An Automatic Garbage Classification System

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Abstract: Trash arrangement has consistently been a significant issue in ecological security, As the economy is developing rapidly and with the improvement of people's living standards, the amount of garbage is also increasing rapidly. To tackle the provincial living trash handling issues, we freely built up a one-of-a-kind innovation of perfect and far-reaching use of trash assets. Based on modern biodegradation and automatic sorting, we built a complete industrial chain with mixed domestic waste as mineral raw material. The natural discharge would be siphoned to an anaerobic maturation framework, while the build-up would be another puncturing through the broken drum to the fundamental gathering framework. With our advanced gadgetry, we secure inorganic materials like sand and glass, mash and sundries, for example, bamboo materials, and unadulterated plastic finally. The items would be extra preparing to mechanical materials as expected of the market. The sand and rock glass and other inorganic materials can deliver empty squares, clearing blocks, and wipe blocks. At last, the prevalence of the proposed grouping calculation is checked with the built trash information.

The trial results show that the grouping precision is pretty much as high as 95%.

Keywords: Deep learning, CNN, resnet-34, resnet-50, ANN, Sequential model, Tensorflow.

1.Introduction

With the fast advancement of economy and the improvement of individualsexpectations for everyday comforts, the measure of trash is increasing quickly. As per the most recent report of Worldwide Lianhe Zaobao, the worldwide trash volume will increment by 70% by 2050, and the errand of trash grouping will be significantly more laborious.

Researchers at home and abroad have done a ton of investigates on trash arrangement, however the majority of the proposed plans are advancements of terminal reusing technique. In 2019, China began to require private trash grouping, in which case the front-end assortment is exceptionally subject to individuals' mindfulness. Along these lines, the effectiveness of the trash order actually should be improved.

It is of extraordinary scholastic worth and pragmatic importance to examine a compelling programmed trash characterization technique. The exploration of trash characterization framework is developed, yet the exactness and speed of trash order actually should be improved. What's more, there are not many investigates on trash arrangement dependent on profound learning. As of now, profound learning innovation is generally utilized in picture order, and has some exceptional accomplishments.

Image classification algorithms are gradually diversified. The mainstream algorithms are AlexNet, VGG, Inception, and ResNet. Scholars implemented experiments using these methods and made attempts to modify them to gain better results. These are helpful for the improvement of network structure in this paper. Thanks to the nonlinear characteristics of activation function, a neural network with improved activation function have shown good results. To learn the distribution characteristics of the nonlinear data better, some improvements of the network are mainly focused on the network's depth.

2. Proposed System

The present way of separating waste/garbage is the hand-picking method, whereby someone is employed to separate the different objects/materials. The person, who separates waste, is prone to diseases due to the harmful substances in the garbage. With this in mind, it motivated us to develop an automated system that can sort waste. and this system can take short time to sort the waste, and it will be more accurate in sorting than the manual way. With the system in place, the beneficial separated waste can still be recycled and converted to energy and fuel for the growth of the economy. The system that is developed for the separation of the accumulated waste is based on the combination of Convolutional Neural Network and Artificial neural networks which helps in image classification. Because the trash image dataset is small, we used a pre-trained ResNet-50 model which is a type of Convolutional Neural Network architecture. When the depth is increased, the recognition accuracy of the convolutional neural network can be increased, but due to the increase in depth, the signal that is supposed to modify the weight is reduced at the earlier layer of the CNN. This will make learning at the earlier layers inconsequentially and this is called vanishing gradient. Adding more and more layers to the network always leads to training errors. Residual Network(ResNet-50) is different from the normal convolutional Neural networks can go around this problem of vanishing gradient by designing the Convolutional neural network.using modules which are called residual models, the ResNet model, and the basic block.

3.Methodology

A. System Architecture

In CNN, a few layers makes-up the network. The layers in CNN carry out certain steps, which permit it to classify input images. The convolutional layer convolves the image that is inputted utilizing a sequence of kernels window sizes of 3 x3, this was utilized because what makes difference of the objects are small and local features. The fundamental features are extricated from the input images. The primitive features are extracated with the help of the initial few layers. As the training moves down the layers more complex and detailed features are extracted, with the help of the loss function probability, that is, Softmax work and furthermore there are other enactment capacities like Relu, tanh and so forth however we use essentially relu and softmax. Our model was created dependent on the ResNet-50 pre-prepared model, this model was pre-prepared on ImageNet pictures with a size of 256 x 256 and characterized into 1000 classes

Our model was created dependent on the ResNet-50 pre-prepared model, this model was pre-prepared on ImageNet pictures with a size of 256 x 256 and characterized into 1000 classes.

The ResNet-50 model consists of 5 stages. In first stage there will be four blocks namely, convolution, batch normalization, Relu, Max pooling and remaining four stages each with a convolution and Identity block. Each convolution block has 3 convolution layers and each identity block also has 3 convolution layers. The ResNet-50 has over 23 million trainable parameters.

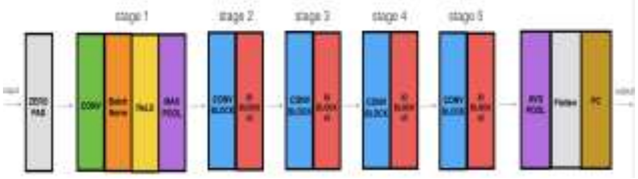


Fig. 1: Resnet-50 model

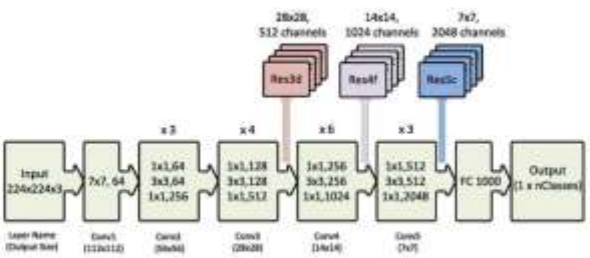


Fig. 2: Resnet-50 Architecture

Model: "resnet50v2"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3)	0	
conv1_pad (ZeroPadding2D)	(None, 262, 262, 3)	0	input_1[0][0]
conv1_conv (Conv2D)	(None, 128, 128, 64)	9472	conv1_pad[0][0]
pool1_pad (ZeroPadding2D)	(None, 130, 130, 64)	0	conv1_conv[0][0]
pool1_pool (MaxPooling2D)	(None, 64, 64, 64)	0	pool1_pad[0][0]
conv2_block1_preact_bn (BatchNo	(None, 64, 64, 64)	256	pool1_pool[0][0]
conv2_block1_preact_relu (Activ	(None, 64, 64, 64)	0	conv2_block1_preact_bn[0][0]
conv2_block1_1_conv (Conv2D)	(None, 64, 64, 64)	4096	conv2_block1_preact_relu[0][0]
conv2_block1_1_bn (BatchNormali	(None, 64, 64, 64)	256	conv2_block1_1_conv[0][0]
conv2_block1_1_relu (Activation	(None, 64, 64, 64)	0	conv2_block1_1_bn[0][0]
conv2_block1_2_pad (ZeroPadding	(None, 66, 66, 64)	0	conv2_block1_1_relu[0][0]
conv2_block1_2_conv (Conv2D)	(None, 64, 64, 64)	36864	conv2_block1_2_pad[0][0]
conv2_block1_2_bn (BatchNormali	(None, 64, 64, 64)	256	conv2_block1_2_conv[0][0]
conv2_block1_2_relu (Activation	(None, 64, 64, 64)	0	conv2_block1_2_bn[0][0]
conv2_block1_0_conv (Conv2D)	(None, 64, 64, 256)	16640	conv2_block1_preact_relu[0][0]
conv2_block1_3_conv (Conv2D)	(None, 64, 64, 256)	16640	conv2_block1_2_relu[0][0]
conv2_block1_out (Add)	(None, 64, 64, 256)	0	conv2_block1_0_conv[0][0] conv2_block1_3_conv[0][0]
conv2_block2_preact_bn (BatchNo	(None, 64, 64, 256)	1024	conv2_block1_out[0][0]
conv2_block2_preact_relu (Activ	(None, 64, 64, 256)	0	conv2_block2_preact_bn[0][0]
conv2_block2_1_conv (Conv2D)	(None, 64, 64, 64)	16384	conv2_block2_preact_relu[0][0]
conv2_block2_1_bn (BatchNormali	(None, 64, 64, 64)	256	conv2_block2_1_conv[0][0]
conv2_block2_1_relu (Activation	(None, 64, 64, 64)	0	conv2_block2_1_bn[0][0]
conv2_block2_2_pad (ZeroPadding	(None, 66, 66, 64)	0	conv2_block2_1_relu[0][0]
conv2_block2_2_conv (Conv2D)	(None, 64, 64, 64)	36864	conv2_block2_2_pad[0][0]
conv2_block2_2_bn (BatchNormali	(None, 64, 64, 64)	256	conv2_block2_2_conv[0][0]
conv2_block2_2_relu (Activation	(None, 64, 64, 64)	0	conv2_block2_2_bn[0][0]
conv2_block2_3_conv (Conv2D)	(None, 64, 64, 256)	16640	conv2_block2_2_relu[0][0]
conv2_block2_out (Add)	(None, 64, 64, 256)	0	conv2_block1_out[0][0] conv2_block2_3_conv[0][0]
conv2_block3_preact_bn (BatchNo	(None, 64, 64, 256)	1024	conv2_block2_out[0][0]

Fig. 3: Layers of Resnet-50

B. Dataset

The performance of the proposed garbage classification was assessed on dataset, specifically the Garbage classification dataset.

Each image in each dataset contains just one object. Consequently, the aim of the two datasets is garbage material classification,rather than the detection of waste materials. The Garbage classification dataset contains 2527 images of garbage isolated into six distinct classes, specifically glass, paper, plastic, metal, cardboard, and trash.

Here, we divide the garbage classification dataset into 80% for training and 20% for validation. We divide 2527 images into 2 categories they are training set and validation set , 2022 for training purpose and 505 for validation.

Fig. 4: Garbage Classification dataset images

C. Algorithms Used

Numpy : It is a general purpose array processing package. It provides a high-performance multi-dimensional array object, and tools for working with these arrays.

Matplotlib : Matplotlib is an amazing visualization library in python for 2D plots of arrays.

Keras : Keras is an open source Neural network library written in python that runs on top of theano and tensorflow. It is designed to be modular, fast and easy to use.

ResNet :A residual neural network(ResNet) is an artificial neural network (ANN) of a kind that builds on constructs known from pyramidal cells in the cerebral cortex . Residual neural networks do this by utilizing skip connections ,or shortcuts to jump over some layers.

D. Modules

1. **Data Collection** : Collect sufficient data samples and legitimate software samples.

2. **Data Preprocessing**: Data Augmented techniques will be used for better performance.

3. **Train and Test Modeling**: Split the data into train and test data Train will be used for training the model and Test data to check the performance.

E. Design

In this resnet-50 we have 5 Stages:

1. Stage-1
2. Stage-2
3. Stage-3
4. Stage-4
5. Stage-5

In stage 1 we have 4 blocks namely

i. Convolution layer
ii. Batch normalization
iii. RELU(Activation function)
iv. Max Pooling

But, whereas coming to remaining 4 layers we have only two blocks namely:

1. Convolution block
2. Identity block

And in this convolution block we have 3 convolution layers and also in in identity block we have 3 convolution layers.

i. Convolution Layer

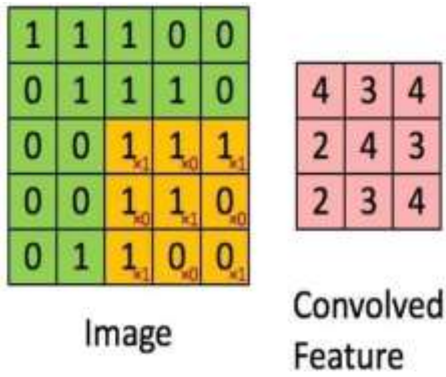


Fig. 5: Convoluting 5*5*1 image with 3*3*1 kernel

Image Dimensions = 5 (Height) x 5 (Breadth) x 1 (Number of channels, eg. RGB)

In the above show, the green segment resembles 5x5x1 input picture, I. The element involved in the convolution activity in the first part of a Convolutional Layer is known as the Kernel/Filter, K, addressed in the colour yellow. We have chosen K as a 3x3x1 grid. The Kernel shifts 9 times on account of Stride Length = 1 (Non-Strided), each time performing multiplication operation between K and the part P of the picture over which the kernel is sliding. The channel moves to right side with a specific Stride Value till it parses the complete width. Proceeding onward, it jumps down to the start (left) of the picture with similar Stride Value and rehashes the cycle until the whole picture is traversed.

ii. Batch Normalization

Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks. Importantly, batch normalization works differently during training and during inference. During training (i.e. when using fit() or when calling the layer/model with the argument training=True), the layer normalizes its output using the mean and standard deviation of the current batch of inputs. That is to say, for each channel being normalized, the layer returns gamma * (batch - mean(batch)) / sqrt(var(batch) + epsilon) + beta, where: epsilon is small constant (configurable as part of the constructor arguments)gamma is a learned scaling factor (initialized as 1), which can be disabled by passing scale=False to the constructor. beta is a learned offset factor (initialized as 0), which can be disabled by passing center=False to the constructor.

During inference (i.e. when using evaluate() or predict() or when calling the layer/model with the argument training=False (which is the default), the layer normalizes its output using a moving average of the mean and standard deviation of the batches it has seen during training. That is to say, it returns gamma * (batch - self.moving_mean) / sqrt(self.moving_var + epsilon) + beta.

iii. RELU

Relu is an activation function , it gives 0 when the value is negative and gives the same number or value if the value is positive.

It’s formula is : max(0,z)

It avoids and rectifies vanishing gradient problem.

ReLu is less computationally expensive than tanh and sigmoid because it involves simpler mathematical operations.

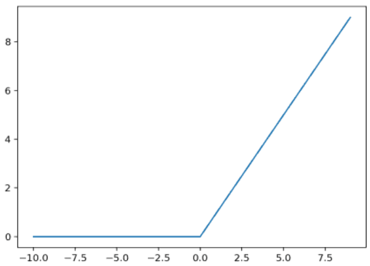


Fig. 6: Plot of Rectified Linear Activation for Negative and Positive Inputs

iv. Max Pooling

There are two types of Pooling: Max Pooling and Average Pooling. Max

Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel.

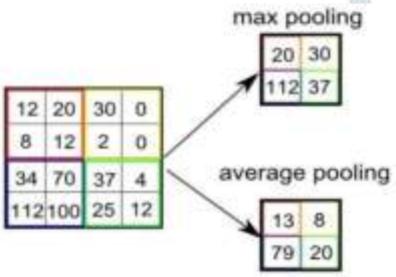


Fig. 7: Max pooling and Average pooling

Max pooling also performs as a Noise suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. On the other hand, Average pooling simply performs dimensionality reduction as a noise supressing mechanism. Hence, we can say that Max pooling performs a lot better than Average pooling.

F. A Residual Neural Network

ResNet is a short name for a residual network, but what’s residual learning?

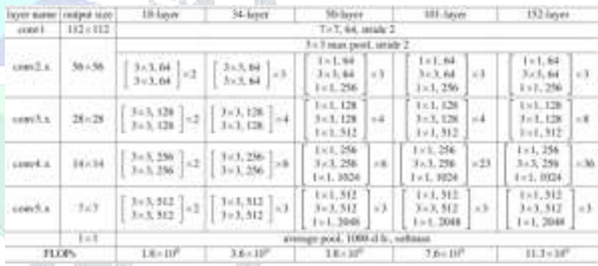
Deep convolutional neural networks have achieved the human level image classification result. Deep networks extract low, middle and high-level features and classifiers in an end-to-end multi-layer fashion, and the number of stacked layers can enrich the “levels” of features. When the deeper network starts to converge, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly. Such degradation is not caused by overfitting or by adding more layers to a deep network leads to higher training error. The deterioration of training accuracy shows that not all systems are easy to optimize.

To overcome this problem, Microsoft introduced a deep residual learning framework. Instead of hoping every few stacked layers directly fit a desired underlying mapping, they explicitly let these layers fit a residual mapping. The formulation of F(x)+x can be realized by feedforward neural networks with shortcut connections.The shortcut connections perform identity mapping, and their outputs are added to the outputs of the stacked layers. By using the residual network, there are many problems which can be solved such as:

ResNets are easy to optimize, but the “plain” networks (that simply stack layers) shows higher training error when the depth increases.

ResNets can easily gain accuracy from greatly increased depth, producingresults which are better than previous networks.

G. ResNet-50



layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	[3×3, 64; 3×3, 64] ×2	[3×3, 64; 3×3, 64] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3
conv3_x	28×28	[3×3, 128; 3×3, 128] ×2	[3×3, 128; 3×3, 128] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×8
conv4_x	14×14	[3×3, 256; 3×3, 256] ×2	[3×3, 256; 3×3, 256] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×23	[1×1, 256; 3×3, 256; 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512; 3×3, 512] ×2	[3×3, 512; 3×3, 512] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig. 8: ResNet 50 Architecture

So, as we can see the Fig. 6 the ResNet-50 contains the following elements:

A convolution with a kernel size of 7*7 and 64 different kernels all with a stride size 2 gives us 1 layer.

We can also see Max pooling also with stride size of 2

In the next convolution there is a 1 * 1,64 kernel following this a 3 * 3,64 kernel and at last a 1 * 1,256 kernel, These three layers are repeated in total 3 time so giving us 9 layers in this step.

Next we see kernel of 1 * 1,128 after that a kernel of 3 * 3,128 and at last a kernel of 1 * 1,512 this step was repeated 4 time so giving us 12 layers in this step.

After that there is a kernel of 1 * 1,256 and two more kernels with 3 * 3,256 and 1 * 1,1024 and this is repeated 6 times giving us a total of 18 layers.

And then again a 1 * 1,512 kernel with two more of 3 * 3,512 and 1 * 1,2048 and this was repeated 3 times giving us a total of 9 layers.

After that we do average pool and end it with a fully connected layer containing 1000 nodes and at the end a Softmax function so this gives us 1 layer.

We don't actually count the activation functions and the max/ average pooling layers.

So,totalling this it gives us a 1 + 9 + 12 + 18 + 9 + 1 = 50 layers Deep Convolutional network.

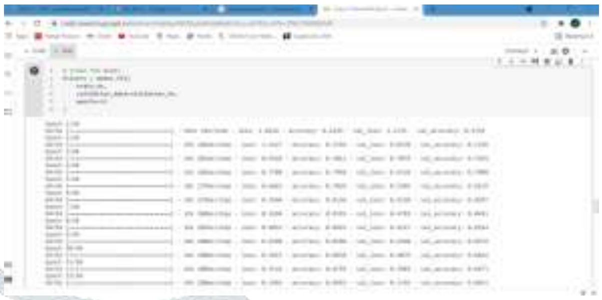
4.Result and discussion

Import the packages which are required to implement the process and set the datapath i.e.,locate the dataset filepath.

Divide the dataset into training and validation sets in the ratio of 80% and 20% ,The total 2527 images are divided into 2022 as training images and 505 as validation images.

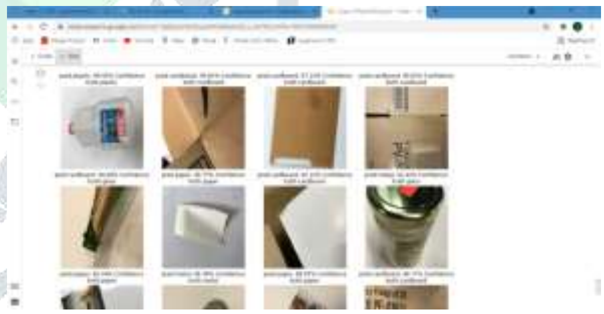
Display randomly six images from the training and validation sets.

Intiate the resnet-50 model.

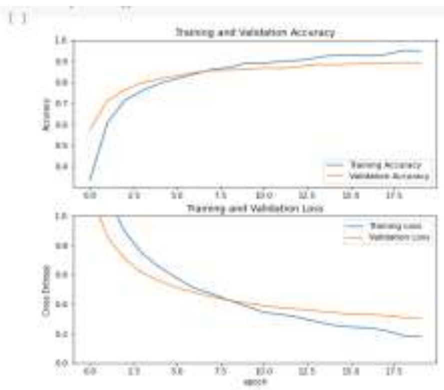


Train the model by giving the epochs size as 20,it means it trains the model twenty times.

Display the accuracy of the model after training the model.



Display the images from the set with the labels of truth,prediction and confidence.



Display the plotted loss and accuracy graphs based on the fluctuations it got during the training.

5. Conclusion

Aiming at the problem of garbage classification, this paper proposes an improved algorithm based on ResNet-50.

Firstly, Experiments on common data sets will be implemented to determine the basic model and ResNet-50 shows the best performance and is chosen.

The model will be tested on the garbage dataset with 6 types of garbage.

After giving 20 epochs we got nearly, 95% accuracy, which is best.

Finally, an automatic garbage classification system will be integrated with the proposed algorithm.

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