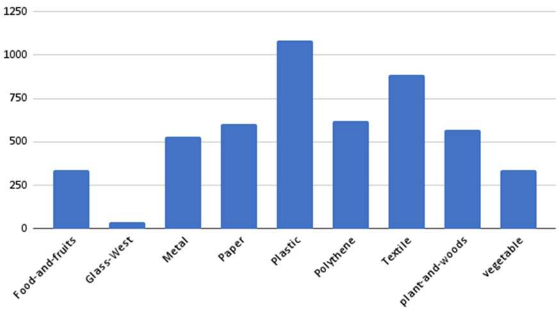


Fig. 2: statistical analysis of images.

Fig. 3: Representative Images of Waste

B. Image Pre-processing:

To meet the EfficientNet models' input requirements, all photos were scaled to 224 by 224 pixels. To keep the model inputs consistent across various image size, this scaling was essential. Pixel values were scaled to the range [0, 1] in order to normalize each image. By ensuring that the images were scaled consistently, this normalization enhanced the stability and convergence of the model training.

C. Model Description

State of the Art of EfficientNet Model: Google AI released the EfficientNet family of convolutional neural networks (CNNs) in 2019 with the purpose of using them for image categorization tasks. Compound scaling, which uses a compound coefficient to equally scale depth, breadth, and resolution, is the main breakthrough of EfficientNet. By using this technique, EfficientNet models are able to surpass earlier models in terms of both parameter size and computing resources, while still achieving state-of-the-art accuracy.EfficientNet produces more effective outcomes by evenly scaling depth, breadth, and resolution while scaling down the model. The major goal of computer vision and deep learning is to find more dependable and accurate ways with smaller models. There are eight models in all, ranging from B0 to B7. The foundation model of the EfficientNet family is called EfficientNet-B0[24]. Fig. Below shows the schematic depiction of the basic EfficientNet model. In this study, EfficientNet B0, EfficientNet B2, EfficientNet B3, and

EfficientNet B4 have been employed for waste classification precisely.

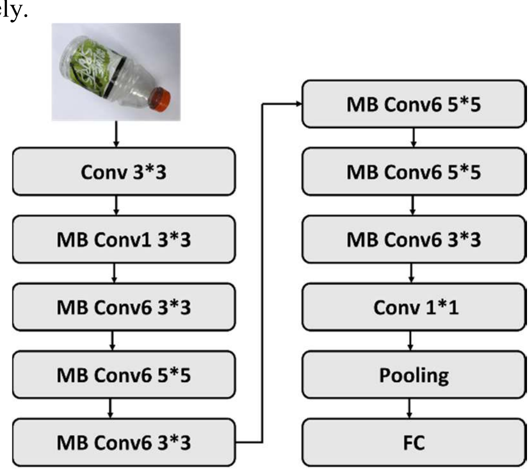


Fig. 4: Block Diagram of EfficientNet.

EfficientNet-B0 is a baseline model that optimizes efficiency and accuracy using depthwise separable convolutions and Mobile Inverted Bottleneck Convolution (MBConv) blocks. It features a Conv3x3 stem with 32 filters and stride 2, multiple MBConv blocks, and a fully connected layer with 1000 outputs. It is designed for efficiency, low computational cost, and serves as the foundation for larger variants. A compound scaling technique is used by EfficientNet-B2, an enhanced version of EfficientNet-B0, to increase accuracy and efficiency. In order to balance complexity and computational expense, its design consists of a fully connected layer with 1000 outputs for ImageNet classification, MBConv blocks, a Conv3x3 layer with 48 filters, and global average pooling. A compound scaling variant of EfficientNet-B0, EfficientNetB3 improves efficiency and accuracy. Its design consists of many MBConv blocks, a Conv Head with 1536 filters, and a Conv3x3 layer with 40 filters. The model uses a fully connected layer for ImageNet classification to strike between computational expense and complexity. In order to achieve the best feature extraction and classification, EfficientNet-B4, an improved version of EfficientNet, uses compound scaling and seven stages of MBConv blocks, a Conv Stem, and a Conv Head.

D. *Model Parameters*

The Convolutional Neural Network (CNN) model was set up with an input size of 224 x 224 pixels. The model was optimized through the use of the Adam optimizer, which is renowned for its effectiveness and capacity for adaptive learning. A dense layer with 512 neurons was added, and non-linearity was added to improve model learning by using the ReLU activation function. Sparse Categorical Crossentropy was the loss function used, and it was suitable for multiclass classification applications. In order to ensure that there were enough learning iterations to attain optimal performance, training was carried out across 25 epochs.

IV. Result Discussion & Analysis

A. *Performance Measurement Metrices*

To evaluate the model performance, accuracy, precision, recall and F1 score computed. [25]

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 = \frac{2 * Precission * Recall}{Precission + Recall} \tag{4}$$

Here TP denotes True Positive, TN denotes True Negative, FP denotes False Positive and Finally FN means False Negative [26].

B. *Result Discussion*

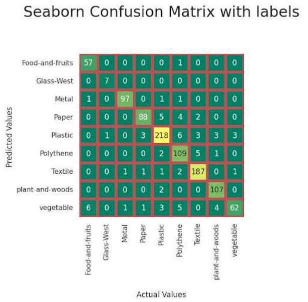
After evaluated all the models we find out that EfficientNetB0 and EfficientNetB2 have outperformed the other Efficient models and the highest accuracy has been achieved by EfficientNet B0 and EfficientNet B2 as 93% .On the other hand, EfficientNetB3 and EfficientNetB4 have achieved 91%.When precision, recall, and f1-score values have taken into account, EfficientNet B0 fared better than the EfficientNet B2 and the others ranging from 85% to 98% precision, 76% to 100% recall, and 84% to 96%. Table I illustrates the performance of applied models.

TABLE I. Resulr Summary of All implemented model's

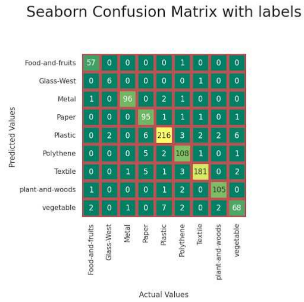
Model	Class	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
EfficientNetB0	Foods	89%	98%	93%	93%
	Glass	88%	100%	93%	
	Metal	98%	97%	97%	
	Paper	95%	89%	92%	
	Plastic	94%	93%	92%	
	Polythene	85%	93%	89%	
	Textile	95%	97%	96%	
	Woods	93%	98%	96%	
	vegetable	94%	76%	84%	
EfficientNetB2	Foods	93%	98%	96%	93%
	Glass	75%	89%	80%	
	Metal	98%	96%	97%	
	Paper	86%	96%	90%	
	Plastic	94%	91%	93%	
	Polythene	89%	92%	91%	
	Textile	97%	94%	96%	
	Woods	96%	96 %	96%	
	vegetable	87%	0.83%	85%	
EfficientNetB3	Foods	93%	0.97 %	95%	91%
	Glass	83%	71%	77%	
	Metal	95%	95 %	95%	
	Paper	81%	92 %	86%	
	Plastic	89%	92 %	91%	
	Polythene	85%	89%	87%	
	Textile	98 %	94 %	96%	
	Woods	98 %	92 %	95%	
	vegetable	87 %	72%	79%	
EfficientNetB4	Foods	85 %	98 %	91%	91%
	Glass	83%	71%	77%	
	Metal	95%	93%	94%	
	Paper	88%	92 %	90%	
	Plastic	94 %	88 %	91%	
	Polythene	87 %	91%	89%	
	Textile	92 %	96%	94 %	
	Woods	91%	97 %	94%	
	vegetable	90%	74%	81%	

C. Confusion Matrix

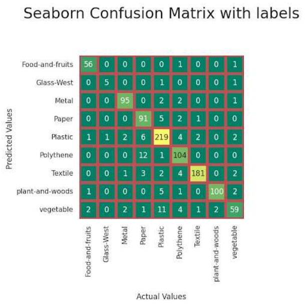
Fig 5 represents the confusion matrix of EfficientNet B0, EfficientNet B2, EfficientNet B3 and EfficientNet B4 respectively



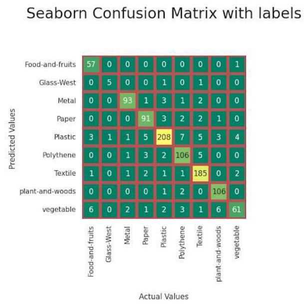
(a) EfficientNetBO



(b) EfficientNetB2



(c) EfficientNetB3



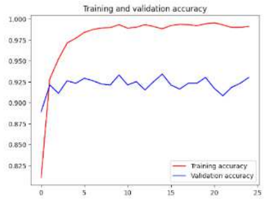
(d) EfficientNetB4

Fig. 5: Confusion Matrix for EfficientNet a) B0 b) B2 c) B3 d) B4

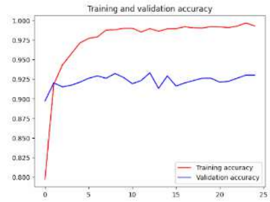
The real values of all the efficientNet models are displayed in the confusion matrix. We also discover that the nine classes provide the real TP and TN rate values. Our two best models have an accuracy of 93%. Three classes have some inconsistencies. It is typically brought about by our deficiency in quality and data. However, our obtained solution has been demonstrated to be stable in the CF matrix. Every student in the class tries to give a healthy TP rate and correspondingly lower the FP and FN rates.

D. Accuracy & Loss Graph

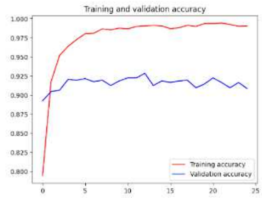
In Fig 6 provides the accuracy graph of four versions of EfficientNet. We can observe in Fig. 6(a) that EfficientNetB0 provides a quality line for train and test, and EfficientNetB2 (6.b) offers a very satisfied graphical line with very few miss match issues in the train and test scenario. All of the models have 25 epochs in our implementation period. There are virtually few model underfitting issues with the other two models, EfficientNetB3 (6.c) and B4 (6.d). We may determine that the quality of the model train and test is satisfactory to the researchers by looking at the accuracy graph.



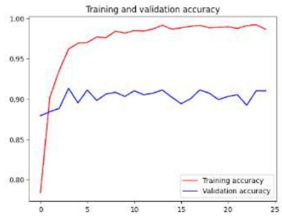
a) EfficientNetBO



b) EfficientNetB2



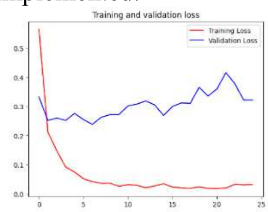
c) EfficientNetB3



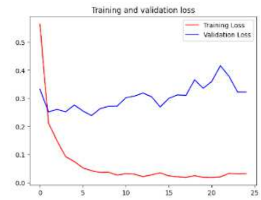
d)EfficientNetB4

Fig. 6: Accuracy Graph for EfficientNet a) B0 b) B2 c) B3 d) B4

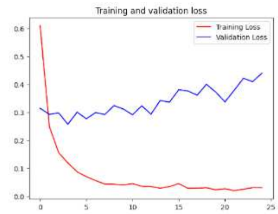
In Below Fig. 7 EfficientNet a) B0 b) B2 c) B3 d) B4 shows the loss graph for every model that has been implemented.



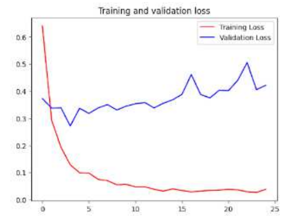
a) EfficientNetBO



b) EfficientNetB2



c) EfficientNetB3



d) EfficientNetB4

Fig. 7: Loss Graph for EfficientNet a) B0 b) B2 c) B3 d) B4

The accuracy graph, shown in Figure 6, is already well-described and satisfactory. We demonstrate the loss graph of the four models to provide further understanding. When the model runs constantly, we can see that the validation loss decreases. As we can see, there aren't many train and test case valuations. Finally finish the 25 epochs of every model we can see that the rate is between 0.1-0.3. Though B3 and B4 is quite noisier than previous two version. However, this is our chance to raise the standard, and we think that the EfficientNet architecture and the method we've suggested have already produced excellent research.

V. CONCLUSION

Waste classification is undergoing a revolution thanks to machine learning models like EfficientNet B0, B2, B3, and B4, which also improve environmental sustainability. These models automate garbage sorting procedures by classifying waste into organic and non-organic categories using convolutional neural networks.For garbage classification, earlier studies mostly used four methods: EfficientNet B0, B2, B3, and B4. This research presents a novel waste classification approach and provides comprehensive experimental validation to support its effectiveness. A condensed version of the EfficientNet model was specifically suggested for the classification of trash images. The main contribution of this study was the careful curation of a dataset of 5012 photos from nine different waste categories. The development of an EfficientNet model followed in order to improve classification performance. The primary benefit of EfficientNet models is their capacity to optimize computing resources by finding a compromise between efficiency and performance. These models provide higher accuracy with fewer parameters by skillfully adjusting depth, width, and resolution through the application of compound scaling. Because of its intrinsic scalability, EfficientNet models are suitable for a wide range of tasks and exhibit consistent performance on a variety of datasets. The results of the experiment demonstrate that transfer learning can lead to remarkably high accuracy rates; the EfficientNet B0 and B2 models both achieve 93\% accuracy. Furthermore, EfficientNet B3 and B4 models outperform traditional image classification methods with notable classification accuracies of 91\%. Notably, in this case, EfficientNet B0 and B2 turn out to be the most accurate models.

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