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Deep Learning Approach to Recyclable Products Classification: Towards Sustainable Waste Management

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Abstract: Effective waste management and recycling are essential for sustainable development and environmental conservation. It is a global issue around the globe and emerging in Saudi Arabia. The traditional approach to waste sorting relies on manual labor, which is both time-consuming, inefficient, and prone to errors. Nonetheless, the rapid advancement of computer vision techniques has paved the way for automating garbage classification, resulting in enhanced efficiency, feasibility, and management. In this regard, in this study, a comprehensive investigation of garbage classification using a state-of-the-art computer vision algorithm, such as Convolutional Neural Network (CNN), as well as pre-trained models such as DenseNet169, MobileNetV2, and ResNet50V2 has been presented. As an outcome of the study, the CNN model achieved an accuracy of 88.52%, while the pre-trained models DenseNet169, MobileNetV2, and ResNet50V2, achieved 94.40%, 97.60%, and 98.95% accuracies, respectively. That is considerable in contrast to the state-of-the-art studies in the literature. The proposed study is a potential contribution to automating garbage classification and to facilitating an effective waste management system as well as to a more sustainable and greener future. Consequently, it may alleviate the burden on manual labor, reduce human error, and encourage more effective recycling practices, ultimately promoting a greener and more sustainable future.

Keywords: smart waste management; AI; garbage classification; green planet; transfer learning

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1. Introduction

Every day, humans generate vast amounts of waste that impact the environment and pose significant challenges for waste management systems worldwide. The world generates 2.01 billion tons of municipal solid waste annually, with at least 33% of the extremely conservative is not managed in an environmentally safe manner [1]. Moreover, the amount of waste produced annually around the world is predicted to rise dramatically from the current 2.01 billion tons to 3.40 billion tons by 2050 [2]. According to the Saudi Press Agency, the Riyadh Municipality removed more than 2 million tons of solid garbage from the capital's various districts during the first half of 2022 [3]. The improper management of waste can have severe consequences for the planet, such as air and water pollution, soil degradation, climate change, and biodiversity loss, which threaten the health and well-being of both humans and wildlife. Recycling is a critical process that contributes to reducing the amount of waste that ends up in landfills, oceans, or other ecosystems [4].

Among the work needed for recycling, garbage sorting is the most fundamental step to enable cost-efficient recycling. However, sorting waste materials manually can be time-consuming, laborious, costly, and error prone. Moreover, the management of solid waste in major urban contexts has become a challenging issue due to the rising volume of waste produced daily by both companies and individuals. Resulting in several issues such as public health, environmental pollution and many others. Fortunately, advances in deep learning and computer vision techniques offer a promising solution to automate waste classification and enable more efficient recycling processes.

In the most celebratory work by Filimonau [5–9], he emphasized food waste management in various sectors around the world. In [5], Filimonau and Gherbin presented exploratory research on food waste management practices in grocery stores in the United Kingdom (UK). As an outcome of the study, it was highlighted that though good policies for food waste management exist in the governance, food donations still need more attention in terms of improvement in consumer awareness, regulations, and effective policies. Based on the study, recommendations were made for retail stores. Similarly, in [6], the authors critically reviewed food waste management in the hospitality industry and highlighted the potential areas of improvement. Moreover, the feasibility analysis was made in terms of core in-house skills; training needs; preliminary financing costs; potential fiscal savings. In [7], the authors presented an important study on food waste management in Shanghai full-service restaurants. In this regard, comprehensive interviews were conducted with senior management to figure out the potential gaps in food waste management in the kitchens. As a result, the study concluded the ways to mitigate food waste by means of social campaigns, involving celebrities for public awareness programs and free-to-attend trainings for the senior management. In [8], the authors extended their work to address the similar as well as diverse nature of issues in ethnic food restaurants with special emphasis on the Chinese and UK markets.

An important and most significant study was conducted in [9] to reveal the aspects of waste management in the hospitality sector in the post-COVID-19 era. It is apparent that amid the COVID-19 pandemic [10], waste management was among the most significant areas of research especially plastic waste management when it comes to strictly restricting the fatal epidemic around the globe. The following were important highlights of the study in [9]:

- COVID-19 has increased food and plastic waste in hospitality operations.
- Alternative food networks (AFNs) can assist in food waste avoidance.
- Short food supply chains (SFSCs) can assist in effective food waste management.
- Corporate coopetition is essential to execute AFNs and SFSCs.
- Administrative revolution and official support can assist in plastic waste mitigation.

Based on the provided introduction to waste management, it is apparent that it is among the most important areas of research for a better, sustainable, and greener planet. Its benefits are manifold, for instance, food donations, public health and safety, recycling products and cleanliness. Moreover, in Saudi Arabia food waste management needs serious attention at the individual as well as government levels. The undergoing study is a contribution in this regard and motivation for a sustainable and green kingdom. It is also aligned to the kingdom's Vision2030 for a greener and more sustainable future.

In [11], the authors used deep learning to conduct a comparative study between custom-build models and pre-trained models to classify garbage images acquired from the Kaggle dataset "Garbage classification". The models should learn different characteristics of different garbage types then they should be used to classify new pieces of garbage into plastic, paper, cardboard, glass, metal, or trash. The proposed approach aims to design and implement deep learning models that can accurately recognize and categorize waste items. We believe that this study can contribute to promoting sustainability and fostering innovation in the field of waste management. In this regard, the following steps have been taken towards contributing to the study.

1- A comprehensive review of related recent studies to analyze the research gap.

2- Investigation of Deep learning models to a recent public dataset of considerable size.
3- Evaluation of the proposed model using well known metrics and contrasting to state-of-the-art studies in literature.

The remaining part of this work is arranged as follows. Section 2 contains a review of related literature. Section 3 contains the proposed models. Section 4 contains methodology that includes dataset description, experiment setup, performance measures, and optimization strategy while Section 5 contains the results and discussion. Finally, Section 6 covers the conclusion.

2. Literature Review

Over the past several years, deep learning (DL) has become increasingly popular in image classification. For this purpose, multiple studies implemented various DL techniques to create classifier models using image data. Below are some literature reviews that identify potential areas for improvement in this research.

In the study conducted by Rahman et al. [12], they introduce a DL-based automatic waste management system. The system utilizes the CNN algorithm as its basis. It is enhanced through the implementation of three key improvements: combining multiple input images with different features, repurposing remaining module features, and designing a novel activation function. The effectiveness of this new classification algorithm was then validated through experimentation using a public garbage dataset from GITHUB. The results of the study show that the proposed system exhibits a classification accuracy of 95.3125%.

Moreover, an image classification model is presented in the study by Niu et al. [13], which efficiently distinguishes recyclable materials. The "Dual-branch Multi-output CNN" is introduced, which is a custom CNN comprised of two branches designed to classify recyclables and identify the type of plastic. The proposed architecture includes two classifiers trained on distinct datasets to encode different attributes of the recyclable materials. The Trash net dataset was used in combination with data augmentation techniques, and the WaDaBa dataset was leveraged using physical variation techniques. The joint utilization of the datasets enabled the learning of separate label combinations. The effectiveness of the model is confirmed through experiments, which shows an accuracy of 90.02% in waste material classification.

Furthermore, in the study by Majchrowska et al. [14], the authors suggest a waste detection method that employs deep learning in a constructive manner. Initially, standardized datasets were formulated for waste detection and classification, integrating open-source information for all probable categories of waste, including metals, plastics, paper, unknown waste, non-recyclables, vital waste, and glass. Following this, a two-stage garbage localizing and classification detector was introduced. The garbage locator was created using Efficientdet-D2, while the waste classifier applied Efficientnet-B2 to sort the detected waste into seven classifications. Semi-supervised training was used to prepare the classifier by exploiting unclassified images. The approach proposed delivered up to 70% of the mean accuracy in waste detection and approximately 75% of accuracy in classification for the test dataset. Similarly, the authors conducted a study to propose a multi-layer system for classifying waste. The proposed method is a deep learning model that combines layers of the CNN model with a multi-layer perceptron (MLP). The study trained the model with a dataset of 5000 images, with 100 images for each waste class. The results showed that the MHS model outperformed the CNN model, achieving 92% and 91% accuracy in two testing scenarios. These findings suggest that the proposed model has the potential for improving waste classification accuracy [15].

The study aimed to develop an automated system for sorting trash and proposed a deep neural network called Deep Neural Network for Trash Classification (DNN-TC). DNN-TC uses the ResNext model with several improvements, including adding two fully connected layers after the global average pooling layer. The model was trained on the VN-trash dataset, which includes 5904 images from Vietnam. Testing the model on two different datasets, VN-trash, and TrashNet, showed that it achieved accuracies of 94% and 98%, respectively. In comparison to state-of-the-art methods, the DNN-TC model outperformed them by a significant margin. These findings demonstrate the potential for the DNN-TC model to improve the accuracy and efficiency of automated trash sorting systems [16]. The aim of this study was to develop a deep neural network image classifier that can identify and classify different types of waste material. The authors utilized multiple CNNs, such as VGG 16 and ResNet, to extract features from the images and feed them into the classifier to make predictions. Among the models tested, Densenet169 outperformed the others with 94.9% accuracy, as measured on a specific dataset after image scraping. These findings demonstrate the potential of Densenet169 for improving waste classification and management systems [17].

The authors of [18] aimed to create a system that can accurately identify metal objects and classify them with high accuracy. Rather than creating a new model, the authors focused on understanding the already-existing models to find the most suitable one. The system proposed in this study consists of four modules: the first is a smart camera to capture the object, the second extracts the region of interest, the third is where preprocessing takes place, and finally, the preprocessed data is fed to a deep learning model. The authors conducted experiments with multiple deep learning models, such as GoogleNet, VGGNet, and AlexNet, and found that AlexNet was the most suitable, with the highest recognition rate in both experiments. Another study aimed to develop a system that automatically classifies waste based on its material without human intervention. The dataset used in the study is the classification of trash for recyclability status. Since the dataset was not large enough, the authors used image augmentation techniques to generate more data. The study employed a CNN model with an input layer that takes an image of size $150 \times 150 \times 3$ and 9 hidden layers, including the output layer. The study found that using hyperparameters such as dropout with a value of 0.5 and the Rectified Linear Unit (ReLU) activation function for the CNN resulted in the highest accuracy of around 85% to 90% on the training data and 80-86% on the validation data. This automated waste classification system has the potential to reduce the environmental impact of improper waste disposal, increase recycling rates, and promote a more sustainable future [19].

Ruiz et al. [20] presented a study that aims to use the TrashNet dataset to improve a deep-learning model for classifying isolated garbage. Mindy Yang and Gary Thung created the dataset at Stanford University, which contains 2527 RGB images of six waste classes. Researchers used several attractive CNN models for the automatic classification of waste. Also, the researchers used many methodologies, and the experiments were about OscarNet based on VGG-19 pre-trained with an accuracy of 88.48% and GarbeNet based on CNN with an accuracy of 87.69%. In conclusion, the best result on the Trash Net dataset was achieved using the Inception-ResNet model with 88.66% of average accuracy. In the future, the researchers want to generate realistic synthetic images with more types of waste for their training model and then test them with actual photos that combine several types of garbage. In a study by Alsubaei et al. [21], the researchers were interested in developing a novel deep learning model to detect and classify the small object for garbage waste management (DLSODC-GWM) technique. In their research, they used data from benchmark datasets to predict the performance validation of the method. Therefore, the goal of using and designing this technique was to detect objects utilizing an arithmetic optimization algorithm (AOA) to select the optimal hyperparameter values to improve the RefineDet (IRD) model detection efficiency. In addition, the researchers applied a model for classifying waste objects into multiple categories called the Functional Link Neural Network (FLNN) model. Thus, after comparing other technologies such as MLH-CNN, AlexNet, RestNet50, and VGG16, the DL model with (DLSODC-GWM) technique reached a high score of 95.23% in precision, 94.29% in the recall, and 94.73% in F-score.

The study by Meng and Chu [22] focused on improving the learning model that can detect the garbage entity from an image and classify it into one of the categories by employing deep learning methods. For garbage classification, the used dataset collected from Kaggle consists of 2527 images. The dataset was divided randomly and the experiment was conducted using the Support Vector Machines (SVM), convolutional neural network (CNN), and the histogram of oriented gradients (HOG), the models runs with and without the data augmentation then models were trained with different hyperparameters which are ReLU, and SoftMax activation functions, with the optimizers Adam and Adadelta, besides 40 epochs, 32 and 16 batch size, the dropout rate of 0.5, and the cross-entropy loss function. The results concluded that the best-performing algorithm was a simple CNN model with 82% training accuracy and 81% test accuracy. In another study by Fu et al. [23], the authors proposed a deep learning-based system to classify wastes. As for the dataset used in this model, it is from the Huawei challenge cup for classifying the garbage [24] including 40 categories and a total of 24,000 images. The design of the system includes two components: the hardware contains six devices and the classification models including ResNEt34, VGG126, InceptionV3, DenseNet121, MobileNetV3, and GNet the experiments were conducted using several learning rates and epochs. The study found that the best results were achieved using the Gnet algorithm and the accuracy was 92.62% for testing. Furthermore, In a paper authored by Ozkaya and Seyfi [25]. The authors provided deep learning-based techniques for developing garbage classification model. The dataset that was collected from TrashNet includes 2527 images and six categories. The predictive model was built using several CNN structures for fine-tuning which are: AlexNet, VGG-16, GoogleNet, ResNet, and SquezeeNe, likewise two classifiers were used to assess the execution Softmax and SVM. The highest accuracy is 97.86% and was obtained by GoogleNet and SVM.

Chen and Xiong [26] aimed to build a garbage classification model by YOLOVE. The model was built based on aVOC dataset consisting of 22,000 images, and three classes each with five kinds of garbage. The dataset was split into 70:30 proportions for training and testing after that trained using YOLOV3, YOLOV4, and improved YOLOV4 algorithms with 1200 iterations and 16 batch size, along with Ciou-Loss's regression loss, and Diou-nums's classification loss. The results showed that the YOLOV4 achieved the highest FBS with 92 f/s and mAP with 64%. Moreover, Zeng et al. [27] focused on developing a model for classifying the garbage by utilizing CNN's structure using a collected public dataset from Stanford University consisting of 10,624 images with four main classes and 10 sub-categories. The Keras package with TensFlow was used to train the algorithms: DenseNet121, DenseNet169, ResNet50, ResNet101, ResNeXt50, ResNeXt101, Efficientnet-B3, and Efficientnet-B4, respectively. Besides the dataset split with a 5:1 ratio to training and testing sets, further, the study used various data augmentation methods, with random flip, random rotation, random translation, center clipping, and random erasure with Adam 0.0001 leaning rate and label smoothing together with PublicGarbageNet that was the best-performing model with 96.35% accuracy.

In [28], authors attempted to improve the efficiency of classifying social garbage and built a CNN classifier. To average the brightness of the image's background, which led to low accuracy due to interference in the light and shadow, they used an adaptive image-brightening algorithm. Moreover, the Canny operator has been utilized to help crop blank backgrounds. The result of the study shows that the classifier reached an accuracy of 96.77% on the self-built dataset and 93.72% on the TrashNet dataset. Similarly, the authors in [29] developed an automated garbage sorting tool to make it simpler for locals to categorize garbage as the problem becomes more prevalent. They divided garbage into six categories using the TrashNet dataset. They were able to accomplish their goals by using CNN classifier and exploring numerous well-known architectures in the beginning phases. They arrived in a modified version of AlexNet by removing two layers, and they experimented with other model architecture-based strategies, such as dropout, data augmentation, and learning rate decay. In the final layer of the model, they experimented with two classifiers: Softmax and SVM. The result of this study attained an accuracy of 79.94% on the test dataset. The authors in [30] developed a CNN classifier to address the real-world waste management system's practical issue. Researchers could attain an accuracy of 79%, according to the study's final findings. According to [31], India generates more than 2 billion tons of waste annually, while solid waste is separated by laborers in an inefficient manner that is both time-consuming and impractical. To distinguish the type of garbage and classify it into predetermined categories, authors created a real-time system. using a CNN classifier on four datasets: Garythung Yang, Waste classifier master, TrashNet, and Real images, they successfully reached a test accuracy of 89% on the TrashNet dataset.

The authors of [32] stated that automation of waste classification is one of the efficient approaches to fully utilize these resources because garbage is an underutilized resource. For the recognition of garbage images, certain deep-learning models were employed. Also, a Garbage Classification Network (GCNet) based on model fusion and transfer learning was suggested in this paper. The EffcientNetv2, Vision Transformer, and DenseNet, respectively, were combined to develop the Neural Network model of GCNet. The dataset was expanded through data augmentation, and the resultant dataset contained 41,650 garbage images. The suggested model has good convergence and a high accuracy compared to other models, in which it successfully attained an accuracy of 97.54%.

In another study presented in [33], the authors aimed to develop a model that can accurately identify and classify different types of garbage. They used the TrashNet dataset consisting of images of six types of garbage, with the YOLOv5 algorithm. YOLOv5 automatically learns features from input, so no feature selection was needed. The model's performance was evaluated using five-fold cross-validation, resulting in 95.51% accuracy. One area that the study lacks is the size of its dataset and the type of garbage it represents. In [34], the authors proposed an intelligent waste classification system that uses convolutional neural networks to automate the process of waste sorting. The dataset they used, called the "Garbage Classification Dataset", was collected by them from multiple sources, but may not have been representative of all garbage types. They used transfer learning on the pre-trained model VGG16 as the base, then added additional layers to fine-tune the network. Using the five-fold cross validation technique, they reported an accuracy of 86%.

The study in [35] aimed to improve waste classification accuracy by developing a system using a fusion of deep learning features. The authors made the dataset [36] using images of 4 different types of waste: plastic paper, metal, and glass. They used a fusion-based deep learning approach that combined the features learned from pre-trained models, including VGG16, ResNet50, InceptionV3, and MobileNetV2. They fine-tuned each model with transfer learning, then performed the final classification using an SVM classifier. For validation, 10-fold cross-validation was used. In the end, they achieved 87% accuracy. Likewise, a study in [37] presents a waste classification model based on a multilayer hybrid CNN (MLHCNN). The authors created the dataset from images of plastic, metal, paper, glass, and residual waste. The images were collected from garbage sorting stations and garbage transfer stations in China. The MLHCNN consists of a feature extraction module that uses two pre-trained CNNs to extract features from the images, a feature fusion module that combines the extracted features, and a classification module that classifies the waste images. The authors used 10-fold cross-validation to evaluate the performance of their MHCNN model. The model achieved an accuracy of 92.6%. The study in [38] proposes a trash classification approach using deep learning. The authors used a deep learning-based approach called ScrapNet, which uses a CNN architecture. They fine-tuned a pre-trained InceptionV3 model on their dataset, TrashNet. Also, data augmentation techniques were used to increase the dataset's size and performance. With 10-fold cross-validation, the reported accuracy on the TrashNet dataset was 92.87%.

In a summary, the respective number of studies are reviewed, investigating various DL techniques and algorithms to develop waste classifying models and most of the studies exhibited promising results as shown in Table 1. It is also observed that most of the studies used pre-trained models, and CNN algorithms and achieved their best outcomes using them. While the poorest result was obtained through Efficientnet-B2 [14] with 75% accuracy. Conversely, the proposed study compared pre-trained models with CNN model. Nonetheless, the proposed model in the current study utilized garbage classification data from

Kaggle, as studies in [22,34] used the same data with CNN model and achieved accuracy of 82% and 86%, respectively. Furthermore, several computational intelligent methods are investigated for health informatics and public safety with promising results [39–42]. Therefore, this study proposed a deep learning model for waste management. In contrast to the studies in the literature, the proposed study investigated a middle eastern dataset while addressing the kingdom's waste management problem, which is first of its kind study in the kingdom.

Table 1. Literature review summary.

Ref	Year	Algorithms	Dataset	Performance Measure
[15]	2018	MHS	-	Accuracy = 92%
[25]	2018	AlexNet, VGG-16, GoogleNet, ResNet and SquezeeNet [43]	TrashNet	Accuracy = 97.86% by GoogleNet, together with SVM.
[19]	2018	CNN [44]	-	Accuracy = 90%
[16]	2019	DNN-TC	VN-trash dataset	Accuracy = 98%
[18]	2019	GoogleNet, VGGNet AlexNet [43]	-	AlexNet has the highest accuracy
[20]	2019	CNN models with OscarNet based on VGG19, GarbeNet based on CNN with an Inception-ResNet model [43].	Mindy Yang and Gary Thung created the dataset at Stanford University	VGG-19 accuracy = 88.48% GarbeNet based on CNN accuracy = 87.69% InceptionResNet accuracy = 88.66%
[35]	2019	CNN, ResNet-50, SVM, InceptionV3, and MobileNetV2 [43]	Gary Thung and Mindy Yang [36]	Accuracy = 87%
[12]	2022	CNN [44]	GITHUB 2020	Accuracy = 95.3125%
[26]	2020	YOLOV3, and YOLOV4 [45]	VOC	YOLOV4 FBS = 92 f/s and MAP = 64%.
[27]	2020	DenseNet121, DenseNet169, ResNet50, ResNet101, ResNeXt50, ResNeXt101, Efficientnet-B3, and Efficientnet-B4 [43]	Stanford University dataset	The best accuracy of 96.35% with PublicGarbageNet
[29]	2020	CNN, and SoftMax [46]	TrashNet	Accuracy = 79.94%
[30]	2020	CNN [46]	-	Accuracy = 79%
[31]	2020	CNN [46]	Garythung Yang, Waste classifier master, TrashNet, and Real images	Accuracy = 89% on TrashNet dataset
[34]	2020	AlexNet, GNet, VGGNet-19, and ResNet-101 [43]	Garbage Classification Dataset	Accuracy 86% on CNN
[13]	2021	Dual-branch Multi-output CNN	TrashNet and WaDaBa	Accuracy = 90%
[17]	2021	CNNs, Densenet169 [43]	-	Accuracy = 94.9%
[22]	2021	SVM, CNN, and HOG	Garbage Classification dataset	CNN with accuracy = 84%
[23]	2021	ResNEt34, VGG126, InceptionV3, DenseNet121, MobileNetV3, and GNet [43]	24,000 images from Huawei challenge cup dataset [24]	GNet accuracy = 92.62%
[33]	2021	YoloV5 [45]	TrashNet	Accuracy = 95.51%
[37]	2021	CNN [44]	TrashNet	Accuracy = 92.6%
[38]	2021	InceptionV3 [43]	TrashNet	Accuracy = 92.87%
[14]	2022	EfficientdetD2 & EfficientnetB2 [43]	14,000 instances	Accuracy = 75%
[21]	2022	MLH-CNN, AlexNet, RestNet50, and VGG16, DL model with (DLSODC-GWM) [43]	Benchmark datasets	Precision = 95.23%, Recall = 94.29% F-score = 94.73%
[28]	2022	CNN [44]	TrashNet, and self-built dataset	Accuracy = 96.77%
[32]	2022	GCNet [43]	Internet collected dataset combined with self-built dataset	Accuracy = 97.54%.

3. Description of the Proposed Models

To achieve the aim of classifying recyclable products, the following algorithms were considered and contributed.

3.1. Convolutional Neural Networks (CNN)

CNNs are a type of artificial neural network utilized for image classification based on their visual features [47]. This type of algorithm consists of numerous layers that evaluate and process data from the images, producing a prediction for the image classification result. The first layer is the input layer receiving the image data, followed by the convolution layer that employs filters to extract important features in the image. The pooling layer then sub-samples the previous layer's output to simplify the visual representation and enable the extraction of more conceptual features. The process may involve stacking additional convolution and pooling layers to boost the visual feature extraction complexity. The culminating result generates a probability distribution portraying different image classes using the SoftMax function normalized output. The CNN algorithm utilizes backpropagation to refine its parameters, minimizing the distinction between its predictions and the accurate class labels.

3.2. MobileNetV2

MobileNetV2 is a convolutional neural network architecture that is designed to be efficient and lightweight for mobile devices [48]. It is based on an inverted residual structure, which allows it to achieve high accuracy while using fewer parameters and computations than traditional CNNs. The architecture of MobileNetV2 consists of a series of inverted residual blocks. Each block consists of three layers: a pointwise convolution layer, a depth-wise convolution layer, and another pointwise convolution layer. The pointwise convolution layers are used to reduce the number of channels in the input, while the depth-wise convolution layers perform feature extraction. The final pointwise convolution layer increases the number of channels back to the original size. In addition to the inverted residual blocks, MobileNetV2 also incorporates several other techniques to improve its performance, such as linear bottlenecks, shortcut connections, and skip connections. These techniques help to reduce the number of parameters and computations required while still achieving high accuracy. MobileNetV2 has achieved state-of-the-art performance on several benchmark datasets, such as ImageNet. It is widely used in a variety of applications for mobile devices, such as image classification, object detection, and natural language processing. Overall, MobileNetV2 is a powerful and efficient convolutional neural network architecture that is well-suited for mobile devices. It has achieved state-of-the-art performance on several benchmark datasets and is widely used in a variety of applications.

3.3. ResNet50V2

ResNet50V2 is a deep convolutional neural network that was created in 2017 as an improvement over the original ResNet50 architecture [49]. It is based on the concept of residual learning, which allows deep networks to be trained without the vanishing gradients issue. ResNet50V2 introduces several enhancements over the original ResNet50, such as: Using bottleneck blocks with a new design to reduce the number of parameters, adding a new skip connection from the first convolutional layer to the output, and Using pre-activation for the residual units. These changes in ResNet50V2 allow for better accuracy, faster training, and faster convergence. Moreover, ResNet50V2 is trained on the ImageNet dataset, which contains over 1 million images and 1000 classes. It has achieved state-of-the-art results in several computer vision tasks, including object detection, image classification, and semantic segmentation. ResNet50V2 is widely used as a pre-trained network and is also used as a backbone architecture in many other deep-learning models. Finally, ResNet50V2 is a powerful and efficient deep convolutional neural network architecture that has been shown to be effective for a variety of tasks.

3.4. DenseNet169

DenseNet169 is a convolutional neural network architecture that was proposed by Huang et al. in 2017 [50]. It is a variant of the original DenseNet architecture, which is designed to address the problem of vanishing gradients in very deep neural networks.

Vanishing gradients is a problem that occurs in deep neural networks when the gradients of the loss function with respect to the weights of the network become very small. This can make it difficult for the network to learn, as the updates to the weights become very small. DenseNet169 addresses the problem of vanishing gradients by connecting each layer to every other layer in a dense, or fully connected, manner. This means that the output of each layer is concatenated with the input to every subsequent layer, allowing the network to reuse features learned at earlier layers. This helps to prevent the gradients from becoming too small and allows the network to learn more effectively. DenseNet169 has 169 layers, with a total of over 14 million parameters. It was trained on the ImageNet dataset, which contains over one million labeled images across 1000 classes. The network achieved a top-5 error rate of 3.46% on the validation set, which is among the best results ever reported on this benchmark. DenseNet169 has been used in a variety of applications, including image recognition, object detection, and medical image analysis. Its compact size and high accuracy make it a popular choice for many computer vision tasks. Largely, DenseNet169 is a powerful and efficient CNN architecture that has been shown to be effective for a variety of tasks.

4. Methodology

4.1. Datasets Description

The dataset, created by Yousefi [11], is a collection of 5000 images of garbage and waste items, divided into five categories: paper, plastic, glass, metal, and others. The images are of various sizes, with the majority being around 300 $\times$ 300 pixels and have been labeled with the corresponding category. This dataset can be used to train a model to classify images of garbage and waste into the appropriate category and is suitable for use with deep learning models such as convolutional neural networks. It was created in 2021 and is available for free on Kaggle. Additionally, the dataset includes metadata such as the date and time the images were taken, as well as the geographical location of the garbage. The dataset corresponds to middle eastern regions, especially Saudi Arabia.

4.2. Experimental Setup

This study builds a model for classifying recyclable products using a deep learning approach through Python programming language on Jupiter Notebook and Google Colab. First, pre-processing was performed on the obtained dataset, where the size of all the images within the dataset was all reshaped to (224,224), and normalization was implemented to each pixel in the image so that every image is in the shape of 224 $\times$ 224 $\times$ 3 and each pixel value inside the image has a range of 0 to 255. Afterward, the dataset was split into 70% and 30% for training and testing. Subsequently, a variety of deep learning algorithms, such as Convolutional Neural Network (CNN), MobileNetV2, ResNet50V2, and DenseNet169, were employed to train the models built with the optimal parameters. Finally, various performance metrics were used to evaluate the models, including (accuracy, precision, recall, and F1-score). Figure 1 shows a summary of the steps used in classification models.

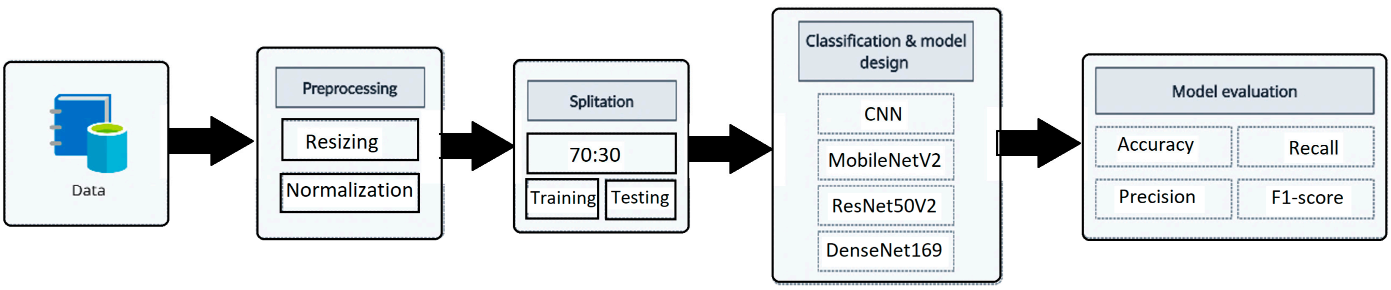


Figure 1. Proposed Methodology.

4.3. Performance Measure

Performance measurement and evaluation are crucial procedures aimed at assessing the effectiveness and efficiency of the model. There are several performance metrics that are mainly used in our classification model are accuracy, precision, recall, and F1-score, in addition to the loss rate. Accuracy works to define the ratio between the correctly classified results and the total number of all results. As for precision and recall, both will measure the correctly predicted positives, but precision aims to show the number of weights that were positively placed. In contrast, recall helps to understand how many positively placed weights the model was able to detect. F1 score can be seen as the harmonic mean of both precision and recall. The performance measures can be implemented using a confusion matrix, that consists of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Furthermore, the loss rate stands for the total errors or the variance between the predicted and the actual values. Using a variety of metrics will significantly help in defining the performance of the proposed study [51–56]. The Equations (1)–(4) of the previously mentioned measures are seen below.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}), \quad (1)$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}), \quad (2)$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}), \quad (3)$$

$$\text{F1-Score} = (2 \times \text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}). \quad (4)$$

4.4. Optimization Strategy

The best performance for the model is experienced by conducting different techniques. Consequently, the hyperparameter tuning is executed to find the optimum values for all hyperparameters in order to reach the best results and to ensure that the model can operate at its best for any given situation. This study utilized Randomized Search CV with CNN, which is a technique used for hyperparameter tuning in deep learning, it is efficient in finding the optimal set of hyperparameters for a model [57–59]. Table 2 enlists the best values to improve performance. Adjusting the hyperparameters of a classification algorithm is vital for generating an effective and optimal model, making it ready to deal with any classification problem it may encounter.

Table 2. The optimal values of hyperparameters.

Classifier	Hyperparameter	Optimal Value
DenseNet169	No Layers	7 layers
	Loss Function	Sparse_categorical_crossentropy
	Optimizer	SGD
	Activation function	ReLU + softmax
	Dropout rate	0.2
	Epochs	20
MobileNetV2	No Layers	5
	Loss Function	Sparse_categorical_crossentropy
	Optimizer	SGD
	Activation function	ReLU + softmax
	epochs	20

Table 2. *Cont.*

Classifier	Hyperparameter	Optimal Value
ResNet50V2	Layers	7
	Loss Function	Sparse_categorical_crossentropy
	Optimizer	SGD
	Activation function	ReLU + softmax
	Dropout rate	0.5
	Epochs	20
CNN	Layers	11
	Loss Function	Sparse_categorical_crossentropy
	Optimizer	SGD
	Kernel size	(3, 3)
	Padding	same
	Activation function	ReLU + softmax
	Pooling size	2
	Dropout rate	0.5
	Epochs	50
CNN with Randomized Search CV	Layers	10
	Loss Function	Sparse_categorical_crossentropy
	Optimizer	SGD
	Kernel size	(3, 3)
	Padding	same
	Activation function	ReLU + softmax
	Pooling size	(2, 2)
	Dropout rate	0.6
	Epochs	150

5. Results and Discussion

To improve the results of the CNN model, we tested several hyperparameters. We experimented with adding 11 hidden layers, three of the Dense types, one of the Flattened types, two of the Dropout type, three of the Conv2D type, and MaxPooling2D. Through this CNN model, we achieved an accuracy of 87.22% with an error rate of 0.517. We tried to enhance the previous model by applying hyperparameter tuning and cross-validation using Randomized SearchCV to classify the best hyperparameters. Consequently, we obtained an accuracy of up to 88.5% and an error rate of 0.324, as shown in Table 3 below.

Table 3. Comparison of two types of model CNN.

Performance Measure	CNN	CNN (Randomized Search CV)
Accuracy	87%	88.5%
Precision	87%	88%
Recall	87%	89%
F-Score	86%	88%
Learning Rate	0.001	0.01
Epochs	50	150
Activation Function	Relu	Relu

Moreover, we employed three pre-training DL models, DenseNet169, MobileNetV2, and ResNet50V2. Table 4 presents the results of the evaluation of each algorithm. The experiments showed that the ResNet50V2 algorithm reached the highest results in terms of Accuracy, Precision, Recall, and F1-score of 98.95%, 98.35%, 98.38, and 98.38%, respectively. On the other hand, the DenseNet169 provided the lowest results with Accuracy, Precision, Recall, and F1-score of 94% each, respectively. Figure 2 shows a comparison between the CNN model and the pre-trained models while Figure 3 shows the accuracy learning curves for each type of algorithm in training and testing, respectively. The pretrained models tapered off after 17 epochs while CNN took around 50 epochs.

Table 4. Algorithms result.

	DenseNet169	**MobileNetV2**	**ResNet50V2**
Accuracy	94.4%	97.6%	98.95%
Precision	94%	95%	98.35%
Recall	94%	97%	98.38%
F-Score	94%	97%	98.38%

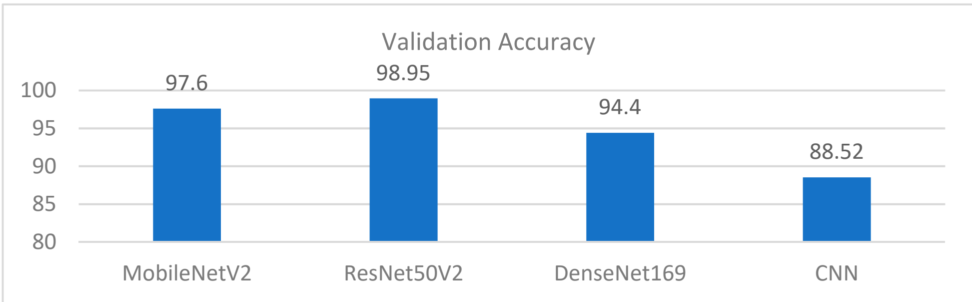
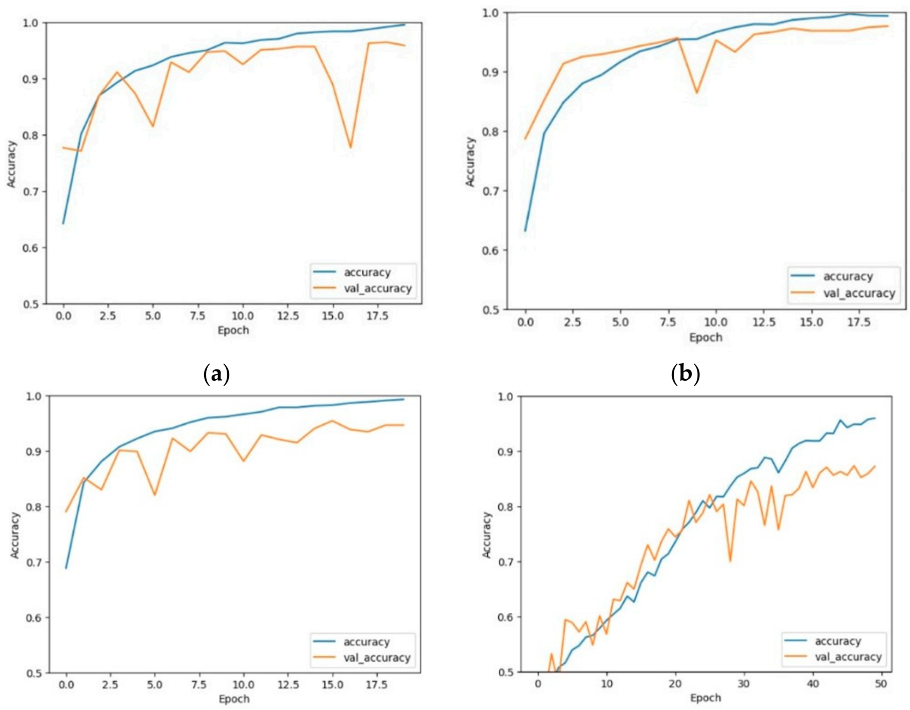


Figure 2. The results of all algorithms.



(**a**) (**b**)

(**c**) (**d**)

Figure 3. The accuracy graph: (**a**) MobileNetV2, (**b**) ResNet50V2, (**c**) DenseNet169, and (**d**) CNN.

An extensive study has been conducted on garbage identification and classification using various DL models on a state-of-the-art middle eastern dataset. The study outperformed various approaches in the literature in terms of different performance parameters such as precision, recall, F1-score, and accuracy.

The proposed scheme has been compared with state-of-the-art studies and a comparison is provided in Table 5. The schemes are chosen based on a common dataset, nature of study and techniques used. It is evident that the proposed schemes outperform both studies [22,34] for the same dataset. The proposed CNN outperforms in terms of accuracy at 4.52% and 2.52%, respectively. While the pretrained models are way better than the schemes in terms of accuracy.

Table 5. Comparison.

Study	Algorithms	Performance Measure
[34]	AlexNet, GNet, VGGNet-19, and ResNet-101	Accuracy 86% on CNN
[22]	SVM, CNN, and HOG	CNN with accuracy = 84%
Proposed Approach	CNN, DenseNet169, MobileNetV2, ResNet50V2	CNN Accuracy = 88.52% DenseNet169 Accuracy = 94.4% MobileNetV2 Accuracy = 97.6% ResNet50V2 Accuracy = 98.95%

Better waste identification and classification help in better management. Like after classification, different items can be easily separated and managed accordingly. The dataset is rich in terms of middle eastern as well as global waste images that show the major implications of the study. As far as the limitations of the study are concerned, it is focused on the dataset provided in [37]; however, for totally different, unseen, and irrelevant waste images, the scheme may not perform that well. The limitations can be overcome in the future by using other techniques such as fusion, transfer learning and ensemble learning [45,46]; moreover, metaheuristic and evolutionary computation approaches [60,61]. The outcome of the study can be used by the government, administration, and the policy makers in the kingdom to implement systems for waste classification and management, consequently. In this regard, the system may be implemented by the municipality to segregate the waste items automatically and transported them for better management.

6. Conclusions

In this study, deep learning approaches have been investigated to efficiently identify and classify the waste items on a publicly available image dataset from the middle east. The models for garbage classification were built using CNN algorithms, as well as pre-trained models included MobileNetV2, ResNet50V2, and DenseNet169. Then, we evaluated them using the matrices: Accuracy, Precision, Recall, and F1-score. To acquire optimum results, the hyperparameters were tuned. For the pre-trained models, ResNet50V2 model achieved the best accuracy of 98.95%. On the other hand, the proposed CNN model achieved an accuracy of 88.5%, higher than the previous studies on the same dataset. Indicating that these models can facilitate a more effective waste management system as well as contribute to a more sustainable and greener future. For further work, we suggest expanding the dataset using the application of data augmentation. Where several types of dataset sources are merged, the model can be robust against the diversity and nature of the dataset. Based on the outcome of the study, the government and administration in the kingdom can make use of the intelligent system for better waste classification and management. In addition, enhance the proposed model's performance by investigating more algorithms and techniques such as fusion and ensemble leaning.

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