Intelligent Classification of Different Types of Plastics using Deep Transfer Learning

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Abstract: Plastic pollution has affected millions globally. Research shows tiny plastics in the food we eat, the water we drink, and even in the air, we breathe. An average human intakes 74,000 micro-plastic every year, which significantly affects the health of living beings. This pollution must be administered before it severely impacts the world. We have substantially compared three state-of-the-art models on the WaDaBa dataset, which containsdifferent types of plastics. These models are capable of classifying different types of plastic wastes which canbe reused or recycled, thus limiting their wastage.

1 INTRODUCTION

Plastics refer to a wide extend of materials that can be formed, cast, spun, or coated as a coating at some point throughout the fabricating process. Synthetic polymers are ordinarily made by polymerizing monomers obtained from oil or gas, and plastics are often manufactured by adding different chemical additives to them, improving manufacturing and material performance such as flexibility, longevity, and aesthetics (Thompson et al., 2009). Plastic has various uses in day-to-day life and is used abundantly around the globe as it is affordable, lightweight and can be used in a wide range of applications. Based onthe application, Some types of plastics are recyclable while others are disposed of after single-use (Bonifaziet al., 2018).

Approximately 359 million tonnes of plastics are produced every year and this number is going to increase in the coming years due to their excessive use (Ferdous et al., 2021). Textiles, industrial machinery, consumer and institutional products, building and construction, electrical and electronic industries use plastic on a large scale (Geyer et al., 2017).

Worldwide, 6.3 billion tonnes of plastic waste have been generated to date (Mazhandu and Muzenda, 2019). This has become a global environmental issue. Moreover, only 19 percent of this waste is recycled and the rest is dumped into landfills or incinerated. Plastic biodegradation is a prolonged process. Almost 40 percent of the plastic waste generated is from the packaging industry, which is the highest waste generator in its segment (Balwada et al., 2021). If one tonne of plastic is recycled around 5,774 kW-hours of energy is generated. Approximately 16.3 barrels of oil and 22.9 cubic meters of landfill space can be saved, together with the environmental impact from its incineration which releases toxic gases into the atmosphere (Ferdous et al., 2021). Plastic has polluted the marine ecosystem and is found in seafood to the deepest ocean trenches. Most of the plastic which enters the ocean is sourced through land (Harris et al., 2021). This massive volume of plastics can be reused and recycled. The main challenge is to reduce plastic pollution by minimizing its use, reusing the existing plastic materials, and recycling the types of a suitable plastic. Domestic and industrial plastics can be segregated and categorized according to their respective types, which helps minimize its impact by differentiating recyclables and reusable from dead-end plastics, which can be done with modern image classification methods. However, it is challenging and time- consuming to classify these waste plastics manually. It leads to the automation of the process for plastic waste segregation based on its types. With the advance of computer vision and deep neural networks, the classification of objects in images and their localization has become accessible commercially and is available at a lower price, with its accuracy increasing every day (Eitel et al., 2015).

This paper aims to benchmark the three widely implemented architectures on the WaDaBa dataset

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Table 1: Types of plastics and examples.

Types of plastic	Examples
1.Polyethylene Terephthalate (PET or PETE)	Beverage bottles, Food bottles
2.High-Density Polyethylene (HDPE)	Milk cartons, detergent bottles
3.Polyvinyl Chloride (PVC or Vinyl)	Plumbing pipes, credit cards
4.Low-Density Polyethylene (LDPE)	Plastic wrap, sandwich and bread bags
5.Polypropylene (PP)	Straws, bottle caps, prescription bottles
6.Polystyrene (PS or Styrofoam)	Cups, takeout food containers
7.Other	baby bottles, electronics, CD, DVDs

to find out the best model with the support of transfer learning. To ease the recycling process worldwide, seven different types of plastic have been categorized based on their chemical composition and is detailed in Table 1. PET, HDPE PP and PS dominate the household waste and segregating them into their respective types will allow the reuse of certain types and recycling of other types of plastics (Bobulski and Kubanek, 2021). This paper is the first benchmark paper aimed towards classifying different types of plastics from the images using deep learning models, and this can stimulate the research in this area and serve as a baseline for future research work.

2 RELATED WORK

Plastics can be sorted manually or by using sophisticated means of technologies based on the differences in their chemical, optical, electrical, and physical property.

In 1994, Inculet et al., patented the separation of waste plastic materials using electrostatics. In this method the waste plastic is shredded into small pieces and then separated electrostatically after charging by suitable means. The waste materials were separated based on of different rates of contact charges picked up by the plastic materials (Inculet et al., 1994).

Safavi et al. proposed the use of visible reflectance spectroscopy which was fast and accurate to separate the polypropylene resins based on their colour using the “Three-Filter” identification algorithm, which was limited to only single type of plastic (Safavi et al., 2010).

In 2012, Masoumi et al., proposed sorting of different types of plastics using near infrared (NIR) spectroscopy (Masoumi et al., 2012). Infrared is used in detecting wide range of materials including plastics and metals (Gao et al., 2017); (Gao et al., 2014). Using the NIR spectroscopy with two specific wave- lengths plastic resins can be correctly identified but its use is limited to light coloured plastics only (Feng et al., 2018). The NIR reflects from the plastic surface and in is received by a receiver, and based on the intensity of reflection the plastics is categorized (Masoumi et al., 2012).

The presence and amount of many elements are identified by a spectroscopic technique called X- ray fluorescence (XRF). The energy irradiated by the XRF can classify plastics based on their chemical composition accurately but at a relatively high cost and health concerns (Chaqmaqchee et al., 2017); (Ahmed et al., 2020).

Agarwal et al. achieved an accuracy of 99.7 % which differentiated 5 types of plastics using supervised deep learning on the WaDaBa database. Triplet loss and Siamese network architectures were used to get the output results (Agarwal et al., 2020).

Having deep architectures and the capacity to learn more complex models, the deep neural networks (DNN) have a superior advantage compared to the traditional approaches for classification. The robust training techniques make it possible to learn complex object representations without having to design features by hand which has been clearly demonstrated on the challenging imagenet classification task on a wide range of classes (Szegedy et al., 2013). These features of the DNN make it an absolute fit for the classification of different types of plastic wastes.

This paper benchmarks existing models like ResNet-50, Alexnet and ResNeXt, which uses transfer learning and under-sampling and weight balancingto classify the WaDaBa dataset.

3 METHODOLOGY

3.1 Database

WaDaBa dataset is used for the experiments and can be requested from its creator, which is available on the WaDaBa website after signing a consent form. The dataset consists of 4000 images in which majority are of PET images (2200) followed by PP images (640), PE-HD images (600), PS images (520) and other images (40). Each image is made out of a single object that has been deformed to certain degrees to mimic the natural settings (Bobulski and Piatkowski, 2017).

3.2 Convolutional Neural Network

With the convolution neural network advancement, deep learning has become the primary tool for classification problems. Deep learning is an end-to-end method based on neural networks (Koh et al., 2021). CNN has made unprecedented success in the field of image processing (Ruan et al., 2020) and because of its superior performance in computer vision, deep learning has changed a variety of sectors (Zhao et al., 2021). The Convolutional Neural Network (CNN) is a popular Deep Learning model for image classification (Fadli and Herlistiono, 2020). A convolutional layer, a pooling layer, and a fully connected layer are used in a CNN to extract features and recognize tar- gets (Luo et al., 2019). The convolutional layer and pooling layer are the foundation of a CNN. The net- work accomplishes its training by a back-propagation algorithm (Yang et al., 2021).

3.3 Deep Transfer Learning

CNNs are great at image recognition. CNNs require a large amount of training data and take ample time to complete a set of training. However, by using transfer learning, we can overcome these limitations. Transfer learning helps to train new data with the help of previously trained data. A pre-trained model is generally utilized for fine-tuning in transfer learning.

The pre-trained model is a deep learning model trained on a large benchmark dataset such as the ImageNet and typically excels in extracting the image features. Transfer learning also helps to avoid the over- fitting of data effectively. Thus, pre-trained models might have better performance while training (Zeng et al., 2021).

3.4 Classification Models

3.4.1 ResNet-50

ResNet-50 is a convolution neural network with 50 layers. Resnet employs residual blocks, mainly consisting of skip connections, which provide a quicker gradient flow. Even if the network is too deep, it reduces the complications like vanishing gradient (He et al., 2016).

3.4.2 AlexNet

AlexNet is a neural network with three convolutional layers and two fully connected layers and was introduced by Alex Krizhevesky in 2012. By expanding network depth and employing multi-parameter optimization techniques, AlexNet improves learning capacity. After AlexNet's outstanding performance on the ImageNet dataset in 2012, CNN-based applications became popular (Krizhevsky, 2014).

3.4.3 ResNeXt

Facebook proposed the ResNeXt model, which ranked second in the ILSVRC 2016 classification competition and improved COCO detection performance. ResNeXt model introduced a new dimension called cardinality along with width and depth as an essential parameter. When it came to expanding model capacity, cardinality is seen to be more effective than going deeper or broader, especially when going deeper and broader resulted in decreased returns (Hitawala, 2018).

3.5 Experimental Settings

The WaDaBa dataset was requested from its creator by signing a consent form. The data set has been described in the section 3.1.

3.5.1 Imbalance in the Data

The classes in the dataset have an unequal number of images. The first class (PET) has 2200 images, and the last class (Others) has only 40 images. It is pretty challenging to get datasets for certain types of plastic due to their size and cost. Due to the imbalance in the classes, the under-sampling approach was adopted along with the balanced weight distribution of the WaDaBa dataset. Five hundred images were selected from the first four classes and were split at 80 percent for the training and the remaining 20 percent for the testing. From the last class, 32 images were taken for training and the remaining 8 for testing.

3.5.2 Model Parameters

The training images were passed through ResNet50, AlexNet, and ResNeXt architectures and has been normalized. The dataset was run through each of these models for 20 epochs. Before passing on the training, the data has been normalized. The data then goes through a series of augmentation techniques such as random horizontal flip and center crop. The optimizer used was Stochastic Gradient Descent (SGD) with a learning rate of 0.001 and momentum of 0.9. The loss used for the experiments was cross-entropy loss.

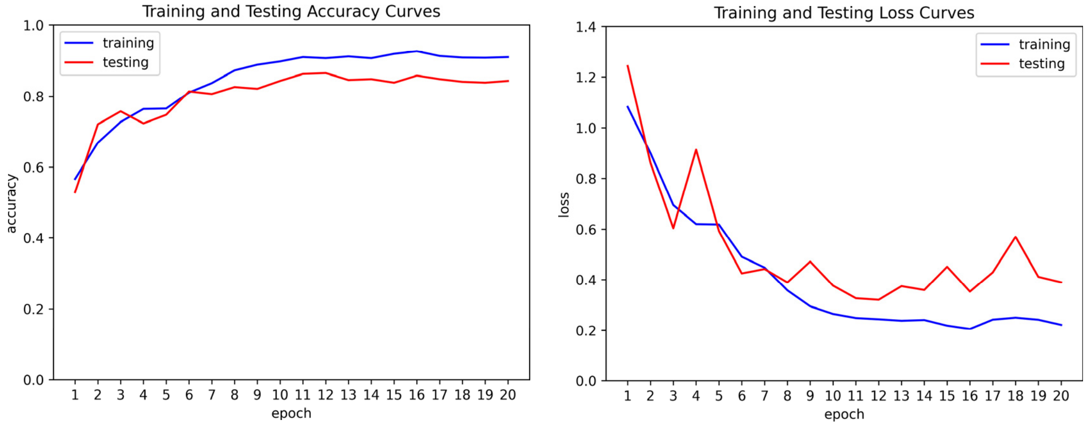

Figure 1: Accuracy and loss curves of training and testing for ResNet50.

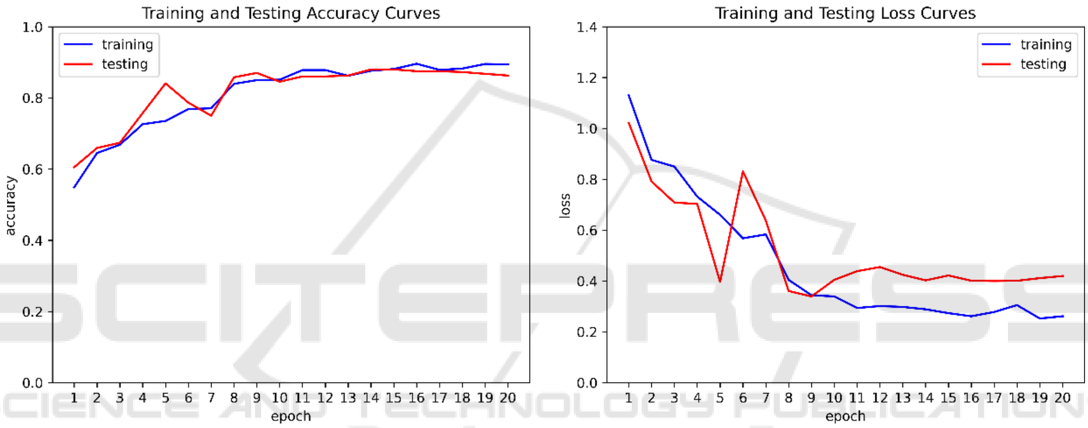

Figure 2: Accuracy and loss curves of training and testing for AlexNet.

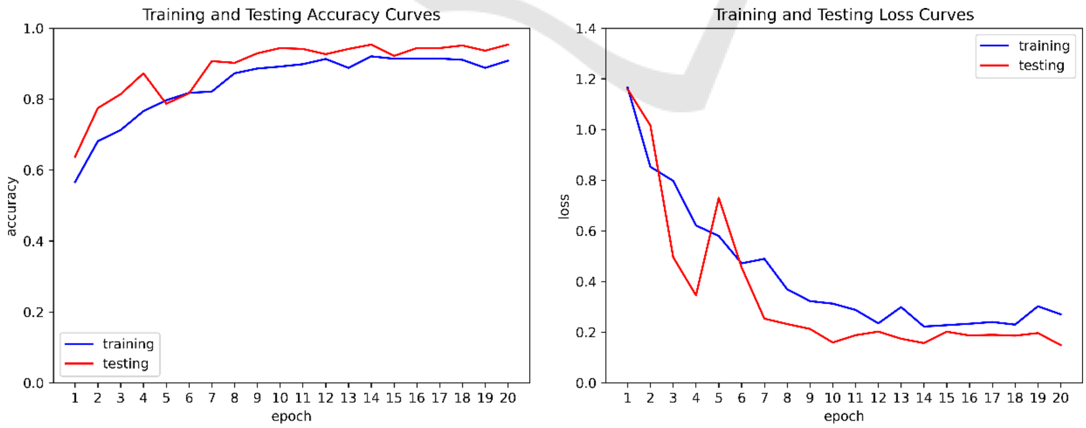

Figure 3: Accuracy and loss curves of training and testing for ResNext.

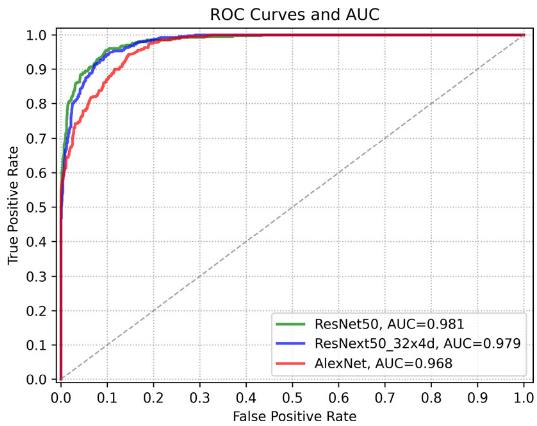

Figure 4: ROC and AUC comparison between different models.

Once the training was completed the testing accuracy was computed and has been given in Table 2.

4 EXPERIMENTAL RESULTS

4.1 Accuracy Results

The ResNeXt architecture shows the highest testing accuracy with 91 percent followed by ResNet-50 with an accuracy of 89 percent and Alexnet with an accuracy of 88 percent. The accuracy curves and the loss curves with respect to epochs for ResNet50, AlexNet and ResNeXt architectures are given in the Fig. 1, 2 and 3 respectively. From the graphs, we can see the training and the testing rates increases with the number of epochs and once it reaches a certain threshold, it maintains its accuracy. Similarly, the loss decreases with the increase in epochs. We can also infer that there is no over-fitting of data after viewing the accuracy versus epoch curves.

From the ROC curves and AUC in Fig. 4, we can see that all three models have very high AUC. ResNeXt achieves the best performance, ResNet-50 has a very similar AUC to ResNet50, followed by AlexNet. The reason is that both ResNet50 and ResNext50 have a deeper model than AlexNet.

Table 2: Accuracy comparison between different models.

Pre-trained Network	Accuracy
ResNeXt	91 %
ResNet-50	89 %
AlexNet	88 %

5 CONCLUSIONS

In this paper, we have benchmarked the accuracy of three different models on the WaDaBa dataset, which helps in automatically classifying different types of plastic wastes that need to be reused and recycled. This will help increase the overall recycling of plastic products and thus reduce plastic wastes. It can be used in the recycling industry to classify different plastic wastes and for further research to segregate them from others with different classes. From the results, we can see that ResNeXt model achieved the highest accuracy.

Once the plastic is correctly classified, it can be segregated with the help of an air nozzle or a robotic arm. Future work includes localization and detection of plastic objects.

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