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Efficient Image Enhancement with Auto-encoder using Tensor flow

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Abstract :
The shaping of image information requires a unique technique in the neural community world. The well known neural network for shaping feature data is the convolutional neural network (CNN) or referred to as convolutional autoencoder. Autoencoder have extensively applied in dimension reduction an photo noise discount an this challenge noise reduction on photos using the fashion – mnist data set is executed. Convolutional autoencoders are used to eliminate the noise of the noisy style – minst pics. The model was then checked for the schooling loss and the validation loss. Image Super Resolution refers to the task of enhancing the resolution of an image from low-resolution (LR) to high (HR). The paper also considers the existing super-resolution algorithms based on convolutional neural networks and deep learning models. Most of the existing super-resolution methods trained only by simulated datasets are difficult to achieve good performance in real-world scenes. Besides, it is difficult to obtain well-aligned real-world image pairs between high-resolution and low-resolution spaces for training. An additional convolutional neural network was used to learn the mapping between the two latent spaces. The paper also considers the existing super-resolution algorithms based on convolutional neural networks and deep learning models.

Keywords : *Deep-Learning, Machine-Learning, Tensor Flow, Autoencoder, Convolutional Neural Network, Keras.*

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I. Introduction:

In the recent years, unsupervised feature learning with deep architecture an autoencoders has been widely studied and applied. Image restoration technique's primary goal is to recover the original image from a damaged observation. Deep learning is subset of machine learning. It is entirely based on artificial neural networks. The auto encoder is neural network based algorithm that conducts unsupervised machine learning. Image denoising method based on deep learning are effective nowadays. Several deep learning architecture implementations used convolutions and autoencoders for image synthesis and feature modifications. Modelling image data requires a unique methodology in order to mimic the human brain. The convolutional neural system is used to model image data convolutional networks also known as CNN or Conv-Net autoencoder. the network architecture for auto encoders can vary between a simple feed forward network, LSTM network or convolutional neural network.

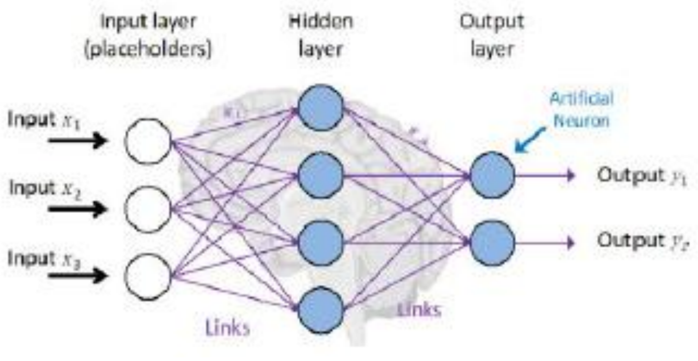


Figure 1. Basic Neural Network

II. Related work:

Jai Sehgal1], Dr Yojna Arora2 [1] The shaping of image data requires a special approach in the neural network world. The well known neural network for shaping image data is the Convolutional Neural Network (CNN) or called Convolutional Autoencoder. Autoencoders have widely applied in dimension reduction and image noise reduction. In this project, Noise Reduction on images using the fashion-mnist dataset is performed. Convolutional Autoencoders are used to remove the noise of the noisy fashion-mnist images. The model was then checked for the training loss and the validation loss.

J. Kim, S. Song[2] A typical sonar image has a plenty of random noise compared to an optical image. Due to poor picture quality, there is a large restriction on recognizing any object. Pattern recognition is exceedingly difficult not only in computer image processing but even in human eyes. Numerous researchers have attempted to apply various types of average filters to sonar images, and have also removed noise by using multiple images in succession. However, each of the algorithms has a limitation in that the resolution of the image itself is degraded or the image of the object is difficult to remove noise. Finally, We performed sonar image noise reduction with the auto-encoder algorithm based on convolutional neural network, which as recently been attracting attention. With the algorithm, we obtained sonar images of superior quality with only a single continuous image. We simply learned a ton of sonar images in a neural network of auto-encoder structures, and then we could get the results by injecting the original sonar images. We verified the results of image enhancement using the acoustic lens based multibeam sonar images.

III. Methodology:

An autoencoder is a neural network architecture capable of discovering structure within data in order to develop a compressed representation of the input. It is commonly used for feature selection and extraction. Many different variants of the general autoencoder architecture exist with the goal of ensuring that the compressed representation represents meaningful attributes of the original data input; typically the biggest challenge when working with autoencoders is getting your model to actually learn a meaningful and generalizable latent space representation. When the nodes in hidden layer increases than nodes in input layer then the output equals the input marking the autoencoder useless. This problem can be solved by randomly turning some of the input values to 0. Other sources suggest a lower count, such as 30%. It depends on the amount of data and input nodes available.

3.1 Components of model:

1. Encoder: Autoencoder is type of artificial neural network used to learn efficient codings of unlabelled data (unsupervised learning). The encoding is validated and defined by attempting regenerate the input from the encoding,
2. Bottleneck: The bottlenecked in a neural network is just a layer with fewer neurons than the layer below or above it. Having such a layer encourages the network to compress feature representation (of salient features for the target variables) to based fit in the available space.
3. Decoder: In which the model learns how to reconstruct the data from the encoded representation to be as close to the original input as possible.
4. Reconstruction Loss: This is the method that measures how well the decoder is performing and how close the output is to the original input.

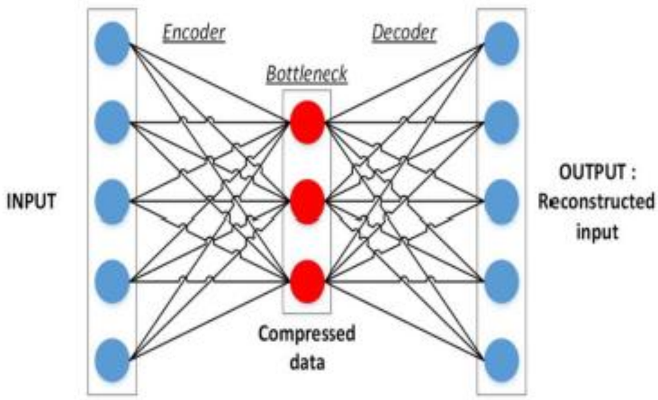
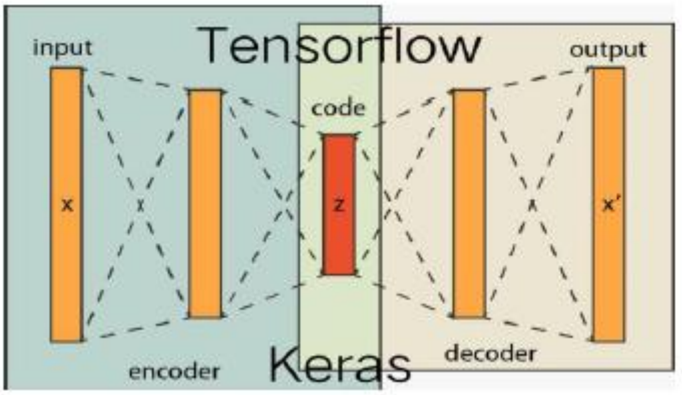


Figure 2. Schematic diagram of Noise Reduction

3.2 Tensor Flow

Tensor Flow is a software library or framework, designed by the Google team to implement machine learning and deep learning concepts in the easiest manner. It combines the computational algebra of optimization techniques for easy calculation of many mathematical expressions.



3.3 Implementation

Import the libraries and helper functions. we are using the popular MNIST data-set. This data-set has 60,000 examples of images of handwritten digits in the training set and 10,000 examples in the test set. The examples are black and white images of 28x28. As in, 28 rows and 28 columns for each example. The labels are simply digits corresponding to the 10 classes from 0 to 9.When we synthesize noise on already clean images, we can train an Auto-encoder to focus on the important parts of the images and then when it's applied to real world noisy data, it knows where to focus and which features to retain.

We will create a classifier and train it to classify handwritten digit images. We will use a very straight-forward neural network with two hidden layers. These are fully connected or dense layers with 256 nodes each in both the layers. The output layer has 10 nodes for the 10 classes and of course, a softmax function to get the probability scores for various classes.

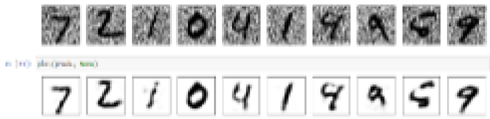
One tricky part here could be that we need to use sparse categorical cross-entropy loss instead of the categorical cross-entropy loss that we would have used if the labels were one-hot encoded. But since the labels are numerical values from 0 to 9 for the 10 classes in a single list with one value for each label, we would need to use the sparse categorical cross-entropy**.**

IV. Result

In order to reduce noise in our data, we want to create a model - the Auto-encoder - which takes a noisy example as input and the original, corresponding example as the label. Now, if one or more hidden layers in this neural network has a lot less nodes as compared to the input and output, then the training process will force the network to learn a function similar to principal component analysis, essentially reducing dimensionality. Another thing to note is that the output layer has the **sigmoid** activation. The higher linear values of the last layer will become closer to the maximum normalized pixel value of 1 and the low linear values will converge towards the minimum normalized pixel value 0. This choice of activation makes sense given the examples in the input are black and white images. There's some scope for having a variety of pixel values but with **sigmoid** most of the values will converge to either 0 or 1 and that works well for us.

Adding noise

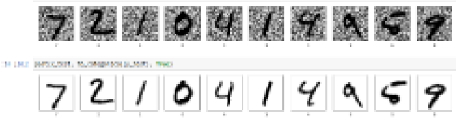
We will use the noisy training set examples as our examples and the original training set examples, the ones without any noise, will be used as our labels for the Auto-encoder to learn de-noising.



Denoised Images

Denoised Images

Now that the Auto-encoder is trained, let's put it to use. In order to get our de-noised images, say for our test data, all we have to do is pass the noisy data through the Auto-encoder! Let's use the predict method on our model to get the results.

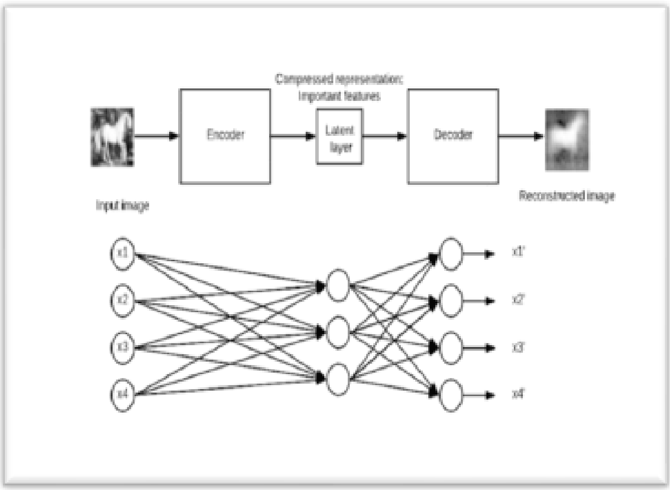


Composite Model

Composite Model

Let's create a composite model to complete our entire prediction pipeline. we want a model in which we can simply feed a noisy image, and the model will first reduce noise in that image and then use this output image and run it through the Classifier to get the class prediction. Idea being that even if our incoming data in a production setting is noisy, our classifier should be able to work well because of the noise reduction from the Auto-encoder.

Flowchart:



V. Conclusion

The described model is based on a CNN that encodes an image into a compact representation, followed by the decoded image to remove the noise from the image. It worked quite well when tested on several images. The image generated after the process was quite accurate. But the source of input image also played an important role in feature extraction and hence the removal of noise. Certain images are not well recognized and it is found that there is, still some scope of improvement. There are certain points which can be incorporated into this model to make it even better like larger dataset.

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