Image Denoising with Color Scheme by Using Autoencoders

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Summary
Image denoising autoencoder is classical issue in the field of digital image processing where compression and decompression function are lossy and data specific. In this paper, we use autoencoder technique on RGB (Red, Green and Blue) color scheme dataset, we added Gaussian noise on CIFER-10 dataset then encode by using 2D convolutional neutral network. Similarly, we decode noisy dataset to train our model. After training, the proposed method can learn denoising data and returns effective results.

Key Words:
Noisy, Autoencoder, Denoising, RGB, CIFAR-10, Encoder, Decoder

1. Introduction

An algorithm is any in image processing, applications and analysis, denoising is one of the most significant techniques currently used. Removing random noise and reserving the details of an image is fundamental goal of image denoising approaches. This approach reduces the visibility of lower contrast objects in addition the noisy image construct unwanted visual quality. Consecutively to improve and recuperate superior facts that are concealed in the data. Noise removal is essential during digital imaging applications. In Gaussian probability distribution noise in digital metaphors is initiate to be preservative in nature with consistent supremacy in the entire bandwidth.

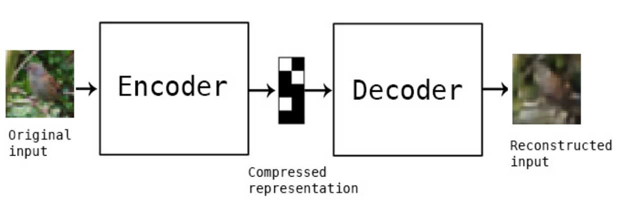

Fig. 1 Image Compression Process

Number of technique proposes for compression and decompression in which autoencoding is popular scheme that uses three functions:

- Data specific
- Lossy
- Erudite automatically since examples fairly than engineered through a human.

Autoencoder implemented with a neural network in almost all contexts is used for compression and decompression.
In data-specific function, it only capable to constrict data alike to what they have been educated on. Like if we use MPEG-2 Audio Layer III (MP3) compression algorithm, which merely be compressed sound in broad-spectrum, although not concerning the exact type of sounds. Similarly, if we trained our model on images of faces autoencoder generate poor squeezing images of plants, for the reason that the facial appearance it would learn about the face dataset.
As compared to the original image inputs, the decompressed outputs will be degraded because of autoencoders are lossy similar to JPEG and MP3 compression. This differs from lossless arithmetic compression.
Third useful property of autoencoders that it learned automatically from data examples. New engineering it doesn't require, the algorithm is simple to edify dedicated occurrences that give excellent results on a particular style of input.
Building block of autoencoder is depended on three major components that are an encoding, decoding and loss function which compares with reconstructed (decompressed) and compressed images. Stochastic Gradient Descent function can optimize in order to minimize reconstructed loss. Parametric functions of neural network will be chosen for encoder and decoder and to be distinguishable with regard to distance function [10].
We use more filters per layer as compared to the previous convolutional autoencoder which is slightly different model for reconstructed images to improve quality.

2. Literature Review

Image denoising is building block for neural network. Its extended standard addition of autoencoder was introduced by Vincent et al [7] to learn reconstruction of input given its noisy version. Work shows denoising autoencoder uses stacked approach by feeding the output of one neural network which becomes input for another network[8]
X. Jiang et al [1] proposed variant of auto encoder to pre-train deep neural network as basic block in comparison with sparse autoencoder with KL Divergence. The employed requires some constraints and the light level of concealed units.

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L. Gondara [3] proposed a technique for finding an optimal architecture for small sample denoising. This work investigated various architectures of images which were similar and have high resolution. He employed various image denoising technique with median filters and SVD(Singular value decomposition)for image preprocessing and previously using DAE and CNN(Convolutional Neural Network), for improving and boosting the performance of denoising to increasing the training sample size and combine by means of additional readily accessible pictures from data-sets such as ImageNet.
Jain et al. [4] projected work on pictures denoising by utilizing convolutional neural systems. It experimented that by utilizing a little example of preparing pictures, execution at standard or superior to state-of-the-workmanship in view of wavelets and Markov arbitrary view can be accomplished.
Xie et al. [5] utilized stacked meager autoencoders for picture denoising and in work of art; it carried out at standard with KSVD. Agostinelli et al. [6] explored different avenues regarding versatile multi-section profound neural systems for picture denoising, constructed utilizing mix of stacked scanty autoencoders. This framework was appeared to be hearty for various commotion composes.
C. Xing at el [2] proposed work DL technique is subjugated for attribute removal of hyper-spectral data, Training a deep network for classification and feature extraction in include supervised fine-tuning and unsupervised pre-training, the employed work produces good discriminability for classification task and SDAE (Stacked Denoise Autoencoder) to pre-train model, in network first layer logistic regression method is used exploited to perform classification and supervised fine-tuning, separation competency might improve with sparsity features and used (Relu) exploited corrected linear unit as foundation function in SDAE to remove high level and sparse attributes. The outcome by means of ROSIS hyper spectral data, Hyper ion, AVIRIS, and established that the SDAE pre-training in aggregation by means of the LR enhancement and categorization (SDAE LR) can get higher accuracies than the famous SVM(Support Vector Machine) classifier.

3. Research Methodology

The dataset used in this paper comprises of 60000 color pictures in 10 modules with 6000 picture per module. Here are 50000 homework pictures or images and 10000 experiment pictures/ images [9]. The dataset is separated into five training bunches and one test group, each with 10000 pictures. The test bunch encloses precisely 1000 arbitrarily chose pictures from each class. The preparation clusters enclose the rest of the pictures in irregular request, yet some preparation groups may contain a bigger number of pictures from one module to another module. Among them, the preparation groups enclose precisely 5000 pictures from each class [9].
Distribution of Gaussian noise over the signal is equally distributed. It indicates that every pixel in the noisy picture is the amount of the true pixel cost and a random Gaussian distributed noise cost. Bell shape probability distribution function used in Gaussian noise as named indicates, anywhere z corresponds to the grey level, μ denotes mean or average of the function and σ indicates standard deviation of the noise.
The probability density function of a Gaussian random variables is given by:

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{1}$$

We add Gaussian noise matrix on both training and testing with noise factor 0.2 and clip images between 0 and 1.

```
noise_fact_val = 0.2

x_train_noise = x_train1 + noise_fact_val *
np.random.normal (loc=0.0, scale=1.0,
size=x_train1.shape)
x_test_noise = x_test1 + noise_fact_val *
np.random.normal (locx=0.0, scale=1.0,
size=x_test1.shape)

x_train_noise = np.clip (x_train_noise, 0., 1.)
x_test_noise = np.clip (x_test_noise, 0., 1.)
```

We use CCN (convolutional neural networks) model for encoders and decoders because of images dataset.
To plot our results we use Matlab plot to visualize data and for better training 100 epochs areused in our model.
Hyper parameters: Each 2D layer in the convolution neural network by means of the dimension of image is 32x32. The relu activation function is used as parameters as set to their default values with padding same. The network is trained with relu activation function with a batch size of 128. The dense layer has relu activation for categorical cross entropy classification.
Instead adding noise on single image, we apply on whole dataset that each row representing an image was corrupted. Simple convolutional denoising autoencoder architecture used for modeling on corrupted dataset as highlighted in Fig 1

4. Results and Discussion

After applying Gaussian noise with noise factor value 0.2 on dataset our results show images are blur as in fig. 3. Images in both training as well as test datasets have been clipped between 0 and 1.

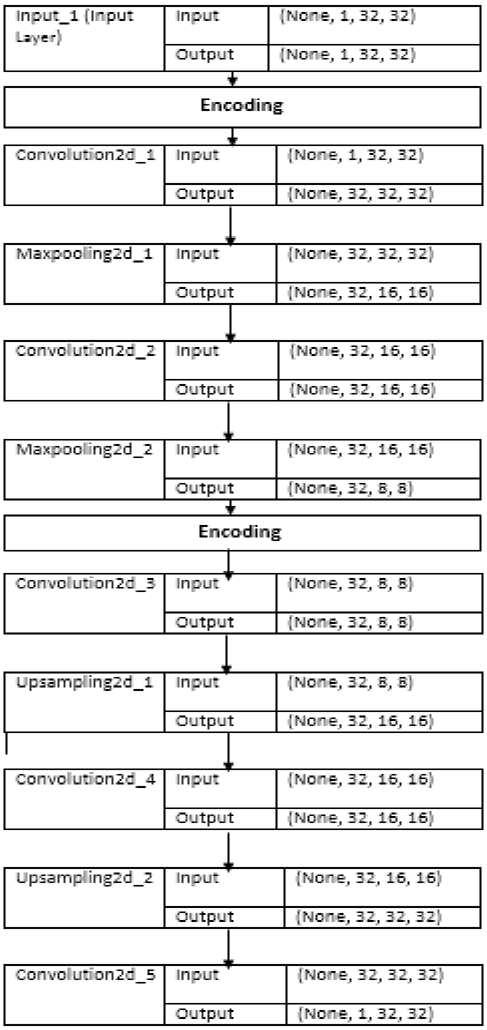

Fig. 2 Architecture for Convolutional Denoising Autoencode

Though the 2D Autoencoder Neural Network has been trained on all the 10 classes provided in the actual dataset, as an example, only 5 are shown in fig. 3.

Fig. 3 Top to Bottom: Original Images, Noisy Images

The results show in fig. 4 are described as following:

o The losses in training have been reduced to 51.6395% after 100 epochs achieved in 15 minutes on Google Colab GPU.

o The validation results also show losses of about 52%.

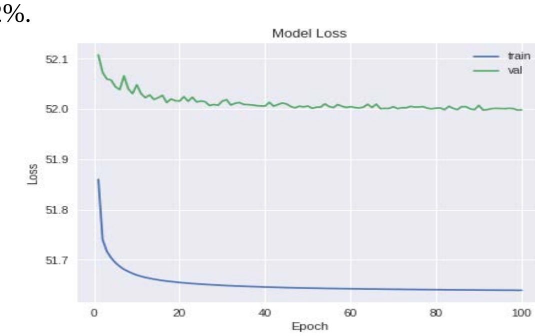

Fig. 4 Training losses in blue. Validation losses in green.

Beloe Fig.5. shows performance of the autoencoder by comparing Original, Noisy, and De-noisy images.

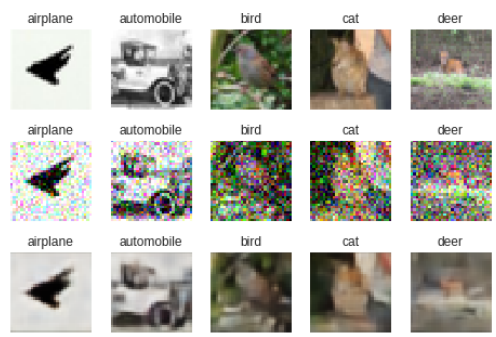

Fig. 5 Top to Bottom: Original Images, Noisy Images, De-noised Images

5. Conclusion

This paper attempted to perform De-noisy Autoencoder on a RGB dataset containing 10 classes each consisting 6000 images of dimensions 32x32. In order to conduct the experiment, Gaussian noise of 0.2 factor is added to distort all the images in the dataset. The autoencoder algorithm was applied to eliminate the Gaussian noise from the pictures.

The results show approximately 52% losses after applying the autoencoder algorithm possibly due to the pre-existing conditions such as image quality, image size, segmentation

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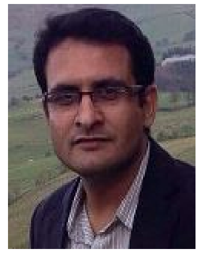

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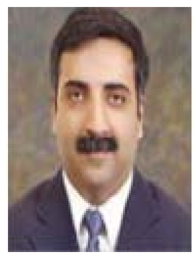

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