TrashBox: Trash Detection and Classification using Quantum Transfer Learning

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***Abstract*—The problem of effective disposal of the trash generated by people has rightfully attracted major interest from various sections of society in recent times. Recently, deep learning solutions have been proposed to design automated mechanisms to segregate waste. However, most datasets used for this purpose are not adequate. In this paper, we introduce a new dataset, TrashBox, containing 17,785 images across seven different classes, including medical and e-waste classes which are not included in any other existing dataset. To the best of our knowledge, TrashBox is the most comprehensive dataset in this field. We also experiment with transfer learning based models trained on TrashBox to evaluate its generalizability, and achieved a remarkable accuracy of 98.47%. Furthermore, a novel deep learning framework leveraging quantum transfer learning was also explored. Experimental evaluation on benchmark datasets has shown very promising results. Further, parallelization was incorporated, which helped optimize the time taken to train the models, recording a 10.84% improvement in the performance and 27.4% decline in training time.**

I. Introduction

The past decade has evidenced an explosive increase in the amount of trash generated every day by urban populations. However, the current practice of directly discarding away items into the trashcan is highly unsustainable - particularly when raw materials are finite resources, and will eventually be exhausted. Instead, such products could be reclaimed, processed and recycled, and thus be used again. Recent surveys have reported that, in Delhi, roughly 80% of the waste sent to landfills daily could be recycled [1]. A similar argument can be made from the perspective of *reducing* the waste disposed off every day. Currently, the two major forms of waste disposal are incineration, where the object is simply burned, and landfilling, where the object is dumped in a pre-determined spot. Of these two methods, landfilling can be said to be far more popular, due to the lack of machinery or investment required to start operations. However, while incineration, even in the most controlled circumstances, does produce air pollution, landfills are much more harmful in nature. Landfills are known to pollute the groundwater in the region, due to toxic chemicals leaching into the water reservoirs. Fires are also known to break out spontaneously in such sites, due to the presence of highly flammable items. Landfills are also quite an eyesore, and give off an odious smell as one approaches the area. Moreover, as land becomes a scarce commodity, it is imperative to reduce the space taken by landfills.

Furthermore, the advent of mass manufacturing has seen the proliferation of a wide variety of product classes, ranging from electronics to medical products. For example, there has been a staggering growth in the number of electronic items produced in the last 20 years, and therefore, similar rise in the e-waste handled by waste processing plants. E-waste is one of the most recyclable class of trash items, for example, smartphones are made using rare earth elements, gold, and other valuable materials, all of which can be salvaged without too much difficulty using standardized processes. Similarly, with the COVID-19 pandemic, there has been a sharp increase in the number of surgical masks, gloves, and other such items discarded as litter, often without any regard to mandated bio-hazardous material disposal procedures. It is imperative that such hazardous items be handled with appropriate care, to protect trash disposal squads and other environmental contamination.

To reduce the the amount of waste sent to landfills, there is a need for automated systems for the segregation of the same. However, manual sorting is a tedious and often hazardous process, which does not scale well as being labour and cost-prohibitive. The trash sorting machines employed currently work on physical sorting processes, not intelligent computerized methods, which can help in more accurate class-wise segregation. Specifically, deep neural models trained on a trash image dataset with large variety of classes, can help classify trash objects based on their type, and boost recyclable product reclamation and productivity.

In this paper, a novel approach leveraging quantum transfer models for trash classification is presented. For initial experiments, we experiment with transfer learning models involving the use of models pre-trained on a very large datasets (ImageNet, COCO, etc.). These pre-trained models are trained to solve a particular problem through a new large-scale dataset encompassing multiple fine-grained classes, which are not supported by most existing trash classification datasets. As the model does not start off with random weights, instead using the weights inherited from the previously trained dataset. This helps to increase the training accuracy, reduce the amount of computations performed and increase the overall performance of the model. Also, we adopted quantum computing for the improvement and optimization of many processes involved for reducing the time and resources spent on performing complex computations in neural model layers.

We focus on a specific field of quantum machine learning called quantum transfer learning, thereby leveraging two powerful concepts, transfer learning and quantum computing to find a possible solution for trash object classification. In addition, to alleviate the problem of inadequate waste datasets, we introduce TrashBox, a new and comprehensive waste dataset with 17,785 real-world trash images divided into 7 classes : cardboard,e-waste, glass, medical waste, metal, paper, and plastic. Hence, hitherto neglected classes such as medical waste and e-waste are also incorporated.

The rest of this paper is organized as below: Section 2 presents a discussion on recent and notable work carried out in the field of trash classification and quantum computing, specially quantum transfer learning. Section 3 discusses the detailed methodology, with respect to the details of the TrashBox dataset, and construction and training optimization of quantum transfer learning models. In Section 4, the specifics of the experiments performed and the results obtained are discussed in detail, followed by conclusion and future work.

II. Related Work

In this section, we present an analysis of the works related to the area of interest. [2] provided a benchmark dataset, called TrashNet, for trash detection and classification. TrashNet contains 2527 plain-background images from 6 different classes, namely metal, plastic, paper, cardboard, glass and (other) trash. The authors experimented with CNN and SVM models and reported that the SVM model achieved the best accuracy at 63%. Moreover, as the authors themselves note, the number of data points in the dataset is very small, hence it is not very suitable for training neural models. Recently, another dataset, called TACO (Trash Annotations in Context) [3] for trash detection and classification was proposed. The authors put together a dataset containing "waste in the wild" trash objects, i.e., images of trash objects and litter found in various locations such as roads, woods, beaches, etc. The images in TACO are manually labeled and segmented according to a hierarchical taxonomy to train and evaluate object detection algorithms. While the dataset is crowdsourced, it currently has only 1,500 annotated images, which is lower than TrashNet.

Several works have explored the effectiveness of machine and deep learning models in the context of classifying waste objects. Adedeji et al. [4] used the ResNet-50 transfer learning model to classify trash objects, using the TrashNet dataset. To compensate for less frequency of images, the authors augmented the dataset by using various techniques such as shearing and scaling. Finally, they use a multi-class SVM model where the classification takes place. The authors got an accuracy of 87% with the TrashNet dataset with this model. Azis et al. [5] used a simple CNN model to classify trash objects, using the Inception-v3 transfer learning model. The training dataset used was the Plastic Model Detection dataset [6] which contained 2,400 images. To simulate real-world conditions, the authors used Raspberry Pi as their processor. Further, they changed the input size of the Inception model to 299x299 as that is the default image dimension of the Raspberry Pi camera, and reported an accuracy of 92.5%.

Masand et al. [7] created ScrapNet, a deep learning model adapted form the architecture of the EfficientNet transfer learning model. They assessed the viability of this dataset by testing it on the benchmark TrashNet dataset, where they achieved a 98% accuracy. They also created a new dataset consisting of 8,135 images, by collating images present in various pre-existing datasets and standardizing them. Running an EfficientNet B3 model on this dataset, they achieved an accuracy of 92.87%. Shi et al. [8] proposed a waste classification method based on a multilayer hybrid convolution neural network. The structure of the network, while similar to VGGNet, is simpler, with higher output performance and fewer input parameters. Experiments with TrashNet achieved a classification accuracy of up to 92.6%.

In recent years, there has been remarkable progress in the field of quantum computing. In particular, it has been applied to a wide variety of tasks for achieving time and cost optimizations when complex computations are to be performed in neural model layers. Killoran et al. [9] introduced a general method of constructing neural networks on quantum computers. The quantum neural network thus built is a variational quantum circuit built in the continuous-variable architecture. They performed extensive modelling experiments on the constructed network, such as, fraud detection classifier, hybrid classical-quantum auto-encoder, etc., which demonstrated its wide-spread capabilities. Mari et al. [10] proposed a framework of transfer learning consisting of hybrid computational models that were constructed using a mixture of variational quantum circuits and classical neural network models. In particular, 3 types of novel classical-quantum models were proposed - CQ (classical-quantum), QC (quantum-classical), and QQ (quantum-quantum). They also proposed the concept of dressed quantum circuits with which custom quantum circuits can be constructed based on the requirement. All the proposed models were implemented on quantum computers of IBM and Rigetti. Mogapalli et al. [11] proposed a quantum transfer learning based approach for different image classification tasks such as organic and recyclable classification of trash, TB detection from chest X-Rays, and detection of cracks in concrete structures. The authors use a concatenation of pre-trained classical feature extractor with a quantum circuit as classifier. Various experiments were performed using VGG-19, DenseNet-169 and AlexNet as pre-trained classifiers. However, no model was concluded to be better for classification, with different models outperforming the others in different tasks.

Following the comprehensive review, we observed a glaring lack of an adequate dataset with multiple categories for trash classification research. The most commonly used dataset, TrashNet, has only 2,527 trash images, which is hardly sufficient for a such a complex problem. Moreover, many relevant and significant classes of trash were not covered by existing datasets. Chief among these were the medical waste and e-waste categories, which have received scant attention so far. In this paper, we present a dataset with ample number of trash images per class. We have also included adequate number of images in the medical waste and e-waste classes. We also propose the use of the quantum transfer-learning models to perform the task of trash classification.

III. Proposed Methodology

This section detailed the proposed methodology designed for creating the new multi-class trash dataset, that provides large-scale images across multiple categories. Experiments were performed using traditional transfer learning models to validate their performance on the new dataset in comparison to other standard datasets. Furthermore, the concept of quantum transfer learning was also used to improve the model's object detection and feature extraction capabilities, and increased the efficiency of the existing model by parallel processing within the model. We describe the detailed workflow in Fig.1.

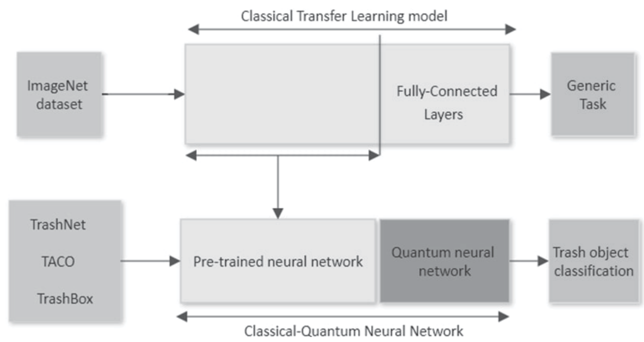

Fig. 1. Workflow diagram of the proposed methodology

A. Proposed Dataset - TrashBox

To address the lack of existing trash detection and classification datasets, a new dataset was put together. The detailed review revealed that the deficiencies in the various benchmark datasets used in this field, such as TrashNet [2] and TACO [3]. We observed that many benchmark datasets such as TrashNet lack the frequency of images required for the task of classification of trash objects. In fact, this has been noted by the authors themselves in their paper [2] on the subject. Further, two of the major modern day waste types are e-waste and medical waste. However, most datasets do not contain any images for these critical classes. This is important in e-waste management [12] as implementing the right practices to recycle can help conserve non-renewable natural resources.

In order to remedy this issue, we created a dataset called TrashBox that contains various trash objects in diverse environments. The images in TrashBox were classified into 7 classes - medical waste, e-waste, glass, plastic, cardboard, paper, metal. Furthermore, these classes are divided into sub-classes to facilitate the distinction between various trash objects, and to enable further research in this field. TrashBox was prepared by extracting images of trash objects by performing a comprehensive search on the web. For this purpose, a batch download software tool called WFdownloader [13] was used. This tool allowed us to download images in bulk from Google Images, Bing Images, among a variety of sources. The downloaded images were then manually cropped and sorted into their respective classes. The details of the sub-classes are given in Table I. The distribution of each class of the TrashBox dataset is illustrated in Fig. 2.

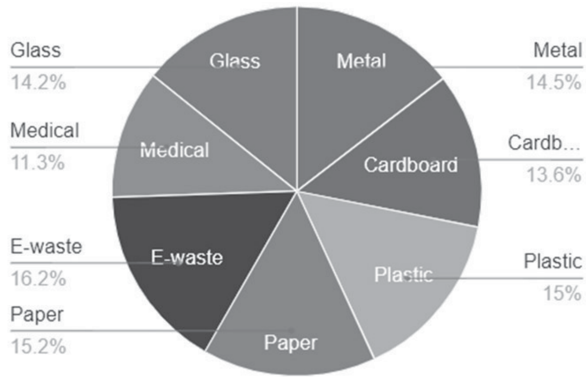

Fig. 2. Distribution of Trash images in TrashBox

The dataset can be downloaded from GitHub[1].

TABLE I. TrashBox dataset - Class-wise Statistics

Trash Classes	Sub-classes	No. of images	Total
Cardboard	Assorted cardboard objects	2414	2414
E-waste	Electrical chips	615	
	Laptops & smartphones	774	2883
	Small appliances	926	
	Electric wires	568	
Glass	Assorted glass objects	2528	2528
Medical	Syringes	507	
waste	Surgical gloves	496	2010
	Surgical masks	500	
	Medicines	507	
Metal	Beverage cans	1000	
	Construction scrap	539	
	Spray cans	500	2586
	Metal containers	505	
	Miscellaneous metal	42	
Plastic	Plastic bags	504	
	Plastic bottles	571	
	Plastic containers	580	2669
	Plastic cups	507	
	Cigarette butts	507	
Paper	Tetra pak	794	
	News paper	200	2695
	Paper cups	639	
	Other paper objects	1062	

B. Transfer Learning Models

For the purpose of measuring performance and benchmarking, we make use of popular standard transfer learning models. In particular, we use the ResNet-34, ResNet-50, ResNet-101,

[1]TrashBox dataset on GitHub, https://github.com/nikhilvenkatkumsetty/TrashBox

VGG-19, and DenseNet-121 models in various scenarios. We construct the models by importing pre-trained weights of the ImageNet dataset. Then, the imported model is optimized by adding a Global Average Pooling, Batch Normalization, and Dense output layers to the model. The main goal of adding the Global Average Pooling layer is to eliminate the need to fine-tune the hyper-parameters of the classical transfer learning models. We then start training the model on each dataset by freezing all base layers and training the output layer by a large learning rate. To further improve the accuracy of the model, we reduce the learning rate after a few epochs. The advantage of this approach is that it does not change the weights of the base layers drastically in the first few epochs when the last few layers have not yet stabilized.

C. Quantum Transfer Learning Models

In this section, we discuss our implementation of the quantum transfer learning (QTL) methodology to classify trash objects. In particular, we implement a hybrid classical-quantum neural network, which helps to train the transfer learning models more effectively and process high-dimensional data in an optimal way. This network is constructed by embedding the quantum circuit layers into the classical transfer learning model. As illustrated in Fig. 1, the quantum circuit layers are introduced towards the closing end of the classical transfer learning model. This is done to: (a) encourage the feature extraction capabilities of the classical transfer learning model and (b) help the quantum circuit layers process the input data and improve the effectiveness of the classification task.

The implemented QTL model mainly consists of two components, the *Preprocessing* block and *Quantum circuit* network.

1) *Preprocessing block:* To build the first part of the QTL model, we import a pre-trained network trained on ImageNet [14] dataset. After importing the network, we remove the last fully connected layers that are used to perform the task of classification. Hence, we have a neural network that acts as a pre-processing block that extracts features from the input data. We then merge this modified pre-trained network with the custom-built dressed quantum circuit network, which help to construct custom quantum circuits based on the requirement of our model.
2) *Quantum circuit network:* The second part is built using an amalgamation of various quantum layers. In this case, an embedding layer is used to initialize the states of quantum bits and input the features extracted from the classical transfer learning model, so as to further process the data and classify the trash objects. Then, the variational layers perform the processing of the data input into the embedding layer. Finally, the measurement layer generates a classical vector as output, by keeping track of expectation value of the Pauli-Z operator for each qubit in the quantum layers.

The quantum circuits described above are constructed using several layers. A quantum layer consisting of one qubit Hadamard gate that maps the basic states (0 and 1) to a qubit that exists in equally probable superposition of both the basic states. A quantum layer of parametrized qubit rotations [15] around the x-axis. A quantum layer of parametrized qubit rotations around the y-axis. A quantum entangling layer helps to perform rotations on each qubit and then cascading the 2-qubit entangling gates.

D. Parallelization of QTL Model Training

After construction, the QTL model was observed to take up excessive amounts of computing resources and time during the training phase, which we attribute to the models' intricate nature. To resolve this issue, we focused on designing a parallelization strategy to speed up the model's training process. Towards this, we assigned a replica of the neural network to each thread. This helps to train the model in concurrent batches depending upon the number of threads and the computation power of the processing unit. Once the training process is complete, the weights computed are updated to their respective threads. At the end, each batch of training data is averaged, thus generating the total performance of the model. We must also be mindful about the effects of parallelizing a neural network on the time taken to finish the process and the performance of the model. Since the TrashBox dataset has large number of data-points to process, parallel computing helped to decrease the time taken to train the network. Detailed observations regarding the various aspects of this strategy are presented in the following section.

IV. Experimental Results and Analysis

A. Experimental Setup

The experimental validation of the proposed models was performed on two standard datasets - TrashNet, TACO and the custom dataset - TrashBox. The models were constructed using Python 3.10.1. The PyTorch open-source library was used to develop the deep neural networks, and PennyLane [16] cross-platform library to construct the quantum neural networks. The models were trained on Nvidia P100 and T4 GPUs with a minimum of 16 GB RAM, and all the proposed models were run for 100 epochs during this experimentation.

B. Evaluation of the proposed models

We measured the performance of TrashBox by using it to train state-of-the-art deep neural models like ResNet-34, ResNet-50, ResNet-101, DenseNet-121 and VGG-19. Table II shows the results obtained by the classical transfer learning models for the TrashBox dataset. We observed that the ResNet-101 model achieved the best results among the considered models for this classification task. This model was able to classify the trash objects with a training accuracy of 98.86%, validation accuracy of 98.29% and testing accuracy of 98.47%.

Next, we performed experiments on our quantum transfer learning models. We created a train, test, validation split for

TABLE II. PERFORMANCE OF CLASSICAL TRANSFER LEARNING MODELS TRAINED ON TRASHBOX

Model	Training	Validation	Testing
ResNet-34	92.17%	92.13%	92.20%
ResNet-50	96.44%	94.83%	93.36%
ResNet-101	**98.86%**	**98.29%**	**98.47%**
DenseNet-121	95.47%	93.60%	93.94%
VGG-19	96.91%	96.08%	95.63%

TABLE III
PERFORMANCE OF QTL MODELS TRAINED ON VARIOUS DATASETS

Dataset	**Model**	**Training**	**Validation**	**Test**
TrashNet	Quantum_ResNet-34	76.97%	77.45%	77.56%
	Quantum_ResNet-50	**81.10%**	**80.20%**	**80.49%**
	Quantum_ResNet-101	79.54%	78.97%	77.34%
	Quantum_DenseNet-121	78.52%	78.50%	78.1%
	Quantum_VGG-19	76.25%	77.50%	77.43%
TACO	Quantum_ResNet-34	78.83%	79.20%	79.5%
	Quantum_ResNet-50	**82.30%**	**81.25%**	**82.1%**
	Quantum_ResNet-101	80.14%	80.74%	80.34%
	Quantum_DenseNet-121	79.22%	79.13%	79.03%
	Quantum_VGG-19	78.40%	78.13%	78.11%
TrashBox	Quantum_ResNet-34	81.53%	80.16%	80.38%
	Quantum_ResNet-50	**85.38%**	**85.12%**	**84.97%**
	Quantum_ResNet-101	83.65%	82.14%	82.94%
	Quantum_DenseNet-121	81.66%	81.27%	81.9%
	Quantum_VGG-19	80.22%	79.56%	79.33%

analyzing the ResNet-34, ResNet-50, ResNet-101, DenseNet-121, and VGG-16 QTL models. Table III shows the results obtained by the QTL models run on the augmented TrashNet dataset. We observed that the Quantum_ResNet-50 model achieved the best results among the considered models for this analysis. This model was able to classify the trash objects with a training accuracy of 81.1%, validation accuracy of 80.2% and testing accuracy of 80.49%. It achieved best results for the TACO and TrashBox datasets as well, with a training accuracy of 82.3%, validation accuracy of 81.25% and testing accuracy of 82.1% for TACO, and a training accuracy of 85.38%, validation accuracy of 85.12% and testing accuracy of 84.97%. for TrashBox.

From Table III, it can be observed that the Quantum_ResNet-50 model trained on all datasets marginally outperformed the Quantum_ResNet-101 model. This may be because, ResNet-101, DenseNet-121, and other similar models are complex models which require more computational resources and more time to train. Hence, these models are more prone to overfit to the train data. However, we avoid this problem by optimizing the model to self-adjust its parameters based on the results obtained by processing the validation set. Therefore, it gives a slightly lower performance than the ResNet-50 model. It can also be observed that the Quantum_ResNet-34, Quantum_ResNet-50, and Quantum_ResNet-101 models achieved better results than the Quantum_VGG-19 model. This is because of the architecture of the ResNet model, which results in the building of a lighter but deeper network in each layer. This in turn helps reduce the number of computation operations performed in each layer and preserves the weights of the inherited ImageNet dataset for a longer period, thereby improving the performance at a faster rate than the VGG model.

C. Evaluation of training the proposed models in parallel

To verify the effect of parallelization of the training process of the QTL models, additional experiments were conducted. We implemented parallel programming on the neural networks in order to improve the performance of the models and to reduce the amount of time it takes to train a QTL model. This step was important especially for QTL model since, the GPU were not very capable of handling such large computations as they had limited processing power. Moreover, the variational quantum networks we used were designed to be processed with Quantum Processing Units (QPU).

Firstly, we investigated the effects of varying the number of threads to the time required to complete the training of the model. From Fig. 3, it can be seen that, the time required to train the models decreases with increase in the number of threads, as expected. However, we note that the rate of decrease is higher for the QTL model than the classical transfer learning model. In particular, while the quantum model and classical model take 11.5 hours and 10.5 hours respectively to train serially, they both take 9.25 hours to train on 5 threads, and 8.25 and 8.75 hours respectively to train on 7 threads.

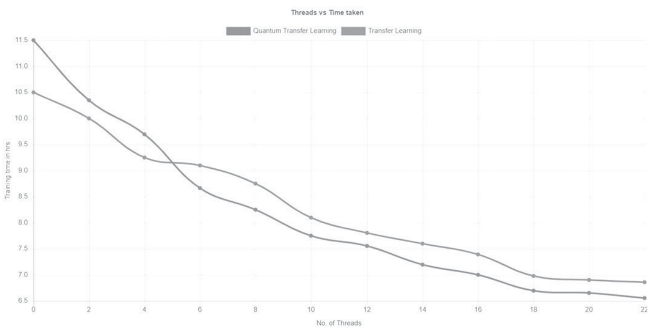

Fig. 3. Number of Threads vs Training time

We also investigated the effects of varying the number of threads to the accuracy of the trained model. From Fig. 4, it can be observed that, while the performance of the neural networks improves upon parallelizing, it does so only until a certain no. of threads, specifically, for a thread range of 6 to 8 threads. Beyond this, the performance degrades. Hence, we implemented our QTL model for 7 threads. As we increase the no. of threads, the neural networks ability to retain and uniformly update the parameter weights during the training of each batch will be impacted severely, thus, resulting in a decrease in the accuracy of the trained models. Therefore, we achieve 10.84% improvement in the training accuracy and 27.4% decline in the time taken to train the models by parallelizing the QTL model.

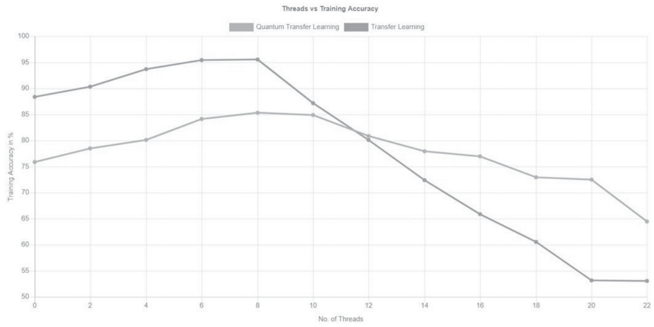

Fig. 4. Number of Threads vs Training accuracy

V. Conclusion and Future work

In this paper, a novel approach incorporating quantum learning in transfer learning models, for the purpose of trash classification, was presented. A new, comprehensive trash classification dataset called TrashBox was put together, consisting of 17,785 images across various classes. Our dataset is larger than any existing trash classification dataset and also contains unique classes such as medical waste and e-waste, hence making the dataset quite diverse in nature. Upon running an optimized ResNet-101 model, an accuracy of 98.47% was achieved. We hope that TrashBox becomes a valuable resource to other researchers in their work. The quantum transfer learning models were applied to the trash classification problem, along with optimizations in the form of parallelization strategies to speed up their training. This improved accuracy up to 10.84%, and decreased training time by 27.4%. We performed several experiments with the designed quantum transfer learning models. In particular, several transfer learning architectures and datasets were experimented with. and best results were achieved with the Quantum_Res-Net-50 model, which gives 84.97% accuracy with the TrashBox dataset, and 80.49% accuracy with the benchmark TrashNet dataset. We believe that there is scope for further optimizations for this model, particularly as quantum transfer learning itself is still under development.

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