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An Evaluation of Various Deep Convolutional Networks for the Development of a Vision System for the Classification of Domestic Solid Street Waste

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Abstract

Artificial intelligence is an emerging technology revolutionizing the modern world and making the life of mankind easier and more efficient. Its application in various fields is growing every moment like tributaries of flooded rivers. To apply Artificial Intelligence in the field of domestic waste collection, the images of 7 various categories of waste such as cardboards and tetra packs, dairy packets, facemasks, footwear, paper cups, plastic bottles, and wrappers taken in the various factual street environments under natural lighting were trained and tested through different pre-trained convolutional neural networks. This work aims at the development of a vision system for the autonomous robot to collect domestic solid waste littered along streets in densely populated areas where the waste collection process is tedious, by evaluating various existing networks. Image categorization and identification technology is a vital part of the vision system. A total of 700 images consisting of 100 images of each category were used for training and testing purposes. Among them 70% of the images were used for training and 30% of the images were used for testing. The pre-trained convolutional neural networks squeezenet, googlenet, inceptionv3, densenet201, mobilenetv2, resnet18, resnet50, resnet101, xception, inceptionresnetv2, shufflenet, nasnetmobile, nasnetlarge, darknet19, darknet53, efficientnetb0, alexnet, vgg16 and vgg19 were used to evaluate the performance of the image categorization and identification. The testing accuracy of Inceptionv3, densenet201, resnet50, resnet101, xception and efficientnetb0 was 90%. The testing accuracy of nasnetlarge and darknet53 was 91% and the highest testing accuracy of 93% was achieved by inceptionresnetv2.

Keywords: CNN, Domestic Solid Waste, Image Dataset, Testing Accuracy.

1 Introduction

Waste management is a challenging task for countries with a rapidly growing population. Varieties of waste are generated daily and thrown on the streets. The waste is mostly of solid and organic types. This waste is generally collected from the streets by municipal workers. Another set of people like rag pickers

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also are mainly dependent on some specific category of street waste for their daily source of life. A thriving technology like Artificial Intelligence, WSN are a promising enrichment for the growth of robust automation technology that will revolutionize the quality of life of all categories of people (Sreenivasu et al., 2022). In the fast-growing modern world, the replacement of human workers and rag pickers collecting street waste with autonomous robots is mandatory to change and improve their lifestyles and safeguard them from being vulnerable to various contagious diseases. The Artificial Intelligence plays a crucial role in recent applications (Prasad Babu & Vasumathi, (2023). Deep learning technology offers a wide scope for research studies on the classification and identification of municipal solid waste through various pretrained convolutional neural networks. The authors (Malik et al., 2022) in their paper had arrived that neural network is one of the efficient techniques recommended by various researchers for the categorization of municipal solid wastes. It was stated (Mookkaiah et al., 2022), that when compared to the other existing methods, the application of CNN in the field of municipal solid waste management provides relatively better accuracy. (Wang et al., 2021), in their research work on the development of smart municipal waste management system to classify all types of municipal waste, used 9 categories of waste such as other waste, kitchen waste, plastic waste, glass waste, paper or cardboard waste, metal waste, fabric waste, other recyclable waste, and hazardous waste (Choi & Zhang, 2022).

The purpose of our research work is to identify the best convolutional neural networks that can be used for the categorization of domestic solid-waste such as cardboards and tetra packs, dairy packets, facemasks, footwear, paper cups, plastic bottles, and wrappers to develop a vision system for the waste collection autonomous robot. The image dataset was formed from the photos of the various wastes of the above-mentioned categories taken by a mobile camera under natural lighting along various streets. Authors (Qin et al., 2022; Vijayan, 2017; Camgozlu & Kutlu, 2023), in their paper, have said that only a few researchers will form their own dataset for their research work. In our research work, we generated our dataset from the photos taken along various streets. The RGB images of interest were cropped out from their surrounding environment manually to improve the accuracy of categorization. Some of the images were rotated and saved manually to balance the number of image files between the folders. The Matlab software version R2022a was used for the categorization of different varieties of domestic solid wastes. The research of (Chu et al., 2018) used 100 RGB images for each category of waste item to construct an image dataset of 5000 images of 50 varieties of waste items. In our research work, a total of 700 images consisting of 100 images of each category of domestic waste were grouped in the image dataset and used for training and testing purposes. Each category of waste is stored in a separate folder which is labelled in the name of that waste. The feature extraction method is used for image categorization. Our image dataset was trained in 19 various convolutional neural networks which have already been experimented with by various researchers in different fields of science around the world, like squeezenet, googlenet, inceptionv3, densenet201, mobilenetv2, resnet18, resnet50, resnet101, xception, inceptionresnetv2, shufflenet, nasnetmobile, nasnetlarge, darknet19, darknet53, efficientnetb0, alexnet, vgg16, and vgg19. Inceptionresnetv2 displays the best performance in the categorization of waste images in our research work.

2 Related Work

The researchers are widely using deep learning technology to carry out and solve their research problems. Predominantly for target identification and recognition, the researchers from various fields tried several CNN models for their image-based research work. The image-based classification research works are widely used in the field of medical science and waste management. Along with other fields, a few research works carried out in the field of medical science and waste management are also discussed in this section. Authors (Raghu et al., 2020) achieved a distinguished classification accuracy of 82.85% and 88.30% with the pretrained neural networks GoogLeNet and Inceptionv3 in their work on the classification of the type of multi-class seizures based on EEG. AlexNet, VGG16, VGG19, SqueezeNet, GoogLeNet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101 were used by them for their classification work. The VGG CNN model shows the highest classification accuracy in the classification of the images of the brain tumors when compared to the other CNN models AlexNet and GoogLeNet in the research work of (Rehman et al., 2020). The pretrained CNN model AlexNet was used by (Dorj et al., 2018) to extract the image features in their research work on the classification of skin cancer. (Lakhani, 2017) used the pretrained CNN networks AlexNet and GoogLeNet for his research work on the classification of X-ray images and the positioning of the endotracheal tube. (Brinker et al., 2019a) used the ResNet-50 for the classification of images of clinical melanoma and atypical nevi. Researchers (Akbarimajd et al., 2022) (Asadov, 2018) concluded that among the other modified pretrained networks EfficientNetb0, GoogLeNet, MobileNetv2, ResNet18, ShuffleNet, and SqueezeNet, ResNet50 recognize the COVID-19 from the noisy X-ray images accurately. It was concluded (Zhang et al., 2021a) from their research work that the classification accuracy of the CNN model DenseNet169 through transfer learning in the classification of waste is higher when compared to that of the other CNN models AlexNet, GooleNet, and VGG. To develop an intelligent management system, based on the classification of indigestible waste such as cardboard, glass, metal, paper, plastic, and trash, the authors (Rahman et al., 2022) used AlexNet, ResNet34, and VGG16. It was found that ResNet34 shows better performance than the other pretrained CNN models. ResNet model was used (Kim et al., 2020) in their research work for the training of waste categorization. The authors (Abinandan et al., 2022) used pretrained CNN models such as VGG-16 and Inception V3 for the development of their garbage detecting system. In the research work on the estimation of the froth grades from the images captured from industries, (Fu & Aldrich, 2019) used the pretrained CNN models AlexNet, VGG16, and ResNet. It was found by the authors that AlexNet shows better performance when compared to the other two network models. In the research work on the detection and recognition of street dumpsters, the authors (Ramirez et al., 2020) tried the pretrained CNN model Inceptionv3. In the research work on the development of a classification model for the classification of wastes, (Muangnak et al., 2021) used the CNN models ResNet-152 and ResNet-50 for investigation purposes. In research work, EfficientNet-B2 was used for the classification of detected wastes into seven categories by the authors (Majchrowska et al., 2022). (Chen et al., 2022) used ShuffleNet v2 for the development of a lightweight waste classification model. In the research work on the classification of images of the waste for the input of the automated waste-picking robotic arm, (Madappa et al., 2020) found that the CNN models ResNet and VGG exhibit better performance than their adapted CNN model. In their research work on the smart garbage classification system, authors (Jain et al., 2022) said that the CNN model EfficientNet-b0 showed effective performance. In the field of agronomy, (Kurtulmuş, 2021) used the pretrained neural networks AlexNet, GoogLeNet, and ResNet for the identification of sunflower seeds. Among the three networks, GoogLeNet could achieve the maximum classification accuracy of 95%. Authors (Wang et al., 2020) used Inception V3, ResNet50, VggA, and VGG16 for the classification and identification of the pest images. To evaluate the performance of their proposed model on the classification of the crop pest, the authors (Thenmozhi & Reddy, 2019) used the pretrained CNN models AlexNet, GoogLeNet, ResNet, and VGGNet. In the field of construction science, in the research work on the classification of robotic plastering images, the authors (Bard et al., 2019) used Inception-v3. Chen et al., (2021) used DenseNet169 for the generation of a visual recognition model for their research work on the unattended gauging of the composition of construction waste. The CNN models GoogLeNet, ResNet, and VGG16 were used by the authors (Sun

& Gu, 2022) for the evaluation of their dataset which was built of various construction waste materials such as brick, concrete, metal, stone, and wood. In the field of ecology, (Chen et al., 2022) used DenseNet-201 for the evaluation of its performance in their research work on the prediction of environmental microorganisms. In the field of disaster science, a CNN model for the prediction of soil particle size deposited during the natural disaster of a Tsunami was developed (Iwashita et al., 2022) with the help of the CNN network model VGG-16. In the field of traffic management, in the research work of seeking the possibility of reducing traffic accidents by monitoring the internal state of the drivers based on 30 channel EEG signals, authors (Chen et al., 2022) tried the pretrained CNN models AlexNet and Resnet 18. In the field of space research, in the research work on the classification of satellite images with the pre-trained neural networks AlexNet, GoogLeNet, ResNet-50, and VGG19, authors (Kadhim & Abed, 2020) concluded that the ResNet-50 showed more encouraging feature extraction results than other networks. In the field of food science, in a research work on the identification of species of coffee beans, authors (Unal et al., 2022) found that the CNN model SqueezeNet showed better performance than other networks Inception v3, VGG16, and VGG19. In the field of general object classification, (Momeny et al., 2021) developed a noise-robust CNN system for the classification of noisy images. To evaluate their proposed CNN model, they have used GoogLeNet, ResNet, VGG-Net-Medium, and VGG-Net-Slow. Sharma et al., (2018) concluded that the CNN networks GoogLeNet, and ResNet 50 showed better performance in the classification of images of general objects than AlexNet in their research work on identifying the objects from the real-time video feeds (Venugopal, 2023).

3 Methodology

Our image dataset is formed by a set of 700 images from photos of seven varieties of commonly littered domestic solid waste such as cardboards and tetra packs, dairy packets, facemasks, footwear, paper cups, plastic bottles, and wrappers on the streets captured in the natural daylight environment. Some of the sample images are shown in Fig. 1. The authors (Chen et al., 2021) used 2000 solid waste images for the construction of their image dataset. 1500 images were captured by the camera under a uniform black color background panel. The remaining 500 images were taken from the network resources. Altikat et al., (2022) constructed the image dataset using pictures of glass, organic waste, paper, and plastic wastes captured from the natural environment for their classification work. The image dataset was built (Ruiz et al., 2019) on the RGB images of waste of the six classes of cardboard, general trash, glass, metal, paper, and plastic captured under a uniform white postcard background with sunlight and room light in their research work. In a research work on the development of a vision-based robot to classify the six categories of solid wastes cardboard, glass, metal, paper, plastic, and trash, (Mao et al., 2021) used CNN for the evaluation of the performance of the classification to improve the recycling process and reduce the labor requirement. (Toğaçar et al., 2020) created the image dataset in their research work on the classification of waste using the recycling wastes cardboard, cloth, glass, metal, paper, plastics, and organic wastes such as organic foods. In the research work on the development of a green smart environment using deep learning, authors (Nguyen et al., 2022) built their image dataset with the recyclable waste glass-metal, paper, and plastic along with some biodegradable, and non-recyclable wastes. In their research work, proposed to develop an innovative deep learning-based approach for the identification and classification of five various types of waste glass, kitchen waste, metal, paper, and plastic. We used the LG-G8 ThinQ 128GB Memory mobile phone camera to take the photos. It has a front and back integrated camera with a rear-facing camera of 16MP. The frame rate is 60 frames per second and the recording resolution is 3840 x 2160 (4K). The images were sorted out according to the classes and saved in different folders with their names. For each category, 100 images were used. To increase the percentage of accuracy of categorization results, the area of the required images of wastes of actual interest was cropped manually from their natural background which was originally surrounded by clusters of other types of wastes and landscape. Some of the images were rotated and saved separately to get the required number of image datasets. Matlab R2022a version is used for training and testing purposes. The laptop Acer Nitro AN515-57 is used for the experiments. The processor is 11th Gen Intel(R) Core (TM) i5-11400H @ 2.70GHz 2.69 GHz. The installed RAM is 16.0 GB (15.8 GB usable). The system type is a 64-bit operating system with an x64-based processor. The laptop is built with the GPU NVIDIA GeForce RTX3050 with 4GB memory.

Figure 1: Sample images of various categories of domestic solid waste

4 Feature Extraction

Image categorization in our research has been done by the feature extraction method. The 700 images of the various types of domestic street waste that are stored category-wise in separate folders are loaded as an image data store. The general function of the image data store is to label the images according to their respective folder names automatically. Ahmad et al., (2021) had said that, because of the overfitting problem, the performance will be poor on the new datasets. To overcome the problem of overfitting the image dataset is normally divided into the training dataset and the test dataset. The training dataset is used to create various network models and the test dataset is used to verify the classification accuracy of the network models. Das & Meher, (2021) concluded from their research work that 70% of the training dataset and 30% of the testing dataset were able to achieve excellent accuracy. In our research work the image data is split into 70% training data and 30% testing data. The pretrained networks such as squeezenet, googlenet, inceptionv3, densenet201, mobilenetv2, resnet18, resnet50, resnet101, xception, inceptionresnetv2, shufflenet, nasnetmobile, nasnetlarge, darknet19, darknet53, efficientnetb0, alexnet, vgg16 and vgg19 were trained over millions of images of thousands of object categories. So, all the pretrained network models which are used in research work are more familiar with the feature representations of a wide range of image categories through their learning process. The various convolutional neural networks are constructed by several deep convolutional layers. Generally, the high-level features of the images held by the deep layers of a convolutional neural network are constructed from the low-level features of earlier layers. In our research work the image features of the training and testing images were extracted by applying activations on the global average pooling layer of each pretrained CNN network model.

Squeezenet is 18 weighted layers deep with 68 layers. Convolutional neural networks work with an image input size of 227 x 227. The squeezenet uses millions of images from the ImageNet database for its training, so it learned rich feature representations for various classes of images. In squeezenet, the activations is applied to the global average pooling layer "pool10". Googlenet is 22 layers deep with an image input size of 224 x 224. Googlenet is trained on millions of image datasets of ImageNet and Places365. So, each version of the pretrained network which is trained either on the datasets of ImageNet or Places365 has learnt several feature representations of different classes of wastes. The activations is applied to the global average pooling layer "pool5-7x7_s1". Inceptionv3 is a 48 layers deep convolutional neural network. The image input size of this network is 299 x 299. This network is also trained on millions of image datasets of ImageNet and learns rich feature representations of various categories of it. The activations is applied to the global average pooling layer "avg_pool". Densenet201 is a 201 deep layered convolutional neural network. The image input size of this network is 224 x 224. Densenet201 is trained on millions of image datasets from ImageNet. It also learned rich feature representations of various categories of images. The activations is applied to the global average pooling layer "avg_pool". Mobilenetv2 is a 53 layers deep convolutional neural network with an image input size of 224 x 224. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "global_average_pooling2d_1". Resnet18 is 18 weighted layers deep with 71 layers convolutional neural network with an image input size of 224 x 224. It also learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "pool5". Resnet50 is 50 layers deep layered convolutional network with an image input size of 224 x 224. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "avg_pool". Resnet101 is 101 weighted layers deep with 347 layered convolutional network with an image input size of 224 x 224. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "pool5". Xception is 71 layers deep layered convolutional network with an image input size of 299 x 299. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "avg_pool". Inceptionresnetv2 is 164 layers deep convolutional neural network with an image input size of 299 x 299. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "avg_pool". Shufflenet is 50 weighted layers deep convolutional neural network with an image input size of 224 x 224. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "node_200". Nasnetmobile is a convolutional neural network that does not have a linear sequence of modules. It learned rich feature representations from various categories of the images of the ImageNet. The image input size of nasnetmobile is 224 x 224. The activations is applied to the global average pooling layer "global_average_pooling2d_1". Nasnetlarge is also a convolutional neural network that does not have a linear sequence of modules. It also learned rich feature representations from various categories of the images of the ImageNet. The image input size of Nasnetlarge is 331 x 331. The activations is applied to the global average pooling layer "global_average_pooling2d_2". Darknet19 is 19 layers deep convolutional neural network with an image input size of 256 x 256. It also learned rich feature representations from various categories of the images of the ImageNet during the learning process. The activations is applied to the global average pooling layer "avg1". Darknet53 is 53 layers deep convolutional neural network with an image input size of 256 x 256 which learned rich feature representations from various categories of the images of the ImageNet during the learning process with millions of images. The activations is applied to the global average pooling layer "avg1". Efficientnetb0 is a 82 layers deep convolutional neural network with an image input size of 224 x 224. It learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "efficientnet-b0| model| head| global_average_pooling2d| GlobAvgPool". Alexnet is 8 weighted layers deep with 25 layers convolutional neural network with an image input size of 227 x 227. It also learned rich feature representations from various categories of the images of the ImageNet. The activations is applied to the global average pooling layer "pool5". Vgg16 is a 16 layers deep convolutional neural network with an image input size of 224 x 224 that learned rich feature representations from various categories of the images of the ImageNet during the learning process with millions of images. The activations is applied to the global average pooling layer "pool5". Vgg19 is a 19 layers deep convolutional neural network with an image input size of 224 x 224. It learned rich feature representations from various categories of the images of the ImageNet during the learning process with millions of images. The activations is applied to the global average pooling layer "pool5".

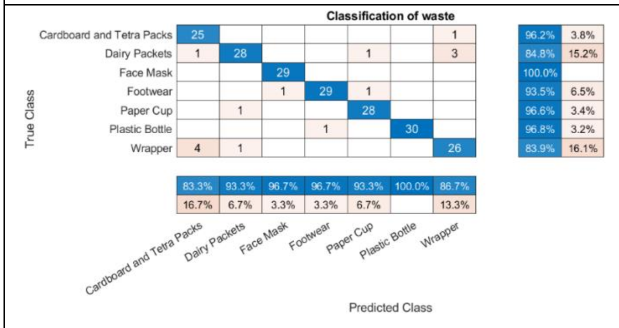
Augmented image data stores were created to resize the training and testing images automatically according to the input requirements of the various networks used in our research work. These data stores were used as the input arguments to activations. A multiclass support vector machine is fit to the predictor variables of the training images with statistics and machine learning toolbox. Finally, the test images were classified using the features extracted from the test images and the trained support vector machine. The accuracy of the support vector machine is high. In our research work, the performance of the required pretrained network is evaluated by calculating the classification accuracy on the test set. Accuracy is the measure of the fraction of labels that are predicted correctly by the network.

5 Results and Discussion

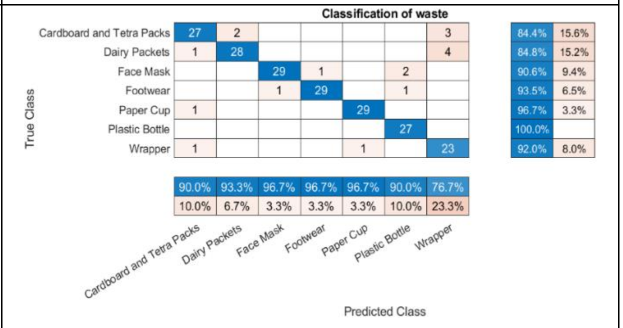
The overall classification accuracy of the various considered pretrained neural networks were evaluated with the help of feature extraction method. The confusion matrix for each of the pretrained convolutional network was also generated and are shown in Table 1, Table 2 and Table 3. The confusion matrix is used to evaluate the efficiency of a pretrained convolutional neural network on the classification of every individual category of solid waste that are considered. In Matlab, the confusion matrix is the representation of the total number of observations by each cell of it. The row of the confusion matrix generally represents the true class, and the column represents the predicted class. The diagonal cell presents the observations that are classified correctly (Zhang et al., 2021b) and the off-diagonal cells exhibit the observations classified incorrectly. A row-normalized row of each true class displays the summary of the percentage of correctly and incorrectly classified observations. Similarly, a column-normalized column of each predicted class displays the summary of the percentage of correctly and incorrectly classified observations. The evaluation of recalling i.e., the class-wise true positive rate is carried out along each row. The evaluation of precision, i.e., the class-wise positive predicted value is carried out along each column. The precision in the identification and classification of wastes should be higher (Li et al., 2021). The common metrics used to verify a classification model's performance are accuracy, precision, recall, and F1 score (Rachapudi & Lavanya Devi, 2021). Since the precision results should be higher, in our research work we considered the percentage of the precision results along each column of the confusion matrix to evaluate the performance of the various pretrained convolutional networks in the classification of each class of domestic solid waste considered.

Table 1: The confusion matrix of inceptionresnetv2, nasnetlarge, darknet53, inceptionv3, densenet201, resnet50, resnet101 and xception

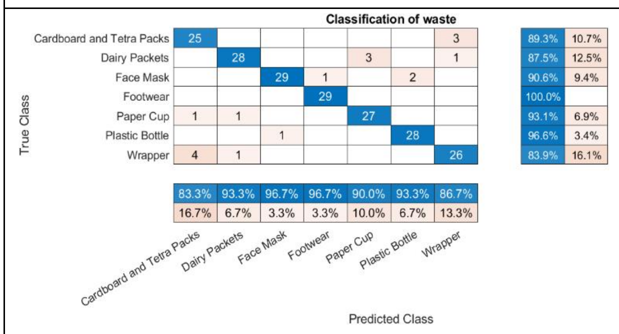
inceptionresnetv2



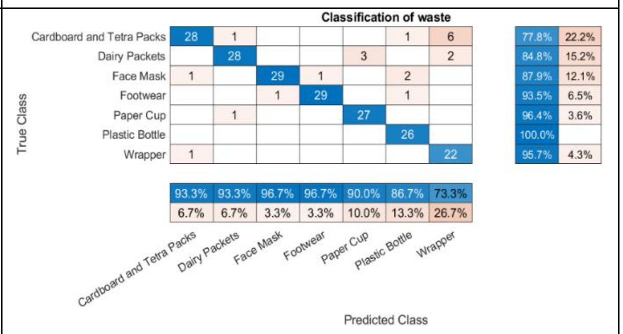
nasnetlarge



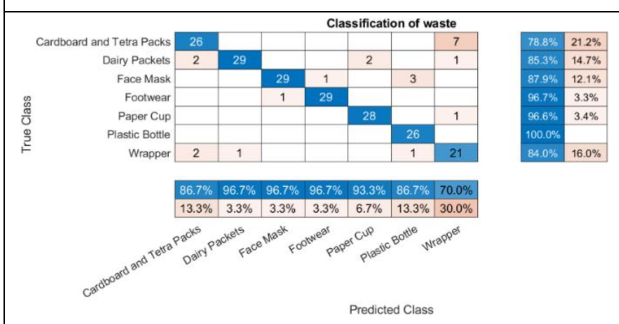
darknet53



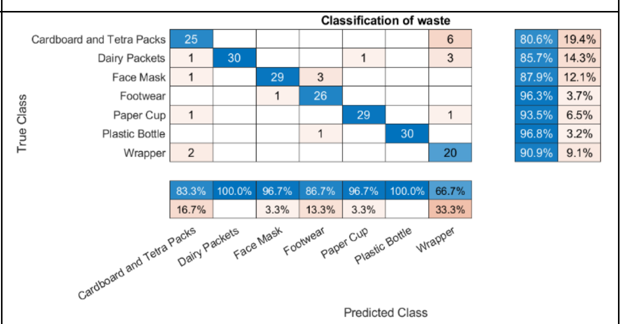
inceptionv3



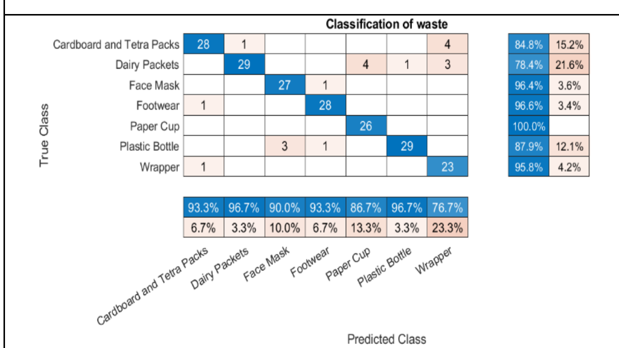
densenet201



resnet50



resnet101



xception

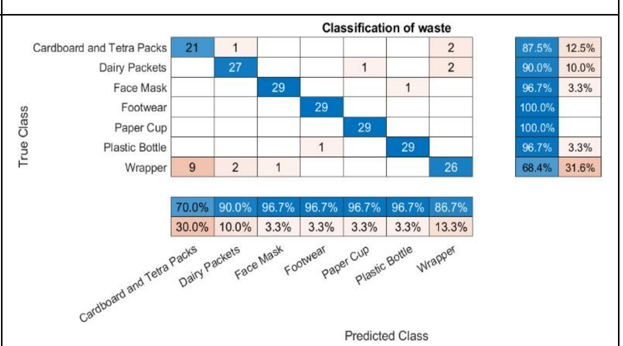
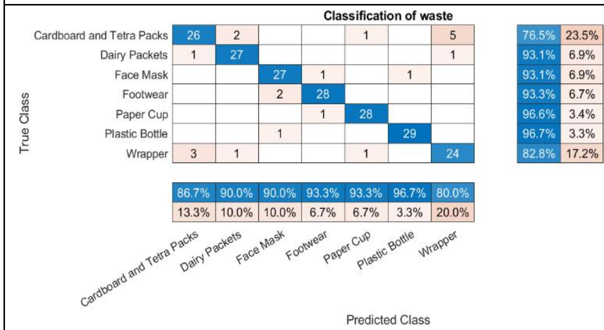
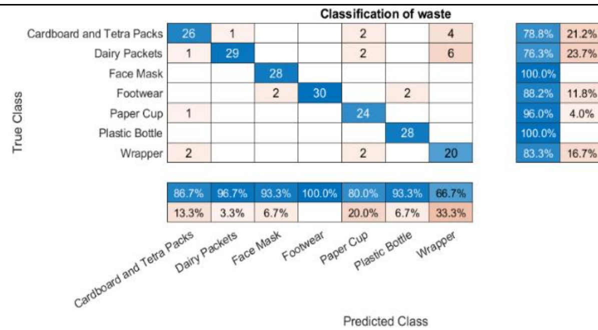


Table 2: The confusion matrix of efficientnetb0, mobilenetv2, darknet19, googlenet, vgg16, resnet18, vgg19 and shufflenet

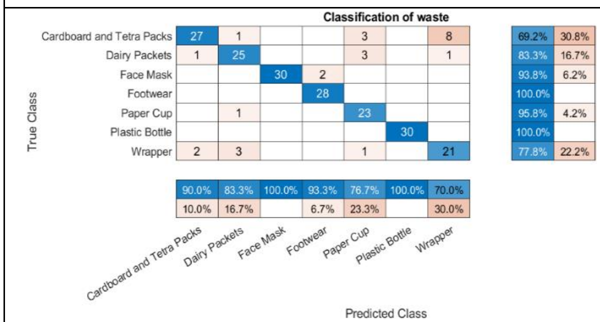
efficientnetb0



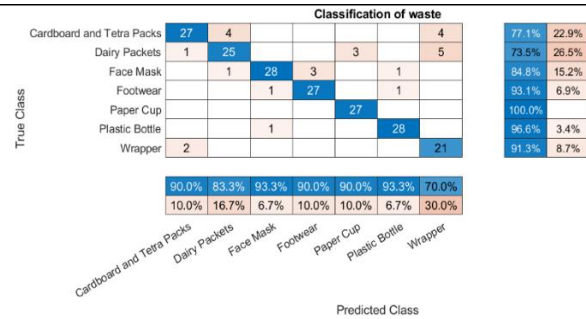
mobilenetv2



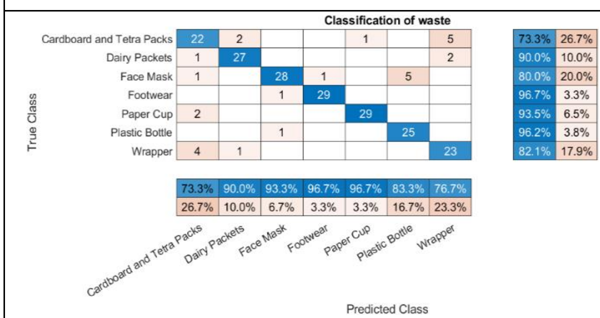
darknet19



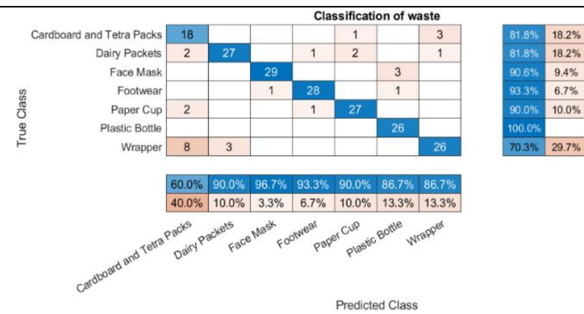
googlenet



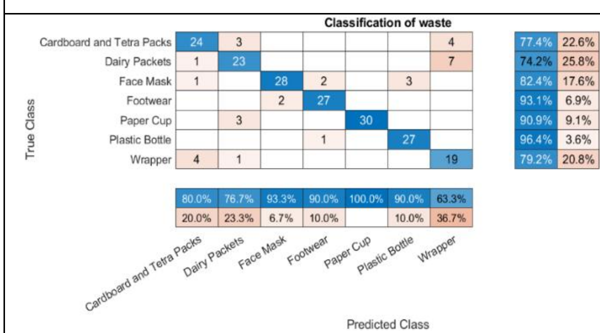
vgg16



resnet18



vgg19



shufflenet

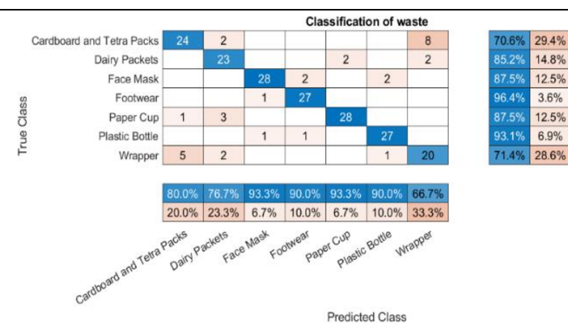
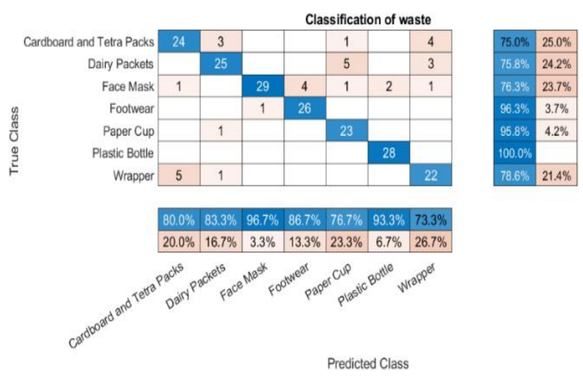
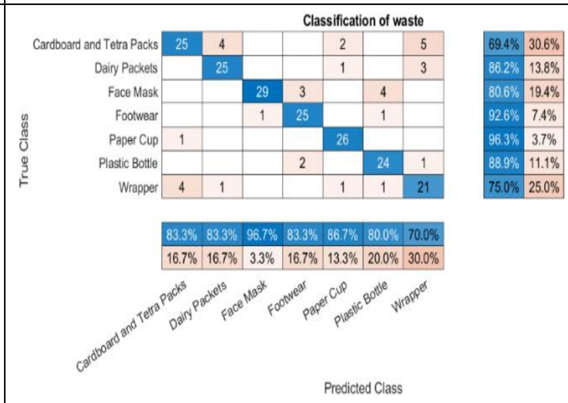


Table 3: The confusion matrix of nasnetmobile, alexnet, and squeezenet

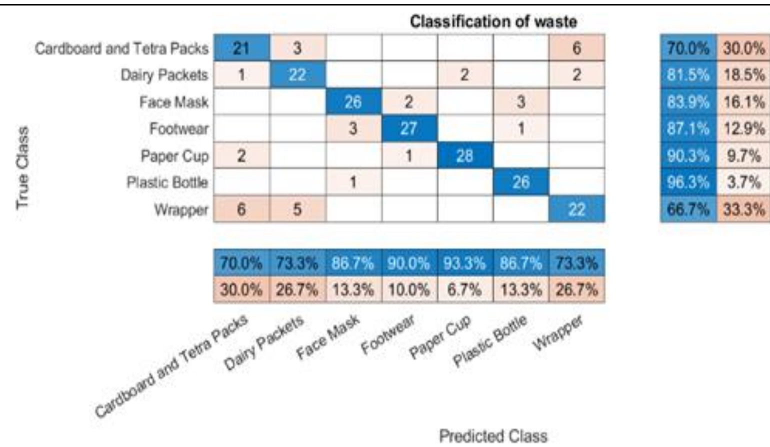
nasnetmobile



alexnet



squeezenet



The precision results chart shown in Fig. 2 was prepared from the highest precision percentage values of each category of domestic solid waste obtained along the column of the confusion matrix of various convolutional neural network considered. The chart clearly shows that the waste category of the paper cup was able to be predicted 100% by the pretrained neural network vgg19. The face mask was predicted 100% by the pretrained neural network darknet19. The pretrained neural networks darknet19, inceptionresnetv2, resnet50 were able to predict the waste category of plastic bottle 100%. The pretrained neural network resnet50 was able to predict the dairy packet waste category 100%. The waste category of footwear was able to be predicted 100% by the pretrained neural network mobilenetv2. The maximum classification accuracy of the wrapper waste was 86.7%, only predicted by the pretrained neural networks darknet53, inceptionresnetv2, xception, and resnet18. The maximum classification accuracy of the waste category cardboard and tetra packs was 93.3% done by the pretrained neural networks resnet101 and inceptionv3. It was seen from the results that a pretrained neural network is good for the classification of only one or a few specific types of solid waste with highest accuracy. Also, it was observed from the results that the classification accuracy of the wrappers is minimal when compared to other domestic solid waste categories. This is because the images of a wide variety of wrappers were used to form the dataset. Naturally, the various characteristics of the wrappers like their collapsible shape, numerous colors, and designs become the reason for lesser classification performance.

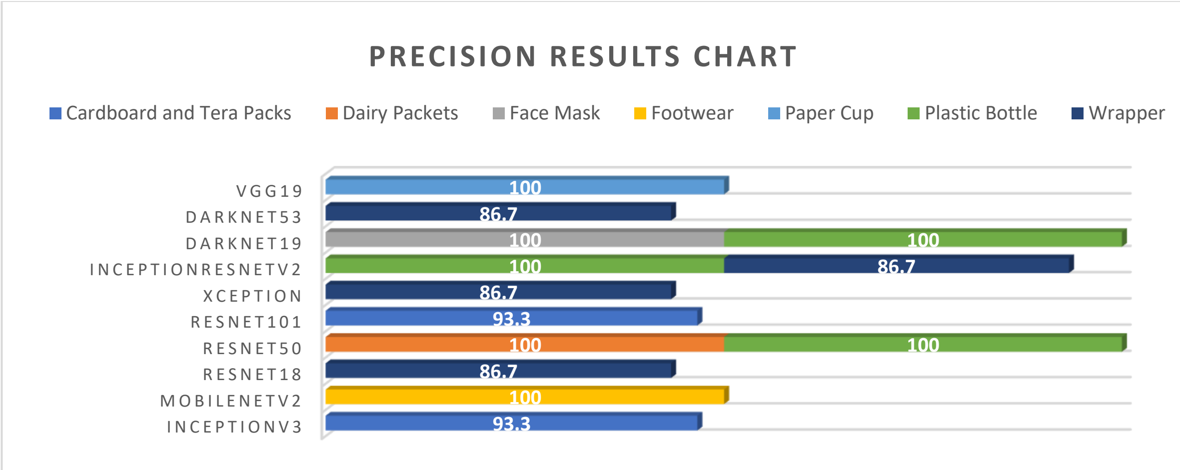


Figure 2: Precision results chart of each category of the domestic solid waste

Fig. 3 shows the overall testing accuracy of the various pretrained convolutional neural networks considered in our research work. In our research work, the testing accuracy of the network inceptionresnetv2 is 93% and this is the maximum when compared to the other 18 pretrained neural networks used by us. In a research work based on the improved inceptionresnetv2 based on depth-wise separable convolution technique in the classification of the garbage images, authors (Yuehua & Huilin, 2022) were able to achieve an accuracy of 95.80% which is 4.58% more than that of the classification accuracy achieved by the original inceptionresnetv2 model. In the research work on the classification of recyclable garbage, authors (Aral et al., 2018) achieved a testing accuracy rate of 94% with a fine-tuned inceptionresnetv2 model. The other networks nasnetlarge and darknet53 were able to achieve an overall testing accuracy of 91%. The other pretrained convolutional neural networks such as inceptionv3, densenet201, resnet50, resnet101, xception, efficientnetb0 showed a testing accuracy of 90%. Mobilenetv2 and darknet19 showed a testing accuracy of 88%, while googlenet and vgg16 showed a testing accuracy of 87%. Resnet18 showed a testing accuracy result of 86%. Vgg19 gave a testing accuracy result of 85%. Shufflenet and nastnetmobile showed a testing accuracy result of 84%. The lowest performance on classification was shown by the networks alexnet and squeezenet in order 83% and 82% respectively.

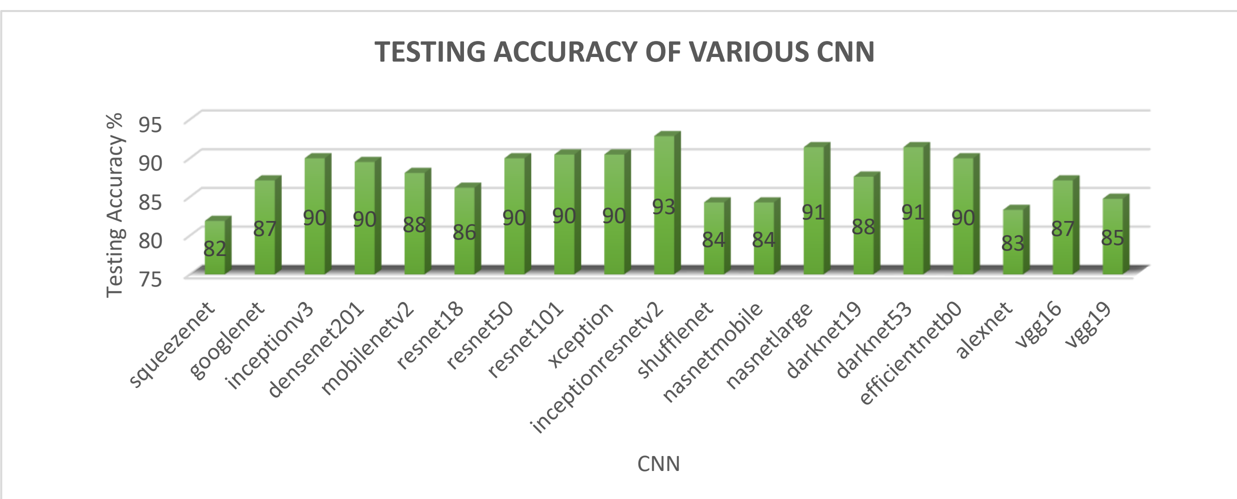


Figure 3: Testing accuracy of various convolutional neural networks

6 Conclusions

As per our studies, on the searching for the suitable pretrained convolutional neural network for the development of our vision system for the autonomous robot in the classification of various categories of domestic solid waste, we found that the pretrained convolutional neural network inceptionresnetv2 showed the best performance. In the process of classification of our self-made image dataset which was formed from the pictures of the various categories of domestic solid waste which were taken from the real environment under natural lighting along various streets, the inceptionresnetv2, can achieve a classification accuracy of 93%. We have conducted our image classification experiments on 19 various pretrained neural networks using the principle of feature extraction. The lowest classification performance was shown by squeeze net as 82%. The waste categories such as facemasks, footwear, paper cups, and plastic bottles, were able to be predicted 100% by the specific convolutional neural networks. The maximum prediction percentage of cardboard and tetra packs is 93.3% and the wrappers is 86.7%. The usage of only 100 number of images as dataset, inhomogeneous shape, variety of design and colors were found as the potential reasons for achieving less classification accuracy with wrappers. Vgg19 shows the best precision results with paper cups. Darknet53, inceptionresnetv2, xception, and resnet18 achieved good precision results for wrappers. Darknet19 shows the best precision results with Face Mask. Darknet19, inceptionresnetv2, and resnet50 achieved the best precision results with Plastic Bottle. Resnet101 and inceptionv3 achieved better precision results with the cardboard and tetra packs. Resnet50 was good for dairy packets. Mobilenetv2 was found to be good for footwear. Only very less volume of research has been carried out so far on the classification of domestic solid waste with its natural environment of occurrence. Our future research work is to aim at developing a simple convolutional neural network to classify domestic solid waste under the influence of its natural occurrence.

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