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Denoising Dirty Document using Autoencoder

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Abstract -An autoencoder is an unsupervised machine learning algorithm [12] that applies back propagation, setting the target values to be equal to the inputs. Deep autoencoders are used to reduce the size of our inputs into a minor representation. If anyone needs the original data, they can reconstruct it from the compressed data.The input seen by the autoencoder is not the raw input but a stochastically corrupted version. A denoising autoencoder is thus trained to reconstruct the original document from the noisy version.In the implementation of Deep autoencoders we have trained the algorithm with noisy and cleaned document images; we generated a model which helps us in removing noise or unnecessary interruption from the documents. Document denoising can be achieved with the deep learning model which automatically learns the discriminative features necessary for classification of input images.

Keywords—document denoising,deep autoencoder,supervised learning, deep learning ,classification,cleaned and noisy images

I. INTRODUCTION

Autoencoder can be broken in to three parts encoder, decoder, latent space, encoder of the network compresses or down samples the input into a fewer number of bits. When the decoder is able to reconstruct the input exactly as it was fed to the encoder, you can say that the encoder is able to produce the best encodings for the input with which the decoder is able to reconstruct well!

MOTIVATION

Many of the recent deep learning models rely on extracting complex features from data. The goal is to transform the input from its raw format, to another representation calculated by the neural network.

This representation contains features that describe hidden unique characteristics about the input.

There are variety of autoencoders, such as the convolutional autoencoder [13], denoising autoencoder, variational autoencoder and sparse autoencoder.The goal of image restoration techniques [1] is to restore the original image from a noisy observation of it and generates the output by removing any noise or unnecessary interruption.

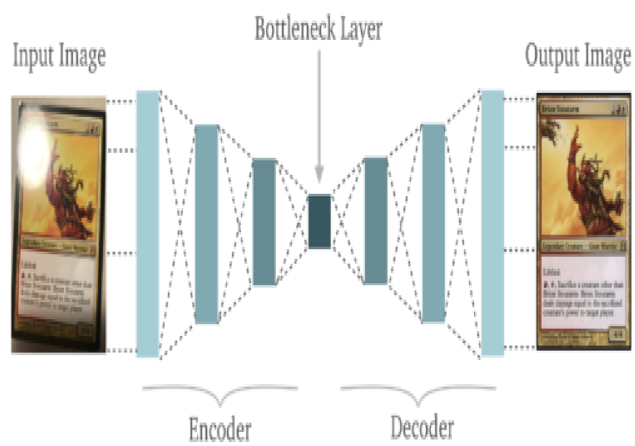


Fig: 1 Feature variation

Dimensionality reduction can be achieved using deep autoencoders,the reconstructed image is the same as our input but with reduced dimensions. It helps in providing the similar image with a reduced pixel value.

Fig: 2 Dimensionality Reduction

Document Denoising is the most prominent and effective technique. The common ideas of these approaches is to transfer image signals to an alternative domain where they can be more easily separated from the noise [2, 3]. In this paper, we use Autoencoder [4] to achieve image denoising.

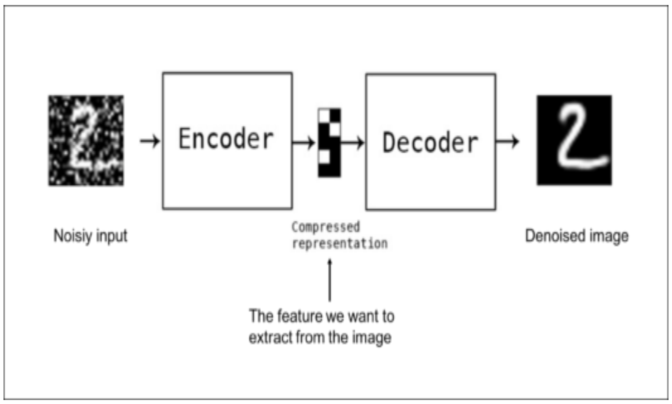


Fig: 3 Denoising Image

Watermark removal. It is also used for removing watermarks from images or to remove any object while filming a video or a movie.

Fig: 4 Watermark Removals

Architecture of Autoencoders [9]

With the prosper development of neural networks, image denoising by neural networks [5] has been a hot topic, an autoencoder consist of three layers:

1. Encoder 2.Code 3.Decoder

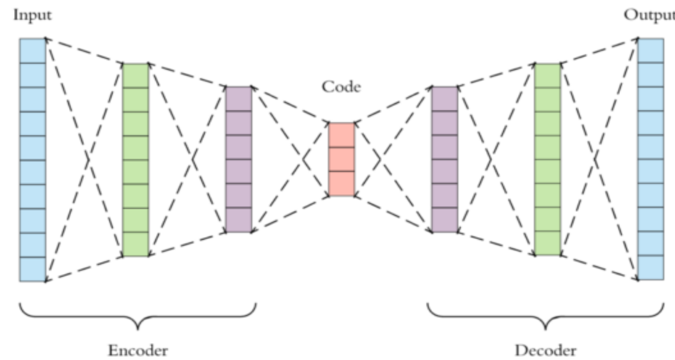


Fig: 5 Architecture of Autoencoders

ENCODER: This part of the network compresses the input into a latent space representation. The encoder layer encodes the input image as a compressed representation in a reduced dimension. The compressed image is the distorted version of the original image.

CODE: This part of the network represents the compressed input which is fed to the decoder.

DECODER: This layer decodes the encoded image back to the original dimension. The decoded image is a lossy reconstruction of the original image and it is reconstructed from the latent space representation.

II. RELATED WORK

The layer between the encoder and decoder, i.e., the code is also known as Bottleneck. This is a well-designed approach to decide which aspects of observed data are relevant information and what aspects can be discarded. It does this by balancing two criteria. Compactness of representation, measured as the compressibility. It retains some behaviourally relevant variables from the input.

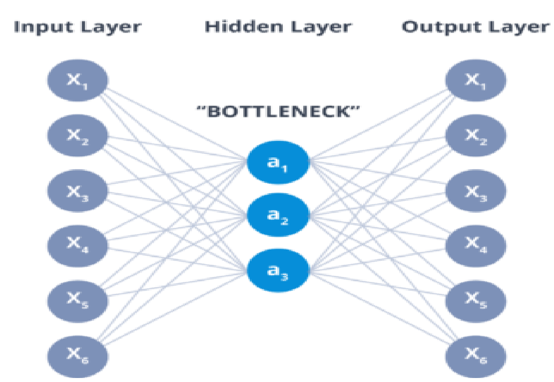


Fig: 6 Layer between the encoder and decoder

$$Y_i = g(f(x_i)) \approx x_i$$

The image shows how a denoising autoencoder may be used to generate correct input from corrupted input. Handwritten digit images are commonly used in optical character recognition and machine learning research [6][7]

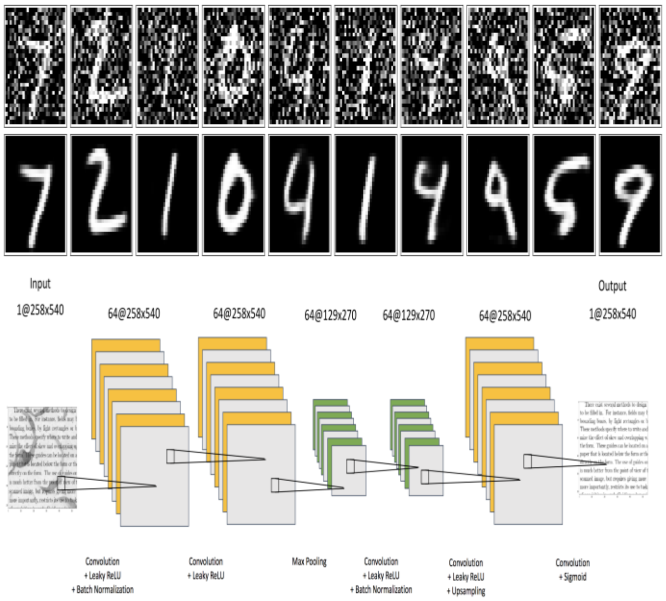


Fig: 7 Algorithm of Denoising autoencoder

As I've mentioned before, autoencoders like the ones we have built so far aren't too useful in practive. However, they can be used to denoise images quite successfully just by training the network on noisy images. We can create the noisy images ourselves by adding Gaussian noise to the training images [8], then clipping the values to be between 0 and 1. We'll use noisy images as input and the original, clean images as targets. Here's an example of the noisy images I generated and the denoised images.

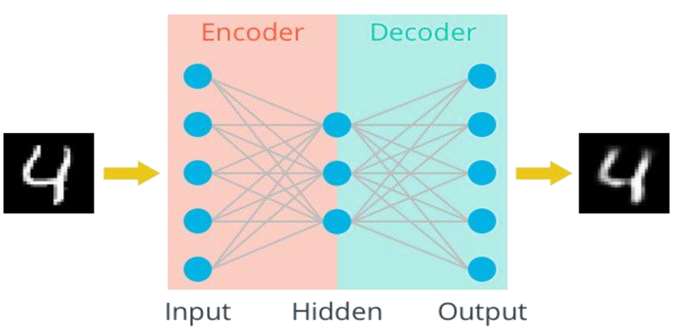


Fig: 8 Simple autoencoder

III.RESULTS AND DISCUSSION

We use keras API [11] which uses tensorflow as backend we loaded the following libraries using keras.layers we load Input[9], Dense, Conv2D, Maxpooling2D[15], and UpSampling2D from keras.models we import Model[10]

We load the following dataset which are having noisy and cleaned images we divide the dataset in to two parts train_fpath and train_cleaned_fpath with these we generate a model using autoencoder.

1. Steps for loading dirty document dataset

```
train_fpath = "../input/denoising/denoising-dirty-documents/train/train/"
train_cleaned_fpath = "../input/denoising/denoising-dirty-documents/train_cleaned/train_cleaned/"
test_fpath = "../input/denoising/denoising-dirty-documents/test/test/"

print (os.listdir (train_fpath))
```

2.Data exploration

Dataset consisting of three directories out of which two are train and one is test directory

```
print ("No. of files in train folder = ",len(os.listdir
       (train_fpath)))
print ("\n No. of files in train_cleaned folder = ",
       len(os.listdir(train_cleaned_fpath)))
print ("\n No. of files in test folder = ",len(os.listdir
       (test_fpath)))
```

```
['27.png', '126.png', '35.png', '117.png', '203.png', '98.png', '167.png', '69.png',
'83.png', '119.png', '141.png', '156.png', '87.png', '56.png', '162.png', '18.png', '1
7.png', '113.png', '72.png', '176.png', '39.png', '9.png', '47.png', '152.png', '66.pn
g', '92.png', '144.png', '189.png', '45.png', '6.png', '143.png', '174.png', '29.png',
'53.png', '188.png', '77.png', '54.png', '60.png', '159.png', '93.png', '89.png', '20
7.png', '170.png', '11.png', '5.png', '132.png', '84.png', '68.png', '111.png', '125.p
ng', '185.png', '90.png', '122.png', '146.png', '95.png', '215.png', '200.png', '171.p
ng', '62.png', '213.png', '42.png', '78.png', '191.png', '96.png', '105.png', '149.pn
g', '164.png', '20.png', '138.png', '194.png', '86.png', '107.png', '110.png', '120.pn
g', '30.png', '74.png', '81.png', '206.png', '197.png', '23.png', '173.png', '99.png',
'150.png', '32.png', '131.png', '137.png', '129.png', '153.png', '177.png', '180.png',
'212.png', '14.png', '48.png', '198.png', '161.png', '26.png', '101.png', '75.png', '2
1.png', '140.png', '44.png', '192.png', '63.png', '116.png', '135.png', '102.png', '11
4.png', '24.png', '182.png', '179.png', '155.png', '128.png', '50.png', '209.png', '3
6.png', '134.png', '8.png', '65.png', '3.png', '57.png', '186.png', '183.png', '104.pn
g', '216.png', '201.png', '2.png', '123.png', '147.png', '41.png', '15.png', '158.pn
g', '51.png', '12.png', '71.png', '59.png', '168.png', '80.png', '108.png', '195.png',
'38.png', '165.png', '204.png', '33.png', '210.png']
```

```
No. of files in train folder =  144

No. of files in train_cleaned folder =  144

No. of files in test folder =  72
```

3. Load noisy images

```
def load_images(fpath):
    images = [ ]
    for image in os.listdir(fpath):
        #print(fpath+image)
        if image!='train' and image!='train_cleaned'
                                        and image!='test':
            img = cv2.imread(fpath+image)
            img = cv2.cvtColor(img, cv2.COLOR_BG
                    R2RGB)

            img_array = Image.fromarray(img, "RGB")

            resized_img = img_array.resize((252,252))

            images.append(np.array(resized_img))
    return images
train_images = load_images(train_fpath)
train_images = np.array(train_images)
print("No. of images loaded = ",len(train_images),"\nShape
of the images loaded = ",train_images[0].shape)
```

```
No. of images loaded =  144
Shape of the images loaded =  (252, 252, 3)
```

4.Load clean images

```
train_cleaned_images = load_images
                        (train_cleaned_fpath)
train_cleaned_images = np.array
                        (train_cleaned_images)
print("No. of images loaded = ",
                len(train_cleaned_images),"\n
Shape of the images loaded = ",
                train_cleaned_images[0].shape)
```

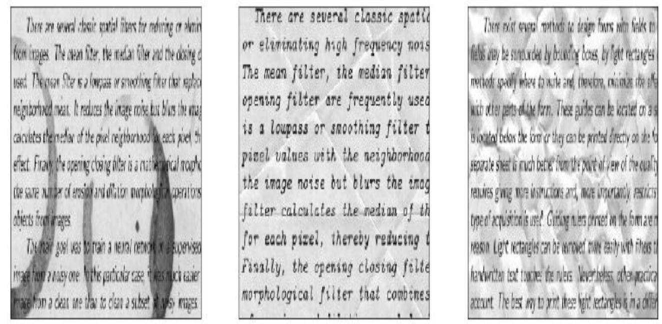
```
No. of images loaded =  144
Shape of the images loaded =  (252, 252, 3)
```

5. Load noisy test images

```
test_images = load_images(test_fpath)
test_images = np.array(test_images)
print("No. of images loaded = ",len(test_images),"
\nShape of the images loaded = ",test_images[0].
shape)
```

```
No. of images loaded =  72
Shape of the images loaded =  (252, 252, 3)
```

```
Displaying noisy training images
```



6. Data normalization [16]

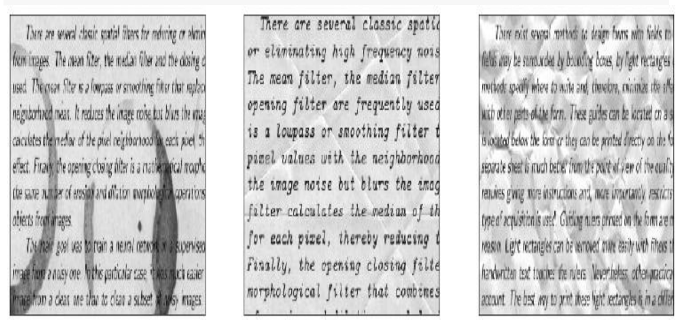
```
train_images = train_images.astype (np.float32)
train_cleaned_images = train_cleaned_images.astype
(np.float32)
test_images = test_images.astype(np.float32)

train_images = train_images/255
train_cleaned_images = train_cleaned_images/255
test_images = test_images/255
print(train_images[0].shape, train_cleaned_images[0].shape,
test_images[0].shape)
```

```
(252, 252, 3) (252, 252, 3) (252, 252, 3)
```

7. Displaying noisy training images after normalization

```
print("Displaying noisy training images
        after normalization")
display_images(train_images)
```



8. Define Deep autoencoder

You are provided two sets of images, train and test. These images contain various styles of text, to which synthetic noise has been added to simulate real-world, messy artifacts[20]. The training set includes the test without the noise (train_cleaned).

we create an algorithm to clean the images in the test set.

```
input_img = Input(shape=(252, 252, 3))

x = Conv2D(32, (3, 3), activation='relu',
        padding='same')(input_img) [14]
x  = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(32, (3, 3), activation='relu',
        padding='same')(x)
encoded = MaxPooling2D((2, 2), padding='same')
(x)
x = Conv2D(32, (3, 3), activation='relu',
padding='same') (encoded)
x = UpSampling2D((2, 2))(x)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = UpSampling2D((2, 2))(x)
decoded = Conv2D(3, (3, 3), activation='sigmoid',
padding='same') (x)

autoencoder = Model(input_img, decoded) [17]
autoencoder.compile(optimizer='sgd', [18] ,
loss='binary_crossentropy')
autoencoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 252, 252, 3)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 252, 252, 32)      896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 126, 126, 32)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 126, 126, 32)      9248
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 63, 63, 32)        9248
_________________________________________________________________
up_sampling2d_1 (UpSampling2 (None, 126, 126, 32)      0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 126, 126, 32)      9248
_________________________________________________________________
up_sampling2d_2 (UpSampling2 (None, 252, 252, 32)      0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 252, 252, 3)       867
=================================================================
Total params: 29,507
Trainable params: 29,507
Non-trainable params: 0
```

Now let's train autoencoder for 400 epochs:[19]

```
Epoch 1/400
144/144 [==============================] - 5s 31ms/step - loss: 0.6621
Epoch 2/400
144/144 [==============================] - 1s 4ms/step - loss: 0.5485
Epoch 3/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3896
Epoch 4/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3584
Epoch 5/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3623
Epoch 6/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3714
Epoch 7/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3712
Epoch 8/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3704
Epoch 9/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3671
Epoch 10/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3676
Epoch 11/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3659
Epoch 12/400
144/144 [==============================] - 1s 4ms/step - loss: 0.3613
```

autoencoder.fit(train_images, train_cleaned_images,epochs=400, batch_size=100, shuffle=True)

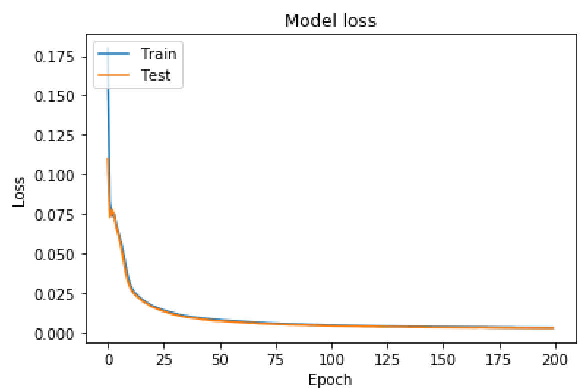


Fig : 9 Model loss

IV.CONCLUSION

The main purpose of this paper is to implement autoencoder for denoising dirty document to generate reconstructed image from the latent space,After 400 epochs, the autoencoder seems to reach a stable train/test loss value of about 0.2065. We can try to visualize the reconstructed inputs and the encoded representations[21]. We will use Matplotlib to display clean images predicted by the autoencoder for the given test images.

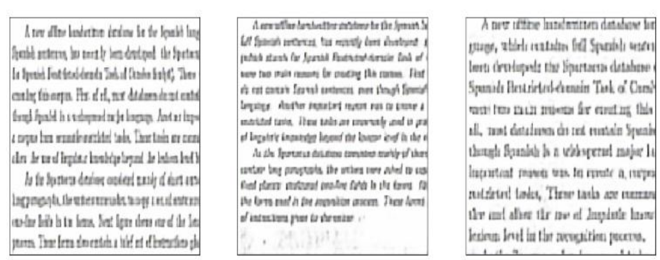


Fig:10 clean image after using auto encoder

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